The Impact of IFRS on the Predictive Ability and Value Relevance of Fundamental Signals and Analysts' Efficiency in using these Signals

by

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ABSTRACT

The adoption of International Financial Reporting Standards (IFRS) represents a milestone in the international accounting environment that has had a significant impact on financial reporting. However, apart from earnings very little is known about IFRS impact on the quality of fundamental accounting information known to be useful in decision-making. Therefore, users of fundamental information (signals) may not be fully aware of the quality of information embedded in these signals after adoption of IFRS. This could affect the efficiency of using this information and hence decision-making based on these fundamental signals. Although analysts are major users of financial statement fundamentals, their efficiency in this use is researched rarely, with no studies using non-United States (US) data from years' post-2000. This study investigates the impact of IFRS on the predictive ability and value relevance of earnings and non-earnings fundamental signals and analysts' efficiency in using these signals. In doing so it makes a significant contribution to our understanding and to the literature.

The sample is selected from 11 European countries and Australia based on the difference between pre-IFRS generally accepted accounting principles (GAAP) and IFRS, plus country-level investor protection. Countries are further partitioned into code and common law observations for analyses. Data are collected from 2001 to 2012 inclusive for all listed, non-financial companies available as at fiscal end 2012 using the Bloomberg and Eikon databases.

One earnings signal and 12 non-earnings signals, claimed by financial analysts to be useful in predicting earnings and valuation of shares, are employed as explanatory variables. These variables are constructed to provide signals about future earnings and contemporaneous excess returns. Statistical techniques employed include multiple regression, test of equality of coefficients based on stacked regression, and interaction terms with IFRS for each signal. Models are based on Lev and Thiagarajan (1993) and Abarbanell and Bushee (1997).

The predictive ability and value relevance of fundamental signals, along with analysts' efficiency in using these non-earnings signals, together with IFRS impact, is examined for individual fundamental signals, signals in combination (non-earnings) and in

aggregate form (F_Score). In addition, analyses are conducted for both pooled and sub-samples such as code and common law countries, and winning and losing stock observations, thereby providing robust evidence by allowing comparison of results. Decision usefulness theory as embodied in the International Accounting Standards Board's (IASB) *Conceptual Framework for Financial Reporting* (2010), together with signalling theory, institutional theory and agency theory, are the theoretical perspectives adopted in this study.

The findings show that earnings and non-earnings signals individually, in combination and in aggregated form (F_Score) are significant in predicting one-year ahead change in earnings per share and are value relevant for contemporaneous excess returns. The predictive ability of earnings increased after adoption of IFRS, particularly for code law countries, while it decreased for non-earnings signals. The impact of IFRS on value relevance is negative for earnings and positive for non-earnings signals, especially for common law countries.

Findings for analysts' efficiency reveal that analysts are aware of fundamental signals useful in predicting change in earnings per share. However, they are inefficient in using the information content embedded in fundamental signals and this reflects in their underreaction or overreaction to certain signals. Analysts are highly inefficient in selecting and using fundamental signals when forecasting losing compared to winning stocks. Generally, they underreact to non-earnings signals when forecasting losers and overreact when forecasting winners. Further, analysts substantially underutilise earnings signals for common compared to code law countries. Analysts are comparatively efficient in selecting appropriate fundamental signals post IFRS, but their efficiency in using the earnings signal decreased, with a higher decrease when forecasting losers. However, efficiency increased for the non-earnings signals for all sub-samples except for losing stocks in the post- compared to pre-IFRS period.

The findings support several theories adopted in the study. Moreover, the findings have high practical application for market participants, particularly for investors, but are likely to be of interest also to financial statement preparers, policy makers, standard setters and those in countries considering IFRS adoption.

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DECLARATION

I hereby certify that,

This thesis does not contain material which has been accepted for the award to the candidate of any other degree or diploma, except where due reference is made in the text of the examinable outcome;

To the best of my knowledge, this thesis contains no material previously published or written by another person except where due reference is made in the text of the examinable outcome.

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TABLE OF ACRONYMS

AAA	American Accounting Association
AICPA	American Institute of Certified Public Accountants
ASOBAT	A statement of basic accounting theory
ASX	Australian Securities Exchange
CEO	Chief executive officer
CFO	Chief financial officer
CMBAR	Capital market based accounting research
ERC	Earnings response coefficient
EU	European Union
FASB	Financial Accounting Standards Board
GAAP	Generally accepted accounting principles
GDP	Gross domestic product
GFC	Global financial crisis
GICS	Global industry classification standard
GNP	Gross national product
IAS	International Accounting Standards
IASB	International Accounting Standards Board
ICAEW	Institute of Chartered Accountants in England and Wales
IFRS	International Financial Reporting Standards
INF	Level of inflation rate
LIFO	Last in first out
OLS	Ordinary least squares
PAT	Positive accounting theory
PYEN	Prior year earnings news
UK	United Kingdom
US	United States

TABLE OF VARIABLES AND MEASURES

Variable	Measurement
Dependent Variables	
Change in One-year-ahead earnings per share (CEPS1)	CEPS1 = $[EPS_{t+1} - EPS_t] \div P_{t-1}$ EPS_{t+1} – One year-ahead earnings per share (EPS) EPS_t – Current year EPS P_{t-1} – Share price at the end of the previous year
Contemporaneous excess (ER)	Difference between the firm's return (percentage) for the period begining11 months prior and ending one month after the earnings announcement date, and the benchmark index return (percentage) for the same period
Forecast change in one-year-ahead earnings per share (FCEPS1)	$[FEPS_{t+1} - EPS_t] \div P_{t-1}$ $FEPS_{t+1}$ - one year ahead EPS forecast EPS_t - Current year EPS
Forecast error (FE)	$[EPS_{t+1} - FEPS_{t+1}] \div P_{t-1}$ EPS_{t+1} - one year ahead EPS $FEPS_{t+1}$ - one year ahead EPS forecast

Independent Variables

Note: Δ represents the difference between the prior two-year average value for the variable and the current year value, deflated by the value for the average for the prior two years for the same variable. For example, for Accounts Receivable, this calculation would be $(AR_t - AR_{avg}) \div AR_{avg}$ where $AR_{avg} = (AR_{t-1} + AR_{t-2}) \div 2$.

Audit Qualification (AQ)	Coded 0 for an unqualified opinion and 1 otherwise. If there is an emphasis of matter paragraph and if it relates to going concern, 1 is assigned and 0 otherwise.
Accounts Receivable (AR)	Δ Accounts Receivable – Δ sales

Capital Expenditure (CAPX)	Δ Industry Capital Expenditure – Δ Firm Capital expenditure
Cash Flows (CF)	$(CFO_{t-1} - CFO_{\ t}) \div Total\ Assets_{\ t-1}$
Current year change in earnings per share (CHGEPS)	$[EPS_{t-1} - EPS_t] \div P_{t-1}$
Discretionary Accruals (CDACCR)	CDACCR = $DACCR_t - DACCR_{t-1}$ *DACCR_t* is measured using the Kothari, Leone, and Wasley (2005) performance matched discretionary accrual model.
Effective Tax Rate (ETR)	$ETR_{Avg} - ETR_t$ $where\ ETR = \frac{TaxExpenses_i}{EBT_i}$
Gross Margin (GM)	Δ Sales – Δ Gross Margin
Goodwill (GW)	$(Goodwill_t - Goodwill_{Avg}) \div Goodwill_{Avg}$
Inventory (INV)	Δ Inventory – Δ sales
Labour Force (LF)	$\left(\frac{Sales_{\ t-1}}{Employees_{\ t-1}} - \frac{Sales_t}{Employees_t}\right) \div \frac{Sales_{\ t-1}}{Employees_{\ t-1}}$
Leverage (LEV)	$\left[\frac{Total\ Debt_t}{Total\ Assets_t} - \frac{Total\ Debt_{Avg}}{Total\ Assets_{Avg}}\right]$
Selling & Administrative Expenses (SA)	Δ Selling & Administrative Expenses – Δ sales

Interaction Variables with IFRS

IFAQ	Interaction term of AQ with IFRS
IFAR	Interaction term of AR with IFRS
IFCDACR	Interaction term of CDACCR with IFRS
IFCF	Interaction term of CF with IFRS
IFCHEPS	Interaction term of CHGEPS with IFRS
IFETR	Interaction term of ETR with IFRS

IFGM	Interaction term of GM with IFRS
IFGW	Interaction term of GW with IFRS
IFINV	Interaction term of INV with IFRS
IFLEV	Interaction term of LEV with IFRS
IFLF	Interaction term of LF with IFRS
IFCAPX	Interaction term of CAPX with IFRS
IFSA	Interaction term of SA with IFRS

Aggregate Fundamental score

F_Score	Value of one (zero) for good (bad) signals and then values across the 12 non-earnings is summed
IFF_Score	Interaction term of F_Score with IFRS

CHAPTER 1: INTRODUCTION

1.1 Introduction

Financial statements are one of the key information sources for investors and financial analysts; the main capital market participants who make decisions about investments. Financial accounting numbers are expected to provide information that is relevant and hence useful to these groups and other stakeholders who use financial statements. Accounting information is relevant "if it has predictive value, confirmatory value or both" (IASB 2010 para. QC7). Therefore, the usefulness of financial information can be gauged by the predictive value of this information, which can be evaluated by examining the ability of this information to predict firm future performance. Concurrently, investors' buy, sell or hold reactions to financial statement and other information are reflected in listed companies' share prices. Accordingly, the relevance and hence usefulness of information in financial statements[1] can be evaluated also by examining the association between information included in the financial statements and share prices/returns; termed in the literature as value relevance.

Decision usefulness theory, adopted by accounting standard setters and others, posits the view that if accountants cannot prepare theoretically correct financial statements, then they should attempt to make financial statements as useful as possible (Scott 1997). Useful information is higher in quality, has less information asymmetry and provides quality signals for market participants, and hence facilitated increased efficiency in using the information. As such, the usefulness of financial information can be viewed also from the perspective of efficiency in using the information.

Two main research approaches have been followed in the literature to test for the value relevance of accounting information. One utilises an information perspective and the other a measurement perspective. According to Francis and Schipper (1999), examining the predictive ability of accounting information comes from the measurement perspective of value relevance research, and examining the association between accounting information and share price and/or returns falls under the information perspective of value relevance research. Providing evidence from both research perspectives, this study

[1] Financial statements are taken to include notes accompanying the statements and the auditor's report.

examines the ability of accounting information to predict future earnings and the value relevance of this information for contemporaneous excess returns.

The International Accounting Standards Board's (IASB) *Conceptual Framework for Financial Reporting* (2010) states that financial statements should provide useful information to stakeholders, such as investors, lenders and other creditors. Lev and Thiagarajan (1993), one of the key research studies relied on by this current study, finds several financial statement elements, or rather ratios made up of these elements, to be value relevant. Known as fundamental information or fundamental signals and long claimed by financial analysts to be useful in share valuation and earnings forecasts, Lev and Thiagarajan (1993) were amongst the first to test the value relevance of these fundamental signals. Other studies have since been published, but few use data from the 21st century and few use data emanating outside the United States (US). Given this, the study examines the usefulness of fundamental signals in terms of their predictive ability and value relevance and also analysts' efficiency in using this fundamental information for their earnings forecasts. More importantly, this study examines the impact of International Financial Reporting Standards (IFRS)[2] issued by the IASB on each of these aspects.

This chapter provides an overview of the thesis, giving emphasis to the background and motivation for this research, together with the broad Research Questions posed and more specific Research Objectives addressed. Accordingly, the chapter is organised as follows. section 1.2 explains the motivation for and significance of this study. Following that, section 1.3 presents the Research Objectives and Questions. section 1.4 gives a brief summary of the theoretical background of the study, and section 1.5 provides a brief explanation of the research design. Then, section 1.6 provides a brief overview of the overall findings and contributions from the research. Finally, section 1.7 outlines the structure of the thesis in what follows subsequent to this chapter.

[2] "International Financial Reporting Standards (IFRS Standards) represents a single set of accounting standards, developed and maintained by the International Accounting Standards Board (the Board) with the intention of those standards being capable of being applied on a globally consistent basis—by developed, emerging and developing economies—thus providing investors and other users of financial statements with the ability to compare the financial performance of publicly listed companies on a like-for-like basis with their international peers." See http://www.ifrs.org/about-us/pages/what-are-ifrs.aspx.

1.2 Motivation for and significance of the study

As explained, this study focuses on the usefulness of fundamental signals in terms of: (i) the predictive ability and value relevance of fundamental information (signals) included in financial statements; (ii) analysts' efficiency in using these signals; and (iii) the impact of IFRS on each of these.

1.2.1 Why study the usefulness of fundamental signals?

Numerous empirical studies seek to identify accounting elements that have predictive ability and are value relevant (e.g. Abarbanell & Bushee 1997; Ball & Brown 1968; Lev & Thiagarajan 1993; Ou & Penman 1989a, b; Stober 1993). The earnings[3] number (hereafter earnings) reported in companies' financial statements is one of the most well-researched fundamental signals found to be important in explaining future earnings and returns (e.g. Ahmed, Schneible & Stevens 2003; Dechow 1994; Francis et al. 2004; Kim & Kross 2005; Schipper & Vincent 2003). However, although useful, current earnings does not capture all variation in future earnings or contemporaneous stock returns/price. Additionally, some studies report that the usefulness of earnings in terms of value relevance has decreased over time (Amir & Lev 1996; Brown, Kin & Lys 1999; Collins, Maydew & Weiss 1997; Francis & Schipper 1999; Ryan & Zarowin 2003). These two observations suggest that research focusing on fundamental signals other than earnings (i.e. on non-earnings signals) remains important, a view supported by studies including Ou and Penman (1989a); Frankel and Lee (1998); Lev and Thiagarajan (1993); Abarbanell and Bushee (1997,1998); Al-Debie and Walker (1999); Ohlson and Penman (1992); Dowen (2001); Swanson, Rees and Juarez-Valdes (2003); Carnes (2006); El-Gazzar, Finn and Tang (2009) and Seng and Hancock (2012).

A review of the literature reveals that most studies of fundamental signals[4] that examine their predictive ability and value relevance were conducted using data from prior to year 2000 (Abarbanell & Bushee 1997; Al-Debie & Walker 1999; Dowen 2001; Lev & Thiagarajan 1993; Ou 1990; Ou & Penman 1989b; Seng & Hancock 2012; Swanson, Rees & Juarez-Valdes 2003). However, in years post-2000, several important changes have occurred in the accounting environment that affect the quality of accounting

[3] The term 'earnings' is used throughout this thesis as a singular noun.

[4] In this type of study, variables are specifically designed to be based on signals used commonly by analysts when forecasting future earnings and assessing stock returns.

information, such as adoption of IFRS in many countries around the world. Consequently, the usefulness of fundamental signals in terms of predictive ability and value relevance may have been affected, but this issue remains unexplored and, therefore, users are not well-informed about quality of this information. As such, given the importance of fundamental analysis and the paucity of this type of research in years post-2000, along with significant change in the accounting environment, it is timely to revisit this area of research to assess whether the fundamental signals examined previously remain useful for decision-making and also to test fundamental signals that have not been included in this type of study before. For this study, using post-2000 data, one earnings and 12 non-earnings fundamental[5] signals are tested for their ability to predict future earnings and their value relevance for contemporaneous excess returns.

1.2.2 Why study IFRS impact on the quality of fundamental signals?

Many countries around the world have adopted IFRS, representing one of the most significant changes in global accounting history (De George, Li & Shivakumar 2016). IFRS adoption has been found to have significant economic and social impact, such as on the cost of capital, the capital market (Daske et al. 2008; Li 2010), foreign direct investment (Gordon, Loeb & Zhu 2012), capital allocation decisions, investment efficiency (Chen, Young & Zhuang 2012; Florou & Pope 2012a, b) and promotion of international trade by narrowing cross country differences (De George, Li & Shivakumar 2016). More importantly IFRS adoption has been and continues to be encouraged largely because of expectations of significant, positive impact on the quality of financial reporting (De George, Li & Shivakumar 2016). Therefore, following IFRS adoption, many researchers have investigated the impact of IFRS on financial statements prepared in different countries around the world. In the main, these studies have found that IFRS adoption had a significant impact on many financial statement fundamentals in terms of recognition, measurement, classification and presentation (e.g. Blanchette, Racicot & Girard 2011; Bradbury & van Zijl 2005; Goodwin, Ahmed & Heaney 2008; Haverals 2007; Horton & Serafeim 2010; Iatridis 2010; Kabir, Laswad & Islam 2010; Stent, Bradbury & Hooks 2010; Tsalavoutas & Evans 2010). These findings suggest a change in the quality of this fundamental information.

[5] Of these 12, this study includes four non-earnings fundamental signals that have not been tested in a similar type of study before.

With this expected change in the quality of information, several studies have been conducted to investigate the impact of IFRS on different aspects of accounting information quality, such as the value relevance of earnings, earnings persistence, accruals quality, timeliness of loss recognition, earnings smoothness, earnings response coefficients (ERCs), and earnings management (e.g. Atwood et al. 2011; Barth et al. 2012; Barth, Landsman & Lang 2008; Callao, Jarne & Laínez 2007; Chalmers, Clinch & Godfrey 2011; Chen et al. 2010; Christensen et al. 2015; Devalle, Onali & Magarini 2010; Fiechter & Novotny-Farkas 2015; Jermakowicz, Prather-Kinsey & Wulf 2007). Most of these studies report a positive impact from IFRS adoption. However, these studies focus on various measures of earnings, whilst IFRS impact on the quality aspects of most non-earnings fundamental signals known to be useful in decision-making, has not been examined. Therefore, users of fundamental signals may not be fully aware of the quality of information embedded in these signals after adoption of IFRS. This could affect the efficiency of using this information and decision-making based on these fundamental signals. As such, this study examines IFRS impact on the predictive ability and value relevance of one earnings and 12 non-earnings fundamental signals, and thereby makes a significant contribution to the literature.

Compared with most countries' previous generally accepted accounting principles (GAAP), IFRS involves recognition and/or measurement of a higher number of balance sheet items at fair value and more precise recognition of intangible assets (Blanchette, Racicot & Girard 2011; Chalmers et al. 2012; Cheong, Kim & Zurbruegg 2010). These changes could be expected to render the information in financial statements timelier, more relevant and faithfully representative of real economic phenomena associated with the entity, compared with the prior situation. This in turn could be expected to enhance the predictive ability and value relevance of fundamental information reported in financial statements.

However, some contrary views have emerged in the literature. Opponents of IFRS argue that fair value accounting, a key change under IFRS, does not support efficient contracting, is less reliable and, unlike the more conservative accounting under countries' previous GAAPs, may not even have survival value (e.g. Boyer 2007; Kothari, Ramanna & Skinner 2009). In addition, fair value accounting assumes that active markets for assets and liabilities exist, when in fact they may not. Opponents claim also that fair value accounting leaves significant room for managerial discretion, allowing for manipulation while adding transitory revaluations which produce excessive earnings volatility (Ball 2006; Boyer 2007; Callao & Jarne 2010; Kothari, Ramanna & Skinner 2009; Wallison 2008). This leads ultimately to less persistence, lower predictability of earnings (Dichev & Tang 2009) and less value relevance compared with prior national GAAPs. Further, some empirical evidence provides that valuation under IFRS makes accounting numbers less useful in terms of debt contracts (Ball, Li & Shivakumar 2015) and also IFRS reporting involves higher income smoothing, greater earnings aggressiveness and more delayed loss recognition (Ahmed, Neel & Wang 2013).

These arguments for and against the benefits of IFRS raise questions about the impact of IFRS on the quality of accounting information. Therefore, this study investigates the impact of IFRS on accounting information quality in terms of predictive ability and value relevance. It does this in various contexts by partitioning the data (e.g. into code and common law countries, winning and losing stocks, extreme and non-extreme returns performers (only for value relevance), growth and value stocks (only for value relevance), thereby maximising the prospect of providing robust evidence.

1.2.3 Why study analysts' efficiency in using fundamental signals?

An important user group in terms of financial statement fundamentals comprises analysts, who use this information in making their earnings forecasts and valuing shares (Lev & Thiagarajan 1993). Of the 12 non-earnings signals selected for this study, eight come from the study by Lev and Thiagarajan (1993), who derive them from analysts' written pronouncements. The four additional fundamental signals included in this study also have been found to be useful for analysts for their forecasting (Dempsey et al. 1997). Despite analysts being one of the major groups making use of fundamental signals, analysts' efficiency in using these fundamental signals has been researched rarely.

There is no known published research that examines analysts' efficiency in using fundamental signals outside the US context using post-2000 data. Findings from the available research[6] document that analysts are inefficient in using fundamental information for their earnings forecasts. However as explained earlier, important changes

[6] Only three published research studies can be identified. They are Abarbanell and Bushee (1997), Swanson, Rees and Juarez-Valdes (2003) and Wahab, Teitel and Morzuch (2015).

have occurred in the accounting environment in the current century, such as IFRS adoption, that affect the quality of the accounting information environment, thereby likely affecting analysts' efficiency in using these signals for their earnings forecasts. Therefore, this study examines the efficiency with which analysts use fundamental signals in a context outside the US using data from years' post-2000.

Following adoption of IFRS, several studies have investigated the impact on analysts' information environment and forecast accuracy (Chalmers et al. 2012; Cheong, Kim & Zurbruegg 2010; Cotter, Tarca & Wee 2012; Preiato, Brown & Tarca 2013). Findings from this research point to the conclusion that IFRS adoption increased analysts' information environment and forecast accuracy. However, no published study examines IFRS impact on analysts' efficiency in using fundamental information. As such, this study fills that research gap by examining IFRS impact on analysts' efficiency in selecting and using one earnings signal and 12 non-earnings signals. It examines these signals individually and in combination (i.e. all non-earnings) and thereby makes a significant contribution to this area of research.

1.3 Research Objectives and Research Questions

The IASB *Conceptual Framework for Financial Reporting* (2010) states that "the objective of general purpose financial reporting is to provide financial information about the reporting entity that is useful to existing and potential investors, lenders and other creditors in making decisions about providing resources to the entity" (IASB 2010 para. OB.2). Therefore, the main objective of financial statements is to provide useful information for different stakeholders for their decision-making purpose(s) with regard to the company(ies) of interest. Many studies investigate the usefulness of earnings, but there has been much less focus on the usefulness of non-earnings items reported in financial statements, especially years post-2000. As explained, given the fact that significant changes in the accounting environment occurred after the year 2000 that affect the quality of financial reporting (both earnings and non-earnings items), it can be argued that the decision usefulness of financial reporting overall has not been researched adequately.

The decision usefulness of fundamental information is examined in this study from different perspectives, such as its predictive ability and value relevance, attributes of most importance to investors and financial analysts. Moreover, since the usefulness of fundamental signals can be assessed by focusing on their usage by different groups of users, this study examines also the usefulness of this information by linking it to analysts' efficiency in using these fundamental signals for their earnings forecasts. If the fundamental information conveys useful information for forecasting, analysts' efficiency in using this information should be increased. Therefore, this study assesses the usefulness of both earnings and non-earnings fundamental information from different perspectives.

In addition, given the importance of IFRS adoption by many countries around the world and its significant impact on financial reporting quality, along with the IASB's objective of encouraging adoption of IFRS, this study also examines IFRS impact on the decision usefulness of these fundamental signals for capital market participants. In order to achieve this task, the following three Research Objectives are developed.

1. To investigate the predictive ability of fundamental signals (fundamental information based on financial statements) in predicting one-year-ahead change in earnings per share and IFRS impact on this predictive ability.

2. To assess the value relevance of fundamental signals for stock returns (contemporaneous excess returns) and IFRS impact on this value relevance.

3. To assess the efficiency with which analysts use the selected fundamental signals that, if found as hypothesised, significantly predict one-year-ahead change in earnings per share and are value relevant, and also to assess IFRS impact on this analysts' efficiency.

By achieving these three Research Objectives, this study attempts to address the following Research Questions.

- What is the decision usefulness of earnings and non-earnings fundamental information reported in financial statements in years post-2000 for capital market participants?
- What is the IFRS impact on the decision usefulness of these fundamental signals?

These Research Questions are examined in different contextual settings, such as for code and common law countries, for winners and losers, extreme and non-extreme performers, growth and value stocks, companies with good and bad prior year earnings news, as well as under different macro-economic conditions, such as taking into account the level of inflation and level of growth in Gross Domestic Product (GDP).

1.4 Theoretical background of the study

The focus for the theoretical background of the study is the usefulness of financial information for decision-making by capital market participants. As such, the main theoretical support for the study comes from decision usefulness theory, which is also the basis for the IASB's *Conceptual Framework for Financial Reporting* (2010) (hereafter *Conceptual Framework*). Decision usefulness theory emerged largely as a result of the work of an American Accounting Association (AAA) committee appointed to develop A Statement of Basic Accounting Theory (ASOBAT) in 1966. The development of a conceptual framework in accounting also was inspired by the normative work of the American Institute of Certified Public Accountants (AICPA) and other scholars (e.g. Moonitz 1961; Sprouse & Moonitz 1962; Zeff 1972). According to decision usefulness theory, management is expected to provide useful financial statements. Accordingly, the most appropriate accounting standard / measurement should be the one that provides the most useful information to financial statement users. The IASB's *Conceptual Framework* states that the objective of financial statements is to provide useful information about the entity for capital contributors for their decision-making (IASB 2010 para OB2).

Users evaluate the usefulness of fundamental information in terms of relevance to their decision-making. "Financial information is relevant if it is capable of making a difference in the decisions made by users", "if it has predictive value, confirmatory value, or both" (IASB 2010 paras QC 6 & QC 7). Therefore, the usefulness of financial information can be assessed using its predictive ability. Furthermore, if the financial information is relevant for investors to make decisions about buying, holding or selling their shares, then the usefulness of this financial information can be gauged by assessing its value relevance in terms of share price and/or returns.

The *Conceptual Framework* states that: "comparability, verifiability, timeliness and understandability are the qualitative characteristics of financial information that enhance the usefulness of information that is relevant and faithfully represented" (IASB 2010 para QC 19). If those characteristics are embodied strongly in financial information, the information should be of higher quality and have higher predictive ability and value relevance, therefore enhancing the decision usefulness of the information. The IASB is pursuing adoption of IFRS around the world with an expectation of increasing the quality of financial reporting (De George, Li & Shivakumar 2016).

Another important theory that supports the usefulness of accounting information is signalling theory, which deals with the information asymmetry between two parties. In the absence of information asymmetry, the correct rather than incorrect or partially correct signal is passed from sender to receiver. As such, the information is more useful for the receiver. If the information is higher in quality, less information asymmetry is present and thus the information is more useful.

The literature reports that adoption of IFRS increased the quantity and quality of financial reporting disclosures, as well as increasing the comparability and transparency of financial statements, thereby minimising information asymmetry (Barth, Landsman & Lang 2008; Daske & Gebhardt 2006; Daske et al. 2008; De George, Li & Shivakumar 2016; Glaum et al. 2013; Hodgdon et al. 2008; Preiato, Brown & Tarca 2013). Thus adoption of IFRS is expected to provide better signals compared with prior accounting standards under national GAAP to users of financial information and consequently, financial statement users should be able to more efficiently use the fundamental information and better assess firms' future prospects and make better investment decisions. Therefore, it is expected that the predictive ability and value relevance of fundamental information/ signals, together with analysts' efficiency in using the fundamental information, increased after adoption of IFRS.

Positive accounting theory (PAT) and agency theory emphasise that members of management as agents have a duty to report to capital contributors their performance based on the resources entrusted to them (Deegan 2014). If this information is relevant and reliable, then the information is more useful in gauging management's stewardship of an entity's resources than if the opposite is the case. Management, as producers of financial information, is expected to meet the required accounting principles and standards that give implied assurance that information reported in the financial statements is relevant and reliable. With evidence of positive IFRS impact on the quality of accounting information (Barth, Landsman & Lang 2008; Daske & Gebhardt 2006; Daske et al. 2008; De George, Li & Shivakumar 2016; Glaum et al. 2013; Hodgdon et al. 2008; Preiato, Brown & Tarca 2013), it is expected that financial information prepared under IFRS is more relevant and reliable, and therefore more useful, than under previous national GAAP.

1.5 Research design

Based on the three Research Objectives, this study investigates the predictive ability and value relevance of fundamental signals and also the efficiency with which analysts use fundamental signals for earnings forecasts. Predictive ability is investigated following Abarbanell and Bushee's (1997) study using one-year-ahead change in earnings per share, while the value relevance of fundamental signals is investigated following the methodology of Lev and Thiagarajan (1993), using contemporaneous excess returns as the dependent variable. In order to examine analysts' efficiency in using fundamental signals, forecast one-year-ahead-change in earnings per share and forecast error are used as the dependent variables, guided by the study of Wahab, Teitel and Morzuch (2015).

This study employs one earnings and 12 non-earnings fundamental signals[7] as explanatory variables to examine the predictive ability, value relevance and analysts' efficiency in their use of these signals. Of the 12 non-earnings signals, eight fundamental signals, namely change in inventory relative to change in sales (INV), change in accounts receivable relative to change in sales (AR), change in selling and administrative expenses relative to change in sales (SA), change in labour force (LF), change in effective tax rate (ETR), change in gross margin (GM), audit qualification (AQ), and change in capital expenditure relative to change in industry capital expenditure (CAPX), are selected from Lev and Thiagarajan's (1993) study and the same construction and definitions are applied. Further, an additional four fundamental signals are included in this study (change in financial leverage (LEV), change in cash flow from operations (CF), change in goodwill (GW) and change in discretionary accruals (CDACCR)), and defined so as to be consistent with signals included in Lev and Thiagarajan's study.

[7] These variables are designed to provide an expected signal about future earnings and contemporaneous excess returns.

In order to test predictive ability, value relevance and analysts' efficiency in using the selected fundamental signals, Ordinary Least Squares (OLS) multiple regression is employed on stepwise[8] basis (Abarbanell & Bushee 1997; Lev & Thiagarajan 1993; Wahab, Teitel & Morzuch 2015) and partial F-tests are used to test the significance of the contribution from groups of variables to the model. Analyses of the predictive ability and value relevance of fundamental signals, along with analysts' efficiency in using these signals, are carried out for individual signals, certain signals in combination and signals in aggregate form[9].

For the purpose of examining IFRS impact robustly, two statistical techniques are used; a test of equality of coefficients based on stacked regression and interactions with IFRS for each signal. Furthermore, a percentage for analysts' efficiency is calculated.

Data are collected for all non-financial listed companies available from the Bloomberg database as at 2012 for 11 European Union (EU) countries plus Australia for the 12-year period from 2001 to 2012, excluding 2005, the year of IFRS transition. Sample countries are selected based on their GAAP difference[10] as per Bae, Tan and Welker (2008) and have similar levels of investor protection based on the Schwab and Sala-i-Martin (2013) Global Competitiveness Report. For extended analysis, selected countries are grouped into code and common law countries. All the selected code law countries (Spain, Finland, Czech Republic, Belgium, Portugal, Poland, Italy, France, Denmark and Sweden) have higher GAAP difference than the common law countries (United Kingdom (UK) and Australia).

The literature reports that IFRS adoption increases earnings quality in countries where investor protection is stronger (Houqe et al. 2012) and IFRS impact is greater for countries having higher GAAP difference (Ding et al. 2007; Narktabtee & Patpanichchot 2011). Therefore, IFRS impact on predictive ability, value relevance and analysts' efficiency is expected to be more significant for code compared to common law countries. Moreover, the literature documents the homogeneity of regulatory mechanisms between EU countries and the "relatively strong legal system and enforcement regime in the EU provide a powerful setting to detect the effects of IFRS adoption" (Li 2010 p.2).

[8] First, earnings alone is entered in the model, then non-earnings fundamental signals are entered.
[9] Using an aggregated fundamental score known as F_Score.
[10] Differences between national or domestic and IFRS accounting standards.

Therefore, the sample countries are selected carefully to control to the extent possible for factors that influence the quality of accounting information, enabling isolation of IFRS impact.

As mentioned earlier, analyses are conducted for different sub-samples, such as code and common law countries, winners and losers, extreme and non-extreme performers, growth and value stocks, good and bad prior year earnings news and macro-economic conditions, such as level of inflation and level of growth in GDP.

1.6 Overview of findings and contributions

1.6.1 Key findings

Findings overall reveal that the earnings and non-earnings signals individually, in combination and also in aggregated form significantly predict one-year-ahead change in earnings per share and are also value relevant for contemporaneous excess returns. The incremental R-Squared contribution over earnings from non-earnings fundamental signals, including the four fundamental signals added in this study, and in aggregate, is significant for predicting one-year-ahead change in earnings per share and also assessing the value relevance of excess returns. This indicates that non-earnings fundamental signals, including in aggregate, contain relevant information incremental to earnings that is useful for predicting future earnings per share change and assessing excess stock returns (Abarbanell & Bushee 1997,1998; Al-Debie & Walker 1999; Dowen 2001; Elleuch 2009; Lev & Thiagarajan 1993; Mahmoud & Sakr 2012; Mohanram 2005; Ou 1990; Piotroski 2000; Seng & Hancock 2012). Current year change in earnings per share (CHGEPS) and all non-earnings fundamental signals are value relevant for excess returns in the direction anticipated except for change in inventory. However, CHGEPS and nine non-earnings signals predict one-year-ahead change in earnings per share (CEPS1) significantly. Of these variables, CHGEPS and five non-earnings signals are in the direction anticipated and for the others, justification for the unexpected relationship is provided.

Analysis for code and common law countries shows no significant difference in the predictive ability of fundamental signals individually, in combination or aggregate form. However, the value relevance of several non-earnings fundamental signals, including in aggregate, is significantly higher for common compared to code law countries.

Results for IFRS impact on predictive ability and value relevance reveal that the predictive ability of the overall model is higher, but lower for value relevance in the post- compared to pre-IFRS period. In terms of earnings signals, IFRS has a positive impact on predictive ability, particularly in code law countries, while a negative impact on value relevance, but mostly for common law countries. The predictive ability of non-earnings fundamental signals, such as change in inventory, change in capital expenditure, audit qualification and goodwill were affected most by IFRS adoption in different sub-samples, and the predictive ability of non-earnings signals in combination and aggregated form decreased after adoption of IFRS. Further, the analysis documents that adoption of IFRS had significant impact on the value relevance of change in selling and administrative expenses, change in gross margin, audit qualification, change in labour force and change in cash flow from operations, but in different sub-samples. Moreover, the incremental value relevance from non-earnings signal over earnings is higher for common law countries, but lower for code law countries after adoption of IFRS. Corresponding to this, the value relevance in aggregate also significantly increased for common law countries in the post- compared to pre-IFRS period.

The results for analysts' efficiency in using the signals reveals that, although analysts seem to be aware of the fundamental signals useful for predicting future change in earnings, they do not incorporate fully the earnings information embedded in fundamental signals for their forecasts, and therefore are inefficient (Abarbanell & Bushee 1997; Swanson, Rees & Juarez-Valdes 2003; Wahab, Teitel & Morzuch 2015). This inefficient use of fundamental signals is reflected though analysts' overreaction and underreaction to certain fundamental signals. Analysts are highly inefficient in using the fundamental signals when forecasting negative change in earnings compared to positive change in earnings, and they generally underreact to fundamental signals when forecasting a negative change and overreact to signals when forecasting a positive change in earnings per share.

After adoption of IFRS, analysts seem to be more efficient in selecting appropriate signals for their earnings forecasts, but remain inefficient in using these signals for earnings forecasts. Further analysis reveals that IFRS impact on the use of earnings signals by analysts is negative and this is more severe when forecasting a negative change compared with positive change in earnings. Moreover, analysis shows that analysts substantially underutilise earnings signals for common law compared to code law countries, in both pre- and post-IFRS periods.

As robustness tests, analyses are conducted excluding the full IFRS transition (2004-2006) and GFC (2007-2009) periods with results supporting the above findings.

1.6.2 Contribution

This study investigates the predictive ability and value relevance of one earnings and 12 non-earnings fundamental signals and also analysts' efficiency in using these signals, along with the impact of IFRS for ten code law and two common law countries over the 12-year period beginning 2001, and thereby makes a significant empirical and theoretical contribution.

As discussed earlier, there is a paucity of fundamental analysis studies of this kind using post-2000 data. Therefore, this study provides robust evidence on the predictive ability and value relevance of both earnings and non-earnings fundamental signals in European and Australian contexts. To the best of the author's knowledge this is the first study to examine both the predictive ability and value relevance of the same set of fundamental signals individually, in combination and in aggregate form using post-2000 data. Additionally, these factors are examined for different settings, such as code and common law countries, positive and negative change in earnings, winners and losers, extreme and non-extreme performers (only for value relevance), and growth and value stocks (only for value relevance), therefore providing robust evidence.

This study provides the first evidence of the impact of IFRS on the predictive ability and value relevance of non-earnings signals, individually, in combination, and in aggregated form. Whilst the earnings fundamental signal has been examined previously, to the best of the author's knowledge there is no published study that examines IFRS impact on the predictive ability of current year change in earnings to predict one-year-ahead change in earnings. The impact of IFRS on these quality aspects of fundamental signals is examined individually, in combination and aggregate form for the above mentioned different settings, therefore providing robust evidence. Moreover, there is no known research that examines IFRS impact on the value relevance of fundamental signals for extreme and non-extreme return performers as well as for growth and value stocks. As such these findings provide comprehensive evidence of IFRS impact on the quality of accounting information.

The study makes another substantial contribution to the literature by providing evidence of analysts' efficiency in using fundamental signals and the impact of IFRS on analysts' efficiency using post-2000 data. The area of analysts' efficiency in using fundamental signals has not been well-researched, and there is no known study that examines the efficiency with which analysts use fundamental signals using post-2000 data outside the US context. Given the statistical power of the large sample size in this study compared with prior studies in this area, the evidence provided is robust. This study also provides new evidence of analysts' efficiency in using these signals in different contexts, such as for code and common law countries and predicting future increase and decrease in earnings, that have not been addressed in a previous study of this type.

In addition, this is the first evidence of IFRS impact on analysts' efficiency in using fundamental signals for earnings forecasts and IFRS impact is examined for the earnings and non-earnings signals individually and in combination in different contexts, as mentioned above, thereby providing robust evidence.

Apart from the above empirical contributions, the study provides supportive evidence for several theories, including decision usefulness theory, signalling theory, positive accounting theory and agency theory, thereby making a significant contribution from theoretical perspectives.

1.6.3 Implications of the study

As mentioned earlier, this study provides robust evidence of the predictive ability and value relevance of fundamental signals and analysts' efficiency in using these signals, together with IFRS impact in different settings. Therefore, the findings have practical application for market participants in understanding the behaviour of fundamental signals in different contexts and making use of these signals for their decision-making. The study identifies useful fundamental signals that are common to and specific to each context (such as for predicting earnings per share increase and decrease), and the results therefore will be useful potentially for making future investment decisions.

In addition, the findings, especially those for IFRS impact on the predictive ability and value relevance of fundamental signals, provide useful insights for financial statement preparers, policy makers, standard setters, and other regulators or quasi-regulators, and as such will be of interest to them. The findings also may be useful for countries considering adoption of IFRS and for the IASB's continuing agenda of encouraging adoption of IFRS, because IFRS impact is different based on countries' legal regime and GAAP difference.

1.7 Outline of remainder of this thesis

This thesis consists of nine chapters. Following this chapter, Chapter 2 discusses the theoretical framework for the study. Chapter 3 reviews the literature on value relevance and the predictive ability of earnings and non-earnings signals, including what is known of IFRS impact on fundamental signals and these accounting quality aspects. Moreover, the chapter summarises the literature on analysts' information environment, analysts' forecasts and analysts' use of fundamental signals, along with what is known of the impact of IFRS on these aspects. Finally, in this chapter (Chapter 3), the research gaps in each area are identified and hypotheses are developed with reference to each of the Research Objectives. Then, Chapter 4 outlines the conceptual framework for the study and discusses the research design and empirical models employed in the study. Chapter 5 presents the descriptive statistics for each selected fundamental signal, together with the significance of differences in these signals between pre- and post-IFRS periods for the full sample, sub-samples by country and sub-samples by industry.

Moving to reporting of findings, Chapter 6 reports the results from testing the hypotheses relating to Research Objective One, that is to examine the predictive ability of fundamental signals and the impact of IFRS on this ability. Chapter 7 documents the results from testing the value relevance of the fundamental signals and the impact of IFRS on this value relevance, which is related to Objective Two of the study, while Chapter 8 presents the results from testing analysts' efficiency in using the fundamental signals and the impact of IFRS on this efficiency, which relates to Objective Three of the study. Finally, Chapter 9 provides an integrated discussion of the findings reported in Chapters 6, 7 and 8 together with a conclusion, and also reports the empirical and theoretical contributions from the study in more detail than appears in this chapter, the practical and policy implications, and the limitations and directions for future research.

CHAPTER 2: THEORETICAL BACKGROUND FOR THE RESEARCH

2.1 Introduction

This chapter discusses information quality from different perspectives and introduces relevant theories that explain information quality, along with how information quality attributes contribute to the usefulness of accounting information. Accordingly, the chapter is organised as follows. section 2.2 discusses information and information quality perspectives. section 2.3 explains decision usefulness theory and accounting information quality. Section 2.4 discusses positive accounting theory, agency theory and the quality of accounting information. Section 2.5 explains the role of the International Accounting Standard Board's (IASB) *Conceptual Framework for Financial Reporting* (2010)[11] with regards to accounting information quality and how adoption of International Financial Reporting Standards (IFRS) is expected to influence the quality of accounting information. Section 2.6 discusses signalling theory and the quality of accounting information and section 2.7 concludes the chapter.

2.2 Information and information quality

Traditionally the term 'information quality' has been used in reference to the accuracy of information (Xu et al. 2003). Current literature on information quality identifies several information quality dimensions, such as accuracy, timeliness, completeness and consistency. However, there is no standard single definition of information quality (Klein 1998). Huang, Lee and Wang (1998) define information quality as information that is fit for use by information consumers (p.43). Within the accounting literature, researchers have given considerable attention to accounting information quality. Accounting information is generally known as the language of business and it is used to construct communication/ interaction between the company and its environment, including those who seek to pursue an interest in companies (Hopwood 1983), such as current and prospective investors, financial analysts, creditors, accounting professionals, consumers, competitors, government and society at large. Under agency theory, the separation of

[11] Some sections of the 2010 *Conceptual Framework for Financial Reporting* are planned for revision under the IASB's Conceptual Framework Project and its 2015 Exposure Draft (ED), with the process expected to be completed by the end of 2016, although this has now been conceded to more likely to occur in 2017. Given this, the discussion in this chapter and the thesis more generally relies on the IASB's 2010 *Conceptual Framework for Financial Reporting*.

ownership and management is argued to lead to information asymmetry between these parties (Jensen & Meckling 1979). As such, financial statements play a significant intermediary role in mitigating information asymmetry between a company and its stakeholders. It follows that the quality of accounting information included in the financial statements is vital in achieving this objective. Dechow and Schrand (2004) indicate that "accounting quality is the extent to which accounting information accurately reflects the company's current operating performance, is useful in predicting future performance, and helps assess firm value" (p.5).

The IASB *Conceptual Framework for Financial Reporting* (2010) (hereafter *Conceptual Framework*), a normative document, identifies that comparability, verifiability, timeliness and understandability are important dimensions that enhance the quality of accounting information. Different proxies have been used in the literature to measure the quality of accounting information, such as earnings persistence, accruals quality, earnings smoothness, asymmetric timeliness and timely loss recognition, target beating, earnings management, earnings response coefficients (ERC), predictive ability and value relevance (Dechow, Ge & Schrand 2010). When analysing these accounting quality measures, almost all proxies for them refer in fact to earnings quality measures, rather than financial reporting quality in general. Therefore, earnings quality measures play a significant role in determining financial reporting quality. Although earnings represents an important variable and a widely researched area in terms of its quality, there remains no commonly agreed definition for earnings quality (Dechow, Ge & Schrand 2010).

Dechow and Schrand (2004) explain what is meant by 'earnings quality' from different perspectives. They argue that earnings quality is contextual and depends on the perspective of the user for its meaning; it means different things to different financial statement users. For example, investors might cite timeliness and predictability as important dimensions of earnings quality. On the other hand, creditors may prefer persistence of earnings, since their main concern is repayment of debt. For regulators, earnings are higher in quality when they conform to the spirit and the rules identified in generally accepted accounting principles (GAAP) (Dechow & Schrand 2004). That is, users of financial statements identify earnings quality based on relevance to their decisions. Dechow and Schrand (2004) explain that high quality earnings should reflect current operating performance; should be a good indicator of future operating performance, and should accurately annuitise the intrinsic value of the company. Further, they identify that “earnings are of high quality when return on equity is a good measure of the internal rate of return on the company’s current portfolio of projects” (Dechow & Schrand 2004 p.5).

Schipper and Vincent (2003) argue that persistence, variability and predictability[12] are time series properties of earnings that can be used to evaluate earnings quality over time. As they explain, relevance, reliability and comparability are other desirable dimensions of earnings quality, qualities also covered by the IASB *Conceptual Framework*. Dichev et al. (2013) report that chief financial officers (CFOs) believe high quality earnings is sustainable and repeatable. Krishnan and Parsons (2008) define earnings quality as “the degree to which reported earnings capture economic reality” (Krishnan & Parsons 2008 p.2) in order to assess appropriately a company’s financial performance.

Dechow, Ge and Schrand (2010) in their review paper describe how higher quality earnings provide more information about the features of a firm’s financial performance that are relevant to a specific decision made by a specific decision-maker. This definition seems to address the decision usefulness aspect of the earnings number, which also is identified as an important qualitative characteristic by the IASB *Conceptual Framework*. Although earnings quality can be viewed from different perspectives, most of the earnings quality indicators used in the literature are constructed using the link between income, cash and accruals (Schipper & Vincent 2003) and, in general, all these measures refer to the quality of disclosures in the financial statements.

As mentioned, many researchers have focused on earnings quality rather than financial reporting quality. This study employs earnings as well as several non-earnings variables to assess the quality of accounting information in terms of its predictive ability and value relevance. The accounting literature discusses financial reporting (accounting) standards, the legal system of a country (La Porta et al. 1998), the tax system (Guenther & Young 2000), entity ownership structure (Ball & Shivakumar 2005; Fan & Wong 2002); the political system (Leuz & Oberholzer-Gee 2006); capital market development (Ali & Hwang 2000), reporting incentives, enforcement and cultural environment (De George, Li & Shivakumar 2016) as some important aspects in determining accounting quality.

[12] Predictability and persistence quality dimensions are explained in detail in the following chapter.

This current study focuses on financial reporting or accounting standard aspects and, in particular, the impact of IFRS on the predictive ability and value relevance of accounting information and analysts' efficiency in using this information. Through its research design, it attempts to control for many of the other aforementioned aspects, and results will need to be interpreted with the difficulty of controlling fully for these other features in mind.

2.3 Decision usefulness theory and information quality

The main theoretical support for the study comes from decision usefulness theory. The decision usefulness approach takes the view that "if we can't prepare theoretically correct financial statements, at least we can try to make financial statements more useful" (see, for instance, the work of Scott 1997) Accordingly, accountants should prepare financial statements that are useful to interested parties (stakeholders). The concept of decision usefulness was introduced in the 1966 report "*A Statement of Basic Accounting Theory* (ASOBAT)", compiled by a committee appointed by the American Accounting Association (AAA). The committee's view was that the most important criteria for selecting the appropriate measurement method is the decision usefulness of accounting information for users. As such, according to this theory, the most appropriate accounting standard is that which provides the most useful information to financial statement users for their decision-making. The IASB's *Conceptual Framework* implies this through the statement that the "objective of general purpose financial reporting is to provide financial information about the reporting entity that is useful to existing and potential investors, lenders and other creditors in making decisions about providing resources to the entity" (IASB 2010 para. OB.2).

The usefulness of accounting information can be gauged using the predictive ability of this information (IASB, 2010). If firm performance can be predicted more accurately using accounting information than without it or with use of other information, then the information is useful. This notion provides guidance to standard setters, policy makers and financial statement preparers in selecting accounting methods or measures that better predict (i.e. measures with smaller error margins) important economic events for users of financial statements (Beaver, Kennelly & Voss 1968).

As mentioned, users are argued to identify the quality of accounting information based on relevance to their decision-making. The IASB *Conceptual Framework* indicates relevance as one of the fundamental qualitative characteristics of financial information (IASB 2010 para QC5). That document identifies capital contributors as one of the most important financial statement user groups. In order to make their capital allocation decisions about which firm(s) in which to invest their capital, financial statements should provide information relevant for their decision-making. Investors' reactions to this information are reflected in companies' share prices. Therefore, a useful way of assessing the relevance of accounting information included in financial statements is to examine the association between this accounting information and either share price or returns (Bebbington & Gray 2001); such studies are known as value relevance studies.

In order to assess the usefulness of fundamental information reported in the financial statements, this study examines the predictive ability and value relevance of the information embedded in earnings and non-earnings fundamental information, together with analysts' efficiency in using this fundamental information and IFRS impact on these phenomena.

2.4 Positive accounting theory, agency theory and information quality

Positive Accounting Theory (PAT) and agency theory are mostly complementary theories that explain discrepancies between the interests of stakeholders, mainly shareholders, and those of management. Positive Accounting Theory was first introduced by Watts and Zimmerman (1978). "PAT focuses on the relationships between the various individuals involved in providing resources to an organisation and how accounting is used to assist in functioning of these relationships" (Deegan 2014 p.273). Accordingly, stakeholders, including resource providers, expect provision of relevant, reliable and useful information in financial statements about the resources entrusted to management and the performance of management. However, this expectation is not always aligned with what management is willing to provide. Sometimes management prepares financial statements in its own best interests via earnings management (Callao & Jarne 2010; DeFond & Park 1997; Ismail et al. 2013), therefore, conflicts of interest between owners and managers can occur. In view of that, PAT focuses mostly on the relationship between capital contributors and management.

According to Jensen and Meckling (1979), the relationship between capital contributors and management can be explained as an agency relationship, where an agency relationship is defined as “a contract under which one or more (principals) engage another person (the agent) to perform some service on their behalf which involves delegating some decision-making authority to the agent” (p.308). The owners (principals) hire management (agents) and entrust resources to managers to act in the best interest of maximising the resources on behalf of owners.

In listed companies, shareholders as owners do not have right to be involved in day-to-day business activities and therefore find it difficult to ascertain whether the decisions and actions taken by managers serve the best interests of shareholders. The main information source available to shareholders is the financial statements. Therefore, management is expected to provide accurate, reliable, and relevant information using financial statements in order for shareholders to assess the firm’s performance and make future investment decisions. As such, financial statement preparers are expected to meet the required accounting principles and standards that give implied assurance that information reported in the financial statements is reliable. The external audit function adds to this assurance.

2.5 The *Conceptual Framework for Financial Reporting*, IFRS and information quality

The IASB’s *Conceptual Framework* “sets out the concepts that underlie the preparation and presentation of financial statements for external users” (IASB 2010 p.6). One of the main purposes of the *Conceptual Framework* is to assist in developing future accounting standards more consistently (currently International Financial Reporting Standards (IFRS)), promoting harmonisation of regulations, accounting standards and procedures and assist users to interpret and understand financial statements (IASB, 2010). The previous version, the *Conceptual Framework for the Preparation and Presentation of Financial Statements* (1989) was first introduced by the International Accounting Standards Committee (IASC) and later adopted by the IASB in 2001. In 2004 the IASB and US Financial Accounting Standards Board (FASB) initiated a project to develop a new *Conceptual Framework*, with the intention of developing high quality accounting standards that could be adopted worldwide. As a result of this project, in 2010, the IASB and FASB issued two chapters of a new *Conceptual Framework*. These two chapters consist of Chapter 1: The Objective of General Purpose Financial Reporting and Chapter 3: Qualitative Characteristics of Useful Financial Information and now form part of the IASB's current *Conceptual Framework for Financial Reporting* (2010)[13].

According to the *Conceptual Framework*, the main objective of financial reporting is to provide useful financial information to existing and potential investors, lenders, creditors and other stakeholders regarding the economic entity of their interest for decision-making (IASB 2010 para. OB.2). Providing high quality financial information for these stakeholders will enhance investment, credit, and similar resource allocation decisions and ultimately overall market efficiency (IASB 2010 para. BC1.25). The IASB *Conceptual Framework* (1989) mentions understandability, relevance, reliability and comparability as the main qualitative characteristics that enhance the quality of financial information. However, the revised (2010) IASB *Conceptual Framework* identifies relevance and faithful representation as the fundamental qualitative characteristics, with comparability, verifiability, timeliness and understandability as enhancing qualitative characteristics (IASB 2010).

Understandability is referred to as the quality of information that enables users to comprehend the meaning of the information (IASB, 2010). Understandability will increase when information is classified, characterised, and presented clearly and concisely (Van Beest, Braam & Boelens 2009). Furthermore, the literature reveals that understandability refers to the transparency and organisation of information included in financial reports. Financial information disclosures, particularly the notes to the income statement and balance sheet, are vital as they provide explanation and additional insights to earnings (Beretta & Bozzolan 2004). Specifically, the narrative explanations increase the understandability of information (IASB 2010; Iu & Clowes 2004). The literature reveals also that well-organised financial reports are easier to understand (Jonas & Blanchet 2000) than less optimally organised reports, and as such are more useful.

An Ernst & Young survey of major European firms' first financial reports under IFRS reveals that the length of financial reports increased compared with the prior year on

[13] Some changes are likely to be introduced to this section given the IASB's 2015 *Conceptual Framework* Exposure Draft (ED), which includes the notion of prudence, the concept of substance over form and measurement uncertainty. At the time of writing this ED remains under discussion, so all references with regards to the *Conceptual Framework for Financial Reporting* in this thesis are based on the 2010 version.

average 20 to 30 per cent due to increased disclosures required under IFRS (Ernst & Young 2007). Several studies support the proposition that IFRS increases the quantity and quality of financial report disclosures (Daske & Gebhardt 2006; Glaum et al. 2013; Hughes 2008; Ismail et al. 2013; Nulla 2014; Rathke et al. 2016). Furthermore, research has found that adoption of IFRS and comprehensive reporting requirements under IFRS increased firms' overall commitment to the transparency, understandability (Ball 2006; Barth, Landsman & Lang 2008; Choi & Meek 2005; Daske et al. 2008; Tan, Wang & Welker 2011) and readability (Cheung & Lau 2016) of financial information. These findings support the view that adoption of IFRS increases the understandability of accounting information.

The next qualitative characteristic noted as desirable in the *Conceptual Framework* is that of comparability; that is: "the quality of information that enables users to identify similarities in and differences between two sets of economic phenomena" (IASB 2010 para. QC21). Comparability comes mainly from consistency, and "consistency refers to the use of the same accounting policies and procedures, either from period to period within an entity or in a single period across entities" (IASB 2010 para. QC22). If a company maintains use of the same accounting standards, accounting policies and procedures over the years, that will enhance the comparability of financial statements for the entity over the period. Similarly, if two different companies follow the same accounting standards, accounting policies and procedures, that will enhance financial statement comparability between those two companies. Accounting policies, financial statement structure, and notes to the accounts or the explanation of transactions are of importance when comparing the annual reports of two different companies (Jonas & Blanchet 2000).

Differences between countries' legal, political and economic systems tend to create diversity between the accounting systems of those countries (Alford et al. 1993; Ali & Hwang 2000; Joos & Lang 1994; La Porta et al. 1998; Leuz & Oberholzer-Gee 2006). Implementation of a common set of financial reporting standards throughout the world creates financial statements that are more comparable and therefore more understandable. Financial reporting standards such as IFRS, provide guidelines for recognition, measuring, classification and presentation of financial statement elements. Following a common set of guidelines and principles when financial statements around the world are prepared minimises differences and makes financial statements more comparable across different countries. Three major auditing firms commenting on IFRS implementation report that IFRS led to far greater disclosure and improved comparability across entities (Ernst & Young 2007; KPMG 2006; PWC/IPSOS-MORI 2007). Similarly, the literature provides supportive evidence to conclude that adoption of IFRS increases the comparability of accounting information (Beuselinck et al. 2010; De George, Li & Shivakumar 2016; Jayaraman & Verdi 2013; Tan, Wang & Welker 2011). Given this evidence, it can be asserted that acceptance in many parts of the world and adoption of IFRS enhances the comparability of financial reports between countries and improves financial reporting efficiency across multiple jurisdictions.

Timeliness is another important characteristic of financial information that enhances the quality of financial reporting. "Timeliness means having information available to decision makers before it loses its capacity to influence decisions" (IASB 2010 para. QC29). Tan, Wang and Welker (2011) report that "the extensive fair value accounting rules under IFRS could possibly incorporate more timely information about economic gains and losses" (p.6). The literature provides evidence that IFRS involves more timely loss recognition (Barth, Landsman & Lang 2008; Christensen et al. 2015; Shivakumar 2013). Therefore, it is expected that implementation of IFRS around the world increases the timeliness of accounting information. However, there is some evidence to the contrary (Ahmed, Neel & Wang 2013; Gebhardt & Novotny-Farkas 2011).

The IASB *Conceptual Framework* identifies verifiability as a separate qualitative characteristic that influences financial reporting quality. "Verifiability is a quality of information that helps assure users that information faithfully represents economic phenomena that it purports to represent. Verifiability means that different knowledgeable and independent observers could reach consensus, although not necessarily complete agreement, that a particular depiction is a faithful representation" (IASB 2010 para. QC26). Verifiability appears to be relevant directly to auditing, although no link is made to auditing or 'auditability' in the IASB framework (ICAEW 2009). If the verifiability is higher, that will enhance the quality of the audit as well. Clearly described and well-founded accounting principles increase the probability that consensus on the information will be reached and misstatements in the financial report will be detected for the benefit of users of the financial report, in particular by the auditor (Van Beest, Braam & Boelens

2009). Yang, Karthik and Xi (2013) document that adoption of IFRS improves earnings quality by lowering earnings management, and increasing value relevance, timeliness and information disclosure and, as such, IFRS improves the verifiability of earnings. Furthermore, it is argued that comprehensive disclosure requirements, increased transparency, comparability and understandability under IFRS (Ball 2006; Barth, Landsman & Lang 2008; Daske & Gebhardt 2006; Daske et al. 2008; Tan, Wang & Welker 2011) tend to increase the verifiability of accounting information. However, some literature argues that fair value measurement and principles-based standards under IFRS can compromise verifiability (Christensen & Nikolaev 2013; De George, Li & Shivakumar 2016).

According to the IASB *Conceptual Framework*, the main objective of the financial report is to provide useful information to users of financial statements for their decision-making (IASB 2010 para. OB2) and, therefore, financial reporting quality can be viewed in terms of decision usefulness. Enhancing the qualitative characteristics can increase the decision usefulness of accounting information included in the financial statements; however, it should be relevant and faithfully represent (IASB, 2010).

Relevance is related to the "capability of making a difference in the decisions made by users, if it has predictive value, confirmatory value or both" (IASB 2010 para. QC7). "Financial information has predictive value if it can be used as an input to processes employed by users to predict future outcomes and it has confirmatory value if it provides feedback about prior evaluations" (IASB 2010 para. QC 8 & 9). In the accounting literature, predictive value has been discussed in terms of the ability of past earnings to predict future earnings and cash flows (Francis et al. 2004; Lipe 1990; Schipper & Vincent 2003).

When assessing the predictive value of financial information, prior literature has used fair value and historical cost accounting as main focus points (Barth, Beaver & Landsman 2001; Hirst, Hopkins & Wahlen 2004; McDaniel, Martin & Maines 2002; Schipper 2003; Schipper & Vincent 2003) and concluded that fair value accounting has higher predictive ability (Blankespoor et al. 2013; Evans, Hodder & Hopkins 2014). Fair value numbers are arguably more relevant than historical cost accounting numbers as they represent the current market value of assets and liabilities. The IASB has allowed increased use of fair value accounting under IFRS[14] to increase the relevance of financial reporting (Fiechter & Novotny-Farkas 2015; Tan, Wang & Welker 2011). Therefore, it can be expected that increased predictive ability and value relevance of financial information occurs under IFRS compared with prior national GAAPs.

Many studies have been conducted that assess the predictive ability of analysts after adoption of IFRS and almost all findings conclude increased analyst forecast accuracy following this adoption (Byard, Li & Yu 2011; Chalmers et al. 2012; Cheong & Al Masum 2010; Cheong, Kim & Zurbruegg 2010; Cotter, Tarca & Wee 2012; Ernstberger, Krotter & Stadler 2008; Preiato, Brown & Tarca 2013). As such, this evidence supports the view that financial information produced under IFRS has higher predictive value than under predecessor standards. This current study, amongst other things, examines IFRS impact on analysts' efficiency in using the fundamental information reported in financial statements for their earnings forecasts. Due to the expected enhancement of the qualitative characteristics of accounting information following adoption of IFRS, together with supportive evidence from the literature, it is expected that analysts' efficiency in using this information increased after adoption of IFRS.

Faithful representation is the next fundamental accounting information quality discussed in the IASB *Conceptual Framework*. In order to be faithfully represented, information needs to be complete, neutral, and free from material error (IASB 2010 para. QC12). The IASB stated in its standard setting work (introducing IFRS) that its aim was "to develop, in the public interest, a single set of high quality, understandable, enforceable and globally accepted financial reporting standards based on clearly articulated principles. These standards should require high quality, transparent and comparable information in financial statements" (Hopper 2012 p.99). Developing the accounting principles used in preparing financial statements increases the likelihood that preparers fully understand the measurement method (Van Beest, Braam & Boelens 2009) and this will reduce the possibility of unintentional material errors in financial reports (Jonas & Blanchet 2000; Maines & Wahlen 2006). The comprehensive disclosure requirements and increased transparency and comparability under IFRS (Ball 2006; Beuselinck et al. 2010; Daske & Gebhardt 2006; Daske et al. 2008; Tan, Wang & Welker 2011) should make financial

[14] For e.g. IFRS 13 fair value measurement requires non-current assets held for sale, commodity inventories, biological assets, share-based payment transactions to be valued at fair value, IFRS 9 financial instrument to be measured at fair value.

information more complete, free from bias and verifiable compared with prior standards. Therefore, it can be argued that faithful representation of financial information increases after adoption of IFRS.

Ideally a conceptual framework would be the foundation for accounting standards. “The application of (the Framework’s) objectives and qualitative characteristics should lead to high-quality accounting standards, which in turn should lead to high-quality financial reporting information that is useful for decision-making” (IASB 2008 para. BC2.47). The IASB’s commitment to developing reporting standards that can be adopted worldwide to increase financial reporting quality (predictive ability and relevance) is an important motivation to believe that IFRS produce higher quality financial information than their predecessors.

2.6 Signalling theory and information quality

Signalling theory focuses on information asymmetry between two parties (Spence 2002). Signalling usually refers to reaction of the capital market to the information disclosures. In the modern business world, especially due to the separation of ownership and management, information asymmetry occurs, as explained earlier in this chapter. The company, or rather its management, has information that owners and investors do not. At the same time, if the company does not disclose its economic position fairly, or manipulates the reported information, information asymmetry occurs between the company and users of its financial statements. With the presence of information asymmetry, information users’ reactions or decisions taken might be different from their reaction when there is no information asymmetry.

Asymmetries can be reduced if the party with more information signals to others (Watson, Shrives & Marston 2002). Healy and Palepu (2001) argue that demand for financial reporting and disclosure arises from information asymmetry and agency conflicts between managers and outside investors. Financial reporting plays a critical role in minimising this information asymmetry. Business enterprises provide disclosures by way of financial reports, which include financial statements and notes, auditors’ reports, and other information. Additionally, press releases, conference calls and analyst reports and company websites, for instance, provide other means of information disclosure by companies. If managers want to disclose quality information or provide a signal, the information must be credible and credibility is achieved via verifiability of the information (Watson, Shrives & Marston 2002). The credibility of management disclosures is enhanced by regulators, standard setters, auditors and other capital market intermediaries (Healy & Palepu 2001).

The IASB *Conceptual Framework*, together with accounting standards, provide the necessary guidelines, principles, policies and procedures for the preparation and presentation of financial statements. Concurrently, they also provide guidelines to users for interpreting and understanding the information included in financial statements. Preparer adherence to the *Conceptual Framework* and accounting standards increases the qualitative characteristics of financial information (IASB, 2010). As a result, the decision usefulness and credibility of the financial information is increased, minimising information asymmetry between information providers and users of the information so as to lead to higher quality signals and better decisions. High quality financial information signifies higher predictive ability and higher relevance of the financial information. Moreover, if financial analysts as a main user group of financial statement information receive higher quality information, their efficiency in using these signals for earnings forecasts should be higher. If information asymmetry is present between financial statement preparers and analysts, then analysts may be inefficient in using this financial information for their earnings forecasts due to poor signalling.

Signalling theory explains that better disclosure reduces information asymmetry and results in better signals (Watson, Shrives & Marston 2002). As discussed previously, IFRS adoption has been found to increase the qualitative characteristics of financial information and thus should present higher quality signalling, which minimises information asymmetry. The literature supports the view that IFRS increases the quantity and quality of financial reporting disclosures, as well as increases the comparability and transparency of financial statements (Barth, Landsman & Lang 2008; Daske & Gebhardt 2006; Daske et al. 2008; Glaum et al. 2013; Hodgdon et al. 2008; Preiato, Brown & Tarca 2013) and therefore minimises information asymmetry. Thus IFRS is expected to provide superior signals compared with prior standards to users of financial information and, consequently, financial statement users should be able to better assess the future prospects of companies. It is therefore expected that adoption of IFRS will improve the predictive ability and value relevance of fundamental signals and analysts' efficiency in using fundamental signals when making earnings forecasts.

2.7 Chapter summary

This chapter focuses on explaining decision usefulness concepts in relation to accounting information using several accounting theories and the IASB's *Conceptual Framework*, and also explains how IFRS is expected to influence the usefulness of accounting information. Further, this chapter defines accounting quality and identifies some quality dimensions, such as accuracy, timelines, completeness, consistency, verifiability, timeliness, understandability, persistence, predictability, relevance, reliability and comparability, based on past literature (Dechow & Schrand 2004; Schipper & Vincent 2003) and with reference to the IASB *Conceptual Framework*.

The accounting literature adopts different proxies for measuring the quality of financial statement information. For example, earnings quality can be measured in terms of persistence, accruals quality, earnings smoothness, asymmetric timeliness and timely loss recognition, target beating, earnings response coefficients (ERC), predictive ability and value relevance (Dechow, Ge & Schrand 2010). As such, this study examines the accounting information quality of earnings and some non-earnings fundamental information with respect to its predictive ability, value relevance and analysts' efficiency in using this information, along with the impact of IFRS on each of these aspects. Therefore, to explain the theoretical underpinnings behind this study, decision usefulness theory, positive accounting theory, agency theory, signalling theory and the normative IASB *Conceptual Framework* are used.

CHAPTER 3: LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

3.1 Introduction

This chapter reviews the literature relating to this study based on three main areas: value relevance, predictive ability and analyst forecasts and the efficiency of using accounting information when making these forecasts. In section 3.2 the review commences with a theoretical discussion of value relevance and different perspectives of value relevance and predictive ability. Section 3.3 discusses the literature on value relevance and the predictive ability of the earnings fundamental signal. Thereafter, section 3.4 reviews the literature on value relevance and the predictive ability of non-earnings fundamental signals. Following that, section 3.5 identifies the research gaps this study seeks to fill and develops hypotheses relevant to these gaps in respect of predictive ability and value relevance of both earnings and non-earnings fundamental signals. Section 3.6 discusses the literature on the impact of International Financial Reporting Standards (IFRS) on the predictive ability and value relevance of fundamental signals. Section 3.7 identifies the research gaps and develops hypotheses related to this IFRS impact. Next, section 3.8 reviews the literature on analyst forecasts and analysts' efficiency in using fundamental signals and what we know of the impact of IFRS on this efficiency prior to identifying research gaps and developing hypotheses in relation to these issues. Finally, section 3.9 provides concluding remarks for the chapter.

3.2 Value relevance and predictive ability

3.2.1 Introduction to value relevance and predictive ability

Capital Market Based Accounting Research (CMBAR) is a broad research area that examines the association between the capital market and accounting information (Dechow 1994). According to Beaver (2002), there are five categories of CMBAR, namely "market efficiency; Feltham-Ohlson modelling; analysts' behaviour; discretionary behaviour; and value relevance studies" (p.453). From a different perspective, Kothari (2001) views value relevance studies as a category of fundamental analysis and valuation research. Generally, value relevance research examines the usefulness of accounting information to shareholders. Barth, Beaver and Landsman

(2001) define value relevance as the “statistical association between the accounting amounts and equity market value” (p.95).

Francis and Schipper (1999) provide four interpretations of value relevance. The first explains that “financial statement information leads stock prices by capturing intrinsic share values toward which stock prices drift” (Francis & Schipper p.325). This interpretation infers that market price does not reflect underlying value (intrinsic value) of the firm, but accounting information does. Their second interpretation is that “financial information is value relevant if it contains the variables used in a valuation model or assists in predicting those variables” (Francis & Schipper 1999 p.325). This interpretation explains the value relevance of accounting information in terms of its predictive ability. According to the third interpretation, value relevance is “measured by the ability of financial statement information to change the total mix of information in the market place” (Francis & Schipper 1999 p.325). This interpretation focuses on financial information released to the market and whether and how investors change their expectations about share price. In other words, it examines how the market price reacts to information release. Their fourth interpretation defines value relevance as “a statistical association between accounting information and market values or returns” (Francis & Schipper 1999 p.325). As such, this definition assesses the ability of financial statement information to capture and summarise information that determines firm value. This fourth interpretation does not limit accounting information to that in financial statements; rather information can come from any source, such as management forecasts, audit reports or other information in annual reports, etc. According to these interpretations, the value relevance research can take the form of an event study or long term association study.

Value relevance studies date back to 1968 and the seminal work by Ray Ball and Philip Brown. They studied stock price reaction to earnings announcements and documented an association between accounting earnings and stock prices. Usually value relevance research measures the usefulness of financial information from the perspective of shareholders. Therefore, value relevance research tries to link accounting information with company value, share price or equity value. Traditional finance theory states that a company’s equity value represents: (a) the present value of future dividends; or (b) the present value of free cash flows to equity (Dechow 1994), as represented in the following equations.

$$EV_0 = \sum_{t=1}^{\infty} \frac{E(d_t)}{(1+r_t)^t}$$

where:

EV_0 = (Theoretical) Equity value

$E(d_t)$ = Expected Dividends

r_t = Discount rate

and

$$EV_0 = \sum_{t=1}^{\infty} \frac{E(FCFE_t)}{(1+r_t)^t}$$

where:

$E(FCFE_t)$ = Expected Free Cash flow to Equity

There are number of versions available of the above two equity valuation models. For instance, Feltham and Ohlson (1995) documented that equity value is equal to today's value of net financial assets plus the present value of all future free cash flows from operating activities, represented in the following equation.

$$EV_0 \quad = NFA_0 + \sum_{t=1}^{\infty} \frac{E(CFO_t)}{(1+r_t)^t}$$

where:

NFA_0 = net financial assets

CFO_t = free cashflow from operating activities

Ohlson (1995) shows that the dividend/cash flow model can be written solely as a function of accounting variables assuming a clean surplus relation holds[15].

$B_t = B_{t-1} + I_t - d_t$

where:

B_t = book value of equity

I_t = net income (earnings)

d_t = net dividends

The definitions and interpretations of value relevance provided by different scholars always refer to the connection between accounting numbers and company value.

[15] The clean surplus relation assumes that the book value of equity changes only with net income and net capital investments and withdrawals (net dividends) by owners.

Similarly, most of the research tests value relevance empirically, based on the relationship between the market value of equity and accounting numbers in the financial statements and notes thereto (financial statements hereafter). Therefore, market value of equity can be identified as a function of accounting numbers included in financial statements. Some value relevance studies involve tests of significance that examine how the accounting number(s) is/are associated with market value, whereas others involve tests of explanatory power that examine how the variation in equity value is explained by accounting information.

One of the regression models used commonly in the value relevance literature is known as the price regression, which examines the relationship between market value of equity and book value of equity (Beisland 2009) according to the following equation.

$$P_t = \beta_0 + \beta_1 BVS_t + \alpha$$

where:

P_t = stock price.

BVS_t = book value per share.

However, an alternative view is that stock price is a function of book value of equity and earnings (Beisland 2009), which is explained using the residual income model by the following equation. Accordingly, earnings can be included as another variable in the model that explains price.

$$P \quad = \beta_0 + \beta_1 BVS_t + \beta_2 EPS_t + \alpha$$

where:

EPS_t = earnings per share.

This equity calculation is in line with the Penman (1998) equity valuation model. He shows how book value and earnings can be combined in equity valuation.

Though the value of a company’s shares is an important indicator, once investors have committed their funds to stocks the focus is on returns coming from the investment. Assuming a clean surplus relation holds (see footnote 14), then change in the book value of equity is equal to earnings for that year, if no dividend is paid during that year. Therefore, another branch of value relevance studies focuses on change in the market value of equity, which is examined by regressing stock returns on accounting earnings, as shown in the following equation:

$$R_t = \beta_0 + \beta_1 E_t + \alpha$$

where:

R_t = stock return

E_t = earnings (typically scaled by total assets or the market value of equity).

In the above regression, the coefficient for earnings is referred to as the Earnings Response Coefficient (ERC), and explains the magnitude of the relation between earnings and stock returns (Kothari 2001 p.123).

Some prior studies assess value relevance using unexpected return. Unexpected return can be calculated by deducting the expected return from total stock return. The literature provides different ways of calculating the expected return, such as the Fama and French three-factor model (Fama & French 1992)[16]. In this model, unexpected return is regressed on unexpected earnings, where unexpected earnings represent the difference between total earnings and expected earnings. Expected earnings can be calculated using analysts' forecasts (Easton & Zmijewski 1989; Freeman & Tse 1992) or from time-series models of earnings (Ahmed 1994; Kormendi & Lipe 1987). The regression model can be depicted as follows.

$$AR_t = \beta_0 + \beta_1 EU_t + \alpha$$

where:

AR_t = abnormal return, i.e., stock return minus expected return

EU_t = unexpected earnings

The coefficient for unexpected earnings is the Earnings Response Coefficient.

3.2.2 Information perspective and measurement perspective of value relevance research

Consistent with the Francis and Schipper (1999) interpretation of value relevance, there are two broad research approaches used to examine the value relevance of accounting information. One utilises an information perspective and the other a measurement

[16] This model is generally known as the market model.

perspective. The information perspective deals with association studies, whilst the measurement perspective deals with predictive studies.

The former perspective assumes, based on the efficient market hypothesis, which is concerned with the degree to which stock prices reflect available information, that stock prices are a sufficient measurement of firms' intrinsic value. It thus employs market price as the benchmark for assessing the value relevance of accounting information. It holds that there is a statistical association between accounting numbers and stock price/returns, which means that accounting information is incorporated in share price, and is thus value relevant. Therefore, accounting information explains company value and investors can use this information to make decisions (buy, hold or sell) with respect to shares. According to this approach, publicly available information cannot be used to predict returns and systematically generate abnormal returns.

As explained, Ball and Brown (1968) is the pioneering study on the relationship between stock returns and accounting earnings. That study shows an association between accounting earnings and stock returns and that thus accounting earnings have information content with respect to stock returns. The Ball and Brown (1968) method is one of the most popular for assessing the value relevance of accounting information and thereafter many researchers have followed this methodology (Ahmed, Schneible & Stevens 2003; Alford et al. 1993; Ali & Pope 1995; Dechow 1994; Kormendi & Lipe 1987; Rayburn 1986), etc. Generally, these studies report that different types of accounting information are value relevant as a statistical association between selected accounting information and stock returns/price is found. This study also examines the association between both earnings and non-earnings accounting information and stock returns (value relevance hereafter), and in this way assesses the value relevance of accounting information.

The measurement perspective, on the other hand, relies on fundamental analysis and holds that a firm's intrinsic value can be determined using information available in the financial statements. It claims that the share price may on occasions deviate from a firm's underlying value, but gravitates slowly to the intrinsic value over time (Ou & Penman 1989b). Instead of taking share price as the benchmark for assessing value relevance, fundamental analysis is used to calculate the intrinsic value of the firm from the financial statements and then compared with stock price to identify mispriced securities. That is, users of the measurement approach consider that a firm's fundamentals have predictive power in terms of earnings and stock returns.

Adopting the second interpretation of value relevance by Francis and Schipper (1999), which takes the view that accounting information is value relevant if it assists in predicting the variables used in a valuation model, this current study examines the ability of earnings and non-earnings accounting information to predict future earnings (predictive ability hereafter). Broadly defined, examining the predictive ability of fundamental signals comes from the measurement perspective of value relevance research. Ou and Penman (1989b) state that fundamental analysis involves obtaining summary measures that have the ability to predict future earnings and returns from the financial statements[17]. This approach is consistent with Francis and Schipper's (1999) fourth interpretation of value relevance of accounting information and falls under the information perspective of value relevance research.

3.3 Value relevance and predictive ability of the earnings fundamental

In the value relevance literature, the accounting information used most for assessing value relevance is earnings. As discussed in Chapter 2 section 2.2, many past studies use earnings quality measures as proxies to infer overall financial reporting quality (Ahmed, Neel & Wang 2013; Ames 2013; Arthur, Cheng & Czernkowski 2010; Barth, Landsman & Lang 2008; Elias 2012; Hope, Thomas & Vyas 2013; Joos 2003; Liu et al. 2011). In other words, earnings has been treated as one of the most important variables in the accounting literature. It has been well-documented that current year earnings are associated with both future earnings and stock returns, and therefore earnings is considered value relevant and has predictive ability (Ahmed, Schneible & Stevens 2003; Alford et al. 1993; Ali & Pope 1995; Arthur, Cheng & Czernkowski 2010; Ball & Brown 1968; Dechow 1994; Easton & Harris 1991; Foster, Olsen & Shevlin 1984; Hong 2001; Kim & Kross 2005; Kormendi & Lipe 1987; Rayburn 1986).

3.3.1 Value relevance of earnings

Finance theory explains that stock price is the present value of future cash flows and if that theory holds true, current earnings should be able to predict future stock price/ stock

[17] The predictive ability of firm fundamental signals is discussed in detail later within this chapter.

returns. As explained earlier in this chapter, Ball and Brown (1968) were the first to examine that relationship between earnings and stock returns and they conclude that the earnings number has information content with regards to stock price and therefore earnings are value relevant. Ball and Brown's (1968) findings were supported by Beaver's study in 1968. His study reports an increase in the traded volume of stocks in the week of earnings announcements. Furthermore, Beaver (1968) reveals that the magnitude of stock price changes is much larger in the week of announcement than the average during the non-report period, thus concluding that earnings is value relevant. Easton and Harris (1991) use both earnings and change in earnings in their regression as explanatory variables for stock returns and find that both current year earnings and change in earnings play an important role in stock valuation.

Rayburn (1986) tests the operating cash flow and accruals' association with stock returns and finds that operating cash flow and accruals are significantly associated with abnormal returns. On the contrary, Bernard and Stober (1989) report that models based on cash flows and accruals are not successful in explaining stock returns around the release of financial statements. Dechow (1994) reports that the association between earnings and stock returns is higher than the association between cash flows and stock returns due to the fact that cash flows suffer from timing and matching problems with firm performance. Subramanyam and Venkatachalam (2007) document that accrual-based earnings dominate operating cash flows as a summary indicator of *ex post* intrinsic value of the firm. Similarly, Liu, Thomas and Nissim (2007) state that: "valuations derived from industry multiples based on reported earnings are closer to traded prices than those based on reported operating cash flows" (p.1).

Although the earnings number is value relevant and important in assessing stock returns, several past studies document that the value relevance of earnings has decreased over time (Amir & Lev 1996; Brown, Kin & Lys 1999; Collins, Maydew & Weiss 1997; Francis & Schipper 1999; Ryan & Zarowin 2003). Lev and Zarowin (1999) document a decline in the value relevance of both earnings and book values over time. Collins, Maydew and Weiss (1997) report that the decrease in value relevance of earnings over time is due to an increase in frequency of one-time items or non-recurring items and also the high frequency of negative earnings. However, Kim and Kross (2005) and Fung, Su and Zhu (2010) document that the value relevance of earnings has decreased over time due to market inefficiencies.

3.3.2 Predictive value of earnings

As discussed, if share price represents the present value of future cash flows/ earnings, value relevance can be studied using the predictive ability of earnings to forecast future cash flows/earnings. This view is consistent with Francis and Schipper's (1999) second interpretation of value relevance; that is: "financial information is value relevant if it contains the variables used in a valuation model or assists in predicting those variables" (p.325).

The persistence, smoothness (also termed variability) and predictability are some important time series attributes of earnings quality. "persistence captures the extent to which the current period innovation becomes a permanent part of the earnings" (Schipper & Vincent 2003 p.99); and "predictive ability is the capacity of the entire financial reporting package, including earnings components and other disaggregations of the summary earnings number, for improving users' abilities to forecast items of interest" (Schipper & Vincent 2003 p.100). Prior literature discusses the predictive value of earnings as the ability of past earnings to predict future earnings and cash flows (Francis et al. 2004; Lipe 1990; Schipper & Vincent 2003).

3.3.3 Earnings persistence

Persistence captures the current portion of earnings that is sustained in a future period. It measures the portion of current earnings that becomes a permanent part of the time series. High quality earnings are most likely to be sustained into future periods and so are helpful to analysts in forecasting future performance (Dechow & Schrand 2004). Several past studies investigate the persistence of earnings components and show that persistence varies across different components. For example, Sloan (1996) disaggregates earnings into accruals and cash flows, examines their ability to predict future earnings and reports that the accrual component of earnings is less persistent than the cash flow component. Consistent with Sloan's (1996) findings, Dechow (1994) also documents that large accruals reduce earnings persistence. Hong (2001) decomposes accruals further into discretionary and non-discretionary components and reports that discretionary accruals are less persistent than non-discretionary accruals. Providing additional evidence on earnings persistence, Dichev and Tang (2009) document an inverse relationship between the volatility of earnings and persistence and predictability; that is low volatility earnings have higher persistence and predictability when compared to high volatility earnings. Further, they report that investors are not aware fully of the impact of volatility of earnings on the persistence and predictability of earnings.

3.3.4 Earnings smoothness/variability

The smoothness of earnings can be seen as the variability or volatility of earnings over time. Higher smoothness of earnings means that earnings are more stable over time and therefore easier to predict (Dichev & Tang 2009). Leuz, Nanda and Wysocki (2003) measure the smoothing of earnings using the ratio of standard deviation of operating earnings to standard deviation of cash from operations. Accordingly, the smaller this ratio, the higher the earnings smoothing. Leuz, Nanda and Wysocki (2003) report that smoothing makes earnings less informative as a result of 'noise' added by management. Managers may include some transitionary components into income for the purpose of earnings smoothing, which reduces earnings persistence and predictability (Schipper & Vincent 2003). However, if managers use private information to smooth earnings and remove the transitory items, earnings figures can be more informative and useful for investors to predict future performance (Sankar & Subramanyam 2001).

3.3.5 Earnings predictive ability

Another important aspect of earnings quality is predictive ability, which is one of the focal points for this current study. The predictive ability of earnings refers generally to the ability of past and current earnings to predict future performance. The IASB *Conceptual Framework* states that "Financial information has predictive value if it can be used as an input to processes employed by users to predict future outcomes" (IASB 2010 para. QC8). Many studies that examine the ability of earnings to predict future earnings, future cash flows and/or future returns (Barth, Cram & Nelson 2001; Dechow 1994; Finger 1994; Jennings 1986; Kim & Kross 2005; Lev, Li & Sougiannis 2005; Nam, Brochet & Ronen 2012; Sloan 1996). Some of these studies examine the predictive ability of components of earnings and report different conclusions, as is elucidated below.

3.3.6 Using earnings to predict future earnings and cash flows

Finger (1994) examines the ability of earnings to predict future earnings and cash flows and concludes that earnings is an important predictor of future earnings over a long period (throughout eight years). She tests the ability of earnings to predict themselves by using a varying number of earnings lags and finds that when the number of earnings lags increases, predictive ability increases. She also finds earnings to be an important predictor of future cash flows. Sloan (1996) documents that current year earnings are a significant predictor of next year earnings, and his findings are consistent under both pooled analysis and industry analysis. This study's findings make it evident that accounting earnings are mean reverting and Sloan rejects the hypothesis that earnings follow a random walk[18] (Kendall & Hill 1953).

Through further analysis, Barth, Cram and Nelson (2001) examine the role of accruals in predicting future cash flows by disaggregating earnings into cash flows and six accruals components; namely (i) change in accounts receivable; (ii) change in accounts payable; (iii) change in inventory; (iv) depreciation; (v) amortisation; and (vi) other accruals. Running a cross sectional regression on future operating cash flows, they find that disaggregation of earnings increases predictive ability significantly compared with current cash flows alone. Arthur, Cheng and Czernkowski (2010) study cash flow disaggregation and predictive ability for future earnings and document that a disaggregated cash flow model is superior to an aggregated cash flow model when predicting future earnings. Lev, Li and Sougiannis (2005) examine the ability of current accruals and current cash flows to predict future earnings and future cash flows. They report incremental predictive ability of accruals beyond cash flows when predicting future cash flow, but only marginal improvement when predicting future earnings. Nam, Brochet and Ronen (2012) report higher predictive ability of accruals over cash flows from operations in forecasting future cash flows. Furthermore, Kim and Kross (2005) provide evidence, using data from 1973 to 2000, that the predictive ability of earnings to predict operating cash flows has strengthened over time.

The literature also documents the reversing nature of current year accruals (Chan, Jegadeesh & Sougiannis 2004; DeFond & Park 2001; Pae 2005; Wahab, Teitel &

[18] The random walk hypothesis explains that future earnings cannot be predicted as there is an equal chance that future earnings can be increased or decreased, irrespective of the past movement of earnings.

Morzuch 2015). Chan, Jegadeesh and Sougiannis (2004) examine how current accruals affect future earnings and they document a negative relationship between current accruals and future earnings, supporting current year accruals reversing in the next year. DeFond and Park (2001) also provide supportive evidence to show that abnormal accruals are reversing. Furthermore, prior studies of fundamental analysis report a mean reverting pattern of current year change in earnings, with a good year followed by a bad year and a bad year followed by a good year (Abarbanell & Bushee 1997; Dowen 2001; Swanson, Rees & Juarez-Valdes 2003).

3.3.7 Predictive ability of cash flows versus earnings: Which is better?

Jennings (1986) tests whether current earnings or current cash flows is a better predictor of future cash flow and finds current year earnings to be a better predictor of future cash flows than current cash flows. Dechow, Kothari and Watts (1998), using a time series model, test the ability of current earnings and cash flows to predict future operating cash flows. They find that earnings better predicts future operating cash flows than current operating cash flows. Barth, Cram and Nelson (2001) also provide evidence to support the view that earnings rather than cash flows better predicts future cash flows. Similarly, Dechow (1994) focuses on quarterly earnings and reports that accruals have more predictive ability than cash flows. However, Finger (1994) finds that cash flow is a marginally superior short-term predictor of future cash flows. Lev, Li and Sougiannis (2005) also report that earnings is not a superior predictor of future cash flows. However, Farshadfar and Monem (2013) show that accrual components and operating cash flow components together are more useful than earnings, operating cash flows or total accruals in predicting future cash flows. Most of the above discussed studies provide evidence to conclude that current year earnings and cash flows have the ability to be used in predicting future earnings and future cash flows.

In summary and simply put, throughout the above discussion the literature supports the view that earnings has the ability to predict future earnings, cash flows and is value relevant for stock price/returns. When compared with cash flows, earnings demonstrates a higher capability in predicting company performance.

3.4 Value relevance and predictive ability of non-earnings fundamental information (signals)

3.4.1 Value relevance of non-earnings fundamental signals

As discussed above, the earnings variable has been examined extensively in the value relevance literature and the conclusion drawn that earnings is value relevant in terms of share prices and returns, and also is capable of predicting future earnings, (Ball & Brown 1968; Barth, Cram & Nelson 2001; Dechow 1994; Finger 1994; Kim & Kross 2005; Lev, Li & Sougiannis 2005; Sloan 1996). However, as mentioned above, some prior studies report that the value relevance of earnings has decreased over time. In a review paper Lev (1989) also found that explanatory power judged by R^2 values, obtained by regressing current year stock returns on earnings, were very low. All this evidence suggests that research focusing on both non-earnings fundamentals and earnings remains important, a view supported by studies including Abarbanell and Bushee (1997, 1998); Al-Debie and Walker (1999); Dowen (2001); Elleuch (2009); Lev and Thiagarajan (1993); Mahmoud and Sakr (2012); Mohanram (2005); Ou (1990); Ou and Penman (1989a); Piotroski (2000) and Seng and Hancock (2012).

Most of a company's stakeholders have special interest in the firm's value. Financial information provided in the financial statements is an important input in assessing firm value. Both earnings and non-earnings fundamental information/signals are used extensively by different stakeholders for their decision-making, in particular by investors, analysts and portfolio managers. For example**,** Kothari (2001) stated in respect of year 2001 that "nearly $5 trillion currently invested in US mutual funds is actively managed, with fundamental analysis as the guiding principle of most mutual fund managers" (p.109). Xue and Zhang (2011) find that institutional investors, especially transient investors, trade securities based on fundamental signals.

Lev and Thiagarajan (1993) identify 12 non-earnings fundamentals used by analysts for security valuation and earnings forecasts by referring to analysts' written pronouncements published in a variety of sources, such as the Wall Street Journal and Barron's from 1984 to 1990, the Value Line publication, major security firms' (e.g. brokers') commentaries, etc. The fundamental information, known as fundamental signals, that Lev and Thiagarajan identify includes inventory, accounts receivable, capital expenditure, research and development (R&D) expenditure, gross margin, sales and administrative expenses, provision for doubtful receivables, effective tax rate, order backlog, labour force, last-in-first-out (LIFO) earnings and audit qualification[19]. Lev and Thiagarajan (1993) examine the value relevance of these variables and find them to be value relevant for contemporaneous abnormal returns. Further they document that non-earnings fundamental signals have incremental information content beyond the earnings fundamental that is value relevant for abnormal returns. This indicates that the inclusion of non-earnings fundamental signals increases the explanatory power of their model when compared with inclusion of earnings alone. They conclude also that the impact of the 12 variables varies according to three economic indicators - consumer price index, Gross Domestic Product (GDP), and the level of business inventory.

Al-Debie and Walker (1999) replicate Lev and Thiagarajan's (1993) research using UK data and extend the approach by allowing the response parameters of non-earnings fundamental signals to be conditioned by both industry and macroeconomic state variables (e.g. recession, growth, monetary and fiscal restraint). The results are partially supportive of Lev and Thiagarajan's (1993) findings in that gross profit margin, selling and administrative expenses, and labour force were highly significant in the UK context. It was also found that non-earnings signals vary significantly with industry factors.

Swanson, Rees and Juarez-Valdes (2003) conduct a fundamental analysis study in the Mexican context and report that earnings loses value relevance for contemporaneous returns in a year of currency devaluation, however, the non-earnings fundamental signals retain considerable explanatory power in that year. Mukherji, Dhatt and Kim (1997) document that book to market, sales to price, and debt to equity ratios are positively related, while firm size is negatively related, to stock returns in the Korean stock market. Carnes (2006) examines and finds that unexpected changes in six quarterly financial statement line items (accounts receivable, inventory, current liabilities, gross margin, selling and administrative expense, and depreciation expense) are value relevant and are also capable of identifying the transitory and permanent components of change in earnings. Khurana and Raman (2003) focusing on the bond market report that fundamental information is priced in the market for new bond issues, and therefore is value relevant.

[19] Of these 12 signals, eight are used in this study.

Kerstein and Kim (1995) investigate the association between capital expenditure and excess return and their results reveal that capital expenditure provides value relevant information over earnings in terms of excess returns. Bradshaw, Richardson and Sloan (2006) provide evidence of a negative relationship between external finance and stock return. Providing supportive evidence, Dimitrov and Jain (2008) show that change in financial leverage is value relevant for contemporaneous returns beyond earnings and cash flows. However, they find that information content in change in financial leverage is not priced in a timely manner. Cai and Zhang (2011) also document a negative impact of an increase in the leverage ratio on stock price and this impact is more severe for firms having higher leverage ratios. However, Caskey, Hughes and Liu (2012) argue that this negative relation between leverage and future returns contradicts with finance theory and they show that this negative relationship is driven by excess leverage.

Another important non-earnings fundamental signal that is value relevant for stock price or returns is cash flows (Habib 2008; Hirshleifer, Hou & Teoh 2009; Rayburn 1986; Sloan 1996). Some previous studies document that cash flow from operations (CFO) is value relevant incremental to earnings (Banker, Huang & Natarajan 2009; Cheng, Chao Shin & Schaefer 1997; Hirshleifer, Hou & Teoh 2009). Sloan (1996) findings suggest that higher proportion of earnings attributable to CFO (compared to accruals) signifies a higher quality of income that will more likely persist into future periods. The evidence in the literature supports the view that CFO has information content incremental to earnings that is value relevant and has the ability to capture earnings persistence.

Intangible assets, including goodwill, is another non-earnings variable that provides useful information about future earnings potential (Cheong, Kim & Zurbruegg 2010; Matolcsy & Wyatt 2006; Wyatt 2005), and therefore captures earnings persistence. Prior studies provide empirical evidence to show that goodwill is value relevant for stock price and returns (Dahmash, Durand & Watson 2009; Duangploy, Shelton & Omer 2005; Oliveira, Rodrigues & Craig 2010). Xu, Anandarajan and Curatola (2011) document that goodwill impairments provide useful, value relevant information and AbuGhazaleh, Al-Hares and Haddad (2012) provide supportive evidence for the same conclusion.

As stated above, earnings, cash flows and accruals are variables discussed frequently in prior literature on value relevance. Within those studies, several researchers make the differentiation between discretionary accruals and other accruals. Discretionary accruals are studied mostly as a proxy for earnings management (Ayers, Jiang & Yeung 2006; Becker et al. 1998; Cohen, Dey & Lys 2008). Guay, Kothari and Watts (1996) report a positive relationship between discretionary accruals and returns using five discretionary accrual models, providing evidence that discretionary accruals is value relevant. However, Choi, Kim and Lee (2011) find that the value relevance of discretionary accruals decreased during the Asian financial crisis period. Moreover, Marquardt and Wiedman (2004) document a decrease in the value relevance of earnings in the presence of earnings management, using discretionary accruals as the measure of earnings management. Therefore, evidence in respect of the value relevance of discretionary accruals is mixed.

All this evidence from the literature supports the view that non-earnings fundamentals provide useful information that is value relevant for stock prices and returns, and as such can be used to assess stocks of interest to investors (Francis & Schipper 1999).

3.4.2 Predictive ability of non-earnings fundamental signals

Several past studies of fundamental analysis, for example Abarbanell and Bushee (1997), Bernard and Stober (1989); Ou and Penman (1989a); Ou (1990); Stober (1993); Lev and Thiagarajan (1993); Kerstein and Kim (1995); Abarbanell and Bushee (1997); Abarbanell and Bushee (1998); Al-Debie and Walker (1999); Dowen (2001); Seng and Hancock (2012)**,** investigate the ability of fundamental information (signals) to predict earnings and returns. Some of these studies explore also how these signals vary according to contextual factors, such as the state of the economy, industry membership, country of origin, and firm specific factors. They investigate the predictive ability of different fundamental signals[20] derived from the income statement, balance sheet and cash flow statement.

A number of studies of fundamental analysis investigate the information content of individual non-earnings accounting numbers and their ability to predict future earnings and future returns. Ou (1990) screened 61 predictor candidates (mostly financial ratios) and filtered them based on their significance in predicting future earnings and future returns to arrive at eight predictors: percentage growth in inventory to total assets,

[20] Some of the fundamentals signals are summary measures (such as ratios), whereas others are individual element fundamental signals (e.g. sales).

percentage growth in net sales to total assets, change in dividend per share relative to previous year, percentage growth in depreciation, percentage growth in capital expenditure to total assets, one-year lag of the previous two indicators, accounting rate of return and change in accounting rate of return. Lipe (1990) establishes a link between some non-earnings numbers and future earnings changes and labels this as a "predictive link". Ou (1990) also establishes a link between predicted future earnings changes and stock returns and labels this as a "valuation link". The valuation link examines the value relevance of non-earnings signals as discussed in the previous section, and the predictive link tests the association between current year fundamental information and future earnings. Ou's (1990) findings suggest that selected non-earning fundamental signals contain information useful in predicting future earnings and stock returns that is not reflected in current and prior earnings.

As explained earlier, Lev and Thiagarajan (1993) identified 12 non-earnings fundamental signals that are value relevant for contemporaneous abnormal returns. They also find and document that these identified signals provide useful information about the persistence and/or growth of reported earnings. Furthermore, Carnes (2006) documents that an unexpected change in financial statement non-earnings signals captures the transitory and permanent components of change in earnings. The information perspective of accounting implies that the contemporaneous association between non-earnings accounting numbers and stock returns can be viewed as resulting from a predictive information link between these non-earnings accounting numbers and future earnings (Ou 1990). As such, Abarbanell and Bushee (1997) comment that the approach followed by Lev and Thiagarajan (1993) of using fundamental signals, including current earnings, to predict returns omits the intermediate link of future earnings with both non-earnings fundamentals and current earnings. Given this, they studied the ability of fundamental signals to predict future short- and long-term earnings.

Due to data limitations, Abarbanell and Bushee (1997) used only nine[21] of the set of 12 non-earnings fundamental signals used by Lev and Thiagarajan (1993). Their results show that their measures of[22] inventory, gross margin, effective tax rate, earnings quality

[21] Those fundamental signals are inventory, accounts receivable, capital expenditure, gross margin, selling and administrative expenditure, effective tax rate, earnings quality, audit qualification, and labour force.

[22] Their measures represent a change in variable relative to some base. For example, their inventory (INV) variable is measured as the annual change in inventory relative to annual change in sales.

and labour force are significantly related to one-year-ahead earnings in the direction anticipated, but the association does not hold for administrative expenses and audit qualification. Capital expenditure and accounts receivable signals are unexpectedly in the direction opposite from that anticipated. Further, their results show that the effective tax rate and labour force signals capture long-term growth in earnings over five years, possibly because these signals capture unidentified risk factors or structural changes. They find that fundamental signals have incremental explanatory power relative to current earnings when predicting future earnings. They also report that macroeconomic variables, such as inflation and Gross Domestic Product (GDP), as well as firm specific variables, such as prior earnings news, affect the relationship between fundamental signals and future earnings.

Seng and Hancock (2012) replicate Abarbanell and Bushee's (1997) research using worldwide data and adding another contextual variable, namely the country of incorporation. They find that most of the fundamental signals are significant in predicting future earnings. The results also show that the model which includes both the non-earnings fundamental signals and current year change in earnings explains more of the variation in future earnings change than the model including current year earnings change alone. Further they report that prior year earnings news, industry membership, macroeconomic conditions and country of incorporation are contextual factors that affect this relationship. Dowen (2001) extends Abarbanell and Bushee's (1997) research by adding new variables from the finance literature (dividend yield, book-to-market value of equity, firm size) and monetary policy as a contextual variable. He documents similar results to those of Abarbanell and Bushee, confirming that fundamental signals are capable of predicting future earnings and this relationship is conditioned by countries' economic growth, inflation and monetary policy. Of the three fundamental signals selected from the finance literature, he reports that the book-to-market ratio and dividend yield had a strong relationship with future earnings; the greater the book-to-market ratio and dividend yield, the lower is the earnings change.

Pierce-Brown (1998) finds five ratios that are useful in predicting earnings and using those ratios, the direction of future earnings changes could be predicted at 69 per cent accuracy. Jackson, Lopez and Reitenga (2008) examine non-earnings fundamentals in relation to chief executive officer (CEO) bonus compensation and document that bonus compensation is significantly associated with firm performance and non-earnings fundamental information. However, the relationship between earnings and CEO bonus compensation is weak, especially when earnings is negative. This supports the ability of fundamental signals to predict firm performance. Khurana and Raman (2003), in providing evidence of the value relevance of fundamental information for new bond issues, conclude that fundamental signals capture the future earnings potential. Witkowska (2006) also shows evidence on the predictive ability of fundamental signals in terms of stock returns and Quirin and Allen (2000) find that the incremental predictive ability from non-earnings information is high when the earnings are highly transitory.

In addition to the above literature, fundamental studies have been conducted to examine the predictive ability of specific fundamental information. For example, Bernard and Noel (1991) study inventory disclosures in seven manufacturing industries and their ability to predict future sales and future earnings. They find that unexpected change in inventories is a positive leading indicator of future sales, whereas it is a weakly negative leading indicator of future earnings and profit margin. Extending Bernard and Noel (1991), Stober (1993) examines the incremental information content of receivables beyond inventories in predicting future sales and future earnings. His study provides evidence that receivables has information that can predict future sales, earnings and profit margins beyond inventories. Kerstein and Kim (1995) investigate the predictive ability of capital expenditure in predicting future returns beyond current year earnings. Their results reveal that changes in the level of capital expenditure are positively associated with excess returns.

Leverage is fundamental information that captures financial risk (Modigliani & Miller 1958). Zhou and Ruland (2006) show a positive relation between leverage and future earnings growth. Using external debt can be good or bad depending on whether the firm earns more or less than after tax interest cost on investments financed with borrowed funds (Modigliani & Miller 1958). If the firm's expected return on investment is greater than the rate of interest, then use of debt should increase future earnings.

As discussed earlier in this chapter, cash flow from operations is another fundamental that is useful in predicting future earnings (Arthur, Cheng & Czernkowski 2010). Further, Arthur, Cheng and Czernkowski (2010) report that disaggregation of cash flow from operations into components increases predictive ability in terms of future earnings. Sloan

(1996) and Pfeiffer and Elgers (1999) document persistence of cash flows is higher than that of accruals, while a higher proportion of earnings attributable to cash flow from operations (CFO) signifies a higher quality of income that will more likely persist into future periods. This finding indicates that CFO is a more important indicator of future earnings. Orpurt and Zang (2009) report that cash flows prepared using the direct method better forecast firm future performance than those under the indirect method.

Goodwill (GW) is one of the most researched non-earnings fundamental signals. Prior literature provides evidence that GW provides useful information about future earnings potential (Cheong, Kim & Zurbruegg 2010; Matolcsy & Wyatt 2006; Wyatt 2005). Capitalised intangible assets provide useful and relevant information for financial analysts to use in their earnings forecasts that increases the accuracy of their forecasts (Matolcsy & Wyatt 2006). However, other literature reports that due to the subjective nature of its assessment, goodwill is associated negatively with the predictability of earnings and forecast accuracy of analysts (Godfrey & Koh 2009; Hope 2004; Kim & Schroeder 1990). Investment in intangible assets can thus increase information risk (Barron, Byard & Kim 2002). However, the literature reports that with appropriate disclosures and capitalising of intangible assets, this information risk can be mitigated (Matolcsy & Wyatt 2006; Wolfe 2009) and, as such, can increase the predictive ability of earnings.

Discretionary accruals is another non-earnings signal that could be useful in predicting future earnings. The theoretical model proposed by Fudenberg and Tirole (1995) suggests that managers consider expected future earnings when making discretionary accounting choices. Providing support for this theoretical model, DeFond and Park (1997) find that managers borrow future earnings by increasing discretionary accruals if expected earnings is high. Therefore, a positive relationship between current year discretionary accruals and future earnings can be expected. Subramanyam (1996) provides evidence to support the ability of discretionary accruals to predict future profits.

All this evidence supports the view that non-earnings fundamental signals possess information content incremental to earnings that is useful in predicting future earnings.

3.4.3 Value relevance and the predictive ability of an aggregated fundamental score (F_Score)

In past literature involving fundamental analysis, researchers have examined the predictive ability and value relevance of several non-earnings fundamental signals using an aggregated fundamental measure (fundamental score) (Abarbanell & Bushee 1997; Lev & Thiagarajan 1993; Seng & Hancock 2012). In addition, past studies examine the predictive ability and value relevance of this aggregated fundamental score based on portfolio performance constructed based on the fundamental score (Abarbanell & Bushee 1998; Mahmoud & Sakr 2012; Mohanram 2005; Piotroski 2000).

Previous scholars categorised fundamental signals into good signals (which are expected to have a favourable impact on future earnings and returns) and bad signals (which are expected to have negative impact on future earnings and returns). They assign a value to each fundamental signal based on its impact on future earnings and returns, aggregate these values and label the aggregation as the fundamental score. In Lev and Thiagarajan's (1993) study, they construct a fundamental score by assigning values to fundamental signals, being 1 for a positive value[23] and 0 for a negative value[24]. Lev and Thiagarajan (1993) find that the aggregated fundamental score (F_Score) reflects information in the fundamental signals and F_Score is significantly associated with ERCs and future earnings growth, both indicators of earnings persistence. Further they document that F_Score is more strongly associated with ERCs than a time series persistence measure of earnings. Therefore, F_Score is useful in capturing the permanent component of earnings. This evidence supports the view that F_Score has the ability to predict future earnings and is value relevant.

Abarbanell and Bushee (1997) examine and find that the aggregated fundamental score has the ability to predict future earnings. Seng and Hancock (2012) also document a similar finding, confirming that the aggregated fundamental score captures earnings persistence and has the ability to predict future earnings.

[23] A positive value implies bad news. For example, their inventory variable is calculated as change in inventory – change in sales. Therefore, a higher increase in inventory compared to sales results in a positive value for this variable, which suggests difficulty in generating sales, therefore impacting negatively on future earnings and returns.

[24] A negative value implies a good signal based on the above calculation.

Abarbanell and Bushee (1998), extending their work from 1997, investigate whether portfolios constructed and managed according to an aggregated fundamental score can yield abnormal returns. They find such portfolios in fact earned an average annual cumulative return of 13.2 per cent, which suggests that non-earnings fundamental signals are able to identify information about future earnings that is related to future stock returns. Piotroski (2000) also provides evidence to support the association between fundamental signals and stock returns using a fundamental score. He focuses on firms with high book-to-market value and concludes that investors use fundamental signals to separate winners from losers among high book-to-market ratio companies. Using nine fundamental predictors relating to firms' profitability, financial leverage, operating efficiency and liquidity, he constructs fundamental scores[25] depending on the signal's implication for future stock price and profitability and forms portfolios based on the level of fundamental score[26]. Using this analysis, he reports that investors can earn at least 7.5 per cent annual stock returns choosing financially strong, high book-to-market firms. Further he shows that buying expected winners (financially strong firms) and selling expected losers generates 23 per cent annual returns to investors.

Mohanram (2005) applies a similar strategy to low book-to-market firms[27] to identify ex-post winners and losers. His analysis documents that the entire low book-to-market group earns mean size-adjusted annual returns of negative 6.0 per cent and negative 4.2 per cent respectively for the first and second years. After categorising into fundamentally sound and weak firms based on the fundamental score, his results reveal that fundamentally sound firms earn a size-adjusted excess return of 3.3 per cent and 2.4 per cent in two years, whereas fundamentally weak firms earn size-adjusted excess returns of negative 17.9 per cent and negative 13.3 per cent respectively. This analysis reveals that a fundamental analysis-based trading strategy applied to growth firms can yield significant abnormal returns. Furthermore, he documents that firms with stronger growth fundamentals have better future realisations of earnings. Providing supporting evidence

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[25] For a good signal, the value 1 is assigned and for a bad signal, the value 0 is assigned.

[26] The fundamental score ranges from 0 to 9 and higher fundamental scores represent financially strong firms, whereas low fundamental scores represent financially poor firms.

[27] Low book-to-market firms, also known as growth or glamour stocks, usually have very high stock performance in the previous year. Therefore, they attract more attention from market intermediaries, such as analysts and institutional investors. These firms are likely to have more disclosures from sources other than financial statements. Therefore, it is unrealistic to expect an abnormal gain from dealing with this type of stock.

for the above findings, Mahmoud and Sakr (2012), using data from Egypt, report that investors can achieve a buy and hold stock return of 24.7 per cent annually through buying expected winners and selling expected losers using a simple investment strategy based on the fundamental score. Furthermore, they also find a positive relation between the fundamental score and subsequent earnings performance.

Xue and Zhang (2011) provide supportive evidence that institutional investors earn abnormal returns using F_Score-based investment strategies. Similarly, Sharma and Sharma (2009) document that F_Score-based investment strategies are useful in identifying extreme performers and one and two year ahead excess returns. However, they report that growth fundamentals, such as investment in research and development, capital expenditure, and advertising expenses, are more effective than traditional fundamentals. The findings from these studies support the conclusion that non-earning fundamental signals reflected in an aggregated measure are capable of predicting future earnings and returns and therefore are value relevant.

3.5 Research gap and hypotheses development for the predictive ability and value relevance of fundamental information (signals)

The above review of literature on the predictive ability and value relevance of earnings and non-earnings fundamental information (signals) points to the conclusion that fundamental signals are highly useful for market participants in predicting future earnings and assessing stocks. Further, the review reveals that most of the fundamental signal studies of this kind[28], especially non-earnings fundamentals studies, that examine predictive ability and value relevance are conducted using data from prior to year 2000 (Abarbanell & Bushee 1997; Al-Debie & Walker 1999; Dowen 2001; Lev & Thiagarajan 1993; Ou 1990; Ou & Penman 1989b; Seng & Hancock 2012; Swanson, Rees & Juarez-Valdes 2003). As such, there is a paucity of fundamental analysis studies in years post-2000. Several important changes have occurred in the international accounting environment that may influence the quality of accounting information, such as adoption of IFRS in many countries around the world in years post-2000. Therefore, users may not be informed about the quality and behaviour of this information following these changes and so information asymmetry may occur. Therefore, it is timely to revisit this area of

[28] In this type of study, variables are designed specifically based on signals used commonly by analysts when forecasting future earnings and assessing stock returns.

research using post-2000 data under the new accounting environment, to assess whether the fundamental signals examined previously remain useful for decision-making.

Pierce-Brown (1998) in her study of fundamental analysis for predicting future earnings states that "it seems that there is more valuable information in a set of accounts than just the bottom line." (p.99). As such, this study includes fundamental signals that have not been examined in this kind of fundamental study previously. Furthermore, this study examines the usefulness of earnings and non-earnings fundamental signals from different perspectives (predictive ability and value relevance) and the predictive ability and value relevance of non-earnings signals is examined for individual signals, for these signals in combination and in aggregate (F_Score). To the best of the author's knowledge, no known published study examines both predictive ability and value relevance of the same set of fundamental signals individually, in combination and in aggregate form using post-2000 data. Doing so provides a check on the consistency of findings, as well as providing a cross-check on the quality of the fundamental signals in terms of their predictive ability and value relevance. Moreover, this study investigates the predictive ability and value relevance of the chosen fundamental signals for different sub-samples[29] and provides robust evidence. Again there is no known such study in the literature that examines the predictive ability and value relevance of the same set of fundamental signals in different contexts.

Accordingly, the following hypotheses are developed to address omissions in the literature and link with the first two Research Objectives discussed in Chapter 1, section 1.4 in relation to predictive ability and value relevance respectively.

Hypotheses relating to Objective One - predictive ability[30]

H1a: *There is a positive relationship between current year change in earnings per share and one-year-ahead change in earnings per share.*

[29] Sub-samples examined include for code and common law countries, for increase and decrease in future earnings, for stocks with gains and losses, for growth and value stocks, and for extreme and non-extreme performers.

[30] Objective One involves investigating the predictive ability of earnings and non-earnings fundamental signals (fundamental information based on financial statements) in predicting one-year-ahead change in earnings and IFRS impact on this predictive ability. The IFRS-related hypotheses are developed in the next section.

H1b: There is a negative relationship between non-earnings fundamental signals and one-year-ahead change in earnings per share[31].

H1c: There is a positive relationship between an aggregated fundamental score and one-year-ahead change in earnings per share.

Hypotheses relating to Objective Two-value relevance[32]

H2a: There is a negative relationship between current year change in earnings per share and contemporaneous excess returns.

H2b: There is a negative relationship between non-earnings fundamental signals and contemporaneous excess returns.

H2c: There is a positive relationship between an aggregated fundamental score and contemporaneous excess returns.

Ou (1990) documents that the contemporaneous association between non-earnings accounting numbers and stock returns can be viewed as resulting from a predictive information link between these non-earnings accounting numbers and future earnings. Abarbanell and Bushee (1997) also comment that "predicting accounting earnings, as opposed to explaining security returns, should be the central task of fundamental analysis" (p.1) and explain that the intermediate link between fundamental signals and returns comes from the ability of fundamental signals to predict future earnings. Therefore, this study first examines the predictive ability of the selected fundamental signals, followed by an examination of their value relevance. As such, from this point onwards discussion of the relevant literature is organised first to discuss predictive ability, followed by discussion of value relevance.

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[31] The fundamental signals used in this study involve change from the prior year in all but one case (audit qualification) and are constructed in a way intended to provide a particular signal about future earnings and excess returns. The expected direction of the relationships between the earnings and non-earnings fundamental signals and each of the dependent variables is created by construction of the variables. For example, earnings is measured as $(EPS_{t-1} - EPS_{t}) / P_{t-1}$, where EPS=earnings per share and P=share price and this variable is expected to have a positive relationship with one-year-ahead change in earnings per share, which is measured as $(EPS_{t+1} - EPS_{t}) / P_{t-1}$, due to the reversal of current year accruals in the future, and a negative relationship is expected with contemporaneous excess return. For leverage, which is measured as this year's leverage minus prior year's leverage, it is expected to have a negative relationship with the dependent variables. The signals, their definitions and construction, are explained in detail in Chapter 4, section 4.5.2.

[32] Objective Two involves examining the value relevance of earnings and non-earnings fundamental signals for stock returns (contemporaneous excess returns) and IFRS impact on the value relevance of these signals. Again the IFRS-related hypotheses are developed in the next section.

3.6 IFRS impact on the predictive ability and value relevance of earnings and non-earnings fundamental signals

3.6.1 Significance of IFRS adoption around the world

The adoption of IFRS has been one of the most important milestones in global accounting history, so it is not surprising that many researchers have investigated the impact of IFRS on economic aspects, e.g., cost of capital and capital market benefits (Daske et al. 2008; Li 2010), investment and asset allocation decisions (Florou & Pope 2012), foreign direct investment (Gordon, Loeb & Zhu 2012) and investment efficiency (Chen, Young & Zhuang 2012), investor protection (Houqe et al. 2012), and promoting international trade by narrowing cross country differences (De George, Li & Shivakumar 2016). More importantly, IFRS adoption significantly affects financial reporting through, for instance, the quality and quantity of financial reporting disclosures, comparability and transparency of financial statements, information asymmetry (Barth, Landsman & Lang 2008; Daske & Gebhardt 2006; Daske et al. 2008; Glaum et al. 2013; Hodgdon et al. 2008; Preiato, Brown & Tarca 2013), and audit quality and fees (De George, Li & Shivakumar 2016; Kim, Liu & Zheng 2012; Redmayne & Laswad 2013). Evidence provided by this literature supports the view that adoption of IFRS has significant economic and social impact. As such, a major contribution of this thesis is to assess the impact of IFRS on earnings and non-earnings fundamental information included in financial statements in terms of the predictive ability and value relevance of that information.

3.6.2 Impact of IFRS on fundamental signals

The IASB's intention behind promulgation of IFRS is "to develop, in the public interest, a single set of high quality, understandable, enforceable and globally accepted financial reporting standards based on clearly articulated principles. These standards should require high quality, transparent and comparable information in financial statements and other financial reporting to help investors, other participants in the various capital markets of the world and other users of financial information make economic decisions" (Hopper 2012 p.99). Therefore, adoption of IFRS can be expected to make significant changes to financial reporting (De George, Li & Shivakumar 2016).

A number of studies have been conducted in different countries to identify the impact of IFRS on financial statements, including Goodwin, Ahmed and Heaney (2008) (Australia);

Haverals (2007), (Belgium); Blanchette, Racicot and Girard (2011), (Canada); Tsalavoutas and Evans (2010), (Greece); Bradbury and van Zijl (2005), Kabir, Laswad and Islam (2010), Fung, Su and Zhu (2010), (New Zealand); Horton and Serafeim (2010), Iatridis (2010) (UK) and (Hung & Subramanyam 2007) (Germany). These studies report a range of findings including that the values for total assets, total liabilities and net profit are higher under IFRS than under pre-IFRS generally accepted accounting principles (GAAPs); IFRS adjustments for goodwill, other intangibles and investment property increase profit and equity; while IFRS treatment of employee benefits, share-based payments, tax, revenue and provisions reduce profits. Most of these changes occur due to accounting treatment differences between previous national or domestic GAAPs and IFRS, but may also occur due to there being no prior corresponding domestic standards.

For instance, after adoption of IFRS in Australia, Goodwin, Ahmed and Heaney (2008) document a decrease in total liabilities and equity, with an increase in the value of total assets and the leverage ratio. These changes to accounting numbers are due mainly to differences in accounting between previous Australian GAAP and IFRS, particularly in the accounting treatment of share-based payments, income tax, goodwill, intangibles, provisions, investments, impairment, foreign exchange transactions, and leases. Tsalavoutas and Evans (2010) study the impact of IFRS adoption on Greek companies' financial position, performance and key ratios and report a positive impact on shareholder equity and net income, while a negative impact on gearing and liquidity (Aisbitt 2006).

Stent, Bradbury and Hooks (2010) examine the impact of NZ IFRS (New Zealand IFRS) on financial statement elements and key financial ratios. On average they show that 87 per cent of their sample companies' financial statements are affected significantly by adoption of IFRS in New Zealand. Moreover, they document a significant increase in liabilities and decrease in equity. Reported financial ratios, such as return on equity, return on assets, leverage and return on sales, increase under NZ IFRS, whereas the asset turnover ratio decreases. Providing supportive evidence for these findings, Kabir, Laswad and Islam (2010) also document that total assets, total liabilities and net profit were significantly higher under NZ IFRS than under pre-IFRS GAAPs. Further they show that adjustments for goodwill, other intangibles and investment property increase equity, while adjustments for employee benefits and share-based payments reduce equity under NZ IFRS.

Blanchette, Racicot and Girard (2011) report that IFRS relies more heavily on fair value accounting than previous Canadian GAAP, affecting assets, liabilities and equity items, as well as profit or comprehensive income in the financial statements. They find that the main differences come from impairment adjustments, accounting for minority interests, leases, pensions and share-based payments. Furthermore, Blanchette, Racicot and Girard (2011) report that IFRS adjustments result in more volatility in the financial ratios and the ratios are generally higher computed under IFRS than under the previous Canadian GAAP, especially liquidity, leverage and profitability ratios. Similarly, for the UK, financial statement ratios, such as profitability (operating profit margin, net profit margin and earnings per share) and leverage (long-term liabilities to capital employed, total liabilities to shareholders' funds and interest cover) are higher under IFRS than under UK GAAP (Iatridis 2010). Hung and Subramanyam (2007) also report higher total assets and book value under IFRS than prior GAAP in a German context.

Lantto and Sahlström (2009) provide evidence of the impact of IFRS on the fundamentals in financial statements for Finland. They also observe a significant change in the financial statements, particularly in the magnitude of financial ratios. They explain that the increase in the profitability ratios and price-to-earnings ratio is due to an increase in income statement profit, mainly caused by removal of amortisation of purchased goodwill under IFRS. Moreover, they show that increases in debt items and decreases in equity explain the change in leverage ratio, whereas the decrease in liquidity ratio is explained mainly by decrease in current liabilities. Overall, their results show that IFRS accounting principles concerning fair value accounting, lease accounting, income tax accounting, and accounting for financial instruments, jointly explain most of the changes in key accounting ratios.

Agca and Aktas (2007) also report that adoption of IFRS led to changes in the magnitude of ratios, such as inventory turnover, asset turnover, cash ratio, return on equity and gearing, in Turkey. Haverals (2007) found that IFRS-based tax accounting increased the effective corporate tax burden in Belgium, a code law country, by 3.8 to 14.6 per cent, depending on the sector, and this effect is mainly attributable to rejection of the declining balance depreciation rule under IFRS (Haverals 2007)**.**

Overall, the findings point to the conclusion that adoption of IFRS has considerable impact on recognition, measurement, classification and disclosure of financial statement fundamentals, and therefore ultimately affects the quality of fundamental signals. If the users of these fundamental signals are not aware of the quality of the information embedded in these signals after adoption of IFRS, information asymmetry occurs and may affect the efficiency and effectiveness of their decision-making. As such, these changes suggest it to be timely and useful to investigate the impact of IFRS on the quality of financial statement fundamental signals. Accordingly, this study aims to compare the quality pre- and post-IFRS of selected financial statement fundamentals in terms of their predictive ability and value relevance.

3.6.3 IFRS impact on the predictive ability and value relevance of earnings

The literature provides compelling evidence that current year earnings can be used to predict future earnings and is value relevant for contemporaneous returns (Barth, Cram & Nelson 2001; Ball & Brown 1968; Beaver 1968; Dechow 1994; Kim & Kross 2005; Lev, Li & Sougiannis 2005; Nam, Brochet & Ronen 2012). Several studies have been carried out to examine IFRS impact on the predictive ability and value relevance of earnings.

The studies of IFRS impact on the predictive ability of earnings mostly report negative or neutral findings. Kabir, Laswad and Islam (2010), for instance, study the ability of current year earnings to predict one year ahead cash flows under IFRS and pre-IFRS (NZGAAP) in New Zealand and find no significant difference in the predictive ability of earnings before and after adoption of IFRS. Similarly, Atwood et al. (2011) examine the persistence and predictive ability of earnings for 33 countries using pre- and post-IFRS data. They report no improvement in the predictive ability of current year earnings in predicting future cash flows under IFRS when compared to domestic GAAPs. They also report no difference in the persistency of positive earnings before and after IFRS transition, however they find that losses reported under IFRS are less persistent than those reported under USGAAP. Doukakis (2010) examines the ability of earnings to predict future return on equity (ROE) by decomposing earnings into operating income, non-operating income, extraordinary charges and credit for the period before and after IFRS adoption. He reports lower persistence of operating and non-operating income and low explanatory power for all regression models during the IFRS adoption period in Greece.

The studies of IFRS impact on value relevance report mixed evidence. Jermakowicz, Prather-Kinsey and Wulf (2007), for instance, report that adoption of IFRS increased the value relevance of earnings in Germany; whilst Callao, Jarne and Laínez (2007) report a decrease in Spain. Goodwin, Ahmed and Heaney (2008) find no evidence to conclude that earnings reported under IFRS is more value relevant than previous Australian GAAP. Gjerde, Knivsflå and Sættem (2008) also document that they find little evidence of increased value relevance of earnings under IFRS. However, they show that reconciliation adjustments to IFRS are marginally value relevant due to increased relevance of the balance sheet and normalised net operating income.

Bartov, Goldberg and Kim (2005) report that IFRS increased the value relevance of earnings in Germany. Providing supportive evidence, Christensen et al. (2015) conclude the same, while Hung and Subramanyam (2007) document no increase in value relevance and timeliness of earnings in the same context after adoption of IFRS. Similarly, Barth et al. (2012) find that the value relevance of net income increases after adoption of IFRS.

Devalle, Onali and Magarini (2010) examine the extent to which earnings is associated with share price and cum-dividend returns for the period before and after adoption of IFRS in five European countries. They find increased value of earnings, decreased value relevance of book value and increased explanatory power of the regression under IFRS for the whole sample. However, in respect of individual countries, findings are mixed. Using 14 European countries, Clarkson et al. (2011) document a decrease in value relevance of earnings for firms in common law countries, while an increase in code law countries after adoption of IFRS.

The level of earnings management is another aspect of interest which affects earnings quality. Higher earnings management reflects poorer earnings quality, thus decreasing the predictive ability and value relevance of earnings and vice versa. Several studies investigate the impact of IFRS on earnings management and find mixed evidence. Van Tendeloo and Vanstraelen (2005) study whether voluntary adoption of IFRS leads to lower earnings management in Germany and find no difference in earnings management behaviour between IFRS adopters and companies applying German GAAP. Callao and Jarne (2010) examine IFRS impact on earnings management in the European Union. They document higher discretionary accruals and therefore higher earnings management after adoption of IFRS. On the contrary Zéghal, Chtourou and Sellami (2011) report that mandatory IFRS adoption for French companies is associated with lower earnings management. Providing more supportive evidence, Ismail et al. (2013) also show that IFRS is associated with lower earnings management and higher value relevance using both price earnings and return-earnings models in an emerging market (Malaysia), thus concluding that IFRS improved earnings quality.

Jeanjean and Stolowy (2008) report that the introduction of IFRS did not decrease the pervasiveness of earnings management in Australia and the UK, but in fact increased it in France. Iatridis (2010) investigates the effects of transition from Greek GAAP to IFRS and finds some evidence of earnings management during the adoption period. However, the level of earnings management is significantly reduced during subsequent periods. Furthermore, Iatridis (2010) shows greater value relevance of IFRS measures in the second year after adoption when compared to the first year of adoption. Barth, Landsman and Lang (2008) provide evidence that firms adopting IFRS are less likely to engage in earnings smoothing, management of earnings towards a target, and more likely to recognise losses in a timely manner than their non-adopting counterparts. Moreover, they show a higher association of accounting earnings with share price and share returns. On the contrary, Ahmed, Neel and Wang (2013) document using 20 countries around world higher income smoothing and higher earnings management after IFRS adoption. Similarly, Lin, Riccardi and Wang (2012) also report more earnings management and less timely loss recognition under IFRS. Paananen and Lin (2009) also report higher earnings smoothing, less timely loss recognition and less value relevance of book value and earnings during the mandatory IFRS adoption period in Germany. Similar findings are documented in Sweden (Paananen 2008) after adoption of IFRS.

3.6.4 IFRS impact on the predictive ability and value relevance of non-earnings fundamental signals

The most researched non-earnings fundamental signal in terms of IFRS impact is intangible assets, particularly goodwill. Chalmers et al. (2012) document that reported intangibles valued under IFRS conveys more useful information for prediction of future earnings than values under previous GAAP. They further report that this result is attributable mostly to reported goodwill, which reveals that the impairment-based goodwill approach under IFRS is more value relevant than the previous domestic GAAP. Goodwin, Ahmed and Heaney (2008) also show that goodwill accounting under IFRS improves the association with market value. Providing more supportive evidence for the above findings, Cheong, Kim and Zurbruegg (2010) also document increased value relevance for intangible assets capitalised in the post-IFRS period, and also the intangibles capitalised under IFRS improved analyst forecast accuracy.

Hodgdon et al. (2008) show how compliance with IFRS disclosure requirements affects analyst forecast accuracy. They find that disclosure requirements under IFRS for the items income tax, segmental reporting, property, plant and equipment, leases, retirement benefit, borrowing cost, financial instruments, earnings per share, discontinued operations, impairment of assets, provisions, contingent liabilities, contingent assets and intangible assets increased analyst forecast accuracy. In other words, reporting of the above items under IFRS reduces information asymmetry and assists analysts in forecasting future earnings. Glaum et al. (2013) show that switching from domestic German GAAP to IFRS increases the quality of companies' disclosures and this quality improvement contributes to some extent to an increase in analyst forecast accuracy. Additionally, there are some studies that examine IFRS impact on discretionary accruals that were discussed in section 3.6.3 in relation to earnings management.

3.7 Research gap and hypotheses development for IFRS impact on the predictive ability and value relevance of fundamental signals

When reviewing the above literature, it is evident that findings in relation to the value relevance of IFRS earnings are mixed. Few studies have investigated specifically IFRS impact on the predictive ability of earnings. However, to the best of the author's knowledge no known study examines IFRS impact on the ability of change in current year earnings to predict one-year-ahead change in earnings. It is this gap that this study fills in terms of examining the earnings signal.

Moreover, the review of the literature of IFRS impact on non-earnings signals reveals no published research that examines the value relevance and predictive ability of the non-earnings signals selected for this study with the exception of goodwill (Chalmers et al. 2012), and even then Chalmers et al. is very different from this current study. In addition, there is no prior study that examines IFRS impact on the predictive ability and value relevance of an aggregated fundamental score constructed from non-earnings signals.

Further, this study investigates IFRS impact on the predictive ability and value relevance of earnings and non-earnings signals individually, in combination and in aggregate form. Moreover, IFRS impact is examined in different contexts, such as for code and common law countries, for future increase and decrease in earnings, for stocks with gains and losses in terms of returns, for growth and value stocks, as well as for extreme and non-extreme performers.

Therefore, this study provides robust evidence of IFRS impact on the value relevance and predictive ability of earnings and non-earnings fundamental signals. This is an extensive study undertaken on the quality aspects of financial information that is not matched in published prior studies. As such, this study addresses omissions or gaps in the literature and so contributes to the stock of knowledge about IFRS impact.

Given the objective of the IASB in introducing IFRS and the number of studies that find a positive change in accounting quality as a consequence of IFRS adoption, such as increased quantity and quality of financial reporting disclosures, as well as greater comparability, transparency (De George, Li & Shivakumar 2016) and overall positive outcome for investors and analysts (Pawsey 2016), the following hypotheses are developed to address omissions in the IFRS-related literature that link with the first two Research Objectives in relation to predictive ability and value relevance.

Hypotheses relating to Objective One – predictive ability

H1d: *The predictability of one-year-ahead change in earnings per share by current year change in earnings per share improved after adoption of IFRS.*

H1e: *The predictability of one-year-ahead change in earnings per share by non-earnings fundamental signals improved after adoption of IFRS.*

H1f: *The predictability of one-year-ahead change in earnings per share by the aggregated fundamental score improved after adoption of IFRS.*

Hypotheses relating to Objective Two – value relevance

H2d: *The value relevance of current year changes in earnings per share for excess returns improved after adoption of IFRS.*

H2e: *The value relevance of non-earnings fundamental signals for excess returns improved after adoption of IFRS.*

H2f: *The value relevance of the aggregated fundamental score (F_Score) for excess returns improved after adoption of IFRS.*

3.8 Analysts' forecasts, use of financial information and efficiency in using fundamental signals

Financial analysts are one of the groups of influential stakeholders that use accounting information included in the financial statements actively. They act as an important information intermediary in the capital market by providing earnings forecasts and stock recommendations for investors.

3.8.1 Analysts' use of information for forecasts

Analyst forecast error, forecast dispersion, analyst following, target pricing forecasts and stock recommendations are some information properties investigated in the analyst literature. In particular, forecast error and forecast dispersion have been used widely in past research as proxies to measure the quality of information available to analysts (Byard, Li & Yu 2011; Cheong & Al Masum 2010; Cotter, Tarca & Wee 2012; Ernstberger, Krotter & Stadler 2008; Preiato, Brown & Tarca 2013; Pawsey 2016). Higher financial information quality lowers forecast error and forecast dispersion (Hope 2003; Lang & Lundholm 1996).

Beuselinck et al. (2010) report that analysts' forecasts represent both public information and individual analysts' private information. Therefore, they use separate proxies to capture the quality of public information available to analysts. Analysts use information from different sources, such as financial reports, regulatory filings, conference calls, other management communications, and industry and macroeconomic information, to make their forecasts and stock recommendations (Ramnath, Rock & Shane 2008).

Previts et al. (1994) document, after analysing 479 sell-side analyst company reports, that analysts' forecasts are based primarily on earnings information relative to balance sheet or cash flow information. However Lev and Thiagarajan (1993) identify 12 pieces of non-earnings[33] fundamental information used by analysts, referring to written

[33] These include inventory, accounts receivable, capital expenditure, research and development (R&D) expenditure, gross margin, sales and administrative expenses, provision for doubtful receivables, effective tax rate, order backlog, labour force, last-in-first-out (LIFO) earnings and audit qualification.

pronouncements by financial analysts published in a variety of sources, such as the Wall Street Journal and Barron's from 1984 to 1990, the Value Line publication, and major security firms' (e.g. brokers') commentaries. Similarly, Dempsey et al. (1997), from a survey of 420 users including analysts, identify a set of financial information that is used frequently by analysts and other stakeholders. This information includes cash flows from operations, net income, return on equity, sales, capital investment, R&D expense, percentage on sales from priority products, return on sales, return on assets, sales per employee, accounts receivable / sales, operating cash flows per employee, cost of goods sold/ inventory, equity/ assets, and sales/ total assets. This evidence shows that analysts use most of the fundamental information related to both earnings and non-earnings included in financial statements in developing their forecasts.

As explained, analysts as experts obtain and analyse financial information from various sources and produce earnings forecasts, target pricing forecasts and stock recommendations. Investors use this information to make decisions regarding share trading and therefore affect the market price.

Ali, Lee Seok and Trombley (2003) report that firm fundamental values based on consensus forecasts are highly correlated with contemporaneous stock prices. However, Womack (1996) shows by analysing analysts' buy and sell recommendations in the US market that analysts' forecast information is not incorporated fully into stock market prices, in particular for sell recommendation information. Similarly, Ali, Lee Seok and Trombley (2003) show that analysts' forecast information is not reflected fully in current stock prices. Chan, Jegadeesh and Lakonishok (1996) report that analysts' earnings forecasts are represented in the stock price sluggishly, especially for firms with the worst past stock performance. If analysts are efficient, they can be expected to incorporate new information into their forecasts immediately and without bias (Easterwood & Nutt 1999). However Easterwood and Nutt (1999) show that analysts underreact to negative information and overreact to positive information. They interpret this analyst behaviour as systematic optimism in response to new information. Zhaoyang and Jian (2007) document that analysts' overreaction to extreme good news is a rational response to earnings uncertainty and is not due to cognitive bias.

Bradshaw, Richardson and Sloan (2001) study how analysts incorporate accruals into their earnings forecasts. They report a negative relationship between accruals and subsequent earnings forecast errors, suggesting that analysts do not adjust forecasts for transitory working capital accruals fully. Burgstahler and Eames (2003) explore whether analysts consider earnings management to avoid losses when they make earnings forecasts. They document that analysts are aware of earnings management to avoid losses in general, but are unable to identify specifically which firms are engaged in earnings management. However, Shane and Stock (2006) show that analysts' forecasts fail to capture earnings management that shifts income from the fourth quarter in a high tax rate setting to the immediate following quarter. Dechow, Hutton and Sloan (1999) show that analysts fail to incorporate the abnormal earnings component of current year earnings fully into their one-year-ahead earnings forecasts and this error is reflected in stock prices. This evidence suggests that analysts underreact to earnings announcements, implying that analysts are inefficient in incorporating earnings information into their forecasts. However, Shane and Brous (2001) show that non-earnings surprise information helps to correct this underreaction significantly, proposing that non-earnings information increases the degree of forecast accuracy.

All this literature supports the view that analysts use both earnings and non-earnings information for their earnings forecasts and stock recommendations.

3.8.2 Analysts' efficiency in using fundamental signals

One of the Research Objectives presented in Chapter 1 section 1.4 focuses on investigating the efficiency with which analysts use fundamental information when making their earnings forecasts. There are few prior studies that investigate this issue. Abarbanell and Bushee (1997) investigate analysts' efficiency in using nine fundamental signals when making their earnings forecast revisions. They compare the relationship between the fundamental signals and one-year-ahead change in earnings to the analogous relations between fundamental signals and one-year-ahead forecast revisions. Using this analysis, they conclude that analysts are inefficient in using fundamental signals and fail to impound all the information about future earnings included in fundamental signals when making their forecast revisions. Further they report that, generally, analysts underreact to some fundamental signals (such as change in inventory, change in gross margin and, and change in labour force), when making their forecast revisions. Similarly, Swanson and Rees (2003) also examine the association of the fundamental signals with analysts' earnings forecast revisions and analysts' forecast errors in a period of currency devaluation. They conclude that analysts underutilise fundamental signals when making their earnings forecast revisions. Lambert (2011) also provides some supportive evidence using US data that analysts are inefficient in using fundamental signals.

Wahab, Teitel and Morzuch (2015) examine analysts' and whisperers'[34] efficiency in using fundamental signals using quarterly data when forecasting change in one-year-ahead earnings per share in a US context. They also document that both analysts and whisperers do not incorporate the information included in fundamental signals fully when forecasting change in one-year-ahead earnings per share. However, the whisperers' efficiency in using fundamental signals is higher than that of analysts, and whisperers' forecasts include unique information incremental to analysts' forecasts. Further they report that analysts underreact to change in earnings and change in gross margin, whilst they overreact to selling and administrative expenses and cash flows from operations.

3.8.3 Research gap and hypotheses development for analysts' efficiency in using fundamental signals

The review of the literature makes it evident that analysts' efficiency in using fundamental signals is researched rarely and there is no published study conducted outside the US context using post-2000 data that examines analysts' efficiency in using fundamental signals. Moreover, this current study examines analysts' efficiency in using earnings and non-earnings signals individually and in combination. Therefore, the findings will provide robust evidence of analysts' efficiency in using fundamental signals. No other study is found in the literature that examines analysts' efficiency to the extent that this study does.

Findings from the available literature conclude that analysts do not fully incorporate the information included in fundamental signals when making their forecast revisions, and are therefore inefficient. Accordingly, analysts underreact or overreact to certain fundamental signals. As such, the following hypotheses are developed to address omissions in the literature and link with the third Research Objective in relation to analysts' efficiency.

[34] Whisperers are "an alternative anonymous source of EPS forecasts" (Wahab, Teitel & Morzuch 2015 p.2).

Hypotheses relating to Objective Three - analysts' efficiency

H3a: Analysts are inefficient in using earnings fundamental signals for forecasting one-year-ahead change in earnings per share.

H3b: Analysts are inefficient in using non-earnings fundamental signals for forecasting one-year-ahead change in earnings per share.

The efficiency with which analysts use fundamental signals is examined in different settings, such as for code and common law countries, and when predicting a future increase (winners) and decrease in earnings (losers).

3.8.4 IFRS and analysts' earnings forecasts

There are many studies that have been conducted in different countries investigating the impact of IFRS on analysts' earnings forecast accuracy and which provide compelling evidence that analyst forecast accuracy improved after adoption of IFRS (e.g.,Cheong & Al Masum 2010; Cotter, Tarca & Wee 2012; Ernstberger, Krotter & Stadler 2008; Pawsey 2016). Cotter, Tarca and Wee (2012) report that analysts coped effectively with the Australian transition to IFRS and increased their forecast accuracy in the year of IFRS adoption. However, they do not observe that disclosure about impact of IFRS adoption in the year of transition is associated with lower error or lower dispersion. On the other hand, Hodgdon et al. (2008) in a study including 13 countries report that compliance with IFRS disclosure requirements reduces information asymmetry and enhances analysts' forecast accuracy. Similar results are recorded in a German context by Glaum et al. (2013).

Preiato, Brown and Tarca (2013) examine the importance of enforcement mechanisms in achieving IFRS benefits in relation to analysts' forecast accuracy in 51 countries. They find lower forecast error and forecast dispersion for IFRS users and no evidence to conclude that IFRS benefits are conditional on the level of enforcement. Horton, Serafeim and Serafeim (2013) explore the actual causes for improvement in analysts' forecast accuracy under IFRS. They find that the quality of the information environment increases significantly for mandatory IFRS adopters when compared with either non-adopters or voluntary adopters. Further, they find that improvement in forecast accuracy is explained partially by the comparability benefit associated with IFRS adoption around the world. Tan, Wang and Welker (2011) examine the effect of mandatory IFRS adoption on foreign analysts in 36 countries. They report that IFRS adoption around the world attracts increased foreign analyst coverage and improves these foreign analysts' forecast accuracy. Further, they find that the increase in foreign analyst following and forecast accuracy is a result of elimination of GAAP differences between the firm's home country and the analysts' home country.

Beuselinck et al. (2010) document a significant improvement in the precision of both public and private information in the analysts' information environment after switching to IFRS, especially for forecasts relating to 2006 and later. However, they find no difference in the consensus among analysts before and after adoption of IFRS. Byard, Li and Yu (2011) report that forecast error and forecast dispersion decreased following adoption of IFRS in the EU and the decrease is stronger for firms with more transparent reporting practices.

3.8.5 IFRS and analysts' efficiency in using fundamental signals

The above literature discusses the overall IFRS impact on analysts' information environment and how adoption of IFRS has been found to contribute to increased analyst forecast accuracy. However, there are some studies that investigate IFRS impact on individual financial statement items and their influence on analysts' forecast accuracy. For example, Chalmers et al. (2012) investigate the impact of IFRS on intangible assets and analysts' forecast accuracy. They find that adoption of IFRS involves more precise recognition of intangible assets than predecessor standards, which conveys useful information to financial analysts in making their earnings forecasts. The impairment approach to goodwill valuation required by IFRS, in contrast to the previous amortisation approach in Australia, conveys useful information to analysts in making their earnings forecasts more accurate. Cheong, Kim and Zurbruegg (2010) also document that intangibles capitalised under IFRS positively aided analysts in forecasting future earnings of firms in the Asia Pacific region.

3.8.6 Research gap and hypotheses development for IFRS impact on analysts' efficiency in using fundamental signals

Apart from the studies cited in the previous section that are focused on intangibles, to the best of the author's knowledge, no other research has investigated the impact of fundamental signals reported under IFRS on analyst forecast accuracy. Further, there are no prior studies that examine IFRS impact on the efficiency with which analysts use fundamental signals when developing their earnings forecasts. This study addresses that research gap.

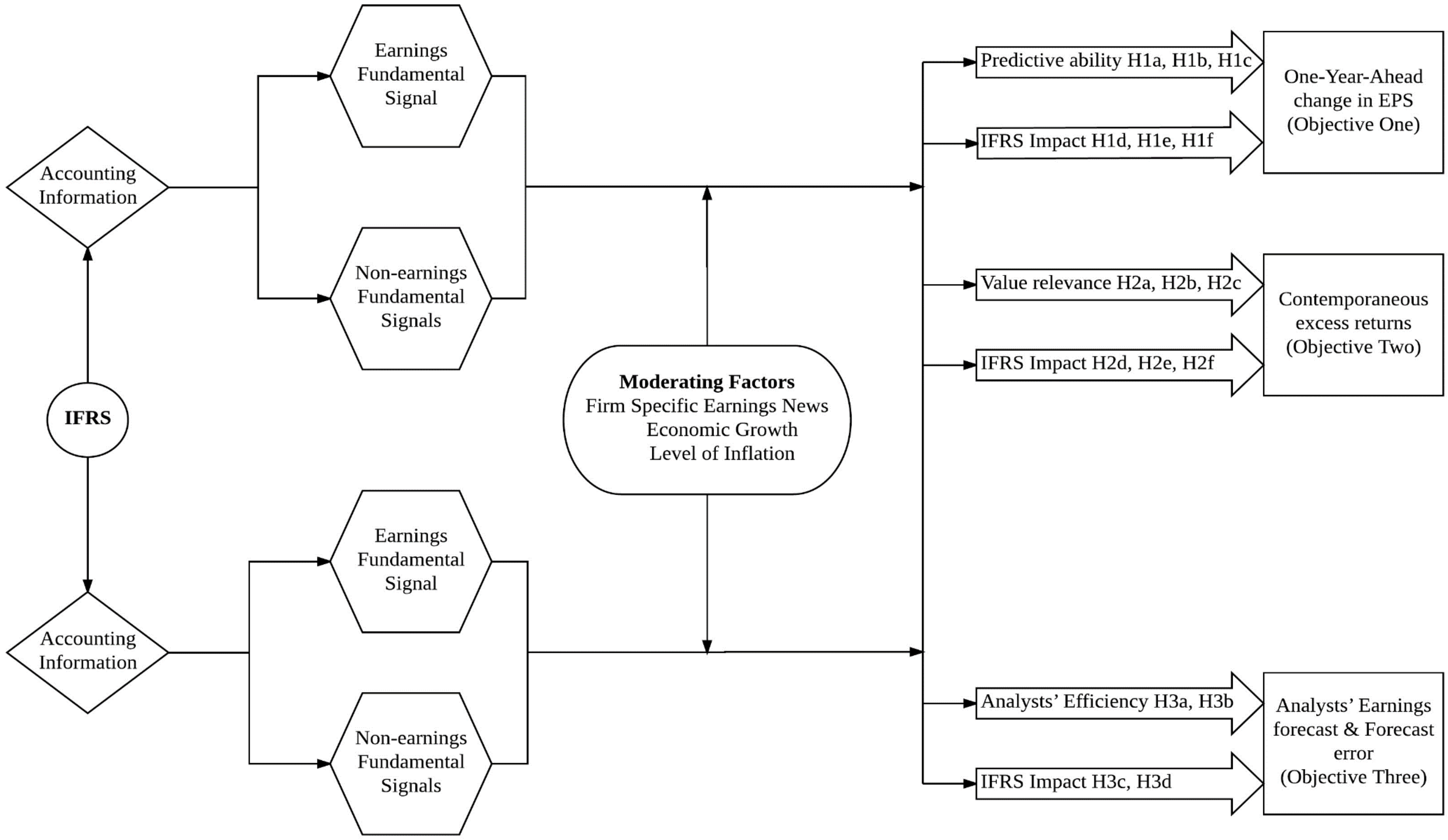
The above discussion provides supportive evidence to conclude that adoption of IFRS has a positive impact on analysts' earnings forecast accuracy. Yet a gap remains in the literature in terms of whether analysts' efficiency in using fundamental information improved after adoption of IFRS. That is, the literature reveals that adoption of IFRS makes significant changes to the accounting environment, specifically an increase in disclosures, transparency and comparability, making financial statements more understandable and useful, particularly to analysts, making their forecasts more accurate compared with the prior situation. Further, the above literature reports an increase in the precision of both public and private information in analysts' information environment after IFRS adoption, which makes financial statements more understandable to analysts. Based on this argument the following hypotheses are developed to support the third Research Objective in relation to investigating analysts' efficiency:

H3c: Analysts' efficiency in using the earnings signal for forecasting one-year-ahead change in earnings per share improved after adoption of IFRS.

H3d: Analysts' efficiency in using non-earnings signals for forecasting one-year-ahead change in earnings per share improved after adoption of IFRS.

In summary, this study addresses the research gaps identified based on a review of the relevant literature by testing 16 hypotheses related to three Research Objectives. The overall conceptual framework for the study is depicted in Figure 3.1 as follows.

Figure 3.1: Conceptual framework



3.9 Conclusion

The first part of this chapter reviews the literature on the predictive ability and value relevance of earnings and non-earnings fundamental information (signals) and the impact of IFRS on these aspects that relate to first two Research Objectives of this study. Documented in the literature is a predictive link between fundamental signals and future earnings (Lipe 1990) and a valuation link between predicted future earnings changes and stock returns (Ou 1990). Further, Abarbanell and Bushee (1997) explain the intermediate link between fundamental signals and returns due to the ability of fundamental signals to predict future earnings. To fill identified gaps in the literature, this study examines the predictive ability and value relevance of earnings and non-earnings fundamental signals, along with the impact of IFRS on these.

The findings in the literature support the view that both earnings and non-earnings fundamental signals are useful in predicting earnings and are also value relevant for contemporaneous returns and stock price. Furthermore, the literature documents that non-earnings fundamental signals have information content incremental to earnings that is useful for predicting earnings and are also value relevant for contemporaneous returns. An aggregated fundamental score is also revealed from the literature to be useful in predicting future earnings and assessing stock returns. The literature review supports the conclusion that most of the fundamental signals studies that examine the predictive ability and value relevance of fundamental signals were conducted using data from prior to year 2000. Therefore, one aspect of the Research Objectives for this current study is to revisit this area of research, including additional variables that have not been examined in this type of study before in the year post-2000 accounting environment.

The review of the literature on IFRS impact provides a great deal of evidence to show that IFRS affected financial statement fundamentals significantly and therefore affected the quality of accounting information. Most studies of IFRS impact on the quality of accounting fundamentals focus on the earnings measure and very few studies investigate IFRS impact on the quality of non-earnings fundamental signals. However, there is no published study that examines the value relevance and predictive ability of the selected non-earnings fundamental information. This study addresses that omission in the literature from different perspectives and in different settings.

In addition, this chapter also focuses on the literature on analysts' efficiency in using fundamental signals and the impact of IFRS on analysts' efficiency. Evidence in the literature reveals that this area is researched rarely and very few studies have been conducted to investigate analysts' efficiency in using fundamental signals. Those that do exist tend to be in non-IFRS environments. The conclusion from prior literature is that analysts appear not to fully incorporate the information included in fundamental signals when making their forecast revisions. As such, they are inefficient in using fundamental signals and this reflects through under or overreaction to certain fundamental signals. There is no known research that examines IFRS impact on the efficiency with which analysts use fundamental signals, and this study addresses these research gaps by proposing 16 hypotheses developed in this chapter for testing.

CHAPTER 4: RESEARCH METHODOLOGY

4.1 Chapter introduction

This chapter explains the research design, the sampling process, data collection techniques and regression models used in testing empirically the hypotheses developed in Chapter 3. Accordingly, this chapter is organised as follows. Section 4.2 summarises the Research Objectives and Questions discussed in Chapter 1. Section 4.3 explains selection of the variables. Section 4.4 defines and explains the measurement of the dependent variables and section 4.5 defines and explains the measurement of the independent variables. Section 4.6 discusses the development of the regression models applied to test the hypotheses and section 4.7 discusses the nature of panel data and related statistical issues. Section 4.8 explains the sample selection process and construction of the sample. Finally, section 4.9 concludes the chapter.

4.2 Research Objectives and Questions of the study

As explained in Chapter 1, the first Research Objective is to investigate the predictive ability of fundamental signals in predicting one-year-ahead change in earnings and IFRS impact on this predictive ability. The second Objective is to assess whether the selected fundamental signals are value relevant for contemporaneous excess returns and IFRS impact on their value relevance. The third and final Objective is to assess the efficiency with which analysts use these fundamental signals that, if found as hypothesised, significantly predict future earnings and are value relevant, and also to assess IFRS impact on analysts' efficiency.

Using the above Research Objectives, this study attempt to address two main Research Questions: i) What is the usefulness for decision-making of fundamental information reported in financial statements in years post-2000, especially for investors and financial analysts? and ii) What is the impact of International Financial Reporting Standards (IFRS) on this usefulness for the same parties?

4.4 Variable selection

The predictive ability and value relevance of fundamental information (signals), and analysts' efficiency in using this fundamental information for their earnings forecasts, together with IFRS impact on these, is investigated in this study. For this purpose, the independent variables are categorised as earnings or non-earnings variables (Abarbanell & Bushee 1997; Lev & Thiagarajan 1993) and in this study one earnings signal and 12 non-earnings signals are included.

The fundamental signals are selected mainly from the study by Lev and Thiagarajan (1993). Those authors select these fundamental signals based on written pronouncements from financial analysts published in a variety of sources and claimed to be useful for earnings forecasts and share valuations. Lev and Thiagarajan (1993) provide evidence that these fundamental signals are value relevant and capture earnings persistence. Of the 12 non-earnings variables used in this study, eight are selected from Lev and Thiagarajan's (1993) study[35] and apply the same definition and construction. These variables are: change in inventory relative to change in sales (INV), change in accounts receivable relative to change in sales (AR), change in selling and administrative expenses relative to change in sales (SA), change in labour force (LF), change in effective tax rate (ETR), change in gross margin relative to sales (GM), audit qualification (AQ), and change in firm's capital expenditure relative to change in industry capital expenditure (CAPX). Additionally, based on findings emanating from the literature, four non-earnings signals, namely change in financial leverage (LEV), change in cash flow from operations (CFO), change in goodwill (GW) and change in discretionary accruals (CDACCR), are added for this study, as each is expected to be useful for decision-making by investors and financial analysts (Dempsey et al. 1997). These four variables are defined and measured so as to be consistent with the eight variables drawn from Lev and Thiagarajan

[35] Lev and Thiagarajan (1993) also used 12 non-earnings signals. However, to be consistent with Abarbanell and Bushee (1997), this study uses only eight of these signals. This is due to LIFO earnings not being available in all selected countries and disclosure limitations for research and development (R&D) expenditure and order backlog. The fourth omitted variable from this study is provision for doubtful debts. LIFO earnings, R&D expenditure and order backlog, together with provision for doubtful debts, were subject to data limitations in the study by Lev and Thiagarajan (1993) also and omitted from some of their analyses in order to maximise the sample size. Provision for doubtful debts they found not to be significant under several contexts and it is omitted from this study too.

(1993). All these variables are designed specifically to give a signal about future earnings and contemporaneous excess returns.

4.5 Definition and measurement of dependent variables

The predictive ability of fundamental signals is examined using change in future earnings per share and their value relevance is tested in relation to contemporaneous excess returns. In order to examine analysts' efficiency, the study employs forecast change in earnings per share and forecast error.

4.5.1 One-year-ahead change in earnings per share (EPS)

Abarbanell and Bushee's (1997) study is considered seminal in the prior literature that examines the usefulness of fundamental information for predicting one-year-ahead change in earnings per share (EPS). Given the expected relationships of the fundamental signals with future earnings posited by Lev and Thiagarajan (1993), Abarbanell and Bushee (1997) examine the ability of nine fundamental signals (including the one earnings and eight non-earnings signals used in this study) to predict one-year-ahead change in earnings per share. Adopting the same definition and measure used by Abarbanell and Bushee (1997) for one-year-ahead change in earnings per share (CEPS1), this study measures this dependent variable as the difference between next year's ($t+1$) EPS and this year's (t) (EPS), divided by the market price (P) at the end of the prior year (t-1). This can be expressed as:

$$\text{CEPS1} = [EPS_{t+1} - EPS_t] \div P_{t-1}$$

4.5.2 Contemporaneous excess returns (ER)

Value relevance can be examined in relation to share price or returns. In this study, value relevance in relation to returns, in particular contemporaneous excess returns, is examined. Following the method used by Dimitrov and Jain (2008) to examine the value relevance of change in leverage, excess return (ER) is calculated as the difference between the firm's return (percentage) for the period and the benchmark index[36] return

[36] Benchmark indices used for each country are as follows: Spain - IBEX 35, Finland - OMX Helsinki 25, Belgium - BEL20, Portugal - PSI20, Poland - WIG30, Italy - MIB, France - CAC40, Denmark - OMX Copenhagen 20, Sweden - OMXS 30, UK - FTSE 350, Australia – S&P ASX200.

(percentage) for the same period. Actual return and the benchmark return for each firm for each year is calculated for the 12-month period commencing 11 months prior and ending one month after the earnings announcement for the year. Once the earnings announcement is released, consistent with the efficient market hypothesis, investors are expected to react to new information that comes to the market and the price is adjusted accordingly. Therefore, excess return is calculated after allowing a reasonable time for investor reaction; it is measured for the 12-month period ending one month after the earnings announcement date. Dimitrov and Jain (2008) also calculated excess return as the difference between the 12-month stock returns of the firm beginning five months after the start of the firm's fiscal year and the corresponding return on value weighted index for the 12 months. This study uses indices that are value weighted. Al-Debie and Walker (1999) followed a similar method to determine excess returns in order to analyse the value relevance of the fundamental signals included by Lev and Thiagarajan (1993).

4.5.3 Forecast one-year-ahead change in earnings per share and forecast error

Abarbanell and Bushee (1997) examine analysts' efficiency in using fundamental information for their forecast revisions by comparing the association between: (a) fundamental signals and one-year-ahead change in earnings per share (CEPS1); (b) fundamental signals and analysts' forecast revisions; and (c) fundamental signals and analysts' forecast error. In respect of (b), rather than using analysts' forecast revisions, Wahab, Teitel and Morzuch (2015) examine analysts' efficiency in using fundamental signals by examining the association between these signals and forecast one-year-ahead change in earnings per share (FCEPS1). This method is used in this study also.

Forecast one-year-ahead change in earnings per share (FCEPS1) is calculated as the difference between mean analysts' forecasts for one-year-ahead EPS ($FEPS_{t+1}$) made at least one month after earnings announcement date, and current year actual EPS (EPS_t), divided by share price at the end of the prior year (P_{t-1}).

$$\text{FCEPS1} = [FEPS_{t+1} - EPS_t] \div P_{t-1}$$

Following the method used by Wahab, Teitel and Morzuch (2015) and Abarbanell and Bushee (1997), analysts' forecast error (FE) is measured as the difference between one-year-ahead actual EPS (EPS_{t+1}) and analysts' one-year-ahead EPS forecast ($FEPS_{t+1}$), divided by share price at the end of the prior year (P_{t-1}).

$$\text{FE} = [EPS_{t+1} - FEPS_{t+1}] \div P_{t-1}$$

4.6. Definition and measurement of independent variables

4.6.1 The earnings fundamental signal (CHGEPS)

The earnings fundamental signal (CHGEPS) is measured as the difference between prior year's (*t-1*) EPS and this year's (*t*) EPS, divided by the market price (P) at the end of the prior year.

$$\text{CHGEPS} = [EPS_{t-1} - EPS_t] \div P_{t-1}$$

Previous studies of fundamental analysis report a mean reverting pattern of current year change in earnings, with a good year followed by a bad year and a bad year followed by a good year (Abarbanell & Bushee 1997; Dowen 2001; Swanson, Rees & Juarez-Valdes 2003). This earnings signal is measured as the difference between last year's earnings per share and current year earnings per share. Therefore, this change mostly represents accruals. Prior literature documents the reversing nature of current year accruals (Chan, Jegadeesh & Sougiannis 2004; DeFond & Park 2001; Pae 2005; Wahab, Teitel & Morzuch 2015). Therefore, for predictive ability, a positive relationship between CHGEPS and one-year-ahead change in earnings per share (CEPS1) is expected. Moreover, for value relevance a negative relationship between CHGEPS and excess returns (ER) is expected.

4.6.2 Non-earnings fundamental signals

As explained above, 12 non-earnings fundamental signals are tested in this study and for those eight signals obtained from Lev and Thiagarajan (1993), an identical definition and construction is used. The remaining signals included in this study are also defined and constructed to be consistent with those included by Lev and Thiagarajan (1993). Therefore, by construction, all non-earnings variables are expected to have a negative relationship with one-year-ahead change in earnings (CEPS1) and contemporaneous excess returns (ER). These identified signals are expected to provide useful information about the persistence and/or growth of reported earnings and also be capable of identifying the transitory and permanent components of change in earnings (Carnes 2006; Lev & Thiagarajan 1993). The definitions, construction and explanation of the expected information arising from these non-earnings signals are as follows.

Inventories (INV)

The Inventory (INV) variable is measured as the annual percentage change in inventory minus the annual percentage change in sales.

$$INV_t = \frac{Inventory_t - Inventory_{Avg}}{Inventory_{Avg}} - \frac{Sales_t - Sales_{Avg}}{Sales_{Avg}}$$

and

$$Inventory_{Avg} = (Inventory_{t-1} + Inventory_{t-2}) \div 2$$

$Sales_{Avg}$ and all variables annotated as average (*Avg*) in what follows are measured similarly to $\mathrm{Inventory_{Avg}}$. That is, these non-earnings variables measure change above or below the average of the prior two years and are used to examine whether each can predict one-year-ahead change in earnings per share, and/ or is value relevant for contemporaneous excess returns (ER).

Lev and Thiagarajan (1993) explain a disproportionate increase (decrease) in inventory relative to sales is considered to be a negative (positive) signal because such an increase suggests difficulties in generating sales or possible slow-moving/ obsolete inventory items. Furthermore, such inventory increases suggest that earnings are expected to decline as management attempts to lower inventory levels (e.g., car manufacturers' periodic price concessions). When production changes by less than change in sales, a disproportionate increase in inventory may result from an unexpected decrease in sales, loss of production or poor inventory control, all reflecting negatively on future earnings and therefore returns. A decrease in inventory compared to sales can be an indication of a decrease in overhead cost absorption (Lev & Thiagarajan 1993) or increase in sales, which is good signal. Further, Lev and Thiagarajan (1993) document that there can be other motives for holding inventory, such as in the event of facing sales fluctuations, for uninterrupted smooth production, or for hedging or speculation against future price movements. As such, it is acknowledged that an increase in inventory also could represent a positive signal, depending on the circumstances. However, in general, a disproportionate increase in inventory compared to sales is more likely to be considered as a negative signal for future earnings and returns. Bernard and Noel (1991) report that unexpected change in inventories is a negative leading indicator of future earnings and profit margin.

Accounts Receivable (AR).

The Accounts Receivable (AR) variable is measured as the annual percentage change in accounts receivable minus the annual percentage change in sales.

$$AR_t = \frac{AccountsReceivable_t - AccountsReceivable_{Avg}}{AccountsReceivable_{Avg}} - \frac{Sales_t - Sales_{Avg}}{Sales_{Avg}}$$

A disproportionate increase (decrease) in accounts receivable relative to sales represents a negative (positive) signal as it could be an indication of difficulties in selling the firm's products or services and/ or more liberal credit terms - hence increases in bad debts, and/ or earnings management via aggressive recognition of revenue. Therefore, a disproportionate increase in accounts receivable may indicate low persistence of current earnings and a decrease in future earnings and therefore, low return. Stober (1993) documents incremental information content of receivables beyond inventories in predicting future sales and future earnings.

Selling and Administrative Expenses (SA)

Selling and Administrative Expenses (SA) is measured as the annual percentage change in selling and administrative expenses minus the annual percentage change in sales.

$$SA_t = \frac{Selling\ and\ AdministrativeExp_t - Selling\ and\ AdministrativeExp_{Avg}}{Selling\ and\ AdministrativeExp_{Avg}} - \frac{Sales_t - Sales_{Avg}}{Sales_{Avg}}$$

As explained by Lev and Thiagarajan (1993), most administrative costs are fixed costs. Therefore, an increase in selling and administrative cost above average compared to sales increase could be an indication of lack of marginal cost control, and/ or unusual sales efforts leading to low earnings persistence and therefore low return. As such, a disproportionate increase (decrease) in selling and administrative costs is a negative (positive) signal about future earnings and contemporaneous excess returns.

Labour Force (LF)

The labour force signal is measured as the annual percentage change in sales per employee.

$$LF_t = \left(\frac{Sales_{\ t-1}}{Employees_{\ t-1}} - \frac{Sales_t}{Employees_t}\right) \div \frac{Sales_{\ t-1}}{Employees_{\ t-1}}$$

As explained by Lev and Thiagarajan (1993 p.197), “financial analysts comment favorably on announcements of corporate restructuring, particularly labour force reductions”. So, if there is a labour force reduction, usually wage related expense for that year increases (e.g. due to severance pay). In such a situation, the earnings number reported does not necessarily reflect future benefits from restructuring, and fundamentals, such as the labour force signal, are used to provide a better assessment of future earnings. Therefore, a significant decrease (increase) in sales per employee (due to change in the number of employees) is a negative (positive) signal about earnings persistence and returns. Sales scaled by the number of employees also captures labour force efficiency. As such, a positive value for this variable indicates decreased labour force/ decrease in efficiency as measured by contribution to revenue.

Effective Tax Rate (ETR)

The Effective Tax Rate (ETR) variable is measured as the average of the last two years ETR minus the current year ETR.

$$ETR_t = ETR_{Avg} - ETR_t \quad where\ ETR_i = \frac{TaxExpenses_i}{EBT_i}$$

Where:

EBT = Pre-tax Income + Amortisation/ Impairment of Intangibles

A significant change in the firm's effective tax rate, not caused by a statutory tax change, is generally considered transitory by analysts (see, for example, Wall Street Journal [January 26, 1990] story on Lotus Development Corporation) (Lev & Thiagarajan 1993). Therefore, an unusual decrease (increase) in the effective tax rate is generally considered a negative (positive) signal of earnings persistence (Lev & Thiagarajan 1993).

Gross Margin (GM)

Gross Margin (GM) is defined as the annual percentage change in sales minus annual percentage change in gross margin.

$$GM_t = \frac{Sales_t - Sales_{Avg}}{Sales_{Avg}} - \frac{Gross\ margin_t - Gross\ margin_{Avg}}{Gross\ margin_{Avg}}$$

The gross margin is relatively a less noisy indicator of profitability than earnings and it demonstrates the relation between input and output prices. This indicator explains factors underlying the business, such as intensity of competition, or the relation between fixed and variable costs (known as operating leverage). As such, changes in this indicator are likely to affect the long-term performance of the firm and its value (Lev & Thiagarajan 1993). Therefore, a disproportionate decrease (increase) in gross margin (relative to sales) is a negative (positive) signal about earnings persistence and contemporaneous returns.

Audit Qualification (AQ)

A qualified, disclaimer, or adverse audit opinion obviously sends a negative message to investors. A qualified (unqualified) audit opinion might represent a negative (positive) signal about financial health or non-compliance with accounting standards or regulation, and so presents questions about earnings persistence and future firm performance. To capture this signal, a dummy variable is used: 0 for an unqualified opinion and 1 otherwise. If there is an emphasis of matter paragraph, that is evaluated separately and the value (0 or 1) decided based on the signal provided by the nature of the emphasis of matter (if the emphasis of matter is related to a going concern issue, then 1 is assigned).

Capital Expenditures (CAPX)

The Capital Expenditure (CAPX) variable is measured as the annual percentage change in industry capital expenditure minus the annual percentage change in the firm's capital expenditure. This capital expenditure pertains only to tangible fixed assets.

$$CAPX_t = \frac{IndustryCapitalExp_t - IndustryCapitalExp_{Avg}}{IndustryCapitalExp_{Avg}} - \frac{FirmCapitalExp_t - FirmCapitalExp_{Avg}}{FirmCapitalExp_{Avg}}$$

This variable represents above average variations in the firm's capital expenditure. A decrease (increase) in a firm's capital expenditure relative to the industry is perceived by analysts as a negative (positive) signal regarding the firm's future growth and hence its future earnings performance. "A decrease in capital expenditure might indicate managers' concerns with the adequacy of current and future cash flows to sustain the previous investment level" (Lev & Thiagarajan 1993 p.195), and so raises questions about earnings persistence. With the absence of a proper benchmark for capital expenditure, Lev and Thiagarajan (1993) use industry capital expenditure to compare with a firm's capital expenditure. Kerstein and Kim (1995) show that capital expenditure is positively associated with excess returns.

Financial Leverage (LEV)

Financial Leverage is measured as the annual percentage change in the ratio of total debt (long-term debt plus current liabilities) to total assets.

$$\mathrm{LEV}_t = \left[\frac{Total\ Debt_t}{Total\ Assets_t} - \frac{Total\ Debt_{Avg}}{Total\ Assets_{Avg}}\right]$$

Leverage measures the extent to which a firm depends on debt financing. Using external debt can be good or bad depending on whether the firm earns more or less than after tax interest cost on the investments financed with borrowed funds (Modigliani & Miller 1958). If the firm's expected return on investment is greater than the rate of interest, then use of debt will increase return on equity. However, it also increases financial risk and thus the new required rate of return on equity may exceed the higher achieved return. It may also constrain the firm's financial flexibility. Bradshaw, Richardson and Sloan (2006) provide evidence that there is a negative relationship between external finance and stock return. Dimitrov and Jain (2008) report that changes in financial leverage provide information about firm future performance beyond that available from earnings and cash flows and show that changes in financial leverage are value relevant beyond accounting earnings. Furthermore, they find that changes in leverage are negatively associated with firms' contemporaneous stock returns, future accounting earnings, and future stock returns. But in the absence of theories predicting the motivation for firms' financing activities, the exact nature of the information conveyed by firms' financing decisions is ultimately an empirical question. Given this evidence from the literature of the usefulness of leverage as a signal, this study includes annual change in leverage (LEV) as one of the non-earnings fundamental signals. It is expected that an increase (decrease) in leverage compared to the average for the previous two years provides a negative (positive) signal about one-year-ahead change in earnings per share and contemporaneous excess returns (ER).

Cash Flow (CF)

The Cash Flow variable is measured as the change in cash flow from operations (CFO) between years *t* and *t-1*, divided by total assets at the end of the financial year *t-1*.

$$CF_t = (CFO_{t-1} - CFO_t) \div Total\ Assets\ at\ end\ of\ _{t-1}$$

This variable provides information about the firm's ability to generate future cash flows (Piotroski 2000). Sloan (1996) findings shows that higher proportion of earnings attributable to CFO (compared to accruals) signifies a higher quality of income that will more likely persist into future periods. This suggests that CFO is an important predictor of future earnings and consequently for returns. The literature reports a positive relationship between current year cash flow and future earnings, and therefore CFO captures the earnings persistence (Arthur, Cheng & Czernkowski 2010; Banker, Huang & Natarajan 2009; Kumar & Krishnan 2008; Lev, Li & Sougiannis 2005). Therefore, an increase (decrease) in CFO in year *t* relative to year *t-1* is expected to have a positive (negative) impact on earnings in year *t+1*. Rayburn (1986) and Hirshleifer, Hou and Teoh (2009) also document that cash flows are associated significantly with returns, and cash flows contain incremental information content over earnings (Banker, Huang & Natarajan 2009; Cheng, Chao Shin & Schaefer 1997); and are value relevant for stock returns (Habib 2008). Therefore, annual change in cash flow from operations (CF) is included as a non-earnings fundamental signal to predict one-year-ahead change in earnings (CEPS1) and to be value relevant for excess returns (ER). This variable is by construction expected to have a negative relationship with CEPS1 and ER.

Goodwill (GW)

The Goodwill (GW) variable is calculated as the annual percentage change in goodwill.

$$GW = \frac{Goodwill_{avg} - Goodwill_t}{Goodwill_{Avg}}$$

Some literature reports that GW provides useful information about future earnings potential (Cheong, Kim & Zurbruegg 2010; Matolcsy & Wyatt 2006; Wyatt 2005). Moreover, previous studies document that goodwill and impairment of goodwill is value relevant for stock price and returns (AbuGhazaleh, Al-Hares & Haddad 2012; Dahmash, Durand & Watson 2009). As such, annual change in goodwill is included as an explanatory variable to predict one-year-ahead change in earnings per share and also is expected to be value relevant for excess returns (ER). The goodwill variable by construction is expected have a negative relationship with one-year-ahead change in earnings per share and contemporaneous excess returns (ER). Accordingly, an increase (decrease) in goodwill from year *t-1* to year *t* is a good (bad) signal**.**

Discretionary Accruals (CDACCR)

The Discretionary Accruals (CDACCR) variable is measured as the average of the prior two years' discretionary accruals minus current year discretionary accruals.

$$CDACCR = DACCR_{Avg} - DACCR_t$$

$DACCR_t$ is measured using the Kothari, Leone and Wasley (2005) performance matched discretionary accrual model. That is, *DACCR* is the residual from the following model:

$$\mathrm{TA}_{it} = \beta_0 + \beta_1 \left(\frac{1}{\mathrm{AT}_{it-1}}\right) + \beta_2 \left(\frac{\Delta\mathrm{REV}_{it} - \Delta\mathrm{AR}_{it}}{\mathrm{AT}_{it-1}}\right) + \beta_3 \left(\frac{\mathrm{PPE}_{it}}{\mathrm{AT}_{it-1}}\right) + \beta_4\,\mathrm{ROA}_{it} + \varepsilon_{it}$$

Where *i* represents firm *i,* and:

TA_{it}	=	Total Accruals, calculated as the difference between income before extraordinary items and operating cash flows for year *t* scaled by AT_{it-1}
AT_{it-1}	=	assets for at the beginning of year *t-1*
ΔREV_{it}	=	change in sales from year *t-1* to *t*
ΔAR_{it}	=	change in accounts receivable from year *t-1* to *t*
PPE_{it}	=	gross property, plant, and equipment
ROA_{it}	=	income before extraordinary items for year *t* divided by AT_{it-1}

Subramanyam (1996) documents that discretionary accruals improve the ability of earnings to reflect real economic value and also finds a positive relationship between current year discretionary accruals and future earnings; hence discretionary accruals capture the persistence of earnings. DeFond and Park (1997) find that managers borrow future earnings by increasing discretionary accruals, if expected earnings is high. Higher expected earnings reflect in higher share price and higher returns. Guay, Kothari and Watts (1996) also find a positive relationship between discretionary accruals and returns using five discretionary accrual models. The theoretical model proposed by Fudenberg and Tirole (1995) suggests that managers consider expected future earnings when making discretionary accounting choices. Considering this evidence, annual change in discretionary accruals is included as an explanatory variable to predict one-year-ahead change in earnings per share (CEPS1) and also is expected to be value relevant for excess returns (ER). CDACCR by construction is expected have a negative relationship with CEPS1 and ER. Accordingly, an increase (decrease) in discretionary accruals from year *t-1* to year *t* is a good (bad) signal.

4.7 Models for testing of hypotheses

The following sections explain the models used in this study to test the hypotheses under each Research Objective.

4.7.1 Examining the ability of fundamental signals to predict one-year-ahead change in earnings per share

As explained above, using nine fundamental signals from Lev and Thiagarajan (1993), Abarbanell and Bushee (1997) examine the ability of these fundamental signals to predict one-year-ahead change in earnings per share and their methodology has later been followed by other scholars (e.g. Al-Debie & Walker 1999; Dowen 2001; Seng & Hancock 2012). This study also follows the same methodology to examine the ability of the selected fundamental signals to predict one-year-ahead change in earnings per share. The data for this study involve multi-year, multi-country, and multi-industry observations. Further, since the literature reports that the quality of accounting information is different across legal regimes (Alford, Jones, Leftwich, & Zmijewski, 1993; Joos & Lang, 1994), code and common law countries are distinguished. Therefore, to control for the fixed effects of years, countries, industries and legal regime, dummy variables for each are included in the models, which results in the following regressions to test the predictive ability of one-earnings and 12 non-earnings fundamental signals in predicting one-year-ahead change in earnings per share (CEPS1). The predictive ability of fundamental signals is examined individually and in combination (for non-earnings signals), using Model 1 to test Hypotheses 1a and 1b.

$$CEPS1_i = \propto \ + \beta_0 \, \mathrm{CHGEPS}_i + \sum_{j=1}^{12} \beta_{ij} \mathrm{Signals}_{ij} \ + \sum \mathrm{Yr} + \ \sum \mathrm{Cty} \ + \sum \mathrm{In} + \mathrm{CodeLaw} + \ \varepsilon_j \quad (1)$$

Where:

$CEPS1_i$ = one-year-ahead change in earnings per share in firm *i*,
CHGEPS_i = current year change in earnings per share in firm *i*,

$\mathrm{Signals}_{ij}$= Non-Earnings Fundamental Signals, *j* = 1 to 12 signals are change in inventory relative to change in sales (INV), change in accounts receivable relative to change in sales (AR), change in selling and administrative expenses relative to change in sales (SA), change in labour force (LF), change in effective tax rate (ETR), change in gross margin relative to change in sales (GM), audit qualification (AQ), change in firm's capital expenditure relative to change in industry capital expenditure (CAPX), change in financial leverage (LEV), change in cash flow from operations (CF), change in goodwill (GW) and change in discretionary accruals (CDACCR).

Yr = Year dummies
Cty = Country dummies
In = Industry dummies
CodeLaw- Code law countries are assigned 1, otherwise 0

If a fundamental signal is significantly associated with one-year-ahead change in earnings per share (CEPS1), then it is concluded that the fundamental signal has the ability to predict CEPS1. The earnings fundamental signal is expected to have positive relationship with CEPS1, while all non-earnings fundamental signals, by their construction as explained in the prior section, are expected to have a negative relationship with CEPS1.

In order to examine the combined predictive ability of non-earning signals, first the CHGEPS is regressed with CEPS1 (earnings alone model), then all the non-earnings signals are added to the regression and the incremental R-Squared contribution from including non-earnings signals over earnings is measured. Using a partial F-test then allows measurement of whether the R-Squared contribution from the non-earning signals is significant or not.

In addition, the predictive ability of the non-earnings signals is examined in aggregate, following the methodology used by Lev and Thiagarajan (1993) and Abarbanell and Bushee (1997), using an aggregated fundamental score termed F_Score. The F_Score is developed by assigning a value of one (zero) for good (bad) signals and then values across the 12 non-earnings fundamental signals included in this study are summed. If any of the selected non-earnings signals results in a positive (negative) value, that represents a bad (good) signal and vice versa. A higher (lower) F_Score indicates an increase (decrease) in future earnings and therefore there is expected to be a positive relationship between F_Score and one-year-ahead change in earnings per share (CEPS1). The model for testing the predictive ability of the aggregated fundamental score (F_Score) that tests Hypothesis 1c is as follows, where other variables are as defined previously.

$$\mathrm{CEPS1}_i = \propto + \beta_0\,\mathrm{CHGEPS}_i + \beta_1\,\mathrm{F\_Score}_i + \sum \mathrm{Yr} + \sum \mathrm{In} + \sum \mathrm{Cty} + \mathrm{CodeLaw} + \varepsilon_j \quad (2)$$

This same methodology has been followed in other fundamental studies, such as Seng and Hancock (2012), to predict future earnings.

4.7.2 Examining the value relevance of fundamental signals

For the purpose of examining the value relevance of fundamental signals for contemporaneous excess returns, this study again follows the methodology used by Lev and Thiagarajan (1993), later followed by other studies. The same data are to be used as previously, so again dummy variables for year, country, industry and legal regime are included in the regression to control for fixed effects. Accordingly, the resultant regression model is as follows to test Hypotheses 2a and 2b. The value relevance of non-earnings fundamental signals also is examined individually, in combination and in aggregate form.

$$ER_i = \propto + \beta_0\,\mathrm{CHGEPS}_i + \sum_{j=1}^{12} \beta_{ij}\mathrm{Signals}_{ij} + \sum \mathrm{Yr} + \sum \mathrm{In} + \sum \mathrm{Cty} + \mathrm{CodeLaw} + \varepsilon_j \quad (3)$$

Where:

ER = Contemporaneous excess returns calculated for the 12-month period commencing 11 months before and ending one month after earnings announcement date and other variables are as defined previously.

If a fundamental signal is significantly associated with contemporaneous excess returns (ER), then it is concluded that the fundamental signal is value relevant in terms of excess returns. The earnings fundamental and all the non-earnings fundamental signals by construction are expected to have a negative relationship with ER.

As for predictive ability in the previous sections 4.7.1, in order to assess the combined value relevance of non-earnings signals over the earnings signal, first the CHGEPS is regressed with ER, then the non-earnings signals are included into the model and regressed with ER. The incremental R-Squared contribution from including non-earnings signals over earnings is then measured. In order to test the significance of the incremental value relevance from the non-earnings signals, a partial F-test is used.

To examine the value relevance of non-earnings signals in aggregate form, the F_Score (explained above) is regressed with ER along with CHGEPS. This results in the following model used to test Hypothesis 2c.

$$\mathrm{ER1M}_i = \propto\ + \beta_0\,\mathrm{CHGEPS}_i + \beta_1\,\mathrm{F\_Score}_i + \sum \mathrm{Yr} + \sum \mathrm{In} + \sum \mathrm{Cty} + \mathrm{CodeLaw} + \varepsilon_j \qquad (4)$$

Where all variables are as defined previously.

This methodology was adopted by Lev and Thiagarajan (1993) to assess the value relevance of F_Score, and later followed by other scholars, such as Al-Debie and Walker (1999), Piotroski (2000), Mohanram (2005) and Mahmoud and Sakr (2012).

4.7.3 Contextual variables

In previous fundamental analysis studies, some authors report that the predictive ability and value relevance of fundamental signals varies significantly based on contextual factors, such as prior year earnings news (PYEN), Gross Domestic Product (GDP) growth and the level of inflation (INF) (Abarbanell and Bushee, 1997; Al-Debie and Walker, 1999; Lev and Thiagarajan, 1993). As such, the predictive ability and value relevance of the earnings and non-earnings fundamental signals is to be tested for any moderating effects of PYEN, GDP growth and level of inflation.

For the purpose of this analysis, the sample is partitioned into good and bad PYEN (good if change in prior year earnings is an increase and bad if a decrease), high and low GDP growth (based on median GDP growth) and high and low inflation (based on median level of inflation) and Models 1,2,3, and 4 are re-estimated for these sub-samples.

If these contextual variables are found to influence the predictive ability and /or value relevance of fundamental signals, then these contextual variables will be included in the analyses involving IFRS impact as controls in order to better isolate the impact of IFRS on those signals.

4.7.4 IFRS impact on the predictive ability of fundamental signals

Following IFRS adoption, a number of studies from different countries around the world report that IFRS had a significant impact on their financial statement fundamentals in terms of recognition, measurement, classification and presentation (Blanchette, Racicot & Girard 2011; Bradbury & van Zijl 2005; Goodwin, Ahmed & Heaney 2008; Haverals 2007; Horton & Serafeim 2010; Iatridis 2010; Kabir, Laswad & Islam 2010; Stent, Bradbury & Hooks 2010; Tsalavoutas & Evans 2010), therefore ultimately affecting the quality of fundamental signals. As such, this study examines the impact of IFRS on the predictive ability of the selected fundamental signals.

In order to test the impact of IFRS on the predictive ability of fundamental signals robustly, two models are employed in this study. In the first, an interaction variable for each fundamental signal is introduced to Model 1. The interaction terms are developed by multiplying each fundamental signal by an IFRS dummy variable (1 for the post-IFRS period and 0 otherwise). Accordingly, the following regression model (Model 5) is used to test Hypotheses 1d and 1e.

$$\mathrm{CEPS1}_i = \propto + \beta_0 \,\mathrm{CHGEPS}_i + \sum_{j=1}^{12} \beta_{ij} \mathrm{Signals}_{ij} + \beta_{13} \mathrm{IFRS} * \mathrm{CHGEPS}_i + \sum_{j=14}^{24} \beta_{ij} \mathrm{IFRS} * \mathrm{Signals}_{ij} + \sum \mathrm{Yr} + \sum \mathrm{In} + \sum \mathrm{Cty} + \mathrm{CodeLaw} + \varepsilon_j \qquad (5)$$

Where:

IFRS*CHGEPS = Interaction of CHGEPS with IFRS, IFRS*Signals_{ij} = interaction of non-earnings fundamental signals with IFRS, j = non-earnings fundamental signals, and other variables are as defined previously.

In the second model, stacked regression as used by Atwood et al. (2011) is employed to test the impact of IFRS. According to this method, first the regression is estimated using pre-IFRS observations and second the regression is run using post-IFRS observations. Finally, these two regressions are stacked into one model[37], resulting in Model 6 to test for significant differences in coefficients between pre- and post-IFRS periods.

$$CEPS1_i = PreIFRS\ x\ [\propto_0 + \propto_1\ \text{CHGEPS}_i + \textstyle\sum_{j=1}^{12} \propto_{ij}\ \text{Signals}_{ij}\ ] + PostIFRS\ x\ [\beta_0\ +\ \beta_1\,\text{CHGEPS}_i + \textstyle\sum_{j=1}^{12} \beta_{ij}\text{Signals}_{ij}\}\ + \sum \text{Yr} + \sum \text{In} + \sum \text{Cty} + \text{CodeLaw} + \varepsilon_j \qquad (6)$$

In order to interpret IFRS impact, two models are used to provide corroborative evidence. If an interaction term is significant in Model 5, it indicates IFRS has significant impact on the predictive ability of that signal. In order to identify clearly whether the impact of IFRS is positive or negative (i.e. is increased or decreased), the result for this signal in Model 5 is compared with that from estimation of Model 6. In Model 6, if the test of equality of coefficients between the pre and post-IFRS periods for that fundamental signal is significant, then by comparing the size of the coefficient between the two periods, it is decided whether the predictive ability of that signal significantly increased or decreased in the post- compared to pre-IFRS period. If the size of the coefficient is higher (lower) in the post- compared to pre-IFRS period, then it is inferred that the predictive ability of that variable increased (decreased) after adoption of IFRS.

For testing IFRS impact on the combined predictive ability of the non-earnings fundamental signals, the incremental adjusted R-Squared contribution from including non-earning signals over earnings for pre-and post-IFRS periods is compared.

[37] Unlike STATA's clustering technique used with regression, which does not provide an adjusted R-Squared, the first step of the stacked regression technique (regressions for Pre-IFRS and Post-IFRS observations separately) does provide an adjusted R-Sq.

In order to test the impact of IFRS on the predictive ability of the aggregated fundamental score (F_Score), an interaction variable for F_Score with IFRS is introduced to Model 2, which results in Model 7 used to test Hypothesis 1f.

$$\mathrm{CEPS1}_i = \propto + \beta_0\,\mathrm{CHGEPS}_i + \beta_1\,\mathrm{F\_Score}_i + \beta_2\,\mathrm{IFRS} * \mathrm{CHGEPS}_i + \beta_3\,\mathrm{IFRS} * \mathrm{F\_Score}_i + \sum \mathrm{Yr} + \sum \mathrm{In} + \sum \mathrm{Cty} + \mathrm{CodeLaw} + \varepsilon_j \quad (7)$$

Where, IFRS * F_Score = Interaction of F_Score with IFRS and other variables are as defined previously.

In addition, to test IFRS impact more robustly, following Atwood et al. (2011), stacked regression is used to test the significance of F_Score coefficients between pre- and post-IFRS periods, which results in Model 8, where all variables are as defined previously.

$$CEPS1_i = PreIFRS\ x\ [\propto_0 + \propto_1\ \mathrm{CHGEPS}_i + \propto_2\ \mathrm{F\_Score}_i\ ] + PostIFRS\ x\ [\beta_0 + \beta_1\,\mathrm{CHGEPS}_i + \beta_1\,\mathrm{F\_Score}_i] + \sum \mathrm{Yr} + \sum \mathrm{In} + \sum \mathrm{Cty} + \mathrm{CodeLaw} + \varepsilon_j \quad (8)$$

Evaluation of the impact of IFRS on the predictive ability of F_Score is made based on these two Models, consistent with the explanation in respect of Models 5 and 6.

4.7.5 IFRS impact on the value relevance of fundamental signals

For the purpose of examining the impact of IFRS on the value relevance of fundamental signals for contemporaneous excess returns, interaction terms for each fundamental signal with IFRS are introduced to Model 3, resulting in Model 9.

$$\mathrm{ER}_i = \propto + \beta_0\,\mathrm{CHGEPS}_i + \sum_{j=1}^{12} \beta_{ij}\mathrm{Signals}_{ij} + \beta_{13}\mathrm{IFRS} * \mathrm{CHGEPS}_i + \sum_{j=14}^{24} \beta_{ij}\mathrm{IFRS} * \mathrm{Signals}_{ij} + \sum \mathrm{Yr} + \sum \mathrm{In} + \sum \mathrm{Cty} + \mathrm{Codelaw} + \varepsilon_j \quad (9)$$

Where all variables are as defined previously.

Moreover, to test IFRS impact more robustly, a test of equality of coefficients based on stacked regression is used. The stacked regression model for testing the impact of IFRS on the value relevance of fundamental signals for contemporaneous excess returns is as follows.

$$ER_i = PreIFRS * [\propto_0 + \propto_1 \text{ CHGEPS}_i + \sum_{j=1}^{12} \propto_{ij} \text{ Signals}_{ij}] + PostIFRS * [\beta_0 + \beta_1 \text{ CHGEPS}_i + \sum_{j=1}^{12} \beta_{ij} \text{Signals}_{ij}] + \sum \text{Yr} + \sum \text{In} + \sum \text{Cty} + \text{Codelaw} + \varepsilon_j \quad (10)$$

Where variables are as defined previously.

As explained in section 4.7.4 in this chapter, in order to interpret IFRS impact, two models are used to provide corroborative evidence. If an interaction term is significant in Model 9, then it indicates that IFRS has significant impact on the value relevance of that signal. For a clear interpretation of whether the impact of IFRS is positive or negative, the result for this signal is compared with that from estimation of Model 10. If the test of equality of coefficients between pre- and post-IFRS periods for that fundamental signal is significant for Model 10, then by comparing the size of the coefficient between the two periods, it can be decided whether the value relevance of that signal significantly increased or decreased in the post- compared to pre-IFRS period. If the size of the coefficient is higher (lower) in the post- compared to pre-IFRS period, then it is inferred that the value relevance of that variable has increased (decreased) after adoption of IFRS.

Models 9 and 10 are used to test Hypotheses 2d and 2e.

In order to examine IFRS impact on the value relevance of F_Score for contemporaneous excess returns, both the model that includes the IFRS interaction term and stacked regression are employed as follows and used to test Hypothesis 2f.

$$\text{ER}_i = \propto + \beta_0 \text{ CHGEPS}_i + \beta_1 \text{ F\_Score}_i + \beta_2 \text{ IFRS} * \text{CHGEPS}_i + \beta_3 \text{ IFRS} * \text{F\_Score}_i + \sum \text{Yr} + \sum \text{In} + \sum \text{Cty} + \text{CodeLaw} + \varepsilon_j \quad (11)$$

$$ER_i = PreIFRS * [\propto_0 + \propto_1 \text{ CHGEPS}_i + \propto_2 \text{ F\_Score}_i] + PostIFRS * [\beta_0 + \beta_1 \text{ CHGEPS}_i + \beta_2 \text{ F\_Score}_i] + \sum \text{Yr} + \sum \text{In} + \sum \text{Cty} + + \text{CodeLaw} + \varepsilon_j \quad (12)$$

Where variables are as defined previously.

Evaluation of the impact of IFRS on the value relevance of F_Score is arrived at based on the same criteria as explained above for IFRS interaction terms and a test of equality of coefficients based on stacked regression.

4.7.6 Analysts' efficiency in using fundamental signals

Analysts are likely the major users of fundamental information included in financial statements in terms of using it for predicting firm performance and share valuation (Lev & Thiagarajan 1993). As explained previously, the fundamentals identified by Lev and Thiagarajan (1993) are derived from written pronouncements by financial analysts published in a variety of sources. Therefore, in addition to testing the predictive ability and value relevance of fundamental signals, this study also examines analysts' efficiency in using the selected fundamental signals for their earnings forecasts.

First analysts' efficiency in selecting appropriate fundamental signals for forecasting change in one-year-ahead EPS is assessed using the method followed by Wahab, Teitel and Morzuch (2015). For that purpose, the selected fundamental signals are regressed with analysts' forecasts of one-year-ahead change in earnings per share (FCEPS1), which results in Model 13.

$$FCEPS1_i = \propto \ +\beta_0 \,\mathrm{CHGEPS}_i + \sum_{j=1}^{12} \beta_{ij}\mathrm{Signals}_{ij} \ + \sum \mathrm{Yr} + \ \sum \mathrm{In} \ + \sum \mathrm{Cty} + \mathrm{CodeLaw} \quad + \ \varepsilon_j \qquad (13)$$

Where, $FCEPS1_i$ = analysts' forecasts for one-year-ahead change in earnings per share and other variables are as defined previously.

In order to assess analysts' efficiency in selecting appropriate fundamental signals for forecasting FCEPS1, Model 13 is compared with Model 1 (repeated for convenience below), estimated for the same sample.

$$CEPS1_i = \propto \ +\beta_0 \,\mathrm{CHGEPS}_i + \sum_{j=1}^{12} \beta_{ij}\mathrm{Signals}_{ij} \ + \sum \mathrm{Yr} + \ \sum \mathrm{Cty} \ + \sum \mathrm{In} + \mathrm{CodeLaw} \ + \ \varepsilon_j \qquad (1)$$

Where variables are as defined previously.

If a fundamental signal is associated with FCEPS1 in the same way that it is related to CEPS1, then analysts can be said to be efficient in selecting that fundamental signal appropriately for their forecast in change in one-year-ahead EPS.

In order to examine analysts' efficiency in using the fundamental signals, analysts' forecasts for one-year-ahead change in earnings per share (FCEPS1) and all fundamental signals are regressed with one-year-ahead change in earnings per share (CEPS1), resulting in Model 14.

$$CEPS1_i = \propto \ + \beta_0 \,\mathrm{CHGEPS}_i + \sum_{j=1}^{12} \beta_{ij} \mathrm{Signals}_{ij} \ + \beta_{13}\, \mathrm{FCEPS1}_i + \sum \mathrm{Yr} + \sum \mathrm{In} \ + \sum \mathrm{Cty} \ + \mathrm{CodeLaw} + \ \varepsilon_j \qquad (14)$$

Where variables are as defined previously.

If analysts are fully efficient in using these fundamental signals, FCEPS1 should embed all the information about CEPS1 included in the fundamental signals. If this is the case, there will not be any incremental R-Squared contribution from including CHGEPS plus the non-earnings signals in Model 14. Furthermore, if analysts are fully efficient in using these fundamental signals, there will not be any significant association between CEPS1 and any of the fundamental signals when estimating Model 14.

If any fundamental signals remain significant when estimating Model 14 and there is an incremental R-Squared contribution from these fundamental signals over FCEPS1, then that would indicate analysts' inefficiency in using the fundamental signals. When measuring analysts' efficiency, results from estimation of Model 14 are always compared with Model 1 results; that is Model 1 becomes the benchmark for analysts' efficiency. As such, based on this benchmark, a percentage for analysts' inefficiency of use of earnings and non-earnings signals can be measured. Analysts' inefficiency in using the earnings signal is calculated as the incremental R-Squared from including CHGEPS in Model 14[38] divided by the R-Squared value from estimating earnings alone in Model 1. In the next step, analysts' inefficiency in using non-earnings signals is calculated as the incremental R-Squared from including non-earnings signals over FCEPS1 and CHGEPS in Model 14, divided by the incremental R-Squared value from including non-earnings signals over earnings in Model 1.

In order to isolate the impact of analysts' inefficient use of fundamental signals, the fundamental signals are next regressed with analysts' forecast error (FE), resulting in Model 15.

[38] First FCEPS1 is regressed with CEPS1, then CHGEPS is included and regressed again with CEPS1, then the incremental R-Squared from including CHGEPS is calculated.

$$FE_i = \propto \ + \beta_0 \, \text{CHGEPS}_i + \sum_{j=1}^{12} \beta_{ij} \text{Signals}_{ij} + \sum \text{Yr} + \sum \text{In} \ + \sum \text{Cty} + \text{Codelaw} + \ \varepsilon_j \quad (15)$$

Where FE = $[EPS_{t+1} - FEPS_{t+1}] \div P_{t-1}$ and all other variables are as defined previously.

As explained by Abarbanell and Bushee (1997) in Footnote 18 of their paper, if a fundamental signal is significantly associated with forecast error in the same direction as its association with CEPS1 (Model 1), it indicates that "analysts fail to adjust their forecasts sufficiently high when a signal conveys good news and sufficiently low when a signal conveys bad news" (Abarbanell & Bushee 1997 p.17). That is, analysts underreact to that fundamental signal. When the coefficient for the signal is of the opposite sign, analysts overreact to that signal.

4.7.7 IFRS impact on analysts' efficiency in using fundamental signals

In order to examine the impact of IFRS on analysts' efficiency in selecting and using the fundamental signals for making one-year-ahead change in earnings per share forecasts, the sample is partitioned into pre-IFRS and post-IFRS periods and Models 1, 13, 14 and 15 are re-estimated separately for both pre- and post-IFRS sub-samples.

To assess IFRS impact on analysts' efficiency in selecting appropriate fundamental signals for forecasting one-year-ahead change in earnings per share, significant variables in Model 1 and 13 are compared for pre- and post-IFRS periods. In order to examine IFRS impact on analysts' efficiency in using fundamental signals, Model 14 is estimated for both pre- and post-IFRS periods and compared with Model 1 for both periods. Then the percentage inefficiency in using the earnings signal and non-earnings fundamental signals is calculated and compared for the pre- and post-IFRS periods. To isolate analysts' inefficient use of fundamental signals, Model 15 is estimated for both pre- and post-IFRS periods and compared with outputs from Models 1 and 13.

4.7.8 Analysts' efficiency in incorporating information in fundamental signals that is priced in the market and the impact of IFRS on this efficiency.

Next examined is analysts' efficiency in incorporating earnings information in fundamental signals that is priced in the market into their forecasts of one-year-ahead change in earnings per share, and the impact of IFRS on this relationship. To analyse the efficiency with which analysts use value relevant information included in fundamental signals, the earnings fundamental and non-earnings fundamental signals, together with forecast one-year-ahead change in earnings per share (FCEPS1), are regressed with contemporaneous excess returns (ER), which results in Model 16.

$$ER_i = \propto\ + \beta_0\,\mathrm{CHGEPS}_i + \sum_{j=1}^{12} \beta_{ij}\mathrm{Signals}_{ij}\ + \beta_{13}\,\mathrm{FCEPS}_i + \sum \mathrm{Yr} + \sum \mathrm{In}\ + \sum \mathrm{Cty} + \mathrm{CodeLaw}\ + \varepsilon_j \tag{16}$$

Where variables are as defined previously.

The results from estimating Model 16 are compared with those from Model 3 estimated for the same sample. If the fundamental signals that are significant in estimating Model 3 are also significant in the same direction in estimating Model 16, and if the fundamental signals reveal incremental R-Squared over FCEPS1 in Model 16, then it can be concluded that analysts are inefficient in incorporating value relevant information in fundamental signals when making their earnings forecasts. The percentage of analysts' inefficiency in using value relevant information included in the fundamental signals is calculated following the same method as explained under Model 15. In order to examine the impact of IFRS on this analysts' efficiency, the same analysis is conducted for pre- and post-IFRS periods and then compared.

4.7.9 Robustness Analyses

In order to analyse the predictive ability and value relevance of fundamental signals and analysts' efficiency in using these signals, along with IFRS impact, in a robust way, in addition to the pooled sample, analysis is conducted for different sub-samples, such as code law and common law observations, and future increase in EPS and decrease in EPS observations, gains and losses, and results compared. When examining the predictive ability of fundamental signals, firms that experience an increase in one-year-ahead EPS are termed Winners, while those experiencing a decrease in one-year-ahead EPS are termed Losers. For the purpose of assessing the value relevance of the fundamental signals, firms that report excess returns (ER) as gains are termed Winners and those with losses are termed Losers. This study partitions country observations into Code and Common law jurisdictions since the literature reports that the quality of accounting information is different across these regimes (Alford, Jones, Leftwich, and Zmijewski, 1993; Joos and Lang, 1994). Furthermore, a control indicator for Code or Common law countries is used when appropriate. As such, this study takes into account the difference between legal regimes when analysing the quality of accounting information through predictive ability, value relevance and analysts' efficiency using fundamental signals and IFRS impact on the quality of information embedded in these signals, so providing robust results.

In terms of ensuring robust analysis, researchers need to be cautious when examining the quality of accounting information during the Global Financial Crisis (GFC) period, generally attributed to years 2007-2009. Similarly, researchers need to be cautious in terms of the date of adoption of IFRS. In some jurisdictions, early adoption was permitted and also differential balance dates may affect the date of adoption. Therefore, when examining IFRS impact, additional analyses are conducted that exclude both the full IFRS transition period[39] (2004 – 2006) rather than just the year of adoption, and the GFC period (2007 - 2009).

In addition, when examining the value relevance of fundamental signals and the impact of IFRS on the value relevance of these signals, separate analyses are conducted for Extreme and Non-extreme performers in terms of contemporaneous excess returns, and for Growth and Value stocks[40].

4.8 Panel data attributes and related statistical issues

4.8.1 Panel Data

Gujarati and Porter (2009) state that panel data have both time and space dimensions. In this study, the sample consists of cross-sectional time series panel data. Panel data can have different attributes. A panel can be a short panel or long panel. A short panel is where the number of cross sectional units (N) is greater than number of time periods (T), while in a long panel, T is greater than N (T > N). In this study, short panel data are involved as the number of included firms is greater than the number of periods. Moreover, a panel can be a balanced panel or unbalanced panel. A balanced panel is where a panel

[39] For the previous analysis, IFRS transition year (2005) observations are excluded from the sample due to the need for lagged data in constructing some variables.

[40] Selection of Extreme and Non-extreme sub-samples and Growth and Value stocks are explained in Chapter 7.

unit has the same number of observations for each time period and if not, unbalanced panel data are involved. Data for the whole study period are unlikely to be available for all firms, creating an unbalanced panel sample.

Another attribute of panel data is that it can be a static or dynamic panel. Usually a dynamic panel uses a "time lag dependent variable with the set of predictors via the Koyck or Almon approach to contract the long- and short-run effect of a change in a unit in the independent variable on the outcome measure" (Sinnewe 2014 p.136). Based on this explanation, all regression models used in this study are applied to static panels.

4.8.2 Handling heteroscedasticity and auto-correlation

Heteroskedasticity and auto-correlation are statistical problems that can be associated with linear regression models when time series and cross-sectional data are involved. Heteroskedasticity occurs when the variance of the error term is different across observations and cross-sections. Gujarati (1995) states that the problem of heteroscedasticity is likely to be greater in cross-sectional data. Autocorrelation is defined as "correlation between members of series of observations ordered in time (time series data) or space (as in cross-sectional data)" (Gujarati 1995 p.400). Therefore, all regression results in this thesis are adjusted using the Huber-White Sandwich estimator (White 1980), which provides robust standard errors to control for heteroskedasticity and auto-correlation using the STATA statistical package, with observations clustered by firm.

4.8.3 Handling outliers

Another issue in statistical analysis is dealing with outliers. Ou (1990) reports that observations involving fundamental signals include many outliers. Gujarati (1995) documents that heteroskedasticity can also arise due to the presence of outliers. Therefore, following the Barth, Landsman and Lang (2008) and Barth et al. (2012) methodology, all continuous variables are winsorised at 5 per cent to mitigate the effect of outliers at a univariate level. This procedure increases the normality of the data distributions. Moreover, observations that produce studentised residuals greater than three or Cook's distance statistics greater than one in estimating the regressions for the pooled sample in each analysis (predictive ability and value relevance) are removed to address multivariate outliers. Lev and Thiagarajan (1993) document that this procedure did not alter their conclusions; rather it increased the explanatory power of their model.

4.9 Sampling process, data collection and composition

4.9.1 Sampling and data collection

As stated in section 4.2, the two main Research Questions examined in this study focus on the decision usefulness of fundamental signals in terms of their predictive ability and value relevance and the impact of IFRS on these aspects. The adoption of IFRS in many parts of the world has been a remarkable milestone in global accounting history. During that transformation, the decision by the European Union (EU) to mandate that all EU-listed companies adopt IFRS had great influence on other countries' adoption of IFRS (Aharony, Barniv & Falk 2010; De George, Li & Shivakumar 2016). Therefore, this study draws on a sample of companies from mainly, but not exclusively, the European Union (EU). The sample is selected from firms listed on stock exchanges in eleven European countries plus Australia.

Selecting firms from a number of countries from within the EU has several advantages when testing for the effect of IFRS. First, the homogeneity of regulatory mechanisms between EU countries reduces the likelihood of unidentified cross-country differences that could affect the predictive ability and value relevance of fundamental signals and analysts' efficiency in using these signals. Second, the "relatively strong legal system and enforcement regime in the EU provide a powerful setting to detect the effects of IFRS adoption" (Li 2010 p.2). Since the EU mandated IFRS adoption from 1st January 2005, all selected locations are amongst the first countries to adopt IFRS. Consequently, a large number of post-IFRS years can be examined in order to draw robust conclusions about the impact of IFRS. Third, all selected countries adopted IFRS during the same period[41], lessening the impact of any confounding events and therefore making it more valid to investigate the impact of IFRS in all these countries as pooled sample.

Sample countries within the EU are selected based mainly on the difference between local generally accepted accounting principles (GAAP) and IFRS and the level of investor

[41] Transition requirements meant that some companies adopted IFRS in 2004 (e.g. newly incorporated companies) and also, depending on the balance sheet date, IFRS adoption occurred at different dates. For instance, in Australia, since IFRS 1 mandated adoption for annual reporting periods commencing on or after 1 January 2004, December balancers reported using IFRS as at 1 January 2005, whereas June balancers not until 1 July 2005. This is not an issue for analysis as the year that the company transitioned to IFRS is always excluded to address the lagged effect of requiring averages for measurement of most independent variables. Moreover, for robustness tests, a fuller IFRS transition period (2004 - 2006) is excluded.

protection in each country. The literature makes it evident that IFRS adoption increases earnings quality in countries where investor protection is stronger rather than weaker (Houqe et al. 2012) and the impact is higher when domestic GAAP is more different from, rather than similar to, IFRS (Ding et al. 2007; Narktabtee & Patpanichchot 2011). Strong investor protection leads to less earnings management (Leuz, Nanda & Wysocki 2003) and greater financial transparency (Bhattacharya, Daouk & Welker 2003; Bushman & Smith 2001), and therefore to higher quality in financial reporting.

Bushman and Smith (2001) state that country-level high investor protection gives rise to high quality accounting information, and that the interaction of these two variables is positively associated with economic growth. The adoption of IFRS cannot guarantee high quality accounting information in the presence of poor institutional factors (Narktabtee & Patpanichchot 2011). Therefore, in this study countries are selected that have relatively high, but similar, levels of investor protection, which enables control for the effects of investor protection on the quality of accounting information. Data on investor protection are obtained from the Schwab and Sala-*i*-Martin (2013) Global Competitiveness Index Report 2012-2013[42], which ranks investor protection on a scale between zero to ten.

The quality of accounting information is different across various accounting regimes (Alford, Jones, Leftwich & Zmijewski, 1993, Joos & Lang, 1994). Some of the literature on the convergence of accounting standards reports that the quality of accounting information improved after adoption of IFRS compared with previous domestic GAAPs (Barth, Landsman & Lang 2008)**.** When domestic GAAP is very different from IFRS (GAAP difference), a greater improvement in the accounting information after adoption of IFRS is expected. Narktabtee and Patpanichchot (2011) report that countries benefiting most from adoption of IFRS are those with local GAAPs more deviate from IFRS. In this current study, data on GAAP difference is gathered using the measurement developed by Bae, Tan and Welker (2008). This index is constructed by comparing local accounting standards with IFRS for 21 key accounting items (see Table 4.1). A score of 1 is assigned if the country's treatment of these items does not conform with IFRS and 0 otherwise.

[42] Investor protection hard data is available within the Global Competitiveness Report only from 2007 onwards. For each country selected for this study, the Investor Protection Score is stable from 2007-2012.

The resulting score (0-21) represents the sum of scores across these 21 accounting items, with higher scores indicating higher deviation of local accounting standards from IFRS.

Table 4.1: GAAP difference accounting items identified by Bae, Tan & Welker (2008)

Item	IAS Rules	Description
1	IAS No. 1.7	Do not require a primary statement of changes in equity
2	IAS No. 12	Do not generally require deferred tax accounting
3	IAS No. 14	Require no or very limited segment reporting
4	IAS No. 17	Require no or very limited capitalisation of leases (other than defined contribution plans in some cases)
5	IAS No. 19	Do not have rules for accounting for employee benefit obligations
6	IAS No. 19.52	Do not have rules for accounting for employee benefits other than pensions
7	IAS No. 2.36	Do not require disclosure of FIFO inventory cost when LIFO is used
8	IAS No. 22.56//38.99	Do not require impairment testing of goodwill or other intangibles with lives in excess of 20 years
9	IAS No. 24	Have no or very limited disclosure requirements for related-party transactions
10	IAS No. 32.18 /.23	Do not require that companies account for their financial instruments based on substance over form
11	IAS No. 32.77	Do not require the disclosure of the fair value of financial assets and liabilities
12	IAS No. 35	Do not have rules outlining the treatment of discontinued operations
13	IAS No. 36	Do not have rules calling for impairment testing for long-term assets, or impairments are recorded only when deemed permanent
14	IAS No. 37	Do not have specific rules dealing with provisions
15	IAS No. 37.14	Permit establishing provision when there is no obligation
16	IAS No. 37.45	Do not have rules calling for the discounting of provisions
17	IAS No. 38.42	Permit capitalisation of research and development costs
18	IAS No. 38.51	Permit capitalisation of some other internally generated intangibles (e.g., brands)
19	IAS No. 7	Do not require a statement of cash flows
20	IAS No. 8.6	Permit a broader definition of extraordinary items
21	SIC 12	Do not require the consolidation of special purpose entities

Accordingly, the sample is selected from countries where pre-IFRS GAAP is furthest from compliance with IFRS (score > 10) and investor protection is relatively high (score > 5). The information about GAAP difference and investor protection is shown in Table 4.2 for the selected countries. Ten European countries are selected based on the above criteria; namely Spain, Finland, Czech Republic, Belgium, Portugal, Poland, Italy, France, Denmark and Sweden, all of which are Code law countries (Clarkson et al. 2011). The United Kingdom (UK) and Australia are included in the sample, representing Common law countries where GAAP difference is relatively low, but where a similar level of investor protection with all other selected EU countries exists. The UK and Australia adopted IFRS during a time period similar to that of the selected EU countries. As such, it is valid to compare results between Code and Common law countries.

Clarkson et al. (2011) state that: "The 2005 switchover to IFRS in Europe and Australia provides a natural quasi-experimental setting" (Clarkson et al. 2011 p.1). As such the sample is selected carefully to control to the extent possible for factors that influence the quality of accounting information, such as investor protection, accounting standards and legal regime, creating the circumstances for robust isolation of IFRS impact on the association between fundamental signals and one-year-ahead change in earnings per share and returns.

Table 4.2: Sample countries, their GAAP difference and investor protection

Countries	GAAP Difference With IFRS (on 21 Items)	Level of Investor Protection (0-10) 2012
Code Law		
Spain	16	5.0
Finland	15	5.7
Czech Republic	14	5.0
Belgium	13	7.0
Portugal	13	6.0
Poland	12	6.0
Italy	12	5.7
France	12	5.3
Denmark	11	6.3
Sweden	10	6.3
Code Law Average	12.8	5.83
Common Law		
Australia	4	5.7
UK	1	8.0
Common Law Average	2.5	6.85

Sources: *Bae, K.-H., Tan, H. & Welker, M. 2008. "International GAAP differences: The impact on foreign analysts". The Accounting Review, 83, 593-628, and Global Competitiveness Index 2011-2012 of World Economic Forum.*

4.9.2 Sample data composition

The sample comprises listed companies from 12 countries as explained above (10 Code law countries, and two Common law countries), over a 12-year period from 2001 to 2012 inclusive, but excluding 2005, the year of transition to IFRS. Data are collected for all listed companies for which all required data are available for any one fiscal year[43] for the selected EU countries, plus Australia, excluding companies in the financial sector. All cross-listed firms are eliminated during the firm selection process. All fundamental financial information is collected from the Bloomberg database and analysts' earnings per share (EPS) mean forecasts are collected from the Thomson Reuters Eikon database in United States Dollars (USD). All macro-economic variables, such as Inflation Rate and Gross Domestic Product growth, are gathered from the World Bank national accounts data file (http://databank.worldbank.org/data/) for the relevant year.

The financial sector is excluded as financial statements for this industry are quite different from other industries. According to the Global Industry Classification Standard (GICS), the remaining nine industries are Basic Materials, Consumer Goods, Consumer Services, Health Care, Industrials, Oil & Gas, Technology, Telecommunications and Utilities. Therefore, the sample comprises cross-sectional, time series data.

4.10 Conclusion

This study examines the predictive ability and value relevance of selected fundamental signals and analysts' efficiency in using these signals, along with IFRS impact on these attributes. For this purpose, one earnings signal and 12 non-earnings fundamental signals are examined. Eight of these latter 12 variables, namely Inventories (INV); Accounts Receivable (AR); Capital Expenditure (CAPX); Selling and Administrative Expenses (SA); Effective Tax Rate (ETR); Gross Margin (GM): Labour force (LF) and Audit Qualification (AQ), are based on Lev and Thiagarajan (1993), and four more financial statement-based signals are included based on prior literature, namely Financial Leverage (LEV); Cash Flows from Operations (CF); Goodwill (GW); and Discretionary Accruals (DACCR). These variables are expected to be value relevant for contemporaneous excess returns and have predictive ability in terms of one-year-ahead change in earnings per share.

All fundamental variables are chosen and designed specifically to provide a signal about future earnings and contemporaneous excess returns. The earnings fundamental signal is expected to have a negative relationship with contemporaneous excess returns (ER) and

[43] That is, the company does not have to be in existence for the full 12-year period, so survivorship bias is not an issue for this study.

a positive relationship with one-year-ahead change in earnings per share (CEPS1). All non-earnings signals, by construction, are expected to be negatively associated with ER and CEPS1.

The sample data for this study are collected from nine industries in 12 countries over a 12 year (2001-2012, but excludes 2005, the year of transition to IFRS, for analysis) period (i.e. cross sectional, time series panel data). Countries are selected on the basis of the difference between their domestic GAAPs and IFRS (GAAP difference), together with their levels of investor protection. This study further partitions these included countries into Code and Common law jurisdictions and the selected Code law countries have high GAAP difference compared to the Common law countries. However, all selected countries have high, but similar, levels of investor protection.

This study employs the regression[44] methodology used by Abarbanell and Bushee (1997) to examine predictive ability, while the methodology used by Lev and Thiagarajan (1993) is employed to test the value relevance of selected fundamental signals. The IFRS impact is examined using an interaction term for each fundamental signal with IFRS (coded 1 for post-IFRS periods) and a test of equality of coefficients based on stacked regression (Atwood et al. 2011). The methodology used by Abarbanell and Bushee (1997) and Wahab, Teitel and Morzuch (2015) is adopted in examining analysts' efficiency in using the selected fundamental signals for earnings forecasts and IFRS impact on this. In addition, contextual analysis is carried out to investigate whether the predictive ability and value relevance varies based on PYEN, level of GDP growth or level of inflation. The predictive ability and value relevance of 12 non-earnings fundamental signals, along with IFRS impact, is examined individually, in combination, and in aggregate form (F_Score).

As robustness tests, all above analyses are conducted for different sub-samples, such as Code compared with Common law observations, Winners compared with Losers, Extreme performers compared with Non-extreme performers (only for value relevance), and Growth compared with Value stocks (only for value relevance). Moreover, the IFRS analysis is also carried out for a sample that excludes a fuller IFRS transition (2004-2006) to allow for learning by financial statement preparers and the possibility of different

[44] In this study, robust regression is used by clustering on firm identity using STATA's cluster technique.

balance dates affecting IFRS adoption dates and the GFC (2007-2009) periods to account for confounding effects that may come from those periods on predictive ability and value relevance of fundamental signals.

CHAPTER 5: DESCRIPTIVE STATISTICS

5.1: Introduction

This chapter reports and discusses the descriptive statistics related to the sample and various partitions of the data into sub-samples. Accordingly, this chapter is organised as follows. Section 5.2 provides an overview of the population and sample. Then section 5.3 discusses the descriptive statistics for each of the variables relevant to testing the hypotheses for the full sample, sub-samples by country and sub-samples by industry. When discussing the descriptive statistics, the significance of differences in the fundamental signals between pre- and post-IFRS periods is reported. Section 5.4 reports the correlations between variables and section 5.5 concludes the chapter.

5.2 Overview of population and sample

As explained in the previous chapter, data are collected for listed non-financial companies for 12 countries across nine industries over a 12 year period[45] but excluding the year of IFRS transition 2005. In order to meet the criteria of generalisability of the research findings, it is important to define the population from which the sample is selected. Based on the Bloomberg database records, Table 5.1 reports the total number of listed non-financial companies available in the Bloomberg database by country and by industry for 2012, the commencing year for sample selection. The Global Industry Classification Standard (GICS) system is used when identifying industries. Nine industries are identified in the Bloomberg database; namely Basic Materials, Consumer Goods, Consumer Services, Health Care, Industrials, Oil & Gas, Technology, Telecommunications and Utilities.

As disclosed in the Bloomberg database, the population of non-financial listed companies for the 10 selected EU code law countries[46] as at the end of fiscal 2012 is 2652, and for the other EU country (UK) and Australia (both common law countries) is approximately 2817, giving a total of 5469 unique companies. That is, an approximately similar number of firms from code law (48.5 per cent) and common law (51.5 per cent) countries is included at the starting point for sample selection.

[45] As the data is collected from 2001 to 2012, the number of listed companies in operation over that period varies in each year.

[46] Belgium, Czech Republic, Denmark, Finland, France, Italy, Poland, Portugal, Spain and Sweden

Table 5.1: Population (number of firms) of non-financial listed companies for selected countries at fiscal year 2012 by industry

Country/Industry	Basic Materials	Consumer Goods	Consumer Services	Health Care	Industrials	Oil & Gas	Tech-nology	Telecomm-unications	Utilities	Total Firms
Code law										
Belgium	17	31	24	13	45	4	16	2	6	158 / (2.9%)
Czech Republic	4	8	5	0	11	3	0	3	5	39 / (0.7%)
Denmark	5	19	33	20	37	2	13	2	2	133 / (2.4%)
Finland	10	14	13	5	45	1	20	1	1	110 / (2.0%)
France	29	123	136	65	171	20	144	7	19	714 /(13.1%)
Italy	6	50	31	11	66	9	25	3	17	218 / (4.0%)
Poland	42	105	124	37	223	14	96	14	18	673 /(12.3%)
Portugal	5	5	16	1	14	1	5	2	2	51 / (0.9%)
Spain	14	23	22	12	36	5	7	4	8	131 / (2.4%)
Sweden	39	40	55	77	118	18	67	7	4	425 / (7.8%)
Total Code law firms	171 (3.1%)	418 (7.6%)	459 (8.4%)	241 (4.4%)	766 (14%)	77 (1.4%)	393 (7.2%)	45 (0.8%)	82 (1.5%)	2652 / (48.5%)
Common law										
UK	160	112	208	87	316	108	143	21	19	1174 / (21.5%)
Australia	856	89	113	111	201	156	68	22	27	1643 / (30.0%)
Total Common law firms	1016 (18.6%)	201 (3.7%)	321 (5.9%)	198 (3.6%)	517 (9.5%)	264 (4.8%)	211 (3.9%)	43 (0.8%)	46 (0.8%)	2817 / (51.5%)
Total Sample	1187 (21.7%)	619 (11.3%)	780 (14.3%)	439 (8.0%)	1283 (23.5%)	341 (6.2%)	604 (11.0%)	88 (1.6%)	128 (2.3%)	5469 / (100%)

*** Percentage of total population is shown in parenthesis. Source" Bloomberg database*

However, data are available for all required variables for the models described in Chapter 4 for only 2923 unique companies (53.5 per cent of the population of companies at 2012), of which 1504 (51 per cent) observations come from code law countries and 1419 (49 per cent) from common law countries. It needs to be noted that this number can vary in each year over the sample period as companies are listed and delisted from the various exchanges. As at 2012, the year which Table 5.1 reports on, these sample company observations represent approximately 56 per cent (1504/2652) of the population of companies from included code law countries and 50 per cent (1419/2817) from included common law countries.

For the population, as can be seen from Table 5.1, the highest percentage of companies as at 2012 (23.4 per cent) is found in the Industrials sector, whereas the lowest (1.5 per cent) is reported in Telecommunications. Approximately 21.5 per cent of companies come from Basic Materials, whilst Consumer Services and Consumer Goods account for 11 and 14 per cent of companies respectively. Companies listed in the Health Care sector represent 8 per cent whilst those within the Oil & Gas and Utilities sectors are reported as 6.2 per cent and 2.3 per cent respectively.

Table 5.2 reports the number of firms by country and by industry for the full sample for observations for which all data are available, comprising 2923 unique companies over the 12-year period between 2001 to 2012. With the exception of Basic Materials (population 21.7 per cent, sample 10.8 per cent), the sample is representative of industry populations.

Table 5.3 highlights the number of sample firm-year observations by country and by industry. The total number of firm-year observations for which all data were available over the period 2001-2012 was 20997 for these sample 2923 companies, however, this number can vary when it comes to multivariate analyses due to adjustments to avoid multivariate outliers and elimination of observations for the year of transition to IFRS[47]. The total number of observations with data available from the sources used varies across the variables, the highest being 42067 observations for audit opinion and the lowest being 23794 for dividend yield. However, as explained previously, due to missing data only 20997 firm-year observations across the 12 years are available for analysis.

[47] For some analyses, other years, such as the Global Financial Crisis (GFC) period, also are excluded.

Table 5.2: Sample (number of firms) of non-financial listed companies for selected countries at fiscal year 2012 by industry

Country/ Industry	Basic Materials	Consumer Goods	Consumer Services	Health Care	Industrials	Oil & Gas	Tech-nology	Telecomm-unications	Utilities	Total Firms
Code law										
Belgium	8	13	6	9	20	1	11	2	2	72 / (2.5%)
Czech Republic	1	2	1		1	1		1	2	09 / (0.3%)
Denmark	2	16	10	15	30	2	9	1	1	86 / (2.9%)
Finland	10	14	11	4	42	1	17	1	1	101 / (3.5%)
France	17	80	71	25	102	8	70	3	10	386 /(13.2%)
Italy	4	40	26	6	54	8	13	2	14	167 / (5.7%)
Poland	31	58	40	12	126	6	42	5	7	324 /(11.1%)
Portugal	4	3	8		8	1	3	2	2	31 / (1.1%)
Spain	11	14	13	8	24	5	5	2	7	89 / (3.0%)
Sweden	14	29	34	31	79	3	44	4	1	239 / (8.2%)
Total Code law firms	102	269	220	110	483	36	214	23	47	1504 / (51.5%)
	(3.5%)	(9.2%)	(7.5%)	(3.8%)	(16.5%)	(1.2%)	(7.3%)	(0.8%)	(1.6%)	
Common law										
UK	53	81	159	49	251	46	102	15	14	770 / (26.3%)
Australia	162	63	74	61	148	57	52	19	13	649 / (21.2%)
Total Common law firms	215	144	233	238	404	103	154	34	27	1419/ (48.5%)
	(7.4%)	(4.9%)	(8.0%)	(3.8%)	(13.7%)	(3.5%)	(5.3%)	(1.2%)	(0.9%)	
Total Sample	317	413	453	220	882	139	368	57	74	2923 / (100%)
	(10.8%)	(14.1%)	(15.5%)	(7.5%)	(30.2%)	(4.8%)	(12.6%)	(2.0%)	(2.5%)	

*** Percentage of total sample is shown in parenthesis. Source: Bloomberg database*

Table 5.3: Sample firm-year observations (2001-2012) (all required variables) for non-financial listed companies by country and industry

Country/Industry	Basic Materials	Consumer Goods	Consumer Services	Health Care	Indust-rials	Oil & Gas	Tech-nology	Telecomm-unications	Utilities	Total Firms
Belgium	75	124	65	50	184	11	69	18	9	605 (2.9%)
Czech Republic	8	17	2		9	8		11	20	75 (0.4%)
Denmark	20	121	73	125	308	16	67	12	8	750 (3.6%)
Finland	91	152	104	28	374	7	149	10	12	927 (4.4%)
France	145	719	580	189	823	78	532	21	85	3172 (15.1%)
Italy	26	297	180	38	439	47	82	13	129	1251 (6.0%)
Poland	215	346	189	41	630	37	198	26	43	1725 (8.2%)
Portugal	32	17	66		47	6	6	15	16	205 (1.0%)
Spain	88	98	88	50	180	41	32	11	75	663 (3.2%)
Sweden	106	207	167	163	669	17	249	30	10	1618 (7.7%)
Total code law	806 (3.8%)	2098 (10.0%)	1514 (7.2%)	684 (3.3%)	3663 (17.4%)	268 (1.3%)	1384 (6.6%)	167 (0.8%)	407 (1.9%)	10991 (52.3%)
UK	361	780	1282	311	2227	280	695	104	126	6166 (29.4%)
Australia	748	467	561	325	914	309	339	94	83	3840 (18.3%)
Total common law	1109 (5.3%)	1247 (5.9%)	1843 (8.8%)	636 (3.0%)	3141 (15.0%)	589 (2.8%)	1034 (4.9%)	198 (0.9%)	209 (1.0%)	10006 (47.7%)
Total Sample firm-years	1915 (9.1%)	3345 (15.9%)	3357 (16.0%)	1320 (6.3%)	6804 (32.4%)	857 (4.1%)	2418 (11.5%)	365 (1.7%)	616 (2.9%)	20997 (100%)

Accordingly, 52.3 per cent of observations are reported from code law countries, while the remainder come from common law countries.

When analysing the country-wise firm-year observations, the highest number of firm-years is from the UK, representing approximately 29 per cent of the total sample, whereas the lowest (75 observations) is accounted for by the Czech Republic with approximately 0.4 per cent of the sample. The Czech Republic is excluded from the multivariate analysis because so few observations are available[48]. In terms of industry-wise observations, the highest at 32.4 per cent of observations belongs to Industrials, while the lowest number of observations is reported for the Telecommunications industry.

5.3 Descriptive statistics for fundamental signals

As explained in Chapter 4, in testing the hypotheses developed in this study, one earnings and 12 non-earnings signals[49] are employed. All explanatory fundamental signal variables are measured as an annual change, and therefore the change can be either positive or negative. By the construction of the variables, as explained in section 4.5 of Chapter 4, a negative number indicates a good signal in terms of one-year-ahead change in earnings and contemporaneous excess returns, and a positive number provides a bad signal about future earnings and contemporaneous returns. Maximum numbers represent the positive end and minimum numbers represent the negative end of the distribution for each variable. Comparative descriptive statistics are provided for pre- (2001 -2004) and post-IFRS periods (2005-2012) for all fundamental signal variables. Mean values for all fundamental signals for pre- and post- IFRS periods are compared using independent sample *t*-tests for continuous variables and Chi-square tests for dichotomous variables.

Ou (1990) reports that samples comprising variables representing fundamental signals include many outliers. Following the Barth, Landsman and Lang (2008) and Barth et al. (2012) methodologies, all continuous variables are winsorised at 5 per cent to mitigate the effect of outliers. This is one of the most accepted methods of dealing with outliers

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[48] For the Czech Republic, data for only 75 firm-years are present, representing less than 0.5 per cent of the sample.

[49] Change in inventory relative to change in sales (INV), change in accounts receivable relative to change in sales (AR), change in selling and administrative expenses relative to change in sales (SA), change in labour force (LF), change in effective tax rate (ETR), change in gross margin (GM), audit qualification (AQ), and change in firm's capital expenditure relative to change in industry capital expenditure (CAPX), change in financial leverage (LEV), change in cash flow from operations (CF), change in goodwill (GW) and change in discretionary accruals (CDACCR).

without the excessive loss of observations for analysis. Winsorisation sets data for each variable below a certain percentile to that selected percentile. In this study all observations for continuous variables below the fifth percentile are set to the fifth percentile. This method for dealing with outliers has been followed in past literature, including by Barth, Landsman and Lang (2008); Barth et al. (2012); André, Filip and Paugam (2012); Bao, Lee and Romeo (2010); and Hou, Jin and Wang (2014). It is important to note that the data distribution for each variable is improved after winsorising. All descriptive statistics presented in Table 5.4 are after winsorisation.

As can be seen from Table 5.4, the number of sample firm-year observations for all variables is 20997, of which 72 per cent are post-IFRS. However, when performing association analyses, especially for IFRS impact on the fundamental signals, the IFRS transition year (2005) observations are dropped due to the need for lagged data in constructing some variables. Therefore, the number of post-IFRS observations for the multivariate analyses is lower than this[50].

5.3.1 Descriptive statistics for dependent variables

One of the dependent variables is one-year-ahead change in earnings per share (CEPS1), which is measured as EPS_{t+1}, minus EPS_t scaled by market price per share at the end of year t-1. The maximum increase in scaled one-year-ahead earnings per share (EPS) is 0.33 and the largest decrease for this variable is 0.24. The mean for the full sample is 0.017 (with a standard deviation of 0.12), indicating an increase in future earnings. Means for both pre- (0.030) and post-IFRS (0.011) periods also indicate an increase in future earnings, however the increase in EPS is lower in the post-IFRS period and the mean difference between these two periods is significant at 1 per cent. The lower standard deviation and smaller change indicate more persistent earnings in the post-IFRS period.

[50] Post-IFRS observations for the multivariate analyses are approximately 69 per cent of the full sample.

Table 5.4: Descriptive statistics for the full sample and pre- (2001-2004) and post-IFRS (2005-2012) sub-samples (firm-years)

Variables	Full Sample N= 20997						Pre-IFRS n =5860 (28%)		Post-IFRS n = 15137 (72%)		Test of difference
	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis	Mean	Std. Deviation	Mean	Std. Deviation	*t*
CEPS1	-0.243	0.333	0.017	0.120	.533	1.493	0.032	0.123	0.011	0.118	**11.489*** **
ER	-98.882	117.904	-0.006	38.043	.453	.267	7.787	39.515	-2.841	37.090	**17.515*** **
CHGEPS	-0.377	0.265	-0.012	0.126	-.507	1.737	-0.019	0.126	-0.010	0.125	**-4.321*** **
INV	-53.490	78.024	2.575	27.524	.732	1.619	0.346	27.157	3.438	27.617	**-7.365*** **
AR	-44.321	61.389	1.422	22.733	.647	1.181	0.869	22.750	1.636	22.724	**-2.194** **
SA	-48.837	39.904	-1.440	17.972	-.448	1.781	-1.427	18.488	-1.445	17.769	0.064
LF	-57.473	33.034	-6.973	20.451	-.507	.667	-9.945	21.903	-5.822	19.741	**-12.567*** **
ETR	-40.580	31.212	-1.015	13.088	-.720	3.679	-1.046	12.665	-1.003	13.249	-0.219
GM	-75.614	65.648	-1.222	28.616	-.377	1.815	-3.059	29.231	-0.511	28.343	**-5.713*** **
CAPX	-250.581	101.046	-16.901	84.146	-1.276	1.441	-18.923	82.266	-16.118	84.852	**-2.197** **
LEV	-81.901	138.229	4.143	48.645	1.018	1.616	0.057	0.472	0.035	0.492	**2.940*** **
CF	-19.226	15.483	-1.128	8.085	-.184	.181	-1.628	8.399	-0.935	7.952	**-5.439*** **
GW	-212.019	48.411	-24.571	59.145	-2.060	3.782	-0.275	0.643	-0.235	0.570	**-4.170*** **
CDACCR	-0.190	0.208	0.003	0.089	.130	-.526	0.009	0.096	0.001	0.087	**5.770*** **
											Chi-Sq
AQ	0.000	1.000	0.007	0.082	11.994	141.873	0.015		0.004		**77.602*** **

Where CEPS1=One year ahead change in earnings per share ($CEPS1 = [EPSt{+}1 - EPSt] \div Pt{-}1$), Contemporaneous excess returns (ER) is measured as the difference between firm return and the benchmark return for the period that begins 11 months before the earnings announcement date and ends one month after the earnings announcement date for year *t*, CHGEPS, Change in Current Earnings per share=change in EPS between year *t-1* and *t* deflated by the stock price at the end of *t-1*., INV=Inventories (annual percentage change in inventories minus the annual percentage change in sales), AR=Accounts Receivable (annual percentage change in accounts receivable minus annual percentage change in sales), SA=Selling & Administrative Expenses (annual percentage change in selling and administrative expenses minus the annual percentage change in sales), LF =Labour Force (LF) (annual percentage change in sales per employee calculated as last two years average sales per employee minus current year sales per employee divided by last two years average sales per employee), ETR=Effective Tax Rate (annual percentage change in ETR or Last two year (*t-1* and *t-2*) average ETR – ETR *t*), GM=Gross Margin (annual percentage change in sales minus annual percentage change in gross margin), CAPX=Capital Expenditure (annual percentage change in industry capital expenditure minus the annual percentage change in the firm's capital expenditure), LEV=Financial Leverage (Annual change in ratio of total debt (long-term debt plus current liabilities) to total assets or leverage ratio in year *t* – last two years average leverage ratio), CF=Cash Flows (Cash flow from operations (CFO) between year *t* and *t-1* divided by total assets at end of financial year *t-1*), GW = Goodwill (Annual percentage change in goodwill calculated as last two years (*t-1* and *t-2*) average goodwill minus goodwill in year *t* divided by last two years average goodwill). CDACCR =Discretionary Accruals, Discretionary accruals is calculated using the Kothari, Leone and Wasley (2005) performance matched discretionary accrual model CDACCR = annual change in discretionary accruals, AQ=Audit Qualification (0 for an unqualified opinion and 1 otherwise. If there is an emphasis of matter paragraph and if it relates to going concern, 1 is assigned and 0 otherwise. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively.

Contemporaneous excess return (ER) is the dependent variable employed to examine the value relevance of fundamental signals. This variable measures the difference between firm return and the benchmark return[51] for the period that begins 11 months before the earnings announcement date and ends one month after that date for year *t*.

The maximum excess returns reported are 117.90 per cent and the largest loss in terms of excess returns is 98.88 per cent, which represents the minimum. The mean ER for the full sample is - 0.006 per cent with a standard deviation of 38.04. The mean ER for the post-IFRS period represents a loss of 2.84 per cent, whereas for the pre-IFRS period, it is a 7.78 per cent gain. The mean difference between these two periods is significant at 1 per cent.

5.3.2 Descriptive statistics for independent variables

There is one earnings fundamental signal used in the study, which is the current year change in EPS (CHGEPS), and it is measured as EPS_{t-1} minus EPS_t deflated by the market price at the end of year *t-1*. Therefore, a negative change indicates that earnings have increased from the prior year to the current year, which is a good signal for future earnings and returns. The largest decrease in EPS in year *t* relative to year *t-1* is 0.265, which represents the maximum and the minimum is -0.377, indicating the largest increase in EPS relative to year *t-1*. The full sample mean CHGEPS is -0.012, indicating an overall increase in EPS, with a standard deviation of 0.126. The mean CHGEPS for each of the pre- and post-IFRS periods indicate an increase in EPS from year *t-1* to year *t*, however the mean of the post-IFRS period (-0.010 per cent) is lower than that of the pre-IFRS period (-0.019 per cent) and the mean difference between the two periods is significant at 1 per cent, with a similar standard deviation. In the literature, mean earnings has been found to be significantly different between pre- and post-IFRS periods (Atwood et al. 2011; Kabir, Laswad & Islam 2010; Stent, Bradbury & Hooks 2010).

The inventory variable (INV) is measured as the annual percentage change in inventory minus the annual percentage change in sales. A positive number for this variable means that there has been a disproportionate increase in inventories compared to sales, which is a bad signal for future earnings. The largest increase in inventory relative to sales is 78.02

[51] Benchmark indices used for each country are as follows: Spain - IBEX 35, Finland - OMX Helsinki 25, Belgium - BEL20, Portugal - PSI20, Poland - WIG30, Italy - MIB, France - CAC 40, Denmark - OMX Copenhagen 20, Sweden - OMXS 30, UK - FTSE 350, Australia - ASX200.

per cent, which indicates the maximum, and the minimum number of -53.49 per cent represents the largest decrease in inventory relative to sales. The mean INV for the full sample is 2.57 per cent with a standard deviation of 27.52. The mean INV for both pre- (0.346 per cent) and post-IFRS periods (3.438 per cent) is positive, however the mean for the post-IFRS period is significantly higher at 1 per cent with a similar standard deviation in both periods. This indicates a larger disproportionate increase in inventory compared to sales in the post-IFRS period.

The Accounts Receivable (AR) variable is constructed as the difference between annual percentage change in accounts receivable to sales. A positive number indicates a disproportionate increase in accounts receivable compared to sales, which is a bad signal for future earnings and returns. The maximum and minimum percentages for this variable are 61.38 per cent and -44.32 per cent respectively. The maximum number explains the largest percentage increase in accounts receivable and the minimum number indicates the largest decrease in accounts receivable relative to sales. The mean is 1.42 per cent and the standard deviation is 25.06. It is also noticeable that the means for both pre- (0.869 per cent) and post-IFRS (1.636 per cent) periods are positive and the mean difference between the two periods is significant at 5 per cent, with a higher mean in the post-IFRS period.

The Selling and Administrative Expenses (SA) variable is constructed as annual percentage change in SA minus annual percentage change in sales. A disproportionate increase in SA compared to sales represents a negative signal regarding future earnings. The maximum SA of 39.9 per cent represents the largest increase in this variable and the minimum of -48.83 per cent represents the largest decrease. The mean change is a decrease of -1.44 per cent and the standard deviation is 17.97. In pre- (-1.427 per cent) and post-IFRS (-1.445 per cent) analysis, both means represent similar negative change with similar standard deviation and therefore the mean difference for this variable between the two periods is not significant.

The Labour Force (LF) variable is measured as the change in the annual percentage change in sales per employee. A positive value for this variable indicates decreased labour productivity as measured by contribution to revenue. Therefore, the maximum value of 33.03 per cent represents the largest decrease in labour productivity/efficiency and the minimum value of -57.47 per cent indicates the largest increase in labour productivity.

The mean indicates an increase in labour productivity/ efficiency of 6.97 per cent and the standard deviation is 20.45. In both the pre- (-9.945 per cent) and post-IFRS (-5.822 per cent) periods, the means indicate an increase in LF, however the increase in LF is lower in the post-IFRS period and the mean difference between the two periods is significant at 1 per cent.

The Effective Tax Rate (ETR) variable is computed as the annual percentage change in ETR. Any unusual change which is not caused by a statutory tax change is considered transitory. The maximum percentage change in ETR is 31.21 per cent, which represents the maximum decrease in effective tax rate from the average of year *t-1* and year *t-2* to year *t* and is a negative signal for future earnings. The minimum of -40.58 per cent is the highest increase in ETR from average of last two years to year *t*. The full sample mean is -1.01 per cent and the standard deviation is 13.08. Both periods' means indicate a marginal increase in ETR and the mean difference between the pre- (-1.046 per cent) and post-IFRS (-1.003 per cent) periods is not significant.

The explanatory variable change in Gross Margin (GM) is measured as the percentage change in sales minus the percentage change in gross margin. A disproportionate decrease in gross margin relative to sales gives a negative signal about future earnings and returns. Therefore, a positive number for GM gives a bad signal regarding future earnings and returns. Accordingly, the maximum number indicates the largest decrease in GM relative to sales, which is 65.64 per cent. The largest increase in GM relative to sales represents the minimum, which is 75.61 per cent. The mean value of -1.22 per cent (standard deviation of 28.61) for the full sample indicates an overall increase in gross margin relative to sales. When comparing the means for the pre- (-3.059 per cent) and post-IFRS (-0.511 per cent) periods, the increase in GM in the post-IFRS period is less than that for the pre-IFRS period and the mean difference is significant at 1 per cent.

The next variable to be discussed is Capital Expenditure (CAPX), constructed as the annual percentage change in the industry's capital expenditure minus the annual percentage change in the firm's capital expenditure. A positive number for this variable means that the industry's capital growth is higher than that of the firm and therefore there is likely to be less growth in future earnings and returns for the firm compared to industry growth in earnings. The maximum CAPX of 101.04 per cent represents the largest percentage decrease in firm capital expenditure relative to industry average growth and the minimum of -250.58 per cent represents the largest percentage increase in firm capital expenditure against the industry's capital expenditure growth. The mean change is around -16.09 per cent, with a standard deviation of 84.14. The means for this variable in both the pre- (-18.923 per cent) and post-IFRS (-16.118 per cent) periods are negative, but lower in the post-IFRS period, with the mean difference being significant at 1 per cent.

Change in Financial Leverage (LEV) is another explanatory variable study and is constructed as the annual percentage change in leverage ratio (leverage ratio in year *t* minus the average leverage ratio in year *t-1* and year *t-2*). The maximum percentage increase in LEV is 138.2 per cent, whereas the largest decrease in the LEV ratio from the prior year is 81.9 per cent. The full sample mean of 4.1 per cent indicates an overall increase in LEV, and the standard deviation is 48.64. The mean difference between the pre- (0.057 per cent) and post-IFRS (0.035 per cent) periods is significant at 1 per cent, where pre-IFRS the mean is a 0.057 per cent increase and post-IFRS the mean is a 0.035 per cent increase in LEV, with a similar level of standard deviation.

Change in Cash Flow from Operations (CF) is another explanatory variable included in the model. This variable is calculated as cash flow from operations for year *t-1* minus cash flow from operations from year *t*, divided by total assets in year *t-1*. An increase (indicated as a negative number) in cash flow from year *t-1* to year *t* provides a positive signal about future earnings and returns. The overall mean CF for the full sample is -1.12 per cent, with the largest increase being 19.22 per cent (minimum) and the largest decrease being 15.48 per cent (maximum). In both pre- and post-IFRS periods, the mean indicates an increase in CF over the period, with a larger increase in the pre-IFRS (1.63 per cent) compared to post-IFRS (0.93 per cent) period. The mean difference between pre- and post-IFRS periods is significant at 1 per cent.

The next explanatory variable is Change in Goodwill (GW), constructed as the annual percentage change in goodwill. An increase in goodwill from the previous two-year average to year *t* represents a good signal for future earnings and returns, which is indicated as a negative value. Accordingly, the largest increase (minimum) in goodwill is 212 per cent and the highest decrease in goodwill (maximum) is 48.4 per cent. The mean indicates an increase of 2.4 per cent with a standard deviation of 59.14. When comparing the means of pre- (-0.275 per cent) and post-IFRS (-0.235 per cent) periods, the increase in GW is lower post-IFRS and the mean difference between these two periods is significant at 1 per cent.

Change in Discretionary Accruals (CDACCR) is another explanatory variable included in the analysis, and is calculated as the average of $DACCR_{t-1}$ and $DACCR_{t-2}$ minus $DACCR_t$. Discretionary accruals are measured using the Kothari, Leone and Wasley (2005) performance matched discretionary accruals model. Discretionary accruals represent the residual term from the regression model with total accruals as the dependent variable. Increasing discretionary accruals from year *t-1* to year *t* indicates expectation of an increase in future earnings and returns, and therefore a good signal. The largest increase in CDACCR is 0.190 and the largest decrease in CDACCR over the year is 0.208. The mean change is a decrease of approximately 0.003. The results in Table 5.4 show that there is larger decrease in discretionary accruals post-IFRS (0.001) compared with the pre-IFRS (0.009) period and the mean difference between the two periods is significant at 1 per cent.

Audit Qualification (AQ) is a dichotomous explanatory variable. This variable is constructed as taking the value 0 for an unqualified opinion and 1 otherwise. Additionally, if there is an emphasis of matter paragraph and if it relates to going concern, 1 is assigned and 0 otherwise. If the audit opinion is unqualified, that provides a good signal about future performance. The total number of qualified opinions is 143 (0.70 per cent) and there are 20854 (99.3 per cent) unqualified opinions in the sample. About 60 per cent of the qualified opinions fall in the pre-IFRS period. The mean frequency in the pre-IFRS period is larger than that post-IFRS. Based on a Chi-square test, the mean difference is statistically significant at 1 per cent between the two periods.

5.3.3 Descriptive statistics by country and pre- versus post-IFRS

As explained at the beginning of this chapter, 12 countries are selected to be included in the sample. Of those, 10 are code law countries within the European Union and two are common law countries (UK and Australia). Following adoption of IFRS, several researchers have examined the impact of IFRS on different countries' financial statements and report that most of the financial statement fundamentals under national generally accepted accounting principles (GAAPs) are significantly different from those under IFRS in many countries, including in Australia (Goodwin, Ahmed & Heaney 2008), Belgium (Haverals 2007), Canada (Blanchette, Racicot & Girard 2011), Greece (Tsalavoutas & Evans 2010), New Zealand (Bradbury & van Zijl 2005; Kabir, Laswad & Islam 2010; Stent, Bradbury & Hooks 2010) and UK (Horton & Serafeim 2010; Iatridis 2010).

Table 5.5 provides a country-wise summary of the means for variables proxying for the fundamental signals pre-and post-IFRS. Of the 13 explanatory variables, between the pre- and post-IFRS periods eight are significantly different for Finland, seven for Belgium, Czech Republic, France, Italy, and Poland, six for Australia, Spain and the UK and 5 for Denmark and Sweden. Of the 12 countries, between the pre- and post-IFRS periods, LF is significantly different for 11 countries, CF and GW for nine, GM for seven, INV and CDACCR for six, LEV for five, AR and AQ for four, and SA for three. Most mean values for the independent variables are higher in the pre- compared to post-IFRS period for all countries. Means for the dependent variables are significantly different between the pre- and post-IFRS periods, with a higher value pre-IFRS for all countries except Belgium and Portugal. These results indicate that many fundamental signals are significantly different between the two periods (pre- and post-IFRS) for most of the selected countries.

Table 5.5: Descriptive statistics by country and pre- and post-IFRS periods

Variables	Australia			UK			Belgium			Czech			Denmark			Finland		
	n-937	n-2903	Test of difference *t*	n-1749	n-4417	Test of difference *t*	n-164	n-441	Test of difference *t*	n-18	n-57	Test of difference *t*	n-216	n-534	Test of difference	n-294	n-633	Test of difference *t*
	Pre-IFRS	Post-IFRS		Pre-IFRS	Post-IFRS		Pre-IFRS	Post-IFRS		Pre-IFRS	Post-IFRS		Pre-IFRS	Post-IFRS		Pre-IFRS	Post-IFRS	
CEPS1	0.035	0.014	**0.020*** **	0.032	0.014	**0.018*** **	0.027	0.014	0.013	0.043	0.004	0.039	0.038	0.011	**0.027*** **	0.032	0.007	**0.025*** **
ER	4.104	-4.842	**8.946*** **	8.332	-2.154	**10.486*** **	1.436	2.084	-0.648	36.193	5.125	**31.068*** **	9.268	-7.275	**16.543*** **	18.871	1.399	**17.472*** **
CHGEPS	-0.028	-0.021	-0.007	-0.017	-0.013	-0.005	-0.029	-0.018	-0.011	-0.014	0.006	-0.020	-0.016	-0.013	-0.003	-0.019	0.000	**-0.018** **
INV	1.823	4.342	-2.519	-0.879	2.877	**-3.757*** **	0.282	3.104	-2.823	-5.536	-1.174	-4.362	-0.690	1.731	-2.421	-1.493	1.688	**-3.181** **
AR	1.634	2.624	-0.990	-0.813	1.908	**-2.720*** **	-0.069	1.046	-1.115	3.698	7.657	-3.959	-0.181	2.053	-2.234	-0.882	0.622	-1.504
SA	-6.457	-2.321	**-4.135*** **	0.247	-1.626	**1.873*** **	-3.118	-1.545	-1.573	1.138	-0.501	1.639	-0.952	-1.558	0.606	1.158	-0.996	**2.154*** **
LEV	-11.704	-8.519	**-3.185*** **	-9.180	-4.675	**-4.505*** **	-9.438	-4.798	**-4.640*** **	-19.614	-8.466	**-11.148** **	-10.858	-5.920	**-4.938*** **	-10.157	-5.342	**-4.815*** **
ETR	-0.323	-0.712	0.389	-0.957	-0.912	-0.045	1.778	-2.068	**3.845** **	-8.735	-0.585	**-8.150***	-1.268	-1.852	0.584	-1.207	-0.247	-0.960
GM	0.841	0.523	0.319	-0.371	-0.016	-0.355	-15.619	-4.492	**-11.127*** **	-37.539	-12.564	**-24.975** **	-12.831	-4.407	**-8.424** **	-15.526	-3.483	**-12.043*** **
CAPX	-27.699	-24.599	-3.101	-21.597	-18.414	-3.183	-8.430	-4.012	-4.418	-6.207	-8.892	2.685	1.253	-2.813	4.066	0.569	0.847	-0.278
LEV	7.483	8.104	-0.622	4.161	2.401	1.760	19.506	2.912	**16.594*** **	45.95	9.824	**36.127** **	18.611	4.983	**13.628*** **	16.489	9.503	**6.986** **
CF	-1.855	-1.616	-0.238	-1.211	-0.914	-0.296	-2.427	-0.603	**-1.824*** **	-3.628	-0.023	**-3.606***	-1.825	-0.502	**-1.323** **	-2.18	-0.454	**-1.726*** **
GW	-24.328	-29.304	**4.975** **	-26.029	-21.547	-4.482	-24.819	-14.795	**-10.024***	-11.843	-9.574	**-2.268*** **	-34.709	-21.732	**-12.977** **	-27.614	-22.931	-4.682
CDACCR	-0.01	-0.002	**-0.008***	-0.01	0.002	**-0.012*** **	-0.006	0.003	-0.009	-0.037	0.010	-0.047*	-0.006	0.001	-0.007	-0.010	-0.001	-0.008
Sq.			Chi Sq.			Chi Sq.			Chi Sq.			Chi Sq.			Chi Sq.			Chi
AQ	0.052	0.002	**0.050*** **	0.005	0.002	0.003	0.012	0.009	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.003

Refer to Table 5.4 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively.

Table 5.5: Descriptive statistics by country pre- and post-IFRS periods (cont.)

Variables	France			Italy			Poland			Portugal			Spain			Sweden		
	n-941	n-2231	Test of difference *t*	n-344	n-907	Test of difference *t*	n-284	n-1441	Test of difference *t*	n-72	n-133	Test of difference *t*	n-138	n-525	T-tests of difference	n-444	n-1174	Test of difference *t*
	Pre-IFRS	Post-IFRS		Pre-IFRS	Post-IFRS		Pre-IFRS	Post-IFRS		Pre-IFRS	Post-IFRS		Pre-IFRS	Post-IFRS		Pre-IFRS	Post-IFRS	
CEPS1	0.026	0.007	**0.019*****	0.018	-0.003	**0.021*****	0.073	0.010	**0.063*****	0.018	0.007	0.012	0.021	-0.001	**0.021*****	0.042	0.019	**0.023*****
ER	8.126	-0.021	**8.146*****	3.062	-1.271	**4.333****	10.292	-8.679	**18.971*****	2.026	-0.691	2.716	10.042	-6.388	**16.43*****	8.116	-1.044	**9.16*****
CHGEPS	-0.013	-0.007	-0.005	-0.001	0.003	-0.003	-0.032	-0.006	**-0.026*****	-0.018	-0.003	-0.015	-0.009	0.005	**-0.015****	-0.027	-0.005	**-0.022*****
INV	1.880	3.172	-1.292	-0.201	1.792	-1.993	2.056	7.087	**-5.031*****	0.411	0.642	-0.232	1.296	3.849	-2.553	-2.435	2.984	**-5.419*****
AR	0.505	0.454	0.051	1.383	-1.341	**2.725****	4.181	3.453	0.728	4.157	-1.939	**6.095****	4.733	0.672	**4.061****	1.881	2.359	-0.478
SA	-0.414	-0.753	0.339	-0.477	-0.015	-0.462	-1.955	-2.195	0.240	1.552	2.224	-0.672	0.684	0.219	0.465	-2.830	-1.329	-1.501
LF	-9.500	-3.753	**-5.747*****	-12.642	-4.130	**-8.512*****	-11.865	-8.098	**-3.767*****	-10.518	-6.106	-4.412	-8.865	-4.997	**-3.868****	-11.587	-5.641	**-5.945*****
ETR	-1.732	-1.921	0.189	-1.194	-0.394	-0.800	-3.596	-0.691	**-2.905*****	-0.729	-1.057	0.328	-0.365	-1.89	**1.526***	-0.471	-0.429	-0.042
GM	-4.286	-1.771	**-2.515****	-1.596	1.672	**-3.267****	-2.836	2.232	**-5.068****	-5.671	-0.822	**-4.849***	-2.514	0.468	**-2.982****	-3.973	-2.069	-1.904
CAPX	-22.279	-12.493	**-9.786*****	-13.886	-6.074	-7.813	-29.33	-24.15	-5.180	-14.729	-8.487	-6.243	-4.108	-9.641	5.532	-9.944	-16.708	**6.764***
LEV	5.296	0.684	**4.612*****	1.022	-0.348	1.370	4.292	2.102	2.189	1.984	0.965	1.019	-1.005	-1.304	0.299	1.025	3.791	-2.766
CF	-1.809	-0.631	**-1.178*****	-1.571	-0.153	**-1.418*****	-1.600	-0.926	-0.674	-2.343	-0.003	**-2.340****	-2.282	-0.787	**-1.495***	-2.035	-1.197	**-0.838***
GW	-37.38	-23.615	**-13.765*****	-32.718	-20.136	**-12.582*****	-11.891	-22.023	**10.132*****	-49.27	-17.834	**-31.437*****	-32.663	-25.032	-7.631	-24.74	-23.193	-1.547
CDACCR	-0.014	0.000	**-0.014*****	-0.013	-0.004	**-0.009***	-0.006	-0.009	0.002	-0.029	0.005	**-0.034*****	-0.014	-0.005	-0.009	-0.002	-0.002	-0.001
			Chi. Sq.			Chi. Sq.			Chi. Sq.			Chi. Sq.			Chi. Sq.			Chi. Sq.
AQ	0.005	0.006	-0.001	0.009	0.006	0.003	0.021	0.000	**0.021*****	0.014	0.000	0.014	0.087	0.015	**0.072*****	0.000	0.009	-0.009

Refer to Table 5.4 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively.

Table 5.6: Descriptive statistics by industry pre- and post-IFRS periods

Variables	Basic Materials			Consumer Goods			Consumer Services			Health Care			Industrials		
	n-469	n-1446	Test of difference *t*	n-1022	n-2323	Test of difference *t*	n-873	n-2484	Test of difference *t*	n-286	n-1034	Test of difference *t*	n-1890	n-4914	Test of difference *t*
	Pre-IFRS	Post-IFRS		Pre-IFRS	Post-IFRS		Pre-IFRS	Post-IFRS		Pre-IFRS	Post-IFRS		Pre-IFRS	Post-IFRS	
CEPS1	0.041	0.013	**0.028*** **	0.025	0.011	**0.014*** **	0.028	0.007	**0.021*** **	0.018	0.015	0.004	0.036	0.011	**0.025*** **
ER	7.347	-4.159	**11.506*** **	12.019	-2.148	**14.167*** **	6.231	-4.068	**10.299*** **	5.436	-4.789	**10.225*** **	10.044	-1.935	**11.98*** **
CHGEPS	-0.019	-0.016	-0.003	-0.019	-0.008	**-0.011*** **	-0.018	-0.008	**-0.010** **	-0.017	-0.016	-0.001	-0.014	-0.009	**-0.006***
INV	3.232	1.840	1.392	0.285	3.058	**-2.773*** **	0.976	3.211	**-2.235** **	0.495	2.021	-1.526	-0.191	3.419	**-3.610*** **
AR	2.590	0.570	2.020	-0.069	1.213	**-1.282***	2.358	2.700	-0.342	1.779	2.292	-0.513	0.064	0.750	-0.686
SA	-2.240	-4.432	**2.192***	-1.567	-0.336	**-1.231** **	-1.078	0.214	**-1.292** **	-4.170	-3.506	-0.664	-0.748	-1.159	0.411
LF	-11.041	-8.900	**-2.141***	-10.162	-5.576	**-4.586*** **	-8.718	-4.139	**-4.579*** **	-10.021	-6.978	**-3.044** **	-10.003	-5.158	**-4.845*** **
ETR	-1.299	-1.289	-0.010	-1.086	-1.491	0.405	-0.850	-0.990	0.140	-1.038	-0.478	-0.560	-1.004	-1.028	0.024
GM	-2.711	0.953	**-3.665***	-5.487	-1.298	**-4.189*** **	-1.348	0.226	-1.574	-2.195	-1.991	-0.204	-4.020	-0.410	**-3.610*** **
CAPX	-16.461	-20.596	4.135	-21.202	-11.562	**-9.641*** **	-20.18	-14.86	**-5.320***	-25.041	-17.780	-7.262	-13.24	-14.181	0.941
LEV	9.182	4.423	4.759	6.963	2.956	**4.007*** **	6.080	0.814	**5.266*** **	3.773	1.961	1.812	6.077	4.041	2.037
CF	-0.872	-1.148	0.275	-1.586	-0.585	**-1.001*** **	-1.865	-0.853	**-1.012*** **	-2.007	-1.274	-0.732	-1.484	-0.788	**-0.696*** **
GW	-22.576	-16.996	**-5.580***	-28.435	-18.51	**-9.925*** **	-32.090	-22.609	**-9.481*** **	-28.929	-22.334	-6.596	-28.618	-26.223	-2.394
CDACCR	-0.011	-0.002	**-0.009***	-0.006	-0.003	-0.003	-0.009	0.000	**-0.009*** **	-0.009	0.001	-0.010	-0.012	-0.001	**-0.012*** **
			Chi. Sq.			Chi. Sq.			Chi. Sq.			Chi. Sq.			Chi. Sq.
AQ	0.043	0.003	**0.040*** **	0.008	0.003	0.005	0.008	0.003	**0.005***	0.014	0.003	**0.011***	0.012	0.003	**0.009*** **

Refer to Table 5.4 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively.

Table 5.6: Descriptive statistics by industry and pre- and post IFRS period (cont.)

Variables	Oil & Gas			Technology			Telecommunications			Utilities		
	n-188	n-669	Test of difference	n-624	n-1794	Test of difference	n-96	n-269	Test of difference	n-153	n-463	Test of difference
	Pre-IFRS	Post-IFRS	*t*	Pre-IFRS	Post-IFRS	*t*	Pre-IFRS	Post-IFRS	*t*	Pre-IFRS	Post-IFRS	*t*
CEPS1	0.031	0.012	**0.019***	0.046	0.013	**0.033*****	0.027	0.017	0.010	0.033	0.002	**0.031*****
ER	9.926	-2.042	**11.968*****	-0.152	-2.947	2.795	-11.893	-1.349	**-10.543****	8.345	-2.476	**10.821*****
CHGEPS	-0.021	-0.016	-0.005	-0.034	-0.012	**-0.023*****	-0.014	-0.013	0.000	-0.024	-0.006	**-0.019***
INV	-7.550	7.184	**-14.735*****	0.042	4.329	**-4.287*****	-9.674	5.444	**-15.117*****	5.377	5.322	0.055
AR	-2.722	3.041	**-5.763****	0.267	3.136	**-2.869****	-5.716	0.642	**-6.357****	5.577	3.964	1.613
SA	-3.809	-3.238	-0.571	-1.682	-1.512	-0.169	-1.388	-1.868	0.480	-0.236	-1.598	1.362
LF	-10.309	-9.382	-0.927	-12.264	-4.132	**-8.132*****	-14.313	-6.950	**-7.363****	-13.903	-8.953	**-4.950****
ETR	-1.311	-1.370	0.059	-1.076	-0.755	-0.321	-3.16	-0.236	-2.924	0.211	0.441	-0.230
GM	-1.533	-0.663	-0.869	-0.081	-1.003	0.922	-7.102	0.423	**-7.525****	-6.788	-0.084	**-6.704*****
CAPX	-25.227	-33.369	8.141	-28.277	-18.409	**-9.868****	-23.918	-25.512	1.594	-6.685	-13.263	6.578
LEV	1.737	3.863	-2.125	2.819	4.470	-1.650	15.02	12.453	2.567	8.969	3.601	5.368
CF	-1.693	-1.673	-0.021	-2.713	-1.313	**-1.400*****	-1.817	-0.746	-1.072	-1.409	-0.547	-0.862
GW	-15.258	-17.387	2.129	-28.969	-28.435	-0.535	-18.934	-32.117	**13.183***	-27.959	-25.667	-2.291
CDACCR	-0.009	-0.004	-0.005	-0.015	0.000	**-0.015*****	0.003	-0.001	0.005	-0.005	0.000	-0.005
			Chi. Sq.			Chi. Sq.			Chi. Sq.			Chi. Sq.
AQ	0.064	0.004	**0.060*****	0.018	0.007	0.011**	0.021	0.007	0.014	0.000	0.000	0.000

Refer to Table 5.4 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively.

5.3.4 Descriptive statistics by Industry and Pre- versus Post-IFRS

Table 5.6 summarises the variables that are significantly different between the pre- and post-IFRS periods by industry. As can be seen from the table, 10 of 13 explanatory variables are significantly different between pre- and post-IFRS periods for the Consumer Goods and Consumer Service industries, whereas this is so only for two variables for the Health Care industry. Analysis for the Technology and Industrials sectors shows that eight and seven variables respectively are significantly different between the two periods. However, only three variables are significantly different between the pre- and post-IFRS periods for the Oil & Gas, and Utilities industries. In terms of Basic Materials and Telecommunications, five explanatory variables are significantly different between the two periods. The means for the two dependent variables are significantly different between the pre- and post-IFRS periods for most industries. Mean values for most of the fundamental signals, including the two dependent variables (CEPS1 and ER), are higher in the pre- compared to post-IFRS periods except for the Technology industry.

5.4 Correlations amongst independent variables

As mentioned earlier, this study employs one earnings and 12 non-earnings variables as explanatory variables. Pearson's correlations between the independent variables are estimated to test whether multicollinearity among these variables is at a level for concern and the results are documented in Table 5.7. As can be seen from the results, none of the correlations is of a level that creates multicollinearity concerns, with the highest at 0.440 between change in discretionary accruals (CDACCR) and change in leverage (LEV). However, variance inflation factors are also examined and reported for the pooled sample regression results reported in Chapters 6-8 to ensure this is the case.

Table 5.7: Pearson's correlations for independent variables (N=20997)

Variables	CHGEPS	INV	AR	SA	LF	ETR	GM	AQ	CAPX	LEV	CF	GW
INV	.065***											
AR	-.005	.179***										
SA	.123***	.165***	.072***									
LF	.196***	.120***	.056***	.212***								
ETR	-.051***	.001	.000	-.015**	-.014**							
GM	.167***	.031***	-.039***	-.073***	.042***	.003						
AQ	-.001	.006	.000	-.016**	-.016*	-.005	.015**					
CAPX	.016**	-.045***	-.048***	.040***	.031***	-.017**	.048***	.011				
LEV	.007	.034***	.046***	-.008	-.031***	-.003	-.277***	.014**	-.063***			
CF	.197***	.071***	.022***	.110***	.179***	-.013	.081***	-.003	.042***	.020***		
GW	.001	-.069***	-.079***	.004	.015**	-.010	.029***	.005	.131***	-.098***	.046***	
CDACCR	-.181***	-.039***	-.010	-.109***	-.025***	.015**	-.124***	-.008	.007	.046***	.440**	.014**

Refer to Table 5.3 for variable definitions. ***, **, * indicates that correlation is significance at the 1%, 5%, and 10% levels respectively.

5.5 Chapter summary

Data for this study are collected for all listed non-financial companies for 12 countries (10 code law countries and two common law countries) for which all required data are available from the Bloomberg database as at 2012. The sample for this analysis consists of 20997 firm-years for 12 countries, across 9 industries, for years 2001 to 2012 (2005 the year of IFRS transition is excluded in multivariate analyses). Of the observations, 52 per cent come from common law countries with the remainder from code law countries. Consumer Goods and Consumer Services industries account for a higher number of observations compared to others and the lowest number is reported for the Telecommunications industry. Country-wise analyses show that the highest number of observations is accounted for by the UK and the lowest by the Czech Republic. Due to insufficient observations, the Czech Republic observations are dropped from the multivariate analyses that follow this chapter.

Analysis further indicates that all variables except change in selling and administrative expense (SA) and change in effective tax rate (ETR) are significantly different between pre- and post-IFRS periods for the full sample and most mean values for the variables are higher for the pre- compared to post-IFRS period. A higher number of fundamental signals are significantly different between the two periods for Finland and Belgium and for industries like Consumer Goods and Consumer Services. Pearson’s correlations for the independent variables indicate that none of the correlations is of a level that creates multicollinearity concerns.

CHAPTER 6: PREDICTIVE ABILITY OF FUNDAMENTAL SIGNALS AND IFRS IMPACT ON THIS PREDICTIVE ABILITY

6.1 Introduction

This chapter summarises the empirical results of and discusses the findings from testing six of the hypotheses (H1a, H1b, H1c, H1d, H1e and H1f[52]) identified in Chapter 3. Accordingly, this chapter is organised as follows. Section 6.2 discusses the main research contributions arising from results reported in this chapter. Section 6.3 discusses findings for tests of the predictive ability of fundamental signals in predicting future earnings that relate to Hypotheses H1a, H1b and H1c. Section 6.4 documents and discusses the findings for IFRS impact on the predictive ability of fundamental signals that relate to testing of Hypotheses H1d, H1e and H1f. Section 6.5 documents findings that relate to robustness and other tests, and finally 6.6 summarises the findings for all six hypotheses.

6.2 Research contribution

This chapter investigates the predictive ability of the one earnings and 12 non-earnings fundamental signals defined in Chapter 4 section 4.5, in predicting one-year-ahead change in earnings per share, together with the impact of IFRS on this predictive ability. As described in Chapter 4, a large data set for the period 2001 to 2012 from European and Australian contexts is assembled to do this. As such, this study makes significant contributions to the literature in several ways. First, many of the previous studies of fundamental signals of this kind have been conducted using data for the period prior to the year 2000. Therefore, as explained Chapter 1, questions arise as to whether the fundamental signals tested for their usefulness previously remain valid for predicting future earnings in 21st century. Major change occurred in the accounting environment with adoption of IFRS that affects the quality of accounting information. As such, this study tests the predictive ability of fundamental signals in predicting future earnings per

[52] For convenience, the hypotheses are reproduced here. *H1a: There is a positive relationship between current year change in earnings and one-year-ahead change in earnings per share, H1b: There is a negative relationship between current year non-earnings fundamental signals and one-year-ahead change in earnings per share, H1c: There is a positive relationship between an aggregated fundamental score and one-year-ahead change in earnings per share, H1d: The predictability of future earnings by current year earnings improved after adoption of IFRS, H1e: The predictability of future earnings by non-earnings fundamental signals improved after adoption of IFRS, and H1f: The predictability of earnings by the aggregated fundamental score improved after adoption of IFRS.*

share using post-2000 data for a 12-year period in a context involving selected European countries and Australia, encompassing both common and code law regimes. Furthermore, a large number of non-earnings fundamental signals are included in the model to test their ability in predicting one-year-ahead change in earnings. Moreover, this study includes some fundamental signals (e.g. discretionary accruals, goodwill) that have not been tested in this type of study before in terms of their ability to predict future change in earnings per share.

Another contribution is that the study examines the predictive ability of fundamental signals individually, in combination and in an aggregated form (F_Score). This study also examines how their predictive ability varies based on: i) prior year earnings news (bad and good news), ii) high and low inflation contexts, and, finally, iii) high and low GDP growth contexts. Therefore, the study tests predictive ability from different perspectives and, as such, provides a check on consistency of results.

Another significant contribution is that this study represents the first known time that IFRS impact on the predictive ability of the selected non-earnings fundamental signals, in terms of predicting future earnings, has been examined. Additionally, although the earnings fundamental has been researched both pre- and post-IFRS, to the best of the researcher's knowledge, this is the first study to test the impact of IFRS on the predictive ability of change in current year earnings per share to predict one-year-ahead change in earnings per share. Moreover, this study examines the impact of IFRS on the predictive ability of fundamental signals for different sub-samples, such as Code and Common law country observations and prediction of positive or negative change in future earnings. Moreover, the impact of IFRS is examined in a very robust way using the interaction of each fundamental signal with IFRS, together with a test of equality of coefficients using stacked regression (Atwood et al. 2011).

Since the sample is selected carefully to control for other factors likely to affect predictive ability, such as investor protection and legal regime, this study enables, to the extent possible, clear identification of the impact of IFRS on the predictive ability of fundamental signals in predicting future earnings. As such this chapter makes a significant contribution to knowledge and to the literature.

6.3 Predictive ability of fundamental signals

In the fundamental analysis literature, several studies examine the predictive ability of fundamental signals in predicting future earnings, including Abarbanell and Bushee (1997), Bernard and Stober (1989); Ou and Penman (1989a); Ou (1990); Stober (1993); Lev and Thiagarajan (1993); Kerstein and Kim (1995); Al-Debie and Walker (1999); Dowen (2001); Seng and Hancock (2012). However, as mentioned earlier, most of these studies were conducted using data from prior to the year 2000. This study tests the predictive ability of fundamental signals for the period 2001 to 2012 in European and Australian contexts.

6.3.1 Fundamental signals predicting future earnings

This study, amongst other things, uses one earnings and 12 non-earnings fundamental signals as explanatory variables and tests the ability of these fundamental signals to predict one-year-ahead change in earnings per share. In order to test the predictive ability of fundamental signals, this study follows the methodology used by Abarbanell and Bushee (1997), later followed by many other scholars (e.g. Dowen 2001; Seng & Hancock 2012). As explained in Chapter 5, the sample data for this study is collected from 2933 firms over a 12-year period (2005, the year of IFRS transition is excluded from analyses), from 12 countries, and nine industries (i.e. cross sectional, time series panel data). In order to control for the fixed effects of years, countries, and industries, dummy variables for each are included in the modelling. Accordingly, the following regression models, which were explained in Chapter 4 and are repeated here for convenience, are employed to examine the predictive ability of the selected fundamental signals.

$$CEPS1_i = \propto + \beta_0 \, \mathrm{CHGEPS}_i + \sum_{j=1}^{12} \beta_{ij} \mathrm{Signals}_{ij} + \sum \mathrm{Yr} + \sum \mathrm{Cty} + \sum \mathrm{In} + \varepsilon_j \qquad (1)$$

Where $CEPS1_i =$ one-year-ahead change in earnings per share for firm *i*, $\mathrm{CHGEPS}_i =$ current year change in earnings per share for firm *i*, $\mathrm{Signals}_{ij}$= non-earnings fundamental signals[53], *j* = 1 to 12, Yr = Year dummies, Cty= Country dummies, In=Industry dummies.

[53] For convenience, the 12 non-earnings fundamental signal variables are repeated here: they are change in inventory relative to change in sales (INV), change in accounts receivable relative to change in sales (AR), change in selling and administrative expenses relative to change in sales (SA), change in labour force (LF), change in effective tax rate (ETR), audit qualification (AQ), change in firm's capital expenditure relative to change in industry capital expenditure (CAPX), change in financial leverage (LEV), change in cash flow from operations (CF), change in goodwill (GW) and change in discretionary accruals (CDACCR).

The definitions and measurement of these fundamental signals are explained in Chapter 4 section 4.5 and Table 6.1.

Regression results are adjusted using the Huber-White Sandwich estimator (White 1980), which provides robust standard errors to control for heteroskedasticity and auto-correlation, by using STATA with observations clustered by firm identity.

As explained in Chapter 5, the original sample selected for this analysis comprises 20997 firm-years. However, in order to maintain the same sample for various analyses, including examining the impact of IFRS on the predictive ability of fundamental signals, observations for the year in which firms transitioned to IFRS (2005) are removed, resulting in loss of 1503 observations. Moreover, in pre-testing, regressions that produced studentised residuals greater than three or Cook's distance statistics greater than one are removed to address multivariate outliers. Lev and Thiagarajan (1993) document that this procedure did not alter their conclusions; rather it increased the explanatory power of their model. This method has been followed in some subsequent fundamental studies (Abarbanell & Bushee 1997; Dowen 2001). This procedure eliminates a further 226 observations and so the final pooled sample comprises 19268 firm-year observations from 2908 unique firms.

Descriptive statistics for the pooled sample, together with tests of difference for the pre- and post-IFRS samples is conducted and results are reported in Annexure 6.1, since the sample size differs from that presented for descriptive statistics in Chapter 5. However, there are no major differences. Moreover, to examine the collinearity among variables for this reduced sample compared with that reported in Chapter 5, Pearson's correlations are calculated and reported in Annexure 6.2. Again results reveal that none of the correlations is of a level that creates multicollinearity concerns, with no correlation higher than 0.446 between change in cash flows from operations (CF) and change in discretionary accruals (CDACCR).

Further, some years under examination fall under the GFC period (2007-2009). Therefore, in order to examine the predictive ability of fundamental signals robustly, the regressions for Models 1 and 2 developed in Chapter 4 are re-run for the sample that excludes the GFC period. In addition, when examining the IFRS impact on predictive ability, as a robustness test, analysis is conducted for the period that excludes observations allowing a full IFRS transition period (2004-2006), in addition to the GFC period. This analysis is conducted to allow a period of learning in IFRS transition and also to cater for different financial year-ends during the IFRS transition period which may have resulted in different adoption periods[54]. Moreover, for the construction of some variables, lagged data are required for the calculation of averages and these data ideally emanate under the same accounting standards.

6.3.2 Predictive ability of fundamental signals for pooled sample and sub-samples of Code and Common law countries

Table 6.1 reports results for the association between the fundamental signals and the one-year-ahead change in earnings per share for both Model (1) used in this study, and the Abarbanell & Bushee (1997) model[55]. The results are obtained by regressing current year change in earnings per share (CHGEPS) and 12 (eight from the Abarbanell & Bushee model plus four introduced in this study) non-earnings fundamentals on one-year-ahead change in earnings per share (CEPS1). Table 6.1 also reports the regression results separately for Code (n=10093 [52 per cent]) and Common (n=9175) law countries. The earnings fundamental signal is expected have a positive relationship with CEPS1, while all non-fundamental signals are expected to have a negative relationship with CEPS1, as was explained in Chapter 4 section 4.5.

When comparing the explanatory power of the two models (Abarbanell and Bushee (1997) and the model used in this study), the latter has higher explanatory power (R-Squared s are 0.131 and 0.141 respectively). For individual fundamental signals common to the models, except for Labour Force (LF) the results are consistent in sign and significance.

When regressing the current year change in earnings per share (CHGEPS) alone in the model as an independent variable, the robust R-Squared value is 0.125 (Table 6.1, R-Sq 2), and when the non-earnings fundamentals are included in the same regression (which represents the full Model for this study), the R-Squared value increases to 0.141. This indicates that the non-earnings fundamentals examined contribute incrementally to

[54] For instance, in Australia adoption of IFRS was the first annual period commencing on or after 1 January 2004. This meant that December balancers adopted in 2005, but June balancers in 2006.

[55] The Abarbanell & Bushee (1997) model is the is the base model and this study includes four additional fundamental variables to test the predictive ability of fundamental signals in predicting future change in earnings. These models are explained in detail in Chapter 4 at section 4.6.

predicting future earnings beyond current year earnings. The partial F-test indicates that the incremental explanatory power from the non-earnings fundamental signals over earnings in predicting future earnings is significant. This is consistent with the conclusion from prior research that non-earnings fundamental signals contain information relevant for predicting future earnings (Abarbanell & Bushee 1997,1998; Al-Debie & Walker 1999; Dowen 2001; Lev & Thiagarajan 1993; Mohanram 2005; Ou 1990; Seng & Hancock 2012). Further, it is noted that each of the four non-earnings signals added for this study are significant at 1 per cent in predicting future earnings, and the partial F-test (Table 6.1) indicates that their incremental explanatory power is significant. As shown in Table 6.1, the results for the sub-sample analyses of Code and Common law countries are consistent with those for the pooled sample.

For individual fundamental signals, the current year change in earnings per share (CHGEPS), as expected, is positively related with one-year-ahead change in earnings per share (CEPS1) and significant at 1 per cent for both the pooled and sub-samples of Code and Common law countries. This result is consistent with the reversing nature of current year accruals (Chan, Jegadeesh & Sougiannis 2004; DeFond & Park 2001; Pae 2005; Wahab, Teitel & Morzuch 2015) and mean reverting pattern of earnings, with a good year followed by a bad year and a bad year followed by a good year (Dowen 2001; Swanson, Rees & Juarez-Valdes 2003).

As explained, this study includes 12 non-earnings fundamental signals as independent variables in Model 1. Of these 12 fundamental signals, eight (INV, AR, SA, LF, ETR, GM, AQ, and CAPX) are based on the Abarbanell and Bushee (1997) study and four additional fundamental signals (LEV, CF, GW, and CDACCR) emanate from past literature. Of these non-earnings fundamental signals, change in inventory relative to sales (INV), change in accounts receivable relative to sales (AR), change in effective tax rate (ETR), audit qualification (AQ), change in firm capital expenditure relative to the industry (CAPX), change in financial leverage (LEV), change in cash flows from operations (CF), change in goodwill (GW) and change in discretionary accruals (CDACCR), all predict one-year-ahead change in earnings per share (CEPS1) significantly for the pooled sample.

Table 6.1: Ability of fundamental signals to predict one-year-ahead change in earnings per share (H1a & H1b)

Model 1 Dep.Var. CEPS1	Abarbanell & Bushee Model	Current Study Model			Test of Equality (a-b)
		Pooled Sample	Code Law (a)	Common Law (b)	
	N = 19268	N = 19268	n = 10093	n = 9175	
	Clusters = 2908	Clusters = 2908	Clusters = 1494	Clusters = 1414	
	Coef.	Coef.	Coef.	Coef.	Coef. Diff
α	0.02026***	0.02201***	0.03812**	0.04022***	
CHGEPS	0.30127***	0.31940***	0.32491***	0.31282***	0.01209
INV	-0.00003**	-0.00003**	-0.00002	-0.00006***	0.00005**
AR	-0.00012***	-0.00011***	-0.00010**	-0.00012**	0.00002
SA	-0.00001	-0.00006	0.00032***	-0.00006	0.00038***
LF	-0.00015***	-0.00007	-0.00010	-0.00004	-0.00005
ETR	-0.00016**	-0.00016**	-0.00018**	-0.00009	-0.00010
GM	-0.00005	0.00003	0.00001	0.00003	-0.00003
AQ	0.02081*	0.02070*	0.00151	0.04314**	-0.04162
CAPX	0.00008***	0.00008***	0.00008***	0.00008***	0.00000
LEV		0.00009***	0.00005	0.00012***	-0.00006
CF		-0.00150***	-0.00161***	-0.00143***	-0.00018
GW		0.00008***	0.00007***	0.00010***	-0.00004
CDACCR		-0.04159***	-0.04858***	-0.03989**	0.00869
R-Sq 1	0.131	0.141	0.164	0.129	
R-Sq 2	0.125	0.125	0.148	0.110	
Incremental R-Sq	0.006	0.016	0.016	0.019	
F-test for 12 signals		23.41	12.22	13.75	
F-test for 4 signals		42.42	20.57	13.3	

Where CEPS1=One-year-ahead change in earnings per share ($CEPS1 = [EPSt{+}1 - EPSt] \div Pt{-}1$), CHGEPS=(Change in Current Earnings per share)=change in EPS between year *t-1* and *t* deflated by the stock price at the end of *t-1*., INV=Inventories (Annual percentage change in inventories minus the annual percentage change in sales), AR=Accounts Receivable (Annual percentage change in accounts receivable minus annual percentage change in sales), SA=Selling & Administrative Expenses (Annual percentage change in selling and administrative expenses minus the annual percentage change in sales), LF =Labour Force (LF) (Annual percentage change in sales per employee calculated as last two years average sales per employee minus current year sales per employee divided by last two years average sales per employee), ETR=Effective Tax Rate (Annual percentage change in ETR or last two year's (*t-1* and *t*-2) average ETR – ETR *t*), GM=Gross Margin (Annual percentage change in sales minus annual percentage change in gross margin), AQ=Audit Qualification (0 for an unqualified opinion and 1 otherwise. If there is an emphasis of matter paragraph and if it relates to going concern, 1 is assigned and 0 otherwise), CAPX=Capital Expenditure (Annual percentage change in industry capital expenditure minus the annual percentage change in the firm's capital expenditure), LEV=Financial Leverage (Annual change in ratio of total debt (long-term debt plus current liabilities) to total assets or Leverage ratio in year *t* – last two year's average leverage ratio), CF=Cash Flows (Cash flow from operations (CFO) between the year *t* and *t-1* divided by total assets at end of financial year *t-1*), GW = Goodwill (Annual percentage change in goodwill calculated as last two years (*t-1* and *t-2*) average goodwill minus goodwill in year *t* divided by last two years average goodwill), CDACCR = annual change in discretionary accruals. Discretionary accruals is calculated using the Kothari, Leone and Wasley (2005) performance matched discretionary accrual model. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm. All standard errors are less than 0.05. Highest VIF is reported for CF (1.49). R-Sq 1: R-Sq1: R^2 for full model, R-Sq 2: R^2 for the earnings alone model. Partial F test for 12 signals indicates the significance of incremental explanatory power from 12 non-earnings fundamental signals over earnings. Partial F test for 4 non-earnings fundamental signals indicates the significance of incremental explanatory power from the 4 additional non-earnings fundamental signals over other fundamental signals included in this study. Test of equality of coefficients is based on stacked regression.

The INV variable is significant in explaining one-year-ahead change in earnings per share (CEPS1) at 5 per cent in the expected direction for the pooled and Common law country samples. The result indicates that a disproportionate increase (decrease) in inventories compared to sales is a negative signal (positive signal) in terms of earnings persistence (Lev & Thiagarajan 1993), since a disproportionate increase in inventory may result from an unexpected decrease in sales, loss of production, or poor inventory control, all reflecting negatively on future earnings.

The AR fundamental signal is significant at 5 per cent in the expected direction in predicting CEPS1 for the pooled sample, as well as for sub-samples of Code and Common law countries. This result explains that a disproportionate increase (decrease) in accounts receivable relative to sales is a negative signal (positive signal) regarding future earnings per share (Lev & Thiagarajan 1993). This is so since it can be an indication of difficulty in generating sales, loosening of credit policy, or earnings management, such as aggressive recognition of revenue which may indicate low persistence of current earnings.

The variable ETR is also significant at 5 per cent in explaining CEPS1 in the direction anticipated for the pooled sample and Code law sub-sample. This result confirms the findings in the literature on fundamental signals, including those of Lev and Thiagarajan (1993) and Abarbanell and Bushee (1997). That is, an unusual decrease (increase) in the effective tax rate which is not caused by a statutory tax change is a negative signal (positive signal) with regard to future earnings.

The next explanatory variable having the expected sign that significantly (at 1 per cent) predicts CEPS1 for both the pooled sample and Code and Common law sub-samples is CF. This result shows that an increase (decrease) in cash flow from operations from last year to this year gives a positive (negative) signal about future earnings. Sloan (1996) reports that the accrual component of earnings is less persistent than the cash flow component, while a higher proportion of earnings attributable to cash flow from operations (CF) signifies a higher quality of income that will more likely persist into future periods. This finding indicates that CF is an important indicator of future earnings. Similarly, Arthur, Cheng and Czernkowski (2010) document a strong relationship between cash flow components and future earnings. This study’s findings confirm the relationship between CF and future earnings.

CDACCR is also significant in explaining CEPS1 for the pooled and Code and Common law sub-samples at 5 per cent in the direction anticipated. This relationship indicates that an increase (decrease) in discretionary accruals from last year to this year signals higher (lower) expected earnings. The literature indicates that when current earnings is low and expected earnings is high, managers borrow earnings from the future by increasing discretionary accruals for their job safety (DeFond & Park 1997). If this is the case, this relationship between current year discretionary accruals and future earnings is justified. Subramanyam (1996) also finds a similar relationship between discretionary accruals and future net income and operating cash flows.

In terms of SA, it is significant in explaining CEPS1 at 1 per cent in the direction opposite to that anticipated and only for the Code law sub-sample. This result indicates that a disproportionate increase (decrease) in selling and administration expenses relative to sales is a good signal (bad signal) about future earnings. A similar finding is reported by Anderson et al. (2007), indicating 'sticky' costs that represent an increase in SA resources available, based on management's expectation of a future increase in revenue.

The Audit Qualification variable (AQ) is significant in explaining CEPS1 for the pooled (at 10 per cent) and Common law sub-sample (at 5 per cent), but not in the direction anticipated. This relationship can be explained as a qualified (unqualified) audit opinion in the current year tending to be associated with an increase (decrease) in earnings in the subsequent year. One possible explanation for this finding could be the mean reverting pattern of earnings and current year accrual reversal given that more than 98 per cent of the sample is in receipt of an unqualified audit opinion. If a firm receives an unqualified audit opinion and has an increase in earnings this year, due to the current year accrual reversal, the next year will experience a decrease in earnings and vice versa. Therefore, a positive relationship could be expected. Another explanation could be that firms with a qualified audit opinion in the current year might work towards achieving a better result in the subsequent year, or this could be an indication of having switched auditors for a favourable opinion in the next year (Chow & Rice 1982). However, audit firm name is not included in the analyses, so this latter suggestion represents conjecture and is worthy of further study.

The CAPX variable is significant at 1 per cent for the pooled sample and sub-samples in explaining CEPS1, but again not in the expected direction. A similar finding is reported on several occasions in the fundamentals literature (Abarbanell & Bushee 1997; Seng & Hancock 2012). This result implies that exceeding (below) industry average capital expenditure provides a bad (good) signal for future earnings. A possible explanation for this positive significant relationship could be that firms that had been performing poorly were attempting catch-up with firms in their industry that had recently made large, successful capital investment (Abarbanell & Bushee 1997). If this was the case, firms with capital expenditure greater than industry averages could be signalling bad news for their future earnings (Seng & Hancock 2012). Another possible explanation could be that large capital investments' immediate impact on subsequent years' earnings might be negative due to high outflow of funds.

LEV has a positive significant (at 1 per cent) relationship with CEPS1 for the pooled sample and Common law country sub-sample, whilst not significant for the Code law country sub-sample but with the same direction. This positive relationship shows that an increase (decrease) in current year debt is a good (bad) signal for future earnings. Using external debt can be good or bad depending on whether the firm earns more or less than the after tax interest cost on the investment(s) financed with borrowed funds (Modigliani & Miller 1958). On the other hand, debt capital has tax benefits (Mackie & Jeffrey 1990; Modigliani & Miller 1963). As such, higher debt will lower the tax expense and increase earnings compared with lower tax deductible debt. Examining this variable in terms of contextual analysis under different inflation and GDP growth conditions, as is done later in this chapter, might provide more meaningful analysis.

The GW variable is positively significant at 1 per cent for the pooled sample and sub-samples of Code and Common law countries in explaining CEPS1. This positive relationship explains that an increase (decrease) in goodwill from last year to this year is a negative signal (positive signal) in terms of future earnings. Capital investment, such as on externally acquired goodwill, usually has long-term benefits, but the short-term impact can be negative. However, this variable has not been tested in this type of study previously so it is not possible to draw comparisons. Arguably, goodwill has been subject to different accounting treatments throughout the period of study to an extent greater than most of the other variables. Therefore, the pre- and post-IFRS period analyses reported in the next section are likely to provide a fuller picture about the relationship between GW and CEPS1. Some literature reports that GW provides useful information about future earnings potential (Cheong, Kim & Zurbruegg 2010; Matolcsy & Wyatt 2006; Wyatt 2005), while other literature reports that due to the subjective nature of its assessment, goodwill affects the predictability of earnings negatively (Hope 2004; Kim & Schroeder 1990).

This current study finds that the LF and GM variables are not significant in explaining CEPS1, both for the pooled sample and sub-sample analyses. The signals from GM might be captured in the aggregated earnings variable and therefore may not provide useful information over earnings in predicting future change in earnings per share.

Results from the sample that excludes the GFC period (2007-2009) (untabulated) are consistent with all of the above findings, with the exception that LF becomes significant in explaining CEPS1 for the pooled sample and Code law sub-sample.

The predictive ability of fundamental signals is compared between Code and Common law countries next using the test of equality of coefficients based on stacked regression[56]. The result (reported in the last column of Table 6.1) indicates that the coefficients for INV and SA are significantly different between Code and Common law countries. The size of the coefficients indicates that the predictive ability of INV is significantly higher for Common law countries, while that of SA is significantly higher for Code law countries. The predictive ability of no other fundamental signals is significantly different between the Code and Common law sub-samples.

In order to examine the combined predictive ability of non-earnings signals over earnings, the incremental R-Squared contribution from including non-earnings signals in Model 1 is compared between Code and Common law country sub-samples (reported towards the end rows of Table 6.1). The result indicates that the incremental R-Squared value is similar (0.016 for Code law and 0.019 for Common law countries) between the two regimes. The result is also consistent based on the sample that excludes the GFC period (untabulated). These results support the view that the earnings and non-earnings

[56] First the regression model is run for Code law country observations, and then for Common law country observations. Finally, these two regressions are stacked into one model and a test of equality between the coefficients is conducted.

fundamental signals individually and in combination are useful in predicting one-year-ahead change in earnings per share, therefore supporting Hypotheses H1a and H1b.

6.3.3 Predictive ability of aggregated fundamental score (F_Score)

In addition to testing the predictive ability of individual fundamental signals, an index is created to "set a sense of the *ex-ante* predictive power of the signals" (Abarbanell & Bushee 1997 p.7). This index is named F_Score, as described in Chapter 4. The index is developed by assigning a value of one (zero) for good (bad) signals and summing the values across the 12 non-earnings fundamental signals included in this study. A higher F_Score indicates an increase in future earnings and, therefore, there is expected to be a positive relationship between F_Score and one-year-ahead change in earnings per share. Model 2 is used to test the predictive ability of F_Score in terms of one-year-ahead change in earnings per share (CEPS1) and is as follows:

$$\mathrm{CEPS1}_i = \propto\ + \beta_0\,\mathrm{CHGEPS}_i + \beta_1\,\mathrm{F}_{\mathrm{SCORE}} + \sum \mathrm{Yr} + \sum \mathrm{In} + \sum \mathrm{Cnt} + \varepsilon_j \qquad (2)$$

This methodology has been followed in prior literature on fundamental analysis, including by Lev and Thiagarajan (1993); Abarbanell and Bushee (1997) and Seng and Hancock (2012). Table 6.2 reports the regression results for F_Score with CEPS1. As can be seen in Table 6.2 (Panel A), there is a positive, significant relationship between F_Score and CEPS1 for the pooled sample and for the Code law sub-sample, but not for the Common law sub-sample.

As mentioned above, F_Score is constructed based on the expected relationship of fundamental signals with CEPS1. However, the Model 1 regression results documented in Table 6.1 reveal that six of the signals do not display the expected relationship and, therefore, the F_Score may not represent the actual relationship in terms of direction. As such, to avoid noise induced from incorrectly assuming the nature of the relationships, for robustness analysis an alternative F_Score is constructed based on the actual relationship by direction of each fundamental signal with CEPS1 and examined in terms of its ability to predict CPES1.

As can be seen from Table 6.2 (Panel B), the alternative F_Score is significant at 1 per cent for the pooled sample and sub-samples in predicting CEPS1, whereas the F_Score based on the expected relationships is not significant for the Code law sub-sample. This relationship indicates that the alternative F_Score in Panel B has better predictive power in terms of one-year-ahead change in earnings per share. (Abarbanell & Bushee 1997; Lev & Thiagarajan 1993; Seng & Hancock 2012). Therefore, the alternative F_Score based on actual relationships as reported in Table 6.1 is used for all other F_Score analyses in this chapter.

Table 6.2: Ability of F_Score to predict one-year-ahead change in earnings per share (H1c)

Model 2 Dep. Var. CEPS1	**Panel A :**F_Score based on expected relationships				**Panel B:** F_Score based on actual relationships (Alternative F_Score)			
	Pooled sample	Code law	Common law	Test of equality	Pooled sample	Code law	Common law	Test of equality
	N = 19268	n = 10093	n = 9175		N = 19268	n = 10093	n = 9175	
	Coef.	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef.	Coef. Diff
α	0.01168	0.02861	**0.03399*** **		-0.00949	0.01716	0.00227	
CHGEPS	**0.29700*** **	**0.30387*** **	**0.29116*** **	0.493	**0.30388*** **	**0.31309*** **	**0.29692*** **	0.016
F_Score	**0.00123*** **	**0.00143** **	0.00087	0.538	**0.00517*** **	**0.00457*** **	**0.00643*** **	-0.002
R-Sq 1	0.126	0.149	0.110		0.130	0.153	0.117	
R-Sq 2	0.125	0.148	0.110		0.125	0.148	0.110	

Refer to Table 6.1 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm. All standard errors are less than 0.05. R-Sq 1: R^2 for the full model, R-Sq 2: R^2 for the earnings alone model.

The R-Squared for this model for the pooled sample is 0.130 (Table 6.2, Panel B), which is not substantially larger than the R-Squared for the earnings alone model. Similar results are reported from regressions using the Code and Common law sub-samples. These results are consistent with prior findings in the fundamental analysis literature. Abarbanell and Bushee (1997) explain that the low incremental explanatory power from using F_Score is due to application of equal weighting to signals in the index. Some signals are more strongly related to CEPS1 than others. Despite the low coefficient for F_Score, this variable significantly explains one-year-ahead change in earnings per share for the pooled and sub-samples and the F-test indicates that the incremental explanatory power from F_Score is significant for these samples. Therefore, F_Score can predict "Winning and Losing" firms in terms of subsequent earnings (Elleuch 2009; Mahmoud & Sakr 2012). The test of equality of coefficients indicates no significant difference between the predictive ability of F_Score for Code compared with Common law countries. The result is also consistent based on the sample that excludes the GFC period (untabulated)

These results support the conclusion that non-earnings fundamental signals in aggregate can predict one-year-ahead change in earnings per share and therefore support Hypothesis H1c.

6.3.4 Predicting an increase or decrease in future earnings per share.

The future change in earnings can represent an increase (Winners) or decrease (Losers) in earnings per share. The examination is extended next by examining the predictive ability of fundamental signals by the direction of one-year-ahead change in earnings per share. Table 6.3 reports the regression results for the separate prediction of positive change in one-year-ahead change in earnings per share (Winners [n=11025 -57 per cent]) and negative change in one-year-ahead change in earnings per share (Losers [n=8243]) using the selected fundamental signals. The model that predicts future Winners reports a R-Squared of 0.161 and the same model when predicting Losers yields a R-Squared of 0.100 for the pooled sample. Therefore, it can be inferred that these fundamental signals better predict future Winners than Losers.

When examining the earnings fundamental (CHGEPS), it is significant in predicting both Winners and Losers. However, the test of equality of earnings coefficients based on stacked regression reported in Table 6.3 (Panel A) reveals that the predictive ability of earnings is significantly higher for Winners compared to Losers.

In terms of non-earnings fundamentals, ETR, GM, CAPX, CF, and GW significantly predict both Winners and Losers. However, INV, AQ, LF, LEV significantly predict Winners only, whereas AR, SA and CDACCR significantly predict Losers only. Moreover, the tests of equality of coefficients indicate that the predictive ability of LF, ETR, GM, AQ, CAPX, LEV and GW is significantly higher for Winners, whereas that for CDACCR is higher for Losers, compared to their counterparts. Therefore, these fundamental signals are useful in predicting and discriminating between future Winners and Losers. The incremental R-Squared contribution from including the non-earnings fundamental signals over earnings for Winners (0.026) is higher than that for Losers (0.010). Therefore, it is concluded that the combined predictive ability of the non-earnings fundamental signals is higher for Winners than Losers. All the above analyses support Hypotheses H1a and H1b.

Table 6.3: Predictive ability of the earnings fundamental and F_Score for Winners and Losers (H1a, H1b & H1c)

Dep. Var. CEPS1	**Panel A:** Model 1- Fundamental Signals			**Panel B:** Model 2- F_Score		
	Winners	Losers	Test of Equality	Winners	Losers	Test of Equality
	n = 11025	n = 8243		n = 11025	n = 8243	
	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff
α	**0.04055*** **	**-0.09205*** **		0.00782	**-0.08777*** **	
CHGEPS	**0.23105*** **	**0.17085*** **	**0.06020*** **	**0.23794*** **	**0.15211*** **	**0.08583*** **
F_Score				**0.00594*** **	-0.00036	**0.00630*** **
INV	**-0.00003** **	-0.00001	-0.00002			
AR	-0.00004	**-0.00007* **	0.00003			
SA	-0.00001	**0.00009* **	-0.00011			
LF	**-0.00011** **	0.00005	**-0.00016** **			
ETR	**-0.00034*** **	**0.00022*** **	**-0.00056*** **			
GM	**0.00012*** **	**-0.00007* **	**0.00018*** **			
AQ	**0.04047*** **	-0.01257	**0.05304*** **			
CAPX	**0.00009*** **	**-0.00002* **	**0.00011*** **			
LEV	**0.00010*** **	0.00001	**0.00009*** **			
CF	**-0.00076*** **	**-0.00091*** **	0.00015			
GW	**0.00015*** **	**-0.00005*** **	**0.00020*** **			
CDACCR	-0.00393	**-0.04535*** **	**-0.04141** **			
Adj. R-Sq 1	0.161	0.100		0.145	0.090	
Adj. R-Sq 2	0.135	0.090		0.135	0.090	

Refer to Table 6.1 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by the firm. All standard errors are less than 0.05. R-Sq 1: R^2 for the full model, R-Sq 2: R^2 for the earnings alone model.

When examining the predictive ability of F_Score for Winners and Losers, it is noted that F_Score significantly predicts only Winners and the test of equality of coefficients also indicates that the predictive ability of F_Score is significantly higher for Winners than Losers (Table 6.3, Panel B). This result for Winners supports Hypothesis H1c.

Results (untabulated) for the sample that excludes the GFC (2007-2009) (Winners n = 7983 [60 per cent], Losers n= 5249) are consistent with the above findings, except that CAPX and AR are no longer significant in predicting Losers.

6.3.5 Contextual analysis and predictive ability of fundamental signals in terms of future earnings

The analysis so far discussed supports the view that fundamental signals, including an aggregated fundamental score, are useful in predicting future change in earnings per share. However, prior literature documents that the association between the fundamental signals and future change in earnings per share varies based on contextual factors, such as prior year earnings news (PYEN), and macro-economic factors like GDP growth and inflation (Abarbanell & Bushee 1997; Lev & Thiagarajan 1993; Seng & Hancock 2012). Therefore, analyses are performed based on these different contextual factors as follows.

(a) Prior Year Earnings News (PYEN)

For the purpose of this analysis, the pooled sample is partitioned into Good (n = 10919 [57 per cent]) and Bad (n = 8349) PYEN sub-samples (Good if change in prior year earnings is an increase and Bad if a decrease) and Models 1 and 2 are run separately for each sub-sample. Results documented in Table 6.4 reveal that PYEN influences the association between fundamental signals and CEPS1. The model performs much better for the Bad news (adjusted R-Squared of 0.216) when compared with the Good news sub-sample (adjusted R-Squared of 0.068). Similar findings are reported in the fundamental analysis literature (Abarbanell & Bushee 1997; Seng & Hancock 2012). A test of equality of earnings coefficients indicates that the predictive ability of CHGEPS is significantly higher under the Bad compared with Good PYEN condition (Table 6.4, Panel A).

In terms of non-earnings signals, the predictive ability of LEV and GW is significantly higher under the Bad PYEN condition, while that for CDACCR is higher under the Good PYEN condition than their counterparts. The incremental R-Squared contribution from all non-earnings signals over earnings is similar for both Good and Bad PYEN conditions. The predictive ability of F_Score is significantly higher, but only at 10 per cent, under the Bad compared to Good PYEN condition. As such PYEN is found to have some influence on the predictive ability of both earnings and non-earnings fundamental signals.

(b) Influence of Gross Domestic Product growth (GDP Gr) on the predictive ability of fundamental signals

One of the macro-economic factors that can influence the association between fundamental signals and future change in earnings is economic growth, which is measured as change in GDP growth (Abarbanell & Bushee 1997; Lev & Thiagarajan 1993; Seng & Hancock 2012). Therefore, the predictive ability of these fundamental signals is examined under High (n=9162 [48 per cent]) and Low (n=10106) GDP growth sub-samples selected based on median GDP growth for the pooled sample.

Table 6.4: Contextual Analysis for PYEN, level of GDP growth and level of Inflation (H1a, H1b & H1c)

Panel A **Model 1** Dep.Var. CEPS1	PYEN		Test of Equality	GDP Growth		Test of Equality	Level of Inflation (IFL)		Test of Equality
	Good	Bad		High	Low		High	Low	
	n = 10919	n = 8349		n = 9162	n = 10106		n = 9369	n = 9899	
	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff
α	0.00316	**0.02420****		**0.01848****	0.00264		**-0.01762****	**0.031000*****	
CHGEPS	**0.17599*****	**0.61370*****	**-0.43772*****	**0.31963*****	**0.31805*****	0.00158	**0.29949*****	**0.34778*****	**-0.04829****
INV	**-0.00003*****	-0.00002	-0.00001	-0.00002	**-0.00004****	0.00002	-0.00001	**-0.00004*****	0.00002
AR	-0.00007	**-0.00012****	0.00005	-0.00008	**-0.00012****	0.00004	**-0.00011****	**-0.00010****	-0.00001
SA	0.00008	-0.00002	0.00011	0.00003	0.00007	-0.00005	-0.00001	0.00012	-0.00012
LF	-0.00001	-0.00002	0.00001	-0.00002	**-0.00011***	0.00009	-0.00002	**-0.00014****	0.00012
ETR	-0.00001	-0.00006	0.00005	-0.00010	**-0.00021****	0.00011	-0.00001	**-0.00025*****	0.00025
GM	-0.00001	0.00003	-0.00005	0.00001	0.00005	-0.00004	0.00003	0.00003	0.00000
AQ	0.00614	0.01655	-0.01041	**0.03330****	-0.00514	0.03844	**0.03266***	-0.00112	0.03378
CAPX	**0.00006*****	**0.00008*****	-0.00002	**0.00008*****	**0.00008*****	0.00001	**0.00009*****	**0.00007*****	0.00002
LEV	**0.00006****	**0.00012*****	**-0.00006***	**0.00006****	**0.00012*****	-0.00006	**0.00008*****	**0.00012*****	-0.00003
CF	**-0.00134*****	**-0.00144*****	0.00010	**-0.00122*****	**-0.00181*****	**0.00059****	**-0.00148*****	**-0.00154*****	0.00006
GW	0.00002	**0.00009*****	**-0.00007****	**0.00008*****	**0.00008*****	0.00000	**0.00011*****	**0.00006*****	**0.00005***
CDACCR	**-0.06194*****	-0.00672	**-0.05522****	-0.01591	**-0.07234*****	**-0.05643****	-0.02257	**-0.06398*****	**-0.04141***
Adj. R-Sq 1	0.068	0.216		0.130	0.154		0.122	0.166	
Adj. R-Sq 2	0.058	0.203		0.118	0.135		0.105	0.150	
Panel 2 : Contextual analysis for F_Score									
Model 2 Dep.Var CEPS1	Good	Bad	Test of Equality	High	Low	Test of Equality	High	Low	Test of Equality
	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff
α	**-0.014480***	-0.006210		-0.01170	**-0.030960*****		**-0.055520*****	0.000200	
CHGEPS	**0.160770*****	**0.618020*****	**-0.45725*****	**0.30889*****	**0.298740*****	0.01014	**0.284330*****	**0.330820*****	0.02200
F_Score	**0.002967*****	**0.004818*****	**-0.00185***	**0.00431*****	**0.006106*****	**-0.00179***	**0.005206*****	**0.005552*****	0.73000
Adj. R-Sq 1	0.060	0.207		0.122	0.142		0.110	0.156	

Refer to Table 6.1 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm. All standard errors are less than 0.05. R-Sq 1: R^2 for the full model, R-Sq 2: R^2 for the earnings alone model. Sample is partitioned into Good and Bad PYEN (Good if change in prior year earnings is an increase and Bad if a decrease), High and Low GDP growth (years that GDP growth is equal to or above the mean fall under the High category and others the Low category), and High and Low inflation (years that inflation is equal to or above the mean fall under the High category and others the Low category).

Observations in years that have equal to or above median GDP growth fall under the High category, while others come under the Low category. Results are documented in Table 6.4.

As can be seen in Table 6.4 (Panel A), Model 1 performs well for the Low GDP growth (adjusted R-Squared of 0.154) sample compared to the High GDP growth sample (adjusted R-Squared of 0.130). A test of equality of coefficients indicates no significant difference in the predictive ability of the earnings signal between these two sub-samples.

However, the predictive ability of some non-earnings signals (e.g. CF and CDACCR) is significantly higher under the Low compared to High GDP growth condition. Moreover, the incremental R-Squared contribution from the non-earnings signals over earnings is also slightly higher under the Low compared to High GDP growth condition. It is also noted that more fundamental signals are significant in predicting CEPS1 under the Low compared to High GDP growth condition. Corresponding to this result, the predictive ability of F_Score is significantly higher (at 10 per cent) under the Low compared to High GDP growth condition. All these results point to the conclusion that the level of GDP growth influences the predictive ability of the non-earnings fundamental signals.

(c) Influence of Inflation (IFL) on the predictive ability of fundamental signals

The inflation rate is another macroeconomic variable that can influence the predictive ability of fundamental signals in terms of future earnings (Abarbanell & Bushee 1997; Dowen 2001; Lev & Thiagarajan 1993; Seng & Hancock 2012). Therefore, Model 1 and 2 are run for High (n=9369 [49 per cent]) and Low (n=9899) inflation sub-samples selected based on median inflation rate. Observations for years that the inflation is equal to or above the median fall under the High category, and others the Low category.

As can be seen from Table 6.4, Model 1 works better under the Low inflation rate condition (R-Squared of 0.166) compared to the High inflation rate (R-Squared of 0.122). This result is consistent with findings reported in the fundamental analysis literature (Abarbanell & Bushee 1997; Lev & Thiagarajan 1993; Seng & Hancock 2012). The test of equality of coefficients indicates that the predictive ability of earnings is significantly higher in the Low compared to High inflationary sample (Table 6.4, Panel A). More non-earnings fundamental signals are significant in predicting CEPS1 under the Low inflationary condition, however the predictive ability of non-earnings signals is not significantly different between High and Low inflationary conditions, except for GW and CDACCR (these two variables are significantly different at 10 per cent). Similarly, the predictive ability of F_Score is not significantly different between the two groups. Therefore, it is concluded that the level of inflation influences on the predictive ability of both earnings and non-earnings signals in predicting CEPS1.

Overall, results support the conclusion that earnings and non-earnings signals individually, in combination and in aggregate form predict one-year-ahead change in earnings per share in different contexts and therefore support Hypotheses H1a, H1b and H1c.

6.4 IFRS impact on the predictive ability of fundamental signals

Following IFRS adoption, a number of studies have been conducted in different countries to identify the impact of IFRS on financial statements, including for these noted countries, Goodwin, Ahmed and Heaney (2008) (Australia); Haverals (2007) (Belgium); Blanchette, Racicot and Girard (2011) (Canada); Tsalavoutas and Evans (2010) (Greece); Bradbury and van Zijl (2005), Stent, Bradbury and Hooks (2010) and Kabir, Laswad and Islam (2010) (New Zealand); Horton and Serafeim (2010) and Iatridis (2010) (UK). The findings from these studies reveal that adoption of IFRS has considerable impact on recognition, measurement, classification and disclosure of financial statement elements, and therefore ultimately affects the quality of fundamental signals. Predictive ability is one of the quality aspects of accounting fundamentals (Francis & Schipper 1999; IASB 2010). Therefore, this section of the study analyses the impact of IFRS on the predictive ability of fundamental signals in terms of predicting one-year-ahead change in earnings per share.

6.4.1 IFRS impact on the predictive ability of individual fundamental signals in predicting future earnings

In order to test the impact of IFRS on the predictive ability of fundamental signals, an interaction variable for each fundamental signal is introduced to Model 1. The interaction variables are developed by multiplying each fundamental signal by the IFRS dummy variable [1 for the post-IFRS period (2006-2012), and 0 otherwise (2001-2004), with observations from 2005, the year of IFRS transition, excluded]. When estimating this regression, the contextual variables discussed above are included in the regression (that is, PYEN (1 for Bad news, and 0 for Good news), GDP Growth (1 for High GDP growth and 0 for Low GDP growth), IFL (1 for High inflation period, and 0 for Low inflation period) and Code law[57] (1 for Code law countries, and 0 for Common law countries)), since they have been found to influence the association between fundamental signals and future change in earnings (Abarbanell & Bushee 1997; Dowen 2001; Lev & Thiagarajan 1993; Seng & Hancock 2012). The following regression models, which were explained in Chapter 4 and are repeated here for convenience, are employed to examine the impact of IFRS on the predictive ability of the selected fundamental signals.

$$\begin{aligned} \mathrm{CEPS1}_i = {} & \propto + \upbeta_0\,\mathrm{CHGEPS}_i + \textstyle\sum_{j=1}^{12} \upbeta_{ij}\mathrm{Signals}_{ij} + \upbeta_{13}\mathrm{IFRS} * \mathrm{CHGEPS}_i + \\ & \textstyle\sum_{j=14}^{25} \upbeta_{ij}\mathrm{IFRS} * \mathrm{Signals}_{ij} + \sum \mathrm{Yr} + \sum \mathrm{In} + \sum \mathrm{Cty} + \mathrm{CodeLaw} + \upvarepsilon_j \qquad (5) \end{aligned}$$

Where: $\mathrm{CEPS1}_i$ = one-year-ahead change in earnings per share for firm *i*, CHGEPS_i = Current year change in earnings per share for firm *i*, *j* = non-earnings fundamental signals, IFRS*CHGEPS = Interaction of CHGEPS with IFRS, IFRS*$\mathrm{Signals}_{ij}$ = interaction variable of non-earnings fundamental signal(s) with IFRS, Yr- Year dummies, In- Industry dummies, Cty = Country dummies, PYEN = prior year earnings news dummy, GDP- GDP growth dummy, INF = Inflation rate dummy, CodeLaw = if the firm belongs to a Code law country 1, otherwise 0.

In addition, following the method used by Atwood et al. (2011), first the Model 1 regression is estimated using the pre-IFRS observations, second the Model 1 regression is run using the post-IFRS observations only. Finally, these two regressions are stacked into one model (Model 6) to test for significant differences in coefficients between the pre- and post-IFRS periods.

$$\begin{aligned} CEPS1_i = {} & PreIFRS\ x\ [\propto_0 + \propto_1\ \mathrm{CHGEPS}_i + \textstyle\sum_{j=2}^{13} \propto_{ij}\ \mathrm{Signals}_{ij}\ ] + \\ & PostIFRS\ x\ [\beta_0 + \beta_1\,\mathrm{CHGEPS}_i + \textstyle\sum_{j=2}^{13} \upbeta_{ij}\mathrm{Signals}_{ij}\} + \sum \mathrm{Yr} + \sum \mathrm{In} + \\ & \textstyle\sum \mathrm{Cty} + \mathrm{CodeLaw} + \upvarepsilon_j \qquad (6) \end{aligned}$$

Tables 6.5 and 6.6 report the regression results for estimation of Models 5 and 6 for the pooled sample, as well for sub-samples of Code and Common law country observations. The results show that the interaction of current year change in earnings per share with IFRS (IFCHGEPS) is significant at 5 per cent for the pooled sample and Code law sub-

[57] This variable is included only for the pooled sample regression.

sample. This indicates that the predictive ability of earnings is affected by adoption of IFRS for Code law countries. As shown in Table 6.6, CHGEPS significantly explains CEPS1 for both the pre- and post-IFRS periods for the pooled sample (Pre-IFRS n = 4090 [21 per cent] and post-IFRS n = 15 178) and Code and Common law sub-samples, with a higher coefficient in the post-IFRS period. The test of equality of coefficients based on stacked regression reports that the earnings coefficient is significantly higher in the post-compared with pre-IFRS period for the pooled sample and Code law sub-sample (at 5 per cent). Therefore, it is concluded that the predictive ability of earnings increased following adoption of IFRS, but only for Code law countries.

Again the relationship between CHGEPS and CEPS1 is positive in both pre- and post-IFRS periods due to the mean reverting pattern of earnings, with a good year followed by a bad year and a bad year followed by a good year (Abarbanell & Bushee 1997; Dowen 2001; Swanson, Rees & Juarez-Valdes 2003) and the reversal of current year accruals (Chan, Jegadeesh & Sougiannis 2004; DeFond & Park 2001; Pae 2005; Wahab, Teitel & Morzuch 2015).

Included countries in the sample all have high investor protection, but Code law countries have higher GAAP difference than the Common law countries. Therefore, this result is consistent with prior findings that IFRS adoption increases earnings quality in countries where investor protection is stronger (Houqe et al. 2012), and the impact is higher when domestic GAAP is more different from IFRS (Ding et al. 2007; Narktabtee & Patpanichchot 2011). Chalmers, Clinch and Godfrey (2011) report an increase in earnings persistence in the Australian context upon IFRS adoption using net income per share, however, Atwood et al. (2011) found that there was no improvement in the persistence of earnings using net income after adoption of IFRS for 33 countries. This study finds that the predictive ability of earnings increased post-IFRS for Code law countries, but not for Common law countries.

Table 6.5: IFRS impact on the predictive ability of fundamental signals for the pooled sample and sub-samples of Code and Common law countries (H1d & H1e)

Model 5 Dep.Var. CEPS1	Current Study Model	Code Law	Common Law
	N = 19268	n = 10093	n = 9175
	Clusters = 2908	Clusters = 1494	Clusters = 1414
	R-Sq = 0.141	R-Sq = 0.168	R-Sq = 0.132
	Coef.	Coef.	Coef.
α	0.02583	0.03506	0.02333
CHGEPS	0.27396	0.25535	0.28743
INV	-0.00006	-0.00005	-0.00010
AR	-0.00019	-0.00013	-0.00027
SA	-0.00004	0.00022	-0.00012
LF	-0.00001	-0.00009	0.00012
ETR	-0.00028	-0.00043	0.00013
GM	0.00004	-0.00011	0.00012
AQ	0.04398	0.03329	0.05041
CAPX	0.00013	0.00009	0.00017
LEV	0.00015	-0.00006	0.00016
CF	-0.00176	-0.00215	-0.0016
GW	0.0001	0.00013	0.00007
CDACCR	-0.05938	-0.09492	-0.03893
IFRS	-0.00949	-0.00421	-0.01522
IFCHGEPS	**0.05774****	**0.08804****	0.03268
IFINV	**0.00005***	0.00005	0.00004
IFAR	0.00009	0.00003	0.00018
IFSA	0.00013	0.00011	0.00010
IFLF	-0.00007	0.00001	-0.00020
IFETR	0.00015	0.00029	-0.00026
IFGM	-0.00002	0.00014	-0.00011
IFAQ	**-0.05356****	**-0.04878***	-0.04497
IFCAPX	**-0.00006****	-0.00001	**-0.00010*****
IFLEV	-0.00007	0.00012	-0.00006
IFCF	0.00031	0.00066	0.00020
IFGW	-0.00003	**-0.00009****	0.00003
IFCDACCR	0.02001	0.05825	0.00462

Refer to Table 1 for variable definitions. IFRS impact is measured based on the interaction of each fundamental signal with IFRS where IFRS is an indicator variable coded 1 for observations in the post-IFRS period (2006-2012) and 0 otherwise (2001-2004). Interaction variables are named starting with "IF" followed by the variable name. For example, IFCHGEPS represents the interaction of CHGEPS with IFRS. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm.

Table 6.6: IFRS impact on the predictive ability of fundamental signals based on stacked regression (H1d & H1e)

Model 6 Dep Var. CEPS1	Pooled sample			Code Law			Common Law		
	Pre-IFRS	Post-IFRS	Test of Equality	Pre-IFRS	Post-IFRS	Test of Equality	Pre-IFRS	Post-IFRS	Test of Equality
	n=4090	n=15178		n=2134	n=7959		n=1956	n=7219	
	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff
α	**-0.03236****	**0.01783***		0.00869	**0.03427*****		0.00241	**0.03706*****	
CHGEPS	**0.27574*****	**0.33218*****	**-0.05644****	**0.25966*****	**0.34402*****	**-0.08437****	**0.28961*****	**0.32050*****	-0.03089
INV	**-0.00007*****	-0.00002	**-0.00005****	**-0.00005***	0.00001	-0.00005	**-0.00009****	**-0.00005****	-0.00004
AR	**-0.00021****	**-0.00009****	-0.00011	-0.00016	**-0.00010***	-0.00006	**-0.00025****	**-0.00009***	-0.00016
SA	-0.00008	0.00009	-0.00016	0.00018	**0.00032*****	-0.00014	-0.00017	-0.00002	-0.00015
LF	0.00002	-0.00008	0.00010	-0.00006	-0.00011	0.00005	0.00010	-0.00009	0.00019
ETR	-0.00025	-0.00013	-0.00012	**-0.00037***	-0.00013	-0.00024	0.00013	-0.00014	0.00026
GM	0.00004	0.00003	0.00001	-0.00014	0.00003	-0.00017	0.00010	0.00001	0.00009
AQ	**0.04250****	-0.01037	**0.05287****	0.02886	-0.01678	**0.04565***	**0.04939***	0.00475	0.04464
CAPX	**0.00013*****	**0.00007*****	**0.00006****	**0.00010*****	**0.00008*****	0.00002	**0.00016*****	**0.00007*****	**0.00009*****
LEV	**0.00015*****	**0.00008*****	0.00007	-0.00006	**0.00007***	-0.00013	**0.00017*****	**0.00010*****	0.00006
CF	**-0.00172*****	**-0.00145*****	-0.00027	**-0.00213*****	**-0.00147*****	-0.00066	**-0.00153*****	**-0.00140*****	-0.00013
GW	**0.00010*****	**0.00007*****	0.00003	**0.00012*****	**0.00004***	**0.00008****	**0.00008****	**0.00011*****	-0.00003
CDACCR	**-0.06037****	**-0.03858*****	-0.02178	**-0.09732****	**-0.03503***	-0.06229	-0.03792	**-0.04450****	0.00658
Adj. R-Sq 1	0.116	0.143		0.128	0.167		0.109	0.128	
Adj. R-Sq 2	0.098	0.131		0.106	0.153		0.082	0.113	

Refer to Table 6.1 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm. All standard errors are less than 0.05. Pre-IFRS period is from 2001 to 2004 and post-IFRS is from 2006 to 2012. Adj. R^2 1: Adjusted R^2 for the full model, Adj. R^2 2: Adjusted R^2 for the earnings alone model. Test of equality of coefficients is based on stacked regression.

With regards to the non-earnings fundamental signals reported in Table 6.5, the interaction of INV with IFRS (IFINV) is significant for pooled sample**.** At the same time, the stacked regression results in Table 6.6 document that INV is significant in predicting CEPS1 in the pre-IFRS period for the pooled sample and sub-samples, but not significant in the post-IFRS period for the pooled and Code law sample. The test of equality of coefficients indicates that the coefficient for INV is significantly lower in the post- compared to pre-IFRS period, but only for the pooled sample. Therefore, it is inferred that the predictive ability of INV significantly decreased after adoption of IFRS for the pooled sample.

The interaction of Audit Qualification with IFRS (IFAQ) is significant at 5 per cent for the pooled sample and Code law sub-sample. The test of equality of coefficients using stacked regression also reveals that the coefficient for AQ for the pre- compared with post-IFRS period is significantly different at 5 per cent for the pooled sample and Code law sub-sample. However, AQ is not significant in predicting CEPS1 in either the pre- or post-IFRS periods for Code law countries, while it is significant only in the pre-IFRS period for the pooled sample with a higher coefficient than post-IFRS period. Therefore, it is concluded that the predictive ability of AQ significantly decreased after adoption of IFRS, but only for the pooled sample.

As shown in Table 6.5, the interaction of CAPX (IFCAPX) is significant for the pooled sample and Common law sub-sample. Table 6.6 results indicate that CAPX is significant in predicting CEPS1 in the pre- and post-IFRS periods for the pooled sample and sub-samples, with a lower coefficient in the post-IFRS period. The test of equality of coefficients indicates that the coefficient for CAPX is significantly lower for the pooled sample and Common law sub-sample in the post- compared to pre-IFRS periods. Therefore, it is concluded that the predictive ability of CAPX significantly decreased for the pooled sample and Common law countries after adoption of IFRS.

In terms of GW, the interaction of GW with IFRS (IFGW) is significant for only the Code law sub-sample. The stacked regression results in Table 6.6 show that GW is significant in predicting CEPS1 in both the pre- and post-IFRS periods for the pooled sample and sub-samples. The GW coefficient is higher for the pooled sample and Common law sub-sample and lower for the Code law sub-sample in the post- compared to pre-IFRS period. The test of equality of coefficients indicates that GW is significantly lower in the post-compared to pre-IFRS period for Code law countries, but there is no significant difference in the coefficients for other samples between the two periods. Therefore, it is inferred that the predictive ability of GW significantly decreased for Code law countries after adoption of IFRS.

As the construction of most independent variables includes averaging over two years, it is important to consider the impact of lagged variables in the IFRS transition period. At the same time, some years during the post-IFRS period fall under the GFC period. Therefore, in order to avoid the effects of these periods, the regressions for Models 5 and 6 are estimated for the sample excluding both the full IFRS transition period (2004-2006) and the GFC period (2007-2009). The results (untabulated) for the sample that excludes both IFRS transition and the GFC periods (pre-IFRS n = 3575 [36 per cent], post-IFRS n = 6425 for the pooled sample) support the above findings, except that AQ is no longer affected by adoption of IFRS.

The predictive ability of the non-earnings fundamental signals as whole in a model incremental to earnings for pre- and post-IFRS sub-samples is tested next. The results, reported in Table 6.6, show that the increase in explanatory power from including non-earnings fundamental signals decreases in the post-IFRS compared with pre-IFRS period for the pooled sample and sub-samples. Therefore, it is inferred that the combined predictive ability of non-earnings signals over earnings decreased after adoption of IFRS. A possible reason could be that earnings in the post-IFRS period is more informative in terms of one-year-ahead change in earnings per share. Therefore, earnings as an aggregated measure might capture most of the information in the non-earnings signals in the post- compared to pre-IFRS period. Results from the sample that exclude both the GFC and IFRS transition periods support the same conclusion.

All these findings support the view that adoption of IFRS had a positive impact on earnings and a negative impact on the non-earnings fundamental signals in predicting one-year-ahead change in earnings and hence support H1d.

6.4.2 IFRS impact on the predictive ability of aggregated fundamental score (F_Score) in predicting future earnings

In order to test the impact of IFRS on the predictive ability of the aggregated fundamental score (F_Score), an interaction variable for F_Score with IFRS is introduced to Model 2, resulting in Model 7 as follows, where variables are as defined previously.

$$\mathrm{CEPS1}_i = \propto\ + \beta_0\,\mathrm{CHGEPS}_i + \beta_1\,\mathrm{F\_Score}_i + \beta_2\,\mathrm{IFRS} * \mathrm{CHGEPS}_i\ +\ \beta_3\,\mathrm{IFRS} * \mathrm{F\_Score}_i + \sum \mathrm{Yr} + \sum \mathrm{In}\ + \sum \mathrm{Cty} + \mathrm{CodeLaw} + \varepsilon_j \qquad (7)$$

In addition, to test IFRS impact more robustly, following Atwood et al. (2011), stacked regression is used to test the significance of F_Score coefficients between pre- and post-IFRS periods, which results in Model 8, where variables are as defined previously.

$$CEPS1_i = PreIFRS\ x\ [\propto_0 + \propto_1\ \mathrm{CHGEPS}_i + \propto_2\ \mathrm{F\_Score}_i\ ] + PostIFRS\ x\ [\beta_0\ + \beta_1\,\mathrm{CHGEPS}_i +\ \beta_1\,\mathrm{F\_Score}_i]\ + \sum \mathrm{Yr} + \sum \mathrm{In}\ + \sum \mathrm{Cty} + \mathrm{CodeLaw} + \varepsilon_j \qquad (8)$$

The regression results for Models 7 and 8 are reported in Table 6.7. The results in Table 6.7 (Panel A) show that the interaction of F_Score with IFRS (IFF_Score) is significant for the pooled sample and for sub-samples of Code and Common Law countries.

The test of equality of coefficients based on stacked regression (Table 6.7, Panel B) indicates that the coefficient for F_Score is significantly lower in the post- compared to pre-IFRS period for the pooled sample and sub-samples. All these results indicate that the predictive ability of F_Score decreased following adoption of IFRS for all samples.

Results reported in section 6.3.3 also indicate that IFRS has a negative impact on non-earnings signals in predicting CEPS1. Consistent with the above results, this section also documents a significant decrease after adoption of IFRS in the predictive ability of the aggregated fundamental score (F_Score), which is the aggregated version of non-earnings signals, and therefore the findings do not support H1f.

The results (untabulated) for the sample that excludes both IFRS transition and the GFC periods (pre-IFRS n = 3575 [36 per cent], post-IFRS n = 6425 for the pooled sample) support the above findings.

Table 6.7: IFRS impact on the predictive ability of F_Score (H1f)

Panel A: *IFRS impact on the predictive ability of F_Score based on interaction terms*

Model 7 Dep.Var. CEPS1	Pooled sample	Code Law	Common Law
	N = 19268	n = 10093	n = 9175
	R-Sq = 0.132	R-Sq = 0.155	R-Sq = 0.119
	Coef.	Coef.	Coef.
α	-0.02612	0.00090	-0.04327
CHGEPS	0.26138	0.23707	0.28176
F_Score	0.00857	0.00715	0.01042
IFRS	0.01480	0.01282	0.01609
IFCHGEPS	**0.05436****	**0.09673*****	0.02048
IFF_Score	**-0.00426*****	**-0.00322****	**-0.00504*****

Panel B: *IFRS impact on the predictive ability of F_Score based on stacked regression*

Model 8 Dep.Var. CEPS1	Pooled sample			Code Law			Common Law		
	Pre-IFRS	Post-IFRS	Test of Equality	Pre-IFRS	Post-IFRS	Test of Equality	Pre-IFRS	Post-IFRS	Test of Equality
	n=4090	n=15178		n=2134	n=7959		n=1956	n=7219	
	Coef.	Coef.	Coef. Diff.	Coef.	Coef.	Coef. Diff.	Coef.	Coef.	Coef. Diff.
α	**-0.08688*****	-0.00695		-0.02877	0.00995		**-0.07320*****	-0.00030	
CHGEPS	**0.26410*****	**0.31643*****	**-0.05233****	**0.24002*****	**0.33493*****	**-0.09491*****	**0.28414*****	**0.30260*****	-0.01846
F_Score	**0.00896*****	**0.00425*****	**0.00471*****	**0.00739*****	**0.00400*****	**0.00339***	**0.01036*****	**0.00536*****	**0.00500*****
Adj. R-Sq 1	0.105	0.133		0.115	0.157		0.099	0.118	
Adj. R-Sq 2	0.098	0.131		0.106	0.153		0.082	0.113	

Refer to Table 1 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm. All standard errors are less than 0.05 in Panel B. Adj.R-Sq 1: Adjusted R-Squared for the full model, Adj. R-Sq 2: Adjusted R-Squared for the earnings alone model. Pre-IFRS period is from 2001 to 2004 and post-IFRS is from 2006 to 2012. Interaction variables are named starting with "IF" followed by the variable name. For example, IFCHGEPS represents the interaction of CHGEPS with IFRS where IFRS is an indicator variable coded 1 for observations in the post-IFRS period (2006-2012) and 0 otherwise (2001-2004). Test of equality of coefficients is based on stacked regression.

6.4.3 Predicting an increase (Winners) or decrease (Losers) in future earnings per share under IFRS

The results from the analysis in section 6.3.4 indicate that fundamental signals better predict Winners than Losers. In this section, results from analysis of the impact of IFRS on the predictive ability of fundamental signals in predicting Winners and Losers are reported. Table 6.8 reports the regression results for Models 5 and 6 for Winners and Losers. As can be seen from Table 6.8 (Panel A), fundamental signals better predict Winners than Losers in both the pre- and post-IFRS periods, and more non-earnings fundamental signals are significant in predicting both Winners and Losers in the pre-compared to post-IFRS period. However, the overall predictive ability of the Model is higher (higher adjusted R-Squared) in the post- compared to pre-IFRS period for Losers.

The results based on the IFRS interaction variables and test of equality of coefficients based on stacked regression indicate that the predictive ability of current year earnings significantly increased after adoption of IFRS, mostly for Losers. In terms of the non-earnings signals, the predictive ability of AQ and CAPX decreased for Winners, while the predictive ability of SA decreased for Losers in the post- compared to pre-IFRS period. The incremental R-Squared contribution from the non-earnings signals over earnings decreased for both Winners and Losers in the post- compared to pre-IFRS period with a higher decrease for Winners. Therefore, it is concluded that the combined predictive ability of non-earnings signals over earnings decreased after adoption of IFRS.

However, overall the predictive ability of the model increased for Losers (Adj. R-Sq for pre-IFRS = 0.089 and post-IFRS = 0.103), whereas it decreased for Winners (Adj. R-Sq for pre-IFRS = 0.186 and post-IFRS period = 0.161) in the post- compared to pre-IFRS period. This is due mostly to the increase in the predictive ability of earnings for Losers and the higher decrease in combined predictive ability of non-earnings signals for Winners after adoption of IFRS.

Findings for the sample that excludes both the GFC and IFRS transition periods (Winners Pre-IFRS n= 2388, post-IFRS n = 3433; Losers pre-IFRS n = 1187, post-IFRS n = 2992) (results untabulated) are also consistent with the above findings, with the exception that the predictive ability of CDACCR decreased for Winners and increased for Losers after adoption of IFRS.

Table 6.8: IFRS impact on the predictive ability of fundamental signals for Winners and Losers (H1d & H1e)

***Panel A:** IFRS impact based on stacked regression*

Model 6 Dep.Var. CEPS1	Winners			Losers		
	Pre-IFRS	Post-IFRS	Test of Equality	Pre-IFRS	Post-IFRS	Test of Equality
	n = 2689	n = 8336		n = 1401	n = 6842	
	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff
α	0.00468	**0.06413*** **		**-0.05180** **	**-0.07420*** **	
CHGEPS	**0.20253*** **	**0.23899*** **	-0.03646	**0.13405*** **	**0.17919*** **	**-0.04514* **
INV	**-0.00010*** **	0.00001	**-0.00010*** **	-0.00002	-0.00001	-0.00001
AR	-0.00007	-0.00003	-0.00004	-0.00011	-0.00006	-0.00006
SA	-0.00006	-0.00002	-0.00004	-0.00008	**0.00014** **	-0.00022
LF	**-0.00016* **	-0.00009	-0.00007	**0.00022** **	0.00001	**0.00022* **
ETR	**-0.00055*** **	**-0.00028*** **	-0.00027	**0.00036** **	**0.00019** **	0.00017
GM	**0.00016** **	**0.00010** **	0.00006	**-0.00018** **	-0.00004	-0.00015
AQ	**0.05959*** **	0.01202	**0.04757** **	-0.02229	-0.01105	-0.01124
CAPX	**0.00014*** **	**0.00008*** **	**0.00006** **	**-0.00005** **	-0.00001	-0.00004
LEV	**0.00012*** **	**0.00009*** **	0.00003	-0.00005	0.00002	-0.00007
CF	**-0.00079*** **	**-0.00074*** **	-0.00005	**-0.00056* **	**-0.00099*** **	0.00043
GW	**0.00012*** **	**0.00014*** **	-0.00002	**-0.00009*** **	**-0.00004** **	-0.00005
CDACCR	-0.03290	0.00547	0.03836	-0.01615	**-0.05277*** **	0.03663
Adj. R-Sq 1	0.186	0.161		0.089	0.103	
Adj. R-Sq 2	0.144	0.141		0.073	0.093	

***Panel B:** IFRS impact based on interaction terms*

Model 5 Dep.Var CEPS1	Winners	Losers
	n = 11025	n = 8243
Interaction variables	Coef.	Coef.
IFRS	**-0.01422** **	-0.00114
IFCHGEPS	0.03694	**0.04253* **
IFINV	**0.00011*** **	0.00001
IFAR	0.00001	0.00005
IFSA	0.00001	**0.00024* **
IFLF	0.00010	**-0.00023** **
IFETR	0.00030	-0.00016
IFGM	-0.00006	0.00015
IFAQ	**-0.04671** **	0.00469
IFCAPX	**-0.00006** **	0.00004
IFLEV	-0.00004	0.00009
IFCF	0.00017	-0.00045
IFGW	0.00002	0.00006
IFCDACCR	0.04356	-0.04167

Refer to Table 1 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm. All standard errors are less than 0.05 in Panel A. Adj. R-Sq 1: Adjusted R-Squared for the full model, Adj. R-Sq 2: Adjusted R-Squared for the earnings alone model. Interaction variables are named starting with "IF" followed by the variable name. For example, IFCHGEPS represents the interaction of CHGEPS with IFRS where IFRS is an indicator variable coded 1 for observations in the post-IFRS period (2006-2012) and 0 otherwise (2001 - 2004). Test of equality of coefficients is based on stacked regression.

Table 6.9 summarises the findings for IFRS impact on the aggregated fundamental score (F_Score) for Winners and Losers. Results based on the interaction variables and test of equality of coefficients based on stacked regression indicate that the predictive ability of F_Score decreased for Winners after adoption of IFRS. Analysis documented in Table 6.8 also indicates a greater decrease in the combined predictive ability of non-earnings signals for Winners in the post- compared to pre-IFRS period.

Table 6.9: IFRS impact of the predictive ability of F_Score for Winners and Losers (H1f)

Panel A: *IFRS impact based on stacked regression*

Model 8 Dep.Var. CEPS1	Winners		Test of Equality	Losers		Test of Equality
	Pre-IFRS	Post-IFRS		Pre-IFRS	Post-IFRS	
	n = 2689	n = 8336		n = 1401	n = 6842	
	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff
α	**-0.05101*****	**0.03367*****		-0.03598	**-0.07043*****	
CHGEPS	**0.21823*****	**0.24456*****	-0.026	**0.11713*****	**0.15955*****	**-0.042***
F_Score	**0.00984*****	**0.00473*****	**0.005*****	**-0.00233***	0.00010	-0.002
Adj. R-Sq 1	0.167	0.147		0.075	0.093	

Panel B*: IFRS impact based on interaction terms*

Model 7 Dep.Var CEPS1	Winners	Losers
	N = 11025	N = 8243
	R-Sq = 0.126	R-Sq = 0.095
	Coef.	Coef.
α	0.00104	-0.08370
CHGEPS	0.21677	0.11895
F_Score	0.00985	-0.00267
IFRS	0.01234	-0.01398
IFCHGEPS	0.02810	**0.04026***
IFF_Score	**-0.00513*****	0.00271

Refer to Table 1 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm. All standard errors are less than 0.05 in Panel A. Adj. R-Sq 1: Adjusted R-Squared for the full model, Interaction variables are named starting with "IF" followed by the variable name. For example, IFCHGEPS represents the interaction of CHGEPS with IFRS where IFRS is an indicator variable coded 1 for observations in the post-IFRS period (2006-2012) and 0 otherwise (2001 - 2004). Test of equality of coefficients is based on stacked regression.

As can be seen from Table 6.8 (Panel A), F_Score is not significant in predicting Losers in the post-IFRS period, but there is no significant difference in the predictive ability of F_Score between the pre- and post-IFRs periods for Losers. The results based on the sample that excludes the GFC (2007-2009) and full IFRS (2004-2006) transition periods (untabulated) are consistent with these findings. These analyses reveal that the results support only H1d, and then only in terms of Losers.

6.5 Further tests

In the following sections, results from additional tests that examine the predictive of fundamental signals using various sub-samples are reported.

6.5.1 Country-wise predictive ability of fundamental signals and IFRS impact

The literature reports that country factors are important in determining the quality of accounting information and for expected quality improvement after adoption of IFRS (Stadler & Nobes 2014). Therefore, as a robustness test, the predictive ability of fundamental signals and the impact of IFRS on this ability is analysed for each country included in this study. The results (untabulated) reveal that both earnings and non-earnings fundamental signals are important in predicting one-year-ahead change in earnings, and non-earnings fundamental signals have information content incremental to earnings that is useful in predicting future earnings per share change for all included countries. The F_Score also is significant in each country in predicting one-year-ahead change in earnings.

The analysis of IFRS impact shows that the overall predictive ability of the model is higher in post- compared to pre-IFRS periods for all countries except Australia. The impact of IFRS on earnings fundamental signals is positive for all countries except Spain. The predictive ability of earnings significantly decreased in Spain after IFRS adoption. The increase in earnings coefficients in the post- compared to pre-IFRS period is lower for Common law countries (UK and Australia) compared to Code law countries (except Spain). The combined predictive ability of non-earnings signals incremental to earnings in the post- compared to pre-IFRS period is lower in Belgium, France, Italy, Poland, Portugal and Australia, while similar in Demark, Spain, Sweden and UK. However, in Finland, the combined predictive ability of non-earnings signals over earnings increased following adoption of IFRS.

6.6 Chapter summary

This chapter reports the results and discusses the empirical findings for analyses of the predictive ability of one earnings and 12 non-earnings fundamental signals for one-year-ahead change in earnings per share and also the impact of IFRS on the predictive ability of those fundamental signals. Analyses are carried out based on a pooled sample and sub-samples of Code and Common law countries, and Winners and Losers, as well as for three contextual factors. A tabular summary of all findings from this chapter is provided in Table 6.10.

The analyses indicate that fundamental signals are significant in predicting one-year-ahead change in earnings per share, individually, in combination and also in aggregated form (F_Score). However, several fundamental signals are significant in a direction not anticipated, although possible justifications for these results can be provided. Results reveal that the non-earnings fundamental signals, including F_Score, contain information content that is incremental to earnings in predicting future earnings. Overall, there is no significant difference in the predictive ability of fundamental signals between Code and Common law countries. However, both earnings and non-earnings fundamental signals, including F_Score, better predict Winners compared to Losers.

Results also reveal that IFRS has a positive impact on earnings and a negative impact on non-earnings in predicting future earnings. The predictive ability of earnings increased, mostly for Code law countries, while the combined predictive ability of non-earnings signals over earnings decreased for both Code and Common Law countries after adoption of IFRS. At the same time, the predictive ability of F_Score significantly decreased in the post- compared to pre-IFRS period for the pooled sample and sub-samples.

Table 6.10: Summary of findings for predictive ability of fundamental signals in predicting one-year-ahead change in earnings per share and IFRS impact on the predictive ability of these signals for the period 2001 -2012 & relates to H1a to H1f

Variables	Predictive ability of fundamental signals					Contextual analysis			IFRS impact on predictive ability of fundamental signals				
	Pooled	Code Law	Code Law	Pooled		PYEN	GDP Gr	IFL	Pooled sample	Code law	Common Law	Increase	Decrease
				Winners	Losers								
CHGEPS	√***	√***	√***	√√***	√***	#***		#**	↑**	↑**			↑*
INV	√**		√√***	√**					↓*			↓***	
AR	√***	√**	√**		√*								
SA		√√***			√*								
LF				√√**									↓*
ETR	√**	√**		√√***	√***								
GM				√√***	√*								
AQ	√*		√**	√√***					↓**			↓**	
CAPX	√***	√***	√***	√√***	√*				↓**		↓***	↓**	
LEV	√***		√***	√√***		#*							
CF	√***	√***	√***	√***	√***		#**						
GW	√***	√***	√√***	√√***	√***	#**		#*		↓*			
CDACCR	√***	√***	√**		√√***	#**	#**	#**					
Incremental R-Sq from non-earnings signals	0.016	0.016	0.019	0.026	0.010	G 0.010 B 0.013	H 0.012 L 0.019	H 0.017 L 0.016	Pre 0.018 Post 0.012	Pre 0.022 Post 0.014	Pre 0.027 Post 0.015	Pre 0.042 Post 0.020	Pre 0.016 Post 0.010
F_Score	√***	√***	√***	√√***		#*	#*		↓***	↓**	↓***	↓***	

Refer to Annexure 6.1 for variable definitions, *** significant at 1%, ** significant at 5%, * Significant at 10%

√	Has ability to predict one-year-ahead change in EPS	√√	Predictive ability is significantly higher than for its counterpart
(grey shading)	Variable is significant, but not in the direction anticipated	(hatched shading)	Variable is not significant for the sample that excludes GFC and IFRS transition period
↑	Predictive ability has increased	↓	Predictive ability has decreased
G	Good news	B	Bad news
H	high	L	Low
Pre	Pre-IFRS	Post	Post-IFRS
#	Predictive ability is significantly different based on the contextual factor		

PYEN – prior year earnings news, GDP Gr – Gross Domestic Product growth, IFL – level of inflation rate

In addition, the predictive ability of earnings increased in predicting Losers, but this is not the case for Winners in the post- compared to pre-IFRS period. Moreover, the predictive ability of non-earnings signals and F_Score decreased mostly for Winners after adoption of IFRS.

The contextual analysis reveals that the Good or Bad nature of prior year earnings news (PYEN) influences the predictive ability of both earnings and non-earnings fundamental signals. GDP growth influences mostly the predictive ability of non-earnings signals, whereas the level of inflation has an impact on the predictive ability of earnings in predicting one-year-ahead earnings. Therefore, the overall results reported in this chapter support Hypotheses H1a, H1b, H1c and H1d, but not H1e and H1f.

CHAPTER 7: VALUE RELEVANCE OF FUNDAMENTAL SIGNALS AND IFRS IMPACT ON THIS VALUE RELEVANCE

7.1 Introduction

This chapter discusses the empirical findings as a result of testing six hypotheses (H2a, H2b, H2c, H2d, H2e and H2f[58]). Hypotheses H2a, H2b and H2c examine the value relevance of one earnings and 12 non-earnings fundamental signals for contemporaneous excess returns respectively and Hypotheses H2d, H2e and H2f examine the impact of IFRS on the value relevance of the selected fundamental signals.

The chapter is organised as follows. Section 7.2 explains the main research contributions arising from this chapter. Section 7.3 reports the findings from testing Hypotheses H2a, H2b and H2c. Section 7.4 documents the impact of contextual factors on the value relevance of the fundamental signals, again relating to Hypotheses H2a, H2b and H2c. Section 7.5 discusses the findings from testing Hypotheses H2d, H2e and H2f. Finally, section 7.6 summarises the findings in relation to these six hypotheses.

7.2 Research contribution

For the purpose of examining the value relevance of accounting information and the impact of IFRS on value relevance, this study uses one earnings fundamental and 12 non-earnings fundamentals, using a data set for the period 2001 to 2012 from European and Australian contexts. As such, the results reported in this chapter make a significant contribution to the value relevance and IFRS literatures from several perspectives.

First, many of the studies that examine the value relevance of non-earnings fundamental signals are conducted using data collected prior to year 2000. Therefore, very little is known about the quality of these fundamental signals found previously to be useful for decision-making under the new accounting environment post-2000. As such, this study

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[58] These hypotheses are developed in Chapter 2 and repeated here for convenience. *H2a: There is a negative relationship between current year change in earnings and contemporaneous returns; H2b: There is a negative relationship between current year non-earnings fundamental signals and contemporaneous returns; H2c: There is a positive relationship between an aggregated fundamental score and contemporaneous returns; H2d: The value relevance of current year earnings for excess returns improved after adoption of IFRS; H2e: The value relevance of non-earnings fundamental signals for excess returns improved after adoption of IFRS, and H2f: The value relevance of the aggregated fundamental score (F_Score) for excess returns improved after adoption of IFRS.*

makes a contribution to the literature on fundamental analysis by examining the value relevance of the selected fundamental signals for contemporaneous excess returns using post-2000 data and in the context of 11 European countries and Australia, jurisdictions which can be further partitioned into Code and Common law countries.

Second, a large number of non-earnings fundamental signals are included in the models to examine their value relevance for contemporaneous excess returns, and this study includes an additional four fundamental signals (e.g. discretionary accruals, goodwill) emanating from past literature that have not been tested previously in this type of study.

Third, this study provides mostly first-time evidence of the impact of IFRS on the value relevance of the non-earnings fundamental signals which are important for decision-making by market participants. This study makes a contribution by examining IFRS impact on the association between current year change in earnings and contemporaneous excess returns in different contexts, such as Code and Common law countries.

Fourth, the study examines the value relevance and impact of IFRS on the value relevance of these selected fundamental signals for contemporaneous excess returns individually, in combination, and in aggregated form (F_Score), providing a check on the consistency of findings. Fifth, in extended analyses, the value relevance and the impact of IFRS on the value relevance of these fundamental signals is examined from different perspectives, such as: i) for Winners and Losers; ii) for Extreme and Non-extreme returns; and iii) for Growth and Value stocks. Finally, the value relevance of the fundamental signals is examined under conditions of different contextual factors, such as the good or bad nature of prior year earnings news (PYEN), level of inflation and level of GDP growth.

Therefore, this chapter provides compelling evidence of the value relevance of the included fundamental signals for contemporaneous excess returns and the impact of IFRS on this value relevance. In so doing, it makes a significant contribution to the IFRS literature.

7.3 Value relevance of fundamental signals individually and in combination for excess returns

In order to examine the value relevance of fundamental signals for contemporaneous excess returns, this study follows the methodology used by Lev and Thiagarajan (1993), later followed by Abarbanell and Bushee (1997) and many other scholars. Excess returns are calculated as the difference between the firm's return for the 12-month period commencing 11 months prior and ending one month after the earnings announcement date and the benchmark index return for the same period. As explained in the previous Chapter, sample firm-year observations are collected from 12 countries, across nine industries and 2908 firms for the period 2001 to 2012 (excluding 2005, the year of IFRS transition). The following regression model, which was explained in Chapter 4 and is repeated here for convenience, is employed to examine the value relevance of earnings and non-earnings fundamental signals for excess returns.

$$ER_i = \propto \ + \beta_0 \, \mathrm{CHGEPS}_i + \sum_{j=1}^{12} \beta_{ij} \mathrm{Signals}_{ij} \ + \sum \mathrm{Yr} + \ \sum \mathrm{In} \ + \sum \mathrm{Cty} + \mathrm{Codelaw} + \varepsilon_j \quad (3)$$

Where ER is calculated the difference between firm *i*'s return for the 12-month period commencing 11 months prior and ending one month after the earnings announcement date and the benchmark index return for the same period. CHGEPS = current year change in earnings, $\mathrm{Signals}_{ij}$= Non-Earnings Fundamental Signals[59], j = 1 to 12, Yr = Year dummies, Cty= Country Dummies, In=Industry dummies, CodeLaw = 1 if the firm belongs to a Code law country, otherwise 0.

Again, as is explained in the prior chapter, regression results are adjusted using the Huber-White Sandwich estimator (White 1980), which provides robust standard errors to control for heteroskedasticity and auto-correlation by clustering on unique firm identities using STATA.

As was the case for the analyses reported in Chapter 6, the initial sample comprises 20997 firm-year observations. However, to maintain the same sample size for subsequent analyses that examine the impact of IFRS on the value relevance of the fundamental signals, observations for the year that firms transitioned to IFRS (2005) are removed since

59 As is explained in the prior chapter, the 12 non-earnings fundamental signal variables are change in inventory relative to change in sales (INV), change in accounts receivable relative to change in sales(AR), change in selling and administrative expenses relative to change in sales (SA), change in labour force (LF), change in effective tax rate (ETR), audit qualification (AQ), change in firm's capital expenditure relative to change in industry capital expenditure (CAPX), change in financial leverage (LEV), change in cash flow from operations (CF), change in goodwill (GW) and change in discretionary accruals (CDACCR). Eight of these variables are drawn from Lev and Thiagarajan (1993) and as was the case for analyses reported in Chapter 6, while LEV, CF, GW and CDACCR are added based on past literature.

construction of the fundamental signal variables in this study involves lagged measures. That adjustment results in loss of 1503 firm-year observations. Moreover, observations that produce studentised residuals greater than three, or Cook's distance statistics greater than one, are removed to address multivariate outliers (Abarbanell & Bushee 1997; Dowen 2001). This adjustment eliminates a further 186 firm-year observations and therefore the final pooled sample is reduced to 19308 firm-year observations[60] and the descriptive statistics for the variables for the period selected for this study with *t*-tests of difference for pre-and post-IFRS reported in Annexure 7.1. In addition, Pearson's correlations between the variables are calculated for the pooled sample to test the multicollinearity among these variables and the results (Annexure 7.2) shows that none of the correlations is of a level that creates multicollinearity concerns with no correlation higher than 0.447 between change in cash flows from operations (CF) and change in discretionary accruals (CDACCR).

Moreover, some years under examination fall under the GFC period (2007 – 2009). Therefore, in order to examine the value relevance of the selected fundamental signals robustly, the regressions for Models 3 and 4 used in this chapter are estimated for a sample that excludes the GFC period. In addition, when examining the IFRS impact on value relevance, as a robustness test, analysis is conducted for the period that excludes not just the IFRS transition year but, rather the full IFRS transition period (2004-2006), in addition to the GFC period. Excluding observations for a wider transition period than just the transition year allows for learning of preparers during IFRS transition and also caters for different financial year-ends during the IFRS transition period that may have resulted in different adoption periods. Moreover, for the construction of some variables, lagged data are required for the calculation of averages and these data ideally emanate under the same accounting standards.

7.3.1 Value relevance of individual fundamental signals for excess returns

The regression results derived from estimation of Model 3, and Lev and Thiagarajan's (1993) Model[61], both of which analyse the association between the selected fundamental signals and contemporaneous excess returns, are reported in Table 7.1 for the pooled

[60] This final sample is different from that reported in Chapter 6 since the number of outliers varies for the different dependent variables.

[61] That is, Lev and Thiagarajan's (1993) model that includes only the eight (of 12) variables common to this study.

sample (n = 19308) and sub-samples of Code (n=10133 [52 per cent]) and Common (n=9175) law country observations. The results are obtained by regressing current year change in earnings (CHGEPS) plus the 12 non-earnings fundamental signals[62] with contemporaneous excess returns (ER). As explained in Chapter 4, section 4.6, earnings and all non-earnings fundamental signals are expected to have a negative relationship with ER.

As can be seen from Table 7.1 Panel A, Model 3 employed in this study has higher explanatory power (0.158) than that for the Lev and Thiagarajan Model (0.137) and the four additional variables (LEV, CF, GW, and CDACCR) included in this study are each significantly associated with excess returns (ER) for the pooled sample and for Code and Common law sub-samples, except for GW for Code law countries. The partial F-test shows that the incremental R-Squared contribution from including these four non-earnings fundamental signals is significant for the pooled sample and sub-samples.

When examining the value relevance of current year change in earnings per share (CHGEPS) for excess returns, as reported in Table 7.1 Panel A (the earnings alone Model), there is a robust R-Squared value of 0.103 for the pooled sample. When the non-earnings fundamental signals are included in the regression with earnings, the robust R-Squared value increases to 0.158. This indicates that the non-earnings fundamentals contain value relevant information in terms of contemporaneous excess returns incremental to CHGEPS. The partial F-test (Table 7.1, Panel A) shows that the incremental explanatory power from including non-earnings fundamental signals over CHGEPS is significant in explaining contemporaneous excess returns for the pooled sample. Analyses based on sub-samples of Code and Common law country observations lead to the same conclusion. This result is consistent with findings from prior studies that non-earnings fundamental signals contain information incremental to earnings that is value relevant for returns (Abarbanell & Bushee 1997,1998; Al-Debie & Walker 1999; Dowen 2001; Elleuch 2009; Lev & Thiagarajan 1993; Mahmoud & Sakr 2012; Mohanram 2005; Ou 1990; Piotroski 2000; Swanson, Rees & Juarez-Valdes 2003).

When individual fundamental signals are the focus, all 13 explanatory variables are significantly associated with excess returns (ER) for the pooled sample. In terms of

[62] Eight from Lev & Thiagarajan's (1993) model.

current year change in earnings (CHGEPS), it is significantly associated with ER at 1 per cent in the direction anticipated for the pooled sample and for sub-samples of Code and Common law country observations. This relationship indicates that CHGEPS contains useful information that is value relevant for contemporaneous excess returns. This result is consistent with findings from prior literature (Abarbanell & Bushee 1997; Lev & Thiagarajan 1993).

It is noted that the R-Squared value for CHGEPS alone for the Model when applied to the Code law sub-sample is higher than that for the same regression for the Common law sub-sample (Table 7.1, Panel A). However, the test of equality of coefficients based on stacked regression (Atwood et al. 2011) shown in Table 7.1 Panel A indicates that the coefficient for earnings is not significantly different between Code and Common law sub-samples[63]. Therefore, it is inferred that the value relevance of current year earnings (CHGEPS) is not significantly different between Code and Common law countries for contemporaneous excess returns.

When focusing on the non-earnings fundamental signals, most of these are value relevant for excess returns in the anticipated direction. There is a significant positive association between change in inventory relative to sales (INV) and ER for the pooled sample and Code and Common law sub-samples. This relationship shows that INV is value relevant for ER for all analyses, but not in the direction anticipated. The positive relationship indicates that an increase (decrease) in inventory relative to sales represents good signal (bad signal) about returns, which capture the persistence of earnings. A possible explanation for this relationship could be an increase in inventory level based on expectations about sales growth, or for un-interrupted smooth production, hedging or speculation against future price movements in the short-term future (Lev & Thiagarajan 1993).

[63] First the regression model is run for Code law country observations, and then for Common law country observations. Finally, these two regression are stacked into one model and a test of equality between the same coefficients is conducted between the two sub-samples (refer Atwood et al. 2011).

Table 7.1: Value relevance of fundamental signals for contemporaneous excess returns for pooled sample and Code and Common law sub-samples (H2a, H2b & H2c)

***Panel A* Model 3** Dep. Var. ER	Lev & Thiagarajan Model	Current Study Model			Test of Equality (a-b)
		Pooled sample	Code Law (a)	Common Law (b)	
	N =19308	N =19308	n =10133	n = 9175	
	Clusters = 2908	Clusters = 2908	Clusters = 1495	Clusters = 1413	
	Coef.	Coef.	Coef.	Coef.	Coef. Diff
α	-4.452	**-5.518***	**10.377*****	**10.832*****	
CHGEPS	**-67.598*****	**-54.070*****	**-53.542*****	**-52.503*****	-1.039
INV	**0.008****	**0.009****	**0.008***	**0.013****	-0.005
AR	**-0.074*****	**-0.066*****	**-0.079*****	**-0.051*****	-0.028
SA	**-0.116*****	**-0.071*****	**-0.090*****	**-0.052****	-0.038
LF	**-0.075*****	**-0.045*****	-0.018	**-0.069*****	**0.051***
ETR	**-0.010*****	**-0.009*****	**-0.009*****	**-0.009****	0.000
GM	**-0.205*****	**-0.188*****	**-0.196*****	**-0.119*****	**-0.077*****
AQ	**-12.567*****	**-11.618*****	-4.936	**-18.460*****	**13.524***
CAPX	**-0.014*****	**-0.012*****	-0.004	**-0.018*****	**0.014****
LEV		**-0.023*****	**0.037*****	**-0.062*****	**0.099*****
CF		**-0.766*****	**-0.680*****	**-0.842*****	**0.162***
GW		**-0.012*****	-0.004	**-0.021*****	**0.017****
CDACCR		**-47.034*****	**-47.948*****	**-47.468*****	-0.480
R-Sq 1	0.137	0.158	0.194	0.154	
R-Sq 2	0.103	0.103	0.132	0.097	
Partial F test		67.470	49.900	37.780	
Controls : Years, Industries and Countries					
Panel B : Model 4 - *Value relevance of F_Score*					
Dep. Var. ER		Pooled sample	Code Law	Common Law	Coef. Diff
α		**-25.355*****	-5.506	**-18.875*****	
CHGEPS		**-73.650*****	**-78.503*****	**-69.015*****	**-9.488***
F_Score		**3.093*****	**2.119*****	**4.049*****	**-1.930*****
R-Sq		0.123	0.137	0.127	

Where Excess Returns (ER) is calculated the difference between the firm's return for the 12-month period commencing 11 months prior and ending one month after the earnings announcement date and the benchmark index return for the same period, CHGEPS= Change in Current Earnings per share (change in EPS between year *t-1* and *t* deflated by the stock price at the end of *t-1*), INV=Inventories (annual percentage change in inventories minus the annual percentage change in sales), AR=Accounts Receivable (annual percentage change in accounts receivable minus annual percentage change in sales), SA=Selling & Administrative Expenses (annual percentage change in selling and administrative expenses minus the annual percentage change in sales), LF =Labour Force (LF) (annual percentage change in sales per employee calculated as last two years average sales per employee minus current year sales per employee divided by last two years average sales per employee), ETR=Effective Tax Rate (annual percentage change in ETR), GM=Gross Margin (annual percentage change in sales minus annual percentage change in gross margin), AQ=Audit Qualification (0 for an unqualified opinion and 1 otherwise. If there is an emphasis of matter paragraph and if it relates to going concern, 1 is assigned and 0 otherwise), CAPX=Capital Expenditure (annual percentage change in industry capital expenditure minus the annual percentage change in the firm's capital expenditure), LEV=Financial Leverage (annual change in ratio of total debt (long-term debt plus current liabilities), CF=Cash Flows (cash flow from operations (CFO) between year *t* and *t-1* divided by total assets at end of financial year *t-1*), GW = Goodwill (Annual percentage change in goodwill calculated as last two years (*t-1* and *t*-2) average goodwill minus goodwill in year *t* divided by the last two years' average goodwill), CDACCR = annual change in Discretionary Accruals calculated using the Kothari, Leone and Wasley (2005) performance matched discretionary accrual model. F_Score is created by assigning a value of one (zero) for good (bad) signals and summing the values across the 12 non-earnings fundamental signals. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively, Results are based on robust standard errors clustered by firm. Standard errors are CDACCR (2.6), AQ (2.1), CHGEPS (1.9) and others are less than 0.1. The highest VIF is reported for CF (1.49). R-Sq 1: R2 for the full model, R-Sq 2: R^2 for the earnings alone model. Partial F test indicates the significance of incremental explanatory power from 12 non-earnings fundamental signals over earnings. Test of equality of coefficients is based on stacked regression (Panels A and B).

Change in accounts receivable relative to sales (AR) is significantly associated with ER at 1 per cent in the expected direction for the pooled sample and sub-samples for Code and Common law countries, and is therefore value relevant for ER. This suggests that a disproportionate increase (decrease) in accounts receivable relative to sales represents bad (good) news about returns. This is so since a disproportionate increase in inventory relative to sales could be an indication of difficulties in selling products or services, more liberal credit terms (hence increase in bad debts), or earnings management via aggressive recognition of revenue, which leads to low earnings persistence (Lev & Thiagarajan 1993).

The explanatory variable change in selling and administrative expenses relative to sales (SA) is also significantly associated with ER in the expected direction for all analyses, and as such is value relevant for ER for the pooled sample and Code and Common law sub-samples. This result, shown in Table 7.1 Panel A, indicates that a disproportionate increase (decrease) in selling and administration expenses relative to sales represents a negative (positive) signal about returns, which may indicate a lack of cost control or unusual sales efforts, leading to low earnings persistence (Lev & Thiagarajan 1993).

Change in labour force relative to sales (LF) is another explanatory variable that is value relevant at 1 per cent for ER in the expected direction for the pooled sample and Common law sub-sample. This association indicates that an increase in labour efficiency, measured as an increase (decrease) in sales per employee, is a good (bad) signal about earnings persistence and hence for returns (Lev & Thiagarajan 1993).

There is also a significant association between effective tax rate (ETR) and ER at 1 per cent for all analyses, in the expected direction. This association indicates that ETR contains useful information value relevant for ER. This finding is consistent with prior fundamental analysis literature, including Lev and Thiagarajan (1993) and Abarbanell and Bushee (1997). This relationship indicates that an unusual decrease (increase) in the effective tax rate is a negative (positive) signal with regard to contemporaneous excess returns, because an effective tax rate decrease, not caused by a statutory tax change, is considered to be transitory, and as such indicative of low earnings persistence (Lev & Thiagarajan 1993).

The change in gross margin relative to sales (GM) signal is also significantly associated with ER in the anticipated direction for the pooled sample and Code and Common law sub-samples, and is therefore deemed value relevant. This finding is again consistent with those of Lev and Thiagarajan (1993), Abarbanell and Bushee (1997) and also Swanson, Rees and Juarez-Valdes (2003). This relationship indicates that a disproportionate decrease (increase) in gross margin relative to sales gives a negative (positive) signal about contemporaneous excess returns, as it indicates the intensity of competition, or a difficult to change relation between fixed and variable costs, and this affects the long-term performance of the firm.

The next variable that is value relevant for ER in the expected direction is audit qualification (AQ). This variable is significantly associated with ER at 1 per cent for both the pooled sample and Common law sub-sample. The result indicates that a qualified (unqualified) audit opinion gives a negative (positive) signal about market price. This result is consistent with the findings of Lev and Thiagarajan (1993) and Abarbanell and Bushee (1997).

The change in firm capital expenditure relative to the industry (CAPX) variable is significantly associated with ER at 1 per cent in the direction expected for the pooled sample and Common law sub-sample and therefore deemed value relevant for those two samples. This finding is again consistent with those of Lev and Thiagarajan (1993) and Al-Debie and Walker (1999) This result implies that a decrease (increase) in capital expenditure relative to the industry provides a negative (positive) signal about firm returns as it might indicate managers' concerns with the adequacy of current and future cash flows to sustain the previous investment level, and so raises questions about earnings persistence (Lev & Thiagarajan 1993).

The association between change in financial leverage (LEV) and ER is significant at 1 per cent in the direction expected for all analyses. As such this variable is value relevant for the pooled sample and Code and Common law sub-samples for ER. This relationship indicates that an increase (decrease) in current year LEV relative to the previous year gives a negative (positive) signal about contemporaneous excess returns. Swanson, Rees and Juarez-Valdes (2003) and Dimitrov and Jain (2008) also document a negative relationship between LEV and stock returns.

The change in cash flows from operations (CF) variable is also significantly associated with ER at 1 per cent for excess stock returns for the pooled sample as well for Code and Common law sub-samples in the direction anticipated. Therefore, CF contains useful information that is value relevant for ER for all analyses. This result shows that a current year increase (decrease) in cash flow from operations compared to the previous year is a positive (negative) signal about contemporaneous returns as it captures the persistence of earnings (Banker, Huang & Natarajan 2009; Kumar & Krishnan 2008; Sloan 1996). Rayburn (1986) and Hirshleifer, Hou and Teoh (2009) also document that cash flows are associated significantly with returns and cash flows contain incremental information content over earnings; that is, they are value relevant for stock returns (Banker, Huang & Natarajan 2009; Cheng, Chao Shin & Schaefer 1997; Habib 2008).

Change in goodwill (GW) is another variable significantly associated with ER (at 1 per cent) in the expected direction for the pooled sample and Common law sub-sample and therefore is value relevant for excess stock returns for these two samples. This relationship can be interpreted as an increase (decrease) in goodwill from last year to this year representing a positive (negative) signal in terms of stock returns. An increase in goodwill is a positive signal indicating higher earnings capacity and higher persistence of earnings in the future. Since share price represents the present value of all future cash flows associated with the share, an increase in GW from last year to this is expected to be positively related with contemporaneous excess returns. The literature also reports that goodwill and impairment of goodwill is value relevant for stock price and returns (AbuGhazaleh, Al-Hares & Haddad 2012; Dahmash, Durand & Watson 2009; Duangploy, Shelton & Omer 2005; Oliveira, Rodrigues & Craig 2010; Xu, Anandarajan & Curatola 2011).

The change in discretionary accruals (CDACCR) is an additional fundamental signal variable included in this study in addition to signals included by Lev and Thiagarajan (1993). It is significantly associated with ER at 1 per cent for all analyses reported in Table 7.1 in the direction expected**.** This relationship indicates CDACCR contains useful information that is value relevant for ER and the increase (decrease) in discretionary accruals from last year to this year is a positive (negative) signal about ER for the pooled and Code and Common law sub-samples.

This negative relationship implies that an increase in discretionary accruals from last year to this year is a positive signal in terms of stock returns. This negative relationship could be due to managers' opportunistic behaviour. The previous chapter also documents a positive relationship between an increase in discretionary accruals from last year to this providing a positive signal about future earnings change. Subramanyam (1996) documents that discretionary accruals improve the ability of earnings to reflect real economic value and also finds a positive relationship between current year discretionary accruals and future earnings, hence discretionary accruals capture the persistence of earnings. DeFond and Park (1997) find that managers borrow future earnings by increasing discretionary accruals, if expected earnings is high. Therefore, higher expected earnings reflect in higher share price and higher returns. Therefore, an increase in discretionary accruals from last year to this year signals an increase in future earnings per share and higher contemporaneous excess returns.

The test of equality of coefficients based on stacked regression[64] shows that the value relevance of LF, AQ, CAPX, LEV, CF and GW is significantly higher for Common law country observations, while that for GM is higher for Code law country observations, compared with their counterparts. With regards to the combined value relevance of the non-earnings fundamental signals, the incremental R-Squared value from including non-earnings fundamental signals into the earnings alone model is significant for all analyses and is similar between Code and Common law country observations[65] (Table 7.1, Panel A).

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[64] First the regression model is estimated for the Code Law sub-sample, and then for the Common Law sub-sample. Finally, these two regression are stacked into one model and a test of equality between the same coefficients is conducted between the two sub-samples (refer Atwood et al. 2011).

[65] The incremental R-Squared contribution from non-earnings fundamental signals over earnings in predicting future returns for Code law countries is 0.062, while for Common law countries it is 0.057.

In order to test the value relevance of fundamental signals more robustly, the regression for Model 5 is re-estimated for a sample that excludes the Global Financial Crisis (GFC) period (2007-2009) (n = 13271 for the full model, results untabulated). Results are in agreement with the above analysis except that INV is not now value relevant and the value relevance of AR is now significantly higher for Code rather than Common law country observations. These results point to the conclusion that the selected fundamental signals individually, and in combination, capture earnings persistence and hence are value relevant and provide useful signals for market participants for their decision-making, thereby supporting Hypotheses H2a and H2b.

7.3.2 Value relevance of aggregated fundamental score (F_Score) for contemporaneous excess returns

In order to examine the value relevance of the non-earnings signals as a whole, an aggregated score (F_Score) is created by assigning a value of one (zero) for good (bad) signals and summing the values across the 12 non-earnings fundamental signals. Lev and Thiagarajan (1993) indicate that the aggregated fundamental score (F_Score) reflects information in the fundamental signals and F_Score is significantly associated with earnings response coefficients (ERCs) and future earnings growth, both indicators of earnings persistence. Further they document that F_Score is more strongly associated with ERCs than a time series persistence measure of earnings. Therefore, F_Score is more useful in capturing the permanent component of earnings. Since all the variables are in the expected direction except INV (inventory is not value relevant in the sample that excludes the GFC), F_Score is developed based on the expected relationships[66].

A higher F_Score indicates strong fundamentals that indicate a future increase in returns and, therefore, a positive relationship between F_Score and contemporaneous excess returns is expected. Model 4 is used to test the value relevance of F_Score (H2c) in terms of excess returns and is as follows**.**

$$\mathrm{ER}_i = \propto \; + \beta_0 \, \mathrm{CHGEPS}_i + \beta_1 \, \mathrm{F\_Score}_i + \sum \mathrm{Yr} + \sum \mathrm{In} + \sum \mathrm{Cnt} + \mathrm{Codelaw} + \varepsilon_j \qquad (4)$$

The Partial F-test above confirms that the incremental R-Squared value from including non-earnings fundamental signals is significant for both sub-samples.

66 This treatment differs from that adopted in Chapter 6, since for the predictive ability of the fundamental signals analysis reported in Table 6.1, six of the 13 signals were significant but not in the direction anticipated.

This methodology is adopted in prior literature, including studies by Lev and Thiagarajan (1993), Abarbanell and Bushee (1998) and Al-Debie and Walker (1999), who show that F_Score is value relevant.

Table 7.1 (Panel B), which reports the results from estimating Model 4, shows that F_Score is significantly associated with contemporaneous excess returns at 1 per cent in the expected direction for the pooled sample as well as for Code and Common law sub-samples. This relationship indicates that F_Score contains useful information that is value relevant for ER (Abarbanell & Bushee 1997; Lev & Thiagarajan 1993; Mohanram 2005; Piotroski 2000). The R-Squared value for Model 4 for the pooled sample is 0.123, which is larger than that for the earnings alone model (0.103), as reported in Table 7.1 (Panel A). In terms of the sub-samples, the incremental R-Squared contribution from F_Score is significant with a higher contribution for Common law country observations. The test of equality of coefficients based on stacked regression indicates the coefficient for F_Score for Common law country observations is significantly higher than that for Code law observations. These findings support the view that the value relevance of F_Score is significantly higher for Common compared to Code law countries for contemporaneous excess returns. When the value relevance of F_Score is examined for the sample that excludes the GFC period (2007-2009), results (untabulated**)** are in agreement with the above analysis and support the same conclusion.

7.3.3 Value relevance of fundamental signals for Winners and Losers for contemporaneous excess returns

An excess return can represent a gain or loss. This section examines the value relevance of earnings and non-earnings fundamental signals for sub-samples of observations exhibiting gains (Winners) and losses (Losers). For the purpose of this analysis, the sample is partitioned into Winners and Losers and then separate regressions for Models 3 and 4 are run for each sub-sample. There are 8769 firm-year observations for Winners and 10539 for losers. As can be seen from Table 7.2 (Panel A), the R-Squared value for Model 3 is slightly higher for Losers compared to Winners. As such the value relevance of the overall model is higher for Losers compared with Winners.

Table 7.2: Value relevance of fundamental signals and F_Score for Winners and Losers (H2a, H2b & H2c)

Panel A *:Value relevance of fundamental signals for Winners and Losers*			
Model 3 Dep. Var. ER	Winners n =8769 Coef.	Losers n =10539 Coef.	Test of Equality Coef. Diff
	25.376***	**-26.847*****	
CHGEPS	**-37.882*****	**-11.963*****	**-25.920*****
INV	0.004	**0.006****	-0.002
AR	**-0.023****	**-0.029*****	0.006
SA	**-0.101*****	0.002	**-0.103*****
LF	-0.026	-0.009	-0.017
ETR	**0.004***	**-0.008*****	**0.012*****
GM	**-0.079*****	**-0.075*****	-0.004
AQ	1.016	**-6.725*****	**7.740****
CAPX	**-0.011*****	**-0.008*****	-0.003
LEV	-0.002	**-0.013*****	0.012
CF	**-0.402*****	**-0.284*****	**-0.118****
GW	**0.012*****	**-0.009*****	**0.021*****
CDACCR	**-16.636*****	**-23.114*****	6.478
Adj. R-Sq 1	0.137	0.149	
Adj. R-Sq 2	0.111	0.116	
Panel B *: Value relevance of F_Score for Winners and Losers*			
Model 4 Dep. Var. ER	Coef.	Coef.	Coef. Diff
α	**19.412*****	**-35.068*****	
CHGEPS	**-47.509*****	**-19.348*****	**-28.161*****
F_Score	**1.059*****	**1.224*****	-0.166
Adj. R-Sq	0.115	0.126	

Refer to Table 7.1 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Adj. R-Sq 1: Adjusted R-Squared for full Model 1, Adj. R-Sq 2: Adjusted R-Squared for earnings alone model. Results are based on robust standard errors clustered by firm. Standard errors are CDACCR (3.3), AQ (3.2), CHGEPS (2.1) with others less than 0.1 Test of equality of coefficients is based on stacked regression.

In terms of the value relevance of individual fundamental signals, current year change in earnings per share (CHGEPS) is significantly associated at 1 per cent with excess returns (ER) for both Winners and Losers and the test of equality of coefficients based on stacked regression shows that the earnings coefficient is significantly higher for Winners rather than Losers[67]. Therefore, it is inferred that the value relevance of CHGEPS is significantly higher for Winners compared with Losers.

Of the non-earnings fundamental signals (Table 7.2, Panel A), ETR, GM, CAPX, GW, and CDACCR are value relevant for both Winners and Losers. However, SA is value relevant only for Winners, while INV, AQ, and LEV are value relevant only for Losers. This indicates that more fundamental signals are value relevant for Losers than Winners. The test of equality of coefficients indicates that the value relevance of SA and CF is significantly higher for Winners, whilst that for ETR, AQ, and GW is significantly higher for Losers, compared to their counterparts. Therefore, it can be concluded that these non-earnings signals are useful in distinguishing between Winners and Losers for market participants.

With regards to the combined value relevance of the non-earnings signals, the Partial F-test (untabulated) indicates that the incremental R-Squared contribution from including all non-earnings fundamental signals into the earnings alone model is significant for both Winners and Losers, with a higher contribution for Losers.

Regression results for Model 4 shown in Table 7.2 (Panel B) document that the aggregated fundamental Score (F_Score) is value relevant for both Winners and Losers with a higher coefficient for Losers, but the test of equality of coefficients indicates that there is no significant difference in the value relevance of F_Score between Winners and Losers.

As a robustness test, the same analysis is performed for the sample that excludes the GFC period (2007-2009) and results (untabulated) are consistent with the above findings and all the above analyses support Hypotheses H2a, H2b and H2c.

7.4 Contextual analysis and value relevance of fundamental signals for contemporaneous excess returns

In previous studies on fundamental analysis, some authors report that the value relevance of fundamental signals varies significantly based on contextual factors, such as the nature

[67] First the regression model is run for Winners, and then for Losers. Finally, these two regressions are stacked into one model and a test of equality between the same coefficients is conducted between the two sub-samples.

of prior year earnings news (PYEN), the level of Gross Domestic Product (GDP) growth and the level of inflation (INF) (Abarbanell & Bushee 1997; Al-Debie & Walker 1999; Lev & Thiagarajan 1993). As such, the value relevance of these earnings and non-earnings fundamental signals is tested for good and bad PYEN, high and low GDP growth and high and low level of inflation in predicting excess returns.

7.4.1 Impact of PYEN on value relevance of fundamental signals for excess returns

In order to analyse the impact of PYEN, the pooled sample is partitioned into Good and Bad PYEN groups (Good if change in prior year earnings represents an increase and Bad if a decrease) and then Models 3 and 4 are estimated for the separate Good (n= 11042 [57 per cent]) and Bad (n=8266) PYEN sub-samples. Results are reported in Table 7.3. The results indicate that the R-Squared value from estimating Model 3 is considerably higher for Bad compared to Good PYEN observations, indicating an overall higher value relevance of the models under the Bad PYEN condition.

The earnings signal is value relevant under both Good and Bad PYEN conditions for excess returns and the test of equality of coefficients reveals that the value relance of earnings is significantly higher under the Bad when compared to Good PYEN condition. Many of the fundamental signals are value relevant for excess returns under both Good and Bad PYEN conditions. However, value relevance is significantly higher for INV and LEV under Bad PYEN, while that for ETR is significantly higher under Good PYEN compared with its counterpart. The incremental R-Squared contribution from the non-earnings signals over earnings alone is similar for both sub-samples. In terms of F_Score, it is value relevant for excess returns (Model 4, Table 7.3, Panel B) under both Good and Bad PYEN conditions and the test of equality of coefficients indicates that the value relevance of F_Score is significantly higher under the Good compared with Bad PYEN condition.

7.4.2 Impact of GDP growth on the value relevance of fundamental signals for excess returns

For the purpose of analysis examining GDP growth, the pooled sample is partitioned into High GDP growth (n=8162 [42 per cent]) and Low (n=10126) GDP growth sub-samples based on median GDP growth (observations with years that have equal or above the median GDP growth fall under the High category, while others come under the Low category). Then Models 3 and 4 are estimated for those two sub-samples. Results are reported in Table 7.3. The explanatory power of Model 3 (Table 7.3, Panel A) is marginally higher for the High GDP compared with Low GDP growth sub-sample, indicating overall higher value relevance under the High GDP growth condition. CHGEPS is value relevant for excess returns for both High and Low GDP growth samples, and the test of equality of coefficients indicates that the value revalue of CHGEPS is significantly higher for the High rather than Low GDP growth sub-sample. It is noted that all selected fundamental signals are value relevant for excess returns under the Low GDP growth condition.

The test of equality of coefficients reveals that the value relevance of SA and GM is significantly higher for the Low compared to High GDP growth sub-sample. It is also worth noting that the incremental R-Squared contribution from including non-earnings signals over earnings is higher for the Low GDP growth sub-sample, indicating higher combined value relevance for non-earnings signals. Again F_Score is value relevant under both High and Low GDP growth conditions (Table 7.3, Panel B) and the value relevance is not significantly different between the two groups.

7.4.3 Impact of level of inflation on value relevance of fundamental signals for excess returns

To examine any impact of inflation, the pooled sample is partitioned into High and Low inflation sub-samples based on median inflation level over the period (observations for years that the inflation rate is equal to or above the median fall under the High category and others the Low category). The regressions for Models 3 and 4 are estimated for High (n= 9373 [49 per cent]) and Low (n=9935) inflation observations and the results are reported in Table 7.3. As can be seen from Table 7.3 (Panel A), Model 3 performs slightly better for the Low compared with High inflation sub-sample, indicating an overall higher value relevance for contemporaneous excess returns under Low inflationary conditions.

Table 7.3: Contextual analysis for PYEN, level of GDP growth and level of inflation (H2a, H2b & H2c)

Panel A	PYEN			GDP Growth			Inflation rate		
Model 3	Good News	Bad News	Test of Equality	High	Low	Test of Equality	High	Low	Test of Equality
Dep. Var. ER	n = 11042	n = 8266		n = 9182	n = 10126		n = 9373	n = 9935	
	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff
α	**15.569*** **	-3.720		**-12.222*** *	-4.078		-1.699	-5.386	
CHGEPS	**-26.891*** **	**-42.348*** **	**15.457*** *	**-57.866*** **	**-49.259*** **	**-8.606***	**-52.612*** **	**-53.824*** **	1.212
INV	0.001	**0.018*** **	**-0.017*** *	0.007	**0.011*** **	-0.003	0.006	**0.013*** **	-0.007
AR	**-0.066*** **	**-0.056*** **	-0.011	**-0.057*** **	**-0.073*** **	0.016	**-0.076*** **	**-0.052*** **	-0.024
SA	**-0.054*** *	**-0.083*** **	0.029	**-0.110*** **	**-0.041***	**-0.069*** *	**-0.085*** **	-0.042	-0.042
LF	-0.017	**-0.065*** **	0.048	-0.027	**-0.062*** **	0.035	**-0.039***	**-0.054*** **	0.015
ETR	**-0.013*** **	-0.001	**-0.011*** **	-0.005	**-0.012*** **	0.006	**-0.010*** **	**-0.007*** **	-0.003
GM	**-0.172*** **	**-0.185*** **	0.014	**-0.159*** **	**-0.217*** **	**0.058*** **	**-0.174*** **	**-0.190*** **	0.016
AQ	**-13.860*** *	-6.457	-7.403	**-11.677*** *	**-12.682*** *	1.006	**-9.729***	**-17.615*** **	7.885
CAPX	**-0.013*** **	-0.004	-0.009	**-0.016*** **	**-0.007***	-0.009	**-0.013*** **	**-0.011*** *	-0.001
LEV	-0.007	**-0.038*** **	**0.032*** **	**-0.024*** **	**-0.023*** **	-0.001	**-0.042*** **	0.001	**-0.043*** **
CF	**-0.728*** **	**-0.591*** **	-0.137	**-0.728*** **	**-0.801*** **	0.073	**-0.768*** **	**-0.777*** **	0.009
GW	-0.006	**-0.010***	0.004	**-0.015*** *	**-0.010***	-0.005	**-0.012***	**-0.014*** *	0.002
CDACCR	**-34.845*** **	**-45.489*** **	-10.644	**-42.217*** **	**-53.361*** **	11.145	**-41.537*** **	**-53.770*** **	12.232
Adj. R-Sq 1	0.095	0.128		0.172	0.156		0.156	0.187	
Adj. R-Sq 2	0.049	0.080		0.124	0.093		0.101	0.131	
***Panel B :** Contextual Analysis for F_Score*									
Model 4	Good News	Bad News	Test of	High	Low	Test of	High	Low	Test of
Dep.Var	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff
α	**-7.907*** *	**-16.371*** **		**-33.57*** **	**-23.924*** **		**-28.992*** **	**-19.890*** **	
CHGEPS	**-39.397*** **	**-55.262*** **	**15.865*** *	**-77.331*** **	**-68.896*** **	**-8.434***	**-69.805*** **	**-76.660*** **	6.855
F_Score	**3.217*** **	**1.695*** **	**1.521*** **	**3.231*** **	**2.937*** **	0.294	**3.824*** **	**2.342*** **	**1.483*** **
Adj. R-Sq 1	0.070	0.087		0.144	0.112		0.130	0.143	
Controls : Year, Industry, Country, CodeLaw, PYEN, GDP Growth, Inflation rate									

Refer to Table 7.1 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm. Standard errors are CDACCR (3.6), AQ (3.5), CHGEPS (2.4) with others less than 0.1. Test of equality of coefficients is based on stacked regression. Sample is partitioned into Good and Bad PYEN (Good if change in prior year earnings is an increase and Bad if a decrease), High and Low GDP growth (years that GDP growth is equal to or above the median fall under High category and others Low category) and High and Low inflation (years that the inflation is equal to or above the median fall under the High category and others the Low category).

Again, earnings is value relevant for both the High and Low inflation sub-samples, with no significant difference between the High and Low inflation sub-samples.

Many non-earnings signals are value relevant for excess returns under both High and Low inflationary conditions and the test of equality of coefficients indicates that only the value relevance of LEV is significantly higher for the High compared to Low inflationary condition. The incremental R-Squared contribution from the non-earnings signals is similar between the High and Low inflation sub-samples. In terms of F_Score, reported in Table 7.3 (Panel B), it is value relevant for contemporaneous excess returns for both the High and Low inflation sub-samples and the test of equality of coefficients indicates that the value relevance of F_Score is significantly higher for the High compared with Low inflation sub-sample.

Overall results indicate that both earnings and non-earnings fundamental signals, including F_Score, are value relevant for excess returns under different contexts (to varying levels), and therefore support again for Hypotheses H2a, H2b and H2c. Further, the analyses indicate that the earnings signal is mostly affected by the type of PYEN, and GDP growth, while non-earnings signals are affected by GDP growth.

7.5 IFRS impact on the value relevance of fundamental signals for excess returns

Much research has been conducted using data from around the world to investigate the impact of IFRS on financial statements produced in different countries (Goodwin, Ahmed and Heaney (2008) (Australia); Haverals (2007) (Belgium); Blanchette, Racicot and Girard (2011) (Canada); Tsalavoutas and Evans (2010) (Greece); Bradbury and van Zijl (2005), Stent, Bradbury and Hooks (2010) and Kabir, Laswad and Islam (2010) (New Zealand); Horton and Serafeim (2010) and Iatridis (2010) (UK)). The main conclusion drawn from findings from these studies is that adoption of IFRS had considerable impact on recognition, measurement, classification and disclosure of financial statement elements, and therefore ultimately affects the quality of fundamental signals. One of the accounting quality aspects is value relevance (Francis & Schipper 1999). As such, this section of the study analyses the impact of IFRS on the value relevance of fundamental signals for contemporaneous excess returns and so addresses Hypotheses H2d, H2e and H2f.

As explained in Chapter 4, the impact of IFRS on the value relevance of fundamental signals for excess returns is examined using interaction terms for each fundamental signal, including F_Score, with IFRS, as well as using stacked regression (Atwood et al. 2011). Accordingly, the following regression models, which were explained in Chapter 4 and are repeated here for convenience, are employed to examine the impact of IFRS on the value relevance of the selected fundamental signals.

IFRS impact on the value relevance of individual fundamental signals

$$\mathrm{ER}_i = \propto + \beta_0\,\mathrm{CHGEPS}_i + \textstyle\sum_{j=1}^{12} \beta_{ij}\mathrm{Signals}_{ij} + \beta_{13}\mathrm{IFRS} * \mathrm{CHGEPS}_i + \textstyle\sum_{j=14}^{25} \beta_{ij}\mathrm{IFRS} * \mathrm{Signals}_{ij} + \sum \mathrm{Yr} + \sum \mathrm{In} + \sum \mathrm{Cnt} + \mathrm{Codelaw} + \varepsilon_j \qquad (9)$$

$$ER_i = PreIFRS\ x\ [\propto_0 + \propto_1\ \mathrm{CHGEPS}_i + \textstyle\sum_{j=2}^{13} \propto_{ij}\ \mathrm{Signals}_{ij}\,] + PostIFRS\ x\ [\beta_0 + \beta_1\,\mathrm{CHGEPS}_i + \textstyle\sum_{j=2}^{13} \beta_{ij}\mathrm{Signals}_{ij}] + \sum \mathrm{Yr} + \sum \mathrm{In} + \sum \mathrm{Cty} + \mathrm{Codelaw} + \varepsilon_j \qquad (10)$$

IFRS impact on the value relevance of F_Score

$$\mathrm{ER}_i = \propto + \beta_0\,\mathrm{CHGEPS}_i + \beta_1\,\mathrm{F\_Score}_i + \beta_2\,\mathrm{IFRS} * \mathrm{F\_Score}_i + \sum \mathrm{Yr} + \sum \mathrm{In} + \sum \mathrm{Cnt} + \mathrm{Codelaw} + \varepsilon_j \qquad (11)$$

$$ER_i = PreIFRS\ x\ [\propto_0 + \propto_1\ \mathrm{CHGEPS}_i + \propto_2\ \mathrm{F\_Score}_i\,] + PostIFRS\ x\ [\beta_0 + \beta_1\,\mathrm{CHGEPS}_i + \beta_2\,\mathrm{F\_Score}_i] + \sum \mathrm{Yr} + \sum \mathrm{In} + \sum \mathrm{Cty} + \mathrm{Codelaw} + \varepsilon_j \qquad (12)$$

Where IFRS is an indicator variable coded 1 for observations in the post-IFRS period (2006-2012) and 0 otherwise (2001-2004), and all other variables are as defined previously in this chapter (and Chapter 4). Models 9 and 10 are used to examine IFRS impact on the value relevance of individual fundamental signals, whereas Models 11 and 12 test the impact of IFRS on the value relevance of the aggregated fundamental score (F_Score).

When examining the impact of IFRS on the value relevance of fundamental signals for contemporaneous excess returns, extended analyses involving the same contextual variables used earlier in this chapter, in terms of Good or Bad prior year news (PYEN), level of GDP growth and level of inflation, are included.

7.5.1 IFRS impact on the value relevance of individual fundamental signals for contemporaneous excess returns

The regression results from estimating Models 9 and 10 that relate to Hypotheses 2d and 2e are reported in Tables 7.4 and 7.5.

The results show that the interaction of current year change in earnings (IFCHGEPS) is significant at 1 per cent for the pooled sample and Common law sub-sample. The stacked regression results (Model 10) reported in Table 7.5 indicate that earnings (CHGEPS) is value relevant for contemporaneous excess returns in pre-(n= 4107 [21 per cent]) and post-IFRS (n= 15201) periods for the pooled sample and Code and Common law sub-samples. The test of equality of coefficients shows that the coefficient for CHGEPS is significantly lower in the post- compared with pre-IFRS period for the pooled sample and Common law sub-sample. The test further reveals that the coefficient for CHGEPS is not significantly different between the pre- and post-IFRS periods for the Code law sub-sample, with a lower coefficient in the post-IFRS period. Therefore, it is inferred that the value relevance of earnings decreased after adoption of IFRS, particularly for Common law countries.

Clarkson et al. (2011) also report a similar finding of a decrease in the value relevance of earnings for Common law countries. Some other IFRS literature also documents evidence of a decrease in the value relevance of earnings in countries such as Spain and Italy (Callao, Jarne & Laínez 2007; Devalle, Onali & Magarini 2010). On the contrary, other research documents that the value relevance of earnings increased in certain countries after adoption of IFRS, such as for Germany (Jermakowicz, Prather-Kinsey & Wulf 2007), France and the UK (Devalle, Onali & Magarini 2010). However, these studies use data for very limited time periods[68] and much smaller samples than this current study.

In terms of non-earnings fundamental signals, the interaction of change in selling and administrative expenses (SA) with IFRS (IFSA) is significant for the pooled sample and Common law sub-sample (Table 7.4). Similarly, the test of equality of coefficients based on stacked regression results reported in Table 7.5 shows that the coefficient for SA is significantly lower in the post- compared to pre-IFRS period for the pooled sample and

[68] Clarkson et al. (2011) use data from 2004 and 2005, Callao, Jarne & Laínez (2007) use data from 2004 and 2005, Devalle, Onali & Magarini (2010) use data from 2002 to 2007.

Common law sub-sample. Therefore, it is inferred that the value relevance of SA decreased significantly after adoption of IFRS for Common law countries.

Table 7.4: IFRS impact on the value relevance of fundamental signals based on interaction of IFRS with each signal (H2d & H2e)

Model 9 Dep. Var. ER	Pooled Sample	Code Law	Common Law
	N = 19308	n =10133	n = 9175
	Clusters = 2908	Clusters = 1495	Clusters = 1413
	R-Sq = 0.174	R-Sq = 0.211	R-Sq = 0.173
	Coef.	Coef.	Coef.
α	-5.798	-1.724	7.232
CHGEPS	-44.511	-42.528	-43.004
INV	0.001	0.001	0.008
AR	-0.063	-0.092	-0.017
SA	-0.204	-0.141	-0.232
LF	0.022	0.047	-0.011
ETR	-0.008	-0.009	-0.007
GM	-0.248	-0.228	-0.157
AQ	-15.396	5.876	-30.327
CAPX	-0.001	0.005	-0.007
LEV	-0.039	0.053	-0.069
CF	-0.422	-0.390	-0.425
GW	-0.008	-0.002	-0.016
CDACCR	-34.404	-38.605	-31.422
IFRS	-1.485	-1.646	-1.299
IFCHGEPS	**16.382*** **	11.383	**19.625*** **
IFINV	0.009	0.008	0.006
IFAR	-0.002	0.020	-0.041
IFSA	**0.175*** **	0.076	**0.235*** **
IFLF	**-0.073** **	-0.068	-0.065
IFETR	0.485	-1.135	4.325
IFGM	**0.088*** **	0.059	0.057
IFAQ	10.948	**-16.841** **	**46.936*** **
IFCAPX	-0.012	-0.010	-0.011
IFLEV	0.019	-0.019	0.014
IFCF	**-0.336*** **	**-0.285** **	**-0.407** **
IFGW	-0.003	-0.004	0.000
IFCDACCR	-7.288	-2.682	-12.932
Controls : Years, Industries, Countries, PYEN, GDP, INF and Code Law- only for pooled sample			

Refer to Table 7.1 for variable definitions. IFRS impact is measured based on the interaction of each fundamental signal with IFRS where IFRS is an indicator variable coded 1 for observations in the post-IFRS period (2006-2012) and 0 otherwise (2001-2004). Interaction variables start with "IF" followed by the variable name. For example, IFCHGEPS represents the interaction of CHGEPS with IFRS. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm.

Table 7.5: IFRS impact on the value relevance of fundamental signals based on stacked regression (H2d & H2e)

Panel A **Model 10** Dep. Var. ER	Pooled sample			Code Law			Common Law		
	Pre-IFRS (a)	Post-IFRS (b)	Test of Equality (a-b)	Pre-IFRS (a)	Post-IFRS (b)	Test of Equality (a-b)	Pre-IFRS (a)	Post-IFRS (b)	Test of Equality (a-b)
	n = 4107	n =15201		n =2149	n =7984		n =1958	n =7217	
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff
α	7.468	6.296		-12.780	**8.580****		**18.255****	-5.871	
CHGEPS	**-42.105*****	**-29.034*****	**-13.071***	**-41.312*****	**-31.844*****	-9.468	**-39.579*****	**-24.408*****	**-15.171***
INV	0.001	**0.010*****	-0.009	0.001	**0.010****	-0.009	0.007	**0.014***	-0.007
AR	**-0.058****	**-0.065*****	0.007	**-0.089****	**-0.071*****	-0.018	-0.017	**-0.058*****	0.041
SA	**-0.188*****	-0.030	**-0.158*****	**-0.144****	**-0.066****	-0.078	**-0.211*****	0.001	**-0.212*****
LF	0.009	**-0.056*****	**0.065***	0.046	-0.026	0.072	-0.016	**-0.078*****	0.062
ETR	-0.007	**-0.008*****	0.001	-0.010	**-0.008*****	-0.002	0.000	**-0.008****	0.008
GM	**-0.242*****	**-0.160*****	**-0.082*****	**-0.230*****	**-0.168*****	-0.062	**-0.158*****	**-0.099*****	-0.059
AQ	**-17.112*****	-5.113	-11.999	3.763	**-11.494***	**15.257****	**-29.677*****	16.913	**-46.590*****
CAPX	-0.004	**-0.013*****	0.009	0.003	-0.006	0.009	-0.011	**-0.018*****	0.007
LEV	**-0.038*****	**-0.021*****	-0.017	0.049	**0.035*****	0.014	**-0.064*****	**-0.055*****	-0.009
CF	**-0.425*****	**-0.761*****	**0.336*****	**-0.390*****	**-0.677*****	**0.287****	**-0.468*****	**-0.832*****	**0.364*****
GW	-0.009	**-0.012****	0.003	-0.005	-0.006	0.001	-0.013	**-0.015****	0.002
CDACCR	**-34.441*****	**-41.499*****	7.058	**-39.080*****	**-41.081*****	2.001	**-32.630*****	**-44.096*****	11.466
Adj. R-Sq 1	0.211	0.149		0.229	0.185		0.217	0.148	
Adj. R-Sq 2	0.172	0.102		0.166	0.129		0.173	0.099	
Controls : Years, Industries , Countries, PYEN, GDP, INF and Code Law- only for pooled sample									

Refer to Table 7.1 for variable Definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% level respectively. Results are based on robust standard errors clustered by firm. Standard errors are CDACCR (4.18), AQ (3.4), CHGEPS (3.6), with others less than 0.1. Adj. R-Sq 1: Adjusted R^2 for the full model, Adj. R-Sq 2: Adjusted-R^2 for the earnings alone model. IFRS impact is measured using test of equality of coefficients is based on stacked regression. Pre-IFRS is from 2001 to 2004 and the post-IFRS period is from 2006 to 2012.

The interaction of change in labour force (LF) with IFRS (IFLF) variable is significant for Model 9, but only for the pooled sample (Table 7.4). The stacked regression results reported in Table 7.5 show that LF is value relevant for excess returns only in the post-IFRS period for the pooled sample and Common law sub-sample, with a higher coefficient compared to the pre-IFRS period. The test of equality of coefficients reported in Table 7.5 also indicates that the coefficient for LF is significantly higher in the post- compared to pre-IFRS period, again for only the pooled sample. Therefore, it is concluded that the value relevance of LF increased following adoption of IFRS for the pooled sample.

The next variable with a reported significant impact of IFRS on value relevance is change in gross margin (GM). As can be seen from Table 7.4, the interaction of GM with IFRS (IFGM) is significant only for the pooled sample. Table 7.5 documents that GM is value relevant in both the pre- and post-IFRS periods for all analyses, with a lower coefficient in the post-IFRS period. The test of equality of coefficients reveals that the GM coefficient is significantly less in the post- compared to pre-IFRS period only for the pooled sample. Therefore, it is inferred that the value relevance of GM for contemporaneous excess returns decreased significantly following adoption of IFRS for the pooled sample.

When the audit qualification (AQ) variable is considered, Table 7.4 indicates that the interaction of AQ with IFRS (IFAQ) is significant for both Code and Common law sub-samples but not the pooled sample. When looking at the stacked regression results documented in Table 7.5, they indicate that AQ is value relevant for excess returns for Common law observations only in the pre-IFRS period, whereas for Code law observations this is the case only in the post-IFRS period with the expected sign. The test of equality of coefficients indicates that the coefficient for AQ is significantly higher in the post-IFRS period for Code law observations, while it is significantly lower in the post-IFRS period for Common law observations. Therefore, it is inferred that the value relevance of AQ increased for Code law countries, while it decreased for Common law countries, after adoption of IFRS.

Results from estimating Model 9, reported in Table 7.4, show that the interaction of change in cash flow from operations (CF) with IFRS (IFCF) is significant for the pooled as well as Code and Common law sub-samples. The stacked regression results show that

CF is value relevant for contemporaneous excess returns in the pre- and post-IFRS periods for the pooled sample and Code and Common law sub-samples, with a higher coefficient in the post- compared to pre-IFRS period. The test of equality of coefficients indicates that the coefficient for CF is significantly higher in the post- compared to pre-IFRS period for all analyses. Therefore, it is inferred that the value relevance of change in cash flow from operations (CF) improved significantly after adoption of IFRS for both Code and Common law countries.

Apart from the above discussed variables, the test of equality of coefficients and the interactions with IFRS indicate that there is no significant impact of IFRS on the value relevance of the remaining signals (INV, AR, ETR, CAPX, LEV, GW, CDACCR). AbuGhazaleh, Al-Hares and Haddad (2012) report that goodwill impairment under IFRS is value relevant in a UK context. Hamberg and Beisland (2014) document that goodwill impairment based on an impairment only approach[69] is not significantly associated with stock returns in Sweden, and therefore is not value relevant. This study also finds a slight increase in the coefficient of GW in the post- compared to pre-IFRS period, but this increase is not significant. Therefore, it is inferred that the value relevance of change in goodwill from last year has not significantly increased following adoption of IFRS in European and Australian contexts.

Furthermore, the literature reports evidence that there is no significant change in earnings management after adoption of IFRS (Jeanjean & Stolowy 2008; Van Tendeloo & Vanstraelen 2005). This study's findings show that although there is an increase in the coefficient of CDACCR in the post- compared to pre-IFRS period for all samples, this increase is not significant. Therefore, it can be concluded that the value relevance of discretionary accruals has not increased following adoption of IFRS for both the pooled sample and sub-samples of Code and Common law countries.

If the adjusted R-Squared value is a proxy for the overall value relevance of the model, Table 7.5 can be interpreted as reporting that the value relevance of the full model is considerably lower for the post (0.149) - compared to pre-IFRS (0.211) period for all analyses. However, the incremental R-Squared contribution from including non-earnings signals is slightly higher in the post- compared to pre-IFRS period for the pooled sample

[69] Based on standard IFRS 3

and lower for the Code law sub-sample, whereas it is similar for the Common law sub-sample.

As a robustness test, similar analysis is conducted for a sample (pre-IFRS n = 3592 [36 per cent] and post-IFRS n = 6444 for the pooled sample) that excludes the full IFRS transition period (2004-2006) and the GFC period (2007-2009). The results (untabulated) are consistent with the above findings, except that the value relevance of CF is not increased for Code law observations. Moreover, there is a slight increase in the combined value relevance of non-earnings signals for Common law observations. This could be due mostly to finding that the increase in the value relevance of CF corresponds with decrease in the value relevance of earnings for Common law countries. That is, cash flows seem to be more informative in terms of excess returns after adoption of IFRS.

Accordingly, the overall analysis supports the conclusion that the value relevance of earnings decreased after adoption of IFRS. Moreover, the value relevance significantly increased for LF (only for the pooled sample) and for CF, particularly for Common law countries. In addition, the value relevance of SA (for the pooled sample and Common law sub-sample) and GM (for the pooled sample) decreased significantly in the post- compared to pre-IFRS period. In terms of AQ, its value relevance increased for Code law countries, while it decreased for Common law countries following IFRS adoption. The combined value relevance of non-earnings signals slightly improved for Common law countries and decreased for Code law countries following adoption of IFRS. In summary, these results do not support Hypothesis H2d, but do support Hypothesis H2e for Common law countries, although not for Code law countries.

7.5.2 IFRS impact on the value relevance of aggregated fundamental score (F_Score) for contemporaneous excess returns

Table 7.6 documents results from estimating Models 11 and 12 that test IFRS impact on the value relevance of the aggregated fundamental score (F_Score) for contemporaneous excess returns.

As can be seen from Table 7.6 (Panel A), F_Score is value relevant for pre- and post-IFRS periods for the pooled sample as well as for Code and Common law sub-samples, with a higher coefficient in the post-IFRS period for all analyses.

Table 7.6: IFRS impact on the value relevance of F_Score (H2f)

Panel A: *Regression results for pre- and post-IFRS periods based on stacked regression*

Model 12 Dep.Var: ER	Pooled Sample			Code Law			Common Law		
	Pre-IFRS	Post-IFRS	Test of Equality	Pre-IFRS	Post-IFRS	Test of Equality	Pre-IFRS	Post-IFRS	Test of Equality
	n = 4107	n =15201		n =2149	n =7984		n =1958	n =7217	
	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff
α	-0.288	-18.870		**-19.689***	-0.092		2.129	-37.317	
CHGEPS	**-55.795*****	**-41.847*****	**-13.948***	**-60.255*****	**-47.270*****	-12.985	**-50.791*****	**-35.872*****	**-14.919****
F_Score	**2.033*****	**2.803*****	**-0.770****	**1.330*****	**1.835*****	-0.505	**2.751*****	**3.639*****	**-0.888****
Adj. R-Sq	0.174	0.119		0.169	0.137		0.186	0.124	
Adj. R-Sq	0.166	0.102		0.166	0.129		0.173	0.099	
Controls	*Years, Industries , Countries, PYEN, GDP, INF and Code Law country observations- only for pooled sample*								

Panel B: *Impact of IFRs on F_Score based on interaction terms*

Model 11 Dep.Var. ER	Pooled Sample	Code Law	Common Law
	N = 19308	n =10133	n = 9175
	Clusters = 2908	Clusters = 1495	Clusters = 1413
	R-Sq = 0.141	R-Sq = 0.159	R-Sq = 0.145
	Coef.	Coef.	Coef.
α	-20.348	-0.078	-13.310
CHGEPS	-58.112	-59.712	-53.309
F_Score	2.119	1.329	2.868
IFRS	-5.242	-4.278	-5.751
IFCHGEPS	**17.265*****	13.153	**18.280****
IFF_Score	**0.653***	0.487	**0.769***

Refer to Table 7.1 for variable definitions. Panel A examines the IFRS impact using the test of equality of coefficients is based on stacked regression. In panel B, IFRS impact is measured based on the interaction of each fundamental signal with IFRS where IFRS is an indicator variable coded 1 for observations in the post-IFRS period (2006-2012) and 0 otherwise (2001-2004). Interaction variables start with "IF" followed by the variable name. Interaction variables are designated by "IF" followed by the variable name. ***, **, * indicates statistical significance at the 1%, 5%, and 10% level respectively. Adj. R-Sq 1: Adjusted R^2 for the full model, Adj. R-Sq 2: Adjusted-R^2 for the earnings alone model. Results are based on robust standard errors clustered by firm. Standard errors are CHGEPS (3.6) and for F_Score less than 0.5.

The test of equality of coefficients indicates that the coefficient for F_Score is significantly higher in the post- compared to pre-IFRS period for the pooled sample and Common law sub-sample.

Providing corroborative evidence, the interaction of F_Score with IFRS (IFF_Score) is significant for the pooled sample and Common law sub-sample (Table 7.6, Panel B). Therefore, it is inferred that the value relevance of F_Score increased after adoption of IFRS, particularly for Common law countries. As such, these results provide support for Hypothesis H2f.

A similar test is carried out for the sample excluding the full IFRS transition (2004-2006) and GFC (2007-2009) periods and the results (untabulated) are consistent with the above findings.

7.5.3 IFRS impact on the value relevance of fundamental signals for Winners and Losers for contemporaneous excess returns

As discussed above in section 7.3.3, excess returns can represent either gains (Winners) or losses (Losers). In extended analysis, this section examines the impact of IFRS on the value relevance of fundamental signals for Winners and Losers. Models 9 and 10 are estimated for Winner and Loser[70] sub-samples and results are documented in Tables 7.7 and 7.8.

The overall value relevance of fundamental signals measured in terms of adjusted R-Squared is less in the post- compared to pre-IFRS period for both Winners and Losers. However, the value relevance of Model 10 is slightly higher for Losers compared to Winners both in pre- and post-IFRS periods. As far as the earnings signal (CHGEPS) is concerned, Table 7.7 (Panel A) indicates that CHGEPS is value relevant for contemporaneous excess returns for both Winners and Losers and in both the pre- and post-IFRS periods. The test of equality of coefficients reveals that the coefficient for CHGEPS is significantly lower in the post- compared to pre-IFRS period, but only for Winners. The interaction of CHGEPS with IFRS (IFCHGEPS) is significant for Winners (Table 7.7, Panel B). Therefore, it is concluded that the value relevance of earnings decreased in the post- compared to pre-IFRS period for Winners but not for Losers.

[70] How Winners and Losers are selected is explained in this Chapter on page177.

Table 7.7: IFRS impact on the value relevance of fundamental signals for Winners and Losers (H2d & H2e)

***Panel A:** IFRS impact on the value relevance of fundamental signals based on Model 10*

Dep. Var. ER	Winners		Test of Equality	Losers		Test of Equality
	Pre-IFRS	Post-IFRS		Pre-IFRS	Post-IFRS	
	n=2325	n=6444		n=1782	n=8757	
	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff
α	**35.979*** **	**40.043*** **		**-26.975*** **	**-25.347*** **	
CHGEPS	**-47.498*** **	**-33.848** **	**-13.650** **	**-11.626*** **	**-11.815*** **	0.189
INV	**-0.012* **	**0.010** **	**-0.023*** **	**0.014*** **	0.004	0.010
AR	-0.010	-0.023	0.014	**-0.031* **	**-0.028*** **	-0.003
SA	**-0.158*** **	**-0.077*** **	**-0.082* **	-0.041	0.013	**-0.053* **
LF	-0.019	**-0.040** **	0.021	**-0.041* **	-0.006	-0.035
ETR	0.003	**0.005* **	-0.002	**-0.007** **	**-0.007*** **	0.001
GM	**-0.129*** **	**-0.060*** **	**-0.069** **	**-0.093*** **	**-0.070*** **	-0.023
AQ	2.032	0.488	1.543	**-8.185*** **	-4.782	-3.403
CAPX	0.003	**-0.015*** **	**0.018** **	-0.009	**-0.009*** **	0.000
LEV	-0.023	0.004	**-0.027* **	**-0.018* **	**-0.013*** **	-0.005
CF	**-0.258** **	**-0.459*** **	**0.201* **	**-0.161** **	**-0.315*** **	**0.154** **
GW	0.012	0.008	0.004	-0.008	**-0.009** **	0.001
CDACCR	0.306	**-22.766*** **	**23.072** **	**-15.983*** **	**-24.401*** **	-8.418
Adj. R-Sq 1	0.164	0.133		0.184	0.150	
Adj. R-Sq 2	0.140	0.103		0.143	0.118	

***Panel B:** IFRS impact on the value relevance of fundamental signals based on Model 9*

	Winners	Losers
IFRS	-3.125	3.802
IFCHGEPS	**15.320** **	-0.613
IFINV	**0.023*** **	-0.010
IFAR	-0.018	0.006
IFSA	**0.104** **	**0.058** **
IFLF	-0.034	0.027
IFETR	0.723	0.517
IFGM	**0.069** **	0.024
IFAQ	-2.461	4.256
IFCAPX	**-0.016** **	-0.003
IFLEV	**0.028* **	0.005
IFCF	-0.166	**-0.149** **
IFGW	-0.005	-0.001
IFCDACCR	**-19.726* **	-7.260

Refer to Table 1 for variable definitions. Panel A examines the IFRS impact using the test of equality of coefficients is based on stacked regression. In panel B, IFRS impact is measured based on the interaction of each fundamental signal with IFRS where IFRS is an indicator variable coded 1 for observations in the post-IFRS period (2006-2012) and 0 otherwise (2001-2004). Interaction variables are designated with "IF" followed by the variable name. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Adj. R-Sq 1: Adjusted R^2 for the full model, Adj. R-Sq 2: Adjusted-R^2 for the earnings alone model. Results are based on robust standard errors clustered by firm. Standard errors are CDACCR (4.2), AQ (3.6), CHGEPS (2.8), with others less than 0.1 for Panel A.

With regards to the non-earnings signals, the analysis based on stacked regression and interactions with IFRS terms reveals that value relevance decreased for INV and for GM, while it increased for CAPX and CDACCR in terms of Winners in the post- compared to pre-IFRS period. The value relevance of CF increased for both Winners and Losers after adoption of IFRS. In terms of SA, the interaction of SA with IFRS (IFSA) is significant for both Winners and Losers and the test of equality of coefficients indicates that the coefficient for SA is significantly higher for both Winners and Losers (Table 7.7, Panel A) in the pre- compared to post-IFRS period. However, the SA coefficient is not significant for Losers in either the pre- or post-IFRS period. Therefore, it is inferred that the value relevance of SA decreased in respect of only Winners after adoption of IFRS.

For LEV, the interaction with IFRS is significant and the test of equality of coefficients also shows that the coefficient for LEV is significantly lower in the post- compared to pre-IFRS period for Winners. However, LEV is not significant in either the pre- or post-IFRS period for Winners. As such, it is concluded that the value relevance of LEV for contemporaneous returns is not significantly changed after adoption of IFRS.

When considering the combined value relevance of the non-earnings fundamental signals, the incremental R-Squared from including these signals is slightly higher for Winners and lower for Losers in the post- compared with pre-IFRS period. Therefore, it is concluded that the combined value relevance of non-earnings signals improved for Winners and decreased for Losers after adoption of IFRS.

In terms of aggregated fundamental score (F_Score), results based on stacked regression reported in Table 7.8 (Panel A) indicate that F_Score is value relevant in both pre- and post-IFRS periods for both Winners and Losers. However, the test of equality of coefficients based on stacked regression indicates no significant improvement in F_Score for Winners or Losers after adoption of IFRS. Even so, the test based on the interaction variable shows that the value relevance of F_Score increased for Winners in the post- compared to pre-IFRS period.

As a robustness test, the same analysis is carried out for the sample that excludes the full IFRS transition (2004-2006) and GFC (2007-2009) periods (Winners Pre-IFRS n= 2092, post-IFRS n = 2797; Losers pre-IFRS n = 1500, post-IFRS n = 3647). The results (untabulated) are mostly in agreement with the above findings. However, there is now no impact on the value relevance of SA and LEV and the value relevance of CDACCR increases for both Winners and Losers after adoption of IFRS. The value relevance of F_Score also increases for Winners after adoption of IFRS. Therefore, the results do not support Hypothesis H2d, but do provide supportive evidence for H2e and H2f in terms of Winners.

Table 7.8: IFRS impact on the value relevance of F_Score for Winners and Losers (H2f)

Dep. Var. ER	Panel A: Model 12						Panel B: Model 11	
	Winners			Losers			Full Sample	
	Pre-IFRS	Post-IFRS	Test of Equality	Pre-IFRS	Post-IFRS	Test of Equality	Winners	Losers
	n =2325	n =6444		n =1782	n =8757		n =8769	n =10539
	Adj. R^2 = 0.143	Adj. R^2 = 0.109		Adj. R^2 = 0.162	Adj. R^2 = 0.127		R-Sq = 0.121	R-Sq = 0.132
	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff	Coef.	Coef. Diff.
α	**32.265***	**33.325***		**- 35.667***	**-33.325***		22.853	-38.825
CHGEPS	**-55.330***	**-44.337***	**-10.992***	**-19.256***	**-19.247***	-0.009	-57.002	-18.993
F_Score	**0.883***	**1.156***	-0.274	**1.577***	**1.162***	0.414	0.889	1.505
IFRS							-4.257	6.527
IFCHGEPS							**13.153****	-0.258
IFF_Score							0.232	-0.353

Refer to Table 7.1 for variable definitions. Panel A examines IFRS impact using the test of equality of coefficients based on stacked regression. In Panel B, IFRS impact is measured based on the interaction of each fundamental signal with the IFRS, where IFRS is an indicator variable coded 1 for observations in the post-IFRS period (2006-2012) and 0 otherwise (2001-2004). Interaction variables are designated by "IF" followed by the variable name. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm. Standard errors are CHGEPS (3.5) and for F_Score less than 0.5.

7.6 Further tests

In this section, results from additional tests that examine the value relevance of fundamental signals and IFRS impact on the value relevance of these signals are reported.

7.6.1 Value relevance of fundamental signals for Extreme and Non-extreme stock performers in terms of excess returns and IFRS impact

As an additional test, the value relevance of both earnings and non-earnings fundamental signals and IFRS impact on this value relevance for Extreme and Non-extreme performers based on excess returns is examined next.

Following the method used by Beneish, Lee and Tarpley (2001), excess returns that are in the top (bottom) 2 per cent (after the 5 per cent winsorising of observations) are categorised as Extreme performers. Model 3 is estimated for both Extreme and Non-extreme sub-samples, and the results are reported in Annexure 7.3. Results indicate that Model 3 performs much better for observations with Extreme excess returns (Adjusted R-Squared of 0.346) than for the Non-extreme sub-sample (Adjusted R-Squared of 0.106). Therefore, overall it can be concluded that there is higher value relevance of fundamental signals for Extreme compared with Non-extreme performers in terms of excess returns. The earnings signal is value relevant for both Extreme and Non-extreme performer sub-samples, and more non-earnings signals are value relevant for the Extreme compared to the Non-extreme performer sub-sample. The value relevance of the earnings and all non-earnings signals, including F_Score, but except for INV and GW, are significantly higher for Extreme performers compared to Non-extreme performers. As such, these signals are useful in distinguishing between Extreme and Non-extreme performers' returns and assessing these stocks, especially for Extreme performers (Beneish et al., 2001). Overall, these results support Hypotheses H2a, H2b and H2c.

Results for the impact of IFRS on the value relevance of fundamental signals for Extreme and Non-extreme performers in terms of contemporaneous excess returns are documented in Annexure 7.4. These results indicate that the overall value relevance of fundamental signals, represented by the adjusted R-Squared, is lower in the post- compared to pre-IFRS period for both Extreme and Non-extreme performer sub-samples. CHGEPS is value relevant in both pre- and post-IFRS periods for both Extreme and Non-extreme performers. However, there is no significant difference in the value relevance of earnings (CHGEPS) between the pre- and post-IFRS period for either Extreme or Non-extreme performer sub-samples. In terms of non-earnings fundamental signals, results indicate that value relevance decreased for SA and GM, while it increased for CF for both Extreme and Non-extreme performer sub-samples after adoption of IFRS. However, the value relevance decreased for LEV and increased for CDACCR only for the Extreme performer sub-sample following adoption of IFRS.

It is also noted that the incremental R-Squared contribution from including non-earnings signals over earnings alone in the model increased for the Extreme performer sub-sample and decreased for the Non-extreme performer sub-sample in the post- compared to pre-IFRS period. IFRS impact on the value relevance of F_Score for Extreme and Non-extreme performers' excess returns is reported in Annexure 7.5. The results indicate that the value relevance of F_Score increased for Extreme performers, but not for the Non-extreme sub-sample in the post- compared to pre-IFRS period. Therefore, the results support only Hypotheses H2e and H2f for the Extreme performer's sub-sample.

7.5.2 Value relevance of fundamental signals for excess returns for Growth stocks and Value stocks and IFRS impact

As another additional test, the usefulness of fundamental signal information in terms of its value relevance for Growth and Value stocks post year 2000 is examined.

The book-to-market (BM) effect is well researched in finance and found to be useful in predicting stock returns (Fama & French 1992; Fama & French 1995; Kothari & Shanken 1997; Pontiff & Schall 1998). Low BM firms in general are termed Growth or Glamour stocks, while high BM firms are referred to as Value stocks. Following the method used by Fama and French (1995), the bottom 30 per cent of the pooled sample by BM ratio is categorised as low BM firms (Growth stocks) and the top 30 per cent as high BM firms (Value stocks). Regressions based on Models 3 and 4 are run for both Growth and Value stock sub-samples, and the results are reported in Annexure 7.6.

The results indicate that current year change in earnings per share (CHGEPS) is value relevant for both Growth and Value stocks in the direction expected and the value relevance of CHGEPS for contemporaneous excess returns is significantly higher for Growth compared to Value stocks. There are several non-earnings fundamental signals (AR, LF, GM, AQ, LEV, CF, GW, CDACCR), including F_Score, that are value relevant for both Growth and Value stocks, with more fundamental signals value relevant for Value than for Growth stocks. However, the incremental value relevance from non-earnings signals over earnings is slightly higher for Growth rather than Value stocks, but there is no significant difference in the value relevance of F_Score between the two sub-samples. This analysis points to the conclusion that both earnings and several non-earnings fundamental signals are useful in distinguishing between and assessing Growth and Value stocks.

These results again support Hypotheses H2a, H2b and H2c, which posit that the earnings signal, non-earnings signals and F_Score are value relevant for excess returns. These different robust analyses provide consistency of results, adding to the reliability of the findings.

In addition to the above analysis, Models 9, 10, 11 and 12 are estimated for both Growth and Value stock sub-samples to investigate the impact of IFRS on the value relevance of fundamental signals for contemporaneous excess returns. Results are reported in Annexures 7.7 and 7.8.

Similarly, to previous analyses, the overall value relevance of Models 10 and 12 is lower in the post- compared to pre-IFRS period for Growth and Value stocks. The earnings signal is value relevant for both Growth and Value stocks in both pre- and post-IFRS periods. However, the value relevance of earnings significantly decreased after adoption of IFRS, mainly for Growth stocks. In terms of non-earnings signals, value relevance decreased for GM, while it increased for CF for both Growth and Value stocks. Also, value relevance decreased for SA and LEV for Growth stocks, while that for GW increased for Value stocks after adoption of IFRS. The incremental R-Squared contribution from including non-earnings fundamental signals over earnings is higher in the post- compared to pre-IFRS period for Growth stocks, while similar for Value stocks. This could be due to the decreased value relevance of earnings being compensated for by the non-earnings signals for Growth stocks. However, there is no significant increase in the relevance of F_Score (Annexure 7.8) for both Growth and Value stocks after adoption of IFRS. As such, the results support only Hypothesis H2e and only for Growth stocks.

7.5.3 Country-wise value relevance of fundamental signals and IFRS impact

As explained in Chapter 6, section 6.5, specific country factors are important in determining the quality of accounting information and affect the expected quality improvement from IFRS adoption (Stadler & Nobes 2014). Therefore, as a robustness test, the value relevance of fundamental signals and the impact of IFRS on this is estimated for each country's observations selected for this study and compared. The smaller sample sizes for country analyses compared with the main analyses in this study need to be noted in interpreting the results.

The results (untabulated) indicate that both earnings and non-earnings fundamental signals are value relevant and non-earnings fundamental signals have incremental information content over earnings that is value relevant for excess returns in each country. The Adjusted R-Squared value of the model (overall value relevance) is comparatively higher for Code law countries than Common law countries and also the combined value relevance of non-earnings fundamental signals incremental to earnings is higher for Code law countries compared to Common law countries. F_Score is significantly associated with contemporaneous excess returns for all countries.

In terms of IFRS impact, the analyses reveal that (results untabulated) the overall value relevance of the model is lower in the post- compared to pre-IFRS period for all countries except Sweden. IFRS had a negative impact on the value relevance of earnings signals for all countries except for Denmark, Portugal and Sweden. The combined value relevance from non-earnings fundamental signals incremental to earnings is lower in Belgium, Denmark, Portugal, Spain and Australia, while higher in Finland, Poland, Sweden and UK, and similar in France and Italy, in the post compared to pre-IFRS period. The countries that are most affected by IFRS adoption in terms of value relevance are in Sweden, UK and Australia. The most frequently affected variables for value relevance after IFRS adoption in different countries are CHGEPS, SA, LF, ETR, AQ, LEV and CF. Previous analysis concluded that the value relevance of earnings significantly decreased in Common law countries after adoption IFRS. However, this analysis indicates that the value relevance of earnings significantly decreased for the UK and not for Australia following IFRS adoption. Value relevance increased for CF and decreased for SA and LF in both Common law countries (UK and Australia) in the post- compared to pre-IFRS period.

7.6. Chapter summary

This chapter analyses the value relevance of fundamental signals for excess returns and the impact of IFRS on value relevance for the selected pooled sample and various sub-samples, such as Code and Common law countries, Winners and Losers in terms of excess returns, Extreme and Non-extreme performers, Growth and Value stocks and also contextual analysis based on Good and Bad PYEN, High and Low GDP growth and High and Low inflation. One earnings fundamental signal and 12 non-earnings fundamental signals are included as explanatory variables in order to assess their value relevance, and the impact of IFRS on their value relevance, for contemporaneous excess returns. As such, this study contributes to better understanding of the value relevance of these fundamental signals and the impact of IFRS on this value relevance in years post-2000. A summary of all findings for this chapter is provided in Table 7.9.

The analyses reveal that both earnings and the selected non-earning signals contain information that is value relevant for excess returns. All identified variables are value relevant for the pooled sample and Common law sub-sample, and all fundamental signals are value relevant in the direction expected, with the exception of INV for the pooled sample. The analyses indicate that the value relevance of LF, AQ, CAPX, LEV, CF, and GW is significantly higher for Common law country observations, while the value relevance of AR and GM is significantly higher for Code law country observations than their counterparts. The combined value relevance of non-earnings signals over earnings is similar between the two sub-samples. However, the value relevance of the aggregated fundamental score (F_Score) is significantly higher for Common compared with Code law country observations. These findings point to the conclusion that the selected fundamental signals individually, in combination and in aggregated form are useful for market participants in their decision-making, with some differences based on Code and Common law countries.

Analysis based on Winners and Losers indicates that more fundamental signals are value relevant for Losers compared with Winners. Earnings and cash flows from operations are highly value relevant for Winners, while some non-earnings signals, such as ETR, AQ, and GW, are more associated with Losers than their counterparts. The combined value relevance of non-earnings signals over earnings is higher for Losers. The F_Score is value relevant for both Winners and Losers, but not significantly different between the two sub-samples.

Additional analysis of the value relevance of fundamental signals indicates that both earnings and many non-earnings signals, including F_Score, are highly value relevant for contemporaneous excess returns for Extreme compared to Non-extreme performers. In addition, analysis shows that earnings and many non-earnings signals are value relevant for contemporaneous excess returns for Growth and Value stocks, with significantly higher value relevance of the earnings signal for Growth compared to Value stocks.

Table 7.9: Summary of findings for value relevance of fundamental signals for excess returns and IFRS impact on value relevance of these signals for the period 2001 -2012 & relates to H2a to H2f

Variables	Value relevance of fundamental signals					Contextual analysis			IFRS impact on value relevance of fundamental signals				
	Pooled	Code Law	Common Law	Pooled		PYEN	GDP Gr	IFL	Pooled sample	Code law	Common Law	Winners	Losers
				Winners	Losers								
CHGEPS	√***	√***	√***	√√***	√***	#**	#*		↓***		↓***	↓**	
INV	√**	√*	√**		√**	#**						↓***	
AR	√***	√***	√***	√**	√***				↓***		↓***	↓*	
SA	√***	√***	√**	√√***			#**						
LF	√***		√√***						↑*				
ETR	√***	√***	√**	√*	√√***	#***							
GM	√***	√√***	√***	√***	√***		#***		↓***			↓**	
AQ	√***		√√***		√√***					↑**	↓***		
CAPX	√***		√√***	√***	√***							↑**	
LEV	√***	√***	√√***		√***	#***		#***					
CF	√***	√***	√√***	√√***	√***				↑***	↑**	↑**	↑*	↑**
GW	√***		√√***	√√***	√***								
CDACCR	√***	√***	√***	√***	√***							↑**	
Incremental R^2 from non-earnings signals	0.055	0.062	0.057	0.026	0.033	G 0.046 B 0.048	H 0.048 L 0.063	H 0.055 L 0.056	Pre 0.039 Post 0.047	Pre 0.063 Post 0.056	Pre 0.044 Post 0.049	Pre 0.024 Post 0.027	Pre 0.041 Post 0.032
F_Score	√***	√***	√***			#***		#***	↑**		↑**		

Refer to Annexure 7.1 for variable definitions, *** significant at 1%, ** significant at 5%, * Significant at 10%

√	Value relevant for excess returns	√√	Value relevance is significantly higher than for its counterpart
	Variable is significant, but not in the direction anticipated		Variable is not significant for the sample that excludes GFC and IFRS transition period
↑	Value relevance has increased	↓	Value relevance has decreased
G	Good news	B	Bad news
H	high	L	Low
Pre	Pre-IFRS	Post	Post-IFRS
#	Value relevance is significantly different based on the contextual factor		

PYEN – prior year earnings news, GDP Gr – Gross Domestic Product growth, IFL – level of inflation rate

Analysis of the impact of IFRS on the value relevance of the selected fundamental signals indicates that overall, the value relevance of the models is lower in the post- compared with pre-IFRS period for the pooled sample, for both Code and Common law sub-samples, for both Winners and Losers, for both Extreme and Non-extreme performers, and for both Growth and Value stocks. The impact of IFRS on the value relevance of the fundamental signals for contemporaneous excess returns is negative for earnings, especially for Common law country observations, and for Winner and Growth stock observations, whilst it is positive for cash flow from operations for all analyses. Apart from that, the value relevance of several non-earnings signals, namely SA, LF, GM, AQ, CAPX, LEV and CDACCR, is affected by adoption of IFRS contingent on the sample or sub-sample, such as for the pooled, Code and Common law country observations, and Winners and Losers.

The combined value relevance of non-earnings signals over earnings is higher for Common law country observations, for Winners, for Extreme performers and for Growth stocks, while it is lower for Code law country observations, for Losers and for Non-extreme performers in the post- compared to pre-IFRS period. At the same time, the value relevance of F_Score increased significantly for some sub-samples, such as Common law country observations, Winners and Extreme performers, with no significant change in the value relevance of these fundamental signals for other sub-samples.

The contextual analysis shows that the value relevance of earnings and some non-earnings signals is significantly different contingent on the nature of PYEN and level of GDP growth. The models perform much better under the Bad PYEN, High GDP growth and Low inflationary conditions; however, many non-earnings signals are value relevant under Low GDP growth conditions. There is no significant impact on the value relevance of individual fundamental signals contingent on the level of inflation. The F_Score performs much better under the Good PYEN condition and High inflation.

Overall, the findings point to the conclusion that both earnings and non-earnings signals over earnings are value relevant for contemporaneous excess returns, and variables are highly value relevant in Common law countries for Winners and Extreme performers' returns compared with their counterparts. The adoption of IFRS has a negative impact on the value relevance of earnings and mostly positive impact on that of non-earnings fundamental signals, including cash flow from operations. The value relevance of fundamental signals is affected by some contextual factors, such as Good or Bad PYEN and level of GDP growth. Therefore, the overall results reported in this chapter support Hypotheses H2a, H2b, H2c. However, the results support H2e and H2f only for some sub-samples and H2d is not supported at all.

CHAPTER 8: ANALYSTS' EFFICIENCY IN USING FUNDAMENTAL SIGNALS AND IFRS IMPACT ON THIS EFFICIENCY

8.1 Introduction

This chapter extends the emphasis on earnings and excess returns reported in the two prior chapters to focus on analysts' forecasts. Before doing this, it is important to recall that selection of the fundamental signals chosen for this study is based mainly on the work of Lev and Thiagarajan (1993). That study identified 12 non-earnings fundamentals that are claimed by analysts to be useful in security valuation; namely inventory, accounts receivable, capital expenditure, research and development expenditure, gross margin, sales and administrative expenses, provision for doubtful receivables, effective tax rate, order backlog, labour force, last-in-first-out (LIFO) earnings and audit qualification. Those authors selected these fundamental signals based on written pronouncements from financial analysts published in a variety of sources, such as the Wall Street Journal and Barron's from 1984 to 1990, the Value Line publication, major security firms' (e.g. brokers') commentaries, etc. (Lev & Thiagarajan 1993 p.191). Lev and Thiagarajan (1993) examined the value relevance of these signals for contemporaneous abnormal returns and found that these signals contain incremental value relevance over earnings and capture earnings persistence and growth.

In a later study, Abarbanell and Bushee (1997) comment that "predicting accounting earnings, as opposed to explaining security returns, should be the central task of fundamental analysis" (p.1). They then test the predictive ability of eight of the 12 non-earnings fundamental signals identified by Lev and Thiagarajan (1993) for one-year-ahead change in earnings per share and analysts' efficient use of these fundamental signals for forecast revisions.

This current study in part replicates the Lev and Thiagarajan (1993) and Abarbanell and Bushee (1997) studies using data from years' post-2000 and including eight fundamental signals drawn from Lev and Thiagarajan (1993) plus four other signals. Using these 12 fundamental signals, this current study examines the ability of fundamental signals to predict one-year-ahead change in earnings per share (Chapter 6), the value relevance of these signals for contemporaneous excess returns (Chapter 7), and importantly, IFRS impact on both.

This chapter examines analysts' efficient use of fundamental signals (H3a and H3b)[71] and the impact of IFRS on the efficiency with which analysts use these fundamental signals (H3c and H3d)[72]. As such, the remainder of the chapter is organised as follows. Section 8.2 discusses the significant research contribution emanating from results presented in this chapter. Section 8.3 presents the descriptive statistics for the sample considered in this chapter's analysis. Section 8.4 discusses analysts' efficiency in identifying fundamental signals for predicting one-year-ahead change in earnings per share (CEPS1). Section 8.5 reports results from testing analysts' efficiency in using the selected fundamental signals in predicting CEPS1. Section 8.6 discusses analysts' efficiency in using fundamental signals for forecasting positive and negative change in earnings per share. Then section 8.7 discusses and tests IFRS impact on analysts' efficiency in selecting and using fundamental signals for earnings forecasts. Section 8.8 reports the IFRS impact on analysts' efficiency in using fundamental signals for forecasting positive and negative change in earnings per share. Section 8.9 documents the results from testing analysts' efficiency in using the fundamental signals contingent on legal regime and IFRS impact on this efficiency. Then section 8.10 explores analysts' efficiency in terms of incorporating earnings information embedded in the selected fundamental signals and priced in the market into their earnings forecasts, together with the impact of IFRS on this efficiency. Finally, section 8.11 concludes the chapter.

8.2 Research contribution

This chapter addresses the key research gap identified in Chapter 3 in relation to analysts' efficiency in using fundamental signals for earnings forecasts, thereby making a significant contribution to the fundamental analysis, analyst efficiency and IFRS literatures. There is a paucity of research in this area that examines analysts' efficiency in

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[71] These hypotheses are developed in Chapter 2 and repeated here for convenience. *H3a: Analysts are inefficient in using earnings fundamental signals for forecasting one-year-ahead change in earnings per share; H3b: Analysts are inefficient in using non-earnings fundamental signals for forecasting one-year-ahead change in earnings per share.*

[72] *H3c: Analysts' efficiency in using the earnings signal for forecasting one-year-ahead change in earnings per share improved after adoption of IFRS; H3d: Analysts' efficiency in using non-earnings signals for forecasting one-year-ahead change in earnings per share improved after adoption of IFRS.*

using fundamental signals, with no known studies conducted outside a US[73] context using post-2000 year data. Therefore, analysts outside the US may be unware of the efficiency in using this information, which ultimately could affect the quality of their forecasts. This could pose some risk to users of analysts' forecasts and also lead to information asymmetry. As such, this study examines the efficiency with which analysts use one earnings and 12 non-earnings fundamental signals in European and Australian contexts.

Importantly, the use in this study of a much larger sample[74] compared with other studies that investigate this issue (Abarbanell & Bushee 1997; Swanson, Rees & Juarez-Valdes 2003; Wahab, Teitel & Morzuch 2015) provides more compelling and robust evidence in respect of analysts' efficiency than has existed to date. Moreover, this study examines analysts' efficiency in using fundamental signals to forecast both positive and negative one-year-ahead change in earnings per share. This is the first time such an analysis has been conducted using fundamental signals and, given the sample size, it provides robust evidence of analysts' use of such fundamental signals. There is no study in years post-2000 that examines analysts' efficiency in incorporating the earnings information included in fundamental signals that is priced in the market. Apart from that, this is the first known time the impact of IFRS on analysts' efficiency in using fundamental signals has been tested. Therefore, this study makes a significant contribution to the analyst efficiency, fundamental analysis and IFRS literatures.

8.3 Descriptive statistics

This study uses mean analysts' forecast data for 2001-2012, for forecasts made at least one month after the earnings announcement date, gathered from the Thomson Reuters Eikon database, whereas as is explained in Chapter 4, all data for fundamental signals are collected from the Bloomberg database. The initial sample size is 8217 firm-year observations. However, observations that produce studentised residuals greater than

[73] As explained in the Chapter 3 review of the literature, there are four published studies that examine analyst efficiency. Of those four, three are conducted in a US context (Abarbanell and Bushee (1997); Lambert (2011) and Wahab, Teitel and Morzuch (2015)). The fourth is a study in a Mexican context, Swanson, Rees and Juarez-Valdes (2003), which replicates Abarbanell and Bushee (1997), but uses data from 1993 to 1998.

[74] Abarbanell and Bushee (1997) use 2609 observations for the period1983 to 1990 in a US context, Swanson, Rees and Juarez-Valdes (2003) use 354 observations, and Wahab, Teitel and Morzuch (2015) use 219 quarterly observations from 2010 and 2011. Lambert's (2011) unpublished study runs yearly regressions from 1991 to 2008 and reports average annual observations as 344.

three, or Cook's distance statistics greater than one, are removed from the sample to address multivariate outliers (Abarbanell & Bushee 1997; Dowen 2001; Lev & Thiagarajan 1993). This adjustment eliminates 246 firm-year observations. Moreover, to maintain the same sample for subsequent analyses that examine the impact of IFRS on the efficiency with which analysts use the fundamental signals, observations for the year in which firms transitioned to IFRS (2005) are removed from the sample. That adjustment results in loss of 605 firm-year observations and, therefore, the final pooled sample is reduced to 7366 firm-year observations, with 1780 (24 percent) pre-IFRS and 5586 (76 percent) post-IFRS. Descriptive statistics for this sample are documented in Table 8.1.

Results reported in Table 8.1 indicate that means for analysts' forecast change in one-year-ahead earnings per share (FCEPS1), change in inventory compared to sales (INV), change in sales per employee (LF), change in firm capital expenditure compared to industry (CAPX), change in cash flow from operations (CF), change in goodwill (GW), change in discretionary accruals (CDACCR) and the proportion of audit qualifications (AQ), are significantly different between pre- and post-IFRS periods. Furthermore, results indicate a higher positive mean INV, and lower negative mean FCEPS1, one-year-ahead change in earnings per share (CEPS1), LF, CAPX, CF, and GW in the post- compared to pre-IFRS period. Positive values indicate a bad signal and negative values indicate a good signal about future earnings and returns. Mean discretionary accruals (CDACCR) is close to zero in the post-IFRS period. As such, the level of earnings management may be lower in the post- compared to pre-IFRS period. The mean absolute forecast error is calculated for the pooled sample and compared between pre-and post-IFRS periods. The results show that there is no significant difference in mean forecast error or in current year change in earnings per share (CHGEPS) between the pre- and post-IFRS periods.

Table 8.1: Descriptive statistics for the pooled sample and pre- and post-IFRS sub-samples

	Pooled sample N = 7366				Pre-IFRS N = 1780 (24 percent)		Post-IFRS N = 5586 (76 percent)		T-tests of difference
Variables	Minimum	Maximum	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	*t*
FCEPS1	-0.098	0.463	0.034	0.098	0.039	0.094	0.032	0.099	**2.544****
ABSFE	0.000	0.428	0.062	0.082	0.063	0.083	0.061	0.078	-0.844
CEPS1	-0.280	0.349	0.009	0.097	0.025	0.098	0.004	0.095	**7.771*****
CHGEPS	-0.361	0.313	-0.001	0.105	-0.002	0.103	-0.001	0.105	-0.444
INV	-46.514	81.861	2.648	22.265	0.686	23.373	3.273	21.865	**-4.130*****
AR	-54.062	54.808	-0.818	20.107	-0.272	18.921	-0.992	20.469	1.370
SA	-44.144	48.541	-0.106	13.917	-0.195	15.145	-0.078	13.503	-0.290
LF	-66.169	35.210	-6.034	18.670	-8.651	19.673	-5.200	18.262	**-6.556*****
ETR	-99.498	82.628	-2.031	26.613	-1.646	25.045	-2.154	27.095	0.729
GM	-101.425	66.367	-3.035	29.117	-3.925	29.623	-2.751	28.951	-1.465
CAPX	-256.590	102.179	-11.484	69.134	-14.233	68.849	-10.608	69.208	**-1.932***
LEV	-0.837	1.540	0.037	0.440	0.042	0.407	0.036	0.450	0.521
CF	-19.048	14.530	-1.071	6.599	-1.754	7.183	-0.853	6.387	**-4.734*****
GW	-258.950	64.227	-27.198	66.452	-32.032	76.212	-25.658	62.955	**-3.198*****
CDACCR	-0.218	0.198	-0.005	0.079	-0.019	0.089	0.000	0.075	**-8.219*****
								Chi-Sq	
AQ	0.000	1.000	0.006		0.012		0.00376		**15.385*****

Where IFRS = an indicator variable coded 1 for observations in the post-IFRS period (2006-2012), and 0 otherwise (2001-2004), FCEPS1 = (mean analysts' forecast for one year ahead EPS made at least one month after earnings announcement date in year *t* – actual EPS in year *t*) divided by price at the end of *t*-1, FE = (actual EPS in year *t*+1 – forecast EPS for year *t+1*) divided by price at end of *t-1*, ABSFE = absolute forecast error, CEPS1=One year ahead change in earnings per share ($CEPS1 = [EPS_{t+1} - EPS_t] \div P_{t-1}$), CHGEPS=Change in Current Earnings per share (change in EPS between year *t-1* and *t* deflated by the stock price at the end of *t-1*), INV=Inventories (annual percentage change in inventories minus the annual percentage change in sales), AR=Accounts Receivable (annual percentage change in accounts receivable minus annual percentage change in sales), SA=Selling & Administrative Expenses (annual percentage change in selling and administrative expenses minus the annual percentage change in sales), LF= Labour Force = (annual percentage change in sales per employee calculated as last two years average sales per employee minus current year sales per employee divided by last two years average sales per employee), ETR=Effective Tax Rate (annual percentage change in ETR or average of last two years (*t-1* and *t-2*) ETR – ETR *t*), GM=Gross Margin = (annual percentage change in sales minus annual percentage change in gross margin), CAPX=Capital Expenditure (annual percentage change in industry capital expenditure minus the annual percentage change in the firm's capital expenditure), LEV=Financial Leverage (annual change in ratio of total debt (long-term debt plus current liabilities) to total assets or leverage ratio in year *t* – last two years average leverage ratio), CF=Cash Flows (cash flow from operations (CFO) between year *t* and *t-1* divided by total assets at end of financial year *t-1*), GW = Goodwill (Annual percentage change in goodwill calculated as last two years (*t-1* and *t-2*) average goodwill minus goodwill in year *t* divided by last two years average goodwill), CDACCR = annual change in Discretionary Accruals . Discretionary accruals calculated using the Kothari, Leone and Wasley (2005) performance matched discretionary accrual model. AQ=Audit Qualification (0 for an unqualified opinion and 1 otherwise. If there is an emphasis of matter paragraph and if it relates to going concern issues, 1 is assigned and 0 otherwise).
***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively

8.4 Analysts' efficiency in identifying fundamental signals useful in forecasting future change in earnings per share

As explained in Chapter 4, analysts' efficiency in selecting fundamental signals for forecasting one-year-ahead change in earnings per share is examined using the method followed by Wahab, Teitel and Morzuch (2015). Accordingly, outcomes from estimating the following two models are compared in order to examine analysts' efficiency in identifying appropriate signals for their earnings forecasts.

$$CEPS1_i = \propto\ + \beta_0\,\mathrm{CHGEPS}_i + \textstyle\sum_{j=1}^{12} \beta_{ij}\mathrm{Signals}_{ij} + \sum \mathrm{Yr} + \sum \mathrm{In} + \sum \mathrm{Cty} + \mathrm{Codelaw} + \varepsilon_j \quad (1)$$

$$FCEPS1_i = \propto\ + \beta_0\,\mathrm{CHGEPS}_i + \textstyle\sum_{j=1}^{12} \beta_{ij}\mathrm{Signals}_{ij} + \sum \mathrm{Yr} + \sum \mathrm{In} + \sum \mathrm{Cty} + \mathrm{Codelaw} + \varepsilon_j \quad (13)$$

Where all variables are as defined and measured in Chapter 4[75].

8.4.1 Change in one-year-ahead actual earnings per share

Abarbanell and Bushee (1997) and other researchers, such as Dowen (2001), Swanson, Rees and Juarez-Valdes (2003), Seng and Hancock (2012) and Wahab, Teitel and Morzuch (2015), replicate the Abarbanell and Bushee (1997) investigation of the usefulness of fundamental signals in predicting one-year-ahead change in earnings. However, with the exception of the US-based study by Wahab, Teitel and Morzuch (2015), these studies are conducted using data from prior to year 2000.

In Chapter 6 of this current study results from testing this same issue (i.e. the usefulness of fundamental signals in predicting one-year-ahead change in earnings) are reported in European and Australian contexts for the period 2001 to 2012, with inclusion of more fundamental signals than the study by Abarbanell and Bushee (1997). Consistent with

[75] For convenience, these definitions are repeated here. Future change in one-year-ahead earnings (CEPS1), Forecast change in one-year-ahead earnings (FCEPS1), Forecast error (FE), Current year change in earnings (CHGEPS). The 12 non-earnings fundamental signal variables are change in inventory relative to change in sales (INV), change in accounts receivable relative to change in sales (AR), change in selling and administrative expenses relative to change in sales (SA), change in labour force (LF), change in effective tax rate (ETR), Audit Qualification (AQ), change in firm's capital expenditure relative to change in industry capital expenditure (CAPX), change in financial leverage (LEV), change in cash flow from operations (CF), change in goodwill (GW) and change in discretionary accruals (CDACCR), Yr = Year dummies, Cty= Country Dummies, In=Industry dummies.

some of the findings of Abarbanell and Bushee (1997), those Chapter 6 results reveal that five non-earnings fundamentals (AR, LF, ETR, AQ, CAPX) of the eight selected from Lev and Thiagarajan (1993) are useful in predicting one-year-ahead change in earnings per share. Although AQ is useful in predicting future change in earnings, it is significant in the direction opposite to that expected.

Abarbanell and Bushee (1997) report that INV, CAPX, GM, ETR and LF are useful in predicting CEPS1. However, findings from this current study reveal that INV, and GM are not useful in the identified context in predicting CEPS1. The four additional non-earnings fundamental signals included in this study (i.e. LEV, GW, CF and CDACCR) are also significant in predicting future change in earnings, however LEV and GW are not in the direction expected. The earnings fundamental signal (CHGEPS) is significant in predicting future one-year-ahead change in earnings per share. As expected, CHGEPS demonstrates the reversing nature of current year accruals (Chan, Jegadeesh & Sougiannis 2004; DeFond & Park 2001; Pae 2005) and mean reverting pattern of earnings, with a good year followed by a bad year and a bad year followed by a good year (Dowen 2001; Swanson, Rees & Juarez-Valdes 2003), and therefore, has a positive relationship with one-year-ahead change in earnings per share by virtue of the way in which it is constructed.

8.4.2 Change in actual and forecast change in one-year-ahead earnings per share

Results from estimating Models 1 and 13 are shown in Table 8.2 and document the association between fundamental signals with one-year-ahead change in earnings per share (CEPS1) and forecast one-year-ahead change in earnings per share (FCEPS1). If results reveal that the fundamental signals are associated with FCEPS1 in the same way as with CEPS1, then it is inferred that analysts are efficient in selecting appropriate fundamental signals for their earnings forecasts.

Results for the Abarbanell and Bushee (1997) Model and the Model used in this study reveal that in terms of the earnings signal (CHGEPS), it is positively associated with both CEPS1 and FCEPS1. This indicates that analysts are aware of the information content in CHGEPS with regard to future earnings and seem to understand the reversing nature of current year accruals and mean reversion in annual earnings changes (Abarbanell & Bushee 1997; Swanson, Rees & Juarez-Valdes 2003). As such, analysts are efficient in selecting earnings signals for their forecasts of change in one-year-ahead earnings per share.

With respect to the non-earnings signals, the overall results (for both the full sample and sub-sample that excludes the GFC period of (2007-2009)) for the eight fundamental signals adopted from Abarbanell and Bushee (1997) show that all variables (LF, ETR, GM, and CPACX) significant in explaining CEPS1 are associated also with FCEPS1 in the same direction. This is not a surprising result since, as noted earlier in this chapter section 8.1, Lev and Thiagarajan (1993) derived these fundamental signals from analysts' written pronouncements. The variables SA and AQ are significantly associated with FCEPS1, but not with CEPS1. However as reported in Chapter 6, section 6.3.2, AQ is significant in explaining CEPS1 for Model 1 using the full sample (N = 19307); that is, for the sample that also includes firm-years not followed by analysts. Nevertheless, there is no defensible justification arising from this study's results for identifying SA as useful in making forecasts of one-year-ahead change in earnings.

Four additional non-earnings fundamental signals (LEV, CF, GW and CDACCR) included in this study are significant in predicting CEPS1. However, of those four variables only three (LEV, CF and GW), are associated with FCEPS1. This result indicates that analysts have not understood the information content in discretionary accruals with regards to future change in earnings per share, as they do not appear to incorporate this signal when making their earnings forecasts. Overall, it can be said that analysts are inefficient in selecting SA and CDACCR.

As can be seen from Table 8.2 (Panels A and B), R-Squared values for estimation of Model 13 are 0.251 (Sec 1), and 0.224 (Sec 2) respectively. This indicates that significant variation in FCEPS is explained by the selected fundamental signals. Moreover, the incremental R-Squared contribution from including the non-earnings signals in the model that forecasts one-year-ahead change in earnings per share (Model 13) is significant. This indicates that analysts are aware of the earnings information embedded in at least some non-earnings fundamental signals and they include this information when making their earnings forecasts (Abarbanell & Bushee 1997).

Table 8.2: Analysts' efficiency in identifying fundamental signals useful for earnings forecasts (H3a and H3b)

Sample Size	***Panel A*: Full Sample N = 7366**				***Panel B*: Sample that excludes GFC (2007-2009) N = 5176**			
Models	Abarbanell and Bushee Model		Full Model		Abarbanell and Bushee Model		Full Model	
	Model 1	Model 13	Model 1	Model 13	Model 1	Model 13	Model 1	Model 13
Dependent Variable	CEPS1	FCEPS1	CEPS1	FCEPS1 5	CEPS1	FCEPS1 5	CEPS1	FCEPS1
R^2 of full Model (a)	0.221	0.248	0.230	0.251	0.221	0.248	0.188	0.224
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
α	**0.02290****	**0.04942*****	**0.02269****	**0.05111*****	**0.02290****	**0.04942*****	0.0019	**0.01826***
CHGEPS	**0.38997*****	**0.43108*****	**0.40945*****	**0.43483*****	**0.38997*****	**0.43108*****	**0.37109*****	**0.39958*****
INV	0.00001	-0.00001	0.00001	-0.00001	0.00001	-0.00001	-0.00002	-0.00001
AR	-0.00007	-0.00005	-0.00006	-0.00005	-0.00007	-0.00005	-0.00006	-0.00004
SA	0.00007	**0.00027*****	0.00016	**0.00030*****	0.00007	**0.00027*****	0.00014	**0.00039*****
LF	**-0.00022*****	**-0.00014****	**-0.00015****	-0.00010	**-0.00022*****	**-0.00014****	**-0.00021****	**-0.00020****
ETR	**-0.01290****	**-0.01406****	**-0.01284****	**-0.01404****	**-0.01290****	**-0.01406****	**-0.01411****	**-0.02098*****
GM	**-0.00069*****	**0.00025***	**-0.00034****	**0.00036***	**-0.00069*****	**0.00025***	**-0.00049****	**0.00068*****
AQ	-0.01298	**-0.02247****	-0.01213	**-0.02149****	-0.01298	**-0.02247****	-0.00816	**-0.01600***
CPACX	**0.00007*****	**0.00011*****	**0.00007*****	**0.00010*****	**0.00007*****	**0.00011*****	**0.00008*****	**0.00011*****
LEV			**0.00799*****	0.00365			**0.01125*****	**0.00698***
CF			**-0.00153*****	**-0.00049****			**-0.00122*****	-0.00035
GW			**0.00529*****	**0.00976*****			**0.00341****	**0.00927*****
CDACCR			**-0.06279*****	-0.00242			**-0.04742****	0.01430
CHGEPS alone Model R-Sq (b)	0.213	0.238	0.213	0.238	0.171	0.206	0.171	0.206
Incremental R-Sq (a-b)	0.008	0.010	0.017	0.013	0.050	0.042	0.017	0.018

Refer to Table 8.1 for variable definitions. GFC=Global Financial Crisis. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm. All standard errors are less than 0.05. The highest VIF reported for any model is for CDACCR (1.71).

8.5 Analysts' efficiency in using fundamental signals for forecasting one-year-ahead change in earnings per share

In order to examine the efficiency with which analysts use fundamental signals, analysts' forecasts for one-year-ahead change in earnings per share (FCEPS1) and all fundamental signals are regressed with one-year-ahead change in earnings per share (CEPS1). This results in the following model, as explained in the Chapter 4, section 4.7.6.

$$CEPS1_i = \propto \; + \beta_0 \, \mathrm{CHGEPS}_i + \sum_{j=1}^{12} \beta_{ij} \mathrm{Signals}_{ij} \; + \beta_{13} \, \mathrm{FCEPS1}_i + \sum \mathrm{Yr} + \sum \mathrm{In} \; + \sum \mathrm{Cty} \; + \mathrm{Codelaw} + \varepsilon_j \qquad (14)$$

Where all variables are as previously defined and measured.

If analysts are fully efficient in using these fundamental signals, FCEPS1 should embed all the information about CEPS1 included in the fundamental signals. If this is the case, there will be no incremental R-Squared contribution from including CHGEPS and the non-earnings signals in the estimation of Model 14. Furthermore, if analysts are fully efficient in using these fundamental signals, there will not be any significant association between CEPS1 and the fundamental signals in estimating Model 14.

Comparing the results from estimating Models 1 and 14, as reported in Table 8.3, for the full sample and the sample excluding the GFC period, the inclusion of FCEPS1 as an independent variable in Model 14 does not change the significance of many fundamental signals.

When undertaking a one-to-one comparison of the significance of variables between Models 1 and 14 results, there is a considerable decrease in the significance level for ETR and GW and the significance level for LF decreases from 5 per cent to 10 per cent in Model 14 compared to Model 1. However, the GM coefficient and significance level increases in Model 14 compared to Model 1. This could be the reason why GM is negatively significant with CEPS1, while it is positively significant with FCEPS1. It would seem that analysts do not understand fully the signal from GM when predicting FCEPS1. Apart from these variations, the levels of significance for other variables (CHGEPS, LEV, CF and CDACCR) do not change after inclusion of FCEPS1 in estimating Model 14.

Table 8.3: Analysts' efficiency in use of fundamental signals in forecasting one-year-ahead change in earnings per share (H3a & H3b)

Sample Size	Full sample (N =7366)			Excluding GFC period (N = 5176)		
Models	Model 1	Model 14		Model 1	Model 14	
Dependent Variable	CEPS1	CEPS1		CEPS1	CEPS1	
R-Sq of full Model (a)	0.230	0.321		0.188	0.279	
	Coef.	Coef.		Coef.	Coef.	
α	0.02269**	0.00450		0.00190	-0.00458	
CHGEPS	0.40945***	0.25948***		0.37109***	0.23595***	
INV	0.00001	0.00001		-0.00002	-0.00001	
AR	-0.00006	-0.00004		-0.00006	-0.00005	
SA	0.00016	0.00005		0.00014	0.00001	
LF	-0.00015**	-0.00012*		-0.00021**	-0.00014*	
ETR	-0.01284**	-0.00805		-0.01411**	-0.00706	
GM	-0.00034**	-0.00047**		-0.00049**	-0.00072***	
AQ	-0.01213	-0.00473		-0.00816	-0.00276	
CPACX	0.00007***	0.00004***		0.00008***	0.00005***	
LEV	0.00799***	0.00661**		0.01125***	0.00879***	
CF	-0.00153***	-0.00136***		-0.00122***	-0.00110***	
GW	0.00529***	0.00184		0.00341**	0.00018	
CDACCR	-0.06279***	-0.06191***		-0.04742**	-0.05225**	
FCEPS1		0.34492***			0.33799***	
CHGEPS/ FCEPS1 alone model R-Sq (b)	CHGEPS 0.213	FCEPS1 0.264		CHGEPS 0.171	FCEPS1 0.228	
FCEPS1 and CHGEPS in the Model R-Sq		0.310			0.268	
Incremental R-Sq from the earnings signal	0.213	0.046	22%[#]	0.171	0.040	23%
Incremental R-Sq from non-earnings signals	0.017	0.011	65%	0.017	0.011	65%

Refer to Table 8.1 for variable definitions. GFC=Global Financial Crisis. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively, Results are based on robust standard errors clustered by firm. All standard errors are less than 0.05. # The percentage adjacent to the incremental R-Squared from the earnings signals represents analysts' inefficiency in using the earnings signal.

The incremental R-Squared contribution from fundamental signals included in Model 14 in Table 8.3 for the full sample (sample that excludes the GFC period) is 0.046 (0.400) for the earnings signal and 0.017 (0.017) for the non-earnings signals over earnings. Partial F-tests indicate that the incremental R-Squared contributions from these signals are significant.

These results point to the conclusion that analysts do not fully incorporate the information content relating to one-year-ahead change in earnings per share included in fundamental signals when making their earnings forecasts. Therefore, analysts are not fully efficient in using these fundamental signals and the inefficiency percentage[76] in comparison to Model 1 (benchmark model for assessing analysts' efficiency in using the fundamental signals) in using the earnings signal is 22 per cent for the full sample and 23 per cent for the sample that excludes the GFC period, and for the non-earnings signals is 65 per cent for both samples.

In order to isolate the impact of this inefficient use of fundamental signals, the fundamental signals are regressed with analysts' forecast error (FE) resulting in the following model, as explained in the Chapter 4, section 4.7.6.

$$FE_i = \propto\ + \beta_0\, \mathrm{CHGEPS}_i + \sum_{j=1}^{12} \beta_{ij} \mathrm{Signals}_{ij} + \sum \mathrm{Yr} + \sum \mathrm{In} + \sum \mathrm{Cty} + \mathrm{Codelaw} + \varepsilon_j \qquad (15)$$

Where variables are as previously defined and measured.

As explained by Abarbanell and Bushee (1997) in footnote 18, if a fundamental signal is significantly associated with forecast error in the same direction that it is associated with CEPS1 (Model 1), it indicates that "analysts fail to adjust their forecasts sufficiently high when a signal conveys good news and sufficiently low when a signal conveys bad news" (Abarbanell & Bushee 1997 p.17). That is, analysts underreact to that fundamental signal. When the coefficient for the signal is of the opposite sign, analysts overreact to that signal.

As can be seen from Table 8.4, CHGEPS is positively significant with one-year-ahead change in earnings per share (CEPS1) and negatively associated with forecast error (FE) for both samples. This indicates that analysts overreact to current year change in earnings per share (CHGEPS) when making their forecasts for change in one-year-ahead earnings per share (FCEPS1). Bradshaw, Richardson and Sloan (2001) document a negative

[76] When calculating analysts' inefficiency, the benchmark model is Model 1. Earnings alone R-Squared for Model 1 is 0.213 and the incremental R-Squared from the earnings signal for Model 14 (representing inefficiency in using the earnings signal) is 0.046 (0.310-0.264). Therefore, the percentage inefficiency in using the earnings signal is calculated as 0.046/0.213 = 22 per cent. The percentage utilisation of the earnings signal is 78 per cent (1 - 22 per cent). In the same way, the incremental R-Squared contribution from the non-earnings signals over earnings is 0.017 for Model 1 and 0.011 for Model 14. As such, the percentage inefficiency in using non-earnings signals over earnings is 0.011/0.017 = 65 per cent. Therefore, the percentage utilisation of non-earnings signal is 35 per cent (1 - 65 per cent).

relationship between accruals and subsequent earnings forecast errors, suggesting that analysts do not fully adjust forecasts for transitory working capital accruals. Findings from this study also show a negative relationship between change in current year earnings (CHGEPS) and forecast error, consistent with the findings of Bradshaw, Richardson and Sloan (2001).

Of the non-earnings fundamental signals, the results reported in Panels A and B of Table 8.4 indicate that analysts overreact to CAPX and GW when making their forecasts. The SA variable is not significant with CEPS1, but is significantly associated with FCEPS1 and FE with different signs. As such, analysts fully overreact to this signal (Wahab, Teitel & Morzuch 2015). The estimation reported in Table 8.4 further reveals that analysts underreact to GM, CF and CDACCR, as these variables are significantly associated with CEPS1 and FE in the same direction. With regards to CDACCR, it is not significantly associated with FCEPS1. Therefore, analysts fully underreact to CDACCR. In addition, the results based on the sample that excludes the GFC period reported in Table 8.4 (Panel B) indicate that variables LF, ETR, and LEV are efficiently used by analysts when making their forecasts of change in one-year-ahead earnings per share.

In comparing the R-Squared values for Models 1 and 13, Model 13, which explains the association between forecast change in one-year-ahead earnings per share (FCEPS1) and fundamental signals, has a higher R-Squared value (R-Sq 0.321) than Model 1 (R-Sq 0.230), which shows the association between CEPS1 and the fundamental signals. This indicates that analysts embed more information from the fundamental signals into their forecast change in earnings than they should in comparison to CEPS1. As such, overall, there is an overreaction to fundamental signals by analysts when formulating their forecast change in earnings per share.

From these analyses, it can be concluded that analysts overreact to fundamental signals CHGEPS, SA, CAPX and GW, whilst they underreact to GM, CF and DACCR. Abarbanell and Bushee (1997) also report that analysts underreact to some fundamental signals, such as INV, GM, and LF, when making their forecast revisions. The findings from this study do not support the conclusion that analysts underreact to LF; rather LF appears to be efficiently used by analysts. The INV variable is not useful in predicting CEPS1 according to this current study. However, some of this study's findings are supportive of those of Wahab, Teitel and Morzuch (2015), which document analysts' overreaction to SA and underreaction to GM.

Table 8.4: Impact on analysts' inefficient use of fundamental signals when forecasting change in one-year-ahead earnings per share (H3a & H3b)

Sample Size	**Panel A:** Full sample N =7366			**Panel B:** Excluding GFC period n = 5176		
Models	Model 1	Model 13	Model 15	Model 1	Model 13	Model 15
Dependent Variable	CEPS1	FCEPS1	FE	CEPS1	FCEPS1	FE
R-Sq of full Model (a)	0.230	0.251	0.055	0.188	0.224	0.067
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
α	**0.02269****	**0.05111*****	**-0.03171***	0.00190	**0.01826***	-0.01689
CHGEPS	**0.40945*****	**0.43483*****	**-0.08202*****	**0.37109*****	**0.39958*****	**-0.09043*****
INV	0.00001	-0.00001	0.00001	-0.00002	-0.00001	0.00001
AR	-0.00006	-0.00005	-0.00001	-0.00006	-0.00004	-0.00001
SA	**0.00016***	**0.00030*****	-0.00013	0.00014	**0.00039*****	**-0.00025****
LF	**-0.00015****	-0.00010	0.00001	**-0.00021****	**-0.00020****	0.00002
ETR	**-0.01284****	**-0.01404****	-0.00381	**-0.01411****	**-0.02098*****	0.00051
GM	**-0.00034****	**0.00036***	**-0.00075*****	**-0.00049****	**0.00068*****	**-0.00128*****
AQ	-0.01213	**-0.02149****	0.01493	-0.00816	**-0.01600***	0.01432
CAPX	**0.00007*****	**0.00010*****	**-0.00004****	**0.00008*****	**0.00011*****	**-0.00004***
LEV	**0.00799*****	0.00365	0.00250	**0.01125*****	**0.00698***	0.00039
CF	**-0.00153*****	**-0.00049****	**-0.00086*****	**-0.00122*****	-0.00035	**-0.00061****
GW	**0.00529*****	**0.00976*****	**-0.00429****	**0.00341****	**0.00927*****	**-0.00568*****
CDACCR	**-0.06279*****	-0.00242	**-0.05084****	**-0.04742***	0.01430	**-0.04865****

Refer to Table 8.1 for variable definitions. GFC=Global Financial Crisis. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm. All standard errors are less than 0.05.

8.6 Analysts' efficiency in using fundamental signals when making forecasts for positive (Winners) and negative (Losers) change in one-year-ahead earnings per share

This section explores whether analysts' efficiency in using fundamental signals differs when making forecasts for positive compared with negative change in earnings per share. For the purpose of analysis, firms with positive change in earnings are termed 'Winners' and those with a negative change in earnings termed 'Losers'.

First, analysts' efficiency in selecting fundamental signals for forecasting Winners [n = 4349 (59 per cent)] and Losers (n = 3017) is examined. When comparing Models 1 and 13 in Table 8.5, seven variables (CHGEPS, LF, ETR, CAPX, CF, LEV and GW) that significantly predict CEPS1, with the exception of LF, are also significantly associated with FCEPS1 for Winners. However, for Losers, the variables (CHGEPS, INV, ETR, GM, CF and CDACCR) that significantly explain CEPS1, with the exception of CHGEPS and INV, are not significantly associated with FCEPS1. Therefore, it is concluded that analysts are mostly efficient in selecting appropriate fundamental signals for forecasting a positive change in earnings, but this is not the case for forecasting a negative change in earnings. Analysts appear to select only the earnings signal appropriately, but, with the exception of INV, not the non-earnings signals, when forecasting negative earnings changes. Results based on the sample [Winners 3275 (63 per cent) and Losers 1901] that excludes the GFC period (untabulated) are also consistent with these findings.

Next, analysts' efficiency in using fundamental signals in their forecasts for Winners and Losers is analysed. For this purpose, the outcomes from estimating Models 1 and 14 are compared for Winners and Losers. In comparison to estimation of Model 1, the inclusion of FCEPS1 along with all fundamental signals as independent variables for Model 14, does not change the significance of the fundamental signals, with the exception of LEV, CF and GW for Winners. In terms of Losers, none of the significance levels of the fundamental signals change for results from estimating Model 14 compared to those from estimating Model 1.

The incremental adjusted R-Squared contribution from the fundamental signals included in Model 14 is 0.019 (0.012 from earnings and 0.007 from non-earnings) for Winners and 0.104 (0.093 from earnings and 0.011 from non-earnings) for Losers. Analysts' inefficiency in using the earnings signal (non-earnings signals over earnings) is 5 per cent (33 per cent) for Winners and 75 per cent (100 per cent) for Losers. These results support the view that analysts do not fully utilise the information content in fundamental signals for their earnings forecasts, and further, analysts are highly inefficient in using fundamental signals in making forecasts for negative changes in earnings when compared to positive changes in earnings.

In order to isolate the impact of inefficient use of fundamental signals for Winners and Losers, outcomes from applying Models 1, 13 and 15 are compared in Table 8.5. The results indicate that analysts overreact to earnings for both Winners and Losers when making their forecasts. For GM and GW, analysts overreact for Winners and underreact for Losers. Apart from that, analysts underreact to AQ, CAPX and CF when making forecasts of negative changes in earnings.

Table 8.5: Analysts' efficiency in using fundamental signals when making forecasts for Winners and Losers (H3a & H3b)

Sample	Winners (n = 4349)				Losers (n =3017)			
Model	Model 1	Model 13	Model 14	Model 15	Model 1	Model 13	Model 14	Model 15
Dependent Variable	CEPS1	FCEPS1 5	CEPS1	FE	CEPS1	FCEPS1 5	CEPS1	FE
Full Model R-Sq	0.263	0.334	0.469	0.118	0.135	0.092	0.135	0.042
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
α	**0.03267*** **	**0.03773*** **	**0.01734** **	-0.01028	**-0.07097*** **	**0.04929*** **	**-0.0698*** **	**-0.1274*** **
CHGEPS	**0.33097*** **	**0.54742*** **	**0.10868*** **	**-0.22382*** **	**0.25304*** **	**0.19814*** **	**0.25775*** **	**-0.04995* **
INV	0.00001	-0.00001	0.00001	0.00001	**-0.00003* **	**-0.00003* **	**-0.00003* **	0.00001
AR	-0.00006	-0.00006	-0.00004	0.00001	-0.00003	-0.00002	-0.00003	-0.00002
SA	0.00013	**0.00030*** **	0.00001	-0.00012	0.00006	0.00008	0.00006	-0.00011
LF	**-0.00025*** **	**-0.00009**	**-0.00021*** **	-0.00007	0.00003	-0.00005	0.00003	0.00008
ETR	**-0.02268*** **	-0.01785**	**-0.01544*** **	-0.00298	**0.01231** **	0.00423	**0.01241** **	-0.00498
GM	0.00034	**0.00078*** **	0.00003	**-0.00040* **	**-0.00059** **	0.00008	**-0.00059** **	**-0.00078** **
AQ	-0.00634	-0.00892	-0.00272	0.00762	0.00684	**-0.03446*** **	0.00602	**0.04584** **
CPACX	**0.00009*** **	**0.00011*** **	**0.00004*** **	-0.00003	-0.00001	**0.00004** **	-0.00001	**-0.00007** **
LEV	**0.00963*** **	**0.01094*** **	**0.00518* **	-0.00387	0.00237	-0.00520	0.00225	0.00781
CF	**-0.00055** **	**-0.00061** **	-0.00030	-0.00013	**-0.00117*** **	-0.00009	**-0.00118*** **	**-0.00058* **
GW	**0.00718*** **	**0.01162*** **	**0.00246* **	**-0.00466*** **	-0.00134	**0.00424** **	-0.00124	**-0.00544* **
CDACCR	-0.01654	-0.01979	-0.00851	-0.01327	**-0.06944*** **	0.00788	**-0.06925*** **	-0.04382
FCEPS1			**0.40606*** **				-0.02375	
CHGEPS/ FCEPS1 alone model R-Sq	CHGEPS 0.242	CHGEPS 0.319	FCEPS1 0.450		CHGEPS 0.124	CHGEPS 0.088	FCEPS1 0.031	
FCEPS1 and CHGEPS in the Model R-Sq			0.462				0.124	
Incremental R-Sq 1	0.242		0.012 5%#		0.124		0.093 75%	
Incremental R-Sq 2	0.021	0.015	0.007 33%		0.011	0.004	0.011 100%	

Refer to Table 8.1 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm. All standard errors are less than 0.05. Incremental R-Sq 1: Incremental R^2 from earnings variable. Incremental R^2 2: Incremental R^2 from non-earnings variables over earnings. # The percentage adjacent to the incremental R-Squared from the earnings signals represents analysts' inefficiency in using the earnings signal.

Analysis based on the sample (results untabulated) that excludes the GFC (2007-2009) period (Winners 3275, Losers 1923) support the same conclusion with the exception that analysts use CHGEPS efficiently for forecasting a negative change in earnings per share**.**

Prior literature documents that analysts systematically underreact (Teoh & Wong 1997) and overreact (De Bondt & Thaler 1990) to new information. Moreover, analysts underreact to negative information and overreact to positive information (Easterwood & Nutt 1999). Zhaoyang and Jian (2007) also find that analysts overreact to good news, such as a high book to market ratio and higher earnings growth. This study provides evidence consistent with these findings, but from a different perspective; that is analysts are highly inefficient and underreact to fundamental information when forecasting a negative change in earnings, whilst being comparatively efficient and overreacting to some fundamental signals when predicting a positive change in earnings.

These results are also consistent with evidence that analysts are biased towards upwards forecasts in line with their incentives (Bonini et al. 2010; Bradshaw, Huang & Tan 2014). Analysts' efficiency in using fundamental signals for forecasting negative change in earnings is lower compared to forecasting a positive change on earnings. A major contribution to the literature from this study is that it investigates analysts' efficiency in using fundamental signals for forecasting each of negative and positive change in earnings, and how analysts underreact or overreact to fundamental signals when making these forecasts.

In conclusion, the findings show that analysts generally do not impound all the future earnings-related information embedded in fundamental signals when making their earnings forecasts, and analysts are highly inefficient in forecasting negative change in earnings compared to positive change in earnings. Analysts generally underreact to most of the fundamental signals when predicting a negative change in their earnings forecasts and overreact when forecasting a positive change in earnings. Overall, these results support Hypotheses H3a and H3b. There is no similar prior study of analysts' use of fundamental signals.

8.7 IFRS impact on the efficiency with which analysts use fundamental signals for earnings forecasts

This section analyses IFRS impact on analysts' efficiency in selecting and using fundamental signals for their earnings forecasts. In order to examine IFRS impact on analysts' efficiency in selecting and using the fundamental signals for making one-year-ahead change in earnings per share forecasts, the sample is partitioned into pre-IFRS [2001-2004, 1780 observations (25 per cent)] and post-IFRS (2006-2012, 5586 observations) periods and Models 1, 13, 14 and 15 are estimated for both pre- and post-IFRS sub-samples. Results are documented in Table 8.6.

In order to analyse IFRS impact on analysts' efficiency in selecting the appropriate fundamental signals for one-year-ahead change in earnings per share forecasts, regression results for Models 1 and 13 are compared pre- and post-IFRS. As can be seen from Table 8.6, of five fundamental signals (CHGEPS, CAPX, LEV, CF and GW) that are significantly associated with CEPS1, only three (CHGEPS, CAPX and GW) significantly explain FCEPS1 for the pre-IFRS period. However, when the post-IFRS period is considered, seven of ten variables (CHGEPS, SA, ETR, AQ, CAPX, CF and GW) that are significant in predicting CEPS1 are also significantly associated with FCEPS1. Therefore, it is concluded that analysts are more aware about fundamental signals useful for making their forecasts for change in one-year-ahead earnings in the post-IFRS compared to pre-IFRS period.

This outcome could be due to an increase in the quality of the information environment (Horton, Serafeim & Serafeim 2013), increased quantity and quality of financial reporting disclosures, and/or increased comparability, transparency and readability of financial statements (Barth, Landsman & Lang 2008; Cheung & Lau 2016; Daske & Gebhardt 2006; Daske et al. 2008; Glaum et al. 2013) after adoption of IFRS.

This result is consistent with findings in the literature that analysts' information environment and forecast accuracy increased after adoption of IFRS (Chalmers et al. 2012; Cheong, Kim & Zurbruegg 2010; Cotter, Tarca & Wee 2012; Preiato, Brown & Tarca 2013).

Table 8.6: IFRS impact on analysts' efficiency in using fundamental signals when making forecasts for one-year-ahead earnings per share (H3c & H3d)

Sample	Pre-IFRS (n = 1780)				Post-IFRS (n = 5586)			
Models	Model 1	Model 13	Model 14	Model 15	Model 1	Model 13	Model 14	Model 15
Dependent Variable	CEPS1	FCEPS1	CEPS1	FE5	CEPS1	FCEPS1 5	CEPS1	FE5
Full Model R-Sq	0.173	0.250	0.254	0.038	0.236	0.251	0.333	0.055
	Coef.	Coef.		Coef.	Coef.	Coef.		Coef.
α	-0.00529	**0.07470****	-0.03107	-0.06129	0.00643	0.02238	-0.00135	-0.02396
CHGEPS	**0.36608*****	**0.42632*****	**0.21897*****	**-0.07673****	**0.42523*****	**0.43676****	**0.27344*****	**-0.08070*****
INV	-0.00002	0.00010	-0.00002	-0.00002	0.00001	-0.00001	0.00001	0.00002
AR	-0.00012	-0.00010	-0.00008	0.00001	-0.00005	-0.00005	-0.00003	-0.00001
SA	-0.00001	**0.00030****	-0.00011	**-0.00031***	**0.00025****	**0.00031*****	0.00014	-0.00003
LF	-0.00012	-0.00020	-0.00005	0.00015	**-0.00017****	-0.00004	**-0.00015****	-0.00009
ETR	-0.01669	-0.02131	-0.00934	-0.00003	**-0.01227***	**-0.01194***	-0.00812	-0.00518
GM	-0.00035	0.00074	-0.00061	**-0.00142****	**-0.00034***	0.00033	**-0.00046****	**-0.00065*****
AQ	-0.00607	0.01002	-0.00953	-0.01723	**-0.02078****	**-0.04145*****	-0.00637	**0.02861*****
CPACX	**0.00012*****	**0.00011*****	**0.00008****	0.00001	**0.00006*****	**0.00010*****	0.00003	**-0.00005****
LEV	**0.02145*****	0.00637	**0.01925****	0.00937	0.00428	0.00373	0.00299	-0.00016
CF	**-0.00134*****	0.00002	**-0.00135*****	**-0.00087****	**-0.00159*****	**-0.00067*****	**-0.00136*****	**-0.00087*****
GW	**0.00767*****	**0.00893*****	0.00459	-0.00133	**0.00406****	**0.00931*****	0.00032	**-0.00548****
CDACCR	-0.04647	0.01439	-0.05143	-0.03397	**-0.06841*****	-0.00838	**-0.06550*****	**-0.05429****
FCEPS1			**0.34507*****				**0.34753*****	
CHGEPS/ FCEPS1 alone model R-Sq (b)	CHGEPS 0.152	CHGEPS 0.235	FCEPS1 0.212		CHGEPS 0.222	CHGEPS 0.239	FCEPS1 0.270	
FCEPS1 and CHGEPS in the Model R-Sq			0.239				0.324	
Incremental R-Sq 1	0.152		0.027 18%[#]				0.054 24%	
Incremental R-Sq 2	0.021		0.015 71%		0.014	0.012	0.009 64%	

Refer to Table 8.1 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm. All standard errors are less than 0.05. Incremental R-Sq 1: Incremental R^2 from earnings variable. Incremental R-Sq 2: Incremental R^2 from non-earnings variables over earnings. Pre-IFRS period is from 2001-2004 and post-IFRS period is from 2006-2012. # The percentage adjacent to the incremental R-Squared from the earnings signals represents analysts' inefficiency in using the earnings signal.

For the purpose of examining the impact of IFRS on analysts' efficiency in using fundamental signals for their earnings forecasts, regression results for Models 1 and 14 reported in Table 8.6 are compared for pre- and post-IFRS period samples. As can be seen from Table 8.6, most variables which are significant in estimating Model 1 are also significant for Model 14, with the same level of significance for both pre- and post-IFRS periods. This indicates analyst inefficiency in using these fundamental signals. There is also evidence from the significant incremental R-Squared contribution from the fundamental signals for Model 14 for both pre-IFRS (0.027 + 0.015 = 0.042) and post-IFRS (0.054 + 0.009 = 0.063) periods.

In the pre-IFRS period, the level of significance is decreased for CAPX, LEV and GW for Model 14 when compared to Model 1. Therefore, analysts use most of the future earnings information embedded in these fundamental signals in the pre-IFRS period. In terms of the post-IFRS period, variables SA, ETR, AQ, CAPX, and GW are not significant for Model 14, but are for Model 1, and the significance of LF is decreased for Model 14 compared to Model 1. As such, analysts are efficient to some extent in using the information included in these signals when forecasting change in one-year-ahead earnings per share in the post-IFRS period.

When comparing the pre- and post-IFRS periods, the efficiency in utilising fundamental signals for forecasting one-year-ahead change in earnings is 76 per cent (100 - 24[77]) in the pre-IFRS and 73 per cent (100 - 27) in the post-IFRS period. Therefore, overall, analysts' efficient utilisation of these fundamental signals seems to be similar in pre- and post-IFRS periods.

In extended analysis, analysts' efficiency in using earnings and non-earnings signals is examined next. The results documented in Table 8.6 indicate that analysts seem to be somewhat better in using non-earnings signals in the post- compared to pre-IFRS period. This is evident from the increase in the percentage of efficient utilisation of non-earnings signals over earnings from 29 per cent (100 - 71) pre-IFRS to 36 per cent (100 - 64) in the post-IFRS period. However, analysts' efficient utilisation of the earnings signal decreases from 82 per cent (100 - 18) pre-IFRS to 76 per cent (100 - 24) post-IFRS.

[77] Inefficiency in utilising the earnings signals is 18 per cent and is calculated as incremental R-Squared for Model 13 (0.027 for pre-IFRS period) divided by the R-squared value for Model 1 (0.152), which is the benchmark model for measuring the efficiency of use of fundamental signals by analysts.

Therefore, the efficiency in using the earnings signal for forecasting one-year-ahead change in earnings per share is lower in the post- compared to pre-IFRS period. Chapter 6 of this study documents that the predictive ability of earnings increased after adoption of IFRS. However, the analysis in this chapter indicates that analysts fail to utilise the increased predictive ability of earnings post-IFRS when making their earnings forecasts, reflecting as a decrease in analysts' efficiency in using the earnings signal in the post- compared to pre-IFRS period. With regard to the non-earnings signals, though the incremental R-Squared contribution from these for Model 1 is less in the post- compared to pre-IFRS period, relatively, analysts use more of their information content when forecasting one-year-ahead change in earnings per share in the post- compared to pre-IFRS period. Consequently, there is an increase in analysts' efficiency in the post- compared to pre-IFRS period.

Overall, the results indicate that analysts are more inefficient in using the information in earnings and more efficient in using non-earnings information in the post- compared to pre-IFRS period. This finding represents an additional contribution to the literature dealing with analysts' efficiency in using fundamental signals. It indicates that IFRS impact on analysts' efficiency in using the earnings signal is negative and on non-earnings signals is positive, therefore the results support only Hypothesis H3d.

To isolate the impact of analysts' inefficient use of fundamental signals for pre- and post-IFRS periods, the regression results from estimating Models 1, 13, 14 and 15 are compared for both samples. The results reported in Table 8.6 document that CHGEPS is positively related with CEPS1 and FCEPS1, but negatively with forecast error (FE) for both pre-and post-IFRS periods. Due to the reversing nature of current year accruals, earnings is positively related with one-year-ahead change in earnings (Chan, Jegadeesh & Sougiannis 2004; DeFond & Park 2001; Pae 2005). The positive association of CHGEPS with FCEPS1 indicates that analysts understand the reversing nature of current year accruals when making their forecasts for one-year-ahead change in earnings (Abarbanell & Bushee 1997) for both pre- and post-IFRS periods. Since CHGEPS is significant in estimating Model 14, analysts are still not fully efficient in using CHGEPS when making their forecasts for change in one-year-ahead earnings per share (FCEPS1). As CHGEPS is negative and significantly associated with forecast FE (but positively associated with CEPS1), analysts overreact to earnings (CHGEPS) in both the pre- and post-IFRS periods. As explained by Bradshaw, Richardson and Sloan (2001) a negative relationship between accruals (major part of CHGEPS) and subsequent earnings forecast errors suggest that analysts do not fully adjust their forecasts for transitory working capital accruals.

In terms of non-earnings signals, analysts underreact to SA and CF in the pre-IFRS period. However, CAPX and GW seem to be effectively used by analysts in the pre-IFRS period for earnings forecasts. In terms of LEV, it is significantly associated with CEPS1 and not with FCEPS1 or FE in the pre-IFRS period. This indicates that analysts do not use LEV for their earnings forecasts and they use other variables that capture the effects of LEV (Wahab, Teitel & Morzuch 2015) in the pre-IFRS period. Though analysts' efficiency in selecting and using non-earnings fundamental signals is higher in the post- compared to pre-IFRS periods, they appear not to fully utilise the information content embedded in these fundamental signals. Accordingly, analysts underreact to GM, CF, and CDACCR, but overreact to fundamental signals AQ, CAPX and GW. However, analysts are fully efficient in using SA and ETR in the post-IFRS period.

Results based on the analysis for the sample (Pre-IFRS 1701 [44 per cent] observations and post-IFRS 2130 observations) that excludes the GFC (2008-2009) and full IFRS transition (2004-2006) periods (untabulated) are consistent with the above findings, with the exception that CDACCR is not more significant in the post-IFRS period for any of the models.

Prior studies report that goodwill is more value relevant (Aharony, Barniv & Falk 2010), and more representative of firm's underlying investment opportunities in the post-IFRS period (Godfrey & Koh 2009). Further Cheong, Kim and Zurbruegg (2010) report that intangible assets under IFRS are more useful than under prior GAAP for analysts in making their earnings forecasts. However, this study's findings document that, although analysts use GW for earnings forecasts, they overreact to GW to a certain extent.

Though as a whole analysts' use of non-earnings fundamental signals improves in the post-IFRS period, analysts underreact or overreact to some fundamental signal information when making their earnings forecasts. At the same time, analysts overreact to the earnings signal and are comparatively inefficient in using this in the post-IFRS period.

8.8 IFRS impact on analysts' efficiency in making forecasts for positive (Winners) and negative (Losers) change in earnings per share

The overall findings relating to analysts' efficiency in selecting and using the fundamental signals for making their forecasts of positive and negative change in earnings per share, as documented in section 8.6, are consistent for both the pre and post-IFRS periods (see Annexures 8.1 and 8.2). As such, analysts are more efficient in selecting and using fundamental signals for forecasting Winners than Losers in both the pre- and post-IFRS periods. Apart from that, the analysis indicates that analysts' efficiency in using the earnings signal decreased, while their efficiency in using non-earnings signals increased when forecasting Winners in the post- compared to pre-IFRS period. However, the efficiency with which analysts use both the earnings and non-earnings signals decreased substantially when forecasting Losers in the post- compared to pre-IFRS period. The decrease in analysts' efficiency in using the earnings signal is more substantial for forecasting a negative change in earnings per share than a positive change in earnings per share in the post-IFRS period.

This result indicates that IFRS negatively impacts analysts' use of the earnings signal and this impact is higher when forecasting a negative change in earnings. This highlights that analysts fail to utilise the increased predictive ability of current year change in earnings per share (CHGEPS) in terms of Losers after adoption of IFRS, when making their forecasts. This could be a reason for analysts focusing more on other information, especially when forecasting an unfavourable change in earnings, due to the significant improvement in analysts' information environment, both public and private (Beuselinck et al. 2010) after IFRS adoption. Alternatively, it can be explained by analysts' bias towards upward forecasts in line with their incentives (Bonini et al. 2010; Bradshaw, Huang & Tan 2014). The results are robust for the sample that excludes the GFC and IFRS transition periods. The results support only Hypothesis H3d, and then only when predicting Winners.

8.9 Analysts' efficiency in using fundamental signals for Code and Common law countries and IFRS impact on this efficiency

As a further test, analysts' efficiency in using fundamental signals for Code and Common law countries is examined and the results are in agreement with the pooled sample analysis discussed in section 8.5. The analysis (Annexure 8.3) further reveals that, on average, analysts' efficiency in using the earnings signal is substantially lower in Common law compared with Code law countries. Moreover, analysts' efficiency in using non-earnings signals over earnings is slightly higher in Common law compared to Code law countries. Analysis based on the sample that excludes the GFC period (2007-2009) supports the same conclusion.

Barniv, Myring and Thomas (2005) examine and document that analysts' forecast accuracy for Common compared to Code law countries is higher due to more effective corporate governance, strong legal protection laws, and higher quality financial reporting in Common law countries. However, in contrast, in this study findings reveal that analysts are highly inefficient in using the earnings signal for Common law countries, but comparatively efficient in using the non-earnings signals.

The IFRS impact on analysts' efficiency in using fundamental signals for forecasting one-year-ahead change in earnings per share for both Code and Common law countries (see annexures 8.4 and 8.5) is also consistent with the findings for IFRS impact on analysts' efficiency for the pooled sample, discussed in section 8.6. Accordingly, analysts' efficiency in using the earnings signal (non-earnings signals over earnings) is lower (higher) in the post- compared to pre-IFRS period. Analysts appear to substantially underutilise the earnings signal in Common law countries compared to Code law countries in both the pre- and post-IFRS periods. Furthermore, the efficiency with which analysts use non-earnings signals over earnings increased considerably in Common law compared with Code law countries in the post- compared to pre-IFRS period. The overall IFRS impact on analysts' efficiency in using the earnings signal is negative, whilst it is positive for non-earnings signals for both Code and Common law countries. Results based on the sample that excludes both the GFC (2007-2009) and full IFRS transition (2004-2006) periods support the same conclusion. Therefore, the results support Hypotheses H3a, H3b and H3d.

8.10 Analysts' efficiency in incorporating information in fundamental signals that is priced in the market and IFRS impact on this efficiency

This section examines analysts' efficiency in terms of incorporating earnings information in fundamental signals priced in the market into their forecasts of one-year-ahead change in earnings per share, and the impact of IFRS on this relationship. As explained in Chapter

4, first in order to investigate the earnings information contained in the fundamental signals priced in the market, fundamental signals are regressed on contemporaneous excess returns (ER) using the following model.

$$ER_i = \propto \ +\beta_0 \,\mathrm{CHGEPS}_i + \sum_{j=1}^{12} \beta_{ij}\mathrm{Signals}_{ij} \ + \sum \mathrm{Yr} + \ \sum \mathrm{In} \ + \sum \mathrm{Cty} + \ \mathrm{Codelaw} + \varepsilon_j \qquad (3)$$

Where ER is calculated the difference between the firm's return for the 12-month period commencing 11 months prior and ending one month after the earnings announcement date and the benchmark index return for the same period, and other variables are defined and measured as previously.

Second, to examine analysts' efficiency in embedding the fundamental information priced in the market into their forecasts, fundamental signals and forecast one-year-ahead change in earnings per share (FCEPS1) is regressed on the contemporaneous excess return (ER), which results in the following equation.

$$ER_i = \propto \ +\beta_0 \,\mathrm{CHGEPS}_i + \sum_{j=1}^{12} \beta_{ij}\mathrm{Signals}_{ij} \ + \beta_{13}\,\mathrm{FCEPS}_i + \sum \mathrm{Yr} + \ \sum \mathrm{In} \ + \sum \mathrm{Cty} + \ \varepsilon_j \qquad (16)$$

Where variables are as defined and measured previously.

In order to assess analysts' efficiency relating to the above issues, results from estimating Models 3 and 16 are documented in Table 8.7 and compared. As can be seen from Table 8.7, the adjusted R-Squared value for Model 3 that documents the value relevance of the fundamental signals is 0.181.

When FCEPS1 is regressed on ER, the adjusted R-Squared value is 0.051, which is lower than that for Model 3. Next, the fundamental signals are included into the FCEPS1 alone model (Model 14) and regressed with ER, and the resulting adjusted R-Squared is 0.183. This indicates substantial incremental value relevance (0.183-0.051) from fundamental signals over FCEPS1 in explaining ER.

Table 8.7: Analysts' efficiency in using information in fundamental signals priced in the market and IFRS impact on that efficiency (H3c & H3d)

Sample Size	Pooled sample (N= 7752)			Pre-IFRS (n = 1864)			Post-IFRS (n = 5888)		
Model	Model 3	Model 16		Model 3	Model 16		Model 3	Model 16	
Dependent Variable	ER	ER		ER	ER		ER	ER	
Full model Adj. R-Sq	0.181	0.183		0.212	0.213		0.157	0.161	
	Coef.	Coef.		Coef.	Coef.			Coef.	
α	**-8.83940****	**-8.62041****		-4.15059	-4.90044		**-9.67523***	**-9.81995*****	
CHGEPS	**-55.63209*****	**-52.49069*****		**-76.36793*****	**-78.66999*****		**-49.49699*****	**-45.17269*****	
INV	**0.01565*****	**0.01532*****		0.00316	0.00337		**0.018520*****	**0.01801*****	
AR	**-0.05294*****	**-0.05312*****		0.00926	0.00904		**-0.06913*****	**-0.06974*****	
SA	**-0.06423****	**-0.06402****		**-0.17088*****	**-0.17163*****		-0.00927	-0.00947	
LF	-0.02908	-0.03166		0.04414	0.04561		**-0.06189****	**-0.06519****	
ETR	**-0.00665***	**-0.00583***		-0.01093	-0.01185		-0.00551	-0.00454	
GM	**-0.20557*****	**-0.20361*****		**-0.25729*****	**-0.25969*****		**-0.18326*****	**-0.18116*****	
AQ	-2.48776	-2.66744		0.87428	0.70268		-7.43916	-7.79620	
CPACX	0.00290	0.00422		**0.02280***	**0.02117***		-0.00582	-0.00419	
LEV	-0.46784	-0.40334		-1.17070	-1.24016		-0.36623	-0.28499	
CF	**-1.03669*****	**-1.03591*****		**-0.97911*****	**-0.98281*****		**-1.07473*****	**-1.07412*****	
GW	-0.46152	-0.33238		-0.77965	-0.87376		-0.27798	-0.11618	
CDACCR	**-58.42734*****	**-57.96235*****		**-64.67556*****	**-65.35540*****		**-55.85055*****	**-55.34805*****	
FCEPS1		**-12.71394*****			9.7112			**-17.37464*****	
CHGEPS/ FCEPS1 alone model Adj. R^2	CHGEPS 0.112	FCEPS1 0.051		CHGEPS 0.140	FCEPS1 0.035		CHGEPS 0.085	FCEPS1 0.039	
FCEPS1 and CHGEPS in the Model R-Sq		0.115			0.141			0.090	
Incremental Adj. R-Sq 1	0.112	0.064	57%#	0.140	0.106	76%	0.085	0.051	60%
Incremental Adj. R-Sq 2	0.069	0.068	98%	0.072	0.072	100%	0.072	0.071	99%

Refer to Table 8.1 for variable definitions. ER is calculated the difference between the firm's return for the 12-month period commencing 11 months prior and ending one month after the earnings announcement date and the benchmark index return for the same period, ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm. Standard errors are CDACCR (4.1), AQ (3.2), CHGEPS (2.8), with others less than 0.1. Incremental R-Sq 1: Incremental R^2 from earnings variable. Incremental R-Sq 2: Incremental R^2 from non-earnings variables over earnings. Pre-IFRS is from 2001-2004 and post-IFRS is from 2006-2012. # The percentage adjacent to the incremental R-Squared from the earnings signals represents analysts' inefficiency in using the earnings signal.

Therefore, analysts appear to be inefficient in embedding the information in the fundamental signals priced in the market into their forecasts (Abarbanell & Bushee 1997). On the other hand, the contribution from FCEPS1 over and above that of the fundamental signals in explaining ER is minimal (0.183 - 0.181).

When undertaking a variable to variable comparison of significance between outcomes from estimating Models 3 and 16, all variables significant in Model 3 (CHGEPS, INV, AR, SA, ETR, GM, CF, and DACCR) are also significant in estimating Model 16. The coefficient for CHGEPS is slightly less for Model 16 (52.49) compared to Model 3 (55.63) for the pooled sample.

The analysis based on the sample (5472 observations) that excludes the GFC period (2007-2009) (untabulated) also reveals the same results, with the exception that ETR is not significant in either of Models 3 or 16. These results indicate that analysts are inefficient in using the information content in non-earnings over earnings priced in the market. This is more evident when looking at the percentage inefficiency in utilising the non-earnings signals over earnings, which is 98 per cent. Moreover, analysts incorporate some of the value relevant information (percentage of efficient utilisation is 44 per cent (100 - 56) included in CHGEPS, when conveying information to the market through their one-year-ahead change in earnings per share forecasts.

However, in general, analysts are inefficient in using the earnings information included in the fundamental signals priced in the market. Abarbanell and Bushee (1997) state that "if the market is efficient, the association between the signals and returns incremental to forecast revisions could reflect the market's "correction" of these forecasts" (p.15). The overall results support Hypotheses H3a and H3b.

In terms of IFRS impact on analysts' efficiency, this is analysed by comparing outcomes from estimating Models 3 and 16 for both the pre- and post-IFRS periods. As can be seen from Table 8.7, the overall results support the same conclusion that analysts are inefficient in both the pre- and post-IFRS periods. However, the analysis indicates that there is a small increase in analysts' efficiency in using value relevant information included in the earnings signals in the post- compared to pre-IFRS period when making their forecasts of change in earnings per share. The analyses based on the sample [pre-IFRS 1765 (43 per cent) observations, post-IFRS 2298 observations] that excludes the GFC (2007-2009) and full IFRS transition (2004-2006) periods (results untabulated) support the same conclusion.

This result is consistent with other findings that analysts' information environment and forecast accuracy improved after adoption of IFRS (Chalmers et al. 2012; Cheong, Kim & Zurbruegg 2010; Cotter, Tarca & Wee 2012; Preiato, Brown & Tarca 2013). This could be due to an increase in the quality of the information environment (Horton, Serafeim & Serafeim 2013), increased quantity and quality of financial reporting disclosures, and/or increased comparability and transparency of financial statements (Barth, Landsman & Lang 2008; Daske & Gebhardt 2006; Daske et al. 2008; Glaum et al. 2013) after adoption of IFRS. Chapter 7 of this study documents that the value relevance of earnings decreased after adoption of IFRS. Although value relevance decreased after IFRS adoption, comparatively, analysts' efficiency has not decreased. As such, there may appear to be an increase in analysts' efficiency in using value relevant earnings information. Further, it is noted that analysts are highly inefficient in using value relevant non-earning signals as a whole in both the pre- and post-IFRS periods. These results support Hypothesis H3c in terms of using value relevant earnings after adoption of IFRS.

8.11 Conclusion

Tabular summaries of findings from this chapter are reported in Table 8.8 and 8.9. Overall, the analyses in this chapter point to the conclusion that analysts are aware of the usefulness of most of the fundamental signals in predicting one-year-ahead change in earnings per share (Abarbanell & Bushee 1997) and use this information when making their earnings forecasts. However, analysts do not fully incorporate the earnings information embedded in fundamental signals when forecasting one-year-ahead change in earnings per share, and therefore are inefficient. Analysts seem to overreact to fundamental signals CHGEPS, SA, CAPX and GW, whilst they underreact to GM, CF and DACCR. Furthermore, analysts are highly inefficient in selecting and using fundamental signals when forecasting negative change in earnings per share compared to positive change in earnings per share, and they generally underreact to fundamental signals for forecasting a negative change in earnings and overreact to signals when forecasting a positive change in earnings.

The analysis of IFRS impact also indicates that analysts are comparatively efficient in selecting the appropriate fundamental signals for forecasting one-year-ahead change in earnings per share. Overall analysts' ability to incorporate future earnings information included in the fundamental signals is similar between the pre- and post-IFRS periods. However, analysts are generally inefficient in using fundamental signals in both the pre- and post-IFRS periods. Further results indicate that IFRS had a negative impact on analysts' use of the earnings signal and this inefficiency is even higher when forecasting a negative change in earnings compared with a positive change in earnings. Moreover, analysts substantially underutilise earnings signals in Common law compared to Code law countries, in both the pre- and post-IFRS periods. However, analysts' efficiency in using non-earnings signals over earnings increased in the post- compared to pre-IFRS period for all analyses, except for forecasting a negative change in earnings.

Furthermore, analysts are inefficient in using future earnings information included in the fundamental signals priced in the market (value relevant information) when making their forecasts of one-year-ahead change in earnings per share. However, while analysts' efficiency in using this value relevant information embedded in the earnings signal increased after adoption of IFRS, this is not the case for the non-earnings signals.

Table 8.8: Summary of findings for analysts' efficiency in selecting appropriate fundamental signals for forecasting change in one-year-ahead EPS and IFRS impact on this for the period 2001 - 2012 & related to H3a to H3d

Sample	Analysts' efficiency in selecting appropriate signals					IFRS impact on analysts' efficiency in selecting appropriate signals									
	Pooled	Winners	Losers	Code Law	Common Law	Pooled		Winners		Losers		Code Law		Common Law	
						Pre-IFRS	Post-IFRS	Pre-IFRS	Post-IFRS	Pre-IFRS	Post-IFRS	Pre-IFRS	Post-IFRS	Pre-IFRS	Post-IFRS
CHGEPS	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
INV			✓					×			×				
AR															
SA	×	×		✓		×	✓		✓	×		×	✓		
LF	✓	×		✓			×	×	×	×			×		
ETR	✓	✓	×	✓			✓	×	×				×		
GM	✓	×	×	×			×	×	×	×	×	×	×		
AQ	✓			✓			✓		×		×		✓	×	×
CAPX	✓	✓		×	✓	✓	✓	✓	✓		×	✓	✓	✓	✓
LEV	✓	✓		×		×		×	×				×	×	
CF	✓	✓	×	✓	×	×	✓		✓		×	×	✓		×
GW	✓	✓		✓	✓	✓	✓	✓	✓		×	✓	×		✓
CDACCR	×		×				×				×		×		×

Refer to Table 8.1 for variable definitions

✓ Analysts are efficient in selecting the signal appropriately

× Analysts are not efficient in selecting the signal appropriately

Table 8.9: Summary of findings for analysts' efficiency in using fundamental signals for forecasting change in one-year-ahead EPS and IFRS impact on this for the period 2001 - 2012 & related to H3a to H3d

Sample	Analysts' efficiency in using the signals					IFRS impact on analysts' efficiency in using the signals									
	Pooled	Winners	Losers	Code Law	Common Law	Pooled		Winners		Losers		Code Law		Common Law	
						Pre-IFRS	Post-IFRS	Pre-IFRS	Post-IFRS	Pre-IFRS	Post-IFRS	Pre-IFRS	Post-IFRS	Pre-IFRS	Post-IFRS
CHGEPS	OR	OR	OR	OR	OR	OR	OR	OR	OR			OR	OR		OR
INV								UR	OR						
AR															
SA	OR			OR		UR				UR					
LF										UR					
ETR															
GM	UR	OR	UR	UR			UR		OR	UR	UR	UR	UR		
AQ			UR				OR				OR		OR		OR
CAPX	OR		UR				OR				OR		OR		
LEV									OR						
CF	UR		UR	UR	UR	UR	UR						UR		
GW	OR	OR	UR		OR		OR	OR	OR						OR
CDACCR	UR			UR			UR						UR		
Analysts Percentage inefficiency in using the fundamental signals															
Earnings signal	22%	5%	75%	14%	36%	18%	24%	1%	7%	62%	75%	7%	17%	34%	36%
Non-earnings signals	65%	33%	100%	60%	33%	71%	64%	49%	28%	75%	100%	65%	59%	83%	20%

Refer to Table 8.1 for variable definitions

OR Analysts overreact to the signal

UR Analysts underreact to the signal

CHAPTER 9: DISCUSSION AND CONCLUSION

9.1 Introduction

This chapter provides an integrated discussion and summary of the findings from testing the hypotheses related to the three Research Objectives of the study. As such, the chapter is organised as follows. Section 9.2 summarises the three Research Objectives and Research Questions and overviews the theoretical support for the study. Section 9.3 highlights the research gaps derived after reviewing the literature and reiterates the hypotheses developed to contribute to knowledge and address the gaps. Section 9.4 summarises the research design for the study. Section 9.5 highlights the findings relating to descriptive statistics. Section 9.6 discusses, summarises the findings and draws conclusions on the predictive ability and value relevance of the chosen fundamental signals, as well as on analysts' efficiency in using the fundamental signals. Section 9.7 discusses, summarises and draws conclusions on the findings related to IFRS impact on the predictive ability and value relevance of the chosen fundamental signals and also on analysts' efficiency in using the fundamental signals[78]. Section 9.8 explains the contribution to theoretical and empirical knowledge arising from the study. Section 9.9 discusses the practical and policy implications of the study. Section 9.10 explains the limitations of the study and Section 9.11 discusses suggestions for future research. Finally, section 9.12 provides concluding remarks.

9.2 Research Objectives and Research Questions, and theoretical background

As set out in Chapter 1, this study is guided by three Research Objectives leading to two broad Research Questions, that is: i) What is the usefulness for decision-making of fundamental information reported in financial statements in years post-2000, especially for investors and financial analysts? and ii) What is the impact of IFRS on this usefulness for the same parties?

The first Research Objective was to investigate the predictive ability of fundamental signals (fundamental information based on financial statements) in predicting one-year-ahead change in earnings per share and IFRS impact on this predictive ability. It was hypothesised that fundamental signals can predict one-year-ahead change in earnings per

[78] Summaries of the overall findings reported in each of Chapters 6, 7 and 8 is provided as part of the Conclusion sections of each of these chapters.

share and that the predictive ability of fundamental signals improved after adoption of IFRS. Given this, the study examines whether the selected fundamental signals contain useful information that predicts change in one-year-ahead earnings per share and whether adoption of IFRS improves this information's quality, enabling better prediction of change in one-year-ahead earnings per share. The results from testing hypotheses H1a, H1b, H1c, H1d, H1e and H1e are reported in detail in Chapter 6.

The second objective was to assess whether the selected fundamental signals are value relevant for stock returns (contemporaneous excess returns) and IFRS impact on their value relevance. Based on the literature, it was hypothesised that fundamental signals are value relevant and that IFRS improves the value relevance of the fundamental signals. If information contained in the fundamental signals is useful, investors and market participants will use this information in making their investment decisions about stocks, so it will thereby be priced in the market. Therefore, investigated is whether there is an association between the selected fundamental signals and contemporaneous excess returns in order to assess the value relevance of these fundamental signals, and whether this association improves after adoption of IFRS. The results from testing hypotheses H2a, H2b, H2c, H2d, H2e, and H2f are reported in Chapter 7.

The third and final objective was to assess the efficiency with which analysts use these fundamental signals that, if found as hypothesised, significantly predict future earnings and are value relevant, and also to assess IFRS impact on this analysts' efficiency. Based on prior literature, it is hypothesised that analysts are inefficient in using the fundamental signals and the efficiency with which analysts use these selected signals improved after adoption of IFRS. The results from testing hypotheses H3a, H3b, H3c and H3d are reported in Chapter 8.

Chapter 2 discusses the main theoretical framework for the study. The theory relates to accounting information quality (Dechow & Schrand 2004), and there are different proxies for accounting information quality, such as earnings persistence, accruals quality, earnings smoothness, asymmetric timeliness and timely loss recognition, target beating, earnings response coefficients (ERCs), value relevance (Dechow, Ge & Schrand 2010) and predictive ability (Dechow & Schrand 2004). The International Accounting Standards Board (IASB) *Conceptual Framework for Financial Reporting* also discusses normative qualitative characteristics of accounting information (IASB, 2010).

This study investigates accounting quality in terms of predictive ability and value relevance, and the main theoretical support for the quality aspects of accounting information comes from decision usefulness theory, the IASB *Conceptual Framework for Financial Reporting (2010)*, and signalling theory. Apart from these, other associated theories, such as agency theory and positive accounting theory, are discussed in Chapter 2.

9.3 Research gap and hypotheses development

Chapter 3 focuses on the review of the literature related to the three Research Objectives and development of the hypotheses based on research gaps identified. The literature review reveals that most of the fundamental signals studies of this kind[79] that examine the predictive ability and value relevance of fundamental signals were conducted using data from prior to year 2000 (Abarbanell & Bushee 1997; Al-Debie & Walker 1999; Dowen 2001; Lev & Thiagarajan 1993; Ou 1990; Ou & Penman 1989b; Seng & Hancock 2012; Swanson, Rees & Juarez-Valdes 2003). However, in years post-2000, several changes have occurred in the accounting environment that affect the quality of accounting information, most importantly adoption of IFRS in many countries around the world. These changes might affect the decision usefulness of fundamental signals and this issue is yet to be investigated for non-earnings signals. Therefore, users may not be fully informed about the quality and behaviour of this information following these changes and therefore this may lead to information asymmetry. As such, it is important and timely to revisit this area of research using post-2000 data, to gauge whether the fundamental signals investigated previously remain useful for decision-making and whether other fundamental signals not tested previously are important for decision-making in years post-2000.

Given the importance of fundamental analysis and the paucity of this type of research in years post-2000, this study examines the predictive ability and value relevance of one earnings signal and 12 non-earnings signals using post-2000 data for 11 European countries plus Australia, and in so doing makes a significant contribution to the fundamental analysis literature. Based on previous studies, it is hypothesised that

[79] In this type of study, variables are designed specifically based on signals commonly used by analysts when forecasting future earnings and assessing stock returns.

fundamental signals have predictive ability in terms of one-year-ahead change in earnings per share and also are value relevant for contemporaneous excess returns.

As explained, adoption of IFRS is one of the most important milestones in recent international accounting history and a great deal of evidence exists that IFRS significantly affected financial statement fundamentals (e.g.Blanchette, Racicot & Girard 2011; Bradbury & van Zijl 2005; Goodwin, Ahmed & Heaney 2008; Haverals 2007; Horton & Serafeim 2010; Iatridis 2010; Kabir, Laswad & Islam 2010; Stent, Bradbury & Hooks 2010; Tsalavoutas & Evans 2010), and therefore affected the quality of accounting information.

Several studies investigate IFRS impact on the quality of accounting information around the world, such as the value relevance of earnings, earnings persistence, accruals quality, timeliness of loss recognition, earnings smoothness, earnings response coefficients (ERCs), and earnings management (e.g. Atwood et al. 2011; Barth et al. 2012; Barth, Landsman & Lang 2008; Callao, Jarne & Laínez 2007; Chalmers, Clinch & Godfrey 2011; Chen et al. 2010; Christensen et al. 2015; Devalle, Onali & Magarini 2010; Ismail et al. 2013; Jermakowicz, Prather-Kinsey & Wulf 2007). Almost all these studies focus on earnings measures and, to the best of the author's knowledge, no known published studies have been conducted of IFRS impact on the predictive ability or value relevance of the non-earnings fundamental signals included in this study other than for goodwill (Chalmers et al. 2012), and even then in a study very different from this. Also, even for earnings, to the best of the author's knowledge, IFRS impact on the predictive ability of current year change in earnings per share in forecasting one-year-ahead change in earnings per share has not been examined previously. Therefore, a research gap arises, since IFRS affects the quality of fundamental signals, which are important for decision-making in terms of recognition, measurement, classification and presentation, but research has not yet explored this issue adequately. Therefore, this study makes a significant contribution to the IFRS impact literature by investigating the impact of IFRS on the predictive ability and value relevance of one earnings and 12 non-earnings signals in Australian and European contexts.

Previous studies provide evidence of an increase in the quality of accounting information after adoption of IFRS (Barth, Landsman & Lang 2008; Chen et al. 2010; Daske & Gebhardt 2006; Daske et al. 2008; Glaum et al. 2013; Hodgdon et al. 2008; Preiato, Brown & Tarca 2013), while others find no difference or a negative effect on accounting quality (Atwood et al. 2011; Callao, Jarne & Laínez 2007; Doukakis 2010; Kabir, Laswad & Islam 2010). Given the objective of the IASB in promulgating IFRS and advocating for worldwide adoption and the number of studies that find a positive change in accounting quality as a consequence of IFRS (De George, Li & Shivakumar 2016), it is hypothesised in this study that the predictive ability and value relevance of fundamental signals improved after adoption of IFRS.

The review of the literature further reveals that the efficiency with which analysts use fundamental signals is researched rarely, and further, there is no known published research outside a US context using post-2000 data. Importantly, the research that does exist on this issue uses a limited number of observations due to restricted analyst following. Moreover, there is no published research that examines the impact of IFRS on analysts' efficiency in using fundamental signals. Analysts are one of the major groups of users of fundamental signals and they provide vital information to the market in terms of earnings forecasts, stock recommendations and other useful information, thereby reducing information asymmetry. As such, the efficiency with which they use fundamental signals under this changed accounting environment is important to investigate. Therefore, this study makes a significant contribution to the analyst literature by investigating the efficiency with which analysts use fundamental signals for earnings forecasts, the efficiency with which analysts use information in fundamental signals priced in the market, and the impact of IFRS on this efficiency of use of information. It does this with post-2000 data, using more than 7350 firm-year observations with analyst following across a 12-year time period (substantially larger than samples used by other researchers) in a non-US context.

The literature review reveals that analysts are inefficient in using fundamental signals for earnings forecasts (Abarbanell & Bushee 1997; Swanson, Rees & Juarez-Valdes 2003; Wahab, Teitel & Morzuch 2015) and that adoption of IFRS increased analysts' information environment and analysts' forecast accuracy (Chalmers et al. 2012; Cheong, Kim & Zurbruegg 2010; Cotter, Tarca & Wee 2012; Pawsey 2016; Preiato, Brown & Tarca 2013). Based on prior findings on analysts' efficiency and the impact of IFRS, it is hypothesised in this study that analysts are generally inefficient in using fundamental signals, and that the efficiency with which analysts use these fundamental signals increased after adoption of IFRS.

9.4 Summary of research design

Chapter 4 discusses the research design and methodology, including sampling and data issues. In this study, one earnings and 12 non-earnings fundamental signals are used to assess the usefulness of fundamental information in terms of predictive ability and value relevance. Of these 12 non-earnings variables, eight are selected from the study by Lev and Thiagarajan (1993) and four others are included based on findings emanating from previous studies. These variables are chosen specifically to give a signal about future earnings and returns. The one earnings signal used is change in current year earnings per share (CEPS) and the 12 non-earnings fundamental signals are change in inventory relative to change in sales (INV), change in accounts receivable relative to change in sales (AR), change in selling and administrative expenses relative to change in sales (SA), change in labour force (LF), change in effective tax rate (ETR), change in gross margin (GM), audit qualification (AQ), change in firm's capital expenditure relative to change in industry capital expenditure (CAPX), change in financial leverage (LEV), change in cash flow from operations (CF), change in goodwill (GW) and change in discretionary accruals (CDACCR) .

Data are collected where available from the Bloomberg database for all except financial industry listed companies for 11 European countries[80] plus Australia for the period 2001 to 2012 inclusive. The Thomson Reuters Eikon database is used to collect mean analysts' forecasts for these companies for this same period. The countries are selected on the basis of the difference between their domestic GAAPs[81] and IFRS (GAAP difference[82]), together with their levels of investor protection.

The included countries are further partitioned into Code and Common law[83] jurisdictions since the literature reports that the quality of accounting information is different across these regimes (Alford et al. 1993; Joos & Lang 1994; La Porta et al. 1998). Code law

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[80] Spain, Finland, Czech Republic, Belgium, Portugal, Poland, Italy, France, Denmark, Sweden and United Kingdom (UK).

[81] Generally Accepted Accounting Principles (GAAP).

[82] GAAP difference means the difference between local GAAP standards and IFRS. GAAP difference information is obtained from Bae, Tan, and Welker (2008).

[83] Australia and UK come under Common law countries, and others are Code law countries.

countries have higher GAAP difference compared to Common law countries, therefore it is expected that the impact of IFRS is higher for Code compared to Common law countries. Further, the selected countries relative to many other countries have higher, but similar, levels of investor protection. The literature reports that IFRS adoption increases earnings quality in countries where investor protection is stronger (Houqe et al. 2012) and the IFRS impact is greater for countries having higher GAAP difference (Ding et al. 2007; Narktabtee & Patpanichchot 2011). The homogeneity of regulatory mechanisms between European Union countries and the "relatively strong legal system and enforcement regime in the EU provide a powerful setting to detect the effects of IFRS adoption" (Li 2010 p.2).

The predictive ability and value relevance of fundamental signals, and analysts' efficiency in using the fundamental signals, together with the impact of IFRS on these, are investigated for one earnings signal, and 12 non-earnings signals, individually, in combination and in aggregate (F_Score). Moreover, analyses are conducted for different sub-samples, such as for Code and Common law country countries, Winning and Losing stocks, Extreme and Non-extreme performers' returns, and Growth and Value stocks. For each analysis, the impact of IFRS is investigated using an interaction term for each fundamental signal with an IFRS indicator, together with a test of equality of coefficients based on stacked regression (Atwood et al. 2011). As such, these analyses provide a check on the consistency of findings, rendering the findings more reliable.

As the sample data for this study are collected for 12 countries (both Code and Common law), nine industries and more than 2900 firms over a 12-year (2001-2012) period (i.e. cross sectional, time series panel data), indicator variables for countries, industries and years, together with a Code or Common law indicator, are included in models to control for fixed effects. Additionally, robust regression is used for every analysis by clustering on firm identity. Moreover, when analysing IFRS impact, some contextual variables found in prior literature to be influential for the predictive ability and value relevance of fundamental signals, such as the nature (good or bad) of prior year earnings news (PYEN), the level of GDP growth (high or low) and the level of inflation (high or low), are included in the models to isolate the impact of IFRS more clearly. Therefore, results documented in this study provide robust and compelling evidence of the impact of IFRS on the predictive ability and value relevance of the selected fundamental signals.

9.5: Descriptive statistics – major results

Chapter 5 explains the descriptive statistics for the pooled sample selected for the analysis and various sub-samples. The population of non-financial listed companies for the pooled sample is based on those existing in year 2012 as per Bloomberg database. These companies number 5469 for year 2012, which comprises 2652 from Code law countries and 2817 from Common law countries. However, data are available for all required variables for 2001-2012 for only 2923 (53 per cent) companies, of which 1504 (52.9 per cent of Code law population) come from Code law countries and the remaining 1419 (50.4 per cent of the Common law population) from Common law countries. The sample represents an unbalanced panel. The data represent more than 50 per cent of the listed companies in both Code and Common law countries and the sample size is similar between Code and Common law countries.

Following the Barth, Landsman and Lang (2008) and Barth et al. (2012) methodology, all continuous variables are winsorised at 5 per cent to mitigate the effect of outliers, improving the normality of the variable distributions. The total number of firm-year observations for which all data are available was 20997, however, this number can vary in multivariate analysis due to adjustments to avoid multivariate outliers and to eliminate observations for the year of transition to IFRS (2005).

The Pearson's correlations between the independent variables show that none of the correlations is of a level that creates multicollinearity concerns. Analysis of the descriptive statistics indicates that means for all variables except SA and ETR are significantly different between pre- and post-IFRS periods and the means of most of the variables are significantly higher in pre- compared to post-IFRS periods.

9.6 The predictive ability and value relevance of fundamental signals

Chapters 6 and 7 report and discuss the results of testing the ability of fundamental signals to predict one-year-ahead change in earnings per share and the value relevance of the fundamental signals in terms of contemporaneous excess returns, respectively. The results from testing analysts' efficiency in using fundamental signals for forecasting one-year-ahead change in earnings per share are presented and discussed in Chapter 8. The following section presents an integrated discussion of these results and draws conclusions.

9.6.1 Results based on the pooled sample

The Chapter 6 results and discussion conclude that the earnings and non-earnings signals individually, in combination and also in aggregated form (F_Score) predict one-year-ahead change in earnings per share (CEPS1). Analyses show a significant R-Squared contribution from including non-earnings signals over earnings. Similarly, the four additional[84] non-earnings signals beyond those of Lev and Thiagarajan (1993) included in this study also contribute significantly to the R-Squared in predicting CEPS1. Additionally, the F_Score significantly predicts CEPS1 and results in an incremental R-Squared over earnings alone. These results indicate that non-earnings fundamental signals, including F_Score, contain information that is incremental to earnings in predicting change in one-year-ahead earnings per share. These results are consistent with findings from previous studies (Abarbanell & Bushee 1997,1998; Al-Debie & Walker 1999; Dowen 2001; Lev & Thiagarajan 1993; Mohanram 2005; Ou 1990; Seng & Hancock 2012). These findings support Hypotheses H1a, H1b and H1c. However, several fundamental signals (AQ, CAPX, LEV, and GW) are significant in the direction not anticipated and possible explanations are provided for this.

Analyses and discussions in Chapter 7 point to the conclusion that both earnings and non-earnings signals are value relevant for contemporaneous excess returns and all fundamental signals are value relevant in the direction expected, with the exception of INV. The analysis shows that the incremental contribution to R-Squared from the non-earnings fundamentals, including the four extra variables added for this study, is significant. The F_Score, which represents an aggregated version of the non-earnings signals, is also value relevant for contemporaneous excess returns. The results reveal that non-earnings fundamental signals individually, in combination and in aggregate (F_Score) possess incremental information over earnings that is value relevant for excess returns (Abarbanell & Bushee 1997,1998; Al-Debie & Walker 1999; Dowen 2001; Elleuch 2009; Lev & Thiagarajan 1993; Mahmoud & Sakr 2012; Mohanram 2005; Ou 1990; Piotroski 2000). These findings support Hypotheses H2a, H2b and H2c.

[84] These variables are LEV, CF, GW and CDACCR.

When considering individual fundamental signals, the earnings variable by construction is expected have a positive relationship with one-year-ahead change in earnings per share[85] (CEPS1) and a negative relationship with contemporaneous excess returns (ER). All non-earnings signals, by construction are expected have a negative relationship with CEPS1 and ER.

The results reveal that the earnings variable has predictive ability in the direction anticipated, demonstrating the current year accruals reversal (Chan, Jegadeesh & Sougiannis 2004; DeFond & Park 2001; Pae 2005; Wahab, Teitel & Morzuch 2015) and mean reverting pattern of earnings, with a good year followed by a bad year and a bad year followed by a good year (Dowen 2001; Swanson, Rees & Juarez-Valdes 2003). The earnings variable also is value relevant for excess returns in the direction anticipated.

As explained above, of the twelve non-earnings signals, eight are drawn from the study by Lev and Thiagarajan (1993) and defined and constructed as per that study, which examined the value relevance of fundamental signals claimed by financial analysts to be useful in share valuations. Consistent with the findings of Lev and Thiagarajan (1993), all eight non-earnings signals (INV, AR, ETR, AQ, SA, LF, GM, CAPX) have the expected sign and are significantly associated with contemporaneous excess returns, and therefore are value relevant. Given the definitions and expected relationships of the fundamental signals posited by Lev and Thiagarajan (1993), Abarbanell and Bushee (1997) examined the ability of nine fundamental signals (including the earnings and eight non-earnings signals used in this study) to predict one-year-ahead change in earnings. They found that INV, GM, ETR, and LF significantly predicted CEPS1 in the direction anticipated, while AR and CAPX, whilst significant, were not in the direction anticipated. SA and AQ were not significant in their study.

This current study finds that INV, AR and ETR are significant in the direction anticipated, while AQ, and CAPX are significant but not in the expected direction, in predicting one-year-ahead change in earnings (CEPS1). However, SA. LF and GM are not significant in predicting CEPS1. The positive relationship of CAPX with CEPS1 could be explained as firms that had been performing poorly attempting to catch-up with firms in their industry

[85] This relationship is expected due to the reversing nature of current year accruals (Chan, Jegadeesh & Sougiannis 2004; DeFond & Park 2001; Pae 2005; Wahab, Teitel & Morzuch 2015).

that recently had made large, successful capital investments (Abarbanell & Bushee 1997). Another possible explanation could be that benefits from higher capital investment might be long-term, and in the short-term, the impact may be negative due to higher capital outflow. Having higher long-term benefits from capital investment is reflected by the value relevance of CAPX for excess returns in the direction expected, since share price is the present value of all future expected cash flows associated with that share. Having a positive relationship between AQ and CEPS1 can be explained as due to accrual reversal, or could reflect auditor switching in an attempt to receive a favourable opinion in the next period (Chow & Rice 1982), a phenomenon beyond the scope of this study to investigate.

The four additional fundamental signals included in this study beyond those of Lev and Thiagarajan (1993) (LEV, CF, GW, and CDACCR) are significant in predicting CEPS1 and are also value relevant. CF and CDACCR have predictive ability and value relevance in the direction anticipated. LEV is value relevant in the expected direction, but predicts CEPS1 in the unanticipated direction. Using debt can be good or bad depending on whether the firm earns more or less than after tax interest cost on the investment(s) financed with borrowed funds (Modigliani & Miller 1958). If the debt gives a higher return than the associated cost, it is positively related with CEPS1 and should be negatively related, as expected, with ER because higher expected earnings in the future increase the share price. GW is also positively associated with CEPS1 (unexpected) and negatively associated with ER (expected). The same argument is valid for GW as was valid for CAPX. New capital investment in GW might give benefits in the long-term, whilst in the short-term the impact may be negative due to higher capital outflow. The higher the long-term benefits associated with shares, the higher the share price.

Finally, Chapter 8 analyses and discussion documents that analysts efficiently select most of the included fundamental signals that are useful in predicting change in one-year-ahead earnings per share (CEPS1) for forecasting change in one-year-ahead earnings per share (FCEPS1). However, analysts do not fully incorporate the future earnings information embedded in these fundamental signals when forecasting one-year-ahead change in earnings per share (EPS), and overreact to CHGEPS, SA, CAPX and GW, while they underreact to GM, CF and CDACCR.

These results point to the conclusion that analysts are aware of the fundamental signals useful in predicting one-year-ahead change in earnings per share (they efficiently select most of the appropriate fundamental signals), however, they are inefficient in using these fundamental signals for their earnings forecasts (Abarbanell & Bushee 1997; Swanson, Rees & Juarez-Valdes 2003; Wahab, Teitel & Morzuch 2015). Moreover, results reported in Chapter 8 reveal that analysts, as hypothesised, are highly inefficient in using the value relevant earnings information included in the fundamental signals for forecasting change in one-year-ahead earnings per share. Therefore, analysts underreact or overreact to certain signals when make their earnings forecasts. As such the findings support Hypotheses H3a and H3b.

9.6.2 Code versus Common law country sub-samples

Prior literature makes it evident that the quality of accounting information is different across Code and Common law regimes (Alford et al. 1993; Joos & Lang 1994), therefore analysis is conducted for separate sub-samples of Code and Common law countries in order to examine the predictive ability and value relevance of fundamental signals, as well as analyst efficiency in using these signals.

The results documented in Chapters 6 and 7 show that the earnings and non-earnings signals, including F_Score, significantly predict one-year-ahead change in earnings per share and are also value relevant for excess returns for both sub-samples of Code and Common law countries. The predictive ability of fundamental signals (individually, in combination and in aggregate) overall is similar between the two Code and Common law country sub-samples. However, the value relevance of certain non-earnings signals (LF, AQ, CAPX, LEV, CF and GW) and F_Score is significantly higher in Common law countries compared with Code law countries. This could be due to higher enforcement attributable to the UK and Australia (Common law countries) compared to other countries selected for this study (Brown, Preiato & Tarca 2014) with higher enforcement leading to higher value relevance (Landsman, Maydew & Thornock 2012).

The analyses and discussion in Chapter 8 reveal that analysts are inefficient in using the selected fundamental signals in forecasting one-year-ahead change in earnings per share for both Code and Common law countries, and analysts' efficiency in using the earnings signal is substantially lower (but slightly higher for non-earnings signals) in Common compared with Code law countries. Results for the non-earnings signals (but not the earnings signal) are consistent with the findings, of Barniv, Myring and Thomas (2005) who attribute higher analysts' forecast accuracy for Common compared to Code law countries to more effective corporate governance, stronger legal protection laws, and higher quality financial reporting in Common law countries. Since the countries included in this study are deliberately selected because of their high and similar levels of investor protection, this finding highlights the importance of examining the quality of both earnings and non-earnings fundamental signals under different legal regimes.

9.6.3 Winners versus Losers sub-samples

Chapter 6 defines Winners and Losers in terms of increase (Winners) or decrease (Losers) in one-year-ahead change in earnings per share, whereas Chapter 7 identifies Winners and Losers in terms of contemporaneous excess return as gains (Winners) or losses (Losers).

The results show that fundamental signals better predict Winners compared to Losers. However, the overall value relevance of the model indicated by the adjusted R-Squared is higher for Losers than Winners. The predictive ability and the value relevance of the earnings signal is significantly higher for Winners than Losers. Further, the results reveal that there are non-earnings fundamental signals both common to and unique to each of Winners and Losers that have predictive ability and value relevance. Many non-earnings fundamental signals are value relevant for Losers and the incremental value relevance from non-earnings signals is higher for Losers compared to Winners. However, the combined predictive ability from non-earnings signals is higher for Winners compared to Losers. The aggregated fundamental score predicts only Winners, but is value relevant for both Winners and Losers. These results point to the conclusion that fundamental signals are useful in distinguishing between, predicting and assessing Winners and Losers

Chapter 8 analyses analysts' efficiency in using the selected fundamental signals for forecasting one-year-ahead earnings change in terms of earnings per share increase (Winners) and decrease (Losers). It is concluded from the results that analysts are mostly efficient in selecting the appropriate fundamental signals for forecasting Winners, but in terms of Losers they are highly inefficient. Analysts appear to select only the earnings signal appropriately when forecasting Losers. Further results reveal that analysts are highly inefficient in using both the earnings (inefficiency percentage 75 per cent) and non-earnings (inefficiency percentage 100 per cent) signals for forecasting Losers compared to Winners (inefficiency percentage for earnings 5 per cent and for non-earnings 33 per cent).

Analysts appear to overreact to earnings irrespective of the direction of earnings change (Winners or Losers), but analysts generally underreact to most of the non-earnings fundamental signals (AQ, GM, CAPX, CF and GW) when predicting Losers and overreact (GM and GW) when forecasting Winners. Prior literature provides evidence that analysts underreact to negative information and overreact to positive information (Easterwood & Nutt 1999). Zhaoyang and Jian (2007) also document that analysts overreact to good news. This study provides some consistent evidence, but from a different perspective. That is, analysts are highly inefficient and underreact to fundamental information when forecasting a negative change in earnings, whilst they are comparatively efficient and overreact to some fundamental signals when predicting a positive change in earnings.

This result is also consistent with evidence that analysts are biased towards upwards forecasts, in line with their incentives (Bonini et al. 2010; Bradshaw, Huang & Tan 2014). Given this, analysts' efficiency in using fundamental signals for forecasting a negative change in earnings may be lower compared to when forecasting a positive change in earnings. On the other hand, Chapter 6 documents that the selected fundamental signals also better predict Winners compared to Losers. Corresponding to this, analysts also might be more efficient in using these signals for forecasting Winners compared to Losers.

9.6.4 Contextual analysis

The predictive ability of the overall model is higher under Bad PYEN, Low GDP growth and Low inflation, while the value relevance of the overall model is higher under Bad PYEN, High GDP and Low inflation. PYEN condition seems to be affected for predictive ability and value relevance of both earnings and non-earnings signals individually and in aggregation (F_Score). The level of GDP growth affects the value relevance of the earnings and non-earnings signals, but influences mostly the predictive ability of non-earnings signals, including F_Score. The level of inflation affects the predictive ability of the earnings signal and the value relevance of F_Score.

9.7 IFRS impact on the predictive ability and value relevance of fundamental signals and the efficiency with which analysts use fundamental signals

The latter analyses in each of Chapters 6-8 deal with IFRS impact on the predictive ability, value relevance and analysts' efficiency in using fundamental signals, respectively. The sections below summarise and discuss the results from these analyses in different contexts.

9.7.1 Pooled sample and Code versus Common law sub-samples

For results reported in Chapter 6, the overall model demonstrates a higher predictive ability (higher adjusted R-Squared) of fundamental signals in the post- compared to pre-IFRS period for the pooled and sub-samples of Code and Common law countries. As documented in Chapter 7, the value relevance of the overall model (adjusted R-squared) is lower in the post- compared to pre-IFRS period for the pooled sample and sub-samples. In terms of analysts' use of fundamental signals, analysts are comparatively efficient in selecting the appropriate fundamental signals for forecasting one-year-ahead change in earnings per share in the post- compared to pre-IFRS period. This may be attributable to increased quality of the information environment (Horton, Serafeim & Serafeim 2013), increased quantity and quality of financial reporting disclosures, and/or increased comparability, readability and transparency of financial statements (Barth, Landsman & Lang 2008; Cheung & Lau 2016; Daske & Gebhardt 2006; Daske et al. 2008; Glaum et al. 2013) after adoption of IFRS. However, overall analysts' efficiency in using the fundamental signals when forecasting change in one-year-ahead earnings per share is similar between the pre- and post-IFRS periods.

When the earnings fundamental is considered, after adoption of IFRS, its predictive ability significantly increased mainly for Code law countries, while its value relevance significantly decreased mostly for Common law countries. Previous studies report that IFRS adoption increases earnings quality (from results of this study, it is predictive ability that increases as an aspect of earnings quality) in countries where investor protection is stronger (Houqe et al. 2012) and the impact is higher when domestic GAAP is more different (Code law countries) from IFRS (Ding et al. 2007; Narktabtee & Patpanichchot 2011). All selected countries have high levels of investor protection, but GAAP difference from IFRS is higher for Code compared with Common law countries. Therefore, the findings related to IFRS impact on the predictive ability of earnings are consistent with prior literature, but this is not the case for findings related to the value relevance of earnings. However, some prior studies also provide evidence of a decrease in the value relevance of earnings for Common compared with Code law countries (Clarkson et al. 2011) after adoption of IFRS. Morais and Curto (2008) document an increase in earnings quality (decrease in earnings smoothing) and decrease in value relevance of earnings after adoption of IFRS in a Portuguese context. This study concludes that IFRS has positive impact on the predictive ability of earnings, while a negative impact on the value relevance of earnings. Kim and Kross (2005) also provide evidence of increased predictive ability of earnings in predicting future cash flows, while decreased value relevance of earnings using data from 1973-2000. They further find that the decrease in value relevance of earnings is attributable to market inefficiencies.

Analysts' efficiency in using the earnings signal for forecasting one-year-ahead change in earnings decreased after adoption of IFRS. This indicates that analysts fail to utilise the increased predictive ability of earnings post-IFRS when making their earnings forecasts, therefore reflecting as a decrease in analysts' efficiency in utilising the earnings signal in the post- compared to pre-IFRS period. At the same time, the results in Chapter 8 show that analysts are more efficient in using value relevant information included in the earnings variable when forecasting one-year-ahead change in earnings per share in the post- compared to pre-IFRS period. Chapter 7 reports that the value relevance of earnings decreased after adoption of IFRS, however concurrently analysts appear to have maintained or increased their efficiency in using value relevant information when forecasting change in one-year-ahead earnings per share after adoption of IFRS.

In terms of the non-earnings fundamental signals, the predictive ability of certain non-earnings fundamental signals (INV, CAPX, AQ) decreased for different samples after adoption of IFRS and the combined predictive ability of the non-earnings fundamental signals over earnings was found to have decreased for the pooled and sub-samples of Code and Common law countries after adoption of IFRS. Therefore, IFRS seems to have had a negative impact on the combined predictive ability of the non-earnings signals. A possible reason could be that earnings in the post-IFRS period is more informative in terms of one-year-ahead change in earnings per share. Therefore, earnings as an aggregated measure might capture more of the information in the non-earnings signals in the post- compared to pre-IFRS period. Corresponding to the above results, the predictive ability of F_Score for one-year-ahead change in earnings per share also decreased significantly in the post- compared to pre-IFRS period for the pooled and Code and Common law sub-samples.

Chapter 7 shows that value relevance decreased for SA and GM while it increased for LF and CF again in different samples in the post- compared to pre-IFRS period. In terms of AQ, its value relevance increased for the Code law sub-sample while it decreased for the Common law sub-sample after adoption of IFRS. The combined value relevance of the non-earnings signals is slightly higher in the post- compared to pre-IFRS period for the pooled sample and Common law sub-sample, while lower for the Code law sub-sample.

The increase in combined value relevance for Common law countries could be due mostly to the increase in value relevance of CF and the contribution from other fundamental signals corresponds with a decrease in the value relevance of earnings. Therefore, cash flow from operations seems to be more informative in terms of excess returns after adoption of IFRS. The value relevance of the aggregated fundamental score (F_Score) also increased significantly for Common law countries after adoption of IFRS. These results also highlight that IFRS impact on the value relevance of the non-earnings signals is higher for Common law countries.

Chapter 8 documents that analysts are efficient in selecting appropriate fundamental signals for forecasting one-year-ahead earnings per share in the post- compared to pre-IFRS period, yet they appear not to fully utilise the information content embedded in these fundamental signals in both pre- and post-IFRS periods. Analysts' efficiency in using earning signals decreased, but increased for non-earnings signals after adoption of IFRS, however analysts still underreact (GM, CF, CDACCR[86]) and overreact (AQ, CAPX and GW) to certain non-earnings signals in the post-IFRS period. Analysts' efficiency in using the earnings signal is substantially lower in Common compared to Code law countries in both pre-and post-IFRS periods, but their efficiency in using non-earnings signals considerably increased for Common law countries after IFRS adoption. This could be due to higher inefficiency in using the earnings signal substitute for non-earnings signals.

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86 Results for the sample that excludes the GFC (2007-2009) and full IFRS (2004-2006) transition periods does not support the result for CDACCR.

GW amongst the non-earnings signals under IFRS seems to have significant impact on analysts' forecast error. Prior studies report that goodwill is more value relevant (Aharony, Barniv & Falk 2010), and more representative of firm's underlying investment opportunities in the post- compared with pre-IFRS period (Godfrey & Koh 2009). However, results from this current study show no significant increase in the value relevance of GW; rather the predictive ability of GW decreased for Code law countries after adoption of IFRS and analysts seem to overreact to GW in the post-IFRS period when forecasting one-year-ahead change in earnings per share.

9.7.2 Winners Vs. Losers sub-samples.

This study also analyses the impact of IFRS on the predictive ability (Chapter 6) and value relevance (Chapter 7) of the fundamental signals and IFRS impact on analysts' efficiency in using the fundamental signals with respect to discriminating between Winners and Losers. As discussed in Chapter 6, the fundamental signals better predict Winners than Losers in both pre- and post-IFRS periods. However, the overall predictive ability of the fundamental signals increased for Losers, but decreased for Winners in the post- compared to pre-IFRS period. Chapter 7 documents that the overall value relevance of the model is slightly higher for Losers compared to Winners in both pre-and post-IFRS periods, however, the overall value relevance of the fundamental signals is lower in the post- compared to pre-IFRS period for both Winners and Losers.

In terms of earnings, it is noted that the predictive ability of earnings significantly increased mostly for Losers, while the value relevance of earnings significantly decreased only for Winners in the post- compared to pre-IFRS period. The combined predictive ability of the non-earnings signals over earnings decreased mostly for Winners, while the combined value relevance of non-earnings signals improved for Winners and decreased for Losers after adoption of IFRS. Corresponding to these results, the predictive ability of F_Score significantly decreased and the value relevance of F_Score significantly increased for Winners, but there was no significant change for Losers.

Chapter 8 documents that analysts are more efficient in forecasting Winners compared to Losers in both pre- and post-IFRS periods. However, analyst's efficiency in using the earnings fundamental decreased when forecasting both Winners and Losers, with a higher decrease for Losers after adoption of IFRS. Moreover, the efficiency with which analysts' use non-earnings signals increased when forecasting Winners, while it decreased when forecasting Losers in the post- compared to pre-IFRS period. The substantial decrease in analysts' efficiency in using the earnings signal when forecasting Losers indicates that analysts fail to make use of increased predictive ability of the earnings signal in the post-IFRS period for their earnings forecasts in respect of Losers. The increase in efficiency with which analysts use non-earnings signals for Winners could be an indication that analysts, in response to a decrease in the combined predictive ability of the non-earnings signals for Winners, maintained or increased their efficiency in using the non-earnings signals for forecasting Winners.

9.7.3 Additional tests

In addition to the above discussion, the analyses reported in Chapter 7 document that the value relevance of the fundamental signals as a whole is substantially higher for Extreme performer returns (Adjusted R-Squared of 0.346) than non-Extreme performer returns (Adjusted R-Squared of 0.106). The value relevance of the earnings and all non-earnings signals (except for INV and GW), and F_Score, is significantly higher for the Extreme compared to the Non-extreme performer sub-sample. The overall value relevance of the model is lower in the post- compared to pre-IFRS period for both sub-samples and most of the fundamental signals (only non-earnings) that are affected by IFRS occur for the Extreme performer sub-sample. Overall, IFRS impact is positive for Extreme performers and negative for Non-extreme performers in terms of non-earnings signals.

Further, additional analysis discussed in Chapter 7 indicates that the earnings and non-earnings fundamental signals and F_Score are value relevant for contemporaneous excess returns for both Growth and Value stocks, with more fundamental signals value relevant for Value than Growth stocks. This analysis points to the conclusion that both earnings and non-earnings fundamental signals are useful in distinguishing between and assessing Growth and Value stocks. Again, the overall value relevance of fundamental signals is less in the post- compared to pre-IFRS period for both Growth and Value stocks. The IFRS impact is negative for earnings, but positive for non-earnings signals for Growth stocks, while there is no significant impact of IFRS for Value stocks.

9.8 Research contribution

Both the earnings and non-earnings fundamental signals are important for financial statement users' decision-making, especially for financial analysts in making their predictions about earnings and returns (Lev & Thiagarajan 1993). It is well-documented that current year earnings are associated with future earnings/ returns and, therefore, earnings has predictive ability and is considered value relevant (Ahmed, Schneible & Stevens 2003; Ball & Brown 1968; Dechow 1994).

Although useful, current earnings does not capture all the variation in future earnings and future stock price/ returns, and also the value relevance of earnings has decreased over time (Collins, Maydew & Weiss 1997; Francis & Schipper 1999). This suggests that research focusing on non-earnings fundamental signals remains important, a view supported by studies including Ou and Penman (1989b), Frankel and Lee (1998), Lev and Thiagarajan (1993), Abarbanell and Bushee (1997) and (1998), Al-Debie and Walker (1999), Ohlson and Penman (1992), Swanson, Rees and Juarez-Valdes (2003), Carnes (2006), Seng and Hancock (2012), El-Gazzar, Finn and Tang (2009), Piotroski (2000), Dowen (2001), and Mohanram (2005).

Most of the fundamental signal studies of the kind cited above are conducted using data collected prior to year 2000. Yet, significant changes have occurred in the international accounting environment since that year, such as adoption of IFRS, that are likely to affect the decision usefulness of the signals. Therefore, users may not be informed about the quality and behaviour of this information following these changes and so information asymmetry may occur. As such, it is important to revisit this area of research using data from years' post-2000 to assess the usefulness of these fundamental signals under the changed accounting environment. Given the importance of fundamental analysis and the paucity of this type of research in years post-2000, this study examines the predictive ability and value relevance of earnings and 12 non-earnings signals using post-2000 data in the context of 11 European countries and Australia. Thereby this study makes a significant contribution to the body of knowledge concerning both fundamental signals and the impact of IFRS.

The adoption of IFRS represents one of the most important events in the international accounting environment, and this is especially so for years post-2000. Given this, many researchers around the world have provided evidence that IFRS adoption had a significant impact on financial statements elements in terms of their recognition, measurement, classification and presentation (e.g. Blanchette, Racicot & Girard 2011; Bradbury & van Zijl 2005; Goodwin, Ahmed & Heaney 2008; Haverals 2007; Horton & Serafeim 2010; Iatridis 2010; Kabir, Laswad & Islam 2010; Stent, Bradbury & Hooks 2010; Tsalavoutas & Evans 2010), and therefore had an impact on financial statement fundamentals.

As explained at the beginning of this chapter, previous studies of the impact of IFRS on accounting information quality focus mainly on the quality attributes of earnings (Atwood et al. 2011; Barth, Landsman & Lang 2008; Callao, Jarne & Laínez 2007; Chalmers, Clinch & Godfrey 2011; Chen et al. 2010; Devalle, Onali & Magarini 2010; Jermakowicz, Prather-Kinsey & Wulf 2007). To the best of the author's knowledge no known published studies have been conducted examining IFRS impact on the predictive ability and value relevance of non-earnings fundamental signals (except for GW) included in this current study. Additionally, there are no known studies that examine IFRS impact on both the predictive ability and value relevance of the same set of non-earnings fundamental signals as in this study. Also, for earnings, the impact of IFRS on the predictive ability of current year change in earnings in forecasting one-year-ahead change in earnings per share has not been examined previously. Therefore, this study makes a significant contribution to the IFRS literature by filling thes research gaps using one earnings and 12 non-earnings signals in Australian and Euoropean contexts, providing insights likely to be of benefit for users and preparers of financial statements, regulators and standard setters and countries deliberating the merits of IFRS adoption.

Analysts are likely the major users of fundamental information included in financial statements in terms of using it for predicting firm performance and share valuation (Lev & Thiagarajan 1993). However, as explained at the beginning of this chapter, the area of research that examines analysts' efficiency in using fundamental signals has not been well-researched. As such, there is a paucity of research[87] in this area, with no known studies conducted outside the US context using post-2000 data. Moreover, there is no research that examines the impact of IFRS on analysts' efficiency in utilising fundamental signals. Therefore, this study, examining as it does the efficiency with which analysts use

[87] Only three published research studies can be identified. They are Abarbanell and Bushee (1997), Swanson, Rees and Juarez-Valdes (2003) and Wahab, Teitel and Morzuch (2015).

one earnings and 12 non-earnings fundamental signals, and the impact of IFRS on this efficiency in European and Australian contexts, using a substantially larger dataset compared with prior research, makes a significant contribution to the stock of knowledge about analyst efficiency. The insights provided are likely to benefit analysts and market participants significantly in using the fundamental signals for decision-making under the changed accounting environment induced by IFRS adoption.

9.8.1 Empirical contribution

As explained earlier, this study provides robust and compelling evidence on the predictive ability, value relevance fundamental signal and analysts' efficiency of use of these signals derived from financial statements. Because these features are investigated for these fundamental signals individually, in combination, and in aggregate (F_Score), a check is provided on the consistency of the findings. In addition, the information quality of the fundamental signals is cross-checked by investigating the predictive ability and value relevance of the same set of fundamental signals across all analyses.

Apart from that, this study investigates the predictive ability, value relevance and analysts' efficiency from different perspectives (sub-samples), such as Code and Common law countries and Winners and Losers. Further, value relevance is examined for Extreme and Non-extreme performer, and Growth and Value stock sub-samples. The impact of IFRS on the above aspects is examined also and in the same contexts, and further, IFRS impact on the predictive ability and value relevance is examined using interaction terms for each fundamental signals with IFRS, as well as using a test of equality of coefficients based on stacked regression. Therefore, the findings for IFRS impact are very robust. Accordingly, this study provides compelling evidence on the quality of accounting information, analysts' efficiency in using that information, and the impact of IFRS on the same. The sample is also selected carefully to control, to the extent possible, factors that influence the quality of accounting information, such as investor protection, accounting standards and legal regime.

The Chapter 6 findings using post-2000 data contribute to the fundamental analysis literature in that both earnings and non-earnings fundamental signals are found to have predictive ability in terms of future earnings. This study finds that the selected non-earnings fundamental signals individually, in combination and also in aggregate

(F_Score) contain information content incremental to earnings useful in predicting future earnings (Abarbanell & Bushee 1997; Dowen 2001; Seng & Hancock 2012; Swanson, Rees & Juarez-Valdes 2003). Four additional fundamental signals beyond those of Lev and Thiagarajan (1993) included in this study are significant in predicting change in one-year-ahead earnings, however some are not in the direction anticipated. The interpretation of these relationships provides some new insights about the particular signals derived from these variables for forecasting future earnings.

Further, this study provides robust evidence on the effect of reversal of current year accruals (Chan, Jegadeesh & Sougiannis 2004; DeFond & Park 2001; Pae 2005; Wahab, Teitel & Morzuch 2015) in different analyses, such as for the pooled sample, sub-samples of Code and Common law countries and analysis for Winners and Losers. Results from this study further indicate that Code or Common law country regime does not make any difference to the predictive ability of fundamental signals. In addition, the study makes a significant contribution to the literature by documenting findings that both earnings and non-earnings signals better predict future increases (Winners) in earnings than decreases in earnings (Losers), whilst the aggregated F_Score predicts only future increases in earnings significantly. As such, these fundamental signals can be used to identify future Winners and Losers in terms of the direction of future earnings change. No prior studies differentiate the predictive ability of non-earnings signals by the direction of future change in earnings and this study thereby makes a significant contribution to the stock of knowledge.

The next major contribution of this study comes from results reported in Chapter 7 through investigation of the value relevance of the fundamental signals from different perspectives. This study again provides robust evidence that both earnings and selected non-earnings signals individually, in combination, and in aggregate (F_Score) are value relevant for excess returns (Abarbanell & Bushee 1997; Al-Debie & Walker 1999; Dowen 2001; Swanson, Rees & Juarez-Valdes 2003). This evidence is consistent with prior literature documenting that non-earnings fundamental signals have information content incremental to earnings (individually, in combination and aggregated form) that is value relevant for contemporaneous excess returns, and are therefore useful for market participants when making their investment decisions. This study reports that the value relevance of several non-earnings fundamental signals, including F_Score, is significantly different based on legal regime (Code versus Common law), and as such, provides important evidence for the value relevance literature.

This study also makes a valuable contribution to the literature by identifying value relevant fundamental signals that are useful in assessing only gains (Winners) and/or only losses (Losers), and those that are common to both sub-samples. It is found that there are some fundamental signals for which the value relevance is significantly different between the two sub-samples. To the best of the author's knowledge, no known prior fundamental studies create this differentiation (especially for non-earnings signals) when examining value relevance. In addition, this study investigates the value relevance of the same set of fundamental signals for both Extreme and Non-extreme performers, as well as for Growth and Value stocks, and identifies the value relevant fundamental signals that are common and different for each counterpart, thereby adding valuable insights to the fundamental analysis and value relevance literatures. No known study exists that examines the value relevance of the same set of fundamental signals for both Growth and Value stocks.

Another significant contribution to the empirical literature lies in the evidence presented in relation to the impact of IFRS on the predictive ability and value relevance of the fundamental signals. In conducting this study, as is explained above, the sample was selected carefully to control for other aspects known to be associated with the quality of accounting information. The literature reports that IFRS adoption increases earnings quality in countries where investor protection is stronger (Houqe et al. 2012). Therefore, countries having higher but similar levels of investor protection are selected for inclusion in the sample. Countries from the European Union are selected due to the homogeneity of regulatory mechanisms, since this minimises cross-country differences that are associated with the quality of accounting information. Moreover, the "relatively strong legal system and enforcement regime in the EU provide a powerful setting to detect the effects of IFRS adoption" (Li 2010 p.2). Previous studies document that the impact of IFRS is higher for countries where domestic GAAP is more rather than less different from IFRS (Ding et al. 2007; Narktabtee & Patpanichchot 2011). All sample Code law countries included in this study have higher GAAP difference than the sampled Common law countries.

The findings document that IFRS has a positive impact on the predictive ability of earnings, but mostly for Code law countries, while that impact for the value relevance of earnings is negative, but mostly for Common law countries (Clarkson et al. 2011). To the best of the author's knowledge, no known study examines IFRS impact on the predictive ability of current year change in earnings in predicting one-year-ahead change in earnings. IFRS impact on the predictive ability of non-earnings signals individually, in combination, and in aggregate, is negative for the pooled sample and sub-samples of Code and Common law countries. The value relevance of the non-earnings signals, mostly in combination, and for F_Score, increased for Common law countries after adoption of IFRS. As such, this evidence provides new insights for the IFRS literature. No prior published study investigates IFRS impact on non-earnings fundamental signals in the depth this study does. The results also highlight the importance of examining both earnings and non-earnings fundamental signals, because the impact of IFRS is different for each.

Further analysis of IFRS impact provides new evidence to the literature based on examination of Winners and Losers. The predictive ability of fundamental signals increased when predicting mostly Losers (decrease in one-year-ahead earnings), while the value relevance of earnings significantly decreased only for Winners (gains), after adoption of IFRS. IFRS impact on the predictive ability of non-earnings signals, mostly in combination and aggregated form, is negative for Winners (increase in one-year-ahead EPS) and IFRS impact on the value relevance of non-earnings signals is positive (mostly in combination and aggregated form) for Winners (gains).

Moreover, based on further tests, this study provides new evidence of the impact of IFRS on the value relevance of earnings and non-earnings signals for Extreme and Non-extreme performers' returns and for Growth and Value stocks. Results reveal that IFRS impact on value relevance is significantly different between the Extreme and Non-extreme performer sub-samples (mostly for non-earnings signals) as well as between Growth and Value stocks. However, the overall value relevance of the signals decreased for all sub-samples after adoption of IFRS. Again no such prior studies that examine the impact of IFRS on value relevance of fundamental signals do so using these perspectives (Winners and Losers, Extreme and Non-extreme performers' returns, or Growth and Value stocks). As such, this study provides compelling evidence of IFRS impact on the quality of accounting information and in so doing makes a significant contribution to the body of knowledge and hence our understanding. There is some evidence in the literature in support of a quality improvement in accounting information after introduction of IFRS (Barth, Landsman & Lang 2008; Chen et al. 2010; Daske & Gebhardt 2006; Daske et al. 2008; Glaum et al. 2013; Hodgdon et al. 2008; Preiato, Brown & Tarca 2013), as well as findings of no increase or decrease in the quality of information quality (Atwood et al. 2011; Callao, Jarne & Laínez 2007; Doukakis 2010; Kabir, Laswad & Islam 2010). This study, as explained earlier, provides robust and compelling evidence of IFRS impact on different quality attributes from different perspectives.

Finally, the study makes another substantial contribution to the literature by providing evidence of analysts' efficiency in using fundamental signals and the impact of IFRS on analysts' efficiency. Given the statistical power of the large sample size in this study compared with prior studies in this area, the evidence provided is very robust. The evidence reveals that analysts are aware of the usefulness of the fundamental signals (i.e. select appropriate fundamental signals) in forecasting future change in earnings, however, they are inefficient in using the information embedded in the signals. As such they either underreact or overreact to certain fundamental signals. Analysts' efficiency in using the earnings signal is substantially different between Code and Common law countries. Furthermore, analysts seem to be more efficient in forecasting one-year-ahead increase (Winners) compared to decrease (Loser) in earnings per share. When forecasting Losers, analysts are highly inefficient in selecting and using the non-earnings signals and they mostly overreact to fundamental signals when forecasting Winners, while underreacting when forecasting Losers. These findings constitute new empirical evidence for the analyst efficiency literature. No known prior study examines analysts' efficiency in using fundamental signals comparatively in Code and Common law countries, or for Winners and Losers.

IFRS impact on analyst efficiency reveals that analysts are more aware of the usefulness of fundamental signals for forecasting in the post- compared to pre-IFRS period. However, analysts fail to utilise the increased predictive ability of earnings after adoption of IFRS, especially when forecasting Losers. Compared to decreased predictive ability of non-earnings fundamental signals after adoption of IFRS, analysts seem to have maintained or increased their efficiency in using non-earnings fundamental signals for earnings forecasts, especially for Winners and for Common law countries. This study is the first time that IFRS impact on analysts' efficiency has been examined. As such this represents new empirical evidence to the literature on analysts' efficiency in use of fundamental signals and to the IFRS literature.

9.8.2 Theoretical contribution

The findings provide useful evidence in support of several theories adopted in the study. The main theoretical support for the study comes from decision usefulness theory. Based on the theory, the most appropriate accounting standard is that which provides the most useful information to financial statement users for their decision-making. Decision usefulness can be evaluated by the predictive ability of the accounting information (IASB, 2010). This study provides comprehensive evidence of the ability of earnings and non-earnings fundamental signals (individually, in combination and in aggregate) to predict one-year-ahead change in earnings per share, and therefore supports the decision usefulness of these signals, consistent with the theory. Further, the study finds that the predictive ability of earnings increased after adoption of IFRS, indicating higher decision usefulness of earnings after adoption of IFRS. However, the impact of IFRS on the predictive ability of non-earnings signals as a whole is negative. That finding indicates a decrease in decision usefulness of non-earnings accounting information after adoption of IFRS. Therefore, standard setters might be served best by focusing on non-earnings fundamentals in order to further increase the decision usefulness of accounting information.

The main objective of financial reporting is to provide useful financial information to existing and potential investors, lenders, creditors and other stakeholders regarding the economic entity of their interest for decision-making (IASB 2010 para. OB.2). In order to be useful, financial information should be relevant for their decision-making. One method of analysing whether this is the case for financial information is to analyse the value relevance of the information. This study provides supportive evidence of the value relevance of earnings and non-earnings fundamental signals and therefore supports the theory. However, analysis of the impact of IFRS on the value relevance of fundamental signals reveals that the value relevance of earnings decreased after adoption of IFRS. That is, the quality of earnings under IFRS decreased in terms of relevance. Prior literature documents that examining the value relevance for stock returns tests the timeliness of accounting information (Easton 1999). As such, a question about the timeliness of IFRS earnings information needs to be asked. However, this study further documents that the value relevance of the non-earning fundamental signals individually, in combination, and in aggregate, increased in some contexts, thereby increasing the relevance and improving the timeliness of accounting information after adoption of IFRS. Therefore, this study provides some positive evidence also for the decision usefulness of the non-earnings signals in terms of value relevance after adoption of IFRS.

Signalling theory focuses on information asymmetry between two parties (Spence 2002). This study uses 13 fundamental signals expected to provide information about contemporaneous excess returns. Most of these fundamental signals are significantly associated with these excess returns in the direction anticipated. Investors' reactions to this information represent the returns. This indicates that investor reaction is consistent with the information content of these signals as expected. As such, the evidence supports signalling theory. However, in this respect, adoption of IFRS provides positive evidence for the non-earnings signals and negative evidence for earnings.

The increased predictive ability of earnings after adoption of IFRS also supports signalling theory through reduced information asymmetry. More evidence is provided on signalling theory by investigating analysts' efficiency in using the fundamental signals. The analysts' underreaction or overreaction to certain signals, as well as analysts' inefficiency in utilising the fundamental signals for earnings forecasts, might be an indication of information asymmetry between financial statement preparers (management) and analysts, which could explain the use of signalling. However, after adoption of IFRS, an increase in analysts' efficiency in selecting appropriate fundamental signals could be due to decreased information asymmetry. If this was the case, it would validate signalling theory.

The study reports that analysts are highly inefficient in forecasting a negative compared to positive change in earnings. This empirical evidence could be an indication of analysts' bias for upwards forecasts in line with their incentives (Bonini et al. 2010; Bradshaw, Huang & Tan 2014). Therefore, the evidence provided by this study supports an optimistic bias on the part of analysts, which fits with institutional theory.

Furthermore, the overall findings of the study also support agency theory and positive accounting theory by providing evidence of accounting information being useful in predicting future earnings and hence being value relevant for stock returns.

9.8.3 Methodological contribution

Several of the methods of analysis used in this study could be claimed as a methodological contribution. Specifically, when testing the impact of IFRS, analysis is conducted using two statistical techniques to cross-check and validate the results obtained. This method makes interpretation of IFRS impact on fundamental signals clear and straightforward. Furthermore, the analysis is conducted for fundamental signals individually, in combination, and in aggregate, again providing a check on consistency of findings. Moreover, the analysis is conducted for different settings, such as Code and Common law countries, Winners and Losers, Extreme and Non-extreme performers, the nature of prior year earnings news, as well as different macro-economic conditions, such as high and low levels of inflation and GDP growth, providing context specific evidence.

Another methodological contribution is the calculation of analysts' inefficiency percentage using a benchmark regression. This is the first time that such an inefficiency percentage has been reported and this calculation represents an extension of analysts' percentage utilisation of information reported in Lambert (2011).

9.9 Practical and policy implications

The findings from this study have practical application for market participants, particularly for investors and financial analysts, as well as policy implications for standard setters and those with oversight of standard setters and other regulators or quasi-regulators.

This study provides compelling evidence that the non-earnings fundamental signals individually, in combination and in aggregate contain information incremental to earnings useful for predicting future earnings and value relevant for contemporaneous excess returns. Therefore, in addition to earnings, it is advisable for stakeholders to use non-earnings fundamental information for their forecasting and investment decisions. The study investigates the predictive ability and value relevance of earnings and non-earnings signals for different sub-samples, such as Code and Common law country observations, Winners and Losers, Extreme and Non-extreme performers' returns (only for value relevance) and Growth and Value stocks (only for value relevance). Therefore, market participants can use these findings when they make decisions in the above contexts. The study informs about the fundamental signals that can be used to predict earnings and assess stocks (value relevance) within each context. Moreover, the study informs about the fundamental signals that can be used to distinguish Winners from Losers, and Extreme from Non-extreme performers. As such, the findings are useful for investors in their predictions about earnings and assessments of returns, including distinguishing between categories of stocks tested.

This study reports that the predictive ability and value relevance of earnings, and some non-earnings signals, individually and in combination, are different between some sub-samples. As such, market participants are advised to pay special attention to these variables when making their investment decisions in these contexts. The study finds also that an aggregated measure representing the non-earnings fundamental signals (F_Score) is useful for predicting Winners in terms of earnings and assessing Winners and Losers in terms of excess returns. Therefore, investors, analysts and other market participants can use these findings for Winners and Losers in terms of excess returns and subsequent earnings prediction. Moreover, the study finds that the predictive ability and value relevance of fundamental signals are affected by contextual variables, such as the nature of prior year earnings news, level of inflation and GDP growth rate. Therefore, financial statement users would do well to consider the potential impact of contextual variables when making decisions based on fundamental signals.

The adoption of IFRS had significant impacts on the quality of fundamental signals in terms of their predictive ability and value relevance. This is the first study to examine the impact of IFRS on the predictive ability of non-earnings signals individually, in combination, and in aggregate, for different sub-samples. As such, the findings will be useful for market participants in better understanding the behaviour of these fundamental signals post-IFRS. The findings inform that the predictive ability of earnings improved for Code law countries, and for Losers (in terms of future earnings), while the value relevance decreased for Common law countries, Winners (in terms of excess returns) and Growth stocks.

These findings imply that investors, analysts and other stakeholders should be cautious about using the earnings variable in the above contexts after adoption of IFRS. In addition, the study documents that IFRS impact on the overall predictive ability of the non-earnings signals, including F_Score, is negative, and that for the value relevance of non-earnings signals as a whole and F_Score, it is mostly positive, but only for some sub-samples, such as Common law countries, Winners, Extreme performers and Growth stocks. IFRS impact on the value relevance of cash flows from operations over earnings is positive for most samples. These findings inform about how financial statement users should change their focus between earnings and non-earnings signals, depending on the nature of the decision (predicting earnings or assessing stocks - value relevance) in different contexts under IFRS.

Findings on analysts' efficiency in using fundamental signals and the impact of IFRS on this efficiency have highly practical implications for analysts (both buy and sell-side) and investors. The findings inform that analysts are aware of the fundamental signals (mostly selecting the appropriate fundamental signals) important for earnings forecasts, but not efficient in using these signals. This study identifies some signals to which analysts overreact or underreact, also revealing that analysts fail to utilise the improved predictive ability of earnings after adoption of IFRS. Further, the study indicates that analysts are highly inefficient in using fundamental signals specifically for some sub-samples, such as for earnings for Code law countries and Losers**.** Hence these findings are helpful in identifying analysts' weaknesses in different contexts and may assist in improving their efficiency in using fundamental signals for earnings forecasts.

This study provides compelling evidence from different perspectives of the fundamental signals that are value relevant for contemporaneous excess returns, and the fundamental signals that can predict one-year-ahead change in earnings per share, as well as analysts' use of these fundamental signals for forecasting one-year-ahead change in earnings per share. Therefore, if a fundamental signal is value relevant, and has predictive ability, and if analysts underreact or overreact to that signal, investors can make use of that signal to earn excess returns (Swanson, Rees & Juarez-Valdes 2003). This study provides evidence in relation to such fundamental signals, and therefore is useful for investors in making their investment decisions. As such, the findings have significant practical application for financial statement users, especially for investors, and analysts and their employers.

The findings on IFRS impact on the predictive ability and value relevance of fundamental signals provide valuable insights for policy makers, standard setters and regulators. The study provides robust evidence on both earnings and 12 non-earnings signals based on different settings, such as Code and Common law regimes, Winners and Losers, Extreme and Non-extreme performers' returns and Growth and Value stocks. The overall finding in relation to IFRS impact on predictive ability is positive for earnings, but negative for non-earnings signals, whereas IFRS impact on value relevance is positive for non-earnings signals, but negative for the earnings signal. Further, the impact of IFRS is different based on legal regime. These findings provide guidance and specific variables to be focused on (earnings versus non-earnings) when developing future accounting standards.

When looking at the impact of IFRS on the predictive ability of change in capital expenditure and change in goodwill, the predictive ability of these decreased following adoption of IFRS. The results indicate that these signals harbour some fundamental information that standard setters and financial statement preparers would do well to look into closely. Under IFRS, these items are recorded at fair value, and the accounting treatment for some fundamentals, especially goodwill, changed significantly after adoption of IFRS. However, in terms of predictive ability, the impact of IFRS is negative. As such, standard setters should pay special attention to these items and financial statement preparers should be careful in making accounting choices for these items under IFRS.

Findings from this study also may be useful for countries that are considering adoption of IFRS and for the IASB's agenda of encouraging adoption of IFRS around the world, because IFRS impact is confirmed to be different based on institutional setting, such as legal regime (Code vs Common law).

9.10 Limitations

Findings from this study need to be interpreted in light of its limitations, although most of these are common to this type of study.

The main limitation relates to the relatively small number of firm-year observations for the pre- compared to post-IFRS period. However, the sample that excludes the GFC and full IFRS transition periods minimises this gap and mostly the additional tests confirm findings from using the larger sample. The sample countries are also limited to 12 and located in specific regions of the world. As such, care needs to be taken when generalising the findings to other countries. Second, when forming the F_Score, similar weight is given to all fundamental signals even though their predictive ability and value relevance are different. However, all prior studies in this area use the same methodology to create an aggregate measure.

Third, there could be other factors that affect the predictive ability and value relevance of fundamental signals not controlled for in this study, such as the dot com bubble or changes in auditing standards. Further, the study assumes that all sample firms equally adopt and comply with IFRS. If compliance is differential, GAAP difference will be affected accordingly. The study uses the country-wide GAAP difference calculated by Bae, Tan, and Welker (2008) and this single calculation may not be equally applicable over the period of the study or across all firms.

Fourth, some literature provides evidence that firm-level incentives and governance characteristics (Daske et al. 2008) are important for achieving the benefits of IFRS. Furthermore, IFRS standards often are revised and new standards are introduced. The study does not control for changes in accounting standards over the period of study.

Fifth, when examining analysts' efficiency, consensus analysts' forecasts are used. However, individual analysts' skills and abilities can be important factors influencing the efficiency with which analysts use fundamental signals, but these are not controlled for. In terms of the audit qualification variable, the quality of the audit is not controlled for, whereas rendering an audit qualification when appropriate will depend on audit quality.

Sixth, the calculation of excess returns is dependent on the robustness of assumptions underlying market efficiencies. There may be differences in market efficiency levels between countries, or Code and Common Law regimes.

Seventh and finally, there may be other important fundamental signals used by market participants omitted from this study.

9.11 Suggestions for future research

Several avenues for future research can be identified based on the findings of this study. First, detailed analysis of individual non-earnings fundamental signals can be investigated for those affected by adoption of IFRS to explore more thoroughly the reason for the detected IFRS impact. To date, goodwill (GW) has been explored, but not the other non-earnings variables. For instance, one of the suggested explanations for the relationship between audit qualification and one-year-ahead change in earnings per share is auditor switching in search of a favourable audit opinion in the next year. However, the name of the audit firm is not included in this study so switching cannot be detected, and hence this suggestion represents conjecture and is worthy of further study. Second, the analyses for Extreme and Non-extreme performers' returns could be conducted in more detail, using total returns, similar to the analysis of value relevance of fundamental signals for Extreme Winners and Losers and Non-extreme performer Winners and Losers, using the same set of fundamental signals. Moreover, the impact of IFRS on the same could be investigated seeking better explanation of the nature of the impact.

Third, detailed analysis of Growth and Value stocks can be investigated for predictive ability and value relevance of fundamental signals. This analysis could be extended to Winners and Losers for each and the impact of IFRS on the predictive ability and value relevance of IFRS. Fourth, the predictive ability of fundamental signals could be investigated using a simple investment strategy based on F_Score, by taking a long position on stocks with high F_Score and a short position for stocks with low F_Score, and then calculating returns earned based on this strategy. This strategy could be a useful tool to predict returns given the evidence that F_Score is value relevant for excess returns and has predictive ability in terms of future earnings. The research can be further extended to examine the impact of IFRS on the effectiveness of this strategy.

Fifth and finally, one could replicate this study including more countries, a longer time period (equal periods before and after IFRS) and including country-wise analysis in detail, since the literature documents that country factors have the greatest influence on IFRS policy choice (Stadler & Nobes 2014). Furthermore, analysis controlling for corporate governance mechanisms, including audit quality, would be valuable.

9.12 Concluding remarks

The review of the literature on fundamental analysis supports the view that the fundamental information include in financial statements is useful for market participants for their decision-making. Further, the review shows that there is a paucity in this area of research using the data post-2000. However, important changes such as adoption of IFRS occurred in the international accounting environment and the literature documents that IFRS adoption had significant impact on financial statement fundamentals in terms of recognition, measurement, classification and presentation, therefore affecting information quality and hence the usefulness of fundamental signals. Many studies have been conducted to examine the impact of IFRS on the quality of earnings fundamental signals, but very limited attention have been given to non-earnings fundamental signals useful for decision-making.

Usefulness of financial information can be assessed also based on information usage. If the accounting information is higher in quality, it becomes more useful and users' efficiency in using fundamental signals will increase and/or usage will be increased. Analysts are one of the major user groups of fundamental information for earnings forecasts and stock recommendations. However, analysts' efficiency in using fundamental signals has been very rarely researched. There is no published work that investigates analysts' efficiency using data from post-2000 that include the IFRS adoption period, and outside the US context.

With this research gap in mind and given the usefulness of fundamental information and the impact IFRS had on financial reporting and the economy as whole (e.g. the cost of capital), this study examines the predictive ability and value relevance of fundamental signals and analysts' efficiency in using these signals, along with the impact of IFRS on these, thereby making a significant contribution.

This study provides compelling and robust evidence on the predictive ability and value relevance of fundamental information in different settings, thereby extending the existing literature in understanding how fundamental signals behave in different contexts, such as for Code and Common law countries (different legal jurisdictions) and for Winners and Losers in predicting future earnings and assessing stock returns. Moreover, the findings also enrich our understanding of the impact of IFRS on the predictive ability and value relevance of fundamental signals individually, in combination and also in aggregate form in the above mentioned different settings.

In addition, the findings also develop the literature by providing evidence of the efficiency with which analysts use fundamental signals in developing their forecasts in different contexts and disseminating information into the market. Further, the study makes a significant contribution to the literature by investigating the IFRS impact on analysts' efficiency in using the fundamental signals and disseminating the information to the market in the above mentioned contexts.

The study provides valuable information about the behaviour of fundamental information in predicting future earnings and assessing stock returns from different perspectives and contexts and also analysts' efficiency in using this information, along with the impact IFRS on these aspects. Therefore, these findings have practical implications for market participants and provide useful information and importance guidance (especially the findings on IFRS impact) for policy makers, standard setters, regulators and financial statement preparers in preparing future standards and making policy choices.

REFERENCES

Abarbanell, J.S. & Bushee, B.J. (1997), 'Fundamental Analysis, Future Earnings, and Stock Prices', *Journal of Accounting Research*, vol. 35, no. 1, pp. 1-24.

Abarbanell, J.S. & Bushee, B.J. (1998), 'Abnormal Returns to a Fundamental Analysis Strategy', *Accounting Review*, vol. 73, no. 1, pp. 19-45.

AbuGhazaleh, N.M., Al-Hares, O.M. & Haddad, A.E. (2012), 'The Value Relevance of Goodwill Impairments: UK Evidence', *International Journal of Economics and Finance*, vol. 4, no. 4, pp. 206-216.

Agca, A. & Aktas, R. (2007), 'First Time Application of IFRS and Its Impact on Financial Ratios: A Study on Turkish Listed Firms', *Problems and Perspectives in Management*, vol. 5, no. 2, pp. 99-112.

Aharony, J., Barniv, R. & Falk, H. (2010), 'The Impact of Mandatory IFRS Adoption on Equity Valuation of Accounting Numbers for Security Investors in the EU', *European Accounting Review*, vol. 19, no. 3, pp. 535-578.

Ahmed, A.S. (1994), 'Accounting Earnings and Future Economic Rents', *Journal of Accounting & Economics*, vol. 17, no. 3, pp. 377-400.

Ahmed, A.S., Neel, M. & Wang, D. (2013), 'Does Mandatory Adoption of IFRS Improve Accounting Quality? Preliminary Evidence', *Contemporary Accounting Research*, vol. 30, no. 4, pp. 1344-1372.

Ahmed, A.S., Schneible, R.A.J. & Stevens, D.E. (2003), 'An Empirical Analysis of the Effects of Online Trading on Stock Price and Trading Volume Reactions to Earnings Announcements', *Contemporary Accounting Research*, vol. 20, no. 3, pp. 413-439.

Aisbitt, S. (2006), 'Assessing the Effect of the Transition to IFRS on Equity: The Case of the FTSE 100', *Accounting in Europe*, vol. 3, no. 1, pp. 117-133.

Al-Debie, M. & Walker, M. (1999), 'Fundamental Information Analysis: An Extension and UK Evidence', *The British Accounting Review*, vol. 31, no. 3, pp. 261-280.

Alford, A., Jones, J., Leftwich, R. & Zmijewski, M. (1993), 'The Relative Informativeness of Accounting Disclosures in Different Countries', *Journal of Accounting Research*, vol. 31, no. 3, pp. 183-223.

Ali, A. & Hwang, L.-S. (2000), 'Country-Specific Factors Related to Financial Reporting and the Value Relevance of Accounting Data', *Journal of Accounting Research*, vol. 38, no. 1, pp. 1-21.

Ali, A., Lee Seok, H. & Trombley, M.A. (2003), 'Residual-Income-Based Valuation Predicts Future Stock Returns: Evidence on Mispricing Vs. Risk Explanations', *Accounting Review*, vol. 78, no. 2, pp. 377-397.

Ali, A. & Pope, P.F. (1995), 'The Incremental Information Content of Earnings, Funds Flow and Cash Flow: The UK Evidence', *Journal of Business Finance & Accounting*, vol. 22, no. 1, pp. 19-34.

Ames, D. (2013), 'IFRS Adoption and Accounting Quality: The Case of South Africa', *Journal of Applied Economics & Business Research*, vol. 3, no. 3, pp. 154-165.

Amir, E. & Lev, B. (1996), 'Value-Relevance of Nonfinancial Information: The Wireless Communications Industry', *Journal of Accounting & Economics*, vol. 22, no. 1-3, pp. 3-30.

Anderson, M., Banker, R., Huang, R. & Janakiraman, S. (2007), 'Cost Behavior and Fundamental Analysis of SG&A Costs', *Journal of Accounting, Auditing & Finance*, vol. 22, no. 1, pp. 1-28.

André, P., Filip, A. & Paugam, L. (2012), 'Accounting Conservatism in Europe and the Impact of Mandatory IFRS Adoption: Do Country, Institutional and Legal Differences Survive', *ESSEC Business School*, vol. 4, pp. 1-57.

Arthur, N., Cheng, M. & Czernkowski, R. (2010), 'Cash Flow Disaggregation and the Prediction of Future Earnings', *Accounting & Finance*, vol. 50, no. 1, pp. 1-30.

Atwood, T., Drake, M.S., Myers, J.N. & Myers, L.A. (2011), 'Do Earnings Reported under IFRS Tell US More About Future Earnings and Cash Flows?', *Journal of Accounting and Public Policy*, vol. 30, no. 2, pp. 103-121.

Ayers, B.C., Jiang, J. & Yeung, P.E. (2006), 'Discretionary Accruals and Earnings Management: An Analysis of Pseudo Earnings Targets', *The Accounting Review*, vol. 81, no. 3, pp. 617-652.

Bae, K.-H., Tan, H. & Welker, M. (2008), 'International GAAP Differences: The Impact on Foreign Analysts', *The Accounting Review*, vol. 83, no. 3, pp. 593-628.

Ball, R. (2006), 'International Financial Reporting Standards (IFRS): Pros and Cons for Investors', *Accounting and Business Research*, vol. 36, no. 3, pp. 5-27.

Ball, R. & Brown, P. (1968), 'An Empirical Evaluation of Accounting Income Numbers', *Journal of Accounting Research*, vol. 6, no. 2, pp. 159-178.

Ball, R., Li, X. & Shivakumar, L. (2015), 'Contractibility and Transparency of Financial Statement Information Prepared under IFRS: Evidence from Debt Contracts around IFRS Adoption', *Journal of Accounting Research*, vol. 53, no. 5, pp. 915-963.

Ball, R. & Shivakumar, L. (2005), 'Earnings Quality in UK Private Firms: Comparative Loss Recognition Timeliness', *Journal of accounting and economics*, vol. 39, no. 1, pp. 83-128.

Banker, R.D., Huang, R. & Natarajan, R. (2009), 'Incentive Contracting and Value Relevance of Earnings and Cash Flows', *Journal of Accounting Research*, vol. 47, no. 3, pp. 647-678.

Bao, D.H., Lee, J. & Romeo, G. (2010), 'Comparisons on Selected Ratios between IFRS and US GAAP Companies', *Journal of Financial Reporting and Accounting*, vol. 8, no. 1, pp. 22-34.

Barniv, R., Myring, M.J. & Thomas, W.B. (2005), 'The Association between the Legal and Financial Reporting Environments and Forecast Performance of Individual Analysts', *Contemporary Accounting Research*, vol. 22, no. 4, pp. 727-758.

Barron, O.E., Byard, D. & Kim, O. (2002), 'Changes in Analysts' Information around Earnings Announcements', *The Accounting Review*, vol. 77, no. 4, pp. 821-846.

Barth, M.E., Beaver, W.H. & Landsman, W.R. (2001), 'The Relevance of the Value Relevance Literature for Financial Accounting Standard Setting: Another View', *Journal of Accounting and Economics*, vol. 31, no. 1, pp. 77-104.

Barth, M.E., Cram, D.P. & Nelson, K.K. (2001), 'Accruals and the Prediction of Future Cash Flows', *The Accounting Review*, vol. 76, no. 1, pp. 27-58.

Barth, M.E., Landsman, W.R., Lang, M. & Williams, C. (2012a), 'Are IFRS-Based and US GAAP-Based Accounting Amounts Comparable?', *Journal of Accounting and Economics*, vol. 54, no. 1, pp. 68-93.

Barth, M.E., Landsman, W.R. & Lang, M.H. (2008), 'International Accounting Standards and Accounting Quality', *Journal of Accounting Research*, vol. 46, no. 3, pp. 467-498.

Bartov, E., Goldberg, S.R. & Kim, M. (2005), 'Comparative Value Relevance among German, US, and International Accounting Standards: A German Stock Market Perspective', *Journal of Accounting, Auditing & Finance*, vol. 20, no. 2, pp. 95-119.

Beaver, W.H. (1968), 'The Information Content of Annual Earnings Announcements', *Journal of Accounting Research*, vol. 6, no. 3, pp. 67-92.

Beaver, W.H. (2002), 'Perspectives on Recent Capital Market Research', *The Accounting Review*, vol. 77, no. 2, pp. 453-474.

Beaver, W.H., Kennelly, J.W. & Voss, W.M. (1968), 'Predictive Ability as a Criterion for the Evaluation of Accounting Data', *The Accounting Review*, vol. 43, no. 4, pp. 675-683.

Bebbington, J. & Gray, R. 2001, *Financial Accounting: Practice and Principles*, 3 edn., Thomson Learning, London.

Becker, C.L., DeFond, M.L., Jiambalvo, J. & Subramanyam, K. (1998), 'The Effect of Audit Quality on Earnings Management', *Contemporary Accounting Research*, vol. 15, no. 1, pp. 1-24.

Beisland, L.A. (2009), 'A Review of the Value Relevance Literature', *The Open Business Journal*, vol. 2, no. 1, pp. 7-27.

Beneish, M.D., Lee, C.M. & Tarpley, R.L. (2001), 'Contextual Fundamental Analysis through the Prediction of Extreme Returns', *Review of Accounting Studies*, vol. 6, no. 2-3, pp. 165-189.

Beretta, S. & Bozzolan, S. (2004), 'A Framework for the Analysis of Firm Risk Communication', *The International Journal of Accounting*, vol. 39, no. 3, pp. 265-288.

Bernard, V. & Noel, J. (1991), 'Do Inventory Disclosures Predict Sales and Earnings?', *Journal of Accounting, Auditing & Finance*, vol. 6, no. 2, pp. 145-181.

Bernard, V.L. & Stober, T.L. (1989), 'The Nature and Amount of Information in Cash Flows and Accruals', *Accounting Review*, vol. 64, no. 4, pp. 624-652.

Beuselinck, C., Joos, P., Khurana, I. & Meulen, S.v. 2010, Mandatory Adoption of IFRS and Analysts' Forecasts Information Properties, INTACCT Working Paper, Tilburg University

Bhattacharya, U., Daouk, H. & Welker, M. (2003), 'The World Price of Earnings Opacity', *The Accounting Review*, vol. 78, no. 3, pp. 641-678.

Blanchette, M., Racicot, F.É. & Girard, J.Y. 2011, *The Effects of IFRS on Financial Ratios: Early Evidence in Canada*, Certified General Accountants Association of Canada.,

Blankespoor, E., Linsmeier, T.J., Petroni, K.R. & Shakespeare, C. (2013), 'Fair Value Accounting for Financial Instruments: Does It Improve the Association between

Bank Leverage and Credit Risk?', *The Accounting Review*, vol. 88, no. 4, pp. 1143-1177.

Bonini, S., Zanetti, L., Bianchini, R. & Salvi, A. (2010), 'Target Price Accuracy in Equity Research', *Journal of Business Finance & Accounting*, vol. 37, no. 9-10, pp. 1177-1217.

Boyer, R. (2007), 'Assessing the Impact of Fair Value Upon Financial Crises', *Socio-Economic Review*, vol. 5, no. 4, pp. 779-807.

Bradbury, M. & van Zijl, T. (2005), 'Shifting to International Financial Reporting Standards', *University of Auckland Business Review*, vol. 7, no. 1, pp. 77-83.

Bradshaw, M.T., Huang, A.G. & Tan, H. 2014, 'Analyst Target Price Optimism around the World,' *Midwest Finance Association 2013 Annual Meeting Paper*, Chicago

Bradshaw, M.T., Richardson, S.A. & Sloan, R.G. (2001), 'Do Analysts and Auditors Use Information in Accruals?', *Journal of Accounting Research*, vol. 39, no. 1, pp. 45-74.

Bradshaw, M.T., Richardson, S.A. & Sloan, R.G. (2006), 'The Relation between Corporate Financing Activities, Analysts' Forecasts and Stock Returns', *Journal of Accounting and Economics*, vol. 42, no. 1, pp. 53-85.

Brown, P., Preiato, J. & Tarca, A. (2014), 'Measuring Country Differences in Enforcement of Accounting Standards: An Audit and Enforcement Proxy', *Journal of Business Finance & Accounting*, vol. 41, no. 1-2, pp. 1-52.

Brown, S., Kin, L. & Lys, T. (1999), 'Use of R^2 in Accounting Research: Measuring Changes in Value Relevance over the Last Four Decades', *Journal of Accounting & Economics*, vol. 28, no. 2, pp. 83-115.

Burgstahler, D.C. & Eames, M.J. (2003), 'Earnings Management to Avoid Losses and Earnings Decrease: Are Analysts Fooled?', *Contemporary Accounting Research*, vol. 20, no. 2, pp. 253-294.

Bushman, R.M. & Smith, A.J. (2001), 'Financial Accounting Information and Corporate Governance', *Journal of Accounting and Economics*, vol. 32, no. 1, pp. 237-333.

Byard, D., Li, Y. & Yu, Y. (2011), 'The Effect of Mandatory IFRS Adoption on Financial Analysts' Information Environment', *Journal of Accounting Research*, vol. 49, no. 1, pp. 69-96.

Cai, J. & Zhang, Z. (2011), 'Leverage Change, Debt Overhang, and Stock Prices', *Journal of Corporate Finance*, vol. 17, no. 3, pp. 391-402.

Callao, S. & Jarne, J.I. (2010), 'Have IFRS Affected Earnings Management in the European Union?', *Accounting in Europe*, vol. 7, no. 2, pp. 159-189.

Callao, S., Jarne, J.I. & Laínez, J.A. (2007), 'Adoption of IFRS in Spain: Effect on the Comparability and Relevance of Financial Reporting', *Journal of International Accounting, Auditing and Taxation*, vol. 16, no. 2, pp. 148-178.

Carnes, T.A. (2006), 'Unexpected Changes in Quarterly Financial-Statement Line Items and Their Relationship to Stock Prices', *Academy of Accounting and Financial Studies Journal*, vol. 10, no. 3, pp. 99-117.

Caskey, J., Hughes, J. & Liu, J. (2012), 'Leverage, Excess Leverage, and Future Returns', *Review of Accounting Studies*, vol. 17, no. 2, pp. 443-471.

Chalmers, K., Clinch, G. & Godfrey, J.M. (2011), 'Changes in Value Relevance of Accounting Information Upon IFRS Adoption: Evidence from Australia', *Australian Journal of Management*, vol. 36, no. 2, pp. 151-173.

Chalmers, K., Clinch, G., Godfrey, J.M. & Wei, Z. (2012), 'Intangible Assets, IFRS and Analysts' Earnings Forecasts', *Accounting & Finance*, vol. 52, no. 3, pp. 691-721.

Chan, K., Jegadeesh, N. & Sougiannis, T. (2004), 'The Accrual Effect on Future Earnings', *Review of Quantitative Finance and Accounting*, vol. 22, no. 2, pp. 97-121.

Chan, L.K.C., Jegadeesh, N. & Lakonishok, J. (1996), 'Momentum Strategies', *Journal of Finance*, vol. 51, no. 5, pp. 1681-1713.

Chen, C., Young, D. & Zhuang, Z. (2012), 'Externalities of Mandatory IFRS Adoption: Evidence from Cross-Border Spillover Effects of Financial Information on Investment Efficiency', *The Accounting Review*, vol. 88, no. 3, pp. 881-914.

Chen, H., Tang, Q., Jiang, Y. & Lin, Z. (2010), 'The Role of International Financial Reporting Standards in Accounting Quality: Evidence from the European Union', *Journal of International Financial Management & Accounting*, vol. 21, no. 3, pp. 220-278.

Cheng, C.A., Chao Shin, L. & Schaefer, T.F. (1997), 'The Value-Relevance of SFAS No. 95 Cash Flows from Operations as Assessed by Security Market Effects', *Accounting Horizons*, vol. 11, no. 3, pp. 1-15.

Cheong, C.S. & Al Masum, M. (2010), 'Financial Analysts' Forecast Accuracy: Before and after the Introduction of AIFRS', *Australasian Accounting Business and Finance Journal*, vol. 4, no. 3, pp. 65-81.

Cheong, C.S., Kim, S. & Zurbruegg, R. (2010), 'The Impact of IFRS on Financial Analysts' Forecast Accuracy in the Asia-Pacific Region: The Case of Australia, Hong Kong and New Zealand', *Pacific Accounting Review*, vol. 22, no. 2, pp. 124-146.

Choi, F.D.S. & Meek, G. (2005), *'International Accounting'*, 5th ed. Upper Saddle River, NJ: Prentice Hall.

Choi, J.-H., Kim, J.-B. & Lee, J.J. (2011), 'Value Relevance of Discretionary Accruals in the Asian Financial Crisis of 1997–1998', *Journal of Accounting and Public Policy*, vol. 30, no. 2, pp. 166-187.

Chow, C.W. & Rice, S.J. (1982), 'Qualified Audit Opinions and Auditor Switching', *Accounting Review*, vol. 57, no. 2, pp. 326-335.

Christensen, H.B., Lee, E., Walker, M. & Zeng, C. (2015), 'Incentives or Standards: What Determines Accounting Quality Changes around IFRS Adoption?', *European Accounting Review*, vol. 24, no. 1, pp. 31-61.

Christensen, H.B. & Nikolaev, V.V. (2013), 'Does Fair Value Accounting for Non-Financial Assets Pass the Market Test?', *Review of Accounting Studies*, vol. 18, no. 3, pp. 734-775.

Cheung, E. & Lau, J. (2016), 'Readability of Notes to the Financial Statements and the Adoption of IFRS', *Australian Accounting Review*, vol. 26, no. 2, pp. 162-176.

Clarkson, P., Hanna, J.D., Richardson, G.D. & Thompson, R. (2011), 'The Impact of IFRS Adoption on the Value Relevance of Book Value and Earnings', *Journal of Contemporary Accounting & Economics*, vol. 7, no. 1, pp. 1-17.

Cohen, D.A., Dey, A. & Lys, T.Z. (2008), 'Real and Accrual-Based Earnings Management in the Pre-and Post-Sarbanes-Oxley Periods', *The Accounting Review*, vol. 83, no. 3, pp. 757-787.

Collins, D.W., Maydew, E.L. & Weiss, I.S. (1997), 'Changes in the Value-Relevance of Earnings and Book Values over the Past Forty Years', *Journal of Accounting & Economics*, vol. 24, no. 1, pp. 39-67.

Cotter, J., Tarca, A. & Wee, M. (2012), 'IFRS Adoption and Analysts’ Earnings Forecasts: Australian Evidence', *Accounting & Finance*, vol. 52, no. 2, pp. 395-419.

Dahmash, F.N., Durand, R.B. & Watson, J. (2009), 'The Value Relevance and Reliability of Reported Goodwill and Identifiable Intangible Assets', *The British Accounting Review*, vol. 41, no. 2, pp. 120-137.

Daske, H. & Gebhardt, G. (2006), 'International Financial Reporting Standards and Experts' Perceptions of Disclosure Quality', *Abacus*, vol. 42, no. 3-4, pp. 461-498.

Daske, H., Hail, L., Leuz, C. & Verdi, R. (2008), 'Mandatory IFRS Reporting around the World: Early Evidence on the Economic Consequences', *Journal of Accounting Research*, vol. 46, no. 5, pp. 1085-1142.

De Bondt, W.F. & Thaler, R.H. (1990), 'Do Security Analysts Overreact?', *The American Economic Review*, vol. 80, no. 2, pp. 52-57.

De George, E.T., Li, X. & Shivakumar, L. (2016), 'A Review of the IFRS Adoption Literature', *Review of Accounting Studies*, vol. 21, no. 3, pp. 898-1004.

Dechow, P., Ge, W. & Schrand, C. (2010), 'Understanding Earnings Quality: A Review of the Proxies, Their Determinants and Their Consequences', *Journal of Accounting and Economics*, vol. 50, no. 2, pp. 344-401.

Dechow, P. & Schrand, C. (2004), 'Earnings Quality ', The Research Foundation of the CFA Institute.

Dechow, P.M. (1994), 'Accounting Earnings and Cash Flows as Measures of Firm Performance: The Role of Accounting Accruals', *Journal of Accounting and Economics*, vol. 18, no. 1, pp. 3-42.

Dechow, P.M., Hutton, A.P. & Sloan, R.G. (1999), 'An Empirical Assessment of the Residual Income Valuation Model', *Journal of Accounting and Economics*, vol. 26, no. 1, pp. 1-34.

Dechow, P.M., Kothari, S.P. & Watts, R.L. (1998), 'The Relation between Earnings and Cash Flows', *Journal of Accounting and Economics*, vol. 25, no. 2, pp. 133-168.

Dechow, P.M. & Schrand, C.M. (2004b), 'Earnings Quality', *CFA Digest*, vol. 34, no. 4, pp. 82-85.

Deegan, C. 2013, *Financial Accounting Theory,* McGraw-Hill Education Australia.

DeFond, M.L. & Park, C.W. (1997), 'Smoothing Income in Anticipation of Future Earnings', *Journal of Accounting and Economics*, vol. 23, no. 2, pp. 115-139.

DeFond, M.L. & Park, C.W. (2001), 'The Reversal of Abnormal Accruals and the Market Valuation of Earnings Surprises', *The Accounting Review*, vol. 76, no. 3, pp. 375-404.

Dempsey, S.J., Gatti, J.F., Grinnell, D.J. & Cats-Baril, W.L. (1997), 'The Use of Strategic Performance Variables as Leading Indicators in Financial Analyst's Forecasts', *Journal of Financial Statement Analysis* vol. 2, no. 4, pp. 61-79.

Devalle, A., Onali, E. & Magarini, R. (2010), 'Assessing the Value Relevance of Accounting Data after the Introduction of IFRS in Europe', *Journal of International Financial Management & Accounting*, vol. 21, no. 2, pp. 85-119.

Dichev, I., Graham, J., Harvey, C.R. & Rajgopal, S. (2013), 'Earnings Quality: Evidence from the Field', *Journal of Accounting and Economics*, vol. 56, no. 2-3, pp. 1-33.

Dichev, I.D. & Tang, V.W. (2009), 'Earnings Volatility and Earnings Predictability', *Journal of Accounting and Economics*, vol. 47, no. 1, pp. 160-181.

Dimitrov, V. & Jain, P.C. (2008), 'The Value-Relevance of Changes in Financial Leverage Beyond Growth in Assets and GAAP Earnings', *Journal of Accounting, Auditing & Finance*, vol. 23, no. 2, pp. 191-222.

Ding, Y., Hope, O.K., Jeanjean, T. & Stolowy, H. (2007), 'Differences between Domestic Accounting Standards and IAS: Measurement, Determinants and Implications', *Journal of Accounting and Public Policy*, vol. 26, no. 1, pp. 1-38.

Doukakis, L.C. (2010), 'The Persistence of Earnings and Earnings Components after the Adoption of IFRS', *Managerial Finance*, vol. 36, no. 11, pp. 969-980.

Dowen, R.J. (2001), 'Fundamental Information and Monetary Policy: The Implications for Earnings and Earnings Forecasts', *Journal of Business Finance & Accounting*, vol. 28, no. 3-4, pp. 481-501.

Duangploy, O., Shelton, M. & Omer, K. (2005), 'The Value Relevance of Goodwill Impairment Loss: While the Market Discounts the Importance of Goodwill Amortization, It Does Not Disregard Goodwill Impairment Loss as Irrelevant', *Bank Accounting & Finance*, vol. 18, no. 5, pp. 23-29.

Easterwood, J.C. & Nutt, S.R. (1999), 'Inefficiency in Analyst's Earnings Forecasts: Systematic Misreaction or Systematic Optimism?', *Journal of Finance*, vol. 54, no. 5, pp. 1777-1797.

Easton, P.D. (1999), 'Security Returns and the Value Relevance of Accounting Data', *Accounting Horizons*, vol. 13, no. 4, pp. 399-412.

Easton, P.D. & Harris, T.S. (1991), 'Earnings as an Explanatory Variable for Returns', *Journal of Accounting Research*, vol. 29, no. 1, pp. 19-36.

Easton, P.D. & Zmijewski, M.E. (1989), 'Cross-Sectional Variation in the Stock Market Response to Accounting Earnings Announcements', *Journal of Accounting & Economics*, vol. 11, no. 2-3, pp. 117-141.

El-Gazzar, S.M., Finn, P.M. & Tang, C. (2009), 'The Value Relevance of Earnings and Non-Earnings Information in Regulated and Deregulated Markets: The Case of the Airline Industry', *International Advances in Economic Research*, vol. 15, no. 1, pp. 88-101.

Elias, N. (2012), 'The Impact of Mandatory IFRS Adoption on Accounting Quality: Evidence from Australia', *Journal of International Accounting Research*, vol. 11, no. 1, pp. 147-154.

Elleuch, J. (2009), 'Fundamental Analysis Strategy and the Prediction of Stock Returns', *International Research Journal of Finance and Economics*, vol. 30, no. 4, pp. 95-107.

Ernst & Young (2007), 'IFRS: Observations on the Implementation of IFRS', E & Y, London.

Ernstberger, J., Krotter, S. & Stadler, C. (2008), 'Analysts' Forecast Accuracy in Germany: The Effect of Different Accounting Principles and Changes of Accounting Principles', *BuR-Business Research*, vol. 1, no. 1, pp. 26-53.

Evans, M.E., Hodder, L. & Hopkins, P.E. (2014), 'The Predictive Ability of Fair Values for Future Financial Performance of Commercial Banks and the Relation of Predictive Ability to Banks' Share Prices', *Contemporary Accounting Research*, vol. 31, no. 1, pp. 13-44.

Fama, E.F. & French, K.R. (1992), 'The Cross-Section of Expected Stock Returns', *The Journal of Finance*, vol. 47, no. 2, pp. 427-465.

Fama, E.F. & French, K.R. (1995), 'Size and Book-to-Market Factors in Earnings and Returns', *The Journal of Finance*, vol. 50, no. 1, pp. 131-155.

Fan, J.P. & Wong, T.J. (2002), 'Corporate Ownership Structure and the Informativeness of Accounting Earnings in East Asia', *Journal of Accounting and Economics*, vol. 33, no. 3, pp. 401-425.

Farshadfar, S. & Monem, R. (2013), 'The Usefulness of Operating Cash Flow and Accrual Components in Improving the Predictive Ability of Earnings: A Re-Examination and Extension', *Accounting & Finance*, vol. 53, no. 4, pp. 1061-1082.

Feltham, G.A. & Ohlson, J.A. (1995), 'Valuation and Clean Surplus Accounting for Operating and Financial Activities', *Contemporary Accounting Research*, vol. 11, no. 2, pp. 689-731.

Fiechter, P. & Novotny-Farkas, Z. (2015), 'Fair Value Categorization under IFRS, Institutional Environment, and the Value Relevance of Fair Values', Working paper, Social Science Research Network.

Finger, C.A. (1994), 'The Ability of Earnings to Predict Future Earnings and Cash Flow', *Journal of Accounting Research*, vol. 32, no. 2, pp. 210-223.

Florou, A. & Pope, P.F. (2012a), 'Mandatory IFRS Adoption and Institutional Investment Decisions', *The Accounting Review*, vol. 87, no. 6, pp. 1993-2025.

Foster, G., Olsen, C. & Shevlin, T. (1984), 'Earnings Releases, Anomalies, and the Behavior of Security Returns', *Accounting Review*, vol. 59, no. 4, p. 574.

Francis, J., LaFond, R., Olsson, P.M. & Schipper, K. (2004), 'Costs of Equity and Earnings Attributes', *The Accounting Review*, vol. 79, no. 4, pp. 967-1010.

Francis, J. & Schipper, K. (1999), 'Have Financial Statements Lost Their Relevance?', *Journal of Accounting Research*, vol. 103, no. 1, pp. 319-352.

Frankel, R. & Lee, C.M.C. (1998), 'Accounting Valuation, Market Expectation, and Cross-Sectional Stock Returns', *Journal of Accounting & Economics*, vol. 25, no. 3, pp. 283-319.

Freeman, R.N. & Tse, S.Y. (1992), 'A Nonlinear Model of Security Price Responses to Unexpected Earnings', *Journal of Accounting Research*, vol. 30, no. 2, pp. 185-209.

Fudenberg, D. & Tirole, J. (1995), 'A Theory of Income and Dividend Smoothing Based on Incumbency Rents', *Journal of Political Economy*, vol. 103, no. 1, pp. 75-93.

Fung, S.Y.K., Su, L. & Zhu, X. (2010), 'Price Divergence from Fundamental Value and the Value Relevance of Accounting Information', *Contemporary Accounting Research*, vol. 27, no. 3, pp. 829-854.

Gebhardt, G.u. & Novotny-Farkas, Z. (2011), 'Mandatory IFRS Adoption and Accounting Quality of European Banks', *Journal of Business Finance & Accounting*, vol. 38, no. 3-4, pp. 289-333.

Gjerde, Ø., Knivsflå, K. & Sættem, F. (2008), 'The Value-Relevance of Adopting IFRS: Evidence from 145 NGAAP Restatements', *Journal of International Accounting, Auditing and Taxation*, vol. 17, no. 2, pp. 92-112.

Glaum, M., Baetge, J., Grothe, A. & Oberdörster, T. (2013), 'Introduction of International Accounting Standards, Disclosure Quality and Accuracy of Analysts' Earnings Forecasts', *European Accounting Review*, vol. 22, no. 1, pp. 79-116.

Godfrey, J.M. & Koh, P.S. (2009), 'Goodwill Impairment as a Reflection of Investment Opportunities', *Accounting & Finance*, vol. 49, no. 1, pp. 117-140.

Goodwin, J., Ahmed, K. & Heaney, R. (2008), 'The Effects of International Financial Reporting Standards on the Accounts and Accounting Quality of Australian Firms: A Retrospective Study', *Journal of Contemporary Accounting & Economics*, vol. 4, no. 2, pp. 89-119.

Gordon, L.A., Loeb, M.P. & Zhu, W. (2012), 'The Impact of IFRS Adoption on Foreign Direct Investment', *Journal of Accounting and Public Policy*, vol. 31, no. 4, pp. 374-398.

Guay, W.R., Kothari, S. & Watts, R.L. (1996), 'A Market-Based Evaluation of Discretionary Accrual Models', *Journal of Accounting Research*, pp. 83-105.

Guenther, D.A. & Young, D. (2000), 'The Association between Financial Accounting Measures and Real Economic Activity: A Multinational Study', *Journal of Accounting and Economics*, vol. 29, no. 1, pp. 53-72.

Gujarati, D.N. 1995, *Basic Econometrics,* McGraw-Hill,Inc.

Gujarati, D.N. & Porter, D. 2009, *Basic Econometrics* International Edition edn., Mc Graw-Hill.

Habib, A. (2008), 'The Role of Accruals and Cash Flows in Explaining Security Returns: Evidence from New Zealand', *Journal of International Accounting, Auditing and Taxation*, vol. 17, no. 1, pp. 51-66.

Hamberg, M. & Beisland, L.A. (2014), 'Changes in the Value Relevance of Goodwill Accounting Following the Adoption of IFRS 3', *Journal of International Accounting, Auditing and Taxation*, vol. 23, no. 2, pp. 59-73.

Haverals, J. (2007), 'IAS/IFRS in Belgium: Quantitative Analysis of the Impact on the Tax Burden of Companies', *Journal of International Accounting, Auditing and Taxation*, vol. 16, no. 1, pp. 69-89.

Healy, P.M. & Palepu, K.G. (2001), 'Information Asymmetry, Corporate Disclosure, and the Capital Markets: A Review of the Empirical Disclosure Literature', *Journal of Accounting and Economics*, vol. 31, no. 1, pp. 405-440.

Hirshleifer, D., Hou, K. & Teoh, S.H. (2009), 'Accruals, Cash Flows, and Aggregate Stock Returns', *Journal of Financial Economics*, vol. 91, no. 3, pp. 389-406.

Hirst, D.E., Hopkins, P.E. & Wahlen, J.M. (2004), 'Fair Values, Income Measurement, and Bank Analysts' Risk and Valuation Judgments', *The Accounting Review*, vol. 79, no. 2, pp. 453-472.

Hodgdon, C., Tondkar, R.H., Harless, D.W. & Adhikari, A. (2008), 'Compliance with IFRS Disclosure Requirements and Individual Analysts’ Forecast Errors', *Journal of International Accounting, Auditing and Taxation*, vol. 17, no. 1, pp. 1-13.

Hong, X. (2001), 'The Mispricing of Abnormal Accruals', *Accounting Review*, vol. 76, no. 3, p. 357.

Hope, O.K. (2003), 'Disclosure Practices, Enforcement of Accounting Standards, and Analysts' Forecast Accuracy: An International Study', *Journal of Accounting Research*, vol. 41, no. 2, pp. 235-272.

Hope, O.K. (2004), 'Variations in the Financial Reporting Environment and Earnings Forecasting', *Journal of International Financial Management & Accounting*, vol. 15, no. 1, pp. 21-43.

Hope, O.K., Thomas, W.B. & Vyas, D. (2013), 'Financial Reporting Quality of U.S. Private and Public Firms', *Accounting Review*, vol. 88, no. 5, pp. 1715-1742.

Hopper, T. 2012, *Handbook of Accounting and Development,* Edward Elgar Publishing.

Hopwood, A.G. (1983), 'On Trying to Study Accounting in the Contexts in Which It Operates', *Accounting, Organizations and Society*, vol. 8, no. 2, pp. 287-305.

Horton, J. & Serafeim, G. (2010), 'Market Reaction to and Valuation of IFRS Reconciliation Adjustments: First Evidence from the UK', *Review of Accounting Studies*, vol. 15, no. 4, pp. 725-751.

Horton, J., Serafeim, G. & Serafeim, I. (2013), 'Does Mandatory IFRS Adoption Improve the Information Environment?', *Contemporary Accounting Research*, vol. 30, no. 1, pp. 388-423.

Hou, Q., Jin, Q. & Wang, L. (2014), 'Mandatory IFRS Adoption and Executive Compensation: Evidence from China', *China Journal of Accounting Research*, vol. 7, no. 1, pp. 9-29.

Houqe, M.N., van Zijl, T., Dunstan, K. & Karim, A. (2012), 'The Effect of IFRS Adoption and Investor Protection on Earnings Quality around the World', *The International Journal of Accounting*, vol. 47, no. 3, pp. 333-355.

Huang, K.T., Lee, Y.W. & Wang, R.Y. 1998, *Quality Information and Knowledge,* Prentice Hall PTR.

Hughes, J. 2008, 'CEOs Need to Take Account of IFRS', Financial Times April 30.

Hung, M. & Subramanyam, K. (2007), 'Financial Statement Effects of Adopting International Accounting Standards: The Case of Germany', *Review of Accounting Studies*, vol. 12, no. 4, pp. 623-657.

IASB 2008, Exposure Draft of an Improved *Conceptual Framework for Financial Reporting.*

IASB 2010, *Conceptual Framework for Financial Reporting.*

IASB 2015, *Conceptual Framework Exposure Draft*

IFRS 1, *First-time Adoption of International Financial Reporting Standards*

IFRS 3, *Business Combinations*

IFRS 9, *Financial Instruments*

IFRS 13, *Fair Value Measurement*

Iatridis, G. (2010), 'IFRS Adoption and Financial Statement Effects: The UK Case', *International Research Journal of Finance and Economics*, vol. 38, pp. 165-172.

ICAEW 2009, *Changes in Financial Reporting and Audit Practice*, Audit and Assurance Faculty, The Institute of Chartered Accountants in England and Wales.

Ismail, W.A.W., Kamarudin, K.A., Van Zijl, T. & Dunstan, K. (2013), 'Earnings Quality and the Adoption of IFRS-Based Accounting Standards: Evidence from an Emerging Market', *Asian Review of Accounting*, vol. 21, no. 1, pp. 53-73.

Iu, J.W. & Clowes, C. 2004, 'Evaluating a Measure of Content Quality for Accounting Narratives (with an Empirical Application to Narratives from Australia, Hong Kong, and the United States),' *Fourth Asia Pacific Interdisciplinary Research in Accounting Conference APIRA 2004 Proceedings*, Nanyang Technological University, Nanyang Business School.

Jackson, S.B., Lopez, T.J. & Reitenga, A.L. (2008), 'Accounting Fundamentals and CEO Bonus Compensation', *Journal of Accounting and Public Policy*, vol. 27, no. 5, pp. 374-393.

Jayaraman, S. & Verdi, R.S. (2013), 'The Effect of Economic Integration on Accounting Comparability: Evidence from the Adoption of the Euro', Working paper, Available at http://papers.ssrn.com/sol3/ papers.cfm?abstract_id=2286699.

Jeanjean, T. & Stolowy, H. (2008), 'Do Accounting Standards Matter? An Exploratory Analysis of Earnings Management before and after IFRS Adoption', *Journal of Accounting and Public Policy*, vol. 27, no. 6, pp. 480-494.

Jennings, R. (1986), 'The Association of Operating Cash Flow and Accruals with Security Returns: Discussion', *Journal of Accounting Research*, vol. 24, pp. 134-137.

Jensen, M.C. & Meckling, W.H. 1979, *Theory of the Firm: Managerial Behavior, Agency Costs, and Ownership Structure,* University of Rochester, U.S.A.

Jermakowicz, E.K., Prather-Kinsey, J. & Wulf, I. (2007), 'The Value Relevance of Accounting Income Reported by DAX-30 German Companies', *Journal of International Financial Management & Accounting*, vol. 18, no. 3, pp. 151-191.

Jonas, G.J. & Blanchet, J. (2000), 'Assessing Quality of Financial Reporting', *Accounting Horizons*, vol. 14, no. 3, pp. 353-363.

Joos, P. (2003), 'Discussion of How Representative Are Firms That Are Cross-Listed in the United States? An Analysis of Accounting Quality', *Journal of Accounting Research*, vol. 41, no. 2, pp. 387-396.

Joos, P. & Lang, M. (1994), 'The Effects of Accounting Diversity: Evidence from the European Union', *Journal of Accounting Research*, vol. 32, pp. 141-168.

Kabir, M.H., Laswad, F. & Islam, M.A. (2010), 'Impact of IFRS in New Zealand on Accounts and Earnings Quality', *Australian Accounting Review*, vol. 20, no. 4, pp. 343-357.

Kendall, M.G. & Hill, A.B. (1953), 'The Analysis of Economic Time-Series-Part I: Prices', *Journal of the Royal Statistical Society*, vol. 116, no. 1, pp. 11-34.

Kerstein, J. & Kim, S. (1995), 'The Incremental Information Content of Capital Expenditures', *Accounting Review*, vol. 70, no. 3, pp. 513-526.

Khurana, I.K. & Raman, K. (2003), 'Are Fundamentals Priced in the Bond Market?', *Contemporary Accounting Research*, vol. 20, no. 3, pp. 465-494.

Kim, J.B., Liu, X. & Zheng, L. (2012), 'The Impact of Mandatory IFRS Adoption on Audit Fees: Theory and Evidence', *The Accounting Review*, vol. 87, no. 6, pp. 2061-2094.

Kim, K. & Schroeder, D.A. (1990), 'Analysts' Use of Managerial Bonus Incentives in Forecasting Earnings', *Journal of Accounting and Economics*, vol. 13, no. 1, pp. 3-23.

Kim, M. & Kross, W. (2005), 'The Ability of Earnings to Predict Future Operating Cash Flows Has Been Increasing-Not Decreasing', *Journal of Accounting Research*, vol. 43, no. 5, pp. 753-780.

Klein, B.D. (1998), 'Data Quality in the Practice of Consumer Product Management: Evidence from the Field', *Data Quality*, vol. 4, no. 1

Kormendi, R. & Lipe, R. (1987), 'Earnings Innovations, Earnings Persistence, and Stock Returns', *Journal of Business*, vol. 60, no. 3, pp. 323-345.

Kothari, S. (2001), 'Capital Markets Research in Accounting', *Journal of Accounting and Economics*, vol. 31, no. 1, pp. 105-231.

Kothari, S., Ramanna, K. & Skinner, D.J. (2009), 'Implications for GAAP from an Analysis of Positive Research in Accounting', *Journal of Accounting and Economics*, vol. 50, no. 2-3, pp. 246-286.

Kothari, S.P., Leone, A.J. & Wasley, C.E. (2005), 'Performance Matched Discretionary Accrual Measures', *Journal of Accounting and Economics*, vol. 39, no. 1, pp. 163-197.

KPMG 2006, The Application of IFRS: Choices in Practice, KPMG IFRG Limited, London.

Krishnan, G.V. & Parsons, L.M. (2008), 'Getting to the Bottom Line: An Exploration of Gender and Earnings Quality', *Journal of Business Ethics*, vol. 78, no. 1-2, pp. 65-76.

Kumar, K.R. & Krishnan, G.V. (2008), 'The Value-Relevance of Cash Flows and Accruals: The Role of Investment Opportunities', *The Accounting Review*, vol. 83, no. 4, pp. 997-1040.

La Porta, Rafael, Lopez-de-Silanes, F., Shleifer, A. & Vishny, R.W. (1998), 'Law and Finance', *Journal of Political Economy*, vol. 106, no. 6, pp. 1113-1155.

Lambert, S.L. 2011, *Fundamental Signals, Future Earnings and Security Analysts' Efficient Use of Fundamental Signals During 1991 through 2008*, thesis, The University of Texas Arlington.

Landsman, W.R., Maydew, E.L. & Thornock, J.R. (2012), 'The Information Content of Annual Earnings Announcements and Mandatory Adoption of IFRS', *Journal of Accounting and Economics*, vol. 53, no. 1, pp. 34-54.

Lang, M.H. & Lundholm, R.J. (1996), 'Corporate Disclosure Policy and Analyst Behavior', *Accounting Review*, vol. 71, no. 4, pp. 467-492.

Lantto, A.M. & Sahlström, P. (2009), 'Impact of International Financial Reporting Standard Adoption on Key Financial Ratios', *Accounting & Finance*, vol. 49, no. 2, pp. 341-361.

Leuz, C., Nanda, D. & Wysocki, P.D. (2003), 'Earnings Management and Investor Protection: An International Comparison', *Journal of Financial Economics*, vol. 69, no. 3, pp. 505-527.

Leuz, C. & Oberholzer-Gee, F. (2006), 'Political Relationships, Global Financing, and Corporate Transparency: Evidence from Indonesia', *Journal of Financial Economics*, vol. 81, no. 2, pp. 411-439.

Lev, B. (1989), 'On the Usefulness of Earnings and Earnings Research: Lessons and Directions from Two Decades of Empirical Research', *Journal of Accounting Research*, vol. 27, no. 3, pp. 153-192.

Lev, B., Li, S. & Sougiannis, T. (2005), 'Accounting Estimates: Pervasive, yet of Questionable Usefulness', Working paper, New York University.

Lev, B. & Thiagarajan, S.R. (1993), 'Fundamental Information Analysis', *Journal of Accounting Research*, vol. 31, no. 2, pp. 190-215.

Lev, B. & Zarowin, P. (1999), 'The Boundaries of Financial Reporting and How to Extend Them', *Journal of Accounting Research*, vol. 37, no. 2, pp. 353-385.

Li, S. (2010), 'Does Mandatory Adoption of International Financial Reporting Standards in the European Union Reduce the Cost of Equity Capital?', *The Accounting Review*, vol. 85, no. 2, pp. 607-636.

Lin, S., Riccardi, W. & Wang, C. (2012), 'Does Accounting Quality Change Following a Switch from US GAAP to IFRS? Evidence from Germany', *Journal of Accounting and Public Policy*, vol. 31, no. 6, pp. 641-657.

Lipe, R. (1990), 'The Relation between Stock Returns and Accounting Earnings Given Alternative Information', *Accounting Review*, vol. 65, no. 1, pp. 49-71.

Liu, C., Yao, L.J., Hu, N. & Liu, L. (2011), 'The Impact of IFRS on Accounting Quality in a Regulated Market: An Empirical Study of China', *Journal of Accounting, Auditing & Finance*, vol. 26, no. 4, pp. 659-676.

Liu, J., Thomas, J.K. & Nissim, D. (2007), 'Cash Flow Is King? Comparing Valuations Based on Cash Flow Versus Earnings Multiples', *Financial Analysts Journal*, CFA Institute, vol. 63, no. 2.

Mackie, M. & Jeffrey, K. (1990), 'Do Taxes Affect Corporate Financing Decisions?', *The Journal of Finance*, vol. 45, no. 5, pp. 1471-1493.

Mahmoud, A. & Sakr, S. (2012), 'The Predictive Power of Fundamental Analysis in Terms of Stock Return and Future Profitability Performance', *International Research Journal of Finance and Economics*, vol. 92, pp. 43-58.

Maines, L.A. & Wahlen, J.M. (2006), 'The Nature of Accounting Information Reliability: Inferences from Archival and Experimental Research', *Accounting Horizons*, vol. 20, no. 4, pp. 399-425.

Marquardt, C.A. & Wiedman, C.I. (2004), 'The Effect of Earnings Management on the Value Relevance of Accounting Information', *Journal of Business Finance & Accounting*, vol. 31, no. 3-4, pp. 297-332.

Matolcsy, Z. & Wyatt, A. (2006), 'Capitalized Intangibles and Financial Analysts', *Accounting & Finance*, vol. 46, no. 3, pp. 457-479.

McDaniel, L., Martin, R.D. & Maines, L.A. (2002), 'Evaluating Financial Reporting Quality: The Effects of Financial Expertise Vs. Financial Literacy', *The Accounting Review*, vol. 77, no. s-1, pp. 139-167.

Modigliani, F. & Miller, M.H. (1958), 'The Cost of Capital, Corporation Finance and the Theory of Investment', *The American Economic Review*, vol. 48, no. 3, pp. 261-297.

Modigliani, F. & Miller, M.H. (1963), 'Corporate Income Taxes and the Cost of Capital: A Correction', *The American Economic Review*, vol. 53, no. 3, pp. 433-443.

Mohanram, P.S. (2005), 'Separating Winners from Losers among Low-Book-to-Market Stocks Using Financial Statement Analysis', *Review of Accounting Studies*, vol. 10, no. 2-3, pp. 133-170.

Moonitz, M. 1961, The Basic Postulates of Accounting, American Institute of Certified Public Accountants, New York.

Morais, A.I. & Curto, J.D. (2008), 'Accounting Quality and the Adoption of IASB Standards: Portuguese Evidence', *Revista Contabilidade & Finanças*, vol. 19, no. 48, pp. 103-111.

Mukherji, S., Dhatt, M.S. & Kim, Y.H. (1997), 'A Fundamental Analysis of Korean Stock Returns', *Financial Analysts Journal*, vol. 53, no. 3, pp. 75-80.

Nam, S., Brochet, F. & Ronen, J. (2012), 'The Predictive Value of Accruals and Consequences for Market Anomalies', *Journal of Accounting, Auditing & Finance*, vol. 27, no. 2, pp. 151-176.

Narktabtee, K. & Patpanichchot, S. (2011), 'Investor Protection, Deviation of Local Accounting Standards from IFRS, and the Effectiveness of the IFRS Adoption', *Journal of Modern Accounting and Auditing*, vol. 7, no. 12, pp. 1329-1343.

Nulla, Y.M. (2014), 'Does IFRS Adoption Influence Financial Reporting? An Empirical Study on Financial Institutions', *Journal of Business and Management*, vol. 20, no. 1, pp. 67-86.

Ohlson, J.A. (1995), 'Earnings, Book Values, and Dividends in Equity Valuation', *Contemporary Accounting Research*, vol. 11, no. 2, pp. 661-687.

Ohlson, J.A. & Penman, S.H. (1992), 'Disaggregated Accounting Data as Explanatory Variables for Returns', *Journal of Accounting, Auditing & Finance*, vol. 7, no. 4, pp. 553-573.

Oliveira, L., Rodrigues, L.L. & Craig, R. (2010), 'Intangible Assets and Value Relevance: Evidence from the Portuguese Stock Exchange', *The British Accounting Review*, vol. 42, no. 4, pp. 241-252.

Orpurt, S.F. & Zang, Y. (2009), 'Do Direct Cash Flow Disclosures Help Predict Future Operating Cash Flows and Earnings?', *The Accounting Review*, vol. 84, no. 3, pp. 893-935.

Ou, J.A. (1990), 'The Information Content of Nonearnings Accounting Numbers as Earnings Predictors', *Journal of Accounting Research*, vol. 28, no. 1, pp. 144-163.

Ou, J.A. & Penman, S.H. (1989a), 'Accounting Measurement, Price-Earnings Ratio, and the Information Content of Security Prices', *Journal of Accounting Research*, vol. 27, no. 3, pp. 111-144.

Ou, J.A. & Penman, S.H. (1989b), 'Financial Statement Analysis and the Prediction of Stock Returns', *Journal of Accounting & Economics*, vol. 11, no. 4, pp. 295-329.

Paananen, M. (2008), 'The IFRS Adoption’s Effect on Accounting Quality in Sweden', *Working paper, University of Hertfordshire, UK*,

Paananen, M. & Lin, H. (2009), 'The Development of Accounting Quality of IAS and IFRS over Time: The Case of Germany', *Journal of International Accounting Research*, vol. 8, no. 1, pp. 31-55.

Pae, J. (2005), 'Expected Accrual Models: The Impact of Operating Cash Flows and Reversals of Accruals', *Review of Quantitative Finance and Accounting*, vol. 24, no. 1, pp. 5-22.

Pawsey, N. (2016), '*AASB Research Report No. 3 - the Impact of IFRS Adoption in Australia: Evidence from Academic Research,* AASB Research Centre.

Penman, S.H. (1998), 'Combining Earnings and Book Value in Equity Valuation', *Contemporary Accounting Research*, vol. 15, no. 3, pp. 291-324.

Pfeiffer, R.J. & Elgers, P.T. (1999), 'Controlling for Lagged Stock Price Responses in Pricing Regressions: An Application to the Pricing of Cash Flows and Accruals', *Journal of Accounting Research*, vol. 37, no. 1, pp. 239-247.

Pierce-Brown, R. (1998), 'Better Odds Than the Lottery', Accountancy-International Edition, pp. March, 98-99.

Piotroski, J.D. (2000), 'Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers', *Journal of Accounting Research*, vol. 38, no. S-1, pp. 1-41.

Preiato, J.P., Brown, P.R. & Tarca, A. (2013), 'Mandatory Adoption of IFRS and Analysts' Forecasts: How Much Does Enforcement Matter?', UNSW Australian School of Business Research Paper.

Previts, G.J., Bricker, R.J., Robinson, T.R. & Young, S.J. (1994), 'A Content Analysis of Sell-Side Financial Analyst Company Reports', *Accounting Horizons*, vol. 8, no. 2, pp. 55-70.

PWC/IPSOS-MORI 2007, Has the Dust Settled Yet?, PricewaterhouseCoopers LLP, London.

Quirin, J.J. & Allen, A. (2000), 'The Effect of Earnings Permanence on Fundamental Information Analysis', *The Mid-Atlantic Journal of Business*, vol. 36, no. 4, pp. 149-165.

Ramnath, S., Rock, S. & Shane, P. (2008), 'The Financial Analyst Forecasting Literature: A Taxonomy with Suggestions for Further Research', *International Journal of Forecasting*, vol. 24, no. 1, pp. 34-75.

Rathke, A.A.T., Santana, V.d.F., Lourenço, I.M.E.C. & Dalmácio, F.Z. (2016), 'International Financial Reporting Standards and Earnings Management in Latin America', *Revista de Administração Contemporânea*, vol. 20, no. 3, pp. 368-388.

Rayburn, J. (1986), 'The Association of Operating Cash Flow and Accruals with Security Returns', *Journal of Accounting Research*, vol. 24, no. 3, pp. 112-133.

Redmayne, N.B. & Laswad, F. (2013), 'An Assessment of the Impact of IFRS Adoption on Public Sector Audit Fees and Audit Effort-Some Evidence of the Transition

Costs on Changes in Reporting Regimes', *Australian Accounting Review*, vol. 23, no. 1, pp. 88-99.

Ryan, S.G. & Zarowin, P.A. (2003), 'Why Has the Contemporaneous Linear Returns-Earnings Relation Declined?', *Accounting Review*, vol. 78, no. 2, pp. 523-553.

Sankar, M.R. & Subramanyam, K. (2001), 'Reporting Discretion and Private Information Communication through Earnings', *Journal of Accounting Research*, vol. 39, no. 2, pp. 365-386.

Schipper, K. (2003), 'Principles-Based Accounting Standards', *Accounting Horizons*, vol. 17, no. 1, pp. 61-72.

Schipper, K. & Vincent, L. (2003), 'Earnings Quality', *Accounting Horizons*, vol. 17, pp. 97-110.

Schwab, K. & Sala-i-Martin, X. 2013, 'The Global Competitiveness Report 2012-2013,' Citeseer.

Scott, W.R. 1997, *Financial Accounting Theory,* Prentice hall Upper Saddle River, NJ.

Seng, D. & Hancock, J.R. (2012), 'Fundamental Analysis and the Prediction of Earnings', *International Journal of Business and Management*, vol. 7, no. 3, pp. 32-46.

Shane, P. & Brous, P. (2001), 'Investor and (Value Line) Analyst Underreaction to Information About Future Earnings: The Corrective Role of Non-Earnings-Surprise Information', *Journal of Accounting Research*, vol. 39, no. 2, pp. 387-404.

Shane, P.B. & Stock, T. (2006), 'Security Analyst and Stock Market Efficiency in Anticipating Tax-Motivated Income Shifting', *Accounting Review*, vol. 81, no. 1, pp. 227-250.

Sharma, M. & Sharma, P. (2009), 'Prediction of Stock Returns for Growth Firms a Fundamental Analysis', *Vision: The Journal of Business Perspective*, vol. 13, no. 3, pp. 31-40.

Shivakumar, L. (2013), 'The Role of Financial Reporting in Debt Contracting and in Stewardship', *Accounting and Business Research*, vol. 43, no. 4, pp. 362-383.

Sinnewe, E.G.T. 2014, *An Empirical Investigation of Voluntary Non-IFRS Earnings Reporting During the Recent Financial Crisis: Australian Evidence*, Thesis, Southern Cross University, Lismore, NSW.

Sloan, R.G. (1996), 'Do Stock Prices Fully Reflect Information in Accruals and Cash Flows About Future Earnings?', *Accounting Review*, vol. 71, no. 3, pp. 289-315.

Spence, M. (2002), 'Signaling in Retrospect and the Informational Structure of Markets', *American Economic Review*, vol. 92, no. 3, pp. 434-459.

Sprouse, R.T. & Moonitz, M. 1962, *A Tentative Set of Broad Accounting Principles for Business Enterprises*, American Institute of Certified Public Accountants, New York,

Stadler, C. & Nobes, C.W. (2014), 'The Influence of Country, Industry, and Topic Factors on IFRS Policy Choice', *Abacus*, vol. 50, no. 4, pp. 386-421.

Stent, W., Bradbury, M. & Hooks, J. (2010), 'IFRS in New Zealand: Effects on Financial Statements and Ratios', *Pacific Accounting Review*, vol. 22, no. 2, pp. 92-107.

Stober, T.L. (1993), 'The Incremental Information Content of Receivables in Predicting Sales, Earnings, and Profit Margins', *Journal of Accounting, Auditing & Finance*, vol. 8, no. 4, pp. 447-473.

Subramanyam, K. (1996), 'The Pricing of Discretionary Accruals', *Journal of Accounting and Economics*, vol. 22, no. 1, pp. 249-281.

Subramanyam, K. & Venkatachalam, M. (2007), 'Earnings, Cash Flows, and Ex Post Intrinsic Value of Equity', *The Accounting Review*, vol. 82, no. 2, pp. 457-481.

Swanson, E.P., Rees, L. & Juarez-Valdes, L.F. (2003), 'The Contribution of Fundamental Analysis after a Currency Devaluation', *The Accounting Review*, vol. 78, no. 3, pp. 875-902.

Tan, H., Wang, S. & Welker, M. (2011), 'Analyst Following and Forecast Accuracy after Mandated IFRS Adoptions', *Journal of Accounting Research*, vol. 49, no. 5, pp. 1307-1357.

Teoh, S.H. & Wong, T.J. (1997), 'Analysts' Credulity About Reported Earnings and Overoptimism in New Equity Issues', Working paper, available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=8529.

Tsalavoutas, I. & Evans, L. (2010), 'Transition to IFRS in Greece: Financial Statement Effects and Auditor Size', *Managerial Auditing Journal*, vol. 25, no. 8, pp. 814-842.

Van Beest, F., Braam, G. & Boelens, S. (2009), 'Quality of Financial Reporting: Measuring Qualitative Characteristics', Nijmegen Center for Economics . Working Paper,available at http://www.dphu.org/uploads/attachements/books/books_ 3437 _0.pdf.

Van Tendeloo, B. & Vanstraelen, A. (2005), 'Earnings Management under German GAAP Versus IFRS', *European Accounting Review*, vol. 14, no. 1, pp. 155-180.

Wahab, S., Teitel, K. & Morzuch, B. (2015), 'How Analysts and Whisperers Use Fundamental Accounting Signals to Make Quarterly Eps Forecasts', *Journal of Accounting, Auditing & Finance*, Published online Nov 2015, available at http://jaf.sagepub.com/content/early/2015/11/11/0148558X15613040.

Wallison, P.J. (2008), 'Fair Value Accounting: A Critique', American Enterprise Institute for Public Policy Research Outlook Series, July.

Watson, A., Shrives, P. & Marston, C. (2002), 'Voluntary Disclosure of Accounting Ratios in the UK', *The British Accounting Review*, vol. 34, no. 4, pp. 289-313.

Watts, R.L. & Zimmerman, J.L. (1978), 'Towards a Positive Theory of the Determination of Accounting Standards', *Accounting Review*, vol. 53, no. 1, pp. 112-134.

Witkowska, M. (2006), 'Fundamentals and Stock Returns on the Warsaw Stock Exchange: The Application of Panel Data Models', Department of Applied Econometrics Working Paper, Available at https://papers.ssrn.com/sol3 /Papers.cfm?abstract_id=903167.

Wolfe, M. (2009), 'Accounting for Intangibles and Managerial Information', Working Paper, Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1470978.

Womack, K.L. (1996), 'Do Brokerage Analysts' Recommendations Have Investment Value?', *Journal of Finance*, vol. 51, no. 1, pp. 137-167.

Wyatt, A. (2005), 'Accounting Recognition of Intangible Assets: Theory and Evidence on Economic Determinants', *The Accounting Review*, vol. 80, no. 3, pp. 967-1003.

Xu, H., Nord, J.H., Nord, G.D. & Lin, B. (2003), 'Key Issues of Accounting Information Quality Management: Australian Case Studies', *Industrial Management & Data Systems*, vol. 103, no. 7, pp. 461-470.

Xu, W., Anandarajan, A. & Curatola, A. (2011), 'The Value Relevance of Goodwill Impairment', *Research in Accounting Regulation*, vol. 23, no. 2, pp. 145-148.

Xue, Y. & Zhang, M.H. (2011), 'Fundamental Analysis, Institutional Investment, and Limits to Arbitrage', *Journal of Business Finance & Accounting*, vol. 38, no. 9-10, pp. 1156-1183.

Yang, I.H., Karthik, B. & Xi, L. (2013), 'Mandatory Financial Reporting Environment and Voluntary Disclosure: Evidence from Mandatory IFRS Adoption', Research

Collection School Of Accountancy Available at: http://ink.library.smu.edu.sg /soa_research/1163.

Zeff, S.A. 1972, *Forging Accounting Principles in Five Countries: A History and an Analysis of Trends*, Champaign, IL: Stipes Publishing Co.

Zéghal, D., Chtourou, S. & Sellami, Y.M. (2011), 'An Analysis of the Effect of Mandatory Adoption of IAS/IFRS on Earnings Management', *Journal of International Accounting, Auditing and Taxation*, vol. 20, no. 2, pp. 61-72.

Zhaoyang, G. & Jian, X. (2007), 'Do Analysts Overreact to Extreme Good News in Earnings?', *Review of Quantitative Finance & Accounting*, vol. 29, no. 4, pp. 415-431.

Zhou, P. & Ruland, W. (2006), 'Dividend Payout and Future Earnings Growth', *Financial Analysts Journal*, vol. 62, no. 3, pp. 58-69.

ANNEXURES

Annexure 6.1: Descriptive statistics for pooled sample and pre- and post-IFRS sub-samples

Variables	Full Sample N = 19268				Pre-IFRS n = 4090		Post-IFRS n = 15178		Test of difference
	Minimum	Maximum	Mean	SD	Mean	SD	Mean	SD	*t*
CEPS1	-0.243	0.333	0.012	0.116	0.029	0.120	0.008	0.114	**10.262*****
CHGEPS	-0.377	0.265	-0.007	0.122	-0.008	0.123	-0.007	0.122	-0.282
INV	-53.490	78.024	2.781	27.531	0.132	27.028	3.495	27.623	**-7.030*****
AR	-44.321	61.389	1.368	22.706	0.228	22.626	1.675	22.718	**-3.627*****
SA	-48.837	39.904	-1.399	17.805	-1.263	18.168	-1.436	17.707	0.544
LF	-57.474	33.034	-6.425	20.190	-9.003	21.626	-5.730	19.729	**-8.747*****
ETR	-40.580	31.212	-1.086	12.998	-1.320	12.392	-1.023	13.156	-1.340
GM	-75.614	65.648	-0.555	28.076	-0.999	27.559	-0.435	28.213	-1.156
CAPX	-250.581	101.046	-16.513	83.604	-16.558	77.928	-16.500	85.071	-0.041
LEV	-81.901	138.229	3.711	48.380	4.706	45.839	3.442	49.041	1.542
CF	-19.226	15.483	-1.088	8.076	-1.734	8.425	-0.914	7.971	**-5.586*****
GW	-212.019	48.411	-24.093	58.532	-26.272	64.182	-23.506	56.901	**-2.504****
CDACCR	-0.208	0.190	-0.005	0.089	-0.019	0.096	-0.001	0.086	**-10.569*****
								Chi-Sq	
AQ	0.000	1.000	0.006		0.017		0.004		**91.464*****

Where, CHGEPS, Change in Current Earnings per share=change in EPS between year *t-1* and *t* deflated by the stock price at the end of *t-1*., INV=Inventories (annual percentage change in inventories minus the annual percentage change in sales), AR=Accounts Receivable (annual percentage change in accounts receivable minus annual percentage change in sales), SA=Selling & Administrative Expenses (annual percentage change in selling and administrative expenses minus the annual percentage change in sales), LF =Labour Force (LF) (annual percentage change in sales per employee calculated as last two years average sales per employee minus current year sales per employee divided by last two years average sales per employee), ETR=Effective Tax Rate (annual percentage change in ETR or Last two year (*t-1* and *t-2*) average ETR – ETR *t*), GM=Gross Margin (annual percentage change in sales minus annual percentage change in gross margin), AQ=Audit Qualification (0 for an unqualified opinion and 1 otherwise. If there is an emphasis of matter paragraph and if it relates to going concern, 1 is assigned and 0 otherwise , CAPX=Capital Expenditure (annual percentage change in industry capital expenditure minus the annual percentage change in the firm's capital expenditure), LEV=Financial Leverage (Annual change in ratio of total debt (long-term debt plus current liabilities) to total assets or leverage ratio in year *t* – last two years average leverage ratio), CF=Cash Flows (Cash flow from operations (CFO) between year *t* and *t-1* divided by total assets at end of financial year *t-1*), GW = Goodwill (Annual percentage change in goodwill calculated as last two years (*t-1* and *t-2*) average goodwill minus goodwill in year *t* divided by last two years average goodwill), CDACCR = annual change in Discretionary. Discretionary accruals is measured using the Kothari, Leone and Wasley (2005) performance matched discretionary accrual model, Pre-IFRS period is from 2001 to 2004 and the post-IFRS period is from 2006 to 2012. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively.

Annexure 6.2: Pearson's r correlations for independent (fundamental signals) variables (N=19268)

Variables	CHGEPS	INV	AR	SA	LF	ETR	GM	AQ	CAPX	LEV	CF	GW
INV	.062***											
AR	-.005	.175***										
SA	.127***	.163***	.073***									
LF	.201***	.111***	.054***	.211***								
ETR	-.050***	.001	.002	-.014**	-.014**							
GM	.169***	.031***	-.039***	-.067***	.034***	.005						
AQ	.008	.009	.006	-.013	-.013	-.008	.014					
CAPX	.023***	-.047***	-.045***	.043***	.031***	-.016**	.050***	.008				
LEV	.009	.034***	.043***	-.006	-.024***	-.005	-.264***	.019***	-.064***			
CF	.200***	.066***	.018**	.108***	.185***	-.012	.083***	.003	.045**	.022***		
GW	.010	-.070***	-.079***	.007	.012	-.012	.029***	.001	.136***	-.101***	.051***	
CDACCR	-.177***	-.038***	-0.011	-.109***	-.019***	.018**	-.119***	-.012	.009	.043***	.446***	.016**

Refer to annexure 6.1 for variable definitions. ***, **, * indicates that correlation is significance at the 1%, 5%, and 10% levels respectively

Annexure 7.1: Descriptive statistics for pooled sample and pre- and post-IFRS sub-samples

Variables	Pooled Sample N= 19308				Pre-IFRS n= 4107		Post-IFRS n = 15201		T-test of difference
	Minimum	Maximum	Mean	Std.	Mean	Std.	Mean	Std.	*t*
ER	-98.882	117.904	-0.952	36.948	7.899	38.332	-3.343	36.197	**16.873*** **
CHGEPS	-0.377	0.265	-0.010	0.125	-0.012	0.127	-0.010	0.125	-.960
INV	-53.490	78.024	2.747	27.478	0.138	27.051	3.452	27.550	**-6.938*** **
AR	-55.995	57.274	-0.582	24.856	-0.615	23.538	-0.573	25.201	-.102
SA	-48.837	39.904	-1.383	17.759	-1.245	18.161	-1.420	17.650	.553
LF	-57.473	33.034	-6.437	20.184	-9.092	21.634	-5.720	19.713	**-9.029*** **
ETR	-281.279	318.996	17.791	117.501	14.454	109.230	18.693	119.625	**-2.161** **
GM	-75.614	65.648	-0.643	28.063	-1.302	27.595	-0.464	28.187	**-1.718* **
CAPX	-250.581	101.046	-16.363	83.426	-16.504	77.802	-16.324	84.885	-.129
LEV	-81.901	138.229	3.642	48.345	4.530	45.714	3.402	49.030	1.381
CF	-19.226	15.483	-1.094	8.060	-1.742	8.422	-0.919	7.951	**-5.624*** **
GW	-212.019	48.411	-24.122	58.596	-26.365	64.199	-23.515	56.976	**-2.583** **
CDACCR	-0.208	0.190	-0.005	0.089	-0.018	0.097	-0.001	0.086	**-9.936*** **
									Chi-Sq
AQ	0.000	1.000	0.007		0.017		0.004		**86.972*** **

Where IFRS = an indicator variable coded 1 for observations in the post-IFRS period (2006-2012), and 0 otherwise (2001-2004), Contemporaneous excess return (ER) is measured as the difference between firm return and the benchmark return for the period that begins 11 months before the earnings announcement date and ends one month after the earnings announcement date for year *t*, CHGEPS, Change in Current Earnings per share=change in EPS between year *t-1* and *t* deflated by the stock price at the end of *t-1*., INV=Inventories (annual percentage change in inventories minus the annual percentage change in sales), AR=Accounts Receivable (annual percentage change in accounts receivable minus annual percentage change in sales), SA=Selling & Administrative Expenses (annual percentage change in selling and administrative expenses minus the annual percentage change in sales), LF =Labour Force (LF) (annual percentage change in sales per employee calculated as last two years average sales per employee minus current year sales per employee divided by last two years average sales per employee), ETR=Effective Tax Rate (annual percentage change in ETR or Last two year (*t-1* and *t-2*) average ETR – ETR *t*), GM=Gross Margin (annual percentage change in sales minus annual percentage change in gross margin), AQ=Audit Qualification (0 for an unqualified opinion and 1 otherwise. If there is an emphasis of matter paragraph and if it relates to going concern, 1 is assigned and 0 otherwise , CAPX=Capital Expenditure (annual percentage change in industry capital expenditure minus the annual percentage change in the firm's capital expenditure), LEV=Financial Leverage (Annual change in ratio of total debt (long-term debt plus current liabilities) to total assets or leverage ratio in year *t* – last two years average leverage ratio), CF=Cash Flows (Cash flow from operations (CFO) between year *t* and *t-1* divided by total assets at end of financial year *t-1*), GW = Goodwill (Annual percentage change in goodwill calculated as last two years (*t-1* and *t-2*) average goodwill minus goodwill in year *t* divided by last two years average goodwill), CDACCR = annual change in Discretionary Accruals. Discretionary accruals is measured using the Kothari, Leone and Wasley (2005) performance matched discretionary accrual model, Pre-IFRS period is from 2001 to 2004 and the post-IFRS period is from 2006 to 2012. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively.

Annexure 7.2: Pearson's r correlations for independent (fundamental Signals) variables (N=19308)

Variables	CHGEPS	INV	AR	SA	LF	ETR	GM	AQ	CAPX	LEV	CF	GW
INV	.010											
AR	.094***	.058***										
SA	.122***	.060***	.133***									
LF	.197***	.093***	.238***	.211***								
ETR	.014	.005	.006	.009	-.001							
GM	.165***	-.030***	.003	-.066***	.035***	.018**						
AQ	.006	-.006	.008	-.012	-.012	.008	.011					
CAPX	.015**	.028***	.023***	.042***	.030***	.014	.050***	.008				
LEV	.010	-.005	.009	-.005	-.025***	.006	-.265***	.016**	-.062***			
CF	.197***	.019***	.073***	.110***	.181***	.012	.082***	.004	.046***	.024***		
GW	.006	.029***	-.008	.008	.013	.010	.030***	.002	.136***	-.101***	.052***	
CDACCR	-.178**	-.007	-.029***	-.105***	-.019***	-.009	-.119***	-.009	.011	.043***	.447***	.017**

Refer to annexure 7.1 for variable definitions. ***, **, * indicates that correlation is significance at the 1%, 5%, and 10% levels respectively

Annexure 7.3: The value relevance of fundamental signals and F_Score for Extreme and Non-extreme performers (H2a, H2b & H2c)

Panel A **Model 3** Dep. Var. ER	**Sec 2:** Value relevance: Extreme & Non-extreme performers		
	Extreme	Non-extreme	Test of Equality
	n =2546	n =16762	
	Coef.	Coef.	Coef. Diff
A	**-19.797****	**-5.789*****	
CHGEPS	**-99.775*****	**-28.686*****	**-71.089*****
INV	0.021	0.004	0.017
AR	**-0.147*****	**-0.040*****	**-0.107****
SA	**-0.177*****	-0.017	**-0.160****
LF	**-0.172*****	-0.015	**-0.157*****
ETR	**-0.023*****	**-0.007*****	**-0.016***
GM	**-0.382*****	**-0.119*****	**-0.263*****
AQ	**-46.978*****	-0.681	**-46.296*****
CAPX	**-0.048*****	-0.002	**-0.046*****
LEV	**-0.080*****	**-0.008***	**-0.072*****
CF	**-1.545*****	**-0.441*****	**-1.104*****
GW	-0.016	**-0.013*****	-0.003
CDACCR	**-79.666*****	**-28.856*****	**-50.811*****
Adj. R-Sq 1	0.386	0.106	
Adj. R-Sq 2	0.282	0.064	
Panel B: ***Model 4-*** *The value relevance of F_Score*			
Dep. Var. ER	Extreme	Non-extreme	Coef. Diff
α	**-95.712*****	**-18.646*****	
CHGEPS	**-142.229*****	**-38.612*****	**-103.617*****
F_Score	**10.386*****	**1.846*****	**8.540*****
Adj. R-Sq	0.340	0.084	

Refer to Annexure 7.1 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Adj. R-Sq 1: Adjusted R-Squared of full model 1, Adj. R-Sq 2: Adjusted R Squared of earnings alone model. Results are based on robust standard errors clustered by firm. Standard errors are CDACCR (5.5), AQ (4.9), CHGEPS (3.8), with others less than 0.1. The test of equality of coefficients is based on stacked regression.

Annexure 7.4: IFRS impact on the value relevance of fundamental signals for excess returns of Extreme and Non-extreme performers (H2d & H2e)

***Panel A:** IFRS impact on the value relevance of fundamental signals based on Model 10*

Dep.Var. ER	Extreme		Test of Equality	Non-Extreme		Test of Equality
	Pre-IFRS	Post-IFRS		Pre-IFRS	Post-IFRS	
	n =587	n =1959		n =3520	n =13242	
	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff
α	15.302	**-42.932****		**-9.067****	**-8.020*****	
CHGEPS	**-106.179*****	**-91.83*****	-14.349	**-28.129*****	**-28.784*****	0.655
INV	**0.060***	0.019	0.041	0.000	0.005	-0.005
AR	-0.127	**-0.168*****	0.041	-0.026	**-0.043*****	0.018
SA	**-0.425*****	-0.116	**-0.309****	**-0.107*****	0.011	**-0.118*****
LF	-0.126	**-0.197*****	0.071	-0.003	**-0.024****	0.021
ETR	-0.022	**-0.021****	-0.001	**-0.009****	**-0.006*****	-0.003
GM	**-0.513*****	**-0.334*****	**-0.179****	**-0.161*****	**-0.104*****	**-0.057*****
AQ	**-43.924*****	-29.892	-14.032	-4.080	0.504	-4.583
CAPX	-0.020	**-0.055*****	0.035	-0.007	-0.001	-0.006
LEV	**-0.163*****	**-0.053****	**-0.111****	-0.009	**-0.008***	0.000
CF	**-0.778*****	**-1.759*****	**0.981****	**-0.296*****	**-0.488*****	**0.192****
GW	-0.032	-0.011	-0.021	-0.010	**-0.014*****	0.004
CDACCR	**-54.255*****	**-84.221*****	**29.965***	**-32.003*****	**-26.977*****	-5.026
Adj. R-Sq - 1	0.480	0.349		0.121	0.086	
Adj. R-Sq - 2	0.381	0.239		0.082	0.054	

***Panel B**: IFRS impact on the value relevance of fundamental signals based on Model 9*

Dep.Var ER		Extreme returns	Non-extreme Returns
IFRS		-0.478	-1.655
IFCHGEPS		13.037	-1.423
IFINV		-0.031	0.003
IFAR		-0.047	-0.015
IFSA		**0.325****	**0.122*****
IFLF		-0.101	-0.023
IFETR		1.993	-0.259
IFGM		**0.186****	**0.066*****
IFAQ		11.853	3.145
IFCAPX		-0.049	0.003
IFLEV		**0.108****	0.004
IFCF		**-0.936*****	**-0.209*****
IFGW		0.001	-0.003
IFCDACCR		-30.544	4.619

Refer to Annexure 7.1 for variable Definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm. Standard errors are CDACCR (4.4), AQ (4.8), CHGEPS (3.6), with others less than 0.1 in Panel A. Panel A examines the IFRS impact using the test of equality of coefficients based on stacked regression. In panel B, IFRS impact is measured based on the interaction of each fundamental signal with IFRS Where IFRS is an indicator variable coded 1 for observations in the post-IFRS period (2006-2012) and 0 otherwise (2001 -2004). Interaction variables are designated with “IF” followed by the variable name. Adj. R-Sq - 1: full model R-Squared, Adj. R-Sq - 2: earnings alone model R-Squared.

Annexure 7.5: IFRS impact on the value relevance of F_Score for Extreme and Non-Extreme performers (H2f)

Dep. Var. ER	**Panel A:** Model 12						**Panel B :** Model 11	
	Extreme			Non-extreme			Full Sample	
	Pre-IFRS	Post-IFRS	Test of Equality	Pre-IFRS	Post-IFRS	Test of Equality	Extreme	Non-Extreme
	n =587	n =1959		n =3520	n =13242		n =2546	n =16762
	Adj. R-Sq = 0.417	Adj. R-Sq = 0.303		Adj. R-Sq = 0.095	Adj. R-Sq = 0.068		R-Sq = 0.393	R-Sq = 0.100
	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff	Coef.	Coef.
α	-41.486	**-127.370*** **		**-20.074*** **	**-20.996*** **		-79.365	-18.051
CHGEPS	**-155.695*** **	**-132.628*** **	-23.067	**-38.545*** **	**-38.601*** **	0.056	-154.294	-37.761
F_Score	**7.642*** **	**10.910*** **	**-3.268** **	**1.829*** **	**1.847*** **	-0.018	8.080	1.826
IFRS							-11.831	-1.703
IFCHGEPS							20.402	-0.993
IFF_Score							**2.761***	0.024

Refer to Annexure 7.1 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm. Standard errors are CHGEPS (3.6) and F_Score less than 1.0. Panel A examines the IFRS impact using the test of equality of coefficients based on stacked regression. In panel B, IFRS impact is measured based on the interaction of each fundamental signal with IFRS Where IFRS is an indicator variable coded 1 for observations in the post-IFRS period (2006-2012) and 0 otherwise (2001-2004). Interaction variables are designated with "IF" followed by the variable name.

Annexure 7.6: Value relevance of fundamental signals for Growth and Value stocks (H2a, H2b & H2c)

Panel A **Model 3** Dep. Var ER	Growth Stocks	Value Stocks	Test of Equality
	Clusters = 1655	Clusters = 1798	
	n =5716	n =5948	
	Coef.	Coef.	Coef. Diff
α	**6.535***	**-25.122*****	
CHGEPS	**-69.559*****	**-49.255*****	**-20.305****
INV	**0.011***	0.005	0.006
AR	**-0.095*****	**-0.052*****	-0.042
SA	-0.022	**-0.096*****	**0.075***
LF	**-0.061****	**-0.073*****	0.012
ETR	-0.002	**-0.009*****	0.007
GM	**-0.172*****	**-0.161*****	-0.011
AQ	**-14.903****	**-12.315***	-2.588
CAPX	-0.004	**-0.010****	0.007
LEV	**-0.026****	**-0.024*****	-0.002
CF	**-0.690*****	**-0.570*****	-0.120
GW	**-0.026*****	**0.023*****	**-0.049*****
CDACCR	**-42.423*****	**-31.146*****	-11.277
Adj. R-Sq 1	0.134	0.194	
Adj. R-Sq 2	0.082	0.158	
Panel B: ***Model 4***- *Value relevance of F_Score*			
Dep. Var. ER	Coef.	Coef.	Coef. Diff
α	**-15.181*****	**-44.701*****	
CHGEPS	**-96.527*****	**-60.983*****	**-35.544*****
F_Score	**2.902*****	**2.468*****	0.435
Adj. R-Sq	0.098	0.172	

Refer to Table 7.1 for variable definitions; ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based standard errors clustered by firm. Standard errors are CDACCR (2.5), AQ (2.5), CHGEPS (2.2), with others less than 0.1. Adj. R-Sq 1: Adjusted R-Squared of full model 1, Adj. R-Sq 2: Adjusted R Squared of earnings alone model. The test of equality is based on stacked regression.

Annexure 7.7: IFRS impact on value relevance of fundamental signals for Growth and Value stocks (H2d & H2e)

Panel A: *IFRS impact on value relevance of fundamental signals based on Model 10*

Dep. Var. ER	**Growth Stocks**		Test of Equality	**Value stocks**		Test of Equality
	Pre-IFRS	Post-IFRS		Pre-IFRS	Post-IFRS	
	N=1101	N=4615		N=1271	N=4677	
	Coef.	*t*	Coef. Diff	Coef.	*t*	Coef. Diff
α	8.350	**49.637*****		-29.641	**-21.373*****	
CHGEPS	**-94.729*****	**-61.092*****	**-33.636****	**-56.226*****	**-46.769*****	-9.457
INV	-0.006	**0.017****	-0.022	-0.001	0.008	-0.009
AR	**-0.091***	**-0.098*****	0.007	-0.049	**-0.046****	-0.003
SA	**-0.153****	0.020	**-0.174****	**-0.112***	**-0.092*****	-0.019
LF	-0.036	**-0.078****	0.042	-0.050	**-0.087*****	0.036
ETR	-0.012	0.001	-0.013	**-0.019****	**-0.006***	-0.013
GM	**-0.250*****	**-0.148*****	**-0.102***	**-0.232*****	**-0.142*****	**-0.090****
AQ	**-22.089*****	-5.298	-16.791	-10.448	**-17.332*****	6.885
CAPX	0.005	-0.006	0.010	-0.018	-0.009	-0.010
LEV	**-0.078*****	-0.019	**-0.059****	-0.015	**-0.029*****	0.014
CF	**-0.392****	**-0.779*****	**.386****	**-0.289***	**-0.659*****	**0.370****
GW	-0.005	**-0.032*****	0.028	-0.004	**0.032*****	**-0.036****
CDACCR	**-29.466****	**-45.82*****	16.354	**-34.507*****	**-28.689*****	-5.817
Adj. R-Sq 1	0.186	0.131		0.210	0.166	
Adj. R-Sq 2	0.143	0.073		0.171	0.126	

Panel B: *IFRS impact on value relevance of fundamental signals based on Model 9*

Dep.Var ER	Growth stocks	Value stocks
IFRS	-1.029	-0.480
IFCHGEPS	**32.030****	11.625
IFINV	0.018	0.010
IFAR	-0.012	0.001
IFSA	**0.191****	0.033
IFLF	-0.062	-0.028
IFETR	0.899	0.422
IFGM	**0.108***	**0.090***
IFAQ	15.828	-7.811
IFCAPX	-0.008	0.004
IFLEV	**0.062****	-0.016
IFCF	**-0.360****	**-0.373****
IFGW	-0.025	**0.034****
IFCDACCR	-14.361	-6.826

Refer to Annexure 7.1 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm. Standard errors are CDACCR (3.5), AQ (3.3), CHGEPS (3.1), with others less than 0.1 in Panel A. Panel A examines the IFRS impact using the test of equality of coefficients based on stacked regression. In panel B, IFRS impact is measured based on the interaction of each fundamental signal with IFRS Where IFRS is an indicator variable coded 1 for observations in the post-IFRS period (2006-2012) and 0 otherwise. Interaction variables are designated with "IF" followed by the variable name. Adj. R-Sq - 1: full model R-Squared, Adj. R-Sq - 2: earnings alone model R-Squared.

Annexure 7.8: IFRS impact on the value relevance of F_Score for Growth and Value stocks (H2f)

Dep. Var. ER	**Panel A:** IFRS impact on based on stacked regression (Model 11)						**Panel B :** Model 12	
	Growth Stocks			Value Stocks			Winners	Losers
	Pre-IFRS	Post-IFRS	Test of Equality	Pre-IFRS	Post-IFRS	Test of Equality		
	n =1101	n =4615		n =1271	n =4677		n =8769	n =10539
	Adj. R-Sq = 0.162	Adj. R-Sq = 0.089		Adj. R-Sq = 0.181	Adj. R-Sq = 0.114		R-Sq = 0.107	R-Sq = 0.179
	Coef.	Coef.	Coef. Diff	Coef.	Coef.	Coef. Diff	Coef.	Coef.
α	-12.496	**27.265*** **		**-49.457** **	**-38.515*** **		-30.945	-41.669
CHGEPS	**-115.365*** **	**-90.773*** **	-24.592	**-69.242*** **	**-58.065*** **	-11.177	-114.323	-71.481
F_Score	**3.309*** **	**2.840*** **	0.469	**2.392*** **	**2.482*** **	-0.090	3.231	2.307
IFRS							4.826	-0.758
IFCHGEPS							23.341	13.430
IFF_Score							-0.390	0.168

Refer to Annexure 7.1 for variable Definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively. Results are based on robust standard errors clustered by firm. Standard errors are CHGEPS (3.5) and F_Score less than 1.0 in Panel A. Panel A examines the IFRS impact using the test of equality of coefficients based on stacked regression. In panel B, IFRS impact is measured based on the interaction of each fundamental signal with IFRS where IFRS is an indicator variable coded 1 for observations in the post-IFRS period (2006-2012) and 0 otherwise. Interaction variables are designated with “IF” followed by the variable name.

Annexure 8.1: IFRS impact on analysts' efficiency in using information in fundamental signals for Winners

Sample	Pre-IFRS n = 1243				Post-IFRS period n = 3106			
Models	Model 11	Model 12	Model 13	Model 14	Model 11	Model 12	Model 13	Model 14
Dependent Variable	CEPS1	FCEPS1 5	CEPS1	FE	CEPS1	FCEPS1 5	CEPS1	FE
Full model Adj. R-Sq	0.255	0.338	0.468	0.114	0.279	0.342	0.481	0.123
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
α	**0.08266*** **	**0.27138*** **	-0.04094	**-0.19823*** **	**0.05634*** **	0.02846	**0.04521** **	0.00661
CHGEPS	**0.30343*** **	**0.52562*** **	**0.06402** **	**-0.18377*** **	**0.33828*** **	**0.55098*** **	**0.12280*** **	**-0.23685*** **
INV	**-0.00004* **	0.00001	**-0.00005*** **	**-0.00005** **	0.00002	-0.00002	**0.00003** **	**0.00004** **
AR	-0.00014	-0.00004	-0.00013	-0.00008	-0.00003	-0.00009	0.00001	0.00006
SA	0.00001	0.00010	-0.00004	-0.00007	**0.00020* **	**0.00044*** **	0.00003	-0.00016
LF	**-0.00030** **	-0.00016	**-0.00023** **	-0.00006	**-0.00020** **	-0.00004	**-0.00019*** **	-0.00009
ETR	**-0.03556** **	-0.02882	**-0.02243** **	-0.00267	**-0.01957*** **	-0.01471	**-0.01382*** **	-0.00320
GM	**0.00106** **	0.00094	0.00063	-0.00034	0.00022	**0.00081*** **	-0.00010	**-0.00043* **
AQ	0.00528	0.00650	0.00232	-0.00290	-0.00871	**-0.02011* **	-0.00085	0.01624
CAPX	**0.00012*** **	**0.00012*** **	**0.00006** **	-0.00003	**0.00008*** **	**0.00012*** **	**0.00003* **	-0.00004
LEV	**0.02630*** **	0.00856	**0.02241*** **	0.01061	0.00469	**0.01234*** **	-0.00013	**-0.00875** **
CF	-0.00024	-0.00001	-0.00023	-0.00014	**-0.00066** **	**-0.00075** **	-0.00037	-0.00022
GW	**0.00548** **	**0.00861*** **	0.00156	**-0.00399* **	**0.00776*** **	**0.01224*** **	0.00297	**-0.00443** **
CDACCR	0.04461	0.00840	0.04078	0.02969	0.00403	0.01613	-0.00228	0.01202
FCEPS1			**0.45547*** **				**0.39109*** **	
CHGEPS/ FCEPS1 alone model R-Sq	0.216	0.324	0.447		0.261	0.326	0.459	
FCEPS1 and CHGEPS in the Model R-Sq			0.449				0.476	
Incremental Adj. R-Sq 1	0.216		0.002 1%[#]		0.261		0.017 7%	
Incremental Adj. R-Sq 2	0.039	0.014	0.019 49%		0.018		0.005 28%	

Refer to Annexure 7.1 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively, Results are based on robust standard errors clustered by firm. All standard errors are less than 0.05. Incremental R-Sq 1: Incremental R^2 from earnings variable. Incremental R-Sq 2: Incremental R^2 from non-earnings variables over earnings. Pre-IFRS period is from 2001 to 2004 and the post-IFRS period is from 2006 to 2012. # The percentage adjacent to the incremental R-Squared from the earnings signals represents analysts' inefficiency in using the earnings signal.

Annexure 8.2: IFRS impact on analysts' efficiency in using information in fundamental signals for Losers

Sample	Losers Pre-IFRS n = 537					Losers Post-IFRS period n = 2480				
Models	Model 11	Model 12	Model 13		Model 14	Model 11	Model 12	Model 13		Model 14
Dependent Variable	CEPS1	FCEPS1 5	CEPS1		FE	CEPS1	FCEPS1 5	CEPS1		FE
Full model Adj. R-Sq	0.116	0.078	0.129		0.044	0.145	0.094	0.145		0.042
	Coef.	Coef.	Coef		Coef.	Coef.	Coef.	Coef		Coef.
α	-0.03612	0.00420	-0.03559		-0.04651	**-0.0349*** **	**0.02624** **	**-0.03492*** **		**-0.05614*** **
CHGEPS	**0.17449*** **	**0.16992*** **	**0.19598*** **		-0.08272	**0.27248*** **	**0.2054*** **	**0.27234*** **		-0.04193
INV	-0.00003	-0.00005	-0.00004		0.00001	**-0.00003* **	-0.00002	-0.00003*		-0.00001
AR	0.00005	-0.00012	0.00003		0.00017	-0.00005	0.00002	-0.00005		-0.00009
SA	-0.00023	**0.00045** **	-0.00018		**-0.00091** **	0.00010	-0.00003	0.00010		0.00008
LF	**0.00039** **	-0.00023	**0.00036** **		**0.00069** **	-0.00005	0.00003	-0.00005		-0.0001
ETR	0.01611	0.00900	0.01724		-0.0064	0.00999	0.00324	0.00999		-0.00597
GM	**-0.00170* **	0.00099	**-0.00158* **		**-0.00294** **	**-0.0005** **	-0.00001	**-0.0005** **		**-0.0006* **
AQ	-0.02056	-0.00090	-0.02068		-0.02276	0.00981	**-0.04818*** **	0.00985		**0.06503*** **
CAPX	-0.00002	0.00005	-0.00002		-0.00006	-0.00001	**0.00005** **	-0.00001		**-0.00008*** **
LEV	-0.00703	0.00748	-0.00608		-0.01850	0.00315	-0.00643	0.00315		**0.01002* **
CF	-0.00063	0.00015	-0.00061		0.00010	**-0.00131*** **	-0.00019	**-0.00131*** **		-0.00069
GW	-0.00396	0.00415	-0.00343		-0.00624	-0.00065	**0.00429* **	-0.00065		-0.00505
CDACCR	-0.02624	-0.03708	-0.03093		-0.02040	**0.09721*** **	0.00296	**0.09720*** **		0.05812
FCEPS1			-0.12646					0.00070		
CHGEPS/ FCEPS1 alone model R-Sq (b)	CHGEPS 0.104	CHGEPS 0.079	FCEPS1 0.056			CHGEPS 0.133	CHGEPS 0.090	FCEPS1 0.033		
FCEPS1 and CHGEPS in the Model R-Sq			0.120					0.133		
Incremental Adj. R-Sq 1	0.104		0.064	62%#		0.133		0.100	75%	
Incremental Adj. R-Sq 2	0.012		0.009	75%		0.012		0.012	100%	

Refer to Table 8.1 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively, Results are based on robust standard errors clustered by firm. All standard errors are less than 0.05. Incremental R-Sq 1: Incremental R^2 from earnings variable. Incremental R-Sq 2: Incremental R^2 from non-earnings variables over earnings. Pre-IFRS is from 2001 to 2004 and the post-IFRS period is from 2006 to 2012. # The percentage adjacent to the incremental R-Squared from the earnings signals represents analysts' inefficiency in using the earnings signal.

Annexure 8.3: Analysts' efficiency in using information in fundamental signals for Code and Common law countries

Sample	Code Law n = 5001				Common Law n = 2635			
Dependent Variable	CEPS1	FCEPS1 5	CEPS1	FE	CEPS1	FCEPS1 5	CEPS1	FE
Full model Adj. R-Sq	0.228	0.279	0.334	0.068	0.226	0.22	0.299	0.038
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
α	0.01750	0.00424	0.01580	0.00596	**0.04625*****	**0.05621*****	**0.03050*****	-0.02174
CHGEPS	**0.40323*****	**0.43161*****	**0.23031*****	**-0.07751*****	**0.42299*****	**0.43275*****	**0.30174*****	**-0.08153****
INV	0.00001	-0.00001	0.00001	0.00001	-0.00002	-0.00002	-0.00001	0.00002
AR	-0.00007	-0.00007	-0.00005	0.00001	-0.00006	-0.00005	-0.00004	-0.00005
SA	**0.00021****	**0.00042*****	0.00004	**-0.00019***	0.00014	0.00018	0.00009	0.00001
LF	**-0.00020****	**-0.00013***	**-0.00015****	-0.00007	-0.00008	-0.00006	-0.00006	0.00013
ETR	**-0.01531****	**-0.01183***	**-0.01057****	-0.00797	0.00016	-0.02278	0.00655	0.01668
GM	-0.00023	**0.00061*****	**-0.00047****	**-0.00097*****	-0.00039	0.00013	-0.00043	-0.00015
AQ	**-0.01523**	**-0.01964***	-0.00736	0.00588	0.00545	-0.02141	0.01145	**0.05546***
CAPX	0.00008***	**0.00009*****	**0.00004****	-0.00003	**0.00007*****	**0.00011*****	0.00004	-0.00004
LEV	**0.00991****	0.00744	**0.00693***	0.00046	0.00524	0.00205	0.00466	0.00116
CF	**-0.00182*****	**-0.00056****	**-0.00159*****	**-0.00096*****	**-0.00100****	-0.00013	**-0.00096****	**-0.00096****
GW	**0.00504*****	**0.00843*****	0.00167	-0.00248	**0.00583****	**0.01115*****	0.00270	**-0.00692****
CDACCR	**0.07673*****	-0.02148	**0.08533*****	**0.07394*****	0.04397	0.03266	0.03481	0.03102
FCEPS1			**0.40062*****				**0.28020*****	
CHGEPS/ FCEPS1 alone model Adj. R-Sq	CHGEPS 0.208	CHGEPS 0.264	FCEPS1 0.293		CHGEPS 0.220	CHGEPS 0.209	FCEPS1 0.218	
FCEPS1 and CHGEPS in the Model R-Sq			0.322				0.297	
Incremental Adj. R-Sq 1	0.208		0.029 14%[#]		0.220		0.079 36%	
Incremental Adj. R-Sq 2	0.020		0.012 60%		0.006		0.002 33%	

Refer to Table 8.1 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively, Results are based on robust standard errors clustered by firm. All standard errors are less than 0.05. Incremental R-Sq 1: Incremental R^2 from earnings variable. Incremental R-Sq 2: Incremental R^2 from non-earnings variables over earnings. # The percentage adjacent to the incremental R-Squared from the earnings signals represents analysts' inefficiency in using the earnings signal.

Annexure 8.4: IFRS impact on analysts' efficiency in using information in fundamental signals for Code law countries

	Code Law							
Sample	Pre-IFRS (n = 1259)				Post-IFRS (n = 3742)			
Dependent Variable	CEPS1	FCEPS1 5	CEPS1	FE	CEPS1	FCEPS1 5	CEPS1	FE
Full model Adj. R-Sq	0.151	0.256	0.248	0.057	0.246	0.288	0.357	0.073
	Coef.	Coef.		Coef.	Coef.	Coef.		Coef.
α	0.01342	0.05044	-0.00644	-0.03582	0.02549	-0.00949	0.02934	0.03062
CHGEPS	**0.31083*** **	**0.40373*** **	**0.15186*** **	**-0.08312***	**0.43221*** **	**0.43980*** **	**0.25378*** **	**-0.07302*** **
INV	-0.00002	-0.00002	-0.00001	0.00001	0.00001	-0.00001	0.00001	0.00001
AR	-0.00006	-0.00003	-0.00005	0.00001	-0.00009	-0.00009	-0.00006	0.00002
SA	0.00005	**0.00040** **	-0.00011	-0.00032	**0.00027** **	**0.00042*** **	0.00010	-0.00015
LF	-0.00012	-0.00005	-0.00010	-0.00004	**-0.00022** **	-0.00014	**-0.00017** **	-0.00009
ETR	-0.02185	-0.02021	-0.01389	-0.00926	**-0.01395** **	-0.00952	**-0.01009***	-0.00778
GM	-0.00068	**0.00116***	**-0.00114***	**-0.00195*** **	-0.00016	**0.00059** **	**-0.00040***	**-0.00088*** **
AQ	-0.01310	0.01055	-0.01725	-0.02606	**-0.01937***	**-0.03801** **	-0.00395	**0.01943***
CAPX	**0.00008** **	**0.00006***	**0.00006***	0.00001	**0.00007*** **	**0.00010*** **	0.00003	**-0.00005** **
LEV	0.00666	0.01198	0.00195	-0.00181	**0.00953***	0.00787	0.00633	-0.00108
CF	**-0.00154*** **	-0.00045	**-0.00136*** **	-0.00044	**-0.00191*** **	**-0.00064** **	**-0.00165*** **	**-0.00108*** **
GW	**0.00963*** **	**0.01003*** **	0.00568	0.00061	0.00239	**0.00710*** **	-0.00049	-0.00390
CDACCR	0.06199	-0.00005	0.06201	0.02625	**0.08032*** **	-0.02448	**0.09025*** **	**0.08077*** **
FCEPS1			**0.39375*** **				**0.40571*** **	
CHGEPS/ FCEPS1 alone model Adj. R-Sq	CHGEPS 0.134	CHGEPS 0.242	FCEPS1 0.228		CHGEPS 0.227	CHGEPS 0.273	FCEPS1 0.308	
FCEPS1 and CHGEPS in the Model R-Sq			0.237				0.346	
Incremental Adj. R-Sq 1	0.134		0.009 7%[#]		0.227		0.038 17%	
Incremental Adj. R-Sq 2	0.017		0.011 65%		0.019		0.011 59%	

Refer to Table 8.1 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively, Results are based on robust standard errors clustered by firm. All standard errors are less than 0.05. Incremental R-Sq 1: Incremental R^2 from earnings variable. Incremental R-Sq 2: Incremental R^2 from non-earnings variables over earnings. Pre-IFRS period is from 2001 to 2004 and the post-IFRS period is from 2006 to 2012. # The percentage adjacent to the incremental R-Squared from the earnings signals represents analysts' inefficiency in using the earnings signal.

Annexure 8.5: IFRS impact on analysts' efficiency in using information in fundamental signals for Common law countries

Sample	Common law							
	Pre-IFRS (n = 521)				Post-IFRS (n = 1844)			
Dependent Variable	CEPS1	FCEPS1 5	CEPS1	FE	CEPS1	FCEPS1 5	CEPS1	FE
Full model Adj. R-Sq	0.214	0.258	0.271	0.024	228	0.214	0.306	0.041
	Coef.	Coef.		Coef.	Coef.	Coef.		Coef.
α	-0.03373	0.01635	-0.03821	-0.04728	**0.01832***	**0.05135*****	0.00393	**-0.03314*****
CHGEPS	**0.45166*****	**0.46591*****	**0.32383*****	-0.06933	**0.42124*****	**0.42671*****	**0.30169*****	**-0.08462*****
INV	-0.00006	0.00003	-0.00007	-0.00006	0.00001	-0.00004	0.00001	0.00004
AR	-0.00032	-0.00024	-0.00025	-0.00001	-0.00002	-0.00001	-0.00002	-0.00007
SA	0.00004	0.00022	-0.00002	-0.00018	0.00025	0.00019	0.00019	0.00013
LF	0.00006	-0.00037	0.00016	**0.00067****	-0.00007	0.00012	-0.00010	-0.00008
ETR	0.00873	-0.03746	0.01900	0.08092	-0.00223	-0.02055	0.00353	0.00355
GM	0.00006	0.00057	-0.00010	-0.00019	-0.00035	0.00017	-0.0004	-0.00010
AQ	**0.04905****	0.01304	**0.04547****	0.04189	-0.04019	**-0.06963*****	-0.02068	**0.06937***
CAPX	**0.00021*****	**0.00019*****	**0.00016****	0.00001	**0.00005***	**0.00011*****	0.00002	-0.00006
LEV	**0.02459****	0.00088	**0.02435****	0.01091	0.00071	0.0024	0.00004	-0.00138
CF	-0.00129	0.00082	-0.00152	**-0.00186****	**-0.00099****	-0.00053	**-0.00084****	-0.00068
GW	0.00404	0.00476	0.00273	-0.00497	**0.00657***	**0.0129*****	0.00295	**-0.0074***
CDACCR	0.03742	-0.01667	0.04199	0.05005	**0.05525***	0.05603	0.03955	0.02601
FCEPS1			**0.27438*****				**0.28017*****	
CHGEPS/ FCEPS1 alone model Adj. R-Sq	CHGEPS 0.196	CHGEPS 0.244	FCEPS1 0.190		CHGEPS 0.223	CHGEPS 0.202	FCEPS1 0.224	
FCEPS1 and CHGEPS in the Model R-Sq			0.256				0.305	
Incremental Adj. R-Sq 1	0.196		0.066 34%#		0.223		0.081 36%	
Incremental Adj. R-Sq 2	0.018		0.015 83%		0.005		0.001 20%	

Refer to Table 8.1 for variable definitions. ***, **, * indicates statistical significance at the 1%, 5%, and 10% levels respectively, Results are based on robust standard errors clustered by firm. All standard errors are less than 0.05. Incremental R-Sq 1: Incremental R^2 from earnings variable. Incremental R-Sq 2: Incremental R^2 from non-earnings variables over earnings. Pre-IFRS period is from 2001 to 2004 and the post-IFRS period is from 2006 to 2012. # The percentage adjacent to the incremental R-Squared from the earnings signals represents analysts' inefficiency in using the earnings signal.