Sensitivity Analysis of Technical Efficiency Using Bootstrap DEA and Matrix Based Approach: With Application to the Australian Banking Industry

A thesis submitted by

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Abstract

Data Envelopment Analysis (DEA) is one of the commonly used non-parametric frontier analysis techniques for measuring the efficiency of Decision Making Units (DMUs). The lack of statistical precision and difficulties in the proper choice of variables are two significant challenges in applying DEA. To address these issues, this study firstly introduces a bootstrap procedure to estimate scale efficiency and the nature of returns to scale for individual DMUs. Secondly, this study improves the variable choice of the most commonly used DEA model in estimating both the pure technical and scale efficiencies of Australian banks. Moreover, the visualization of bootstrapped results using a novel efficiency matrix is introduced to present confidence intervals of pure technical and scale efficiency estimates as two determinants of technical efficiency. Such visualization facilitates any efficiency comparison between sample DMUs and provides a helpful tool for managers and policy makers to identify the source of technical inefficiency. Empirical applications are also given for Australian banks in two specific time periods including the post-Wallis period and the global financial crisis.

In a bootstrap DEA application, this study re-examines pure technical and scale efficiencies of 10 Australian banks during the period 1997-2005. This represents a new contribution to the literature, since it is the first banking efficiency study utilizing the bootstrap approach in Australia. It is found firstly that the discriminatory power of the DEA core profit efficiency model is significantly increased with the improvement of the choice of variables in the core profit efficiency model. Specifically, the proportion of fully pure technical efficient observations decreased to 23% which is significantly lower than the 81% which was reported in a recent study. Secondly, applying the bootstrap approach reveals the sensitivity of the obtained efficiency scores to sampling variation and measurement errors. The study also discusses how the lack of application of statistical approaches in such efficiency studies could lead to biased and misleading conclusions regarding the efficiency levels of individual banks.
This study also applies bootstrap DEA to examine both pure technical and scale efficiencies of Australian banks over the period 2006-2012. Since there has been no research which covers this recent time period, this study makes a major contribution to the literature and to an understanding of Australian banking efficiency during and post the global financial crisis. The success of Australian banks in coping with the recent global financial crisis motivates us to investigate the efficiency level of Australian banks. We also examine whether efficient financial systems are affected less during financial turmoils and crises as in the case of Australian banks. The original estimates show that the number of pure technical efficient banks dropped considerably during the global financial crisis and no bank in the sample was pure technical efficient in 2009. The results also show that the number of pure technical efficient banks was at its highest prior to the recent global financial crisis in 2006 and that bank recovery is still continuing over the post crisis period. While the pure technical efficiency level of major banks is returning to its level prior to the financial crisis, other banks are still struggling to improve their efficiency in the current tough business environment after the recent crisis.

Finally, scale efficiency results from both time periods show that regional banks are the worst performers followed by major banks. The presence of scale inefficiency among major banks is an argument supporting the continuation of the four pillars policy which prevents any merger among major banks. It seems that banning mergers among the four major banks not only prevents an adverse impact on the scale efficiency of the Australian banking sector but also can protect competition and customers’ bargaining power. Overall, to improve scale efficiency of the banking sector in Australia, mergers between the small sized banks or other financial institutions such as building societies or credit unions seems to be more beneficial than any mergers between the major banks.
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And finally, words cannot suffice in expressing my gratitude to Somayeh, my wife, for her unconditional love and support which made the completion of this research possible.
Declaration

I declare that this thesis contains no 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. I further declare that to the best of my knowledge contains no material previously published or written by another person except where due reference is made in the text of this thesis.

Amirhossein Moradi Motlagh
To my loving wife and parents
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1 Chapter One: Introduction

1.1 Background

Frontier analysis methods are one of the common approaches in measuring and analysing efficiency levels of organisations and business units. A number of methods for estimating efficiency based on the frontier approach have been developed over the past decades. In general, under such methods, efficient firms are supposed to be those operating on the production frontier, while inefficient firms are those that operate below the production frontier function. Consequently, the first step in assessing efficiency of firms using the frontier approach is constructing a frontier production function.

In the literature, frontier functions can be estimated using two alternative approaches; parametric and non-parametric. The main distinction between these methods is that parametric methods impose a particular functional form on the frontier while nonparametric methods do not. In fact, parametric methods involve the application of econometric techniques where efficiency is measured relative to statistically estimated frontier production functions. The non-parametric methods, on the other hand, employ mathematical programming techniques to construct frontier production functions. The most commonly used non-parametric method is called Data Envelopment Analysis (DEA) and was initially introduced by Charnes et al. (1978) to measure efficiency of Decision Making Units (DMUs). DEA as a mathematical programming technique can deal with multi-input and multi-output environment and employs input and output variables to estimate the relative efficiency of a DMU in comparison with the best-performing rivals.
Reviewing the literature in the field of efficiency and productivity analysis indicates that DEA has been used in a variety of industries such as banks, universities, hospitals, hotels, airports and farms. Over the last decade DEA has gained considerable attention as a powerful managerial tool in efficiency studies and it has been widely utilized for analysing the efficiency of the public and private sectors (Emrouznejad et al., 2008). Fethi and Pasiouras (2010) in a review of 196 studies which employ operational research and artificial intelligence techniques to assess banks’ performance conclude that DEA is the most widely applied operations research technique in this field. Its wide application in efficiency measurement of bank branches in 24 countries has been discussed in a recent survey by Paradi and Zhu (2013). Sherman and Zhu (2006) also emphasise that DEA is a powerful benchmarking tool for evaluating DMUs to identify best-practices in multiple input and output environments.

One of the advantages of DEA is that it enables us to identify the sources of technical inefficiency by decomposing it into pure technical and scale efficiency. Pure technical efficiency measures how efficiently a DMU operates to convert inputs to outputs in comparison to similar DMUs in terms of size. In contrast, scale efficiency measures whether a DMU operates at an optimal size of scale. One of the main drawbacks of DEA is the lack of statistical precision of the efficiency estimates. Although, Simar and Wilson (1998a) proposed a procedure based on the statistical technique of bootstrapping to provide statistical properties of DEA pure technical efficiency estimates, no similar consistent practice has been suggested for scale efficiency estimates. This study addresses this issue by introducing a bootstrap procedure which provides statistical properties of scale efficiency estimates for individual DMUs.

The application of the bootstrap approach is examined in the case of Australian banks. There is no doubt that the banking industry plays a central role in the development of a country’s economy by providing financial services and funding to other commercial sectors. Thus, it is not surprising that the efficiency of the banking industry has become of interest to academics, decision makers, managers,
regulators and the general public (Tsolas, 2011). In Australia, the financial sector is a major sector of the economy. The financial industry contributed 35% of the total capital in share market with a value of $456 billion in June 2011 (ASX, 2011). The ASX (2011) also reports that four major banks have 57% of market capitalisation among all 288 companies in the financial sector. In addition, as a result of compulsory superannuation, Australia has the 4th largest pension fund pool in the world and this highlights the role of banking industry in the economy. Due to the key position of banks in Australia, measuring banks’ efficiency has been an issue of major interest to academics (e.g., Avkiran, 2000, Avkiran, 2004, Kirkwood and Nahm, 2006, Neal, 2004, Paul and Kourouche, 2008, Sturm and Williams, 2004, Moradi-Motlagh et al., 2011b, Moradi-Motlagh et al., 2012b). However, all earlier Australian banking efficiency studies using DEA suffer from the lack of statistical precision of the efficiency estimates. This study for the first time investigates both pure technical and scale efficiency of Australian banks using bootstrap DEA to provide more accurate and reliable results which original DEA estimates cannot offer.

The rest of this chapter firstly defines technical problems in applying DEA and its applications along with gaps in the earlier Australian banking efficiency literature. Secondly, Section 1.3 provides the objectives and contributions of this study. Finally, Section 1.4 outlines the organisation of other chapters.

1.2 Statement of the Problem and Objectives

Despite the popularity of DEA as a powerful methodology and widespread use of this technique in efficiency studies, it suffers from the lack of statistical precision due to its deterministic nature and does not provide any information regarding the uncertainty of estimated results. Bootstrap techniques are able to remedy this shortcoming by offering statistical precision of the original estimates. Bootstrapping is based on the idea of simulating the data generating process through re-sampling with replacement to mimic the sampling distribution of the original estimator (Simar and Wilson, 1998a).
Although, bootstrapping methods can be applied for any statistic, the data generating process for nonparametric frontier estimations is complex and simple bootstrap methods do not provide consistent results. For instance, Lothgren and Tambour (1999b) proposed a procedure based on naive bootstrap to provide statistical properties of scale efficiency and the nature of returns to scale. As detailed in Simar and Wilson (2000) the procedure proposed by Lothgren and Tambour is inconsistent and is seriously flawed. In contrast, Simar and Wilson (2002) introduced a nonparametric test of returns to scale which only focuses on examining the nature of returns to scale for the whole sample (global level) and cannot be applied for analysing scale efficiency for individual DMUs.

As recent bootstrap procedures proposed to estimate scale efficiency and the nature of returns to scale suffer from serious drawbacks or have not been designed to examine the nature of returns to scale for individual DMUs, this study aims to address this issue by introducing a procedure to estimate scale efficiency using bootstrap DEA which is discussed in detail in Chapter 4.

The bootstrap DEA approach recently has been used to examine the efficiency and productivity of banks in various countries. However, to the best of our knowledge, none of the studies examining Australian banking efficiency have used this statistical approach. This raises issues concerning the accuracy and reliability of earlier studies’ findings where measurement errors and sampling variations exist. To address this issue, this study is the first to use bootstrap DEA to analyse the technical efficiency of Australian banks.

Demonstrating the results of complex techniques such as bootstrap DEA is another challenge that academics encounter in presenting their findings in an easily understandable way for managers and policy makers. This study introduces a novel efficiency matrix to present statistical properties of both pure technical and scale efficiency in order to facilitate any comparisons and to assist in analysing the results.
The proper choice of input and output variables is one of the controversial issues in DEA models specially in estimating the efficiency level of banks and financial institutions. There are some common approaches such as the production, intermediation and core profit efficiency approach in selecting input and output variables. In Australian efficiency studies, the most common used approach has been core profit efficiency which views banks as business units that use interest expense and non-interest expense as the input variables to generate net interest income and non-interest income as the output variables (e.g., Avkiran, 1999b, Avkiran, 1999a, Avkiran, 2000, Avkiran, 2004, Paul and Kourouche, 2008, Sathye, 2002, Sturm and Williams, 2004). By selecting net interest income as an output variable in the core profit efficiency model, earlier studies confound efficiency estimates by ignoring the impact of unaccounted interactions between endogenous and exogenous variables and by adding unnecessary duplications as discussed in detail in Avkiran and Thoraneenitiyan (2010). It seems that these problems began with early studies by Avkiran in 1999 and, possibly to assist in comparisons, has continued thereafter by other authors. This study improves the choice of model’s variables and compares the results with one of the recent studies to examine the effect of this improper choice of variables in the earlier literature.

The recent global financial crisis has had a detrimental effect on the economies and financial systems of many countries around the globe. Thus, it is of interest to investigate the efficiency level of the Australian banking industry during the periods pre the crisis, during the crisis and post the crisis. Although, there are few studies examining the impact of the recent global financial crisis on the Australian banking sector (e.g., Avkiran and Tripe, 2011a, Vu and Turnell, 2011), no study has considered the post-crisis period to provide a better picture regarding the trend of efficiency in this crucial economy sector of Australia through such a big event. To the best of our knowledge this study is the first which analyses both pure technical and scale efficiency of Australian banks over the period 2006-2012 to cover the pre-crisis, during crisis and post crisis periods.
1.3 Contributions of the Study

This study addresses the problems stated in Section 1.2 and aims to add to the earlier literature by making several contributions. Firstly, this study offers a methodological contribution by applying the bootstrap technique in estimating scale efficiency and the nature of returns to scale for individual DMUs. Using the bootstrap procedure introduced in this study, statistical properties of scale efficiency of individual DMUs such as confidence intervals and bias can be estimated and it is possible to test statistical hypothesis regarding the nature of returns to scale. Accordingly, by testing the nature of returns to scale, it is possible to determine whether a DMU operates at optimum scale of operation or it needs up-scaling or down-scaling to be scale efficient.

Secondly, to present the bootstrapped results in a simple and understandable way for managers and policy makers who are not familiar with such complex techniques, this study introduces a novel technical efficiency matrix. This matrix not only presents the position of each DMU in terms of pure technical and scale efficiency but also at the same time displays confidence intervals of these estimates in a matrix with four zones to facilitate any comparison between efficiency levels of DMUs. By examining technical efficiency using such a visual tool, managers and decision makers are able to find the source of technical inefficiency (either scale or pure technical inefficiency) and uncover opportunities for improvement while monitoring the position of rivals.

Thirdly, this study improves the choice of output variables in earlier Australian banking efficiency studies by selecting “interest income” over “net interest income” in the core profit efficiency model. Earlier Australian banking efficiency studies which use the core profit efficiency approach in choosing variables of DEA models, select interest expense and non-interest expense as input variables while defining net interest income and non-interest income as output variables (e.g., Avkiran, 2000, Avkiran, 2004, Paul and Kourouche, 2008). By choosing net interest income as an output variable, earlier studies confound efficiency estimates by ignoring the impact of unaccounted interactions between endogenous and
exogenous variables and adding unnecessary duplications as discussed in detail in Avkiran and Thoraneenitiyan (2010). To investigate the impact of this improper choice, this study re-examines the technical efficiency components and highlights the differences between the obtained results with one of the recent studies conducted by Paul and Kourouche (2008). The results show that improving the choice of variables in the core profit efficiency model considerably enhanced the discriminatory power of the efficiency estimates.

Fourthly, to the best of our knowledge this study is the first to offer statistical insights into efficiency estimates of Australian banks using the bootstrap DEA technique. Thus, it contributes to the earlier literature by providing more accurate and reliable estimates which offer statistical properties of the efficiency estimates such as confidence intervals and bias corrected estimations. Comparing the results obtained from the original and bootstrap estimates indicates the existence of measurement errors and sample variations in the case of earlier Australian banking studies and raises questions relating to the reliability of the results of these earlier studies.

Finally, this is the first Australian banking efficiency study which covers the pre, during and post global financial crisis periods. Due to severity of the recent financial crisis and its effect on banking systems around the world, it is of interest to investigate the impact of such an event on the Australian banking sector. Covering the period 2006-2012 provides a better picture on the trend of Australian banking efficiency and the ways different Australian banks dealt with the recent global financial crisis. Specifically, this study investigates both pure technical and scale efficiency of Australian banks over a seven-year period not only to investigate the impact of the recent financial crisis on individual Australian banks but also to examine the assumption that efficient banks are less affected during financial crises.
1.4 Organisation of the Study

This thesis is composed of seven chapters. After this introductory chapter, the remainder of this study is organised as follows: Chapter 2 provides an overview of the Australian financial institutions with particular attention on banks, discusses financial regulation and supervision in Australia and introduces the sample banks used in this study and their financial performance.

Chapter 3 reviews the literature on the efficiency of financial institutions across the globe. Specifically, the chapter focuses on application of the DEA method. Firstly, it reviews the application of DEA in individual countries located in America, Europe and Asia. Secondly, cross country efficiency studies are discussed. Thirdly, as this study examines the efficiency level of Australian banks, a detailed review is provided on earlier Australian efficiency studies in a separate section. Finally, the chapter reviews the limited number of recent studies that employ bootstrap DEA in various countries.

Chapter 4 discusses methodologies on efficiency assessments. In particular, this chapter focuses on the non-parametric method of DEA and the application of bootstrap statistical techniques in the context of DEA. This chapter makes methodological contributions by introducing a procedure to provide statistical properties of scale efficiency using bootstrap DEA. It also introduces a novel efficiency matrix which presents the confidence intervals of both pure technical and scale efficiency as a visual tool to facilitate comparison and analysis of DMUs’ efficiencies.

Chapter 5 reports the results of a re-examination of both pure technical and scale efficiency of 10 Australian banks during the period 1997-2005. This chapter addresses the improper choice of model’s variables in earlier Australian banking efficiency studies. The improved model and re-examined results are presented and obtained efficiency scores are compared with those of a recent study conducted by Paul and Kourouche (2008). This chapter also provides statistical properties of efficiency estimates using bootstrap DEA and compares the original and
bootstrapped results. It emphasizes the existence of measurement errors and the necessity of using statistical approach in such studies.

Chapter 6 investigates both pure technical and scale efficiency of 8 Australian banks during the period 2006-2012 which covers the period prior, during and post the global financial crisis. Due to importance of the recent global financial crisis on financial systems of many countries across the globe, it is of interest to examine the impact of such an event on the efficiency of individual Australian banks. Furthermore, the efficiency levels of small, medium and large banks are compared and possible opportunities for improvement of technical efficiency of banks are discussed.

Chapter 7 presents a summary of contributions and empirical findings along with the policy implications of this study. It discusses important issues in the context of Australian banking including the four pillars policy, the future of small banks, the financial crisis, and the effect of technology and innovation in improving the efficiency of Australian banks. Limitations and suggestions for future studies also are provided in the last section of this chapter.
2 Chapter Two: An Overview of the Australian Financial Institutions

2.1 Introduction

This chapter aims to provide background knowledge on the financial institutions in Australia in order to present the role and place of banks in the Australian financial system. Banks traditionally fund their loans using short-term liabilities such as deposits and short-term debt. Banks also are highly involved in non-traditional banking activities such as wealth management and insurance which overlaps with the role of other financial institutions. Thus, reviewing characteristics of Australian financial institutions is beneficial for the purpose of this study to identify non-traditional banking businesses in which banks are also involved.

Australian financial institutions are categorised as Authorised Deposit-taking Institutions (ADIs), non-ADI financial institutions, and insurers and fund managers by the Reserve Bank of Australia. The following sections discuss the above types of institutions. The focus is on the banking sector as the major ADIs.

This chapter consists of four sections. Section 2.2 provides an overview of Australian’s financial institutions. Section 2.3 focuses on the banking sector and covers banking history in Australia. It also provides a brief history of each bank in this study along with each bank’s financial performance. Section 2.5 provides a summary of the discussion.
2.2 Overview of Australian Financial Institutions

Financial institutions play a key role in the Australian Stock Exchange (ASX). As reported by the ASX (2011), the financial sector was the largest industry sector accounting for 33% of the market’s capitalisation in June 2011. To provide an overview of the financial sector in Australia, this section discusses 13 types of financial institutions that operate under three main categories of authorised deposit-taking institutions, non-ADI financial institutions, and insurers and fund managers.

2.2.1 Authorised Deposit-taking Institutions (ADIs)

Authorised Deposit-taking Institutions (ADIs) are corporations which are authorised under the Banking Act 1959 to take deposits from their customers. ADIs consist of banks, building societies and credit unions. All ADIs are subject to similar prudential standards. However, using the names of bank, building society and credit union are subject to different conditions. The main characteristics of ADIs are set out below.

Banks

Australian Banks as the most important financial institutions have total assets of $2,859bn in March 2012 which is the highest level among all other financial institutions. About 60% of the total assets of the financial institutions belong to the banks. Furthermore, as reported by RBA (2013) around 95% of the total assets of the ADIs belong to 65 banks. As the focus of this study is in measuring the efficiency of Australian banks, a detailed report on the banking sector in Australia is provided in Section 2.3.

Building Societies

Building societies are mutual organisations offering banking and related financial services such as mortgage lending and savings accounts (Alfon et al., 2004). The first Building Societies were established by British workers to offer affordable home loans for labourers and workers in the UK (Plackett, 2003). In
Australia, the first building societies began their operations in the 1850s. According to RBA (2013), 9 building societies with total assets of $22bn (which is only 0.75% of ADIs’ total assets) operate currently in Australia. Additionally, building societies are subject to the same regulatory standards as banks, and they are regulated by the Australian Prudential Regulation Authority (APRA).

Credit Unions
A credit union is a member-owned financial cooperative. Members are both borrowers and depositors (Koot, 1978). Credit unions have demonstrated strong growth in both assets and deposits in recent years. They compete with banks in providing financial services (KPMG, 2011). Although, the number of Australian credit unions is more than that of banks and building societies, they have only 1.7% of the asset size of the ADIs in 2013 (RBA, 2013). Similar to banks and building societies, credit unions are regulated by the APRA. Table 2-1 summarizes the characteristics of ADIs and presents total assets and number of institutions as stated by the Reserve Bank of Australia (RBA).

<table>
<thead>
<tr>
<th>Type of institutions</th>
<th>Main characteristics</th>
<th>Number of institutions</th>
<th>Total assets ($bn)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Banks</td>
<td>Provide a wide range of financial services to all sectors of the economy, including (through subsidiaries) funds management and insurance services. Foreign banks authorised to operate as branches in Australia are required to confine their deposit-taking activities to wholesale markets</td>
<td>65</td>
<td>2,859</td>
</tr>
<tr>
<td>Building societies</td>
<td>Building societies raise funds primarily by accepting deposits from households, provide loans (mainly mortgage finance for owner-occupied housing) and payment services. Traditionally mutually owned institutions, building societies increasingly are issuing share capital.</td>
<td>9</td>
<td>22</td>
</tr>
<tr>
<td>Credit unions</td>
<td>Mutually owned institutions, credit unions provide deposit, personal/housing loan and payment services to members.</td>
<td>93</td>
<td>50</td>
</tr>
</tbody>
</table>

Source: RBA (2013)
2.2.2 Non-ADI Financial Institutions

Non-Authorized Deposit-taking Institutions (Non-ADIs) are financial institutions that usually loan money to corporations. They do not have a full banking license or are not supervised by banking regulatory agencies. There are three types of Non-ADIs in Australia classified as money market corporations, finance companies and securitisers. Each of these is discussed below.

Money Market Corporations (merchant banks)

Merchant banks as Non-ADI financial institutions provide capital to large corporations and government agencies. In Australia, money market corporations or merchant banks operate primarily in wholesale markets and provide a full range of financial services such as advise on corporate finance and capital markets. The total assets of money market corporations is only 17% of the non-ADIs’ total assets. The money market corporations are regulated by the Australian Securities and Investments Commission (ASIC) which is an independent Commonwealth government body. The Australian Prudential Regulation Authority as the regulator of the prudential regulator of the financial services industry has recently revoked consent for non-regulated financial businesses to use the term of ‘merchant banks’.

Finance Companies (including general financiers and pastoral finance companies)

Finance companies are regulated by ASIC and offer loans to individuals and small businesses for buying goods and services. These institutions own about 37% of the total assets of non-ADI financial intuitions in Australia.

Securitisers

Securitisers are the corporations that purchase various types of contractual debts and sell them as a package to investors. Securitisers account for the highest proportion of total assets of non-ADI financial institutions in Australia. 46% of total non-ADI assets are owned by securitisers.
The main characteristics of Non-ADIs are summarized by the Reserve Bank of Australia (RBA) as presented in Table 2-2:

Table 2-2: Non-ADI Financial Institutions

<table>
<thead>
<tr>
<th>Type of institutions</th>
<th>Main characteristics</th>
<th>Number of institutions</th>
<th>Total assets ($bn)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Money market corporations (merchant banks)</td>
<td>Operate primarily in wholesale markets, borrowing from, and lending to large corporations and government agencies. Other services, including advisory relate to corporate finance, capital markets, foreign exchange and investment management.</td>
<td>20</td>
<td>48</td>
</tr>
<tr>
<td>Finance companies (including general financiers and pastoral finance companies)</td>
<td>Provide loans to households and small- to medium-sized businesses. Finance companies raise funds from wholesale markets and, using debentures and unsecured notes, from retail investors.</td>
<td>101</td>
<td>103</td>
</tr>
<tr>
<td>Securitisers</td>
<td>Special-purpose vehicles that issue securities backed by pools of assets (e.g. mortgage based housing loans). The securities are usually credit enhanced (e.g. through use of guarantees from third parties).</td>
<td>N/A</td>
<td>128</td>
</tr>
</tbody>
</table>

Source: RBA (2013)

2.2.3 Insurers and Fund Managers

Insurers are institutions that sell insurances which transfer the risk of loss from insurees to insurers in exchange for specified payments. The APRA has the power to enforce the Insurance Act as the regulator of general insurers. In contrast, fund manager firms regulated by ASIC are responsible for managing investments in various types of securities and assets in favour of investors’ benefits. These two groups of insurers and fund managers possess more than 36% of the total assets of financial institutions in Australia. They have been divided in eight groups of life insurance companies, general insurance companies, superannuation funds, public unit trusts, cash management trusts, common funds and friendly societies. Each of these is discussed below.
Life Insurance Companies
Life insurance companies are registered under Section 17 of the Life Insurance Act 1995. Life insurers usually sell term life insurance and disability income insurance. They also sell superannuation investment products. As shown in Table 2-2 this group of companies possesses 12.8% of total asset of insurers and fund managers.

General Insurance Companies
General insurance companies provide insurance for property, motor vehicles, employers' liability, etc. General insurance products in Australia are divided into liability insurance such as Compulsory Third Party (CTP) motor insurance, worker's compensation, professional indemnity insurance and public liability insurance, and property insurance such as home insurance, travel insurance, and comprehensive motor vehicle insurance. According to the RBA (2013) around 7.8% of the total assets of insurers and fund managers belong to the general insurance companies.

Superannuation and Approved Deposit Funds
Superannuation in Australia refers to the accumulation of wealth while people work. It then provides significant funds for them at the time of retirement. Superannuation funds accept and manage contributions from employers and employees and release these funds after retirement or under conditions of release contained in Schedule 1 of the Superannuation Industry Regulations 1994. APRA supervises regulated superannuation funds under the Superannuation Industry (Supervision) Act 1993. These companies possess the highest percentage (62.8%) of total assets of the insurers and fund managers.

Public Unit Trusts
Public unit trusts pool funds of investors with relatively small amounts of money to invest in a wide range of markets and stocks such as property, money market investments and mortgages. In Australia, a public unit trust is defined as a trust
whose units are listed on the stock exchange, or offered to the public, or held by 50 or more people. Public unit trusts are regulated and supervised by the Australian Securities and Investment Commissions (ASIC).

**Cash Management Trusts**

Cash management trusts operate as an alternative option for personal investment open to the public. They require a low initial investment thus making them suitable for investors with limited starting funds. In Australia, cash management trusts generally confine their investment in securities like stocks and bonds. Cash management trusts are regulated and supervised by ASIC and possess 1.3% of the total assets of the insurers and fund managers.

**Common Funds**

Common funds are not open to the general public and are only available for recognised clients of the Public Trustee which invests common funds under section 55 of the Public Trustee Act 1985. In Australia, common funds are used by trustee companies to pool money or assets on behalf of retail clients and mostly are supervised and regulated by states and territory authorities.

**Friendly Societies**

Friendly societies are mutually owned associations for the purposes of insurance, pensions, savings or cooperative banking formed by people who join together for a common financial or social purpose. Friendly societies are regulated and supervised by APRA and have only 0.3% of the total assets of insurers and fund managers in Australia as reported by RBA (2013). Table 2-3 presents a summary of the main characteristics of insurers and fund managers as reported by RBA (2013).
### Table 2-3: Insurers and Funds Manager

<table>
<thead>
<tr>
<th>Type of institutions</th>
<th>Main characteristics</th>
<th>Number of institutions</th>
<th>Total assets ($Bn)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Life insurance companies</td>
<td>Provide life, accident and disability insurance, annuities, investment and superannuation products. Assets are managed in statutory funds on a fiduciary basis, and are mostly invested in equities and debt securities.</td>
<td>29</td>
<td>238</td>
</tr>
<tr>
<td>General insurance companies</td>
<td>Provide insurance for property, motor vehicles, employers' liability, etc. Assets are invested mainly in deposits and loans, government securities and equities.</td>
<td>124</td>
<td>145</td>
</tr>
<tr>
<td>Superannuation and approved deposit funds</td>
<td>Superannuation funds accept and manage contributions from employers (incl. self-employed) and/or employees to provide retirement income benefits. Funds are controlled by trustees, who often use professional funds managers/advisers. ADFs are generally managed by professional funds managers and, as with superannuation, may accept superannuation lump sums and eligible redundancy payments when a person resigns, retires or is retrenched. Superannuation funds and ADFs usually invest in a range of assets (equities, property, debt securities, deposits).</td>
<td>3627</td>
<td>1162</td>
</tr>
<tr>
<td>Public unit trusts</td>
<td>Unit trusts pool investors' funds, usually into specific types of assets (e.g. cash, equities, property, money market investments, mortgages, overseas securities). Most unit trusts are managed by subsidiaries of banks, insurance companies or merchant banks.</td>
<td>N/A</td>
<td>264</td>
</tr>
<tr>
<td>Cash management trusts</td>
<td>Cash management trusts are unit trusts which are governed by a trust deed and open to the public and generally confine their investments (as authorised by the trust deed) to financial securities available through the short-term money market.</td>
<td>N/A</td>
<td>25</td>
</tr>
<tr>
<td>Common funds</td>
<td>Trustee companies pool into common funds money received from the general public, or held on behalf of estates or under powers of attorney. Funds are usually invested in specific types of assets (e.g. money market investments, equities, mortgages).</td>
<td>N/A</td>
<td>8</td>
</tr>
<tr>
<td>Friendly societies</td>
<td>Mutually owned co-operative financial institutions offering benefits to members through a trust-like structure. Benefits include: investment products through insurance or education bonds; funeral; accident; sickness; or other benefits.</td>
<td>N/A</td>
<td>6</td>
</tr>
</tbody>
</table>

*Source: RBA (2013)*

### 2.3 The Banking Sector

Banks are financial institutions that operate as financial intermediaries receiving depositors’ money and lending it to borrowers or undertaking investments.
The banking sector in Australia is competitive and well developed, and consists of a number of banks licensed to provide banking services under the Banking Act 1959. To provide more details on the banking sector in Australia, this section aims to review this sector by examining the history of banks, financial regulation and supervision and public inquiries into the banking sector. The section also presents detailed information on individual banks which are the focus of this study.

2.3.1 History of Banks in Australia

In Australia, the Bank of New South Wales was the first bank established in Sydney in 1817. First branches of this bank were established in Moreton Bay (Brisbane) in 1850, Victoria (1851), New Zealand (1861), South Australia (1877), Western Australia (1883), Fiji (1901), Papua New Guinea (1910) and Tasmania (1910). In 1835 the Bank of Australasia began its services as a London-based bank. It merged with the Union Bank of Australia, another London-based bank in 1951. Then a merger with the English, Scottish and Australian Bank Limited formed the Australia and New Zealand Banking Group Limited in 1970 which is now one of the four major Australian banks.

In 1911, the Commonwealth Bank of Australia was founded by the Labour government and was the first bank in Australia which received a Federal Government guarantee. Playing the role of the central bank while at the same time being a commercial bank caused controversial debates regarding conflict of interest. To respond to this concern, in 1961, the government split the bank and transferred the central bank duties to the newly established Reserve Bank of Australia (RBA) and commercial banking activities to the newly created Commonwealth Banking Corporation.

By the end of the 1970s, tight regulation was recognized as the main cause of declining market share of banks in Australia. To address this issue, the Australian Financial System Inquiry (known as the Campbell Inquiry) was announced in 1979. In its final report, the Campbell Inquiry (1981) recommended the removal of many regulations thus commencing the deregulation process. For instance, the
recommendation for the removal of barriers to entry into the financial system opened the door for foreign banks and foreign ownership in the industry.

Although entrance of foreign banks increased the number of banks operating in Australia, domestic banks saw this as a threat. Foreign bank entrance was the impetus for many mergers among the domestic banks during the deregulation period. For instance, in 1981, The Bank of NSW merged with the Commercial Bank of Australia and established Westpac, and the National Bank of Australasia merged with the Commercial Banking Company of Sydney to create National Australia Bank (NAB).

Deregulation and intensified competition, increased the number of mergers and acquisitions in the Australian banking sector. To protect the competitive environment and prevent monopoly, the six pillars policy was initiated by the Keating Labor Government in 1990. This policy restricted any mergers between the four major banks (Australia and New Zealand Banking Group, Commonwealth Bank of Australia, National Australia Bank and Westpac Banking Corporation) and the two largest Australian life insurance companies AMP and National Mutual Life Association of Australia.

The Wallis-Inquiry (1997) recommended the abandonment of the six pillars policy and viewed mergers in the banking sector as being no different to mergers in other industry sectors. However, in rejecting the Inquiries recommendations, the Australian government modified the policy replacing the six pillars policy by the four pillars policy and announcing that any mergers between the four major banks will not be permitted. As a result, the Australian banking sector is dominated by four major banks. It should be noted that the four pillars policy still allows the four major banks to acquire smaller competitors. For instance, Commonwealth Australia Bank acquired the Colonial group in 2000 and Westpac Bank acquired Challenge Bank in 1995, the Bank of Melbourne in 1997 and St.George Bank in 2008.
2.3.2 Financial Regulation and Supervision

Due to the influence of the banking sector within the financial system and the national economy, governments and policy makers tend to highly regulate banks and financial institutions. In general, bank regulations are imposed government regulations which bind banks to certain requirements, restrictions and guidelines. These regulations also create transparency, reduce systematic risk, and protect banks.

In Australia, banking regulations are extensive and detailed. Australia’s banking regulations are split basically between the Australian Prudential Regulation Authority (APRA) and the Australian Securities and Investment Commission (ASIC). As mentioned before, APRA regulates and supervises Authorised Deposit-Taking Institution (ADIs) (banks, building societies, credit unions, friendly societies and participants in certain credit card schemes and certain purchaser payment facilities), life and general insurance companies and superannuation funds. On the other hand, ASIC is responsible for supervision and regulation of certain financial institutions (including investment banks and finance companies).

APRA was established in July 1998 under the Australian Prudential Regulation Authority Act 1998. Before APRA, the Insurance and Superannuation Commission (ISC), the Reserve Bank of Australia, and the Australian Financial Institutions Commission (AFIC) were predecessor regulators. These changes occurred in response to the Wallis-Inquiry (1997) recommendations. Accordingly, the Reserve Bank of Australia is responsible for monetary policy and systemic stability and APRA regulates authorised deposit-taking institutions, life and general insurance and superannuation.

APRA is responsible for financial stability by requiring financial institutions under its supervision to manage risk prudently. Thus, it minimises the likelihood of financial losses to depositors, policy holders and superannuation fund members. Furthermore, through its supervision, APRA aims to identify potential
weaknesses of its regulated institutions by employing a risk-based approach. Consequently, institutions which face greater risks receive more supervision. All licensed institutions under APRA are subject to ongoing supervision to ensure they meet prudential requirements and can manage their risk. To do so achieve this, APRA uses two common supervisory methods of on-site and off-site analysis. These supervisions are undertaken by experts with in-depth knowledge of institutions in a particular sector. As a result, by applying this level of supervision, APRA is able to identify those institutions that are unable or unwilling to comply with established requirements.

Apart from its supervisory role, APRA publishes regular updates on the financial performance of industries and individual institutions under its regulation and supervision. APRA also shares its data with the Australian Bureau of Statistics (ABS) and the Reserve Bank of Australia and provides relevant statistics to international agencies such as the Organisation for Economic Co-operation and Development (OECD), the International Monetary Fund (IMF) and the Bank for International Settlements.

### 2.3.3 Wallis Inquiry

The Financial System Inquiry known as Wallis-Inquiry (1997) was conducted to address continuous major changes occurring in the financial system such as globalisation, new technologies and changing customer needs. More specifically, it investigated the factors driving these changes and provided 115 recommendations to deal with challenges and emerging issues in the Australian financial system. The Wallis-Inquiry (1997) defined its scope as:

- "Considering the impact of deregulation of the Australian financial system since the early 1980s;"
- "Analysing the forces driving further change in the system; and"
- "Making recommendations on regulatory arrangements that will best ensure an efficient, responsive, competitive and flexible financial system:
  - To underpin stronger economic performance;"
The main focus of the Wallis Inquiry was on financial regulations aimed at improving flexibility, transparency, safety, stability, competition and competitiveness. The Inquiry acknowledged that its key aim was to create a more competitive and efficient financial system which could only be achieved by changing regulatory structures. To do so, the Inquiry proposed the establishment of several new regulatory bodies. The Australian Prudential Regulation Commission (APRC) was proposed to oversee prudential regulation. The Corporations and Financial Services Commission (CFSC) was proposed to be responsible for market integrity and consumer protection. The Reserve Bank of Australia would remain responsible for monetary policy and the payments system.

In response to the Wallis-Inquiry (1997) recommendations regarding the new regulatory bodies, the Australian Prudential Regulation Authority (APRA) was established on 1 July 1998 as a statutory authority and the regulator of the Australian financial services industry. Furthermore, the Australian Securities & Investments Commission (ASIC) was established on 1 July 1998 to be responsible for consumer protection in superannuation, insurance and deposit taking. Although, the government agreed with the general approach of the inquiry and endorsed a range of recommendations, there was a controversial recommendation that has not been accepted so far. The Wallis inquiry recommended the abandonment of the six pillars policy which prohibits any merger between the four major banks and two large insurance companies. However, in response, the Treasurer only removed the pillar status of the two insurers and the ban on mergers of the four major banks did not change. Interestingly, despite the fact that the four pillars policy was initially established by a Coalition government, the current Labour government’s Treasurer is a great defender of it. That is, this policy has great supporters and may not change in the near future.

Overall, the Wallis-Inquiry (1997) made 115 recommendations for regulatory reform in the Australian financial system in seven areas relating to conduct and
disclosure, financial safety, stability and payments, mergers and acquisitions, promotion of increased efficiency, coordination and accountability, and management of change. The Wallis Inquiry concluded that the efficiency of Australia's financial sector has improved since the major de-regulation measures of the 1980s. However, the sector performance is close to the world average rather than among the world's best. This conclusion highlights the importance of the banking efficiency analysis to identify improvement opportunities in this critical economy sector.

2.4 An Overview of Sample Banks’ Performance

Banks that operate and provide banking services in Australia can be grouped into three categories: Australian-owned banks, foreign subsidiary banks and branches of foreign banks. This study focuses only on Australian-owned banks due to availability of data. As this study estimates and analyses technical efficiency of the 10 largest Australian-owned banks, this section aims to provide a background on the history and financial performance of the banks under study. To do so, firstly, the list of banks along with their abbreviations and sizes category is provided. Secondly, total assets, market capitalization, Return on Asset (ROA) and Return on Equity (ROE) of different banks’ sizes are presented and compared. Finally, focusing on all ten banks, the trend of their total assets, ROA and ROE is illustrated and compared with average figures in separate charts.

Table 2-1 provides the list of 10 banks examined in this study consisting of four major banks, three medium sized and three small banks. This categorisation has been made based on banks’ asset size in 2005. The banks with asset size of more than $200bn are referred to as large banks, the banks with less than $40bn are referred to as small banks and the banks with asset size in between are assumed to be medium sized banks. The abbreviations used in this study are the same as the Australian Securities Exchange (ASX) codes.
Table 2-4: List of Sample Australian Banks

<table>
<thead>
<tr>
<th>Row</th>
<th>Bank Name</th>
<th>Abbreviation</th>
<th>Category</th>
<th>Asset (A$bn)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Australia and New Zealand Bank</td>
<td>ANZ</td>
<td>Large</td>
<td>293,18</td>
</tr>
<tr>
<td>2</td>
<td>Commonwealth Bank</td>
<td>CBA</td>
<td>Large</td>
<td>329,035</td>
</tr>
<tr>
<td>3</td>
<td>National Australian Bank</td>
<td>NAB</td>
<td>Large</td>
<td>419,588</td>
</tr>
<tr>
<td>4</td>
<td>Westpac</td>
<td>WBC</td>
<td>Large</td>
<td>259,753</td>
</tr>
<tr>
<td>5</td>
<td>St George</td>
<td>SGB</td>
<td>Medium</td>
<td>77,589</td>
</tr>
<tr>
<td>6</td>
<td>Suncorp Group</td>
<td>SUN</td>
<td>Medium</td>
<td>48,682</td>
</tr>
<tr>
<td>7</td>
<td>Macquarie Bank</td>
<td>MQG</td>
<td>Medium</td>
<td>49,313</td>
</tr>
<tr>
<td>8</td>
<td>Adelaide Bank</td>
<td>ADB</td>
<td>Small</td>
<td>13,396</td>
</tr>
<tr>
<td>9</td>
<td>Bank of Queensland</td>
<td>BOQ</td>
<td>Small</td>
<td>11,065</td>
</tr>
<tr>
<td>10</td>
<td>Bendigo Bank</td>
<td>BEN</td>
<td>Small</td>
<td>13,262</td>
</tr>
</tbody>
</table>

2.4.1 Total Assets and Market Capitalisations

Figure 2-1 shows the total assets of the four major banks during the period 1997-2012. It is clear from the figure that the total assets of all banks have had a steady growth through the whole period. Comparing individual banks, the National Australia Bank (NAB) has held the highest level of total assets among the big four in the entire period. Figure 2-2 shows that this bank has not performed well in terms of market capitalization. Furthermore, it is shown that market capitalizations of all major banks dropped considerably in 2008 as a result of the financial crisis. However, all banks except NAB could go back on track and continue their growth.

Figure 2-1: Total Assets of Major Banks, 1997-2012
Figure 2-2: Market Capitalisations of Major Banks, 1997-2012

Figure 2-3 and Figure 2-4 respectively show the total assets and market capitalizations of medium sized banks. As St. George Bank was acquired by Westpac in 2008, both charts only present relevant figures for this bank until 2008. Contrary to the large banks, as presented in Figure 2-4, both total assets and market capitalizations of medium sized banks have been affected by the financial crisis and no sign of significant improvement can be seen since that period.
The total assets and market capitalizations of small banks are shown in Figure 2-5 and Figure 2-6 respectively. Due to the merger between Adelaide Bank and Bendigo Bank, the total assets of Bendigo Bank (changed its name to Bendigo and Adelaide Bank after the merger) significantly increased in 2008. All banks have experienced a steady growth in their total assets through the whole period with the exception of Bendigo Bank whose total assets decreased in 2009. In contrast the market capitalisations of both Bendigo Bank and Bank of Queensland have not grown and are below their levels in 2008.
Figure 2-6: Market Capitalizations of Small Sized Banks, 1997-2012

Figure 2-7 compares the total assets of sample banks in 1997, 2004 and 2012. Overall, it can be seen that the largest percentage of total assets belongs to major banks. Four major banks possessed 88%, 86% and 89% of total assets of sample banks in 1997, 2004 and 2012 respectively which demonstrates the significant role of these four banks in the Australian banking industry. It is also noticeable that intense competition caused the proportion of total assets among the big four becomes closer. More specifically, the difference between the highest and lowest percentage of total assets among four major banks decreased from 13% in 1997 to only 4% in 2012.
Figure 2-8 presents the changes in market capitalizations of sample banks in 1997, 2004 and 2012. As shown in Figure 2-8, four major banks are dominant and cover 91%, 83% and 92% of market capitalization in 1997, 2004 and 2012 respectively. Although, the chart shows that in the middle of the study period medium and small sized banks increased their proportion in terms of market capitalization, recent data indicates that the proportion of larger banks’ market capitalisations has increased and the market has become more concentrated.

![Figure 2-8: Market Capitalizations of Australian Banks, 1997-2012](image)

2.4.2 Return on Assets and Return on Equity

Return on assets of large, medium and small sized banks is compared in Figure 2-9. It is apparent from the figure that the medium sized banks perform better in generating revenue from their assets. Furthermore, larger banks on average have a higher level of ROA than small banks. In contrast, Figure 2-10 shows that except for the period between 2004 and 2006, larger banks on average were performing better in terms of return on equity than other banks. It is notable also that medium-sized banks were seriously affected by the financial crisis and their ROE indices were lower than small banks in 2010 and 2011.
2.4.3 Individual Banks

Adelaide Bank

The Adelaide Bank was a publicly listed bank established in January 1994 in Adelaide, South Australia from the Co-operative Building Society of South Australia Limited, which was Australia's largest building society at that time. In August 2007, Adelaide Bank agreed to merge with the Bendigo Bank. The Shareholders voted for the merger and the Federal Court then approved the merger in November 2007. The merged bank officially changed its name to Bendigo and Adelaide Bank Limited in March 2008.
Figure 2-11 exhibits the trend of total assets for Adelaide Bank and the average of total assets of small banks during the period 1997-2007. As illustrated, there is a big jump in total assets from $13.4 billion in 2005 to $26.2 billion in 2006. This increase is due to the preparation of the financial statements in accordance with the Australian equivalents to International Financial Reporting Standards (AIFRS). This effect has been explained in detail in the bank’s annual report released in 2006. Accordingly, the total assets in 2005 based on AIFRS are about $21.5 billion which is $8 billion more than the previous figures reported in 2005.

**Figure 2-11: Total Assets of Adelaide Bank versus Small Banks Average**

Figure 2-12 shows that although Adelaide Bank had a higher level of ROA than the small banks average in the early study period, it experienced a lower or the same level of average ROA from 2000 to 2007. In contrast, as presented in Figure 2-13, Adelaide Bank experienced a higher ROE than the small banks’ average except in 2000. However, its ROE has been lower than total average (average of all sample banks) in the sample except in the early periods.
Australia and New Zealand Banking Group Limited

The Australia and New Zealand Banking Group Limited (ANZ) is the third largest bank by market capitalization in Australia, after the Commonwealth Bank and Westpac Banking Corporation. It commenced its operation as the Bank of Australasia in Melbourne in 1835. ANZ also operates in 31 other markets globally with representation in New Zealand, Asia, Pacific, Europe, America and the Middle East. ANZ world headquarters is located in Melbourne. Although, its global operations boosted ANZ’s financial performance, ANZ became vulnerable during the financial crisis as a result of more global banking involvement than its counterparts in Australia.

Figure 2-14 exhibits the trend of total assets for ANZ Bank and the total assets average of major banks. It is shown that throughout the whole study period total assets of ANZ have been below the average. It is worth mentioning that total assets...
assets increased from $138 billion in 1997 to $642 billion in 2012 implying a rise of almost 364% in 15 years. The main acquisitions which contributed to this increase were acquiring the National Bank of New Zealand in 2003, ETrade Australia in 2007, ING Group in 2009, and Royal Bank of Scotland in 2010.

Figure 2-14: Total Assets of ANZ Bank versus Major Banks Average

Figure 2-15 shows the trend of ROA of ANZ Bank during the period 1997-2012. ROA in most years is above the major banks average. Interestingly, contrary to the ROA figures, the ROE of ANZ was mostly above the average before 2005 as demonstrated in Figure 2-16.

Figure 2-15: ROA of ANZ Bank versus Major Banks Average and Total Average
Bendigo Bank

Bendigo Bank started in 1858 as a building society in Bendigo during the gold rush era in Victoria. In 2007 Bendigo Bank rejected Bank of Queensland's takeover proposal but agreed to merge with Adelaide Bank to form Bendigo and Adelaide Bank. This $4 billion merger completed in November 2007 made this bank a significant participant in the Australian banking industry. The bank's national headquarters is in the city of Bendigo, and Bendigo Bank is represented in all states and territories with almost 900 branches.

Figure 2-17 compares the total assets of Bendigo Bank with the small sized banks’ average during the period 1997-2012. As can be seen, the merger with Adelaide Bank increased total assets by 182% from $17 billion in 2007 to $48 billion in 2008. As a result of this merger, Bendigo and Adelaide Bank possesses more assets than its regional counterpart, the Bank of Queensland.
The trends of ROA and ROE of Bendigo bank are illustrated in Figure 2-18 and Figure 2-19 during the period from 1997 to 2012. The effect of the financial crisis on ROA and ROE is apparent and no sign of recovery can be seen as both ratios are under the level that they were before the financial crisis in 2007. However, it seems this bank has operated better than its counterpart, the Bank of Queensland post-crisis as both ratios for Bendigo and Adelaide Bank are higher than the small banks average.

Figure 2-18: ROA of Bendigo Bank versus Small Banks Average and Total Average

Figure 2-19: ROE of Bendigo Bank versus Small Banks Average and Total Average

Bank of Queensland
The Brisbane Permanent Benefit Building and Investment Society was established in 1874 as the first building society in Queensland. In 1887, this building society converted to a bank and following mergers with various financial institutions in Queensland became a trading bank five decades later in 1942. The name Bank of Queensland was adopted in 1970 and a year after it became a public company
listed on the Australian Stock Exchange. Recently, Bank of Queensland acquired Pioneer Permanent Building Society in 2006 and purchased St Andrew's Insurance in 2010.

As shown in Figure 2-20, the total assets of Bank of Queensland are below the average and this difference has intensified since 2008 due to the merger between Adelaide Bank and Bendigo Bank. Thus, this bank is the smallest bank in the sample in terms of total assets.

![Figure 2-20: Total Assets of Bank of Queensland versus Small Banks Average](image-url)

As illustrated in Figure 2-21 and Figure 2-22, both ROA and ROE of Bank of Queensland are above the small banks average in most years. However, a considerable decline can be seen in 2011 and 2012 due to lending losses from the 2010–2011 Queensland floods and also troubled commercial properties loans in the Gold Coast.

![Figure 2-21: ROA of Bank of Queensland versus Small Banks Average and Total Average](image-url)
Commonwealth Bank of Australia

The Commonwealth Bank was founded under the Commonwealth Bank Act in 1911. The bank opened its first branch in Melbourne in 1912 but it moved its head office to Sydney in 1916. The bank started its role as a central bank gradually after 1920. However, debate in 1958 and 1959 regarding its dual functioning as the central bank and a commercial bank caused the separation and transfer of the central bank duties to the Reserve Bank of Australia. During the wave of mergers in the Australian banking industry, the Commonwealth Bank acquired the Colonial Group of companies in 2000. Focusing on the Asia-Pacific, particularly China, India, Indonesia and Vietnam, the Commonwealth Bank completed its first merger in Asia with the acquisition of the Bank Arta Niaga Kencana (Bank ANK) in 2007. It also opened a branch in Shanghai, China, in March 2010 and in Mumbai, India in August, 2010.

Figure 2-23 shows the trend of Commonwealth Bank total assets since 1997 and indicates a steady rise in line with the major banks’ average. Total assets increased considerably after the financial crisis and these are above the average in 2009, 2010 and 2012. The big rise in assets in 2009 was due to the acquisition of Bankwest and St Andrews Insurances which subsequently raised the Commonwealth Bank market share in Western Australia during the mining boom era.
Return on assets of the Commonwealth Bank has been above the major banks’ average since 2005 as illustrated in Figure 2-24. Figure 2-25 also shows that this bank performed very well in terms of return on equity during the post financial crisis despite its weak performance in comparison with the major banks’ average between 2000 and 2004.

**Figure 2-24: ROA of Commonwealth Bank versus Major Banks Average and Total Average**

**Figure 2-25: ROE of Commonwealth Bank versus Major Banks Average and Total Average**
Macquarie Bank

Macquarie is the largest investment bank and the top ranked mergers and acquisitions advisor in Australia. It began its operations in 1969 as merchant bank Hill Samuel Australia (HSA), a subsidiary of Hill Samuel & Co. Limited, London. Macquarie Bank commenced operations in March 1985 with a retail branch in Sydney. In November 1986, a trading bank branch was opened in Melbourne and a few months later in Brisbane. Macquarie Bank officially entered the ASX in October 1996. Following the restructuring to a non-operating holding company, it established Macquarie Group Limited in 2007. Currently, Macquarie Group as a global provider of banking, financial, advisory, investment and funds management services operates in 28 countries.

It is not surprising that due to extensive international business involvement, Macquarie Group was severely affected as a result of the financial crisis and as shown in Figure 2-26 its level of total assets still is below its the level in 2008.

Figure 2-26: Total Assets of Macquarie Bank versus Medium-Sized Banks Average

Both Figure 2-27 and Figure 2-28 show a decline in ROA and ROE respectively during the period 1997-2012. It is also shown that both profitability indexes of ROA and ROE sharply declined during and post financial crisis. However, ROE is above the medium sized banks’ average throughout the study period.
National Australia Bank

National Australia Bank (NAB) is the fourth largest financial institution in Australia in terms of market capitalisation. It was established in 1893 under the name of National Bank Limited. It continued its operation with the name of The National Bank of Australasia Limited until October 1981 and changed its name to National Australia Bank after the merger with the Commercial Banking Company of Sydney Limited. NAB has an extensive international involvement in about 15 countries in Europe, the United States and Asia.

It is clear from Figure 2-29 that NAB has a higher level of total assets in comparison to other rivals throughout the period from 1997 to 2012. However, as shown in Figure 2-8, NAB’s market capitalisation is not in line with its total
assets and its market capitalisation proportion has decreased from 35% in 1997 to only 18% in 2012.

Figure 2-29: Total Assets of NAB versus Major Banks Average

Figure 2-30 and Figure 2-31 respectively indicate steady declines for both ROA and ROE during the study period. Although, during the first half of the period, NAB was performing relatively well and mostly above the major banks’ average, it has experienced a weak performance since 2004 in terms of return on assets and equity.

Figure 2-30: ROA of NAB versus Major Banks Average and Total Average

Figure 2-31: ROE of NAB versus Major Banks Average and Total Average
St.George Bank
St.George was founded as a building society in southern Sydney in 1937. It became a bank under the name of Advance Bank in 1985. Advance Bank acquired the State Bank of South Australia and changed the name for the merged entity to the Bank of South Australia in 1995. Finally, its name changed to St.George Bank in 1997. St.George was taken over by the Westpac Group in 2008.

Figure 2-32 exhibits a steady rise in total assets of St.George Bank throughout the period 1997-2008. It also shows that the total assets of the bank were above the average of medium sized banks. It is worth mentioning that the sharp increase in the level of assets in 2006 was due to adoption of AIFRS for the preparation of the bank’s financial statements.

Figure 2-32: Total Assets of St.George versus Medium Sized Banks Average

As shown in Figure 2-33 and Figure 2-34, ROA has not changed significantly and was far below the average of medium sized banks. In contrast, ROE increased sharply from only 6.9% in 1997 to 18.8% in 2008.

Figure 2-33: ROA of St.George versus Medium Sized Banks Average and Total Average
Suncorp

Suncorp Group Limited is an Australian insurance and banking corporation based in Brisbane. It is the largest general insurance group, formed in December 1996 by the merger of Suncorp, Metway Bank and the Queensland Industry Development Corporation (QIDC). Suncorp Metway acquired AMP's Australian general insurance interests in 2001 and simplified its brand to Suncorp in 2002.

Figure 2-35 illustrates the trend of total assets during the time period 1997-2012. The major increase in total assets occurred in 2007, the year Suncorp merged with the Promina Group, an Australian and New Zealand insurance company, and lifted its total assets to $84.9 billion.

Figure 2-36 and Figure 2-37 indicate that, although Suncorp performed well in terms of return on assets, its ROE was below the average throughout the whole
period. A downward trend also can be seen in both profitability measures of ROA and ROE since 2007.

**Figure 2-36: ROA of Suncorp versus Medium Sized Banks Average and Total Average**

![Graph showing ROA trends for Suncorp, Medium Banks Average, Total Average over years from 1997 to 2012.]

**Figure 2-37: ROE of Suncorp versus Medium Sized Banks Average and Total Average**

![Graph showing ROE trends for Suncorp, Medium Banks Average, Total Average over years from 1997 to 2012.]

**Westpac**

The Bank of New South Wales was established in Sydney as Australia's first and oldest bank in 1817. The Bank of New South Wales merged with the Commercial Bank of Australia to form Westpac Banking Corporation in 1982. In 2008 Westpac merged with St.George Bank Limited and in March 2010, the Westpac Group commenced operating as a single authorised deposit-taking institution (ADI), and the legal entity St.George Bank Limited was deregistered. Since then St.George Bank has been an operating division within the Westpac Group. In July 2011, Westpac Group established the Bank of Melbourne through St.George Banking Group.
The trend of Westpac’s total assets is exhibited in Figure 2-38. Total assets were below average before merging with St.George Bank. The merger increased the bank’s total assets by 34% to $589 billion.

Figure 2-38: Total Assets of Westpac versus Major Banks Average

Figure 2-39 and Figure 2-40 illustrate the trend of ROA and ROE respectively. Westpac’s ROA is slightly above the major banks’ average in most years. In contrast, its ROE was much better than the major banks’ average from 2000 to 2008. The effect of the financial crisis also is clear in both ratios and despite some improvements in 2010, they are almost steady and below their levels prior to the financial crisis.

Figure 2-39: ROA of Westpac versus Major Banks Average and Total Average
2.5 Summary

This chapter provided background information on the Australian financial institutions and a brief review on the history and performance of 10 Australian banks during the period 1997-2012. Thirteen different types of financial institutions operate in Australia. These institutions are categorized in three groups of Authorised Deposit-taking Institutions (ADIs), non-ADIs, and insurers and fund managers. Focusing on banking group as the major ADIs, history of Australian banking, regulations, banking regulatory bodies and the financial system inquiry were discussed. In the section of sample banks, the trend of total assets, market capitalisations and two key profitability ratios of ROA and ROE for each bank were presented.

To investigate the effect of the financial deregulation of the Australian financial system since the early 1980s, an inquiry into the Australian financial system was announced by the Treasurer in May 1996. This inquiry known as the Wallis inquiry examines issues such as globalisation, new technologies and changes in customer needs. It also provided 115 recommendations to deal with the competitive and challenging environment of globalisation. In response to the Wallis recommendations, the Australian Prudential Regulation Authority (APRA) was established in 1998 as a new regulator of the Australian financial services industry.
Although, in general, the government positively responded to the Wallis recommendations, the Treasurer did not accept the recommendation regarding the removal of the six pillars policy which was prohibiting any merger among the four major banks and two big insurance companies. However, the Coalition government implemented a modified version of the six pillars policy which banned any mergers among the four major banks. This is called the four pillars policy. This policy is supported by the current Labour government and suggests that the four pillars policy has support from both major parties and will not change in the near future.

Grouping ten sample banks in large, medium and small banks indicates that the four large banks have dominated the industry by possessing around 89% and 92% of total assets and market capitalisation respectively in 2012. Although the medium sized banks performed better in terms of return on assets, larger banks demonstrated a higher level of return on equity except in 2004, 2005 and 2006. On the contrary, small banks were the worst performers and had the lowest level of ROA and ROE except in 2010 and 2011 when medium sized banks on average had the lowest level of ROE.

Looking at individual banks during the period 1997-2012 shows that on average Suncorp had the highest level of return on asset at 3.27% followed by Macquarie at 3.8%. In contrast, the worst performer in terms of ROA was the Bank of Queensland with 0.54% followed by the other small counterpart Adelaide Bank (0.57%). On the other hand, Westpac on average had the highest level of ROE of 17.21% followed by Macquarie (16.97%). Bendigo Bank had the lowest ROE of 9.18% followed by Suncorp (9.59%).

Overall, a number of banks experienced considerable fluctuations in both profitability ratios during the period 1997-2012. For instance, while Macquarie had the highest level of ROA of 5.32% in 1997, the current level in 2012 was only 2.32%. Similarly, its ROE decreased from 25.33% in 1999 to 6.52% in 2012.
These changes imply the importance of analysing the trend in measuring the banking sector performance.
3 Chapter Three: A Literature Review on Banking Efficiency

3.1 Introduction

The efficiency analysis literature includes a considerable number of papers and reports focusing on the performance of the banking industry using a range of methods and techniques. Data Envelopment Analysis (DEA) is one of the popular methods in measuring the efficiency and productivity of financial institutions. Since the focus of this study is on the application of DEA in examining the pure technical and scale efficiency of Australian banking, studies reviewed in this chapter are mostly confined to those which employ DEA or a combination of DEA with other techniques in their analyses. As frontier methods such as DEA measure the relative efficiency of business units in the sample, results could be very sensitive to sampling variation and the combination of input and output variables. This means that any comparison between studies’ findings can be problematic. The DEA methodology and its applications are discussed in Chapter 4. More details on the methodology and some technical terms which have not been introduced in Chapter 4 can be found in Cooper et al. (2011b) and Cooper et al. (2011a) as complementary references.

In this chapter, a review of the DEA literature is discussed under the following five main sections. Section3.2 provides an overall overview of efficiency studies in the banking industry. Section 3.4 presents the application of financial ratios analysis in analysing financial institutions. Section 3.4 discusses the application of frontier models and parametric and non-parametric techniques in efficiency
studies. Section 3.5 focuses on efficiency studies using the DEA method. It divides such studies into those that examine individual countries other than Australia, cross country studies and finally, studies that only focus on Australian banking. It is also discusses how these studies address different efficiency related issues such as the impact of deregulation and liberalization or the influence of mergers and acquisitions on the efficiency of banks under study. Section 3.6 reviews limited studies which apply the bootstrap technique combined with the DEA method. Section 3.7 summarises the application of the DEA method in banking industry efficiency studies.

3.2 Overview of Efficiency Studies

This section aims to provide a brief overview on the importance of efficiency studies in the banking industry. It begins with the definition of some basic concepts and terms such as performance, efficiency and productivity. Next is a discussion regarding the importance of efficiency studies in the banking industry. Finally, it concludes by introducing the use of financial ratios and frontier models in efficiency and productivity analysis of financial institutions.

Measuring organisational performance is a critical factor in determining how well an organisation operates to convert its resources (inputs) to desired products or services (outputs). Accordingly, performance measurement can be defined as a process by which an organisation monitors resources and investments to reach desired targets (Thompson et al., 2007). In practice, efficiency and productivity are the key dimensions of organisational performance and are used interchangeably. However, in econometrics, efficiency and productivity measure different things. While productivity is measured by the ratio of outputs to inputs, efficiency is a relative measure and is estimated by considering the best practices in the sample under study. Further and detailed discussions regarding these terms and their measurement methods are provided in the next chapter.
There is no doubt that the performance of the banking sector can affect the whole monetary system and other industries. Thus, a well-performing banking system is crucially important for businesses development, given the role it plays in the economy. For instance, in Australia, in March 2011, the financial sector was the largest industry sector accounting for $480 billion or 32% of Australian market capitalisation (Moradi-Motlagh et al., 2012b). Due to the prominent position of banking in national economies, efficiency analysis of financial institutions has always been an issue of interest. Consequently, managers and decision makers are constantly looking for reliable and accurate methods to evaluate the performance of this crucial sector of the economy.

To address the above issue, a large body of literature can be found which measures the performance of the banking sector. There are different methods used in these measurements and there is no consensus among researchers regarding the preferred methods. The choice of method depends on the aims of research as each method has its own advantages and limitations. In addition to financial ratios analysis as a common and widely used approach, an econometric technique known as frontier analysis is also employed. As discussed before, this study focuses mostly on the DEA method as one of the popular frontier analysis techniques. Thus, the following sections review mostly the application of DEA in different countries. However, as an introductory review, the next section provides a discussion on the application of financial ratios analysis along with the merits of this approach and its restrictions.

### 3.3 Application of Financial Ratios in Banking Studies

Traditionally, financial ratios have been widely employed in assessing the performance of different type of organisations especially financial institutions and banks. The popularity of these ratios derives from their simplicity and ease of use and their understanding by all interested parties such as managers, stakeholders, regulators and decision makers. Financial ratios are used to measure different aspects of organisational performance such as profitability, efficiency, liquidity,
growth and market performance. There is no doubt that profitability is one of the primary dimension of organisational performance and among the profitability ratios the Return on Asset (ROA) and Return on Equity (ROE) have been commonly utilized. The total asset turnover is one of the key efficiency ratios used to determine how efficiently an organisation utilizes its assets to produce income. On the other hand, liquidity ratios are one of the risk measurements and show the availability of cash to pay debt. Finally, marketability ratios are one of the performance measures which have recently drawn more attention of researchers. More details regarding the application of financial ratios in performance measurement can be found in Carton and Hofer (2006).

This section reviews a number of studies which have employed financial ratios to measure the performance of financial institutions in different countries and continents. Table 3-1 provides a summary of these studies and includes the authors, study period, country, financial ratios and conclusion. As shown in Table 3-1, ROA and ROE have been used in the majority of studies as one of the performance indicators. Overall, three studies investigated and compared the performance of different types of financial institutions or banks and found a significant disparity among sample institutions. For instance, in a comparison between bank types in China by Lin and Zhang (2009), it was found that the big four state-owned commercial banks are less profitable than other banks except the policy banks. Examining the effect of privatization on efficiency is another area of interest. Boubakri et al. (2005) investigated this impact among 23 countries in 4 continents and found a significant improvements in economic efficiency after privatization. Two other studies conducted by Beccalli (2007) and DeYoung et al. (2007) examined the effect of internet banking and IT investment on performance and reported a positive impact on the efficiency of banks under study.
<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Study Period</th>
<th>Country</th>
<th>Financial ratios</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vittas (1991)</td>
<td>1980 to 1989</td>
<td>Belgium, Canada, Finland, France, Germany, Italy, Japan, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States</td>
<td>Operating asset ratios, Operating income ratios, Operating equity ratios, Return on asset, Return on equity</td>
<td>U.K building societies, German saving banks, and the Netherlands are highly profitable and efficient while American money centre banks and foreign banks in Canada are the least profitable.</td>
</tr>
<tr>
<td>Berger et al. (2000)</td>
<td>1991 to 1997</td>
<td>France, Germany, UK, US</td>
<td>Return on asset, Return on equity</td>
<td>On average, domestic banks of France, Germany, the UK and US experience higher level of cost and profit efficiency than foreign banks from Canada, Italy, Japan, the Netherlands, South Korea and Switzerland</td>
</tr>
<tr>
<td>Boubakri et al. (2005)</td>
<td>1986 to 1998</td>
<td>Africa and the Middle East: Kenya, Lebanon, Malawi, Morocco, Nigeria and Uganda, Asia: India, Indonesia, Korea, Pakistan, Philippines and Sri Lanka, Latin America: Argentina, Brazil, Colombia, Guyana, Jamaica, Mexico, Peru and Venezuela, Europe: Portugal and Turkey</td>
<td>Profitability ratio: net income to equity, Efficiency: Net interest margin, Risk exposure: Past due loans to total loans and Short term assets minus short term liabilities over total assets, Capital adequacy: Risky assets to equity</td>
<td>A significant improvements in economic efficiency and credit risk exposure is found after privatization</td>
</tr>
<tr>
<td>Thomson and Jain (2006)</td>
<td>2004 to 2005</td>
<td>Australia</td>
<td>Return on asset, Return on equity, Net interest income to average assets, Cost to income</td>
<td>The National Australia Bank has the lowest ROA, ROE and net interest income to average assets and the highest ratio of cost to income ratio among other major Australian banks</td>
</tr>
<tr>
<td>Beccalli (2007)</td>
<td>1995 to 2000</td>
<td>France, Germany, Italy, Spain and UK</td>
<td>Return on asset, Return on equity</td>
<td>Investment in IT services from external providers have a positive impact on profit efficiency, while the acquisition of hardware and software has an adverse effect on banks' performance</td>
</tr>
</tbody>
</table>
### Table 3.2: Examples of Financial Rations Used by DeYoung et al. (2007) and Lin and Zhang (2009)

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Study Period</th>
<th>Country</th>
<th>Financial ratios</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>DeYoung et al. (2007)</td>
<td>1999 to 2001</td>
<td>United States</td>
<td>Interest income to assets, Interest expense to deposits, Interest margin, Non-interest income to assets, Service charges to assets, Other non-interest income to assets, Labour expense to assets, Workers to assets, Return on assets, Return on equity</td>
<td>Internet has improved the profitability of community banks mostly through increased revenues from deposit service charges</td>
</tr>
<tr>
<td>Lin and Zhang (2009)</td>
<td>1997 to 2004</td>
<td>China</td>
<td>Return on assets, Return on equity, Impaired assets to total loans, Costs to operating income</td>
<td>The big four state-owned commercial banks are less profitable, efficient than other types of banks except the policy banks</td>
</tr>
</tbody>
</table>

Although the use of financial ratios assists the evaluation of bank performance, there are several limitations that must be considered. The possibility of generating unlimited number of ratios from financial statements may lead to contradictory and confusing conclusions (Paradi et al., 2004). In addition, failure to deal with a multi-input and multi-output environment, combined with the inability to distinguish the best performers makes financial ratios analysis inadequate as a single tool for measuring and analysing the performance of financial institutions. Finally, it is common that one bank might be strong on one ratio and poor on another one. Due to these shortcomings, academics and researchers have recently begun using more advanced methods such as frontier models in their assessments.

### 3.4 Application of Frontier Models in Efficiency Studies

There is no consensus in the efficiency literature on the best approach to measure efficiency of organisations. Frontier analysis is one of the widely employed approaches to evaluate resource optimization for complex business units such as banks. Overall, the frontier analysis provides numerical values to rank business units based on their relative efficiency scores in comparison to the best performers. This attribute makes the frontier analysis approach a valuable tool not
only in assessing the efficiency of the banking sector and its trend but also in providing useful information regarding government policy implications such as mergers and deregulations.

In general, frontier models can be classified into parametric and non-parametric. Parametric models include the Stochastic Frontier Approach (SFA), Thick Frontier Approach (TFA) and Distribution Free Approach (DFA) while non-parametric methods include Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH). The lack of agreement among academics regarding the preferred method is due to the various drawbacks of each model. While parametric methods impose a functional form on the production function that may be problematic if the function form is misspecified, non-parametric methods, on the other hand, suffer from the inability to allow for random errors in the efficiency estimates.

Berger and Humphrey (1997) surveyed and contrasted the result of 130 studies which had applied frontier models to analyse the efficiency of financial institutions or their branches. The survey included 21 countries. Studies focusing on US financial institutions are the most numerous and consist of more than half of all studies. Among the surveyed studies, 69 apply non-parametric techniques while 60 use parametric methods (some have used more than one approach). The authors concluded that, although, efficiency estimates from both approaches have some similarities, in general, the non-parametric methods generate slightly lower efficiency scores than parametric methods. Furthermore, the authors point out that the mean of efficiency estimates at the industry level seemed more reliable for policy making than efficiency scores of individual firms. Finally, the authors comment on the necessity of providing confidence intervals in efficiency studies in either the bank or branch level. Fortunately, as will be discussed in detail in the next chapter, the idea of using confidence intervals in efficiency analysis has come true for the non-parametric methods since the introduction of the bootstrap procedure by Simar and Wilson (1998a).
Australian banking efficiency studies are dominated by the non-parametric methods due to limited sample size. Recently, more studies employ the stochastic frontier method to evaluate the efficiency of Australian banks (e.g. Shamsuddin and Xiang, 2012, Vu and Turnell, 2011). As our study focuses only on the application of the DEA technique as a non-parametric method in the banking sector, this chapter reviews only studies that utilize this mathematical tool or its combination with parametric methods in assessing efficiency and productivity of banks across the globe.

3.5 Efficiency Studies using DEA

Since 1978, the DEA method as an operational research technique has been widely employed in measuring efficiency and productivity of business units. DEA as a non-parametric technique has also been used by researchers and academics in assessing the performance of the banking sector in many countries. In a recent survey, Fethi and Pasiouras (2010) reviewed 196 studies that employed DEA and artificial intelligence techniques in assessing the performance of the banking sector. 181 of these studies used DEA to estimate different measures of efficiency and productivity in either the bank or branch level.

Overall, reviewing the literature indicates that the application of DEA in efficiency analysis of financial institutions is quite widespread and includes examination of the impact of deregulation, mergers, market structure, comparison of the results from different techniques and investigation of the general efficiency level of banks or their branches. Due to the large number of studies using DEA in evaluating efficiency and productivity of the banking sector, providing a full review of all studies is not feasible. For that reason, this study only reviews the most prominent literature and presents the results and discussions in four sections of individual country studies, cross country studies, Australian banking studies and finally recent studies use the statistical approach of bootstrap DEA. Dividing the following sections in this order facilitates analysing the results and avoids
unnecessary and misleading comparisons between studies due to the relativity of DEA efficiency scores and sensitivity of DEA estimates to sample variation.

3.5.1 Efficiency Studies in Individual Countries

In any country that has a sufficient number of banks, using DEA is quite feasible (Paradi et al., 2004). A number of such studies have been conducted in both developed and developing countries. This section provides examples of banking efficiency studies in a number of countries from different continents. These studies investigate a variety of topics from the impact of deregulation on efficiency to individual comparison between efficiency of banks.

3.5.1.1 US Banking Efficiency Studies

It is not unexpected that the number of studies that have been conducted on US banks’ efficiencies are considerably more than those of other countries. For instance, among 116 single country studies reviewed by Berger and Humphrey (1997), 66 studies relate to US banks. This section reviews ten US banking efficiency studies consisting of four studies that investigate the general efficiency level and its relationship with explanatory factors such as size and location, two studies which focus on developing models and providing methodological contributions, two studies which investigate the impact of input and output selections in efficiency estimates, one study which examines the effect of mergers on the efficiency of the US banks and one study providing a comparison between the results of parametric and nonparametric methods.

Four studies conducted by Aly et al. (1990), Miller and Noulas (1996), Wheelock and Wilson (1999) and Mukherjee et al. (2001) investigated the general efficiency level of varying samples of US banks in different time periods. They also examined the relationship between estimated efficiency scores and some explanatory factors such as size, product mix and location. It was commonly found that size is positively correlated with productivity and efficiency scores. However, there is no consensus on whether location has a positive effect on
efficiency. While it was suggested by Aly et al. (1990) and Miller and Noulas (1996) that location influences efficiency, it was found by Luo (2003) that location is not a significant factor on the performance of US banks. This discrepancy may come from different study periods and the impact of IT and communication technologies on reducing the effect of location on efficiency measures.

Focusing on methodological issues, Thompson et al. (1997) and Luo (2003) developed and proposed different approaches in their efficiency measurements. For instance, Luo (2003) introduced marketability efficiency for the first time and showed that marketability efficiency of US banks was much less than the profit efficiency which implies the importance of this neglected aspect in earlier studies. The impact of different combinations of input and output variables is the other issue addressed by Alam (2001) and Cinca et al. (2011). It was concluded that DEA is very sensitive to the choice of variables and different input and output combinations measure different aspects of banks’ efficiency.

In a methodological comparison, the impact of mergers and acquisitions on efficiency of US banks was investigated using both DEA and SFA by Al-Sharkas et al. (2008). It was found that a merger had a positive impact on efficiency measures. In a different study, two methods of DEA and SFA were compared by Choi et al. (2007) and it was suggested that bank-specific characteristics can explain DEA efficiency scores better than SFA scores. A detail review of the above studies is provided as follows:

In one of the early efficiency studies of the U.S banks, Aly et al. (1990) examined technical, scale and allocative efficiency of 322 independent banks using the DEA method in the year 1986. Their findings showed a low level of overall efficiency with the mean of 65% while technical efficiency was the source of overall inefficiency. Looking at the components of technical efficiency reveals that pure technical inefficiency was the major source of technical inefficiency and scale inefficiency was negligible. The authors also investigated whether there is a
difference between efficiency of branching and non-branching banks and found there is no significant difference between overall efficiency of these two groups. Finally, they examined the relationship between efficiency measures and three variables of size, product diversity and urbanization. Empirical results showed that pure technical efficiency was positively related to size while overall and pure technical efficiency were negatively correlated to product diversity. On the other hand, both overall and pure technical efficiency were positively correlated with urbanization.

Miller and Noulas (1996) investigated the relative technical efficiency of 201 large US banks using DEA from 1984 to 1990. The authors also examined the effect of bank size, profitability, market power, and location on pure technical efficiency in the second stage. The empirical results showed that the average of pure technical and scale efficiency are 96.7% and 98%, respectively which are relatively high in comparison with previous studies such as Aly et al. (1990) possibly due to the different sample banks and study period. However, it was shown that over 55% of banks experience decreasing returns to scale while 20% of the banks experience increasing returns to scale. That is, the majority of banks in this study were too large. The second stage findings showed that larger and more profitable banks had lower pure technical efficiency and the market power effect was not significant in determining pure technical efficiency. Moreover, banks in the Mideast states were operating more efficiently than banks in the Southeast.

Focusing on developing DEA weighted restriction models, Thompson et al. (1997) applied several important DEA assurance region (AR) concepts to measure efficiency of the 100 largest U.S. banks during the period from 1986 to 1991. Two inputs of total capital and total number of employees, and one output of total earnings were used in this study. Empirical results showed a high level of inefficiency while the role of slacks was prominent. Using factor analysis they demonstrated that the Linked-Cone profit ratio was superior to the Cone Ratio AR model.
In a study of the US banks’ productivity, Wheelock and Wilson (1999) examined the Malmquist productivity index pure technical and scale efficiency of 14,108 banks over the period between 1984 to 1993. It was found that productivity declines over time among banks of all sizes which is consistent with results provided by Berger and Mester (1997) for the same time period. Examination of banks’ size suggests that banks with assets less than $300 million exhibited larger declines in comparison to other counterparts. The results also showed a substantial decline in technical efficiency of all banks during the 1980s and early 1990s. Similarly, it was shown that the banks became less scale efficient during the sample period.

Alam (2001) evaluated the productivity of 166 large U.S. banks during the time period from 1980 to 1989. Six inputs of equity, capital, labor, purchased funds, demand deposits and other deposits were chosen. Securities, real estate loans, commercial and industrial loans, and instalment loans were defined as the outputs of the Malmquist productivity DEA model. The authors also used three other combinations of input and output variables to examine the sensitivity of productivity and efficiency measures. They demonstrated that as the number of variables in the model increases, average efficiency rises. Furthermore, to eliminate the effect of different regulatory environments, they separated the sample in three categories of banks in states allowing wide branching, banks in states with limited branching and uni-banking states. Empirical results showed that banks in the first group were consistently inefficient in all four models, while the last group had the highest level of efficiency in 3 out of 4 models. However, all three groups were demonstrating a similar trend.

Mukherjee et al. (2001) used DEA to examine productivity of 201 large US banks during the post deregulation period from 1984 to 1990. Empirical results showed on average 4.5% growth in overall productivity scores per year. However, productivity experienced a decline by 7.61% between 1984 and 1985 and by 0.33% between 1988 and 1989. It is also worthy of note that productivity change differs across the banks and over the years. For instance, between 1984 and 1985
around 40% of the banks experienced productivity growth while this figure increase to around 60% between 1989 and 1990. Turning to Malmquist productivity components, average of technical efficiency was at its lowest point in 1984 at 82.2% and grew to 91.9% at its peak in 1986 and then declined gradually to 85.6% in 1990. Furthermore, the scale change indexes experienced no significant change with an average rate of 0.88% per year. They also examined in the second stage the relationship between productivity change with size, equity to asset and product mix. The second stage results reveal that larger asset size and specialization of product mix positively correlated with productivity growth while higher equity to asset correlated with lower productivity growth.

In a study by Luo (2003) profitability and marketability efficiency of 245 large US banks was examined in 2000. To accomplish this, the author developed a two stage DEA model. In the first stage, profitability efficiency was measured using three inputs of number of employees, total assets and equity, and two outputs of revenue and profit. In the second stage, marketability efficiency was measured using two inputs of revenue and profit (outputs of first stage), and three outputs of market value, EPS and stock price. Results show that the means of pure technical profitability efficiency and its associated scale efficiency were equal to 97% while the means of pure technical marketability efficiency and its associated scale efficiency were 93% and 95%, respectively. Looking at the difference between profitability and marketability efficiency scores, the author applied three statistical tests (t-test, Wilcoxon test and Sign test) to provide strong evidence that US banks perform much worse in marketability efficiency than profitability efficiency. The author also examined whether the locations of banks are related to bank efficiencies. It was found that both profitability and marketability efficiencies did not differ significantly across four different locations. That is, location was not a factor related to the performance of banks, a finding which is inconsistent with findings of previous studies (e.g. Aly et al., 1990, Miller and Noulas, 1996). The author provided the following two reasons for this discrepancy: 1) the effect of location on efficiency might have been mitigated by time as a result of technological changes 2) different data sources had been used. Finally, the
capability of overall technical profitability in predicting bank failure was discussed.

For measuring the cost efficiency for a balanced panel data set covering 519 US agricultural banks, Choi et al. (2007) utilised both DEA and Stochastic Frontier Analysis (SFA) and regressed the results on different bank specific characteristics to explain the cost efficiency differences among the sampled banks during the period 1996-2005. Comparing the results of the two methods of DEA and SFA, the authors emphasized that bank-specific characteristics can explain DEA efficiency scores better than SFA efficiency measures. In addition, their empirical results show that cost efficiencies were positively related to profitability while negatively related with the raw cost inefficiency measure. Finally, the authors revealed that older agricultural banks seem to be more efficient.

Al-Sharkas et al. (2008) investigated the impact of mergers and acquisitions on the efficiency of the US banking industry using DEA and SFA during the period 1987 to 2000. To analyse the effect of mergers a sample of 440 bank mergers were chosen during the study period. Empirical results showed that mergers improved the cost and profit efficiency of sampled banks. For example, the cost efficiency of merged banks was 89.4% on average while for non-merged banks it was 82.5%. Similarly, merged banks had higher profit efficiency than non-merged banks by approximately 15%. In order to investigate the effect of merger size, they separately repeated calculations for large and small mergers. Findings indicated that mergers of large banks caused a higher improvement in profit efficiency compared to the small bank mergers.

Recently, Cinca et al. (2011) applied the combination of DEA and multivariate statistical analysis to investigate to what extent the various combinations of inputs and outputs affect efficiency scores. In order to conduct this study, 85 US banks were chosen for the year 2003. The inputs of this study included labor, physical capital and deposits. The outputs were defined as interest and non-interest income deposits and loans. They used a various combination of the above inputs and
outputs to analyse the results by means of multivariate statistical methods. Relying on results obtained from different mixtures of inputs and outputs, they concluded that each combination measures a particular aspect of banks’ efficiency. That is, efficiency is a multidimensional concept and decision makers need to know different aspects of that before taking actions for improving the efficiency.

A summary of the above studies on the US banking efficiency and input and output variables used are provided in Table 3-2. The major findings also are highlighted as follows:

1) Although, banks’ location influenced efficiency measures in earlier studies, recent ones reveal less impact possibly due to improvement in communication and information technologies which can reduce the effect of location.
2) Mergers have a positive influence on the cost and profit efficiency measures.
3) Efficiency measures are very sensitive to the choice of input and output variables making their choice critically important to the successful implementation of DEA models.
4) There are some contradictory results due to different samples or study periods. For instance while a decline in productivity over the time period between 1986 to 1991 is reported by Thompson et al. (1997), Mukherjee et al. (2001) point out a considerable growth in overall productivity during the period from 1984 to 1990. Thus, as discussed before a direct comparison between studies should be made with great caution due to the contradictory efficiency estimates derived from the different studies.
### Table 3-2: Summary of the US Banking Efficiency Studies using DEA

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Study Period</th>
<th>banks</th>
<th>Inputs</th>
<th>Outputs</th>
<th>Indexes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aly et al. (1990)</td>
<td>1986</td>
<td>322</td>
<td>Labor, Capital, Loanable funds</td>
<td>Real estate loans, Commercial and industrial loans, Consumer loans, All other loans, Demand deposits</td>
<td>Technical efficiency, Scale efficiency, Allocative efficiency</td>
</tr>
<tr>
<td>Miller and Noula (1996)</td>
<td>1984 to 1990</td>
<td>201</td>
<td>Total transactions deposits, Total non-transactions deposits, Total interest expense, Total non-interest expense</td>
<td>Commercial and industrial loans, Consumer loans, Real estate loans, Investments, Total interest income, Total non-interest income</td>
<td>Technical efficiency</td>
</tr>
<tr>
<td>Thompson et al. (1997)</td>
<td>1986 to 1991</td>
<td>100</td>
<td>Total asset, Total employees</td>
<td>Total earning</td>
<td>Technical efficiency</td>
</tr>
<tr>
<td>Wheelock and Wilson (1999)</td>
<td>1984 to 1993</td>
<td>14108</td>
<td>Number of employees, Physical capital, Purchased funds</td>
<td>Real estate loans, Commercial and industrial loans, Consumer loans, All other loans, Total demand deposits</td>
<td>Technical efficiency, Pure technical efficiency, Scale efficiency</td>
</tr>
<tr>
<td>Alam (2001)</td>
<td>1980 to 1989</td>
<td>166</td>
<td>Model 1 Equity, Capital, Labor, Purchased funds, Demand deposits, Other deposits</td>
<td>Model 1 Securities, Real estate loans, Commercial and industrial loans, Installment loans</td>
<td>Malmquist Productivity</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Model 2 Equity, Capital, Labor, Purchased funds, Demand deposits, Other deposits</td>
<td>Model 2 Securities, Total loans</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Model 3 Equity, Capital, Labor, Purchased funds, Core deposits</td>
<td>Model 3 Securities, Total loans</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Model 4 Equity, Capital, Labor, Loanable funds</td>
<td>Model 4 Securities, Total loans</td>
<td></td>
</tr>
<tr>
<td>Mukherjee et al. (2001)</td>
<td>1984 to 1990</td>
<td>201</td>
<td>Transaction deposits, Non-transaction deposits, Equity, Labor, Capital</td>
<td>Consumer loans, Real estate loans, Investments, Total non-interest income</td>
<td>Productivity, Technical efficiency, Scale efficiency</td>
</tr>
<tr>
<td>Author(s)</td>
<td>Study Period</td>
<td>banks</td>
<td>Inputs</td>
<td>Outputs</td>
<td>Indexes</td>
</tr>
<tr>
<td>-----------------</td>
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</tr>
<tr>
<td>Aly et al.</td>
<td>1986</td>
<td>322</td>
<td>Labor, Capital, Loanable funds</td>
<td>Real estate loans, Commercial and industrial</td>
<td>Technical efficiency</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>loans, Consumer loans, All other loans, Demand</td>
<td>Scale efficiency</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>deposits</td>
<td>Allocative efficiency</td>
</tr>
<tr>
<td>Luo</td>
<td>2000</td>
<td>245</td>
<td>Stage 1 Number of employees, Total assets,</td>
<td>Stage 1 Revenue, Profit</td>
<td>Profitability efficiency</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Stage 2 Revenue, Profit</td>
<td>Stage 2 Market value, EPS, Stock price</td>
<td>Marketability efficiency</td>
</tr>
<tr>
<td>Choi et al.</td>
<td>1996 to 2005</td>
<td>519</td>
<td>Labour Expenses for promises and fixed assets, Sum of interest and other expenses</td>
<td>Sum of total loans and total deposits</td>
<td>Cost efficiency</td>
</tr>
<tr>
<td>Al-Sharkas et al.</td>
<td>1987 to 2000</td>
<td>440</td>
<td>Purchased funds, Deposits, Labor</td>
<td>Consumer loans, Business loans, Real estate loans, Securities</td>
<td>Cost efficiency</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Profit efficiency</td>
</tr>
<tr>
<td>Cinca et al.</td>
<td>2003</td>
<td>85</td>
<td>Labor, Physical capital, Deposits</td>
<td>Interest income, Non-interest income, Deposits, Loans</td>
<td>Technical efficiency</td>
</tr>
</tbody>
</table>

### 3.5.1.2 European Banking Efficiency Studies

Europe is one of the key economic centres with GDP of 17,578 billion dollars in 2011. The significance of the region is a key motive in studying productivity and efficiency of financial institutions in European countries. Therefore, as expected, efficiency studies of banking sectors have been conducted in many countries of this region such as the UK, Spain, Italy, Austria, Germany, Poland and Greece.

This section reviews nine studies which have utilized DEA in analysing efficiency including one study investigate the general efficiency level of banks in Greek, two studies examine the impact of mergers in efficiency and productivity of Austrian and Spanish banks, one study probes the impact of deregulation and liberalization in Greece, two studies apply different approaches in the choice of input and output variables in investigating the efficiency of UK banks, one study compares
efficiency scores from different parametric and non-parametric approaches in German banks and one study focuses on foreign banks in Poland.

Examining the general efficiency of UK banks Webb (2003) showed a decline in overall technical efficiency, while in a different study period Pasiouras et al. (2011) found an improvement in technical efficiency of Greek banks. Furthermore, examining the relationship between the efficiency of the UK banks and some explanatory factors such as size and GDP indicated a positive impact of size and a negative impact of GDP per capita on both scale and allocative efficiencies. The impact of mergers is an interesting area in bank efficiency studies investigated by Hahn (2007) and Guzman and Reverte (2008) in Austria and Spain. In general, both studies confirmed the positive impact on mergers in the productivity and efficiency of banks under study. Different approaches in selection of input and output variables were compared in two studies in Italy and the UK by Favero and Papi (1995) and Drake (2001). While the results of the Italian banking study showed no sensitivity to the selection of different approaches in the choice of inputs and outputs, the results obtained from the study of the UK banks demonstrated a high disparity between the results of different approaches.

The impact of liberalisation and deregulation on efficiency and productivity of Greek banks was examined by Rezitis (2006). The study showed that liberalisation had a positive impact on total factor productivity. Comparison between foreign and local banks is another area of interest in efficiency studies. This comparison was conducted in the Polish banking by Havrylchyk (2006) and it was shown that foreign banks exhibited a higher level of efficiency than domestic banks. A detail review of the above studies is provided as follows:

In a study of the Italian banking industry, Favero and Papi (1995) examined the technical and scale efficiency of 174 banks in 1991 using the non-parametric method of DEA. For this purpose, the two approaches of asset and intermediation were chosen to select variables of the DEA models. In the asset approach, labor,
capital and financial capital available for investment were defined as the inputs while loans to other banks, investments in securities and non-interest income were chosen as the outputs. In the intermediation approach, current accounts and saving deposits were shifted from the input side of the asset model to the output side. Interestingly, the authors found that results are not too sensitive to the selection of these approaches. They found that firstly, there was a strong relationship between specialisation and efficiency. Secondly, a lower efficiency level for popular banks and those located in Southern Italy. Thirdly, there was a strong correlation between size and efficiency.

Using DEA, Drake (2001) investigated efficiency and productivity of 9 banks in the UK during the time period from 1984 to 1995. The author employed two production and intermediary approaches and defined accordingly two sets of input and output variables. In model 1, fixed assets, number of employees and deposits are assumed as the inputs. The outputs of model 1 are defined as loans, liquid assets and investments, and other income. In model 2, fixed assets and number of employees are defined as the inputs. Outputs were defined as loans, liquid assets and investment, other income, and deposits. Results suggested that while four major banks exhibited a high level of scale inefficiency and operate under decreasing returns to scale, small banks were suffering from increasing returns to scale. It was also found that the minimum efficient scale of operation was at an asset size between £18bn to £23bn. Looking at technical efficiency measures, the production approach (model 1) demonstrated a higher level of inefficiency than the intermediation approach (model 2). Interestingly, in the case of UK banks, scale inefficiency seemed to be the main source of inefficiency. Turning to the Malmquist productivity index, findings revealed a modest productivity growth over the study period with a maximum level of 4.9%.

In a study of UK banks’ efficiency, Webb (2003) utilized DEA window analysis to examine the efficiency of the 7 largest retail banks during the period 1982 to 1995. More specifically, 10 windows each of 5 years were considered to eliminate the effect of environmental variables during this long study period. Aggregate
efficiency shows a decline on average of overall efficiency levels from window 6 onwards. Turning to scale efficiency, the results indicated a grouping of scale efficient banks around asset levels ranging £6bn to £24bn. Pure technical findings also showed that, although, during the 1980s the majority of banks reported a high level of efficiency (98% or higher), the efficiency level was much lower during the 1990s.

Rezitis (2006) investigated productivity growth and technical efficiency of 6 Greek banks for the period 1982 to 1997. The empirical results of this study revealed that total factor productivity and its components, technological progress, technical efficiency, scale efficiency and pure technical efficiency were improved on average by 2.4%, 1.2%, 1.2%, 0.8% and 0.4% respectively over the study period. The author also compared two sub-periods of 1982-1992 and 1993-1997 to examine the impact of liberalization and deregulation in 1992 in the Greek banking industry. It was found that total factor productivity in the second period was higher than the first period, with an average of 4.4% versus 1.7% per year.

Efficiency of the Polish banking system was investigated during the study period from 1997 to 2001 by Havrylchyk (2006). More specifically, in this study, cost, allocative, technical and scale efficiency of 38 domestic and 14 foreign banks were examined using DEA method. Under two assumptions of a common and separate frontier for domestic and foreign banks, it was shown foreign banks exhibit a higher level of efficiency than domestic banks. Havrylchyk also found that foreign banks acquired domestic banks were not successful in improving their efficiency.

In examining the consistency of efficiency scores derived from non-parametric and parametric methods, Fiorentino et al. (2006) used DEA and SFA to estimate cost efficiency of 34192 German banks between 1993 and 2004. It was found that the mean of cost efficiency derived from SFA was substantially higher than DEA. Outliers and sensitivity to measurement errors seemed as the main reason of this difference. It was also shown that efficiency rank stability of both methods was
very high in the short run. Finally, the authors concluded that only a weak correlation can be seen between efficiency estimates and traditional indicators such as return ratios.

Hahn (2007) examined the efficiency of the Austrian banks which had participated in mergers since 1996. To do so, the DEA method was employed to measure the technical efficiency of an unbalanced sample of 800 Austrian banks over the period from 1996 to 2002. Two models based on profit and intermediation approaches were employed. According to the profit approach, employee expense, non-interest expense and risk-weighted assets were chosen as the input variables and outputs were defined as net interest income and net commission and other income. The second model which follows the intermediation approach consists of two inputs of total costs and total deposits which are assumed to generate two outputs of total loans and other earnings. The empirical results showed that the average efficiency of Austrian banks in the two models was low and there was no sign of improvement in efficiency levels over the study period. However, it was also found that banks which have participated in domestic mergers experience a higher level of efficiency than those did not participate in such processes.

In a study on the Spanish banking sector, Guzman and Reverte (2008) analysed productivity and efficiency change of 14 banks during the period 2000 to 2004. They also examined the relationship between shareholder value and change in efficiency and productivity of the sample banks. Additionally, Guzman and Reverte used both assumptions of constant and variable returns to scale while the variable assumption was applied in both input and output orientation models (there is no difference between input and output orientations under constant returns to scale). A high efficiency level was obtained from all models over the study period, implying that mergers and acquisitions during the 1990s in Spain had positively influenced efficiency improvement. This is in line with Hahn’s (2007) findings. It was also found that productivity grew by 2.2% in the sample period mostly attributable to technological progress. Finally, the results revealed
that efficiency and productivity measures were positively related to shareholder value measured by total shareholder return. That is, banks with a higher efficiency level experience a higher total shareholder return.

Pasiouras et al. (2011) assessed the cost efficiency of 16 Greek cooperative banks over the period from 2000 to 2005. Due to data availability, sample size per year varies, ranging from 14 to 16. The results revealed that the overall efficiency score ranged between 78.4% in 2005 to 83.6% in 2002 while the average was 81.6% over the entire study period. It was also found that allocative inefficiency was always higher than technical efficiency. Specifically, technical and allocative efficiency can be improved on average by 8% and 11.4%, respectively. Using Tobit’s regression model, the authors found that the ratio of equity capital to total assets was positively related to technical efficiency while it did not impact scale and cost efficiency. The logarithm of total assets as a proxy of size was positively related to both allocative and scale efficiency. In contrast, GDP per capita seem to have a negative impact on both allocative and scale efficiency. Finally, applying a window analysis did not change the ranking of banks in the sample implying the existence of homogeneity of DMUs over the study period.

To provide an overview, Table 3-3 presents a summary of European banking efficiency studies employing DEA. In addition, the major findings of the above studies are highlighted as follows:

1) Liberalization and deregulation in 1992 had a positive impact on the Greek banking industry
2) Foreign banks in Poland exhibited a higher level of efficiency than domestic banks
3) Austrian banks which participated in domestic mergers experienced a higher level of efficiency than other banks. Similarly, mergers and acquisitions during the 1990s in Spain had a positive impact on efficiency measures.
<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Study Period</th>
<th>Country</th>
<th>Number of banks</th>
<th>Inputs</th>
<th>Outputs</th>
<th>Indexes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Favero and Papi</td>
<td>1991</td>
<td>Italy</td>
<td>147</td>
<td>Labor, Capital, Financial capital</td>
<td>Loans to other banks Investments in securities, Non-interest income</td>
<td>Technical efficiency</td>
</tr>
<tr>
<td>Drake (2001)</td>
<td>1984 to 1995</td>
<td>UK</td>
<td>9</td>
<td>Model 1 Fixed Asset, Number of employees, Deposits</td>
<td>Model 1 Loans, Liquid assets and investments, Other income</td>
<td>Malmquist productivity</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Model 2 Fixed assets, Number of employees</td>
<td>Model 2 Loans, Liquid assets and investments, Other income, Deposits</td>
<td>Technical efficiency</td>
</tr>
<tr>
<td>Fiorentino et al.</td>
<td>1993 to 2003</td>
<td>Germany</td>
<td>34192 (observation during the study period)</td>
<td>Fixed assets, Number of employees, Borrowed funds</td>
<td>Interbank loans, Customer loans, Investment in stocks and bonds</td>
<td>Cost efficiency</td>
</tr>
<tr>
<td>Hahn (2007)</td>
<td>1996 to 2002</td>
<td>Austria</td>
<td>800 (observation during the study period)</td>
<td>Model 1 Employee expense, Non-interest expense, Risk-weighted asset</td>
<td>Model 1 Net interest income, Net commission and other income</td>
<td>Technical efficiency</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Model 2 Total costs, Total deposits</td>
<td>Model 2 Total loans, Other earnings</td>
<td></td>
</tr>
<tr>
<td>Guzman and Reverte (2008)</td>
<td>2000 to 2004</td>
<td>Spain</td>
<td>14</td>
<td>Total deposits, Interest expense and commission paid, Personnel and administration expenses</td>
<td>Total loans, Interest income and commissions received</td>
<td>Malmquist productivity</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Technical efficiency</td>
</tr>
<tr>
<td>Pasiouras et al.</td>
<td>2000 to 2005</td>
<td>Greece</td>
<td>14 to 16</td>
<td>Fixed assets, Deposits, Number of employees</td>
<td>Loans, Other earning assets</td>
<td>Cost efficiency</td>
</tr>
</tbody>
</table>
3.5.1.3 Asia and Middle East Banking Efficiency Studies

As countries grow in Asia and the Middle East, efficiency studies in the banking sector in this region become more important. It is the reason that more recent studies can be found in Asia in comparison to other continents.

This section reviews 10 efficiency studies consisting of three studies investigating the general efficiency level of banks and its relationship to some explanatory factors in Singapore and Pakistan, two studies focusing on selection of input and output variables in Taiwan and Hong Kong, three studies examining the impact of deregulation and liberalisation on efficiency in Turkey, India and Korea, one study examining the impact of mergers on banks efficiency in New Zealand and one study comparing the efficiency of different bank types in Japan.

Chu and Lim (1998), Sufian and Majid (2007) and Aftab et al. (2011) investigated the general efficiency level of banks in Singapore and Pakistan. The major findings these researches indicate a positive relationship between efficiency measures of Singaporean and Indian banks with their stock returns. Furthermore, Sufian and Majid (2007) found large banks have lower levels of both pure technical and scale efficiencies.

The impact of deregulation and liberalisation on efficiency and productivity of Turkish banks, Indian banks and Korean banks was investigated by Isik and Kabir Hassan (2003), Das and Ghosh (2006) and Banker et al. (2010), respectively. While the results from both Turkish and Korean banks showed a positive impact of deregulation and reforms on efficiency and productivity of sample banks, no sign of significant improvement was found in the case of Indian banks after liberalisation. The impact of mergers on bank efficiency is the other interesting area examined in New Zealand by Liu and Tripe (2003). Their research suggests that only some acquiring banks are more efficient than their target banks which may have been due to the limited number of banks in New Zealand. That is, mergers will not necessarily be effective in enhancing efficiency.
Different approaches in choosing input and output variables were used by Ho and Zhu (2004) and Cheng-Ru et al. (2008) to analyse different aspects of bank efficiencies in Taiwan and Hong Kong. Empirical results confirmed the sensitivity of the DEA method in selecting inputs and outputs. For instance, Cheng-Ru et al. (2008) examined operational and profitability efficiencies distinguished by specifying two different sets of input and output variables. As expected, a significant difference was found between operational and profitability efficiency. A detail review of all above studies is presented below.

Chu and Lim (1998) examined the relative cost and profit efficiency of six Singaporean banks using DEA models over the period 1992 to 1996. Three inputs and two outputs are used in the DEA models. For the profit efficiency model, shareholders’ funds, interest expense and operating expense were defined as the inputs. The outputs were defined as annual increase in average assets and profit. The cost efficiency model defines the same input and output variables of the profit efficiency model while replacing profit by total income. It was found that the mean of the x-efficiency of sample banks for the study period is 95.3% while larger banks exhibited a higher level of x-efficiencies than smaller banks. In contrast, the mean of profit efficiency was much lower at about 82.6% which may have been due to the low degree of financial leverage in the Singaporean bank sector. The authors also investigated the impact of x-efficiency and profit efficiency on the share prices of sample banks during the study period. To do so, they used supper efficiency models to overcome the boundary problem of DEA scores and then regressed the annual stock returns on modified efficiency scores. R-squared values for the moving average of x-efficiency and profit efficiency scores were 0.19 and 0.67 respectively, implying that share prices reflect profit efficiencies more than x-efficiencies.

In an empirical study of Turkish commercial banks, Isik and Kabir Hassan (2003) investigated the impact of financial deregulation by analysing productivity growth, efficiency change and technical progress of 56 banks during the period from 1981 to 1990. The results indicated that the average efficiency score
substantially improved after deregulation. Specifically, the mean of technical, pure technical and scale efficiency between 1981 and 1986 had increased from 63%, 76% and 83% to 72%, 85% and 85%, respectively between 1987 to 1990. However, different banking groups did not perform equally efficiently during the same time period. While the average technical efficiency scores for private banks increased from 56% to 62%, this growth for foreign banks was found to be 19% (from 62% to 83%). On the contrary, state banks experienced a decline in the average of technical efficiency from 77% to 71%. Turning to the productivity of Turkish banks, on average a growth of 7.1% was found during the study period. Although, all type of banks benefited from the increase in productivity, foreign banks exhibited a higher growth followed by domestic private banks.

Using DEA, Drake and Hall (2003) analysed the technical and scale efficiency of 149 Japanese banks in 1997. The average of overall efficiency for all banks was 72.4%. This inefficiency was more attributed to the pure technical inefficiency with the mean score of 78.1% rather than scale inefficiency with mean score of 92.8%. Among five groups of bank types, Trust and Long-Term Credit Banks exhibited the highest efficiency level in both pure technical and scale efficiency measures. This was followed by the City banks which exhibited a mean overall efficiency score of 87.1% which was composed of scale efficiency of 91.2% and pure technical efficiency of 95.6%. In contrast, the overall efficiency score of Regional banks was only 68.5% composed of a higher level of pure technical efficiency of 71.65% and a scale efficiency of 95.5%. Finally, the Second Association Regional banks exhibited a slightly higher mean of overall efficiency of 69.5% due more to pure technical efficiency of 78.4% than scale efficiency of 89%. It was also found that controlling for the effect problem loans, increases the mean pure technical efficiency of all banks to 89.4% which demonstrates the importance of risk factors in efficiency measures of Japanese banks.

Liu and Tripe (2003) investigated New Zealand bank mergers and efficiency gains during the period between 1989 to 1998. The authors explored the impact of 6 bank mergers using three DEA models. Interest expense and Non-interest expense
were defined as the inputs of all three models. Two outputs of model 1 were net interest income and non-interest income. Model 2 used three outputs of customer deposits, net loans and advances, and operating income. Finally, in model 3, deposits, loans and advances, and operating income were chosen as the outputs of the DEA model. Under models 1 and 2, the number of efficient banks tended to increase during the 1990s. However, after 1996, DEA scores tended to be slightly decreased possibly due to the presence of new entrant (foreign) banks. The DEA results also show that only some acquiring banks were more efficient than their target banks prior to mergers. More specifically, four banks had obvious post-merger efficiency gains. It should be noted that a significant difference between the results obtained using Models 1 and 2 clearly shows the sensitivity of DEA results to the choice of input and output variables.

Ho and Zhu (2004) measured the efficiency and effectiveness of 41 Taiwanese commercial banks during 2001. Selection of DEA input and output variables were chosen based on the DuPont model. Accordingly, two ratios of total asset turnover and profit margin were extended to two DEA models which measure efficiency and effectiveness, respectively. In the first stage, capital stocks, assets, branches and employees were defined as the inputs. Sales and deposits were chosen as the outputs. In the second stage, the outputs of the first stage were considered as the inputs and net income, interest income and non-interest income were defined as the outputs. The empirical results showed that 12 banks operated at 100% efficiency level. However, only 5 of them operated at 100% effectiveness level. That is, a bank with a high efficiency score does not necessarily having a high level of effectiveness and these two scores are measuring two different aspects of performance.

An empirical analysis of Indian banks during the post reform period was conducted by Das and Ghosh (2006). The study investigated the efficiency of 74 to 90 Indian commercial banks between 1992 and 2002. An intermediation, value-added and operating approach are used to select input and output variables for the DEA models. The empirical results show that different approaches generate
different efficiency estimates. In general, the value-added approach resulted in a higher level of efficiency in comparison with the intermediation and operating approaches. The maximum number of efficient banks per year during the sample period for intermediation, operating and value-added approaches were 32, 9 and 65 respectively. The authors concluded that no significant increase can be seen in the number of efficient banks after the liberalisation period and that some Indian banks were suffering from a high level of inefficiency during the period of liberalisation.

Sufian and Majid (2007) examined the long term trend in the efficiency of 6 Singaporean commercial banks between 1993 to 2003. In this study, window analysis was employed and 9 windows of 3 years were defined to cover 11 years of the study period. Looking at overall efficiency measures, it was found that all Singapore banking groups exhibit improvement and upward trend during the late study period. Furthermore, smaller banks demonstrated a higher mean overall efficiency of 96.5% in comparison to larger banks ranging between 77.3% and 86%. Similarly, larger banks had a lower level of pure technical efficiency while an ascending trend can be seen for all banks in the latter period of the study. Analogous to pure technical efficiency, the scale efficiency of smaller banks showed a higher level of performance than other banks. As expected, larger banks tended to operate at optimum scale or decreasing returns to scale. Smaller banks, on other hand, operated at optimum scale or increasing returns to scale. Finally, examining the relationship between efficiency scores and size and market value showed both size and market value were negatively correlated to all efficiency measures.

In an analysis of Hong Kong commercial banks, Cheng-Ru et al (2008) evaluated operational and profitability efficiency of 18 banks in the period from 2004 to 2006. To do so, a two stage DEA model was developed. In the first stage, total deposits and gross loans were defined as the inputs while other income and interest income were chosen as the outputs. In the second stage, while the outputs of the first stage were considered as the inputs, pre-tax income and total assets
were defined as the outputs. A significant difference between operational and profitability efficiency scores was found for all banks. For instance, this difference for a bank can be as high as 64%.

Banker et al. (2010) examined the impact of Korean banking system reform on bank efficiency over the period 1995 to 2005. The number of banks varies during the study period from 25 in 1995 to 14 in 2005. The results showed that there is a significant change in the average efficiency of sample banks during the study period. With respect to technical efficiency, the mean of this measure was 88% and 32 out of 154 observations were fully efficient. The means of aggregate and technical efficiency decreased between 1995 and 1998 to the lowest level at 57% and 68%, respectively due to the financial crisis. However, an upward trend can be seen between 1998 and 2005 to the highest level of 85% and 96%, respectively due to banking system reforms and restructurings.

Aftab et al. (2011) investigated technical efficiency of seven major Pakistani banks for a period of five years between 2003 and 2007. They used cumulative annual stock returns as a proxy of share performance in the second stage to examine the relationship between efficiency and share performance. The average of efficiency scores under two different assumptions of constant and variable returns to scale were 60.5% and 80%, respectively. Pure technical efficiency scores experienced a downward trend from 90.8% in 2004 to 65.3% in 2007. The regression results showed that efficiency was positively related to cumulative annual share returns. That is, stock returns of Pakistani banks can be reasonably predicted through changes in efficiency.

To provide an overview, Table 3-4 illustrates a summary of banking efficiency studies employing DEA in Asia. In addition, the major findings of the above studies are listed below:

1) Share prices are reflected in profit efficiency scores of Singaporean banks. Similarly, efficiency is positively related to cumulative annual share
returns in Pakistani banks.

2) Deregulations had a positive influence on Turkish banks’ efficiency. In contrast, no significant increase can be seen in the number of efficient banks after the liberalisation period in India.

3) Banking system reforms and restructurings had a positive influence on efficiency measures in Korea.

4) Some acquiring banks are more efficient than their target banks prior to mergers in New Zealand.

5) A study of Japanese banks demonstrates the impact and importance of risk factors in efficiency measures.

Table 3-4: Summary of the Asian Banking Efficiency Studies using DEA

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Study Period</th>
<th>Country</th>
<th>Number of banks</th>
<th>Inputs</th>
<th>Outputs</th>
<th>Indexes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chu and Lim</td>
<td>1992 to 1996</td>
<td>Singapore</td>
<td>6</td>
<td>Shareholder’s fund, Interest expense, Operating expense</td>
<td>Annual increase in average asset, Total income/profit</td>
<td>Cost efficiency, Profit efficiency</td>
</tr>
<tr>
<td>Drake and Hall</td>
<td>1997</td>
<td>Japan</td>
<td>149</td>
<td>General and administrative expense, Fixed assets, Retail and wholesale deposits</td>
<td>Total loans and bills discounted, Liquid assets and other investments in securities, Other income</td>
<td>Technical efficiency, Scale efficiency</td>
</tr>
<tr>
<td>Liu and Tripe</td>
<td>1989 to 1998</td>
<td>New Zealand</td>
<td>7 to 15</td>
<td>Model 1 Interest expense, Non-interest expense</td>
<td>Model 1 Net interest income, Non-interest income</td>
<td>Technical efficiency</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Model 2 Interest expense, Non-interest expense</td>
<td>Model 2 Customer deposits, Net loans and advances Operating income</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Model 3 Interest expense, Non-interest expense</td>
<td>Model 3 Deposits Loans and advances Operating income</td>
<td></td>
</tr>
</tbody>
</table>

77
<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Study Period</th>
<th>Country</th>
<th>Number of banks</th>
<th>Inputs</th>
<th>Outputs</th>
<th>Indexes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ho and Zhu</td>
<td>2001</td>
<td>Taiwan</td>
<td>41</td>
<td>Stage 1 Capital stocks, Assets, Branches, Employee</td>
<td>Stage 1 Sales Deposits</td>
<td>Efficiency</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Stage 2 Sales Deposits</td>
<td>Stage 2 Net income Interest income Non-interest income</td>
<td>Effectiveness</td>
</tr>
<tr>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Das and Ghosh</td>
<td>1992 to 2002</td>
<td>India</td>
<td>98</td>
<td>Model 1 Demand deposits Saving Deposits Fixed deposits Capital related operating expense Employee expenses Model 2 Employee expenses Capital related expenses Interest expenses Model 3 Interest expenses Employee expenses Capital related operating expenses</td>
<td>Model 1 Advances Investments Model 2 Advances Investments Demand deposits Saving deposits Fixed deposits Model 3 Interest income Non-interest income</td>
<td>Technical efficiency Pure technical efficiency Scale efficiency</td>
</tr>
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<td></td>
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</tr>
<tr>
<td>Sufian and Majid</td>
<td>1993 to 2003</td>
<td>Singapore</td>
<td>6</td>
<td>Total deposits Fixed assets</td>
<td>Total loans Other income</td>
<td>Overall efficiency Pure technical efficiency Scale efficiency</td>
</tr>
<tr>
<td>Cheng-Ru et al</td>
<td>2004 to 2006</td>
<td>Hong Kong</td>
<td>18</td>
<td>Stage 1 Total deposits Gross loans</td>
<td>Stage 1 Other income Interest income</td>
<td>Operational efficiency Profitability efficiency</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Stage 2 Other income Interest income</td>
<td>Stage 2 Pre-tax income Total assets</td>
<td></td>
</tr>
<tr>
<td>Banker et al.</td>
<td>1995 to 2005</td>
<td>Korea</td>
<td>25</td>
<td>Interest expense Other operating expense</td>
<td>Interest revenue Other operating revenue</td>
<td>Pure technical efficiency Scale efficiency</td>
</tr>
<tr>
<td></td>
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<td></td>
<td></td>
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<tr>
<td>Aftab et al.</td>
<td>2003 to 2007</td>
<td>Pakistan</td>
<td>7</td>
<td>Operating expense Interest expense</td>
<td>Net profit</td>
<td>Technical efficiency Scale efficiency</td>
</tr>
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### 3.5.2 Cross Country Studies

The growing internationalisation of banking systems requires more emphasis on cross-country comparisons. Cross country efficiency studies can provide valuable information regarding the performance of the banking industry in
different countries. However, cross-country comparison is not simple and any interpretations should be made with caution due to the possibility of different regulatory and economic environments or a different level and quality of services in different countries (Berger and Humphrey, 1997).

This section reviews ten studies investigating efficiency and productivity of banks in a variety of countries. As the aim of such studies is to compare the efficiency level of banks in countries under study, it is not surprising that majority of reviewed studies provide such comparisons. However, some studies investigate other issues such as the impact of deregulation and mergers on efficiency or productivity of banks.

In total, six studies focused on measuring and comparing the general level of efficiency or productivity of banks in different countries either in the same region or different continents. For instance, in a comparison between the efficiency level of eleven countries in Asia-Pacific by Abidin et al. (2011), it was suggested that Singaporean banks were inefficient in both profit and banking services efficiencies. In an international banking efficiency comparison between 41 countries conducted by Oliveira and Tabak (2005), it was found that banking efficiency among developed and emerging countries is not significantly different.

The impact of deregulation on efficiency of German and Austrian banks was examined by Hauner (2005). Despite the common effect of deregulation, no improvement was found in the efficiency level of banks under study. In a cost efficiency analysis of ten of the biggest banks from six countries, Brack and Jimborean (2009) found a positive influence of mergers in the efficiency level of banks in France, Germany, Italy, Spain, the UK and the US. It was also found that banks that operate in countries that control foreign ownership were likely to be more efficient than domestically owned rivals. A detailed review of all ten cross-country efficiency studies is provided below.
Considering three Nordic countries, Berg et al. (1993) used DEA to examine the efficiency and productivity of 503 Finish, 150 Norwegian and 126 Swedish banks in the year 1990. The study included almost the entire banking industries of these three counties. Labour and capital were used as the inputs while total loan, total deposits and number of branches were defined as the outputs. Individual country analysis revealed that structural efficiency measured as the efficiency score of the average bank in Finland, Norway and Sweden were 53%, 57% and 78% respectively. Using a pooled data set, an inter-country comparison showed that the large Swedish banks remained efficient and large Finish and Norwegian banks were inefficient. Overall, the results indicated that Swedish banks operated more efficiently than their counterparts in the Nordic banking market.

In an international comparison, Pastor et al. (1997) analysed the productivity, efficiency and differences in technology of banking systems of 7 European countries and the US. Empirical results showed under the constant returns to scale assumption, France had the highest technical efficiency at 95% followed by Spain 82%, Belgium 80%, Italy 77.3%, Germany 65%, US 62.4%, Austria 60.8% and UK 53.7%. In contrast, assuming variable returns to scale, France had still the highset technical efficiency at 95.1% followed by Germany 93.6%, Italy 92.6%, Belgium 92.4%, Austria 92.2%, Spain 89.4%, %, US 81.1%, and UK 54.8%. In contrast, banks from Belgium, Spain, the UK and France had smaller scale efficiencies. Turning to productivity results, decomposing Malmquist productivity index into its two components showed that banking systems exhibited completely different combinations of both factors in various countries. For instance, while Spain and France had banking systems with relatively high efficiency and low level of technological efficiency, Austria and Germany combined a very productive technology with a low level of technical efficiency.

Hauner (2005) analysed cost efficiency, scale efficiency, and productivity change among 120 large German and Austrian banks during the period from 1995 to 1999. The average cost efficiency score of 63% for 485 observations of German and Austrian banks during the study period implies no improvement despite the
deregulation and merger wave of the 1990s. Furthermore, a comparison suggests that German banks were more cost efficient than Austrian banks with a score of 66% versus 42% respectively. The decomposition of cost efficiency into its components showed the average score of technical efficiency at 94% was higher than the average score of allocative efficiency at 66%. That is, the cost efficiency was mostly due to the use of inappropriate inputs rather than waste of inputs. Regression analysis suggested that size, securitized liabilities had a positive impact on cost efficiency while standard deviation of return to asset as a risk factor was negatively related to the cost efficiency. The author also found that customer deposits and branches had insignificant impact on cost efficiency.

An international comparison of banking sectors using DEA was conducted by Oliveira and Tabak (2005). This study covered 41 countries during the period from 1995 to 2002. Instead of using accounting data the study employed market data to measure returns and risk. Accordingly, two market risk measures of the standard deviation of the annual profitability of the banks’ stocks and beta as a measure of a stock's volatility in relation to the market were assumed and the profitability of the stocks of the banks were defined as the only output. Grouping the counties by continent and development level showed that North America presented the best average efficiency between 1995 to 1997, while the US banks demonstrated a declining trend in efficiency levels. Looking at European countries, Sweden and Switzerland exhibited the greatest falls on efficiency from the first position in 1995 to the 34th position in 2002. Turning to the Asian countries, the block of developed counties in this region represented by Japan, Singapore, Hong Kong and Taiwan were severely affected by the Asian crisis in 1997 while among them a significant loss on efficiency can be observed in Japan. Although, on average, in the beginning of the sample the Asian banks exhibited a higher efficiency than Latin American banks, a significant decline can be seen in Asian banks during the financial crisis 1997 to 1998. Overall, the authors found that banking efficiencies among developed and emerging counties were not significantly different.
Brown and Skully (2006) examined the cost efficiency of 322 banks in 12 countries in the Asia-Pacific region in 2004. They also investigated the possible impact of environmental variables such as bank regulation and population density of countries. It was found that using the basic cost efficiency model, Australian banks were the most cost efficient with the score of 83.6% followed by Singapore 75.4%, Korea South 71.4%, Hong Kong 68.7%, New Zealand 56.5%, Japan 52.6%, Indonesia 51.5%, China 51.3%, Taiwan 51.2%, Thailand 43.6% and Philippines 38.7%. Running the model using environmental variables increased the overall efficiency scores. However, the results did not considerably change the ranking of banks operating in weaker economies as expected. That is, environmental variables were not the source of inefficiency in banks operating in poorer economies.

Beccalli et al. (2006) investigated the relationship between efficiency and stock performance of 90 European banks in six counties using both parametric and non-parametric methods over the period 1999 to 2000. The mean of efficiency scores varies across countries and ranges between 70.6% for French banks and 93.3% for German banks. Looking at the relationship between changes in efficiency scores and changes in stock prices revealed a positive and statistically significant correlation. The results also suggested that efficiency measures were able to explain stock price changes better than financial ratios. It is worthy of note that this study showed that the DEA estimates had higher statistical significance in explaining the changes in stock price than SFA estimates.

Mostafa (2007) measured the relative efficiency of 43 banks in the Persian Gulf Cooperation Council states. The inputs of this study were assets and equity. The outputs were defined as net profit, return on assets (ROA) and return on equity (ROE). The empirical results indicated that the mean of the pure technical efficiency was 73% with a minimum score of 19.57%. Overall, 23% of banks were found to be fully efficient while only 11.6% were scale efficient which demonstrated a high level of scale inefficiency. With respect to the sensitivity analysis using slack variables, it was found that there was a potential to decrease
asset values of all banks by $18 billion. It was also shown that the maximum contributions of ROA, ROE and profit in the efficiency measures were 38%, 30% and 28%, respectively.

The effect of ownership on bank efficiency in Latin America is investigated by Figueira et al. (2009). In this study, 204 banks from 20 countries were chosen for study during 2001. Their findings show that banks which had some state ownership, on average, exhibited a higher level of efficiency than entirely private owned banks. The results for domestically owned versus foreign owned banks showed the first group were more efficient than the second group. The authors also found that differences in efficiency scores were more related to the economic environments of counties in the sample rather than the type of ownership.

Brack and Jimborean (2009) analysed the cost efficiency of the ten biggest banks from six counties of France, Germany, Italy, Spain, the United Kingdom and United States during the time period from 1994 to 2006. The results of DEA analysis indicated a rise in the average scores of cost efficiency of French and Spanish banks by 4.5% and 3.2%, respectively. In contrast, Britain, German, American and Italian banks in the sample experienced a decline by 11.5%, 9.7%, 2.9% and 1.4% respectively. The second stage regression outcomes revealed that while market capitalisation and size did not influence the banks’ efficiency, banks which operated in countries that control foreign ownership were likely to be more efficient than domestically owned rivals. It was also found that newly established banks as a result of mergers and acquisition seemed to be more efficient than those performing prior to 1990.

More recently, Abidin et al. (2011) investigated the cost efficiency of producing banking services and the profit of banks using DEA in 11 Asia-Pacific countries during the time period from 2005 to 2009. The authors selected three of the largest banks for each country which resulted in a sample of 165 data observations in a 5 year study period. Two different models were employed to measure the banking service efficiency and profit efficiency of banks in the sample. Model A
measured banking service efficiency using three inputs of number of employees, interest bearing liabilities and property, plant and equipment. The outputs of model A were interest bearing assets and non-interest income. In contract, model B measured the profit efficiency using the same inputs of model A, and defined profit before tax as the only output. In the case of Australian banks, three banks, the Commonwealth, Westpac and ANZ Bank were chosen. Empirical results showed that Australian banks were more efficient in transforming the inputs into banking services/products than making profits which is consistent with the study by Kirkwood and Nahm (2006). An overall examination of efficiency of all banks in the sample showed that banks in Japan, Hong Kong, Malaysia and Philippines experienced improvement in both banking services and profit efficiency. In contrast, banks in Australia, China, South Korea and Taiwan were more efficient in banking efficiency services than profit efficiency. On the other hand, Singaporean banks were suffering from inefficiency in both aspects.

To provide an overview, Table 3-5 illustrates a summary of cross-country banking efficiency studies employing DEA. The major findings of the above studies are:

1) German and Austrian banks showed no improvement in efficiency despite the deregulation and merger wave of the 1990s.
2) Efficiency comparisons between developed and emerging countries indicated no significant differences.
3) Efficiency measures were able to explain stock price changes better than financial ratios.
4) Domestically owned banks were more efficient than foreign banks in Latin America.
5) Environmental variables were not the source of inefficiency in banks operating in poorer economies in the Asia-Pacific region. On the contrary, economic environments were related to efficiency differences in Latin American banks.
Table 3-5: Summary of the Cross-Country Banking Efficiency Studies using DEA

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Study Period</th>
<th>Countries</th>
<th>Inputs</th>
<th>Outputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Berg et al (1993)</td>
<td>1990</td>
<td>Finland, Norway, Sweden</td>
<td>Labor, Capital</td>
<td>Total loan, Total deposits, Number of branches</td>
</tr>
<tr>
<td>Pastor et al. (1997)</td>
<td>1992</td>
<td>Spain, Germany, Italy, Austria, United Kingdom, Belgium, France, United State</td>
<td>Non-interest expense, Personal expense</td>
<td>Loans, Productive assets, Deposits</td>
</tr>
<tr>
<td>Hauner (2005)</td>
<td>1995 to 1999</td>
<td>Germany, Austria</td>
<td>Interest-bearing funds, Number of employees</td>
<td>Loans to customers, Fixed-interest securities</td>
</tr>
<tr>
<td>Oliveira and Tabak (2005)</td>
<td>1995 to 2002</td>
<td>Chile, Sri Lanka, Portugal, Australia, Greece, Peru, Austria, Denmark, Canada, Philippines, India, Israel, Ireland, United states, Norway, Spain, Germany, Finland, Singapore, Sweden, United Kingdom, Pakistan, Hong Kong, Switzerland, Malaysia, Poland, Czech Republic, Brazil, Netherlands, Taiwan, Hungary, France, Japan, Argentina, Korea, Mexico, Turkey, Thailand, Indonesia</td>
<td>Standard deviation of the annual profitability of the banks stock, Market risk beta</td>
<td>Profitability of the stocks of the banks</td>
</tr>
<tr>
<td>Brown and Skully (2006)</td>
<td>2004</td>
<td>Australia, China, Hong Kong, Indonesia, Japan, Malaysia, New Zealand, Philippines, Singapore, Republic of Korea, Taiwan, Thailand</td>
<td>Deposits, Employee costs, Physical capital</td>
<td>Loans, Other earning assets</td>
</tr>
<tr>
<td>Beccalli et al. (2006)</td>
<td>1999 to 2000</td>
<td>France, Germany, Italy, Spain, UK</td>
<td>Personnel expense, Other administrative expense, Interest expense, Non-interest expense</td>
<td>Total loans, Other earning assets</td>
</tr>
<tr>
<td>Mostafa (2007)</td>
<td>2005</td>
<td>Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, United Arab Emirates</td>
<td>Asset, Equity</td>
<td>Net profit, Rate on assets (ROA), Rate on equity (ROE)</td>
</tr>
</tbody>
</table>
3.5.3 Efficiency Studies in Australian Banks

Given the importance of the banking industry for the whole economy in general and for the financial sector in particular, a considerable number of studies have been conducted to measure and analyse the efficiency and productivity of Australian banks. This section reviews all efficiency studies employing DEA in examining efficiency and productivity of Australian banks.

Studying the impact of mergers on banking efficiency is one the common practices in Australian context. This issue is discussed in different time periods by Avkiran (1999b), Avkiran (1999a), Sathye (2002), Avkiran (2004), Paul and Kourouche (2008), Wu (2008) and Wu (2009). Although, some earlier studies found acquiring banks were more efficient than target banks, almost all of the above studies warn against further mergers among major banks. For instance, Paul and Kourouche (2008) emphasise that any merger between large banks could
intensify scale inefficiency of the banking sector in Australia. Similarly, Wu (2008) concluded that abolition of the four pillars policy and merger activities do not necessarily improve efficiency.

Using various combinations of input and output variables to measure different aspects of the efficiency of Australian banks is another common practice. Among all reviewed studies, four studies conducted by Avkiran (1999a), Sturm and Williams (2004), Kirkwood and Nahm (2006) and Moradi-Motlagh et al. (2011a) compared the results of different approaches in choosing model variables. For instance, Kirkwood and Nahm (2006) introduced two models for measuring profit efficiency and banking services efficiency. It was found that the level of banking services efficiency was higher than profit efficiency in the context of Australian banking.

The core profit efficiency approach was most commonly used in choosing model variables in Australian banking efficiency studies using DEA. This approach was applied in half of the studies. The profit efficiency approach defines interest expense and non-interest expense as two input variables which are used to generate two outputs of net interest income and non-interest income. Unfortunately, as discussed before, the choice of net interest income is not appropriate and following the recommendation of Avkiran and Thoraneenitiyan (2010) it is substituted by interest income in this study.

Due to the limited number of banks in Australia, individual comparison between banks is possible and provides very useful information for policy makers. Avkiran (1999b), Avkiran (1999a), Avkiran (2000), Sathy (2002), Avkiran (2004), Paul and Kourouche (2008) and Moradi-Motlagh et al. (2011a) evaluated individual banks in their studies. This information can be used by bank managers and decision makers to compare their position against other rivals. For instance, in the study by Paul and Kourouche (2008), it was shown that the National Australia Bank and Commonwealth Bank were fully efficient, while Westpac was found to
be least efficient. Such comparisons also provide useful information for finding the best choices for targeting or acquiring banks in the context of mergers.

Linking banking efficiency to market measures such as stock returns and shareholder returns is the other interesting area investigated by Kirkwood and Nahm (2006) and Moradi-Motlagh et al. (2012b) in the context of Australian banking. Both studies confirmed a positive relation between their efficiency measures and market indexes. A detailed review of all sixteen efficiency studies is presented below.

In one of the early efficiency studies using DEA, Avkiran (1999b) examined the efficiency of 23 Australian trading banks from 1986 to 1995. In this study, three areas of efficiency during the deregulation period, the effect of mergers in efficiency improvement and possible benefits of mergers to the public were investigated. Overall operating efficiency, employee productivity, profit performance and the industry mean relative efficiency scores were measured to examine the efficiency improvement during the study period. Moreover, relative efficiency scores before and after a merger were used to investigate the effect of the merger on efficiency improvement. Finally, the change in banks share of deposits in the market were used to investigate the effect of mergers on the public. Two different models under constant returns to scale were utilised to measure efficiency. In the first DEA model (Model A), interest expense and non-interest expense were defined as the input variables, and net interest income and non-interest income were defined as the output variables. In the second model (Model B), deposits and staff numbers were defined as the inputs, and net loans and non-interest income were defined as the outputs. Empirical results showed model A and B present a different picture of bank efficiency. The average efficiency scores in model A ranged from 78.99% in 1991 to 91.48% in 1986 while in model B they ranged from 37.23% in 1986 to 79.43% in 1994. The difference between the two models demonstrates that they measured different dimensions of banking performance. In the first model a profitability approach was used for selecting inputs and outputs while in the second model an intermediation approach was
used for choosing input and output variables. However, in general, Avkiran concluded both efficiency measures increased during the study period. Moreover, in three out of four merger cases, he pointed out that acquiring banks were more efficient than target banks. Nevertheless, it was not clear that the acquiring banks can maintain their pre-merger efficiencies. Finally, the author observed that mergers do not necessarily pass efficiency gains to the public. It was also shown that only half of the samples support the assumption of positive correlation between change in the market share and change in overall operating efficiency.

In the same study period of his earlier study (1986-1995), Avkiran (1999a) analysed the technical efficiency of 10 Australian banks using DEA and window analysis. More specifically, he investigated the efficiency of banks in the sample by decomposing the technical efficiency into pure technical efficiency and scale efficiency during the study period. He also probed the nature of returns to scale of individual banks and discussed the optimum size of banks. The profitability approach was used to select input and output variables. Similar to model A in his previous study, interest expense and non-interest expense were chosen as the input variables and net interest income and non-interest income were chosen as the output variables. Empirical results showed a decline on average efficiency scores before the 1990s, followed by a steady rise thereafter. However, there was no clear trend for pure technical efficiency measures during the study period. The average efficiency scores for pure technical and scale efficiency ranged from 89.9% in 1994 to 89.6% in 1986 and 95.7% in 1993 to 99.1% in 1986. It was also found that there was a significant difference between major and regional banks in terms of nature of returns to scale. While almost all regional banks tended to operate at increasing returns to scale, the major four banks operated mostly at decreasing returns to scale. The analysis showed that Macquarie and National Australian Bank were the only two banks which constantly operated at maximum productive scale size throughout the whole study period. The author concluded that regional banks may raise their efficiency by up-scaling and becoming larger. It is shown that scale efficient banks do not share a common size and mixed size of banks operating at most productive scale size. That is, reaching to the optimal
size for regional banks through targeting one of major banks may not be an appropriate policy.

Again for the same study period of 1986-1995, Avkiran (2000) investigated changes in productivity of 10 Australian banks using Malmquist productivity indices. Two inputs and two outputs of interest expense, non-interest expense, net interest income and non-interest income were chosen respectively to investigate not only overall change in productivity (total factor productivity), but also its breakdown into technical and technological changes. Results indicated that total factor productivity experienced an overall rise on average by 3.2% per year driven more by technological change than technical efficiency. More specifically, the technical efficiency increase was only 0.7% on average per year while the overall rise in technological change was 2.8% on average per year. Similarly, comparing technological change in terms of size of banks revealed that larger banks exhibited higher technological progress than smaller banks. Looking at the contribution of individual banks to the rise in total factor productivity, National Australian Bank made the largest contribution while the State Bank of NSW had the most negative impact. Finally, due to the importance of technological progress, the author believes instead of planning for mass redundancies to reduce the cost, staff who are redundant as a result of technological changes can be re-trained to be employed in selling and customer service.

Turning to the x-efficiency, Sathye (2001) applied DEA to investigate overall, technical and allocative efficiency of 29 Australian banks in 1996. In this study, three inputs of labour, capital and loanable funds and two outputs of loans and demand deposits were used to examine various efficiency measures. The author estimated the score of 58% for the overall efficiency of Australian banks which was lower than that of 86% provided by Berger and Humphrey (1997). The results indicated that the technical efficiency of Australian banks in the sample was lower than their allocative efficiency. This implies that among the two components of overall efficiency, technical efficiency was more important and there was a need for Australian banks to focus on efficient use of their resources. Furthermore,
regression analysis was used to examine the relationship between the overall efficiency indices and the size of banks, market power, ownership (domestic or foreign), use of technology and cost per employee. The regression results demonstrated that market power had a significant negative influence on overall efficiency. On the contrary, the author found that cost per employee had a positive influence on overall efficiency. Sathye’s study also provided a comparison between domestic and foreign banks’ efficiency. The author made this comparison between 17 domestic and 12 foreign banks incorporated in Australia for the year of 1996. The results showed on average domestic banks were more efficient than foreign banks and mean scores of their efficiency were closer to the world mean efficiency score. It is also concluded that the removal of the four pillars policy cannot be supported due to increasing market power concentration.

Using the DEA method, the change in the productivity of Australian banks was examined by Sathye (2002). In this study, the Malmquist index was employed to measure the productivity of 17 banks during the period 1995 to 1999. The inputs used in measuring productivity indices were interest expense and non-interest expense. The outputs used were net interest income and non-interest income. The empirical results of this study showed that the total factor productivity index declines by 3.5 per cent over the five year period. However, the mean total factor productivity and technical efficiency change remained positive. To answer the question of whether or not productivity has improved since the Wallis Inquiry in 1997, he compared productivity indices for 1996 and 1998 and found both technical efficiency and total factor productivity indices declined by 2.8% and 1.3%, respectively. The author also provided analysis results of productivity change in individual banks. Only six banks out of seventeen experienced mean technical efficiency of more than one (Adelaide bank, ANZ, Bank of Tokyo, Citibank and Macquarie Bank). Among the four major banks, ANZ was the only one that showed an increase in its technical efficiency. Moreover, two major banks (the National Australian Bank and Westpac) experienced a decline in mean technical efficiency scores. Turning to total factor productivity, the author pointed out that three major banks experienced a rise in this index in the last three years of
the study period and Westpac was the one that experienced a decline in total factor productivity. Finally, Sathye investigated the relationship between total productivity and size using a simple regression. The analysis showed that there was no correlation ($R^2 = 0.067$) between the size of banks and their total factor productivity which was an important finding in the context of mergers among banks in Australia.

Sturm and Williams (2004) employed DEA and stochastic frontier analysis to investigate the impact of foreign bank entry on banking efficiency in Australia during the period 1988-2001. To investigate this impact, the authors used two sets of models. Model 1 had three inputs of number of employees, deposits and borrowed funds and equity capital. Two outputs were loans advances and other receivables, and commitments and contingent liabilities. For comparison purposes, input and output variables of model 2 were similar to early studies by Avkiran. Accordingly, inputs were interest expense and non-interest expense, while outputs were net interest income and non-interest income. Using sample sizes of 15 banks and 13 banks for model 1 and 2, respectively, the authors found that scale inefficiency was the source of technical inefficiency in Australian banking. However, their productivity analysis results showed that Australian banks’ productivity has improved (except in model 2) and the main source of this improvement was technological change. Turning to foreign banks, the DEA results showed that they experience a higher scale efficiency compared to big four banks. They also exhibited a higher level of efficiency in comparison to domestic banks while their profit efficiency was no higher than domestic banks. Interestingly, the relationship between DEA and stochastic frontier analysis, exhibited a high correlation between scores obtained from these two approaches (parametric vs. non-parametric). Finally, the authors concluded that diversity in bank types may enhance efficiency gains and cause innovation and should be encouraged by policy makers.

Avkiran also investigated the nature of returns to scale for individual banks in the sample and determined whether they operated under constant returns to scale, increasing returns to scale or decreasing returns to scale. Similar to his previous studies, two inputs of interest expense and non-interest expense, and two outputs of net interest income and non-interest income were used. Empirical results showed that a decline in average efficiency scores until 1991 turned to a steady rise thereafter. Furthermore, looking at the source of technical inefficiency revealed that, contrary to Sturm and Williams (2004), pure technical inefficiency had a greater impact than scale inefficiency. This discrepancy may be due to the different time period and different sample banks used in the studies. In relation to individual banks, Advance Bank and Bank of Queensland were the main driving forces behind the rise in technical efficiency while the worst banks were Bank of South Australia and State Bank of NSW. Interestingly, scale efficiency results demonstrated a different picture, showing that Bank of South Australia, Macquarie and State Bank of NSW experienced a higher level of scale efficiency in comparison to other banks. It was also found that, in general, regional banks operated under increasing returns to scale while major banks operated under both decreasing returns to scale and most productive scale size. However, the author emphasised that there was no common size for banks operating at optimal returns to scale in line with Avkiran (1999a).

Neal (2004) probed productivity and x-efficiency in Australian banking using Malmquist productivity and DEA methods. Two inputs of number of branches and loanable funds, and three outputs of loans and advances, demand deposits and operating income were used to investigate efficiency and productivity of 12 sample banks during the period 1995 to 1999. The empirical results of study demonstrated that allocative efficiency was higher than technical efficiency while the mean technical efficiency index ranged between 75% and 78%. Allocative efficiency was high and its score is greater than 90%. The results also showed that overall efficiency ranged between 71% and 83% while scale efficiency ranged from 80% to 90% over the study period. Interestingly, the author found almost all medium and large banks exhibited decreasing returns to scale that is merger
between large or medium sized banks may intensify the scale inefficiency level. Turning to productivity results, total factor productivity increased by an average of 7.6% over the study period which was a significant improvement. This improvement mostly results from technological change rather than technical change which is in line with other studies that argue technical efficiency is the main source of inefficiency in Australian banking (e.g. Avkiran, 2000). Finally, for individual banks in the sample, the author points out that the average annual growth in total factor productivity ranged between -10.3% for Bank of Queensland to 16.8% for Macquarie Bank. However, interestingly, all banks experienced a positive technical change - even the worst performer, Bank of Queensland.

Kirkwood and Nahm (2006) investigated the cost efficiency of Australian banks in producing banking services and profit. Two DEA models, A and B were used to evaluate the efficiency and productivity of 10 sampled banks during the period 1995 to 2002. Model A measured banking service efficiency by viewing banks as entities using three inputs of number of employees, physical capital and interest-bearing liabilities to produce two outputs of interest-bearing assets and non-interest income. In contrast, model B measured profit efficiency by using the same inputs as model A to generate profit as the only output. In general, empirical results imply that banks under study were more efficient in transforming inputs into outputs specified in model A (banking service efficiency) rather than transforming those inputs into profit (profit efficiency). Looking at the results in terms of size, the authors revealed that larger banks exhibited an improvement in both banking service and profit efficiency while smaller banks experienced little change in banking service efficiency, and a decline in profit efficiency. Turning to the result of the productivity analysis, the authors show that total factor productivity increased by 31%. However, this rise was driven by a 33% increase in technological change while it was offset by a 2% decline in technical efficiency. Finally, for the first time the authors attempted to relate the changes in efficiency to stock returns of Australian banks. As expected, they concluded that changes in profit efficiency were statistically significant \( (R^2 = 0.29) \) in
determining stock returns of sampled banks. Interestingly, this relationship was considerably stronger ($R^2 = 0.49$) for regional banks.

Paul and Kourouche (2008) examined the pure technical and scale efficiency of 10 Australian banks using DEA during the period 1997 to 2005. Similar to majority of previous banking studies in Australia the authors used interest expense and non-interest expense as the inputs, and net interest income and non-interest income as the outputs. They also investigated the nature of scale efficiency for individual banks and whether those banks operate at the most productive scale size, increasing returns to scale or decreasing returns to scale. Empirical results showed among four major banks, National Australia Bank and Commonwealth Bank were fully efficient and operating at the most productive scale size during the period studied. In comparison, Westpac Bank was found to be the least efficient while ANZ Bank performed well and was fully efficient except in 1997 and 2005. Of the medium-sized banks, Macquarie Bank was found to be fully efficient while the other two banks (St George Bank and Suncorp Metway) in this category were found to be inefficient in both pure technical and scale efficiency for most of the years. Interestingly, although, technical efficiency of regional banks was the lowest in comparison to other two categories of large and medium sized banks, all three small banks in the sample were found to be efficient in terms of pure technical efficiency. However, these banks were suffering from scale inefficiency and operating at increasing returns to scale for most of the years. It was also found that banks that were operating at the most productive scale size did not share a common size, implying that banks with different size could reach the optimum scale size by optimizing combinations of their inputs and outputs which is in line with the finding of Avkiran (2004) and Avkiran (1999a). Finally, the authors provide a discussion on the ongoing debate concerning mergers between the four major banks. They conclude that while two of the major banks were operating at decreasing returns to scale, any merger between large banks can intensify scale inefficiency in this industry.
In an evaluation of the four pillars policy in the Australian banking sector, Wu (2008) examined the efficiency of 36 banks using DEA to investigate the impact of bank mergers and acquisitions over the period from 1983 to 2001. In the DEA model, three inputs of labour, physical capital and loanable funds were defined. Net loans, investments and number of branches were chosen as the output variables. The mean technical efficiency level of 79% for acquiring banks was significantly lower than the efficiency level of 91% for target banks. Decomposing technical efficiency into pure technical and scale efficiency revealed that scale efficiency was the main source of this diversity. Overall, the results indicate that on average the acquiring banks were larger in size and achieving lower scale efficiency and technical efficiency than the target banks. However, no significant difference between acquiring and target banks was found in terms of profitability, capital adequacy and pure technical efficiency. The study suggested that abolition of the four pillar policy and merger activities may not always improve efficiency.

Wu (2009) probed the impact of the Wallis inquiry into the Australian financial system and efficiency performance of banks by considering the time period between 1983 to 2001. To conduct this study, the author used a DEA model with three inputs and three outputs. Specifically, labour, physical capital, and loanable funds were defined as the inputs. Net loans, investment and number of branches were defined as the outputs. To investigate banking efficiency, a super efficiency model was employed on data of two groups of incumbents and entrant banks. The data set was broken into two time periods a pre-Wallis Inquiry period (1986 to 1995) and a post-Wallis Inquiry period (1996 to 2001). A Mann-Whitney non-parametric test was used to determine whether the two bank groups were equally efficient. Empirical results showed that mean efficiency was higher for incumbents than entrants in both pre-Wallis and Post-Wallis periods. However, excluding major banks form the incumbents group caused this group to become less efficient. The author also found that the relative efficiency of existing regional banks was much poorer than other medium sized and large banks, implying that the incumbents group was inefficient relative to the entrants group.
However, similar to all bank types, efficiency of existing regional banks has improved since the Wallis Inquiry. Furthermore, the results showed that the banking industry in Australia has been under pressure to improve efficiency since the Wallis Inquiry and inefficient banks will eventually be taken over by other banks. The study also concluded that the abolition of the four pillars policy may increase competition and improve efficiency in the Australian banking industry due to threat of domestic take over. Nevertheless, even without any mergers, the threat of take over itself can lead to efficiency improvement. It is also worthy of note that the author emphasized that merger among the four larger banks is only beneficial if the market remains competitive.

In a recent study, Abbott et al (2011) used both financial ratios and DEA to investigate the productivity and efficiency of four major banks during the period 1983 to 2009. In this study the inputs used were labour, physical capital and loanable funds. The outputs chosen were loans, investments and number of branches. Over the 25 years study period, technical efficiency increased in 8 years, decreased in 11 years and remained constant during the rest of the period. The greatest progress in technical efficiency occurred in 1997 and 2006 with 5.7% and 2.95 respectively. Furthermore, technological progress can be seen for most of the periods with the highest being 6.5% in 1997. In regard to Malmquest productivity, it was shown that total factor productivity increased during most of the period with the highest growth of 11.2% in 2006. The above results imply that the main driver of productivity change has been the improvement in technological change rather than technical efficiency. It is worthy to note that despite the increasing size of banks, scale efficiency has not influenced any improvements in total factor productivity which has remained unchanged.

In a comparison between the efficiency of credit unions, building societies, and commercial banks, Avkiran and Tripe (2011b) employed DEA technique to examine to what extent credit unions have been able to compete with commercial banks during the period 2006 to 2010. These two financial institutions are viewed as business units with two inputs of interest expense and non-interest expense
which are used to produce two outputs of interest income and non-interest income. The total of 24 financial institutions in this study comprises 10 credit unions, 8 building societies, and 6 commercial banks. The five year average efficiency shows that major banks were on the top of the list. More specifically, the five year average efficiency measures for banks, credit unions and building societies were 91.4%, 74.7% and 65.1%, respectively. In a statistical sense, testing the significance of such differences using the Mann-Whitney test revealed banks were more efficient than the two other groups at the 1% level and credit unions were more efficient than the building societies at the 5% level. These findings imply that taking into account an intermediation approach, banks performed better than other financial institutions in Australia during the study period.

In another recent study, Moradi-Motlagh et al (2011a) examined three aspects of profitability of six Australian banks over the period from 2000 to 2010. In this study the DuPont financial ratio analysis approach was used to develop a three stage DEA model to measure three aspects of profitability named risk, efficiency and effectiveness. In the proposed model, the outputs of each stage were assumed as the inputs of the next stage. In view of that, to measure the risk in the first stage, equity was defined as the only input and total assets and number of employees were defined as the outputs. In the second stage, total assets and number of employees were the inputs and interest income, non-interest income and deposits were the outputs used to measure efficiency. Effectiveness was measured using three inputs of interest income, non-interest income and deposits, and profit as the only output. Empirical results indicated that the effectiveness of the large banks was greater than the small sized banks. On the contrary, the small sized banks were able to obtain a higher efficiency level. In addition, the results showed some banks gain their profit as a result of taking higher risk which might not be sustainable in the longer term. The results also demonstrated that the averages of the risk scores of the small sized banks were greater than large banks during the study period.
More recently, Moradi-Motlagh et al. (2012b) examined the relationship between the total shareholder return (TSR) and performance of Australian banks over the period 2001 to 2010. In particular, this study aimed to investigate whether returns of banks in the stock market can be explained by changes in their performance. To measure the overall performance of seven banks in the sample, the authors developed a weighted financial ratio based DEA model. The proposed model in the study consisted of four financial ratios related to four main dimensions of overall performance. More specifically, profitability, growth, efficiency, and marketability are measured by return on assets, change in total assets, asset turnover and price to book value, respectively. The results showed that the average of the overall performance of the sampled banks decreased in the second half of the study period. Specifically, the average of performance between 2001 and 2005 (0.69) was greater than the period 2006 to 2010 (0.64). To examine the relationship between the overall performance and total shareholder return, changes in performance measures were regressed on TSRs. The results indicated that changes in performance were reflected in TSR implying that well-performing banks tended to generate more return for their stockholders.

Table 3-6 provides a summary of Australian banking efficiency studies. The major findings of these studies are:

1) Acquiring banks were more efficient than target banks implying the positive impact of mergers on efficiency measures. However, almost all studies warn against more mergers among major banks.

2) Almost all regional banks were operating at increasing reurns to scale while the major four banks mostly operated at decreasing returns to scale. However, scale efficient banks did not share a common size and mixed size of banks were operating at most productive scale size.

3) Overall rise in total factor productivity during the time period of 1986-1995 was driven more by technological change than technical efficiency change.

4) On average, domestic banks were more efficient during the time period between 1986 and 1995.
5) Scale inefficiency was the source of technical inefficiency during the period 1988 to 2001.

6) Diversity in bank types seems to enhance efficiency gains and causes innovation in the banking industry and should be encouraged by policy makers.

7) Profit efficiency measures were statistically significant in determining stock returns of Australian banks.

8) Australian banks perform better in terms of profit efficiency than other financial institutions such as credit unions and building societies.

9) While larger banks had a higher level of effectiveness, smaller banks performed better in terms of efficiency. However, smaller banks demonstrated a higher level of risk.

### Table 3-6: Summary of Australian Banking Efficiency Studies using DEA

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Study Period</th>
<th>Inputs</th>
<th>Outputs</th>
<th>Indexes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avkiran (1999b)</td>
<td>1986 to 1995</td>
<td>Model A Interest expense, Non-interest expense</td>
<td>Model A Net interest income, Non-interest income</td>
<td>Technical efficiency</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Model B Deposits, Staff numbers</td>
<td>Model B Net loans, Non-interest income</td>
<td></td>
</tr>
<tr>
<td>Avkiran (1999a)</td>
<td>1986 to 1995</td>
<td>Interest expense, Non-interest expense</td>
<td>Net interest income, Non-interest income</td>
<td>Pure technical efficiency</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Scale efficiency</td>
</tr>
<tr>
<td>Avkiran (2000)</td>
<td>1986 to 1995</td>
<td>Interest expense, Non-interest expense</td>
<td>Net interest income, Non-interest income</td>
<td>Malmquist productivity</td>
</tr>
<tr>
<td>Sathye (2001)</td>
<td>1996</td>
<td>Labour, Capital, Loanable Funds</td>
<td>Loans, Demand deposits</td>
<td>Overall efficiency, technical and allocative efficiency</td>
</tr>
<tr>
<td>Sathye (2002)</td>
<td>1995 to 1999</td>
<td>Interest expense, Non-interest expense</td>
<td>Net interest income, Non-interest income</td>
<td>Malmquist productivity</td>
</tr>
<tr>
<td>Sturm and Williams (2004)</td>
<td>1998 to 2001</td>
<td>Model 1 Employee numbers, Deposits and borrowed funds, Equity capital</td>
<td>Model 1 Loans advances and other receivables, Commitments and contingent liabilities</td>
<td>Technical efficiency</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Model 2 Interest expense, Non-interest expense</td>
<td>Model 2 Net interest income, Non-interest income</td>
<td>Scale efficiency</td>
</tr>
<tr>
<td>Author(s)</td>
<td>Study Period</td>
<td>Inputs</td>
<td>Outputs</td>
<td>Indexes</td>
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<td>---------------------------------</td>
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</tr>
<tr>
<td>Avkiran (2004)</td>
<td>1986 to 1995</td>
<td>Interest expense, Non-interest expense</td>
<td>Net interest income, Non-interest income</td>
<td>Pure technical efficiency Scale efficiency</td>
</tr>
<tr>
<td>Neal (2004)</td>
<td>1995 to 1999</td>
<td>Number of branches, Loanable funds</td>
<td>Loans and advances, Demand deposits, Operating income</td>
<td>Productivity x-efficiency</td>
</tr>
<tr>
<td>Kirkwood and Nahm (2006)</td>
<td>1995 to 2002</td>
<td>Model 1 Number of employees, Property, plant and equipment, Interest-bearing liabilities</td>
<td>Model 1 Interest-bearing assets, Non-interest income</td>
<td>Technical efficiency Scale efficiency Productivity</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Model 2 Number of employees, Property, plant and equipment, Interest-bearing liabilities</td>
<td>Model 2 Profit before tax and abnormal items</td>
<td></td>
</tr>
<tr>
<td>Wu (2008)</td>
<td>1983 to 2001</td>
<td>Labour, Physical capital, Loanable funds</td>
<td>Net loans, Investments, Number of branches</td>
<td>Technical efficiency Scale efficiency</td>
</tr>
<tr>
<td>Wu (2009)</td>
<td>1983 to 2001</td>
<td>Labour, Physical capital, Loanable funds</td>
<td>Net loans, Investments, Number of branches</td>
<td>Technical efficiency</td>
</tr>
<tr>
<td>Avkiran and Tripe (2011b)</td>
<td>2006 to 2010</td>
<td>Interest expense, Non-interest expense</td>
<td>Interest income, Non-interest income</td>
<td>Technical efficiency Scale efficiency</td>
</tr>
<tr>
<td>Moradi-Motlagh et al (2011a)</td>
<td>2000 to 2010</td>
<td>Stage 1 Equity</td>
<td>Stage 1 Total Asset, Number of Employees</td>
<td>Efficiency Effectiveness Risk</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Stage 2 Total Asset, Number of Employees</td>
<td>Stage 2 Interest income, Non-interest income, Deposits</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Stage 3 Interest income, Non-interest income, Deposits</td>
<td>Stage 3 Profit</td>
<td></td>
</tr>
<tr>
<td>Moradi-Motlagh et al. (2012b)</td>
<td>2001 to 2010</td>
<td>N/A</td>
<td>ROA, Change in total asset, Asset turnover, Price to book value</td>
<td>Performance</td>
</tr>
</tbody>
</table>
3.6 Efficiency Studies using Bootstrap DEA

All studies mentioned above suffer from lack of statistical precision and do not provide confidence intervals for efficiency measures due to the deterministic nature of the DEA technique. Fortunately, Simar and Wilson (1998a) proposed a practical and consistent approach combining the DEA linear programming method with bootstrap statistical techniques to enrich efficiency measures by adding the capability of testing statistical significance of efficiency estimates. Thus, this new approach allows for in depth analysis of firms’ efficiencies. Reviewing the literature shows that researchers have become increasingly interested in applying this new approach to provide more reliable and accurate results in their studies.

This section reviews some of applications of the DEA bootstrap technique in measuring the efficiency and productivity of the banking industry in different countries and attempts to provide examples to demonstrate the disparity between the original estimates and bootstrap results. In general, the majority of reviewed studies focus on the general efficiency level of banks and compare the original and bootstrap results. Specifically, the studies conducted by Tortosa-Ausina et al. (2008), Nguyen and De Borger (2008), Arjomandi et al. (2011), (Moradi-Motlagh et al. (2012a) and Sezgin (2012) provide sensitivity analysis of the efficiency and productivity of banks in Spain, Vietnam, Iran, US and Turkey. Overall, all studies confirmed the difference between the original and bootstrap results at least for some individual banks. For instance, Tortosa-Ausina et al. (2008) concluded that based on the bootstrap results some banks have more similar efficiency scores than what was obtained by the original results, and vice versa.

Apart from studies that investigate the general efficiency and productivity level of banks in individual countries using bootstrap DEA, some other topics examined include a cross-country study for European banks by Murillo-Melchior et al. (2009), the impact of liberalization in productivity and efficiency of Singaporean banks by Boon et al. (2010), the impact of government regulation in the efficiency level of Iranian banks by Arjomandi et al. (2011), the effect of financial crisis in
Turkish banks by Sezgin (2012) and an examination of different choices of input and output variables in efficiency results of Chinese banks by Matthews et al. (2009). A detail review of all above studies is provided as follows:

In an application of sensitivity analysis of efficiency and Malmquist productivity indices obtained using DEA bootstrap, Tortosa-Ausina et al. (2008) explored productivity growth and productive efficiency for 50 Spanish saving banks over the period 1992 to 1998. The results showed a growth of 119% in productivity from 1992 to 1998. Moreover, the productivity growth in all consecutive years was more than unity and all institutions experienced productivity growth with exception of five banks. The analysis showed a notable difference between the original estimates and the bootstrap results. For example, from the original results it can be concluded that one of the banks (No.19) experienced a decline of about 4.4% in productivity and another (No. 15) exhibited 3.2% growth. The bootstrap results, on the contrary showed neither of these banks had a significant change in productivity different from unity. Similarly, this shortcoming of the original results can be seen in the technical change component. For instance, a decline in technology change can be seen for 78 observations while only 9 cases were found to be significantly different from unity at the 1% level. Overall, the authors concluded that some banks had more similar efficiency scores than suggested by the original results, and vice versa.

Nguyen and De Borger (2008) analysed the efficiency and productivity of 15 Vietnamese commercial banks over the period 2003 to 2006. The bootstrap technique combined with the DEA method was employed to construct the confidence intervals for the Malmquist total factor productivity and its components. With regard to the technical efficiency, it was found that state owned banks had a higher level of efficiency than private banks in the sample. The results also suggested that technical efficiency declined substantially in the last two years of the study period. However, looking at the bootstrap results showed that this decline was statistically significant in the last year (2005/2006). Similarly, although, the mean of productivity index showed an increase between
2004 and 2005, it was not significant according to the bootstrap confidence intervals.

Matthews et al. (2009) used bootstrap DEA to examine the Malmquist productivity indices of 14 Chinese banks over the period 1997 to 2006. The study attempted to test the robustness of the results by accounting for the effect of non-performing loans. Accordingly, four models based on production and intermediation approaches were defined. In the first model using a production approach, number of employees and fixed assets were set as the input variables while total deposits, total loans, other earning assets and non-interest income were chosen as the output variables. The second model followed the intermediation approach and differs from model 1 by transferring the total deposits to the input side. Model 3 and model 4 are modified versions of above models and replace the variable of total loans less nonperforming loans by total loans in model 1 and model 2, respectively. It was found that joint-stock banks generally have better performance than other banks. The results from model 1 showed only the top five joint-stock banks experienced significant productivity gains driven by technological change. In contrast, the results derived from model 2 which followed the intermediation approach revealed no growth in productivity. It was also found that larger banks had lower productivity than smaller banks during the study period.

Using DEA bootstrap, Murillo-Melchor et al. (2009) examined productivity growth for all European banks except those in Greece during the period between 1995 to 2001. The empirical results showed a significant productivity growth of 3.3% over the entire period from 1995 to 2001. Productivity components demonstrated a different trend. While technical progress was 3.6%, efficiency showed a decline by 0.27%. However, productivity growth was not common for all European countries. In particular, Portugal, Spain, the Netherlands, Denmark and Sweden experienced a significant decline. In contrast, banks in Austria, Belgium, Finland, France, Germany, Ireland, Luxembourg and the UK experienced an increase over the study period. A comparison between the original
and bootstrap results indicates the importance of statistical approaches in analysing the efficiency of EU banks. For instance, with regard to the original results, 150 banks demonstrated a growth in technological progress measures between 1995 and 1998 while according to the bootstrap results only 86 banks experienced significant growth during the same time period. Similar evidence can be observed for changes in productivity and changes in efficiency estimates.

Boon et al. (2010) used the Malmquist index to investigate productivity, technological and efficiency change in the Singaporean banking sector during the period between 1995 to 2005. The inputs defined in the DEA model for the period 1995 to 1999 which represents pre-deregulation are customer deposits and fixed assets. The only output variable that was chosen was loans to non-bank customers. For the post-deregulation period from 2000 to 2005, the sample size reduced from 26 to 10 while personnel cost was added to the input variables. For the first period from 1995 to 1999, on average, the total factor productivity increases 1.2% due to a 48.8% improvement in efficiency. In contrast, for the second period from 2000 to 2005, the mean of total factor productivity decreased by 3.6% due to technological change. Interestingly, this comparison showed that the total factor productivity was lower in the second period after liberalization. The authors believe this decline may be explained by taking into account the different sample size in the two study periods and the effect of outliers in the samples. The authors also attempted to test the reliability of their original results using a bootstrap approach. Bootstrap findings suggested that for the period 1995 to 1999, the original estimates were not statistically significant, a result which highlights the importance of statistical analysis in efficiency studies using non-parametric methods, especially, where the sample size is small.

Arjomandi et al. (2011) employed DEA bootstrap to investigate the effect of government regulation on the performance of 14 Iranian banks during the period between 2003 and 2008. In their model, number of employees, physical capital and purchased funds were chosen as the inputs and total demand deposits, public sector loans and non-public sector loans were chosen as the outputs. The authors
provide original efficiency estimates, bias-corrected scores and confidence intervals for the two years of 2003 and 2008. The results suggest that the most efficient type of banks in both years were the specialised banks in the sample while results were mixed for private and commercial banks. It is shown that, in general, the confidence intervals were narrow and the bias-corrected efficiency scores tended to be higher in 2008 in comparison to 2003. This study also estimated the Malmquist index and its components, efficiency change and technological change. It was found that although, individual banks demonstrated different trends, overall the productivity of the banking industry declined since the introduction of regulations launched in 2005 that obligated all banks to reduce deposit and loan interest rates. Particularly, productivity fell significantly in 2007-2008 largely due to the substantial rise in the banks’ non-performing loans as a result of the regulations.

George Assaf et al. (2011) analysed the productivity and efficiency of 291 Shinkin banks in Japan over the period from 2000 to 2006. The study employed two methods of bootstrap Malmquist index and Bayesian approach to estimate the efficiency and productivity growth of sample banks. Looking at the confidence intervals of the average efficiency and productivity growth indicates that neither efficiency or productivity estimates were significantly improved during the study period. To further explain the efficiency and productivity growth at Shrinkin banks, the authors regressed productivity and efficiency scores on some explanatory variables including market share on deposits, number of branches, return on assets, net interest margin and concentration ratio of deposits. Empirical results showed that apart from net interest margin, all other explanatory variables significantly influenced both efficiency and productivity growth of the banks in the sample.

Recently, Moradi-Motlagh et al. (2012a) examined the technical efficiency of a sample of 100 large US banks in 2010. Using the profit approach, two inputs were defined as interest expense and non-interest expense and two outputs were defined as interest income and non-interest income. The results based on the DEA method
revealed a high level of inefficiency. A comparison between the original and bootstrap results showed a significant bias in the original estimates. For instance, while considering the original results, JPMorgan Chase Bank seemed fully efficient; the bias-corrected results, however, demonstrated a high level of inefficiency. The authors also investigated the scale efficiency of the US banks and concluded that only two banks operate at optimal scale, meaning that, the US banks suffered from a high level of scale inefficiency. More precisely, one may conclude that the scale inefficiency was the main source of inefficiency in this industry. The results also show that large banks experienced decreasing returns to scale, while smaller banks suffered from increasing returns to scale.

More recently, Sezgin (2012) investigated the technical efficiency of 13 Turkish banks in 2010 using bootstrap DEA. Three ratios of equities/total assets, credits obtained/total assets and liquid assets/total assets were defined as the inputs. Two outputs were defined as the ratios of profit/total assets and total operating income/total assets. A comparison between the original and bootstrap results revealed a significant difference between the results. For instance, while the original result showed the Merrill Lynch Yatirirm Bank and GSD Yaritim Bank were equally and fully efficient, the bias corrected results revealed Merrill Lynch Yatirirm Bank was more efficient than its counterparts. The authors also concluded that Turkish banks have not been affected by the global financial crisis and were able to maintain their solid performance.

A summary of efficiency studies using bootstrap DEA are illustrated in Table 3-7. It is found in almost all studies that statistical properties of efficiency estimates influence the results and conclusions. The disparity between the original and bootstrap results was more obvious at individual bank level. Overall, reviewing these studies confirms the necessity of using statistical approaches in nonparametric efficiency analysis to avoid misleading results. This problem is also more prominent when the sample size is small.
Table 3-7: Summary of Banking Efficiency Studies using Bootstrap DEA

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Study Period</th>
<th>Country</th>
<th>Number of banks</th>
<th>Inputs</th>
<th>Outputs</th>
<th>Indexes</th>
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<tr>
<td>Tortosa-Ausina et al. (2008)</td>
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<td>Spain</td>
<td>50</td>
<td>Total labor expense, Physical capital, Purchased funds</td>
<td>Total loans, Total deposits, Non-interest income</td>
<td>Productivity, Technical efficiency</td>
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<td>Matthews et al. (2009)</td>
<td>1997 to 2006</td>
<td>China</td>
<td>14</td>
<td>Model 1: Number of employees, Fixed assets</td>
<td>Productivity</td>
<td>Changes in efficiency, Changes in technology</td>
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<td>Model 2: Number of employees, Fixed assets, Total deposits,</td>
<td>Productivity</td>
<td>Changes in efficiency, Changes in technology</td>
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<td>Model 3: Number of employees, Fixed assets, Total deposits,</td>
<td>Productivity</td>
<td>Changes in efficiency, Changes in technology</td>
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<td>Model 4: Number of employees, Fixed assets, Total deposits</td>
<td>Productivity</td>
<td>Changes in efficiency, Changes in technology</td>
</tr>
<tr>
<td>Murillo-Melchor et al. (2009)</td>
<td>1995 to 2001</td>
<td>Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, UK</td>
<td>571</td>
<td>Total labour expense, Physical capital, Borrowed funds</td>
<td>Customer loans, Deposits, Securities and equity investments, Earning assets, Non-interest income</td>
<td>Productivity, Changes in efficiency, Changes in technology</td>
</tr>
<tr>
<td>Boon et al. (2010)</td>
<td>1995 to 2005</td>
<td>Singapore</td>
<td>26</td>
<td>Customer deposits, Fixed assets, Personnel cost</td>
<td>Loans to non-bank customers</td>
<td>Productivity, Changes in efficiency, Changes in technology</td>
</tr>
<tr>
<td>Arjomandi et al. (2011)</td>
<td>2003 to 2008</td>
<td>Iran</td>
<td>14</td>
<td>Number of employees, Physical capital, Purchased funds</td>
<td>Total demand deposits, Public sector loans, Non-public sector loans</td>
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</tr>
<tr>
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<td>Study Period</td>
<td>Country</td>
<td>Number of banks</td>
<td>Inputs</td>
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<td>Indexes</td>
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<td>Moradi-Motlagh et al. (2012a)</td>
<td>2010</td>
<td>United States</td>
<td>100</td>
<td>Interest expense, Non-interest expense</td>
<td>Interest income, Non-interest income</td>
<td>Technical efficiency, Scale efficiency</td>
</tr>
<tr>
<td>Sezgin (2012)</td>
<td>2012</td>
<td>Turkey</td>
<td>13</td>
<td>Equities/total assets, Credits, obtained/total assets, Liquid assets/total assets</td>
<td>Profit/total assets, Total operating, income/total assets</td>
<td>Technical efficiency</td>
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### 3.7 Summary

Financial ratios have been employed traditionally as a tool to measure and analyse organisational performance of financial institutions. However, financial ratios suffer from some important drawbacks described in this chapter. Frontier analysis techniques are a suitable alternative for traditional measures which provide more comprehensive and reliable measures by estimating the relative efficiency of production units in comparison with the best practices which construct the production function. In general, the frontier analysis approach can be undertaken using parametric and non-parametric methods. However, it is suggested that non-parametric methods deal better with small sample sizes compared to parametric methods. Due to the limited number of banks in Australia, non-parametric methods seem more appropriate in examining the efficiency and productivity of Australian banks.

Consistent with the majority of earlier works, this study focuses on the application of non-parametric methods in the banking sector.

The literature on efficiency analysis of financial institutions using the DEA method as a non-parametric technique has expanded rapidly due to its advantages and the shortcomings of traditional efficiency measures. This chapter outlined the results of banking efficiency studies in more than 100 countries. These studies...
investigate the following issues 1) the impact of government policies such as deregulation and mergers on efficiency and productivity of banks 2) examination of the performance of individual banks and comparison and ranking of banks against other rivals in the sample 3) examination of the relationship between efficiency measures and some explanatory factors such as size and ownership 4) development and modification of DEA models and presentation and interpretation of the results of new proposed models 5) investigation of the effect of input and output selections and comparison of the results of different approaches 6) comparison of the result of different methods such as parametric vs. non-parametric approaches.

The outcomes from the above applications sometimes provide contradictory results. For instance, while, mergers and acquisitions during the 1990s have positively influenced the efficiency of Spanish banks, the results from an efficiency study on German and Austrian banks demonstrate no significant improvement in efficiency of 120 banks in the sample, despite the deregulation and merger waves of the 1990s. Another example shows liberalization and deregulation had a positive impact on productivity of Greek banks while an empirical efficiency analysis of Indian banks concludes that no significant improvement can be seen in the number of efficient banks after the liberalisation period and that some banks experience a high level of inefficiency during the period of liberalisation. This implies that comparison between efficiency measures in different countries may not provide similar results due to the relative nature of efficiency estimates and the different economic and regulatory environments.

Finally, this chapter discusses the deterministic nature of the DEA estimates and the application of the recent bootstrap procedure initially developed by Simar and Wilson (1998a) to address this issue. This new procedure solves the main drawback of the DEA technique as a deterministic approach and adds statistical precision to the list of advantages of this non-parametric method. Recently, academics and researches have become more interested in improving efficiency analysis by providing statistical precision in the DEA results. Unfortunately, to
the best of my knowledge, no statistical properties of efficiency estimates are provided in efficiency analysis of Australian banks. Thus, all earlier studies in this country suffer from the lack of statistical significance of the efficiency estimates.
4 Chapter Four: Efficiency Measurement Methods

4.1 Introduction

Efficiency analysis is one of the crucial aspects of organisational performance studies. Efficiency represents how well a business unit utilises its resources to provide intended goods and services. Efficiency and productivity are not clearly distinguished in some studies and measured by the ratio of outputs to inputs. Although usually authors do not suggest that there is any difference between productivity and efficiency, Daraio and Simar (2007) provide distinctly different definitions. Specifically, they define efficiency as the distance between the quantity of input and output of a firm, and the quantity of input and output of the best possible frontier for a firm in a cluster of firms in an industry in which the firm operates. Moreover, they argue that the measure of efficiency is more accurate than the measure of productivity in the sense that efficiency is measured based on the distance of a given point to the best practises (called frontiers) while productivity is only based on the ratio of outputs on inputs.

Financial ratios traditionally have been used in efficiency analysis because of their simplicity and ease of understanding. Although, the use of financial ratios assists the evaluation of organisational performance, there are several limitations with such ratios that should be considered where they are applied. An unlimited number of ratios that can be created from financial statement data and are often contradictory and confusing, thus inappropriate for the assessment of overall performance (Paradi et al., 2004). Failure to account for generating an overall performance measure, combined with the inability to distinguish between the
performance of different firms make financial ratios analysis inadequate as the sole tool in performance measurement studies. Additionally, it is very common that a business unit is shown as performing well based on one ratio and performing badly based on another.

To overcome the above limitations, an alternative form of analysis involves frontier techniques which are essentially methods to estimate production frontiers and measure efficiency of business units relative to the constructed frontiers. The application of frontier methods is becoming more prevalent in efficiency studies (e.g., Asmild et al., 2004, Chang et al., 1998, Drake, 2001, Fiorentino et al., 2006, Lin and Zhang, 2009, Parker et al., 2007, Vu and Turnell, 2011, Williams, 2003).

In examining the advantages of the frontier analysis approach, Bauer (1990) identifies a number of reasons as to why the use of frontier models is becoming increasingly widespread. They include:

- Consistency of the frontier approach (production or cost frontier) with the principal economic theory of optimising behaviour.
- The ability to interpret the distance of any economic unit from the constructed frontier as a measure of efficiency.
- The fact that it assists policy making by providing useful information about the best practices and the relative efficiency of economic units.

Due to its advantages over traditional methods, it is not surprising that frontier analysis methods are widely applied in efficiency measurement of financial institutions in many countries. For instance, in a survey on 130 studies that apply frontier efficiency analysis to financial institutions in 21 countries, Berger and Humphrey (1997) identify that frontier methods have been applied in:

- Examining the effect of deregulations, mergers, or market structure on efficiency to inform government policies.
- Describing the efficiency of industries and ranking individual firms operate in a particular industry.
- Examining the difference between various efficiency analysis methods and the effect of their application on obtained results.
- Providing useful information which helps to identify opportunities for improvement of managerial performance by identifying ‘best practices’ and ‘worst practices’

Despite the wide applications of frontier models, they suffer from a number of drawbacks. For instance, Data Envelopment Analysis (DEA) as the most applied non-parametric method suffers from the lack of statistical precision of efficiency estimates. This chapter address this issue in estimating scale efficiency as detailed in Section 4.7.

The reminder of this chapter is organised as follows. Section 4.2 presents an introductory overview of the frontier methods including parametric and non-parametric models. Section 4.3 discusses the history and applications of Data Envelopment Analysis (DEA) as the most applied non-parametric method and its basic models. Section 4.4 introduces more advance DEA models which increase discriminatory power of efficiency estimates. Section 4.5 discusses the statistical approach of bootstrapping and its applications. Section 4.6 outlines the application of the bootstrap method in providing statistical properties of DEA efficiency estimates. Section 4.7 and Section 4.8 introduce our methodological contributions. Specifically, Section 4.7 introduces a new bootstrap procedure to provide statistical properties of DEA scale efficiency estimates. It also discusses how statistical hypothesis testing can be conducted to test the nature of returns to scale. Section 4.8 introduces the efficiency matrix as an analytical tool to demonstrate confidence intervals of pure technical and scale efficiencies which visualizes the source of technical inefficiency. Section 4.9 provides a summary of the above discussions.
4.2 Frontier Methods

The economic theory underlying efficiency analysis dates back to the work of Koopmans (1951), Debreu (1951) and Farrell (1957) who made the first attempt at empirical estimation of efficiencies for a set of observed production units (Simar and Wilson, 2008). For purposes of efficiency analysis economic theory attempts to estimate production frontiers or efficient boundaries. Production frontiers represent the maximum attainable outputs from provided inputs. Hence, a production frontier reveals the current status of technology in a particular industry.

Berger and Humphrey (1997) summarize the power of frontier analysis. First, frontier analysis assists analysts to select ‘best practice’ organisations within an industry (or best practice branches within the organisation), assign numerical efficiency values, broadly identify areas of input overuse and/or output underproduction, and relate these results to questions of government policy or academic research interest. Second, frontier analysis also assists managers and decision makers in identifying best practices within the complex service operations. Third, frontier analysis techniques use powerful optimizing methodologies such as linear programming to provide necessary information supporting managerial decisions which traditional benchmarking techniques are not able to offer.

To illustrate frontier analysis application, it is useful to consider a simple production process in Figure 4-1 where a single input $x$ is utilized to produce a single output $y$. The line $0P$ in Figure 4-1 demonstrates the production frontier (technology) which represents the maximum output attainable from available inputs. A firm on the frontier line is deemed technically efficient. On the other hand, if a firm is placed beneath the frontier it is technically inefficient. As shown in Figure 4-1, the point A is inefficient as a firm could technically increase its output to the level point A1 without requiring more input or decrease its input to the level of point A2 while producing the same amount of output. Moreover, the
hatched area in Figure 4-1 illustrates the feasible production set which demonstrates all feasible combinations of input and output variables.

**Figure 4-1: Production Frontier**

Measuring efficiency using the frontier approach requires first to determine what the boundary of the production set can be and then estimating the distance between a given unit and the boundary of the production function. By expanding the above concept to a multi-input and multi-output environment where \( p \) inputs \((x \in R^+_p)\) produce \( q \) outputs \((y \in R^+_q)\) a production set may defined as

\[
\varphi = \{ (x,y) \in R^+_{p+q} | x \text{ can produce } y \} 
\]

(4-1)

The production set \( \varphi \) consists of all input/output vectors, such that \( x \) can produce \( y \). As mentioned before, for the purpose of efficiency measurement, estimating the efficient boundary (upper boundary of \( \varphi \)) called the production technology (frontier) is of interest. This boundary may be defined in terms of inputs or outputs as:

\[
\varphi^\text{input}_b = \{ (x,y) \in \varphi | (\theta x, y) \notin \varphi, \forall 0 < \theta < 1 \}
\]

(4-2)
\[ \varphi_b^{\text{output}} = \{(x, y) \in \varphi | (x, \lambda y) \notin \varphi, \forall \lambda > 1\} \] (4-3)

The above sets respectively illustrate the minimum level of input to produce the given output and the maximum level of output using the given inputs. The production set may defined by its sections either input or output orientated as follows:

\[ X(y) = \{x \in \mathbb{R}_b^+ | (x, y) \in \varphi\} \] (4-4)

\[ Y(x) = \{y \in \mathbb{R}_d^+ | (x, y) \in \varphi\} \] (4-5)

In a multi-input, multi-output production technology, distance functions are widely used to measure efficiency and productivity. In an input distance function the production frontier is constructed by taking into consideration a minimum proportional decrease of the input vector, given an output vector. On the contrary, an output distance function is defined as a maximum proportional increase of the output vector, given an input vector (Coelli, 2005). Accordingly, input and output Farrell distance functions for a particular point \((x_i, y_i)\) are given by

\[ \theta_i = \inf \{\theta | \theta x_i \in X(y_i)\} \] (4-6)

\[ \lambda_i = \sup \{\lambda | \lambda y_i \in Y(x_i)\} \] (4-7)

The input distance measure of \(\theta_i\) demonstrates the proportionate reduction in inputs needed for the point \((x_i, y_i)\) to be technically efficient. Similarly, taking the output-oriented model, the output distance measure of \(\lambda_i\) demonstrates the proportionate increase of outputs required for the point \((x_i, y_i)\) to be technically efficient. Both the input and output distance functions are the radial measures of technical efficiency and may be estimated using two diverse approaches: i) parametric (known as the econometric methods) ii) nonparametric (known as mathematical programming models). Although, some studies have attempted to compare these approaches in practice, no consensus has arisen on the preferred
method for estimating relative efficiencies. For instance, Berger and Humphrey (1997) believe that it is not possible to determine which of these approaches has preference over the other where the true level of efficiency is unknown. A summary of both approaches is presented in the following sections:

4.2.1 Parametric Methods

Parametric methods are widely used in efficiency studies. They impose a functional form on the production technology to describe the transformation of inputs into outputs. These functional forms vary from simple (such as Linear or Cobb Douglas function) to complex (such as Normalised Quadratic or Translog functions). In this approach, the deviation from the supposed technology is composed of a random error (statistical noise) and inefficiency. Random errors are assumed normally distributed while inefficiencies are assumed to have an asymmetric half-normal distribution. The random errors generally include environmental variables outside the control of firms and econometric errors like data measurement errors.

The main advantages of parametric methods are the ability to apply economic interpretation to the parameters and the statistical properties of estimators while the main disadvantages are the possibility of a wrong choice of function form and difficulties in handling multiple inputs/outputs problems (Daraio and Simar, 2007). As the focus of this study is on application of non-parametric models, this section only briefly introduces three main parametric models the Stochastic Frontier Analysis (SFA), Distribution Free Approach (DFA) and Tick Frontier Approach (TFA).

Stochastic Frontier Analysis (SFA)

Stochastic frontier analysis is a method of economic modelling which has been widely used to estimate technical inefficiencies of production firms. SFA has its roots in the early work of Aigner and Chu (1968). However, their deterministic frontier model suffers from not taking into account measurement errors and other noise upon the frontier. To address these issues, Aigner et al (1977) and Meeusen
and Van Den Broeck (1977) independently introduced a stochastic frontier production function which involved adding an additional symmetric random error variable into the earlier model. That is, this production frontier function consists of a production function of the usual regression type but with an error term equal to the sum of two parts. The first part is typically assumed to be normally distributed and represents the usual statistical noise beyond the control of the firm. The second part represents technical efficiency which can be interpreted as a failure to produce the maximum output using a set of given inputs. The output is bounded by a frontier that includes the deterministic part of the regression and the error part which represents noise, subsequently the frontier is stochastic (Schmidt and Sickles, 1984).

SFA can be utilized to examine a variety of efficiency measures such as technical efficiency, pure technical efficiency, scale efficiency, allocative efficiency and the Malmquest Productivity Index. The use of stochastic frontier models is recommended by Simar (1996) in situations where outliers cannot be identified and eliminated in deterministic models. For more details, interested readers may refer to Kumbhakar and Lovell (2003).

*Distribution Free Approach (DFA)*

The Distribution Free Approach was originally suggested by Schmidt and Sickles (1984). Similar to SFA it assumes a functional form for the production technology but unlike SFA, the DFA approach is relatively "distribution free" which means it does not impose a specific shape on the distribution of efficiency nor does it impose strong assumptions regarding random errors. In this method deviations within one group of firms are defined as random errors and deviations between groups are defined as inefficiencies. DFA assumes that efficiency variations are stable over time while random error averages are not (Berger et al., 1993).

*Thick Frontier Approach (TFA)*

Another popular method called 'thick frontier analysis' or TFA was introduced by Berger and Humphrey(1991). In this method, firms are separated by size and the
thick frontier is estimated based on the lower quartile of average costs in each of the several size categories. The deviations from predicted costs within the lowest average cost quartile of firms represent random errors and deviations of predicted cost between the highest and lowest quartiles represent inefficiency.

TFA estimates separate cost functions for the lowest and highest average cost quartile. The residuals for both functions represent only random errors, while the predicted difference between the two functions represents x-efficiency difference (Berger and Humphrey, 1991). This method measures a general level of overall efficiency, rather than a point estimate for individual firms. It is useful in order to reduce the effect of outliers in the sample.

It should be noted that allowing for noise in frontier models presents difficult problems. Parametric models can be highly problematic where, in the data generating process, inefficiency is reflected by a one-sided error process and the statistical noise is reflected by a two-sided error process. Unfortunately, this problem cannot be solved for numerical identification of the model even for large (but finite) samples (Simar and Wilson, 2008). They estimate only expected efficiency scores rather than the actual efficiency scores. Finally, there is always a possibility of drawing samples with the wrong skewness (see Simar and Wilson (2008) for more details).

**4.2.2 Non-parametric Methods**

The advantage of the non-parametric approach is that there is no need for imposing any functional form for the frontier (Daraio and Simar, 2007). The non-parametric studies require less assumption on the frontier but impose the cost of not allowing for random errors. Therefore, measured efficiency deviates from the true efficiency frontier where random error exists (Berger and Humphrey, 1997).

There are two main nonparametric approaches in the literature - Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH). The FDH estimator
was initially proposed by Deprins et al. (1984). It relies on the free disposability assumption and does not require the convexity assumption. More details on the FDH can be found in Simar and Wilson (2008). On the other hand, the DEA estimators use the convex cone (rather than the convex hull) of the FDH estimators which may be appropriate if returns to scale are constant. This method and its applications are detailed in the following sections.

Similar to all other methods, nonparametric techniques have their own advantages and disadvantages. The main advantage of this approach is the robustness to model choice and the capability of handling multiple inputs and multiple outputs (Daraio and Simar, 2007). On the other hand, a key draw back of the nonparametric approaches is that they assume no measurement error in constructing the frontier. This section introduces both DEA and FDH methods while focusing on DEA and its application.

*Data Envelopment Analysis (DEA)*

Generally non-parametric methods are known as DEA. Common DEA methods and their history are detailed in section 4.3.

*Free Disposal Hull (FDH)*

The FDH estimator, proposed by Deprins et al. (1984), is a more general version of the DEA estimator as it relies only on the free disposability assumption and hence does not impose convex restrictions (Daraio and Simar, 2007). It needs to be noted that the principal advantage of FDH analysis is that it utilizes a single observed unit as the basis for comparison and efficiency evaluation of desired units. An observed unit is considered as a reference instead of a convex combination of them which is not observed. Both the DEA and FDH are consistent estimators where the true production set is convex. However, FDH requires less assumption than DEA and demonstrates a lower rate of convergence. On the contrary, if the true production set is not convex then FDH is a consistent estimator of the production set while DEA is not consistent in such cases. Some researchers have raised questions about the economic meaning of FDH, but from
the discussion between Thrall (1999) and Cherchye et al. (2000), it appears that FDH can be economically more meaningful than convex monotone hull (Daraio and Simar, 2007). Figure 4-2 demonstrates the difference between frontier lines in the DEA and FDH models in a single input, single output technology.

**Figure 4-2: A Comparison between FDH and DEA Frontiers**

FDH is a mixed integer programming problem as the choice of weights for variables in the model is 0 or 1. However, the restriction requiring the summation of weights to be 1 makes this problem much easier to solve. More details and formulas of the FDH method are provided in the original study conducted by Deprins et al. (1984).

### 4.3 Data Envelopment Analysis (DEA)

#### 4.3.1 Introduction

Data Envelopment Analysis (DEA) is a non-parametric method of measuring the efficiency that can assist in the identification of best practices in the use of resources among a homogeneous set of peer entities called Decision Making Units (DMUs). A DMU is a generic term which can be a firm, a department or branch of an organisation, a country, a region or a city. Generally, DEA models measure relative efficiency scores of DMUs relative to similar DMUs in the population which form the best practises. DEA has been widely applied in
examining the efficiency of many different kinds of units involved in different activities and businesses in numerous countries (Cooper et al., 2007).

The main reason that DEA can be used in many different industries to measure performance lies in its advantage over parametric techniques. That is, it does not require imposing a functional form to define the relationship between inputs and outputs which can be very complex by nature. The capability of DEA on constructing the best-practice frontier and introducing a new way for measuring and analysing the efficiency of individual business units has resulted in new managerial and theoretical insights (Charnes et al., 1994).

Recent studies demonstrate that DEA is becoming a popular method for efficiency analysis. For instance, Emrouznejad et al. (2008) present a bibliography which includes most of the references published in the field of DEA from 1975 to 2007 which identifies more than 4000 research articles published in journals or book chapters. To demonstrate ongoing expansion of DEA applications and developments, they point out that counting unpublished dissertations, working/research manuscripts, and papers presented at conferences, the bibliography could have exceeded 7000 entities. Moreover, they provide some statistics and insight on DEA applications such as the distribution of DEA publications by year as illustrated in Figure 4-3. They also emphasise that this trend will continue in the future.

The role and importance of DEA in efficiency analysis has been emphasised in another recent study by Fethi and Pasiouras (2010) who review 196 studies which employ operational research and artificial intelligence techniques in the assessment of banks' performance. They conclude that DEA is the most widely applied operations research technique in this field.
DEA is a nonparametric method based on mathematical programming methodologies which incorporate convexity assumptions to measure the efficiency of DMUs. As a linear programming method, DEA can handle a large number of variables thus relaxing the limitation imposed on the number of inputs and outputs by some other techniques. Relaxing the input/output limitation makes DEA a suitable method of dealing with complex problems in multi-input/multi-output environments. Extensive mathematical programming methodologies and techniques are available which can be used by analysts and decision makers to develop and enhance DEA method capabilities. Moreover, programming and software solutions needed to apply DEA have already been developed and a variety of software applications are now freely or commercially available. DEA also provides opportunities to answer “what if” questions, address benchmarking practices and compare possible scenarios to analyse behaviours of rivals in efficiency studies.

DEA also has additional advantages. First, not only is DEA able to estimate amounts of inefficiency but it also is capable of identifying sources of inefficiency in each input and each output for each business unit. Second, DEA is able to estimate the frontier technology and identify benchmark units to measure the efficiency of other units and sources of their inefficiency (Cooper et al., 2007).
All of the above features of DEA highlight possible efficiency improvement opportunities that may help managers and decision makers enhance the efficiency of their firms or business units.

Although, the idea of DEA estimators was first introduced by Farrell (1957) to measure technical efficiency for a group of firms, the idea did not develop in its present form until the paper by Charnes et al. (1978) appeared 21 years later (Simar and Wilson, 2008). Since DEA in its present form was first introduced by Charnes et al. (1978), researchers and academics with different backgrounds have acknowledged that it is an excellent and rather easily used methodology for efficiency analysis in their fields (Cooper et al., 2011a). In their originating study, Charnes et al. (1978) described DEA as a ‘mathematical programming model applied to observational data [which] provides a new way of obtaining empirical estimates of relations - such as the production functions and/or efficient production possibility surfaces – that are cornerstones of modern economics.’

4.3.2 DEA and Regression Analysis

To discuss DEA in more detail it is necessary to look at its distinctions in comparison to other efficiency measurement techniques. In essence, DEA is a technique directed to best practice frontiers rather than the center of the data similar to statistical regression. In contrast to parametric approaches which use a single regression through the data, DEA focuses on each individual unit by constructing a piecewise frontier determined by the set of Pareto-efficient DMUs (Charnes et al., 1994). Basically, DEA involves the use of linear programming techniques to construct a non-parametric piece-wise frontier over the data (Coelli, 2005).
Figure 4-4: Comparison of DEA and Regression.

Figure 4-4 represents the difference between the DEA and the regression approach. The solid line in the figure illustrates the frontier derived by the DEA method while the dotted line demonstrates the population average. The efficiency score for each DMU relative to all other DMUs is estimated by measuring the distance between the desired point and the estimated frontier.

4.3.3 DEA Advantages

DEA as an analytical technique offers a number of unique and advantageous features which open new insights in the field of efficiency and productivity analysis. The key advantage of DEA over parametric techniques lies in its ability to deal with multi-input multi-output environments where production technology is unknown. Consequently, DEA is able to model complex multidimensional operations to provide a single score to measure the efficiency and productivity of firms or business units. Moreover, DEA has the advantage of avoiding the need for assigning a priori weight or price to any input or output.
4.3.4 Input and Output Oriented Models

DEA methods typically measure technical efficiency in one of the two following ways. Input oriented models measure the possible reduction in the input level of a firm while producing the given level of output. On the other hand, output oriented models measure how a firm can increase its output while holding inputs fixed (Burgess and Wilson, 1996). In DEA models a relative efficiency measure is estimated for each DMU in comparison to other DMUs in the sample. A DMU is fully efficient in an input-oriented model in comparison with other DMUs if its inputs cannot be decreased without declining it's outputs. On the contrary, in an output-oriented model, a DMU is fully efficient if its output cannot be decreased without increasing its inputs.

From a technical view point, there is no distinction among these two approaches and either the input or the output oriented method can be used. However, the way of looking at the direction towards the frontier will basically depend on the case under study. For instance, the input oriented approach is preferred where the outputs are exogenous and not under the control of managers or decision makers. On the other hand, the output oriented approach is suitable where inputs are not under the control of managers and decision makers.

The advent of DEA in 1978 has led to the establishment of interrelationships between engineering and economic approaches in the field of efficiency measurement and has provided new ways of interpreting evaluating and improving the efficiency of public programs (Charnes et al., 1978). An appealing property of the DEA method is that multiple-input, multiple-output operations can be modelled without any assumptions regarding the form of production function and cost data, unlike the standard cost-function approach (Lothgren and Tambour, 1999a).

4.3.5 DEA Highlights and Pitfalls

DEA’s outstanding features are summarized as:
- Possibility of utilizing multiple inputs and multiple outputs with different units
- Do not require any assumption on the functional form of variables
- It is value free and does not require any prior weight or value for input and output variables (non-reliance on price information)
- Produces a single aggregate score
- Exogenous variables can be added to models

However, there are some critical factors that should be considered in the application of DEA models. For instance, Dyson et al(2001) present some of the pitfalls relating to homogeneity of the units under assessment, the input and output sets, the measurement of variables and their attributed weight. They also suggest protocols to address these issues and guide the application of the methodology in order to avoid the possible pitfalls. Similarly, Angulo-Meza and Lins (2002) highlight three drawbacks of DEA. They are:

1) Lack of discrimination among efficient DMUs that occurs specially when the number of samples is relatively small compared to the total number of inputs and outputs
(2) Inappropriate and unreal weighting. For instance, assigning higher weights to variables with less importance or assigning less or even zero weights to significant variables;
(3) In addition to common drawbacks of traditional DEA methods, DEA cannot deal with negative inputs or outputs.

Focusing on statistical aspects, Simar and Wilson (2000) list some drawbacks of the DEA method as follows:

(1) As results are asymptotic they may be misleading for small samples
(2) Additional noise is introduced when constructing estimates of confidence intervals; and
Most applications of the DEA estimators have involved multivariate frameworks.

To address these issues, Simar and Wilson (1998b) propose an algorithm based on Efron (1979) bootstrapping techniques to provide statistical inferences and confidence intervals to analyse the efficiency of DMUs which is detailed in the following sections.

4.3.6 CCR Model

The initial DEA model known as CCR, as originally presented in Charnes et al. (1978), developed on the assumption of constant returns to scale. To demonstrate the CCR model graphically, suppose a production set with a single input (x) and output (y) in Figure 4-5. The production frontier line is drawn to connect the origin to other points that covers all other pints. As shown in Figure 4-5, the hatched area below the production frontier line is named the production set. The CCR model is based on this assumption that if (x,y) is a feasible point in the production set, then (tx,ty) for any value of t >1 is also feasible. Efficiency scores are measured relative to the production frontier. That is, for any point in the production set, the efficiency score can be estimated by measuring the distance between the given point to the production frontier line.

Figure 4-5: Production Set for CCR Model
Suppose that there are n DMUs, each with p inputs and q outputs, the relative efficiency score of a DMU \( k \) under assumption of constant returns to scale is the maximum of a ratio of weighted outputs to weighted inputs obtained by solving the following linear programming.

\[
\text{Max} \sum_{i=1}^{q} \frac{v_i y_{ik}}{\sum_{j=1}^{p} u_j x_{jk}}
\]

Subject to
\[
\sum_{i=1}^{q} \frac{v_i y_{ir}}{\sum_{j=1}^{p} u_j x_{jr}} \leq 1, \quad r = 1, \ldots, n
\]
\[ v_i, u_j \geq 0 \quad \forall i, j \quad (4-8) \]

Where

\( i = 1 \) to \( q \),
\( j = 1 \) to \( p \),
\( r = 1 \) to \( n \),
\( y_{ir} \) = the \( i \)th output of the \( r \)th DMU
\( x_{jr} \) = the \( j \)th input of the \( r \)th DMU

By solving the above mathematical model the optimal weights are estimated. This involves estimating values for weights of \( u \) and \( v \) for each type of input and output such that the efficiency ratio for the \( r \)th DMU is maximised, subject to the condition that the ratio of the summation of weighted all outputs to inputs must be less than or equal to unity. Unfortunately, this form of ratio mathematical model provides an infinite number of solutions. To prevent this problem, as detailed in Charnes et al (1978) the fractional program shown in (4-8) can be converted to a linear programming (multiplier form) as follows:

\[
\text{Max} \sum_{i=1}^{q} v_i y_{ik}
\]

Subject to
\[
\sum_{j=1}^{p} u_j x_{jk} = 1
\]
\[ \sum_{i=1}^{q} v_i y_{ir} - \sum_{j=1}^{p} u_j x_{jr} \leq 0, \quad r = 1, \ldots, n \]
\[ v_i, u_j \geq 0 \quad \forall i, j \]  \hspace{1cm} (4-9)

The above liner model is run \( n \) times to gain the relative efficiency scores of all DMUs. Each DMU choses input and output weights that maximize the summation of its weighted outputs in the objective function subject to constrains shown in (4-9). Using the duality in linear programming, the equivalent envelopment form of the linear programming of (4-9) can be converted to its dual form (envelopment form) as follows:

**Min \( \theta \)**

Subject to
\[ \sum_{r=1}^{n} \lambda_r x_{rj} - \theta x_{rk} \leq 0, \quad j = 1, \ldots, p \]
\[ \sum_{r=1}^{n} \lambda_r y_{ri} - y_{rk} \geq 0, \quad i = 1, \ldots, q \]
\[ \lambda_r \geq 0, \quad r = 1, \ldots, n \]  \hspace{1cm} (4-10)

Where

\( \theta = \) Efficiency score
\( \lambda = \) dual variable

The above liner programming is run \( n \) times to obtain the relative efficiency scores of all in the sample. Based on this envelopment form, a DMU is deemed inefficient if a linear combination of all DMUs can be found which utilizes less inputs while produces the same level of outputs or greater. The composition of DMUs with positive weights in each run can be used as benchmarks for improving the inefficient DMU. In other words, this version of the CCR model aims to minimize inputs while producing at least the same level of output. As discussed before, this model which minimizes the input is called the input oriented model. Similarly, the other model called the output oriented model attempts to maximize outputs without requiring a higher level of inputs.
As a general rule, in an input-oriented model efficiency scores are rated on 0 to 1 scale and a DMU is deemed to be efficient if it obtains a score of unity while a score less than unity implies that it is inefficient.

### 4.3.7 BCC Model

Technical efficiency is a measure of how efficiently given inputs have been used to produce the maximum level of outputs (Emrouznejad and De Witte, 2010). The CCR ratio model proposed by Charnes et al. (1978) measures technical efficiency assuming constant returns to scale. The BCC model relaxes the constant returns to scale assumption of the original CCR model and distinguishes between technical and scale efficiency. More precisely, the BCC model introduced by Banker et al. (1984) eliminates the condition in obtaining the envelopment surface of efficient DMUs. In other words, it allows a variable returns to scale condition in constructing the envelopment surface. It is worth mentioning that a variable returns to scale frontier in the BCC model is a frontier that exhibits increasing, constant and decreasing returns to scale in different regions. We now try to clarify the difference between the CCR and BCC model by reference to the illustration in Figure 4-6. This figure portrays the production set in terms of a single output y and a single input x.

**Figure 4-6: Production Frontiers of the CCR and BCC Models**

The production function represents the maximum output that can be produced for any data point. However, in DEA models constructing the production function
depends on the assumption on returns to scale. Considering the variable returns to scale, the DMUs associated with A, B and C achieve the maximum possible outputs for their given inputs, while other points fall short of the output level which is attainable from their given inputs. On the other hand, assuming the most restrictive technology that is constant returns to scale, the DMU B is the only one in the sample which produces the maximum level of output using the given level of input and all other points under this assumption including A and C are inefficient and produce less outputs attainable from their certain level of inputs. To evaluate the efficiency of a desired point, the distance between that point and the constructed production function can be measured in terms of input or output (vertical or horizontal). It is clear in Figure 4-6 that efficiency measures in the CCR model do not exceed the equivalent scores in the BCC models. In other words, efficiency scores obtained from the CCR model always are equal or less than scores attained from the BCC model.

Mathematically, the input oriented BCC model (envelopment form) measures the efficiency of DMUr (r = 1,… , n) by solving the following linear program:

\[ Min \ \theta \]

Subject to

\[
\sum_{r=1}^{n} \lambda_r x_{rj} - \theta x_{rk} \leq 0, \quad j = 1, \ldots, p
\]

\[
\sum_{r=1}^{n} \lambda_r y_{ri} - y_{rk} \geq 0, \quad i = 1, \ldots, q
\]

\[
\sum_{r=1}^{n} \lambda_r = 1,
\]

\[
\lambda_r \geq 0, \quad r = 1, \ldots, n
\]  \hspace{1cm} (4-11)

Where

\( \theta \) = Efficiency score

\( \lambda \) = Dual variable

Comparing linear programs in (4-10) and (4-11) demonstrates that the BCC and CCR models differ only in the convexity condition \( \sum_{r=1}^{n} \lambda_r = 1 \).
4.3.8 Scale Efficiency

As detailed in previous sections, the CCR and BCC models are two main and basic model types in DEA. Their differences lie on the assumptions of production possibility sets. The CCR assumes constant returns to scale. On the other hand, the BCC assumes variable returns to scale. The efficiency value calculated in CCR is the “overall technical efficiency”, whereas the efficiency value computed by BCC is “pure technical efficiency”. The former divided by the latter is “scale efficiency”. The comparison of the scale efficiency score and the pure technical score opens an insight to the main source of inefficiency of DMUs. This characteristic demonstrates the cause of inefficiency whether it is due to uneconomic combinations of inputs and outputs or the large or small operational scale (Lee, 2009).

Practically, the scale efficiency is measured by dividing the CRS efficiency score by the VRS efficiency score. This ratio tells us if a DMU has scale inefficiency due to being too small or too big. Thus, it is reasonable to characterize the scale efficiency of DMUs by calculating the ratio of CRS and VRS models. Let the efficiency scores under the CRS and VRS models for a DMU be $\theta_{\text{CRS}}$ and $\theta_{\text{VRS}}$, respectively. The scale efficiency is defined by:

$$\frac{\theta_{\text{CRS}}}{\theta_{\text{VRS}}} = S \quad (4-12)$$

Where $\theta_{\text{CRS}}$ is the efficiency score estimated using the DEA model under constant returns to scale, $\theta_{\text{VRS}}$ is the efficiency score estimated using the DEA under variable returns to scale and $S$ represents the scale efficiency measure. In other words, technical efficiency (efficiency score under constant returns to scale) can be decomposed into pure technical (efficiency score under variable returns to scale) and scale efficiencies. Using this concept, relationship (4-13) demonstrates the decomposition of technical efficiency as follows:
\[ \theta_{\text{CRS}} = \theta_{\text{VRS}} \times S \] (4-13)

The above equation means that technical efficiency is the product of pure technical efficiency and scale efficiency. This concept is very useful in interpreting and analysing the source of inefficiency as presented in the next sections. This decomposition demonstrates the sources of inefficiency; whether they are caused by inefficient operation or by disadvantageous scale conditions or by both. Therefore, if a DMU is fully efficient under both the CRS and VRS assumptions, it operates in the most productive scale size. Otherwise, if a DMU is fully efficient under the VRS assumption but has a lower score under the CRS assumption, then it is only locally efficient and it is not globally efficient due to the size of the DMU which can be too small or too large. To illustrate the distinction between two CRS and VRS models we utilize Figure 4-7. In this figure, points A and D operate locally (under VRS) efficient but they are globally (under CRS) inefficient while their overall technical inefficiencies are caused by their failure to achieve the optimal scale. On the other hand, DMUs B and C are scale efficient and operate at the most productive scale size. Their technical efficiencies are also one so they are both scale and technically efficient. Overall inefficiency of other points represented in Figure 4-7 is caused by technically inefficient operations and at the same time by disadvantageous scale conditions.

**Figure 4-7: Scale Efficiency**
Although the scale efficiency measure provides information pertaining to the degree of inefficiency resulting from the failure to operate with constant returns to scale, it does not provide information as to whether a scale inefficient DMU operates below or above the optimum size.

According to a standard definition in economics, returns to scale arise when a proportional change in inputs affects a proportional change in outputs (Daraio and Simar, 2007). In other words, constant returns to scale exist if an n per cent rise in all inputs ends an n per cent increase in all outputs. Increasing returns to scale exist if output rises by a larger percentage than inputs and finally decreasing returns to scale exists if outputs rise by a smaller percentage than inputs.

Whether the underlying technology exhibits constant, increasing, or decreasing returns to scale is a crucial question in efficiency analysis studies (Simar and Wilson, 2002). The scale return analysis identifies whether a DMU is in the region of increasing or decreasing returns to scale so as to determine the increase or decrease of the scale. Fare et al. (1985) propose a method for determining returns to scale of individual DMUs by comparing different efficiency measures under the alternative assumptions of constant, variable and non-increasing returns to scale. The first two assumptions of constant and variable returns to scale were described in previous sections. To describe the non-increasing returns or decreasing returns to scale model, let us begin with Figure 4-8 for a single input and single output case. The solid line in this figure represents the production frontier function under non-increasing returns to scale. For comparison reasons, other frontiers under constant and variable returns to scale are presented by dotted lines. As illustrated in Figure 4-8 the ratio of output to input of efficient points is decreasing with respect to the input scale.
The mathematics underlying the non-increasing return to scale is illustrated in Figure 4-8. Comparing linear programs in (4-10) and (4-11) demonstrates that the NIRS and CCR models differ only in the convexity condition $\sum_{r=1}^{n} \lambda_r \leq 1$. In this model, scaling down of DMUs is allowed while scaling up is restricted. Hence, non-increasing returns to scale models focus on the scale efficiency of relatively large DMUs.

$$
\begin{align*}
\text{Min } \theta \\
\text{Subject to} \\
\sum_{r=1}^{n} \lambda_r x_{rj} - \theta x_{rk} &\leq 0, \quad j = 1, \ldots, p \\
\sum_{r=1}^{n} \lambda_r y_{ri} - y_{rk} &\geq 0, \quad i = 1, \ldots, q \\
\sum_{r=1}^{n} \lambda_r &\leq 1, \\
\lambda_r &\geq 0, \quad r = 1, \ldots, n
\end{align*}
$$

(4-14)

$\lambda$ = Dual variable

$\theta$ = Efficiency score

The nature of scale inefficiencies for a given DMU can be determined by examining whether its technical efficiency score under non-increasing returns to
scale is equal to its technical efficiency score under variables returns. If they are unequal, increasing returns to scale exist for that DMU. Otherwise, if they are equal then decreasing returns to scale exist. To sum up, the scale inefficiency estimates described here give a remarkable insight and knowledge into the strategic choices of expanding, merging or closing smaller firms, business units or branches of a firm.

4.4 Sensitivity of Results and Discrimination in DEA Models

4.4.1 Fuzzy Methods

One of the approaches to account for statistical noise in DEA models and to overcome their deterministic nature is to add chance-constrained programming to the DEA programs. This approach allows us to have stochastic DEA models by allowing violation in the models’ constraints with some probability. However, this approach suffers from some drawbacks as described by Daraio and Simar (2007). Firstly, a large sample is required in the chance-constrained efficiency approach. Secondly, probability of violation of constraints is based on strong distributional assumptions. Finally, the information on expected values of all variables should be determined. As an alternative approach, Sengupta (1992) was the first to introduce the application of fuzzy set theory in the context of DEA. He uses fuzzy statistic to illustrate the type of decisions and solutions that are achievable when data are vague and prior information is inexact and fails to satisfy the usual conditions required for random variables. Fuzzy programs in DEA models are suitable where the robustness of the efficiency results is questionable. Nevertheless, existing fuzzy DEA models have some drawbacks. Wang and Chin, (2011) list some examples as follows:

“Fuzzy DEA models derived from the direct fuzzification of crisp DEA models ignore the fact that a fuzzy fractional program cannot be transformed into an LP model in the traditional way that we do for a crisp fractional program. Fuzzy DEA models built on the basis of $\alpha$-level sets require the solution of a series of LP models and thus considerable
computational efforts. Fuzzy DEA models constructed from the perspective of fuzzy arithmetic demand a rational yet easy-to-use ranking approach for fuzzy efficiencies”

Recently, Hatami-Marbini et al. (2011) provide a taxonomy and review of the fuzzy DEA methods used over the past 20 years. Angulo-Meza and Lins (2002) review, classify and compare methods for increasing discrimination in DEA. According to their study these methods can be classified into two groups. The first group comprises those methods that incorporate a priori information. Alternatively, the second group of methods are those that do not require or minimize the use of such prior information. Within the first group they review three approaches: weight restrictions, preference structure and value efficiency analysis. In contrast, within the second group they present three methodologies: super efficiency, cross-evaluation, and a multiple objective linear programming approach.

4.4.2 Methods with a Priori Information

According to Angulo-Meza and Lins (2002) classification, methods with a priori information are methods that the weight of input and output variables can be added into the DEA model by analysts or experts where relevant knowledge and information are available. Three main streams of this approach are described in the following sections:

Weight Restrictions

Weight flexibility is known as one of the most important advantages of DEA in the literature because it minimizes the need for priori knowledge or for making assumptions regarding the importance of variables. However, there are situations where additional information exists or different assumptions need to be made for particular cases. Moreover, important variables could be ignored in the model by mistakenly assigning a zero weight to the corresponding variable or on the contrary, assigning a higher weight to the corresponding variable than what would
be appropriate in practice. Weight restriction as a value judgement method is a solution to overcome this drawback of DEA models. The main objective of the weight restrictions methods is to allow some flexibility regarding the value of the weights (Angulo-Meza and Lins, 2002). There are several approaches to apply weight restrictions.

(1) Direct weight restrictions is an approach which is useful to ensure inputs or outputs are not over estimated or ignored in DEA models. For instance, in this approach it is possible to set an upper or lower bound on an input or output weight to control the effect of them in the model. Assuming vectors $u$ and $v$ as weights of inputs and outputs in a multiplier DEA model, the following constraints can be added in a direct weight restriction to control the weight of inputs and outputs:

\begin{equation}
\alpha_i \leq u_i \leq \beta_i \text{ for input } i
\end{equation}

\begin{equation}
\alpha_j \leq v_j \leq \beta_j \text{ for output } j
\end{equation}

(4-15)

Where $\alpha$ and $\beta$ are determined by decision makers using priori knowledge.

(2) Assurance Region approach initially developed by Thompson et al. (1986) to identify feasible sites for location of a very high-energy physics lab in Texas and to examine the competitive advantages of different sites. This approach imposes some constraints on the relative magnitude of the weights in DEA models. These type of ratio restrictions are of the form:

\begin{equation}
\alpha_q \leq u_i / u_j \leq \beta_q \text{ for inputs}
\end{equation}

\begin{equation}
\alpha_p \leq v_i / v_j \leq \beta_p \text{ for outputs}
\end{equation}

(4-16)
It should be noted that choosing these restrictions can change the result and can turn an efficient unit to inefficient one and vice versa. Cooper et al. (2007) point out that choosing these bounds using auxiliary information such as prices and unit costs provides a generalization of allocative and price efficiency methods which require precise knowledge of price and cost.

(3) The Cone Ratio model is more general than the assurance region approach. The Cone Ratio Model was initially developed by Charnes et al. (1989). In this model the feasible region of the input $u$ and the output $v$ in the polyhedral convex cone spanned by admissible nonnegative direction vectors as follows:

$$u = \sum_{i=1}^{q} \alpha_i a_i \quad \alpha_i \geq 0 \quad \forall \ i = 1, ..., q$$

$$v = \sum_{j=1}^{p} \beta_j b_j \quad \beta_j \geq 0 \quad \forall \ j = 1, ..., p$$

(4-17)

If the weights selected by the original formulation are not consistent with the objectives of some DMUs, then DEA could have overestimated the efficiency score of these DMUs. Applying restrictions of the Cone Ratio type, it is possible to determine weights in a way that is more consistent with objectives (Angulo-Meza and Lins, 2002).

More details about the weight restriction methods can be found in Allen et al. (1997) which provides a review of the evolution, development and future research directions on the application of weight restrictions and value judgements in DEA models.

**Preference Structure Models**

As an important extension to the traditional CCR models, Zhu (1996) develops a series of weighted CCR (WCCR) models with user-specified preference structure (Zhou and Fan, 2010). On the basis of the so-called Russell measure, Zhu (1996)
develops weighted non-radial CCR models by specifying a proper set of ‘preference weights’ that reflect the relative degree of importance of current input or output levels. In the proposed model, input or output adjustments can be either less or greater than one meaning that the proposed model allows for the increase of some inputs in an input-oriented model or the decrease of some outputs in an output-oriented model. The preference structure approach prevents unrealistic weights which may cause an inefficient DMU to be presented as an efficient one. Also, it provides further discrimination based on the preference structure specified by the decision makers (Allen et al., 1997).

Value Efficiency Analysis

Value efficiency analysis was initially developed by Halme et al. (2000) as a way of incorporating the decision maker’s value judgements and prior knowledge into the analysis (Angulo-Meza and Lins, 2002). This method contains two stages. The first stage is searching for the best input/output vector and involves an identification of the Most Preferred Solution (MPS) by decision makers. This MPS can be determined using a multiple objective linear program. As a multi objective model does not have a single solution, a decision-maker should decide which solution is more suitable. The second stage includes estimating the frontier based on the MPS chosen. Efficiency scores estimated through this approach can be interpreted as the relative difference in values between the Most Preferred Solution and the unit under study.

Although, methods that incorporate a priori information provide a better discrimination among DMUs by inclusion of priori knowledge, there are disadvantages incorporated into these methods because of their subjectivity. Angulo-Meza and Lins (2002) summarize drawbacks of this approach as follows:

“1) The value judgements, or a priori information can be wrong or biased, or the ideas may not be consistent with reality.
2) There may be a lack of consensus among the experts or decision-makers, and this can slow down or adversely affect the study.”

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4.4.3 Methods that do not Require a Priori Information

These methods avoid or minimize the intervention of decision makers or experts while at the same time are able to increase discrimination in efficiency scores resulting from DEA models. Three main streams of this approach are described in the following sections.

Super Efficiency
Andersen and Petersen (1993) propose a modified version of DEA based on comparison of efficient DMUs relative to a reference technology constructed by all other units. Their procedure provides a framework for ranking efficient units and facilitates comparison with rankings based on parametric methods. The difference of this method with original DEA models is that it involves comparing the efficiency of an efficient DMU against other DMUs of the sample while the DMU under evaluation is eliminated from DMUs which construct the production function. It is worth mentioning that this method only is designed to re-assess and rank efficient DMUs. That is, efficient DMUs in the original model can obtain an efficiency score greater than one in supper efficiency models. In this approach ranking of efficient DMUs is similar to the ranking of inefficient DMUs (greater means more efficient). However, the problem of unrealistic weights cannot be solved using this method (Angulo-Meza and Lins, 2002).

Cross Evaluation
Cross evaluation is another method to increase discrimination among efficient DMUs originally developed by Silkman (1986). In this approach instead of a self-evaluation in traditional DEA models, a peer evaluation is employed. A peer-evaluation means that each DMU is evaluated using the optimal weighting of other DMUs (Angulo-Meza and Lins, 2002). In practice, the difference is that the weight values obtained from estimation of a DMU’s efficiency are used to calculate an efficiency score for other DMUs in the sample. To implement this model a cross efficiency matrix is formed to record all efficiency scores resulting
from the self-evaluation of each DMU. By repeating this process for all DMUs, each DMU has not only its own self-evaluation but also the peer evaluations which resulted from the weighting of other DMUs in the sample. Finally, a DMU’s cross efficiency score is obtained by calculating the average of all peer evaluations and the self-evaluation scores. Therefore, a DMU which has a high cross efficiency value has passed a more rigorous test since it is considered efficient by the majority of its peers. As discussed before, while the traditional DEA constructs the production frontier using efficient DMUs which represent best performers, in comparison, the cross evaluation method lets even inefficient DMUs be incorporated in the identification of the best practices (Anderson et al., 2002).

A Multiple Objective Approach
Lack of discrimination and inappropriate weighting schemes are two drawbacks of classical DEA models. The first problem usually occurs when the number of DMUs is not enough greater than the total number of inputs and outputs and causes too many DMUs to be classified as efficient in the classic models. The second problem happens when an efficient DMU chooses large weights for some variables, and very small or zero weights for some other variables. This causes unrealistic results. Two address these issues, Li and Reeves (1999) develop a multiple objective approach called Multiple Criteria Data Envelopment Analysis (MCDEA). In their proposed model, two more objective functions are included in the classical DEA model. Thus, DMUs are evaluated in the Multi objective Linear Programming context. Compared to the classical model, MCDEA avoids the problem of multiple optimal solutions, which appears when solving the classic DEA models for extreme efficient DMUs.

Although, all methods described above increase the discriminatory power of DEA models, they do not allow for statistical sensitivity analysis as they do not rely on statistical aspects of efficiency scores. That is, these methods are not able to provide statistical inferences based on construction of confidence intervals, estimation of the bias, statistical tests of hypothesis and so on. A recently
developed approach aims to provide statistical properties of non-parametric estimators. This new approach not only overcomes common limitations of non-parametric methods but also opens a new insight in making statistical inferences and developing relevant procedures (Daraio and Simar, 2007). This innovative approach relies on the bootstrapping method which is a new technique in statistics science. The next section describes the bootstrapping technique in detail and is then followed by a discussion of the application of bootstrap methods in DEA models.

4.5 Bootstrapping Technique

Traditional statistical approaches fail to provide solutions for many common problems due to a formidable wall of mathematics (Efron and Tibshirani, 1994). To avoid these limitations Efron (1979) introduces a modern alternative to the traditional approach called the bootstrapping method. The bootstrap is a computer-based statistical technique that uses data resampling to estimate values of interest and can answer many practical statistical questions without formula. It has spread very rapidly in statistical science since it was introduced in 1994. Statistical inference is defined as the process of drawing conclusions from data subject to random variation. The outcome of statistical inference may be an answer to the question “how accurate are data summarized?”

As a recently developed technique for making statistical inferences, the bootstrap assesses measures of accuracy of statistical estimates and requires high computing power to simplify the common complicated calculations of traditional methods. Fortunately, modern computers allow us to utilize this technique simply by taking into account minimum statistical assumptions.

One of the central aims in statistical theory is to summarize a sample based study and extend relevant findings from the sample to the parent population that the sample comes from. A statistic is a single measure of some attribute of a sample. It is measured by applying a function to the values of a set of data. More formally,
statistical theory defines a statistic as a function of a sample where the function itself is independent of the sample's distribution data. For instance, some basic sample statistics are sample mean, sample standard deviation and sample median. A statistic is distinct from a statistical parameter, which is not computable because often the population is too large or it is not economical to examine and measure all its parameters. However, a statistic called an estimator can be used to estimate a population parameter using the given samples. For instance, the sample mean is a statistic which estimates the population mean, which is a parameter. It is obvious that an estimated statistic varies from sample to sample. Thus, it is of interest to estimate the magnitude of theses variations around the corresponding population parameter.

Bootstrap methods are more flexible than classical methods which may be analytically unusable due to assumptions that cannot be satisfied (Johnson, 2001). For instance, the elegance that lies behind the central limit theorem for testing mean is not simply achievable for many other statistics. As such, resampling methods like the bootstrap were developed to provide a solution to overcome problems of classical methods. As mentioned before, although, it is possible to have a sound estimation of the sampling distribution of a particular statistic by drawing samples from the population many times; it is not practical or economical in many cases. Bootstrapping solves this problem by utilizing the data of an available sample study to estimate the sampling distribution of the statistic of interest. This can be implemented by drawing a large number of resamples of the observed dataset (available sample) with replacement. That is, in the bootstrap method, the random sampling from the true population is replaced by the random sampling from the observed data. This can be justified by the argument that the empirical distribution of the observed data is similar to the true distribution.

Suppose a random sample \( X = (x_1, x_2, \ldots, x_n) \) which has been drawn from an unknown probability distribution \( F \).
We wish to estimate a population parameter \( \theta \) using the random sample \( X \). To do so, we calculate an estimate of the statistic of interest \( \hat{\theta} \) using the given formula \( \hat{\theta} = f(x) \). It is of interest to know how accurate the result is. That is, we would like to determine the bias \( (\hat{\theta} - \theta) \). For this purpose, let us define the empirical distribution \( \hat{F} \) that is meant to estimate the true but unknown probability distribution \( F \). In this case, \( \hat{F} \) needs to be calculated from the observed data set \( X = (x_1, x_2, ..., x_n) \) in such a way that if we draw random samples \( X^* = (x_1^*, x_2^*, ..., x_n^*) \) from \( \hat{F} \), the underlying process of true data generation is properly mimicked by

\[
\hat{F} \rightarrow X^* = (x_1^*, x_2^*, ..., x_n^*)
\] (4-19)

Where the notation * is a symbol to distinguish bootstrap variables. Using the bootstrap sample, \( \hat{\theta}^* \) can be calculated as an estimate of \( \hat{\theta} \) by

\[
\hat{\theta}^* = s(x^*)
\] (4-20)

Then, it is possible to construct an estimate for the sampling distribution of \( \hat{\theta} \) by repeating resampling from \( \hat{F} \) and calculating \( \hat{\theta}^* \).

**Figure 4-9: Bootstrap World**

![Bootstrap World Diagram](source: Efron and Tibshirani, 1994, p87)
Figure 4-9 is a schematic diagram which demonstrates the relationship between the real world and the bootstrap world. As shown, on the left side in the real world, an unknown distribution $F$ has given the observed data $X = (x_1, x_2, ..., x_n)$ using random sampling. Moreover, the true statistic of interest $\theta$ has been estimated using $\hat{\theta}$. On the other hand, in the right side of the diagram, in the bootstrap world, the empirical distribution $\hat{F}$ gives bootstrap samples $X^* = (x_1^*, x_2^*, ..., x_n^*)$ using random sampling where the bootstrap replications of the statistic of interest $\hat{\theta}^*$ is calculated. Thus, in the real world there is only one observed value of $\hat{\theta}$, while in the bootstrap world it is possible to generate as many bootstrap replications $\hat{\theta}^*$. This allows us to do probabilistic estimations directly. For instance, the unknown standard error of $\hat{\theta}$ can be estimated using $\hat{\theta}^*$.

The double arrow in Figure 4-9 indicates the calculation of $\hat{F}$ from $F$. In fact, it is the most crucial stage in the bootstrapping process and we need to ensure the accuracy and consistency of the empirical distribution $\hat{F}$. As shown, every other part of the bootstrap picture is defined by analogy: $F$ gives $X$ by random sampling, so $\hat{F}$ gives $X^*$ by random sampling; $\hat{\theta}$ is obtained from $x$ using function $s(x)$, so $\hat{\theta}$ is obtained from $X^*$ in the same way (Efron and Tibshirani, 1994). Thus, there are numerous ways to carry out this Data Generating Process (DGP). However, although it looks easy to implement this process in many cases, the underlying DGP is not easily identified for complex data structures (This issue will be discussed in the next section in more detail). Thus, it can be shown that if $\hat{F}$ is a reasonable estimator of $F$, the known bootstrap distribution $\hat{\theta}^*$ will mimic the original unknown sampling distribution of the statistic of interest $\theta$. More specifically, the bootstrap distribution of $\hat{\theta}^* - \hat{\theta}$ approximates the sampling distribution of $\hat{\theta} - \theta$.

The most simple and commonly used bootstrap model is called naïve bootstrap where the bootstrap sample set is drawn randomly with replacement from the observed random sample. In this approach, the empirical distribution $\hat{F}$ is
estimated assuming the equal probability $1/n$ on each of the observed random samples where the bootstrap samples $(x_1^*, x_2^*, ..., x_n^*)$ are random samples drawn with replacement from the observed random samples $(x_1, x_2, ..., x_n)$. That is, a bootstrap sample consists of observed random samples where some samples can be drawn more than one time and some can be ignored. In the following section various applications of the bootstrap method are introduced.

### 4.5.1 Estimating Standard Errors

Summary statistics such as $\hat{\theta}$ are usually of interest in data analysis and the accuracy of $\hat{\theta}$ is an important consideration (Efron and Tibshirani, 1994). Suppose that $\theta$ is a population parameter and $\hat{\theta}$ is a consistent estimator of $\theta$. In order to estimate the standard error of $\hat{\theta}$ Efron and Tibshirani (1994) develop the following algorithm:

1) Select $B$ independent bootstrap samples $X^{*1}, X^{*2}, ..., X^{*B}$ where each have $n$ data values drawn with replacement from $X$.

2) Compute the bootstrap value for each bootstrap sample,

$$\hat{\theta}^*(b) = s(x^*) \quad b=1,2,\ldots,B \quad (4-21)$$

3) Estimate the standard error by the sample standard deviation of the $B$ replications

$$s_{\hat{\theta}} = \left[\frac{\sum_{b=1}^{B}[\hat{\theta}^*(b) - \hat{\theta}^*(.)]^2}{(B-1)}\right]^{1/2} \quad (4-22)$$

Where $\hat{\theta}^*(.) = \frac{\sum_{b=1}^{B} \hat{\theta}^*(b)}{B}$
4.5.2 Estimates of Bias using Bootstrap Method

Although, it is common to use the standard error as a measure of accuracy for an estimator, there are other valuable measures of statistical accuracy measuring this aspect of an estimator. Similar to the previous section, assume an unknown probability distribution \( F \) with sample data of \( X = (x_1, x_2, \ldots, x_n) \) obtained from a random sampling process. In addition, assume the true value of a probability distribution parameter \( \theta \) be estimated using the statistic \( \hat{\theta} = s(x) \). The bias of \( \hat{\theta} \) is defined as the difference between the expectation of \( \hat{\theta} \) (as an estimator of \( \theta \)) and the true value of population parameter \( \theta \).

\[
\text{Bias} (\theta, \hat{\theta}) = E(\hat{\theta}) - \theta
\]  

(4-23)

Although, naturally, unbiased estimates are preferred, in reality, estimators are not necessarily unbiased and measuring this bias plays an important role in statistical theory and practice. The bootstrap method can be used to estimate the bias of an estimator like \( \hat{\theta} \) using the following procedure suggested by Efron and Tibshirani (1994):

1) Select \( B \) independent samples \( X^{*1}, X^{*2}, \ldots, X^{*B} \) from the empirical distribution \( \hat{F} \).

2) Compute the bootstrap bias for each bootstrap sample

\[
\hat{\theta}^*(b) = s(x^*) \quad b = 1, 2, \ldots, B
\]  

(4-24)

3) Approximate \( E(\hat{\theta}^*) \) as the bootstrap expectation by the following average

\[
E(\hat{\theta}^*) = \sum_{b=1}^{B} [\hat{\theta}^*(b)]
\]  

(4-25)
4) Compute the bootstrap estimate of bias based on the B replications using the following equation:

\[ \text{Bias (}\hat{\theta}^*,\hat{\theta}) = E(\hat{\theta}^*) - \hat{\theta} \quad (4-26) \]

5) Calculate the bias-corrected of \( \hat{\theta} \) using the following formula:

\[ \tilde{\theta} = \hat{\theta} - \text{Bias (}\hat{\theta}^*,\hat{\theta}) = 2\hat{\theta} - E(\hat{\theta}^*) \quad (4-27) \]

### 4.5.3 Bootstrap Confidence Interval

In statistics, a confidence interval is a type of interval estimate of a population parameter and is used to indicate the reliability of an estimate. A confidence interval provides an estimated range of values which is likely to consist of an unknown population parameter \( \theta \). That is, the selection of a confidence level for an interval determines the probability that the confidence interval produced will contain the true parameter value. This estimated range can be calculated from a given set of sample data. There are several methods for constructing confidence intervals from the bootstrap distribution of a true parameter. Among them the percentile method is one of the popular bootstrap approaches to construct a confidence interval due to its simplicity. To construct the bootstrap percentile interval the following algorithm can be used:

1) Select B independent bootstrap samples \( X^{*1}, X^{*2}, \ldots, X^{*b} \) from the empirical distribution \( \hat{F} \).

2) Compute the bootstrap replication corresponding to each bootstrap sample similar to (4-24)

3) Sort the bootstrap replications \( \hat{\theta}^*(b) \) in an ascending order as follows:
\[ \hat{\theta}^{(1)}, \hat{\theta}^{(2)}, \ldots, \hat{\theta}^{(B)} \quad \text{Where} \quad \hat{\theta}^{(B)} \leq \hat{\theta}^{(B)} \] (4-28)

4) The 100(1-2\alpha) bootstrap percentile interval can be constructed as follows:

\[ \left[ \hat{\theta}_{\text{low}}^*, \hat{\theta}_{\text{up}}^* \right] = \left[ \hat{\theta}^{(\alpha)}, \hat{\theta}^{(1-\alpha)} \right] \] (4-29)

The methods presented provide only a brief introduction to many applications of the bootstrap method. For instance, there are other bootstrap approaches to construct the confidence intervals such as bias corrected and accelerated models. More details regarding the application of bootstrap methods can be found in Efron and Tibshirani (1994).

4.6 Bootstrap DEA

4.6.1 Introduction

A key question in the application of DEA methods is how estimated efficiencies indicate significance of the results. This issue is crucial and of importance to managers and decision makers who wish to focus their efforts on increasing efficiency in today’s competitive environment. Unfortunately, practical applications of DEA estimators offer no guidance to the statistical inference of efficiency estimates (Lothgren, 1998). Moreover, the main drawbacks of deterministic frontier models either nonparametric or parametric is that they are very sensitive to outliers and extreme values (Simar and Wilson, 2008). As DEA measures the efficiency of a DMU relative to its best practice peers, the given score is directly correlated to the relative positioning of other peers from the frontier. While this is known as one of the advantages of DEA, it makes it difficult to develop statistical tests and to analyse obtained results.

Typically, DEA techniques are considered deterministic in the literature. The problem with the non-statistical nature of DEA is fundamental. In fact, the lack of statistical properties of the technical efficiency obtained by solving a linear programming was known as a limitation of this procedure from the beginning.
(Ray, 2004). Fortunately, researchers recently have attempted to develop and extend statistical aspects to the DEA models. In the first attempts, Banker (1993) points out that the DEA efficiency estimates can enable us to provide interesting statistical properties. He suggests the use of hypotheses statistical tests based on asymptotic distributions to make a comparison between two groups of DMUs. Kneip et al. (1996) examined the consistency and the convergence speed of estimated efficiency scores using DEA in a very general multi-output and multi-input case.

Another approach to add statistical aspects to DEA efficiency scores is the application of the bootstrap method in conjunction with DEA. This is a rather recent and extensive development. The first use of the bootstrap method in frontier models dates to Simar (1992) However, the application of the bootstrap method in nonparametric envelopment estimators was developed by Simar and Wilson (1998a). Bootstrap methods are very useful to assess the uncertainty due to sampling variation in nonparametric DEA or FDH methods. Thus, they provide estimations for bias, confidence intervals and testing hypothesis.

### 4.6.2 DEA Bootstrap Algorithms

In frontier models, as efficiency measures are obtained from finite samples, the results are sensitive to the sampling variations (Simar and Wilson, 1998a). Fortunately, the bootstrap approach assists in providing a solution to this issue because it allows for statistical precision of DEA estimations. The crucial step in any application of the bootstrap is a clear specification of the data generating process underlying the observed data. The basic idea of the bootstrap process method is to approximate the sampling distributions of the estimator by using the empirical distribution of resampled estimates obtained from a consistent DGP. Thus, the validity of the bootstrap results depends on how well the resampling simulation is mimicked by the DGP (Lothgren, 1998).
Simar and Wilson (1998a) describe the DGP for an input oriented model as follows: For a given value of y (the output vector), we know that x ∈ X(y). Due to the presence of inefficiency, x may not be on the efficiency boundaries of the production set but is generated along a fixed ray (fixed proportion of inputs) away from the efficient level of input denoted by \( x^\alpha(x_i|y_i) \). Thus, a particular unit \((x_i, y_i)\) may be considered as being generated, conditionally on \( y_i \) and on the observed proportion of inputs by the random variables \( \theta_i \in (0,1] \) such that \( x_i = x^\alpha(x_i|y_i)/\theta_i \). Assume F is a density function on \((0,1]\) that generates \( \theta_i \) as follows:

\[
(\theta_1, \theta_2, \ldots, \theta_n) \sim i.i.d. F
\]

(4-30)

Accordingly, the DGP, \( \rho_i \) generating \( x_i \) conditionally on the observed output values \( y_i \) :

\[
\rho_i = \left( x^\alpha(x_i|y_i), F \right), \quad i = 1, \ldots, n
\]

(4-31)

Then, the empirical distribution function of the \( \theta_i \) can be used as to estimate F:

\[
\hat{F}(t) = \begin{cases} 
\frac{1}{n} & \text{if } t = \hat{\theta}_i, \quad i = 1, \ldots, n \\
0 & \text{Otherwise}
\end{cases}
\]

(4-32)

Now, the bootstrap inputs \( x_i^* \) can be generated by random selection with replacement from \((\hat{\theta}_1, \hat{\theta}_2, \ldots, \hat{\theta}_n)\):

\[
x_i^* = \frac{\hat{\theta}_i}{\theta_i} x_i
\]

(4-33)

Finally, pseudo samples can be defined as \( \{x_i^*, y_i\} \).

The above approach called the naive bootstrap has been used in some studies to generate pseudo samples. For instance, Lothgren and Tambour (1999a) present a
naive bootstrap approach to calculate confidence intervals for firm-specific Malmquist productivity indices obtained from DEA models. They demonstrate the application of the proposed model in Swedish eye-care departments and assess the difference between the original and bootstrap results. In the original results, about half of the sample had a positive change in productivity and the other half experienced a decline in productivity. In contrast, the bootstrap result shows that 40% of departments had a significant positive productivity growth whereas only 10% of them had a significant decline in productivity. Although, this method was originally proposed for bootstrapping Malmquist productivity, it can be adapted for estimating technical efficiency. The algorithm is summarized by Lothgren (1998) as follows:

1) Compute the efficiency score for any given point \((x_k, y_k)\) using the following linear program providing \(\{\theta_i, i = 1, \ldots, n\}\)

\[
\hat{\theta}_k = \min\{\theta > 0 \mid y_k \leq \sum_{i=1}^{n} \gamma_i y_i; \theta x_k \geq \sum_{i=1}^{n} \gamma_i x_i ; \sum_{i=1}^{n} \gamma_i = 1; \gamma_i \geq 0, i = 1, \ldots, n\} (4-34)
\]

2) Resample independently with replacement, \(n\) technical efficiencies from the set of original estimates \(\{\theta_i, i = 1, \ldots, n\}\) and let \(\{\theta'_i, i = 1, \ldots, n\}\) denote the re-sampled efficiencies.

3) Define the bootstrap pseudo-data be given by

\[
(x_i', y_i') = (x_i / \theta'_i, y_i)
\]

(4-35)

4) Estimate the bootstrap efficiencies \(\hat{\theta}_k^*\) using the pseudo-data and the linear program as:

\[
\min\{\theta > 0 \mid y'_k \leq \sum_{i=1}^{n} \gamma_i y'_i; \theta x_k^* \geq \sum_{i=1}^{n} \gamma_i x_i^* ; \sum_{i=1}^{n} \gamma_i = 1; \gamma_i \geq 0, i = 1, \ldots, n\} (4-36)
\]

5) Repeat steps 2 to 4 \(B\) times to create a set of \(B\) firm-specific bootstrapped efficiency estimates \(\{\hat{\theta}^*_{k,b}, b = 1, \ldots, B\}\)
As shown in this algorithm, Lothgren and Tambour (1999a) use a naive bootstrap in the re-sampling process. Moreover, both the bootstrap frontier estimates and the bootstrap efficiency estimates of the given point are based on the re-sampled data as shown in (4-36). Lothgren (1998) argues that the suggested re-sampling method provides more accurate replication of the DGP than the algorithm proposed by Simar and Wilson (1998a). Unfortunately, this argument is flawed as the naive bootstrapping is not consistent for complex nonparametric methods such as DEA and FDH. As discussed in Simar and Wilson (2000), using the naive bootstrap in the non-parametric methods causes serious problems due to the discreteness of the empirical probability density function of \( \hat{\theta} \), along with the boundary problem that comes from the fact that at least one of the \( \hat{\theta} \) is necessarily fully efficient and its value is equal to 1. In this case for any \( i=1,\ldots, n \) we have:

\[
\Pr(\theta_i^* = 1) \geq 1 - (1 - n^{-1})^n > 0
\]  

(4-37)

The above inequality holds only if there is just one \( \theta_i^* \) equal to 1. Interestingly, when \( n \) tend to infinity (\( n \to \infty \)) then probability of \( \Pr(\theta_i^* = 1) \) tends to be greater than the constant number of 0.632 as shown below:

\[
\lim_{n \to \infty} \Pr(\theta_i^* = 1) \geq 1 - e^{-1} \approx 0.632
\]  

(4-38)

Unfortunately, this shows that the result does not depend on the DGP generating the \( \theta \) even in higher dimensions as detailed in Simar and Wilson (2000). Thus, in general, the naive bootstrap is inconsistent and does not mimic the desired distribution. Another drawback of the Lothgren and Tambour (1999a) method lies in the use of the bootstrap values in (4-36). This inequality means the efficiency score of a given point \( k \) is estimated from a different and random point. That is not only does the frontier in each replication of the bootstrap method alter randomly but also the reference point is changing in each replication. As a result, it is unclear what the proposed method estimates where the reference point changes in each replication. Simar and Wilson (2000) explain all deficiencies of
the Lothgren and Tambour (1999a) procedure in detail and emphasize that in any estimation of a problem where inference is to be performed, it is essential to remember what is known and what is unknown and needs to be estimated, issues which have been ignored in the Lothgren and Tambour algorithm.

Although the bootstrap seems a useful technique where sampling properties of estimators are either difficult or impossible to obtain, as shown in the Lothgren and Tambour algorithm the naïve bootstrap is inconsistent and is not able to provide satisfactory results. Thus, the key point in order to ensure the bootstrap method is able to provide consistent results in the complex nonparametric context lies on defining a reasonable data generating process. To make up for this deficiency, Simar and Wilson (1998a) propose a smooth bootstrap algorithm that avoids inconsistency of the naïve bootstrap applied by Lothgren and Tambour. The smoothed bootstrap is a modified version of the naïve bootstrap to avoid repeated values drawn from the original sample in each replication. The main idea of the smoothed bootstrap is to draw samples from $\hat{F}$, a smooth version of the discrete distribution function $F$. In the other words, the samples are drawn from a continuous distribution not from a discrete one. Following this approach, Simar and Wilson (1998a) employ the a Gaussian kernel density estimate to offer a smoothed estimator for DEA and FDH methods as follows.

$$
\hat{F}_h(t) = \frac{1}{nh} \sum_{i=1}^{n} N \left( \frac{t - \hat{\theta}_i}{h} \right)
$$

Where $N$ is the standard normal probability density function and $h> 0$ is the smoothing parameter - also called bandwidth or window width. There are different methods to compute the value of $h$ as a fixed variable in (4-39). For instance, $h$ can be estimated using the likelihood cross validation method suggested by Silverman (1986). However, in practical applications, the optimal choice for $h$ can also be achieved by
The smoothing parameter \( h \) plays an important role in the estimated results. More specifically, large values of \( h \) cause an over smoothness and small values cause under smoothness of the density function. It should be noted that the density to be estimated is bounded in the DEA method and (4-39) is not consistent since it is bounded on one or both sides. Fortunately, the reflection method proposed by Silverman (1986) provides a solution to overcome the boundary condition. Simar and Wilson (1998a) adopt the reflection method for the case of the DEA method by generating symmetric image 2- \( \hat{\theta}_i \) for each \( \hat{\theta}_i \) \( i = 1, \ldots, n \) and form the set \( \{\hat{\theta}_1, \hat{\theta}_2, \ldots, \hat{\theta}_n, 2 - \hat{\theta}_1, 2 - \hat{\theta}_2, \ldots, 2 - \hat{\theta}_n\} \) to construct the following kernel density estimate from this new data set of size 2n.

\[
\hat{F}_h(t) = \begin{cases} 
\frac{1}{nh} \sum_{i=1}^{n} \left[ N \left( \frac{t - \hat{\theta}_i}{h} \right) + N \left( \frac{t - 2 - \hat{\theta}_i}{h} \right) \right] & \text{if } t \leq 1, \\
0 & \text{otherwise} 
\end{cases} \tag{4-41}
\]

Finally, \( t \) and the reflection of \( t^R \) can be estimated as follows:

\[
t_i = \beta_i^* + h \epsilon_i^* \sim \frac{1}{n} \sum_{i=1}^{n} \frac{1}{h} N \left( \frac{t - \hat{\theta}_i}{h} \right) \tag{4-42}
\]

\[
t_i^R = 2 - \beta_i^* - h \epsilon_i^* \sim \frac{1}{n} \sum_{i=1}^{n} \frac{1}{h} N \left( \frac{t - 2 - \hat{\theta}_i}{h} \right) \tag{4-43}
\]

Accordingly, as discussed by Simar and Wilson (1998a) bootstrap random variables are generated as follows:

\[
\hat{\theta}_i^* = \begin{cases} 
\beta_i^* + h \epsilon_i^* & \text{if } \beta_i^* + h \epsilon_i^* \leq 1 \\
2 - \beta_i^* - h \epsilon_i^* & \text{otherwise} 
\end{cases} \tag{4-44}
\]
Finally, the following steps summarize the bootstrap procedure for the DEA method proposed by Simar and Wilson (1998a).

1) For any given point \((x_k, y_k)\) \(k=1,\ldots,n\) compute \(\hat{\theta}_k\) using the following linear program formula:

\[
\hat{\theta}_k = \min\{\theta > 0 \mid y_k \leq \sum_{i=1}^n y_i' \gamma_i' ; \theta x_k \geq \sum_{i=1}^n y_i' \gamma_i' ; \sum_{i=1}^n y_i = 1 ; \gamma_i \geq 0, i = 1, \ldots, n\} \tag{4-45}
\]

Where \(y\) is the vector of outputs, \(x\) is a vector of inputs and \(\gamma\) is a vector of constants.

2) Generate a standard bootstrap set \(\{\beta_i', i = 1, \ldots, n\}\) by drawing with replacement from the original estimations \(\{\hat{\theta}_i, i = 1, \ldots, n\}\).

3) Smooth the sampled values \(\{\beta_i', i = 1, \ldots, n\}\) using

\[
\bar{\beta}_i^* = \begin{cases} 
\beta_i^* + h \varepsilon_i^* & \text{if } \beta_i^* + h \varepsilon_i^* \leq 1 \\
2 - \beta_i^* - h \varepsilon_i^* & \text{otherwise}
\end{cases} \tag{4-44}
\]

4) Correct the variance of the generated bootstrap sequence by computing

\[
\hat{\theta}_i^* = \bar{\theta}^* + \frac{\bar{\theta}^* - \hat{\theta}^*}{\sqrt{1 + h^2/\hat{\sigma}_0^2}} \tag{4-46}
\]

Where \(\bar{\theta}^* = \sum_{i=1}^n \beta_i^* / n\) and \(\hat{\sigma}_0^2\) is the sample variance of \(\{\hat{\theta}_i, i = 1, \ldots, n\}\).

5) Compute pseudo-data set \(\eta_b^* = \{(x_{ib}', y_i), i = 1, \ldots, n\}\) given by

\[
x_{ib}^* = \frac{\hat{\theta}_i}{\hat{\theta}_{ib}} x_i \tag{4-47}
\]

6) Calculate the bootstrap estimate of \(\hat{\theta}_{k,b}\) for \(k=1,\ldots,n\) by solving the following linear programming problem
7) Repeat steps 2-6 \( B=2000 \) times to provide for \( k=1,\ldots,n \) a set of estimates \( \{ \hat{\theta}_{k,b}^* , b = 1, \ldots , B \} \)

To conserve space in this study, we focus only on the input-oriented models. However, equivalent output oriented models can easily be developed by translation of the notation in the above algorithm. It should be noted that the quality of the approximation depends on the value of \( B \). if \( B \) tends to infinity, the error of the bootstrap resampling tends to zero. In practical applications, Simar and Wilson (2000) suggest \( B=2000 \) or more for a reasonable approximation.

### 4.6.3 Bias Correction

Once the set \( \{ \hat{\theta}_{k,b}^* , b = 1, \ldots , B \} \) is obtained from the above algorithm, the bootstrap bias estimate of the original estimate of \( \hat{\theta}_k \) can be obtained by

\[
\text{Bias}_{\hat{\theta}_k} = \frac{1}{B} \sum_{b=1}^{B} \hat{\theta}_{k,b}^* - \hat{\theta}_k
\]  

(4-49)

Hence, a bias corrected estimator of \( \hat{\theta}_k \) is equal to:

\[
\tilde{\hat{\theta}}_k = \hat{\theta}_k - \text{Bias}_{\hat{\theta}_k}
\]  

(4-50)

However, the bias correction may introduce additional noise where the mean square error of bias corrected estimator \( \tilde{\hat{\theta}} \) is greater than the mean square error of the original estimate \( \hat{\theta} \). Therefore, the bias correction should not be used unless

\[
\tilde{\hat{\theta}}^2 < \frac{1}{3} (\text{Bias}_{\hat{\theta}_k})^2
\]  

(4-51)

Where \( \tilde{\hat{\theta}}^2 \) is the variance of \( \hat{\theta}_k \) and can be estimated using the sample variance of the bootstrap values \( \hat{\theta}_k^* \):

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\[ \hat{\sigma}^2 = \frac{1}{B} \sum_{b=1}^{B} (\hat{\theta}_{k,b} - \frac{1}{B} \sum_{b=1}^{B} \hat{\theta}_{k,b})^2 \] (4-52)

### 4.6.4 Confidence Interval

Among a number of alternatives to construct the bootstrap confidence intervals for the true values \( \hat{\theta}_k \), the percentile method is the most straightforward (Lothgren and Tambour, 1999a). Unfortunately, the percentile method is not appropriate as the empirical density function in DEA methods is skewed. As an alternative, Simar and Wilson (1998a) suggest that the median-bias corrected method is a preferable approach which centres the median of the distribution on \( \hat{\theta}_k \) detailed in Efron (1982). In 1999, an improved procedure was proposed by Simar and Wilson (1999) which allows for the correction of the bias automatically without using a bias calculation.

If the distribution of \( (\hat{\theta} - \theta) \) was given, it would be straightforward to find values \( a_\alpha \) and \( b_\alpha \) such that:

\[ P\left(-b_\alpha \leq \hat{\theta} - \theta \leq -a_\alpha\right) = 1 - \alpha \] (4-53)

Fortunately, the bootstrap method provides an easy and practical solution to estimate the value of \( a_\alpha \) and \( b_\alpha \). As discussed before, the bootstrap distributions mimic the original unknown sampling distributions of the estimators of interest. Hence, in the case of efficiency measures we have:

\[ (\theta - \hat{\theta}) \sim (\theta^* - \bar{\theta}) \] (4-54)

Thus, it is possible to rewrite (4-53) as

\[ P\left(-b_\alpha \leq \theta^* - \hat{\theta} \leq -a_\alpha\right) = 1 - \alpha \] (4-55)
Using (4-55), finding \( a_\alpha \) and \( b_\alpha \) is a trivial exercise involving sorting values \( \theta^* - \hat{\theta} \) in ascending order and then removing \( \alpha/2 \) of the values from both ends of the sorted list. Hence, the bootstrap estimation of (4-53) is

\[
 p \left(-\hat{b}_\alpha \leq \theta^* - \hat{\theta} \leq -\hat{a}_\alpha\right) \approx 1 - \alpha \tag{4-56}
\]

Where \( -\hat{a}_\alpha \) and \( -\hat{b}_\alpha \) are equal to the end points of the truncated sorted list while \( \hat{a}_\alpha \leq \hat{b}_\alpha \). Finally, it is straightforward to define the estimated \((1 - \alpha)\)% confidence interval as follows:

\[
\hat{\theta} + \hat{a}_\alpha \leq \theta \leq \hat{\theta} + \hat{b}_\alpha \tag{4-57}
\]

The above algorithm can be used to construct the confidence interval for each DMU in the sample where \( \hat{\theta} \) exists.

4.6.5 DEA Software Packages

As the field of DEA has grown, both commercial and non-commercial DEA software packages have become widely available today for users who deal with DEA such as practitioners and researchers (Barr, 2004). A number of reviews of existing software packages are provided by Hollingsworth (1999) and Barr (2004) including advantages and disadvantages of reviewed software packages. In the former one, Hollingsworth (1999) reviews four packages, the Frontier Analyst Professional, IDEAS Professional, OnFront and DEAP. He compares various aspects such as ease of use, package facility, package updates and performance. He concludes that none of these 4 reviewed packages is able to generate user friendly format outputs while DEAP is the least user friendly among them. In the latter review, Barr (2004) describes eight commercial and non-commercial packages of DEA - SolverProbVer 4.0, Frontier Analysis Ver. 3.1.5, On Front Ver. 2.02, Wawick DEA Ver. 1.0, DEA Excel Solver Ver.1, DEAP Ver. 2.1, Efficiency Measurement System (EMS) Ver. 1.3.0 and Pioneer Ver. 2. He evaluates them in terms of model selection, key DEA features and capabilities,
user interface, platform and interpretability, reporting capabilities, documentation and support, test performance, and affordability. Besides the eight listed packages, some other solution options are documented in his review and updated results, resources, and link to additional information are available on line through the following link: http://faculty.smu.edu/barr/deahandbook/

It is expected that more standard DEA software will add the bootstrapping analysis feature in the near future (Ray, 2004). However, due to complexity of the bootstrap method, there are not many options currently available and in some cases researchers should develop their own programming codes using software such as Matlab and R. Another available option is using the FEAR package in R software originally developed by Paul Wilson. Wilson (2008) describes the application of this software package for computing non-parametric efficiency estimates, making inference, and testing hypotheses in frontier models. Although, FEAR is a very useful and fast package, some programming using commands in FEAR and R is still required for special purposes. Another available package is Performance Improvement Management Software (PIM-DEAsoftware) that in its recent version (Ver. 3) uses bootstrap methods to provide estimates of confidence intervals on DEA efficiencies and bias correction factors. More details and updated information regarding this package is available online through http://www.deasoftware.co.uk/AboutPIM.asp

### 4.6.6 Scale Efficiency

One of the fundamental questions in any efficiency study is whether the true technology is increasing, constant or decreasing returns to scale. Therefore, developing a reliable test procedure for examining returns to scale is imperative from both economic and statistical aspects (Simar and Wilson, 2002). For instance, if the underlying technology of a firm exhibits increasing returns to scale, upsizing and extending the size of business may be an appropriate solution to improve efficiency. Quite the opposite, if the underlying technology of a firm exhibits decreasing returns to scale, downsizing the size of operation may be an
appropriate alternative to enhance efficiency. Despite the importance of returns to scale analysis in policy decision making and its significant economic implications, there are a few studies that directly address the question of how statistical inferences on scale efficiency can be conducted for each DMU in the DEA models.

Banker (1996) was the first to discuss the statistical tests for returns to scale. In his approach for an output oriented model, the inefficiency of a given DMU is \( \theta_i = \sup \{\theta | (x, \theta y_i) \in \varphi \} \) where \( \varphi = \{(x, y) | x \text{ can produce } y \} \). Accordingly, \( \theta \) is a scalar random variable that is distributed with probability density function \( f(\theta) \) in the range of \([1, \infty)\). In this method, an additional structure on the distribution of the inefficiency variable \( \theta \) should be imposed which requires non-zero likelihood of nearly efficient performance. Let define \( \hat{\theta}_i^{CRS} \) and \( \hat{\theta}_i^{VRS} \) consistent estimator of inefficiency measures of \( \theta_i^{CRS} \) and \( \theta_i^{VRS} \) under constant and variable returns to scale in an output oriented model respectively. Scale inefficiency is then estimated as \( \hat{S}_i^1 = \frac{\hat{\theta}_i^{CRS}}{\hat{\theta}_i^{VRS}} \). If \( \hat{S}_i^1 \) is significantly greater than one, the DMU is scale inefficient due to the divergence from the most productive scale size (MPSS). Accordingly, all DMUs in the sample are scale efficient when they are from a production set under constant returns to scale (Banker and Natarajan, 2004). Specifically for statistical tests of returns to scale, Banker (1996) proposed two semi parametric and one non-parametric test statistic for the total number of \( n \) samples under different assumptions regarding the efficiency distribution function as follows:

1) On the assumption of an exponential distribution function for the logarithm of the true inefficiency \( \theta \) over \([0, \infty)\):

Under the null hypothesis of constant return to scale, the test statistic of \( \sum \ln \hat{\theta}_i^{CRS} / \sum \ln \hat{\theta}_i^{VRS} \) is evaluated compared to the critical value of the half-F distribution with the degrees of freedom of \( 2n, 2n \) over the range of \([1, \infty)\).
2) On the assumption of a half-normal distribution function for the logarithm of the true inefficiency $\theta$ over $[0, \infty)$:

Under the null hypothesis of constant return to scale, the test statistic of $\sum (\ln \hat{\theta}_i^{\text{CRS}})^2 / \sum (\ln \hat{\theta}_i^{\text{VRS}})^2$ is evaluated compared to the critical value of the half-F distribution with the degrees of freedom of $n, n$ over the range of $[1, \infty)$.

3) No assumption for the probability distribution of inefficiency:

In this case, a nonparametric statistical test of equality between two probability distribution functions is recommended using the two-sample Kolmogorov-Smirnov test. This test is to check whether the two data samples come from the same distribution. Under the null hypothesis of constant return to scale, the maximum distance between empirical distribution of $\ln \hat{\theta}_i^{\text{CRS}}$ and $\ln \hat{\theta}_i^{\text{VRS}}$ is as follows:

$$d = F^{\text{CRS}}(\ln \hat{\theta}_i^{\text{CRS}}) - F^{\text{VRS}}(\ln \hat{\theta}_i^{\text{VRS}})$$

(4-58)

The null hypothesis is rejected at level $\alpha$ if

$$nd / \sqrt{2n} > K_\alpha$$

(4-59)

Critical values $K_\alpha$ are available in Pearson and Hartley (1972).

The above tests are defined to test whether the technology is constant returns to scale or exhibits the alternative of variable returns to scale. These tests easily can be adopted to test existence of non-decreasing returns to scale against decreasing returns to scale. The following constraint $\sum_{i=1}^n Y_i = 1$ in an output-orientated version of (4-34) can be replaced by $\sum_{i=1}^n Y_i \leq 1$ and $\sum_{i=1}^n Y_i \geq 1$ to calculate decreasing returns to scale $\hat{\theta}_i^{\text{DRS}}$ and increasing returns to scale $\hat{\theta}_i^{\text{IRS}}$ respectively. Accordingly, Banker (1996) developed the following three statistical tests to evaluate the nature of scale inefficiency.
1) On the assumption of an exponential distribution function for the logarithm of the true inefficiency $\theta$ over $[0, \infty)$:
Under the null hypothesis of non-decreasing return to scale, the test statistic of $\sum \hat{\ln} \theta_{i}^{\text{IRS}} / \sum \hat{\ln} \theta_{i}^{\text{VRS}}$ or $\sum \hat{\ln} \theta_{i}^{\text{CRS}} / \sum \hat{\ln} \theta_{i}^{\text{DRS}}$ is evaluated compared to the critical value of the half-F distribution with the degrees of freedom of $2n, 2n$ over the range of $[1, \infty)$.

2) On the assumption of a half-normal distribution function for the logarithm of the true inefficiency $\theta$ over $[0, \infty)$:
Under the null hypothesis of non-decreasing return to scale, the test statistic of $\sum (\ln \hat{\theta}_{i}^{\text{IRS}})^2 / \sum (\ln \hat{\theta}_{i}^{\text{VRS}})^2$ or $\sum (\ln \hat{\theta}_{i}^{\text{CRS}})^2 / \sum (\ln \hat{\theta}_{i}^{\text{DRS}})^2$ is evaluated compared to the critical value of the half-F distribution with the degrees of freedom of $n, n$ over the range of $[1, \infty)$.

3) No assumption for the probability distribution of inefficiency:
In this case, a nonparametric statistical test of equality between two probability distribution functions is recommended using the two-sample Kolmogorov-Smirnov test. Under the null hypothesis of non-decreasing return to scale, the maximum distance between empirical distribution of $(\ln \hat{\theta}_{i}^{\text{IRS}}$ and $\ln \hat{\theta}_{i}^{\text{VRS}})$ or $(\hat{\theta}_{i}^{\text{CRS}}$ and $\ln \hat{\theta}_{i}^{\text{DRS}})$ is as follows:

$$d = F^{\text{CRS}} (\ln \hat{\theta}_{i}^{\text{CRS}}) - F^{\text{DRS}} (\ln \hat{\theta}_{i}^{\text{DRS}}) \quad (4-60)$$

$$d = F^{\text{IRS}} (\ln \hat{\theta}_{i}^{\text{IRS}}) - F^{\text{VRS}} (\ln \hat{\theta}_{i}^{\text{VRS}}) \quad (4-61)$$

Similarly, the test statistics for the null hypothesis of non-increasing returns to scale against the alternative of increasing returns to scale can be defined by interchanging $\hat{\theta}_{i}^{\text{IRS}}$ and $\hat{\theta}_{i}^{\text{DRS}}$ in the above procedures.

Although, Banker’s approach opened a new insight regarding the scale efficiency tests, it does not provide any statistical tests for individual firms. This test concerns global tests for returns to scale aspects of the production technology as a
whole (Lothgren and Tambour, 1999b). Moreover, Simar and Wilson (2002) consider the Banker approach as rather ad hoc and criticize the possibility of the incorrect size in these tests. As an alternative, Lothgren and Tambour (1999b) propose a bootstrap DEA approach for testing scale efficiency at the firm-specific level. They also introduce a new method to calculate confidence intervals based on statistical linear approximations. Empirical results were illustrated for Swedish eye-care departments. Lothgren and Tambour (1999b) use an output-oriented DEA model to develop their scale efficiency tests and define scale efficiency estimates for a given DMUi as:

\[
\hat{S}_i^1 = \frac{\hat{\theta}_i^{CRS}}{\hat{\theta}_i^{VRS}}
\] (4-62)

As discussed before, in such cases if \(\hat{S}_i^1 = 1\) then the DMU is scale efficient and otherwise it suffers from either increasing returns to scale or decreasing returns to scale inefficiency which can be determined by using the following ratio:

\[
\hat{S}_i^2 = \frac{\hat{\theta}_i^{CRS}}{\hat{\theta}_i^{DRS}}
\] (4-63)

If \(\hat{S}_i^2 = 1\) increasing returns to scale and where \(\hat{S}_i^2 > 1\) decreasing returns to scale exist. To add the statistical aspects to the above measures, Lothgren and Tambour (1999b) suggest a bootstrap algorithm given by following steps:

1) Compute the efficiency for a given point \((x_k, y_k)\) under constant returns to scale

\[
\hat{\theta}_k = \max\{\theta > 0 | \theta y_k \leq \sum_{i=1}^{n} y_i ; x_k \geq \sum_{i=1}^{n} x_i ; y_i \geq 0, i = 1, \ldots, n\}
\] (4-64)

2) Resample with replacement from \(\{\hat{\theta}_i^*, i = 1, \ldots, n\}\) and let \(\{\hat{\theta}_i^*, i = 1, \ldots, n\}\)

3) Let the bootstrap pseudo-data be given by \((x_i, y_i^*/\hat{\theta}_i^*)\)
4) Estimate the bootstrap efficiency measures using pseudo-data under constant returns to scale, variable returns to scale and non-increasing returns to scale respectively as follows

\[
\hat{\theta}_{k,b}^{\text{CRS}*} = \max \{ \theta > 0 | \theta y_k' \leq \sum_{i=1}^{n} y_i' ; x_k \geq \sum_{i=1}^{n} x_i' ; \gamma_i \geq 0, i = 1, \ldots \} (4-65)
\]

\[
\hat{\theta}_{k,b}^{\text{VRS}*} = \max \{ \theta > 0 | \theta y_k' \leq \sum_{i=1}^{n} y_i' ; x_k \geq \sum_{i=1}^{n} x_i' ; \sum_{i=1}^{n} y_i = 1 ; \gamma_i \geq 0, i = 1, \ldots, n \} (4-66)
\]

\[
\hat{\theta}_{k,b}^{\text{NIRS}*} = \max \{ \theta > 0 | \theta y_k' \leq \sum_{i=1}^{n} y_i' ; x_k \geq \sum_{i=1}^{n} x_i' ; \sum_{i=1}^{n} y_i \leq 1 ; \gamma_i \geq 0, i = 1, \ldots, n \} (4-67)
\]

5) Calculate following scale efficiency measures

\[
S_{1k}^{\text{b}} = \hat{\theta}_{k,b}^{\text{CRS}*} / \hat{\theta}_{k,b}^{\text{VRS}*} \quad (4-68)
\]

\[
S_{2k}^{\text{b}} = \hat{\theta}_{k,b}^{\text{CRS}*} / \hat{\theta}_{k,b}^{\text{NIRS}*} \quad (4-69)
\]

6) Repeat step 2-4 B times to create B bootstrap score for given DMUk

\[
\{S_{1k}^{\text{b}}, b = 1, \ldots, B \} \quad (4-70)
\]

\[
\{S_{1k}^{\text{b}}, b = 1, \ldots, B \} \quad (4-71)
\]

Then, given the DEA scale efficiency estimates, it is possible to test the significance of estimates using a nested test procedure as detailed in Lothgren and Tambour (1999b).

Although, Lothgren and Tambour were the first to propose an algorithm to analyse the sensitivity of scale efficiency and returns to scale, their bootstrap procedure was not consistent as they used a naive bootstrap. Moreover, instead of
using the originally observed output in (4-65), (4-66) and (4-67), they use the resampled bootstrap output which is based on a complete misunderstanding of what is known and what should be estimated (Simar and Wilson, 2002).

More recently, Simar and Wilson (2002) introduced a number of statistics and testing hypotheses regarding returns to scale. Their approach is designed to test returns to scale at the industry level, or what they call the global level. There proposed algorithms are only useful in determining the type of technology at the industry level and in choosing the right technology for further analysis such as estimating technical efficiency at the firm level or analysing returns to scale of the industry. The Simar and Wilson method examines the null hypothesis that the technology is global constant returns to scale against the alternative hypothesis of variable returns to scale. To explain the Simar and Wilson approach let define

\[ \hat{\delta}_i = \hat{\delta}_i^{\text{CRS}} / \hat{\delta}_i^{\text{VRS}} \]  

(4-72)

Calculating (4-72) for each observation \((x_i, y_i)\) produces \(n\) estimates of scale efficiency \(\{\hat{\delta}_i, i = 1, \ldots, n\}\). For an observation, the null hypothesis can be rejected when \(\hat{\delta}_i\) falls below a defined critical value. Suppose the test is repeated for all \(n\) observations then the number of rejections of the null hypothesis would be a binominal distribution function. The probability of \(r\) or more rejections when repeating the test \(n\) times with nominal size \(\alpha\) is given by the following beta function:

\[ l_\alpha(r, n - r + 1) = \frac{\binom{n}{r} \alpha^r (1 - \alpha)^{n-r}}{\binom{n}{r}} \]  

(4-73)

Simar and Wilson also introduced various alternative test statistics such as the mean of ratios, a ratio of means, the median of ratios, the ratio of medians, the 10% trimmed mean of ratios or the ratio of 10% trimmed means as follows respectively:

\[ \tilde{\delta}_i = n^{-1} \sum_{i=1}^n \hat{\delta}_i^{\text{CRS}} / \hat{\delta}_i^{\text{VRS}} \]  

(4-74)
To use any of the above tests, the appropriate critical values should be estimated. Simar and Wilson (2002) extended their earlier work in 1998 to bootstrap the test statistics. Three different approaches based on critical value, p-value and binomial test were proposed. These are set out below.

**Critical Value Approach**

In this method the null hypothesis is true for $\omega$ as a univariate parameter when $\omega = \omega_0$. Otherwise, the alternative hypothesis is true when $\omega < \omega_0$. In addition, when $\omega$ is unknown $\hat{\omega}$ is assumed as a consistent estimator of $\omega$. In the case of testing scale efficiency, the null hypothesis is true when $\omega_0 = 1$ and $\omega$ might be defined as any of the test statistics introduced above and $\hat{S}$ represents its estimation. Thus, the null hypothesis is rejected if $\hat{\omega} \leq \omega_0 - c_\alpha$ such that

$$P(\hat{\omega} \leq \omega_0 - c_\alpha) = \alpha$$

Unfortunately, $c_\alpha$ cannot be determined as the distribution function of $\hat{\omega}$ is unknown. The bootstrap method offers an easy solution to approximate $c_\alpha$. The idea behind the bootstrap is to use known $(\omega^* - \hat{\omega})$ to approximate the unknown distribution of $(\hat{\omega} - \omega)$.

$$(\hat{\omega} - \omega) \sim (\omega^* - \hat{\omega})$$
For the case of scale efficiency (4-81) is equivalent to

\[(\hat{\omega} - 1) \sim (\hat{\omega}^* - \hat{\omega}) \tag{4-82}\]

Given the bootstrap values \(\hat{\omega}_b^*, b=1,..,B\) the equivalent of (4-80) is

\[P(\hat{\omega}^* \leq \hat{\omega} - c_\alpha^*) = \alpha \tag{4-83}\]

In (4-83) \(c_\alpha^*\) is an approximate of \(c_\alpha\) can be determined easily by sorting the values \(\hat{\omega}_b \leq \hat{\omega}\) and deleting \((1- \alpha) \times 100\) percent of the values at the right-hand end of the sorted list. \(c_\alpha^*\) is equal to the right-hand endpoint of the new emerged list.

Then, by replacing \(c_\alpha\) by \(c_\alpha^*\) in (4-80), the bootstrap approximation is

\[P(\hat{\omega} \leq \omega_0 - c_\alpha^*) \approx \alpha \tag{4-84}\]

As described before, for the scale efficiency test \(\omega_0 = 1\). Thus, the test of constant returns to scale under the null hypothesis is rejected for a test of size \(\alpha\) if

\[\hat{\omega} \leq 1 - c_\alpha^* \tag{4-85}\]

**p-value Approach**

The p-value is an alternative approach for testing scale efficiency. Suppose the observed value of the test statistic is \(\hat{\omega}_{obs}\) and the p-value for the null hypothesis is defined as:

\[p = P(\hat{\omega} \leq \hat{\omega}_{obs}) \tag{4-86}\]

The null hypothesis is rejected for small p values such as values less than 0.05. Adding \(\omega_0\) to the both side of inequality in (4-86) we have
Using the bootstrap results as discussed before (4-87) can be approximated by

\[ \hat{p} = P(\hat{\omega}^* - \hat{\omega} \leq \hat{\omega}_{\text{obs}} - \omega_0) \]  \hspace{1cm} (4-88)

As \( \hat{\omega} = \hat{\omega}_{\text{obs}} \), (4-86) is equivalent to

\[ \hat{p} = P(\hat{\omega}^* \leq 2\hat{\omega}_{\text{obs}} - \omega_0) \]  \hspace{1cm} (4-89)

The probability in (4-87) is equivalent to

\[ \hat{p} = P(\hat{\omega}^* \leq \hat{\omega}_{\text{obs}}) \]  \hspace{1cm} (4-90)

Finally, the null hypothesis is rejected when \( \hat{p} \) is equal or less than the nominal size of the test \( \alpha \).

**Binomial Test**

As described, (4-73) can be used to determine the number of rejections needed to reject the null hypothesis. Scale efficiency bootstrap values \( \hat{S}_{ih}^* \), \( i=1,...,n \) can be used to carry out \( n \) individual tests using (4-73). Finally, the null hypothesis can be rejected if a predetermined number of rejections happen in performing \( n \) independent tests. All introduced tests can be easily extended to the test of non-increasing returns to scale for those rejected in the test of constant returns to scale.

### 4.7 Test of Returns to Scale for Individual Firms

As discussed before, one of the crucial questions in efficiency analysis is investigating the nature of scale economies and discovering whether the underlying technology exhibits increasing, decreasing or constant returns to scale. This is especially vital for managers and decision makers to test the optimum
scale size of their business units which can influence strategic decisions such as mergers or scaling down the size of their operations.

Unfortunately, all of the models discussed suffer from various problems or have not been designed to test scale efficiency at the firm level. For instance, although, Lothgren and Tambour (1999b) proposed a bootstrap DEA algorithm for testing returns to scale at the firm level, their proposed approach was technically flawed as detailed and discussed in Simar and Wilson (2000). The other two methods proposed by Banker (1996) and Simar and Wilson (2002) have been designed for testing returns to scale at the industry level. To address such shortfalls, this study aims to develop a DEA bootstrap method to estimate scale efficiency which yields confidence intervals for the test of returns to scale for individual DMUs. To do so, assume the sets $\Phi^{\text{CRS}}$, $\Phi^{\text{VRS}}$ and $\Phi^{\text{NIRS}}$ of attainable points of a production process under different technology assumptions of constant returns to scale (CRS), variable returns to scale (VRS) and non-increasing returns to scale (NIRS).

$$\Phi^{\text{CRS}} = \{(x,y) \in R_{p+q}^+ | y \leq \sum_{i=1}^{n} x_i y_i ; \theta x \geq \sum_{i=1}^{n} y_i x_i ; y_i \geq 0, i = 1, \ldots, n\}$$

$$\Phi^{\text{VRS}} = \{(x,y) \in R_{p+q}^+ | y \leq \sum_{i=1}^{n} x_i y_i ; \theta x \geq \sum_{i=1}^{n} y_i x_i ; \sum_{i=1}^{n} y_i = 1; y_i \geq 0, i = 1, \ldots, n\}$$

$$\Phi^{\text{NIRS}} = \{(x,y) \in R_{p+q}^+ | y \leq \sum_{i=1}^{n} x_i y_i ; \theta x \geq \sum_{i=1}^{n} y_i x_i ; \sum_{i=1}^{n} y_i \leq 1; y_i \geq 0, i = 1, \ldots, n\}$$

The crucial issue in the bootstrapping process of scale efficiency at the firm level is which production technology should be assumed to generate the pseudo data. For instance, Lothgren and Tambour (1999b) assumed constant returns to scale to generate pseudo data. This approach seems inappropriate where the technology displays variable returns to scale. As we know $\Phi^{\text{VRS}} \subseteq \Phi^{\text{NIRS}} \subseteq \Phi^{\text{CRS}}$. Thus, the constant returns to scale assumption may generate infeasible data points. In view of this, two approaches can be used to deal with the problem. The first, is to investigate returns to scale at the industry level using Banker (1996) or Simar and Wilson (2002). If the chosen test confirms existence of constant returns to scale then this assumption can be used to generate pseudo data in the bootstrapping process.
process. Otherwise, variable returns to scale is the true assumption. Second, where
the technology is unknown, variable returns to scale is the proper choice as it
guarantees all pseudo data points are feasible as we know $\Phi^{\text{VRS}} \subseteq \Phi^{\text{CRS}}$.

The other crucial issue in the bootstrap process of scale efficiency is ensuring the
alternative technology assumptions of CRS, VRS and NIRS have been applied in
each bootstrap replication on the same pseudo data and this requires re-ordering
the bootstrap method proposed by Simar and Wilson (1998a). Finally, as
discussed before, scale efficiency is equal to the ratio of the efficiency measure
under constant returns to scale to this efficiency measure under variable returns to
scale. Similarly, bootstrap scale efficiency is calculated by dividing the bootstrap
efficiency measure under two different assumptions of constant and variable
returns to scale. It should be noted that both these bootstrap measures have bias
and before computing the ratio of scale efficiency in each bootstrap replication,
the bias should be corrected for both measures. Otherwise it can cause
inconsistent bootstrap scale efficiency measures.

The above arguments can be extended to test the nature of scale inefficiency for
individual firms or business units. Due to the importance of sensitivity analysis of
scale efficiency measures in nonparametric methods, we develop a bootstrap
procedure which addresses all drawbacks explained before in a detailed algorithm.
This algorithm can be used by other researchers to test returns to scale efficiency
of individual firms in different industries and provides a new insight to analyse
scale efficiency.

To introduce our algorithm, we firstly define DEA measures used in this proposed
algorithm. As discussed before, efficiency of a given point $(x_k, y_k)$ under three
different assumptions of constant, variable and non-increasing returns to scale on
production technology is computed by solving the following linear programs:

$$
\hat{\delta}_{k}^{\text{CRS}} = \min \{ \theta > 0 | y_k \leq \sum_{i=1}^{n} \gamma_i y_i ; \theta x_k \geq \sum_{i=1}^{n} \gamma_i x_i ; \gamma_i \geq 0, i = 1, \ldots, n \} \quad (4-94)
$$
To develop our bootstrap method, we use the data generating process proposed by Simar and Wilson (1998a). Accordingly, our proposed bootstrap scale efficiency algorithm is summarized by the following steps:

1) For any given point \((x_{k}, y_{k})\)\(k=1,\ldots,n\) compute \(\hat{\theta}_{k}\) under variable returns to scale using (4-95).

2) Generate a standard bootstrap set \(\{\beta_{i}^{*}, i = 1,\ldots,n\}\) by drawing with replacement from the original estimations \(\{\hat{\theta}_{i}, i = 1,\ldots,n\}\).

3) Smooth the sampled values \(\{\beta_{i}^{*}, i = 1,\ldots,n\}\) using (4-44).

4) Correct the variance of the generated bootstrap sequence by computing (4-46)

5) Compute pseudo-data set \(\eta_{b}^{*} = \{(x_{ib}^{*}, y_{i}^{*}), i=1,\ldots,n\}\) given by (4-47)

6) Calculate the bootstrap estimate of for \(k=1,\ldots,n\) by solving the following linear programming problem

\[
\hat{\theta}_{k}^{VRS} = \min \{\theta > 0| y_{k} \leq \sum_{i=1}^{n} y_{i} y_{i} ; \theta x_{k} \geq \sum_{i=1}^{n} y_{i} x_{k}^{*} ; \gamma_{i} \geq 0, i = 1,\ldots,n\}\]

\[
\hat{\theta}_{k}^{NRS} = \min \{\theta > 0| y_{k} \leq \sum_{i=1}^{n} y_{i} y_{i} ; \theta x_{k} \geq \sum_{i=1}^{n} y_{i} x_{k}^{*} ; \gamma_{i} \geq 0, i = 1,\ldots,n\}\]

(4-96)

(4-97)

(4-98)

(4-99)
7) Compute bias corrected of $\theta_{k,b}^{*\text{CRS}}, \theta_{k,b}^{*\text{VRS}}$ and $\theta_{k,b}^{*\text{NIRS}}$ using:

$$\tilde{\theta}_{k,b}^{*\text{CRS}} = \theta_{k,b}^{*\text{CRS}} - 2\text{bias}_{k}$$

(4-100)

$$\tilde{\theta}_{k,b}^{*\text{VRS}} = \theta_{k,b}^{*\text{VRS}} - 2\text{bias}_{k}$$

(4-101)

$$\tilde{\theta}_{k,b}^{*\text{NIRS}} = \theta_{k,b}^{*\text{NIRS}} - 2\text{bias}_{k}$$

(4-102)

Where $\text{bias}_{k} = \frac{1}{B} \sum_{b=1}^{B} \tilde{\theta}_{k,b} - \hat{\theta}_{k}$

8) Compute $S_{1\, k,b}^{*} = \frac{\tilde{\theta}_{k,b}^{*\text{CRS}}}{\tilde{\theta}_{k,b}^{*\text{VRS}}}$ and $S_{2\, k,b}^{*} = \frac{\tilde{\theta}_{k,b}^{*\text{NIRS}}}{\tilde{\theta}_{k,b}^{*\text{VRS}}}$

9) Repeat steps 2 and 6, B=2000 times to provide for $k=1,\ldots,n$ a set of estimates $\{S_{1\, k,b}, b = 1,\ldots,B\}$ and $\{S_{2\, k,b}, b = 1,\ldots,B\}$

$S_{1\, k,b}$ and $S_{2\, k,b}$ are set of 2000 bootstrap scale efficiency for $k=1,\ldots,n$. The next section describes how these set can be used to develop hypothesis testing for returns to scale.

From the viewpoint of statistical hypothesis testing, the first issue is whether a DMU is scale efficient or not. To address this issue, we follow the Simar and Wilson (2002) approach. Assume the null hypothesis $H_{0}$ is $S_{1} = 1$ where $S_{1}$ is presented the true value of scale efficiency. The alternative hypothesis $H_{1}$ is $S_{1} < 1$ and a consistent estimator of $S_{1}$ is represented by $\hat{S}_{1}$ and $\hat{S}_{1}^{*}$ represents bootstrap estimates. Considering the bootstrap approach we have:

$$(\hat{S}_{1} - 1)|H_{0} \sim (\hat{S}_{1}^{*} - \hat{S}_{1})|H_{0}$$

(4-103)

The null hypothesis is rejected if $\hat{S}_{1}^{*} \leq 1 - c_{\alpha}$ for $c_{\alpha} > 0$ for a test size $\alpha$ such that
$P(\hat{S}_1 \leq 1 - c_\alpha|H_0) = \alpha \quad (4-104)$

$c_\alpha$ can be estimated by $c_\alpha^*$ using bootstrap values $\hat{S}_1^*$

Finding $c_\alpha^*$ involves sorting the values $(\hat{S}_{1b}^* - \hat{S}_1^*)$ in increasing order and then deleting $(1 - \alpha) \times 100$ percent of elements at the right hand end of the sorted list. Then set $-c_\alpha^*$ equal to the endpoint of the resulting list. Replacing $c_\alpha$ with $c_\alpha^*$ the null hypothesis is rejected if

$\hat{S}_1 \leq 1 - c_\alpha^* \quad (4-105)$

A similar approach can be applied to determine the nature of scale inefficiency by substituting $s_{2,k,b} = \hat{b}_{k,b}^{NIRS}/\hat{b}_{k,b}^{VRS}$ in the above equations to test whether an inefficient DMU operates under increasing or decreasing returns to scale.

$\hat{S}_2 \leq 1 - c_\alpha^* \quad (4-106)$

If (4-106) is correct then the DMU operates under increasing returns to scale, otherwise, it operates under decreasing return to scale.

### 4.8 Efficiency Analysis Matrix

It is vital to investigate the sources of firms’ inefficiency. Whether it is caused by the inefficient operation of firms or by other disadvantageous conditions like size are crucial questions in efficiency analysis. As discussed above, Banker et al. (1984) developed a method to decompose technical efficiency to pure technical and scale efficiency. Following this approach, this study introduces the technical efficiency matrix to demonstrate this decomposition and to illustrate the confidence intervals for both pure technical and scale efficiency estimates by portraying an ellipse for each DMU which facilitates a statistical and comprehensive analysis of technical efficiency. The efficiency matrix is a $2 \times 2$
matrix with scale efficiency on the vertical axis and pure technical efficiency on the horizontal axis. This means that there are four zones or relative positions for each firm. The properties of each zone have been noted in Figure 4-10. For instance, Zone 1 represents firms that rate poorly both in scale and pure technical efficiency.

By analysing technical efficiency using a visual tool, decision makers and managers are able to find the source of inefficiency and assess opportunities for improvement while considering other rivals. For instance, firm A in Figure 4-10 operates better than firm B in terms of scale efficiency but poorer in terms of pure technical efficiency. Moreover, the size of each ellipse demonstrates the confidence intervals for scale and technical efficiency. As demonstrated in Figure 4-10, firm B has a narrow confidence interval in terms of pure technical efficiency while it has a wide confidence interval in terms of scale efficiency.

Figure 4-10: Technical Efficiency Decomposition using Efficiency Matrix

![Figure 4-10: Technical Efficiency Decomposition using Efficiency Matrix](image)

NOTE: the larger size of the ellipse means a wide confidence interval and less accurate result.

A visualization of the analysis results allows us to absorb valuable information in a visual way. This is especially helpful when analysts and decision makers look at firms in the corresponding peer group to obtain a better understanding of two important dimensions of technical efficiency. It also provides solutions and
recommendations to improve the most critical aspects of technical efficiency for a particular firm or for the whole industry.

4.9 Summary

This chapter provided an overview of the application of frontier models in efficiency analysis. It focused on DEA as the most frequently used non-parametric technique in this field. DEA is a linear programming technique used to construct a frontier that envelops all units in the sample. It estimates the distance of each unit to the constructed frontier to provide relative efficiency scores for units in the sample. Two common assumptions of constant returns to scale and variable returns to scale allow for decomposing technical efficiency to pure technical and scale efficiency. This assists analysts in finding the source of technical inefficiency and in examining options for improvement.

DEA has a number of advantages including not requiring assumptions on the functional form of production and generating a single efficiency measure in a multi-input / multi-output environment. These advantages have made it a popular tool in efficiency analysis studies. Apart from its advantages, however, DEA has been criticized for its deterministic nature and lack of statistical precision since it was initially introduced in 1978. Fortunately, this problem can be successfully addressed using the statistical based method of bootstrapping introduced by Simar and Wilson (1998a). Since then researchers have been able to provide the statistical properties of their efficiency estimates such as bias and confidence intervals. Although, bootstrap DEA is a consistent and reliable approach, some studies are still using standard DEA possibly due to shortage of friendly software solutions and lack of knowledge of the advantages of bootstrapping. This issue can seriously affect the validity of results especially when the sample size is small. This study addresses this gap and highlights the difference between the original and bootstrapping results in the case of Australian banking in the following chapters.
Although, recent applications of bootstrap DEA in different industries and various countries have proven its capability in dealing with practical cases, no consistent bootstrap procedure has been introduced to add statistical properties for scale efficiency measures of individual units. Due to the importance of analysing scale efficiency as one of the key aspects of technical efficiency, this study develops a bootstrap DEA procedure to provide not only statistical properties of scale efficiency estimates but also to determine the nature of scale inefficiency including the impact of increasing returns to scale or decreasing returns to scale. This chapter also proposes an efficiency matrix to demonstrate the confidence interval of both pure technical and scale efficiency of units to assist managers and decision maker in efficiency analysis.
Chapter Five: Technical Efficiency of Australian Banks during the Post-Wallis Period (1997 to 2005)

5.1 Introduction

Data Envelopment Analysis (DEA) arguably is the most applied non-parametric frontier analysis technique in measuring the efficiency of the banking sector. However, this method has its disadvantages. The proper choice of variables and lack of statistical precision are two significant challenges in using DEA. This chapter addresses these issues by re-examining the technical efficiency of ten Australian banks during the post-Wallis period between 1997 and 2005. The post-Wallis period is important because of the regulatory changes that occurred as a result of the Wallis enquiry findings in 1997. Thus, it is of interest to investigate the impact of changes in regulation on the efficiency level of Australian banks during the post-Wallis period.

The chapter presents firstly the result of improving the variable choice of the profit core efficiency approach in estimating both the pure technical and scale efficiency of Australian banks. Secondly, using bootstrap DEA methods explained in Chapter 4, statistical properties of efficiency estimates such as confidence intervals and bias-corrected estimates are provided. Furthermore, for the sake of comparison both original and bootstrap estimates are presented in this chapter. The difference between original and bootstrap results implies the necessity of considering sampling variations and measurement errors in such efficiency studies. This issue had been overlooked in earlier Australian banking efficiency studies which employed non-parametric methods. To facilitate our analysis and discussion, the bootstrap results are also portrayed using the efficiency matrix.
introduced in Chapter 4. The rest of this chapter is organised as follows: Section 5.2 introduces variables and sample banks. Section 5.3 presents empirical results consisting of the results obtained from improving the choice of variable and the statistical properties of efficiency estimates. The bootstrapped results are also illustrated in the efficiency matrix to visualize the findings. Finally, Section 5.4 summarizes the major findings of this chapter.

5.2 Choice of Variables and Sample Banks

Taking a systematic approach, banks can be seen as entities that convert inputs to outputs (e.g. asset and equity as inputs and profit as output). Surprisingly, despite the importance of variables’ choice in DEA models, there is no consensus in the banking efficiency literature in relation to output and input selection methods (Yang, 2011). Intermediation, production and core profit are the most commonly used approaches in choosing variables of the DEA models in the literature.

The intermediation approach suggests that banks transform deposit expenses into revenues from loans and other investments (Yang and Liu, 2012). In contrast, the production approach assumes banks are firms that produce different types of deposits and loan services while employing some resources such as capital and labour (Webb, 2003). The third approach, the core profit efficiency model was introduced to examine the process of how well a bank uses inputs such as different expenses to generate outputs such as various types of income. In its general form, this approach views banks as business units that use interest expense and non-interest expense as the input variables to generate net interest income and non-interest income as the output variables.

The core profit efficiency approach is the most commonly used in the Australian literature. However, by selecting net interest income as an output variable in the core profit efficiency model, earlier studies confound efficiency estimates by ignoring the impact of unaccounted interactions between endogenous and exogenous variables and adding unnecessary duplications as discussed in detail in
Avkiran and Thoraneenitiyan (2010). Furthermore, when two inputs are defined as interest and non-interest expenses, it seems logical to define outputs as interest and non-interest incomes. Earlier efficiency studies replaced interest income by net interest income which is the difference between interest income and interest expense.

Reviewing earlier Australian banking efficiency studies shows that the improper choice of input and output variables arose with an early study by Avkiran (1999a) and possibly has continued since then for comparison reasons in all Australian efficiency studies using the core profit efficiency approach (e.g., Avkiran, 1999b, Avkiran, 2000, Avkiran, 2004, Paul and Kourouche, 2008, Sathye, 2002, Sturm and Williams, 2004). To address this issue, we aim to improve the choice of output variables in the earlier studies by selecting “interest income” over “net interest income” in the core profit efficiency model. To determine the impact of this change, we also re-examine the technical efficiency components and highlight differences by comparing our obtained results to one of the recent studies conducted by Paul and Kourouche (2008).

Following a modified version of the core profit efficiency approach, banks are viewed as financial institutions using two inputs of interest income and non-interest income to generate two outputs of interest income and non-interest income. Interest expenses as a proxy of deposits includes expenses associated with attracting and maintaining depositors’ funds while non-interest expenses consist of operating and overhead expenses such as salaries and employee benefit. In contrast, interest income can be seen as a proxy of loans and includes the amount of revenue which banks gain from interest on loans they provide to their clients. On the other hand, non-interest income is a proxy for non-traditional banking activities such as wealth management and securitisations. This new approach has been recently used to undertake efficiency analysis of banks in Korea and United Arab Emirates by Avkiran and Thoraneenitiyan (2010) and Banker et al. (2010). For comparison reasons, similar to the recent study by Paul and Kourouche (2008), we choose ten Australian banks as illustrated in Table 5-1.
Table 5-1: Australian Banks Listed in the Australian Stock Exchange (ASX)

<table>
<thead>
<tr>
<th>DMU</th>
<th>Bank Name</th>
<th>Abbreviation</th>
<th>Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Australia and New Zealand Bank</td>
<td>ANZ</td>
<td>Large</td>
</tr>
<tr>
<td>2</td>
<td>Commonwealth Bank</td>
<td>CBA</td>
<td>Large</td>
</tr>
<tr>
<td>3</td>
<td>National Australian Bank</td>
<td>NAB</td>
<td>Large</td>
</tr>
<tr>
<td>4</td>
<td>Westpac</td>
<td>WBC</td>
<td>Large</td>
</tr>
<tr>
<td>5</td>
<td>Macquarie Bank</td>
<td>MQG</td>
<td>Medium</td>
</tr>
<tr>
<td>6</td>
<td>St George</td>
<td>SGB</td>
<td>Medium</td>
</tr>
<tr>
<td>7</td>
<td>Suncorp Group</td>
<td>SUN</td>
<td>Medium</td>
</tr>
<tr>
<td>8</td>
<td>Adelaide Bank</td>
<td>ADB</td>
<td>Small</td>
</tr>
<tr>
<td>9</td>
<td>Bendigo Bank</td>
<td>BEN</td>
<td>Small</td>
</tr>
<tr>
<td>10</td>
<td>Bank of Queensland</td>
<td>BOQ</td>
<td>Small</td>
</tr>
</tbody>
</table>

As presented in Table 5-1 banks are categorised in three different sizes of large, medium and small based on their asset size as described in Chapter 2. Accordingly, the sample consists of four major banks, three medium sized and three small banks. We also opted to examine the same study period used by Paul and Kourouche (2008) to provide a realistic examination regarding the impact of improper choice of output variables in the core profit efficiency model in earlier banking efficiency studies.

Input and output data are collected from the DataAnalysis database created and maintained by Morningstar, Inc. This well-recognised database provides comprehensive and detailed financial information on all ASX listed companies from 1989. We also used banks’ annual reports for some banks where the data was not available in the DataAnalysis database. The summary statistics of all four variables during the period between 1997 and 2005 are reported in Table 5-2

Table 5-2: Summary Statistics of Variables (1997-2005)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean $billion</th>
<th>Standard Deviation $billion</th>
<th>Minimum $billion</th>
<th>Maximum $billion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interest expense</td>
<td>3,439</td>
<td>3,727</td>
<td>106</td>
<td>13,790</td>
</tr>
<tr>
<td>Non-interest expense</td>
<td>2,627</td>
<td>2,903</td>
<td>72</td>
<td>16,798</td>
</tr>
<tr>
<td>Interest income</td>
<td>5,614</td>
<td>6,031</td>
<td>181</td>
<td>20,872</td>
</tr>
<tr>
<td>Non-interest income</td>
<td>2,186</td>
<td>2,681</td>
<td>23</td>
<td>16,505</td>
</tr>
</tbody>
</table>


5.3 Empirical Results

As discussed in Chapter 4, a production function can be constructed to exhibit the maximum level of outputs using a certain level of inputs (Emrouznejad and De Witte, 2010). Accordingly, we employ an input oriented DEA model on a panel data of 90 observations (ten banks in nine years) to estimate the original efficiency score of all bank-year observations. All input and output variables are deflated to 1997 using the GDP deflator to control for the effect of inflation. We firstly present the original estimates from the improved profit efficiency model. Then, the statistical properties of the original efficiency estimates along with a detail discussion on individual banks performance is provided.

5.3.1 Original Results

This section presents the results from the improved version of the profit efficiency model and compares the results with one of the recent studies. The original estimates of the pure and scale technical efficiency between 1997 and 2005 are reported in Table 5-3. Large differences arise when comparing the original results obtained from the improved profit efficiency model in Table 5-3 and one of the latest studies by Paul and Kourouche (2008).

Our results reported in Table 5-3 reveal that only 23% of the observations are fully pure technical efficient, while this figure in Paul and Kourouche’s study is 81%. Similar differences also can be observed for scale efficiency scores. While their results show about 51% of observations are scale efficient, this figure was less than 9% in the improved model. This implies that according to Paul and Kourouche’s results, it is not possible to distinguish between the efficiency levels of the majority of banks and it raises a question about the usefulness and reliability of such results.
<table>
<thead>
<tr>
<th>Bank</th>
<th>Year</th>
<th>Pure Technical Efficiency</th>
<th>Scale Efficiency</th>
<th>Bank</th>
<th>Year</th>
<th>Pure Technical Efficiency</th>
<th>Scale Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADB</td>
<td>1997</td>
<td>1</td>
<td>0.9745</td>
<td>MQG</td>
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<td>1</td>
<td>0.9395</td>
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<tr>
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<td>0.9223</td>
<td>0.9252</td>
<td>MQG</td>
<td>1998</td>
<td>1</td>
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<td>0.9743</td>
<td>0.9458</td>
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<td>0.9750</td>
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<td>ADB</td>
<td>2000</td>
<td>0.9280</td>
<td>0.9709</td>
<td>MQG</td>
<td>2000</td>
<td>0.9727</td>
<td>0.9757</td>
</tr>
<tr>
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<td>0.9515</td>
<td>0.9405</td>
<td>MQG</td>
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<td>0.9033</td>
<td>MQG</td>
<td>2002</td>
<td>0.9099</td>
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<td>0.9025</td>
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<td>0.9797</td>
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<td>SUN</td>
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</tr>
<tr>
<td>BOQ</td>
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<td>0.9398</td>
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</tr>
<tr>
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<td>2005</td>
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<tr>
<td>CBA</td>
<td>1997</td>
<td>0.9614</td>
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<td>WBC</td>
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<td>0.9147</td>
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<td>0.9879</td>
<td>0.9754</td>
<td>WBC</td>
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<td>0.9165</td>
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</tr>
<tr>
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<td>0.9690</td>
<td>WBC</td>
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<td>0.9474</td>
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</tr>
<tr>
<td>CBA</td>
<td>2000</td>
<td>0.9571</td>
<td>0.9911</td>
<td>WBC</td>
<td>2000</td>
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</tr>
<tr>
<td>CBA</td>
<td>2001</td>
<td>0.9296</td>
<td>0.9549</td>
<td>WBC</td>
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</tr>
<tr>
<td>CBA</td>
<td>2002</td>
<td>1</td>
<td>0.9534</td>
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<td>0.9293</td>
<td>WBC</td>
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<td>CBA</td>
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<td>1</td>
<td>0.9290</td>
<td>WBC</td>
<td>2005</td>
<td>0.9455</td>
<td>0.9905</td>
</tr>
</tbody>
</table>
As we expected, the modified version of the profit efficiency model improved the discriminatory power of the efficiency estimates as suggested by Avkiran and Thoraneenitiyan (2010). Thus, our results provide more useful information for managers and decision makers to compare banks’ efficiency and reveal improvement opportunities for each bank in comparison with other rivals.

5.3.2 Bootstrapped Results

Although, improving the choice of output augmented the discriminatory power of pure technical efficiency estimates, the original estimates still suffer from the lack of degree of significance and do not take into account the possibility of sampling variations and measurement errors. Hence, to enrich the original estimates, the confidence intervals and bias corrected efficiency scores for all bank-year observations are estimated using the FEAR package provided by Wilson (2008) and R codes developed by the authors. Re-sampling also is carried out for B=2000, considering a 99% confidence interval. The results include the original and bias corrected estimates along with lower and upper bounds of confidence intervals and are reported in Table 5-4. The bootstrap results show that the average efficiency score is 93.9% which is almost 1.8% less than the average efficiency of the original scores. It implies that the efficiency estimates are statistically significant and relatively stable.

Figure 5-1 shows the trend of bias corrected pure technical efficiency of individual banks. Figure 5-1 (a) shows that the pure technical efficiency of all small banks declined over the study period, suggesting that to be competitive the small banks needed to reduce their inputs (expenses) while producing at least the same amount of outputs (incomes). On the other hand, notable variations occur for the medium and large sized banks. Figure 5-1 (c) and Figure 5-1 (b) show that the large banks tend to exhibit a higher growth in pure technical efficiency while at the same time the medium sized banks show mixed results of ascending, descending and flat trends.
Table 5-4: Bootstrapped Pure Technical Efficiency of Australian Banks (1997-2005)

<table>
<thead>
<tr>
<th>Bank</th>
<th>Year</th>
<th>Original</th>
<th>Bootstrap</th>
<th>Lower bound</th>
<th>Upper bound</th>
</tr>
</thead>
<tbody>
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<td>ADB</td>
<td>1997</td>
<td>0.9575</td>
<td>0.8936</td>
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<td>0.9242</td>
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<td>0.9195</td>
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</tr>
<tr>
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<td>1998</td>
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<td>2005</td>
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<td>0.8716</td>
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</tr>
<tr>
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<td>1997</td>
<td>1</td>
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<td>0.9284</td>
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</tr>
<tr>
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</tr>
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<tr>
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<td>CBA</td>
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</tr>
<tr>
<td>CBA</td>
<td>2000</td>
<td>0.9571</td>
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</tr>
<tr>
<td>CBA</td>
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<td>0.9099</td>
<td>0.8894</td>
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</tr>
<tr>
<td>CBA</td>
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<td>CBA</td>
<td>2003</td>
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</tr>
<tr>
<td>CBA</td>
<td>2004</td>
<td>1</td>
<td>0.9733</td>
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<tr>
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<tr>
<td>CGB</td>
<td>1997</td>
<td>0.9826</td>
<td></td>
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</tr>
<tr>
<td>CGB</td>
<td>1998</td>
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<td>0.978</td>
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<td>CGB</td>
<td>1999</td>
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<td>0.9595</td>
<td>0.9385</td>
<td>0.9736</td>
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<tr>
<td>CGB</td>
<td>2000</td>
<td>0.9727</td>
<td>0.9635</td>
<td>0.9489</td>
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</tr>
<tr>
<td>CGB</td>
<td>2001</td>
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<tr>
<td>CGB</td>
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<td>0.9455</td>
<td>0.9243</td>
<td>0.8978</td>
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As shown in Figure 5-1 more notable disparities between individual banks in both the large and medium sized bank groups can be observed. For instance, while Suncorp experiences considerable growth during the sample period, the efficiency scores of St. George Bank are relatively flat and Macquarie Bank’s efficiency declines every year except in 2003. Similar fluctuations exist in efficiency of the large banks. While the ANZ Bank has the lowest level of pure technical efficiency among the large banks in 1997, it improves its pure technical efficiency significantly thereafter. However, other large banks do not show a similar trend. For instance, efficiency of the National Australia Bank is more or less unchanged while the Commonwealth Bank and Westpac Bank experience significant fluctuations during the study period.

A graphical representation of the technical efficiency distribution for individual banks is presented in Figure 5-2 using box plots to facilitate the evaluation of efficiency trends across the 9 years study period. The box plots reveal that while the confidence interval is quite narrow for some banks (Westpac and St. George), it is rather wide for some others (National Australia Bank). This type of representation is useful when the bias corrected estimations of two banks are close. In this case, by looking at the confidence interval the more efficient bank can be easily identified. For instance, the efficiency scores of the ANZ Bank in 2002 and 2005 are almost equal but the narrower confidence interval in 2002 shows that this bank was operating more efficiently in 2002 than 2005.
Additionally, differences between the original estimates and bootstrap results are more apparent in particular cases. For instance, from the original estimates we would conclude that the National Australia Bank has improved its pure technical efficiency over the study period and operates efficiently in 2001, 2002, 2003 and 2005. Nevertheless, the conclusion from the bootstrap results is different and the National Australia Bank in 2003 is more pure technical efficient than other years. That is, in the context of non-parametric methods any relative efficiency comparison among individual banks based only on the original estimates can be misleading. Thus, in cases where measurement errors and sample variations exist, using the bootstrap method obtains more accurate and reliable results on the efficiency level of an organisation.

Figure 5-2: Box Plots of Bootstrapped Pure Technical Efficiency of Banks (1997-2005)
As shown in Table 5-3, the original estimates show that out of 90 samples, 21 operate on the best practice frontier and are equally efficient, but this result does not provide decision makers with useful information as it is not possible to
distinguish between the performance of many banks in the sample. In this case, the bootstrap procedure turns out to be a very useful tool. Figure 5-3 indicates the differences between efficient banks obtained from the original estimates using the bootstrap method. Surprisingly, the bootstrap results presented in Figure 5-3 reveal that all fully pure technical efficient banks are not operating at the same level of efficiency. It is shown that the estimated confidence intervals are quite wide for a number of banks and rather narrow for some others. As shown in Figure 5-3, the Commonwealth Bank in 1999 seems to be the most pure technical efficient, followed by ANZ Bank in 2003 and Macquarie Bank in 1997, respectively.

Figure 5-3: Differences between Efficient Banks using Bootstrap Method (1997-2005)

Examining the scale efficiency as the other dimension of technical efficiency is important for both economic and statistical reasons (Simar and Wilson, 2002). For instance, where technology does not exhibit constant returns to scale it may show some banks are either too large or too small. From the preceding discussion, it is possible to make statistical inference on the nature of returns to scale using our proposed bootstrap approach in Chapter 4.
Table 5-5: Comparison of Scale Efficiency of Banks using Original DEA vs.
Bootstrap DEA (1997-2005)
Original

Bootstrap

Bank

Year

CRS

VRS

NIRS

Original

Bootstrap

IRS
IRS
IRS
IRS
IRS
IRS
IRS
IRS
IRS

SE
IRS
IRS
SE
IRS
IRS
IRS
IRS
IRS

MQG
MQG
MQG
MQG
MQG
MQG
MQG
MQG
MQG

1997
1998
1999
2000
2001
2002
2003
2004
2005

0.9395
0.9520
0.9360
0.9490
0.9417
0.8973
0.9558
0.9589
1.0000

1.0000
1.0000
0.9750
0.9727
0.9586
0.9099
0.9650
0.9640
1.0000

0.9395
0.9520
0.9360
0.9490
0.9417
0.8973
0.9558
0.9589
1.0000

IRS
IRS
IRS
IRS
IRS
IRS
IRS
IRS
SE

IRS
IRS
IRS
IRS
SE
SE
SE
SE
SE

DRS
DRS
DRS
DRS
IRS
SE
SE
SE
SE

SE
SE
SE
SE
SE
SE
SE
SE
SE

NAB
NAB
NAB
NAB
NAB
NAB
NAB
NAB
NAB

1997
1998
1999
2000
2001
2002
2003
2004
2005

0.9322
0.9152
0.9205
0.9060
0.9862
0.9174
0.9690
0.8832
0.8883

0.9582
0.9751
0.9552
0.9815
1.0000
1.0000
1.0000
0.9584
1.0000

0.9582
0.9751
0.9552
0.9815
1.0000
1.0000
1.0000
0.9584
1.0000

DRS
DRS
DRS
DRS
DRS
DRS
DRS
DRS
DRS

DRS
DRS
SE
DRS
SE
DRS
SE
DRS
DRS

0.8771
0.9003
0.8971
0.9056
0.8777
0.9329
0.9414
0.9009
0.8667

IRS
IRS
IRS
IRS
IRS
IRS
IRS
IRS
IRS

IRS
IRS
IRS
IRS
IRS
IRS
IRS
IRS
IRS

SGB
SGB
SGB
SGB
SGB
SGB
SGB
SGB
SGB

1997
1998
1999
2000
2001
2002
2003
2004
2005

0.9620
0.9429
0.9276
0.9135
0.9222
0.9541
0.9474
0.9466
0.9550

0.9662
0.9463
0.9305
0.9168
0.9254
0.9563
0.9496
0.9494
0.9578

0.9620
0.9429
0.9276
0.9135
0.9222
0.9541
0.9474
0.9466
0.9550

IRS
IRS
IRS
IRS
IRS
IRS
IRS
IRS
IRS

SE
SE
SE
SE
SE
SE
SE
SE
SE

1.0000
1.0000
1.0000
0.9797
0.9398
0.9915
0.9722
0.9079
0.8887

0.9301
0.9379
0.9376
0.9102
0.8767
0.8818
0.8802
0.8811
0.8658

IRS
IRS
IRS
IRS
IRS
IRS
IRS
IRS
IRS

IRS
IRS
IRS
IRS
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IRS
IRS

SUN
SUN
SUN
SUN
SUN
SUN
SUN
SUN
SUN

1997
1998
1999
2000
2001
2002
2003
2004
2005

0.8450
1.0000
0.8737
0.9219
0.9029
0.9836
1.0000
1.0000
0.9949

0.8649
1.0000
0.8832
0.9234
0.9044
0.9879
1.0000
1.0000
1.0000

0.8450
1.0000
0.8737
0.9219
0.9029
0.9836
1.0000
1.0000
1.0000

IRS
SE
IRS
IRS
IRS
IRS
SE
SE
DRS

IRS
SE
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SE
SE
SE

0.9614
0.9879
1.0000
0.9571
0.9296
1.0000
0.9782
1.0000
1.0000

0.9614
0.9879
1.0000
0.9571
0.9296
1.0000
0.9782
1.0000
1.0000

DRS
DRS
DRS
DRS
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DRS
DRS

SE
DRS
DRS
SE
DRS
DRS
DRS
DRS
DRS

WBC
WBC
WBC
WBC
WBC
WBC
WBC
WBC
WBC

1997
1998
1999
2000
2001
2002
2003
2004
2005

0.9069
0.9062
0.9288
0.8981
0.9255
0.9681
0.9626
0.9283
0.9366

0.9147
0.9165
0.9474
0.9063
0.9368
0.9970
0.9780
0.9387
0.9455

0.9147
0.9165
0.9474
0.9063
0.9368
0.9970
0.9780
0.9387
0.9455

DRS
DRS
DRS
DRS
DRS
DRS
DRS
DRS
DRS

SE
SE
DRS
SE
SE
DRS
SE
SE
SE

Bank

Year

CRS

VRS

NIRS

ADB
ADB
ADB
ADB
ADB
ADB
ADB
ADB
ADB

1997
1998
1999
2000
2001
2002
2003
2004
2005

0.9745
0.8534
0.9215
0.9010
0.8949
0.8306
0.8670
0.8861
0.8831

1.0000
0.9223
0.9743
0.9280
0.9515
0.9195
0.9025
0.9103
0.9033

0.9745
0.8534
0.9215
0.9010
0.8949
0.8306
0.8670
0.8861
0.8831

ANZ
ANZ
ANZ
ANZ
ANZ
ANZ
ANZ
ANZ
ANZ

1997
1998
1999
2000
2001
2002
2003
2004
2005

0.8672
0.9056
0.9470
0.9380
0.9625
1.0000
1.0000
1.0000
1.0000

0.8773
0.9153
0.9582
0.9398
0.9626
1.0000
1.0000
1.0000
1.0000

0.8773
0.9153
0.9582
0.9398
0.9625
1.0000
1.0000
1.0000
1.0000

BEN
BEN
BEN
BEN
BEN
BEN
BEN
BEN
BEN

1997
1998
1999
2000
2001
2002
2003
2004
2005

0.8771
0.9003
0.8971
0.9056
0.8777
0.9329
0.9414
0.9009
0.8667

0.9864
0.9790
0.9454
0.9550
0.9152
0.9605
0.9665
0.9209
0.8834

BOQ
BOQ
BOQ
BOQ
BOQ
BOQ
BOQ
BOQ
BOQ

1997
1998
1999
2000
2001
2002
2003
2004
2005

0.9301
0.9379
0.9376
0.9102
0.8767
0.8818
0.8802
0.8811
0.8658

CBA
CBA
CBA
CBA
CBA
CBA
CBA
CBA
CBA

1997
1998
1999
2000
2001
2002
2003
2004
2005

0.9529
0.9637
0.9690
0.9486
0.8877
0.9534
0.9090
0.8898
0.9290

193


For the purpose of comparison, Table 5-5 presents scale efficiency results from both the original and bootstrap methods. The original results show that only 9% of banks are scale efficient, 55.5% are operating under Increasing Returns to Scale (IRS) and 35.5% are operating under Decreasing Returns to Scale (DRS). On the contrary, the bootstrap results indicate that 50% of banks are scale efficient, 33% are operating in the IRS region and 17% are operating in the DRS region. It seems that for a number of samples, the bootstrapped results are different from those obtained by the original estimates. In other words, the results imply that the original estimates can be misleading and emphasises the importance of using statistical based methods in measuring the scale efficiency of sample banks.

In respect to scale distribution by size, the results show that only 7% of samples related to small banks are efficient and the rest are operating on increasing returns to scale. Interestingly, the scale efficient samples among medium and large banks are found to be 81.5% and 58%, respectively. This important finding indicates that while the optimum scale belongs to the medium sized banks, on the other hand, all small banks suffer highly from scale inefficiency and the major banks demonstrate a mixed result during the study period.

5.3.3 Efficiency Matrix

In general, decomposing technical efficiency into pure technical and scale efficiency is a common practice to disclose weaknesses and strengths of DMUs in terms of these two key efficiency components. The technical efficiency matrix proposed in this study illustrates visually the sources of technical inefficiency and their statistical precision to facilitate comparisons to rivals and to analyse efficiency trends. This tool would also help managers with strategic decisions such as mergers or downsizings by portraying the statistical properties of scale inefficiency. Due to wide confidence intervals for some observations and to avoid interference of drawn ellipses in this matrix, we present only 90% of confidence intervals for both the scale and pure technical efficiencies. Moreover, to provide a
more realistic view, we draw zone borders based on the minimum and average of technical efficiency components which result in unequal areas for each zone.

As shown in Figure 5-4, all small banks are suffering from scale inefficiency. Among them Adelaide Bank is both scale and pure technical inefficient in most of the years examined. Nevertheless, an improvement can be seen in scale efficiency in 2004 and 2005 while the pure technical efficiency remains low. Bendigo Bank, the other small bank, is very scale inefficient in the early study period (1997 and 1998) and remains scale inefficient thereafter. Its scale efficiency considerably improves toward the end of the study period based on the bootstrapped results. The Bank of Queensland performs similarly to the other two small banks in terms of pure technical efficiency but it suffers more from scale inefficiency. Overall, although, the magnitude of scale efficiency is getting better for small banks during the sample period, nevertheless, these banks are less scale efficient than other banks and operate under increasing returns to scale. Additionally, it can be concluded that the decline in pure technical efficiency has offset the rise in scale efficiency. Hence, on average the technical efficiency of regional banks has remained unchanged or has deteriorated. This is consistent with the findings of Kirkwood and Nahm (2006) who measured banking service efficiency of regional banks during 1995-2002.

Among medium sized banks Macquarie Bank was suffering from scale inefficiency from 1997 to 1999. In subsequent years this bank is scale efficient while experiencing pure technical inefficiency in 2002. In comparison, St. George Bank seems fully scale efficient in all years and quite stable in terms of pure technical efficiency. The other medium-sized bank, Suncorp, is almost scale efficient except in 1997 but experiences pure technical inefficiency in 1997, 1999, 2000 and 2001. Overall, the results suggest that medium sized banks are operating at the optimal scale but were suffering seriously from pure technical inefficiency at the beginning of the study period.
Among the big four banks, ANZ Bank is found to be fully scale efficient during the entire period but experiences pure technical inefficiency in 1997, 1998 and 2000, respectively. Westpac Bank also performs equally well in terms of scale efficiency during the study period except in 2002. On the contrary, both National Australia Bank and Commonwealth Bank are operating under decreasing returns to scale in most years. Additionally, although, a wide confidence interval exists for both banks, it is possible to compare the efficiency results using the efficiency matrix. For instance, as shown in Figure 5 the Commonwealth Bank is more pure technical efficient than the National Australia Bank in 2004 and 2005. The result is consistent with the findings of Miller and Noulas (1996) that report larger banks are more likely to operate at decreasing returns to scale. Our results differ from some studies because of the application of the bootstrapping method. For instance, our bootstrap results are in contrast to the findings of Paul and Kourouche (2008) who concluded that the National Australia Bank and Commonwealth Bank have been fully efficient during the same study period. This distinction originates from the difference between standard and bootstrap methods as discussed in this study.

Finally, although, in the short term, banks may operate under increasing or decreasing returns to scale, gradually, they will shift towards constant returns to scale by changing into larger or smaller sizes (Tsolas, 2011). Consequently, it is expected that scale inefficient Australian banks will develop strategies for up-scaling or down-scaling in size. For instance, the merger between Bendigo Bank and Adelaide Bank in 2008 may be the start of a process which aims at increasing scale efficiencies of small banks.
Figure 5-4: Technical Efficiency Matrix, a Graphical Illustration of Technical and Scale Efficiencies (1997-2005)
5.4 Summary and Conclusion

The proper choice of variables and lack of statistical precision are two significant challenges in using DEA. To address these issues in the case of Australian banking, we re-examined both the pure technical and scale efficiencies of ten Australian banks during the period of 1997-2005. We contributed to the earlier literature by providing more robust statistical properties of estimated measures and by improving the choice of the output variables in the core profit efficiency model. Particular attention is also given to data visualization to facilitate the efficiency analysis of the sample banks. To the best of our knowledge, it is the first study that adopts the bootstrap technique for measuring technical efficiency and the nature of returns to scale that overlooked in earlier Australian efficiency studies. We also present the statistical properties of both pure and technical efficiency via the efficiency matrix as a valuable benchmarking and analytical tool to reveal which aspect of technical efficiency (pure technical or scale efficiency)
needs to be improved. It is worth mentioning that our findings can be generalised to the efficiency analysis of the banking industry in other countries. The proposed tools and methods can also be applied across other sectors of the economy to identify the sources of technical inefficiency and opportunities for improvement.

The original pure technical efficiency results revealed that 23% of bank-year observations were fully efficient which is much lower than 81% obtained in the recent study by Paul and Kourouche (2008). This difference is due to substituting interest income for net interest income in our core profit efficiency model which improves the discriminatory power of efficiency estimates. Thus, improving the choice of output variables and re-examining earlier studies are crucial to ensure the validity of previous Australian efficiency studies which have used the core profit efficiency model.

The bootstrap procedure introduced by Simar and Wilson (1998a) was also employed to control the influence of measurement errors. Comparing the original and bootstrapping results reveals the sensitivity of the efficiency scores of some Australian banks to sampling variations and measurement errors and brings into question the accuracy and reliability of all earlier studies due to the lack of statistical precision. For instance, 21 out of 91 bank-year observations were fully and similarly efficient based on the original estimates, while the bootstrap results reveal that they were not equally efficient. Specifically, the Commonwealth Bank in 1999, ANZ Bank in 2003 and Macquarie Bank in 1997 had narrower confidence intervals and seem the most efficient observations. Consequently it seems appropriate for researchers to take into account measurement errors by combining standard non-parametric techniques with advanced statistical approaches in efficiency analysis to enrich their results.

Our empirical findings also show that the small banks are suffering from both pure technical and scale inefficiencies during the study period. Improvement in scale efficiency at the end of the study period (2004 and 2005) coincides with a significant decline in pure technical efficiency, implying an overall decline in
technical efficiency of the regional banks during the study period. Additionally, medium sized banks operate at the most productive scale size and their pure technical efficiencies vary over the years and across the banks. Among the major banks, the National Australia Bank and Commonwealth Bank are operating under decreasing returns to scale, suggesting that these two banks can achieve a better technical efficiency by decreasing their scale of operations.

Although, there is no consensus regarding the benefits of Australian bank mergers due to small sample sizes (Avkiran, 1999b), we can argue that the “Too big to fail” argument may be applied in the case of Australian banking industry as two major banks are suffering from scale inefficiency and operating under decreasing returns to scale. Thus, contrary to the Wallis inquiry (1997) recommendations, our results support the government’s four pillars policy to prevent mergers among major banks and validates the claim that removing the four pillar policy may have intensified the scale inefficiency in the Australian banking sector. It also proves the importance of using advanced mathematical models in analysing the impact of mergers on bank efficiency levels. An issue has been emphasized by Avkiran (1999b) who believes economic and political benefits are behind most mergers in Australian banking industry rather than using mathematical models or calculations. Additionally, we can conclude that where two large banks are operating under decreasing returns to scale and all small banks are operating under increasing return to scale, mergers between the small banks or the acquisition of other financial institutions by them seem to be more beneficial.
6 Chapter Six: Technical Efficiency of Australian Banks during the Financial Crisis (2006 to 2011)

6.1 Introduction

This chapter analyses both pure technical and scale efficiencies of eight Australian banks during the period 2006-2012. Choosing this time period enables us to investigate the impact of the global financial crisis on Australian banking efficiency. The global financial crisis was the most significant economic event since the 1970s which affected financial system of many countries (Quiggin, 2011). The good performance of Australian banks during the recent financial crisis when other global banks have suffered might be explained by their higher efficiency level during the period preceding the crisis (Vu and Turnell, 2011). Thus, it is of interest to investigate the efficiency level of Australian banks prior, during and post the global financial crisis and to examine this assumption that countries with efficient financial systems are affected less during financial turbulences as claimed by Blejer (2006).

Similar to Chapter 5, the bootstrap DEA methods developed and explained in Chapter 4 are used to provide statistical properties of efficiency estimates such as confidence intervals and bias-corrected results for all the banks in our sample. To ensure the validity of results, two banks which have been heavily involved in non-traditional banking activities are eliminated to increase the homogeneity of samples. However, the results show no significant difference implying the reliability of the primary results.

This chapter is organised as follows: Section 6.2 introduces the DEA model’s variables and sample banks. Section 6.3 presents the empirical results. A
comparison between original and bootstrap results is presented in Section 6.3.1, and the statistical properties of technical efficiency components using the efficiency matrix are presented in Section 6.3.2. Section 6.3.3 provides possible cost reduction estimates to improve the efficiency level of banks in the sample. Finally, Section 6.4 provides a summary of the chapter’s findings.

6.2 Sample Banks and Model’s Variables

Eight out of ten banks used in the previous chapter are chosen. Specifically, the Adelaide Bank and St. George Bank are eliminated from the sample as these two banks merged with Bendigo Bank and Westpac respectively during the period 2006-2012. As illustrated in Table 6-1 banks are categorised in three different sizes of large, medium and small sized banks similar to Chapter 5 based on asset size. To ensure the homogeneity of the sample and the validity of the results, Macquarie and Suncorp are also eliminated from the sample due to their heavy involvement in non-traditional banking activities and efficiency measures are re-examined with six banks in the same time period.

<table>
<thead>
<tr>
<th>DMU</th>
<th>Bank Name</th>
<th>Abbreviation</th>
<th>Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Australia and New Zealand Bank</td>
<td>ANZ</td>
<td>Large</td>
</tr>
<tr>
<td>2</td>
<td>Commonwealth Bank</td>
<td>CBA</td>
<td>Large</td>
</tr>
<tr>
<td>3</td>
<td>National Australian Bank</td>
<td>NAB</td>
<td>Large</td>
</tr>
<tr>
<td>4</td>
<td>Westpac</td>
<td>WBC</td>
<td>Large</td>
</tr>
<tr>
<td>5</td>
<td>Macquarie Group</td>
<td>MQG</td>
<td>Medium</td>
</tr>
<tr>
<td>6</td>
<td>Suncorp Group</td>
<td>SUN</td>
<td>Medium</td>
</tr>
<tr>
<td>7</td>
<td>Bendigo and Adelaide Bank</td>
<td>BEN</td>
<td>Small</td>
</tr>
<tr>
<td>8</td>
<td>Bank of Queensland</td>
<td>BOQ</td>
<td>Small</td>
</tr>
</tbody>
</table>

The core profit efficiency model is used to choose input and output variables. As mentioned in detail in the previous chapter, this approach views banks as business units that use two inputs of interest expense and non-interest expense to generate two outputs of interest income and non-interest income. All four input and output variables are extracted from annual reports of the banks for seven years between
The summary statistics of these four variables for the seven year period are provided in Table 6-2.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean $\text{billion}$</th>
<th>Standard Deviation $\text{billion}$</th>
<th>Minimum $\text{billion}$</th>
<th>Maximum $\text{billion}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interest expense</td>
<td>11,295</td>
<td>9,197</td>
<td>592</td>
<td>28,287</td>
</tr>
<tr>
<td>Non-interest expense</td>
<td>6,334</td>
<td>4,054</td>
<td>261</td>
<td>14,799</td>
</tr>
<tr>
<td>Interest income</td>
<td>16,731</td>
<td>14,054</td>
<td>907</td>
<td>39,385</td>
</tr>
<tr>
<td>Non-interest income</td>
<td>4,579</td>
<td>3,247</td>
<td>115</td>
<td>14,632</td>
</tr>
</tbody>
</table>

### 6.3 Empirical Results

As reviewed in Chapter 3, earlier Australian banking efficiency studies using DEA suffer from the lack of statistical precision and ignore the effect of measurement errors and sample variations in their efficiency estimates. This chapter on the contrary provides statistical precision of efficiency scores by employing the bootstrap DEA methods introduced in Chapter 4 to estimate both pure technical and scale efficiency scores of the sample banks. As shown in Chapter 5, taking into account the statistical properties of the efficiency estimates, the bootstrap approach provides more accurate and reliable results than the original DEA estimates. As mentioned earlier, the sample includes panel data for eight banks over seven years resulting in 56 bank-year observations.

The FEAR package provided by Wilson (2008) and R codes developed by the authors are used for the calculations. Re-sampling also is carried out for $B=2000$ while confidence intervals are assumed at 99%. As indicated earlier, the results are re-examined for six banks during the study period by eliminating Macquarie and Suncorp from the sample as these two banks earn the majority of their income from non-interest income and focus more on non-traditional banking activities. Therefore, all calculations are repeated for a modified sample consisting of 42 observation sand the results of these two different sample sizes are also compared in Section 6.3.1. Overall, the results are reported in three sections covering
bootstrapped results, the efficiency matrix and efficiency improvement. The bootstrapped results consist of statistical properties of the efficiency estimates while the efficiency matrix presents the technical efficiency decomposition by illustrating the confidence intervals of both pure technical and scale efficiency to facilitate our analysis. Finally, different scenarios to improve technical efficiency in 2012 are discussed.

6.3.1 Bootstrapped Results

Table 6-3 illustrates the original, bootstrap and confidence interval of pure technical efficiency scores. The average efficiency score of the bootstrap results is 96.6% which is 1.4% less than the average of original scores. Although, it may imply that the original results are statistically significant, the confidence intervals show the importance of using the statistical properties of efficiency estimates for any comparisons between banks’ efficiency levels.

**Table 6-3: Bootstrapped Pure Technical Efficiency of Australian Banks (2006-2012)**

<table>
<thead>
<tr>
<th>Bank</th>
<th>Year</th>
<th>Original</th>
<th>Bootstrap</th>
<th>Lower bound</th>
<th>Upper bound</th>
<th>Bank</th>
<th>Year</th>
<th>Original</th>
<th>Bootstrap</th>
<th>Lower bound</th>
<th>Upper bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANZ</td>
<td>2006</td>
<td>1</td>
<td>0.9872</td>
<td>0.9718</td>
<td>0.9992</td>
<td>MQG</td>
<td>2006</td>
<td>1</td>
<td>0.9859</td>
<td>0.9561</td>
<td>0.9992</td>
</tr>
<tr>
<td>ANZ</td>
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<td>1</td>
<td>0.9786</td>
<td>0.9361</td>
<td>0.9994</td>
<td>MQG</td>
<td>2007</td>
<td>1</td>
<td>0.9786</td>
<td>0.9337</td>
<td>0.9993</td>
</tr>
<tr>
<td>ANZ</td>
<td>2008</td>
<td>0.9311</td>
<td>0.9226</td>
<td>0.8890</td>
<td>0.9326</td>
<td>MQG</td>
<td>2008</td>
<td>1</td>
<td>0.9759</td>
<td>0.9168</td>
<td>0.9993</td>
</tr>
<tr>
<td>ANZ</td>
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<td>0.9509</td>
<td>0.9422</td>
<td>0.9273</td>
<td>0.9503</td>
<td>MQG</td>
<td>2009</td>
<td>0.8932</td>
<td>0.8847</td>
<td>0.8724</td>
<td>0.8927</td>
</tr>
<tr>
<td>ANZ</td>
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<td>1</td>
<td>0.9852</td>
<td>0.9669</td>
<td>0.9994</td>
<td>MQG</td>
<td>2010</td>
<td>0.9355</td>
<td>0.9278</td>
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<td>0.9349</td>
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<tr>
<td>ANZ</td>
<td>2011</td>
<td>0.9937</td>
<td>0.9849</td>
<td>0.9710</td>
<td>0.9931</td>
<td>MQG</td>
<td>2011</td>
<td>0.9182</td>
<td>0.9099</td>
<td>0.8992</td>
<td>0.9175</td>
</tr>
<tr>
<td>ANZ</td>
<td>2012</td>
<td>1</td>
<td>0.9867</td>
<td>0.9700</td>
<td>0.9993</td>
<td>MQG</td>
<td>2012</td>
<td>0.8985</td>
<td>0.8903</td>
<td>0.8774</td>
<td>0.8980</td>
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<tr>
<td>BEN</td>
<td>2006</td>
<td>1</td>
<td>0.9747</td>
<td>0.9063</td>
<td>0.9994</td>
<td>NAB</td>
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<td>1</td>
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<tr>
<td>BEN</td>
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<td>0.9858</td>
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<td>NAB</td>
<td>2007</td>
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<td>0.9764</td>
<td>0.9225</td>
<td>0.9995</td>
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<tr>
<td>BEN</td>
<td>2008</td>
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<td>NAB</td>
<td>2008</td>
<td>1</td>
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<td>0.9993</td>
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<tr>
<td>BEN</td>
<td>2009</td>
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<td>0.8967</td>
<td>0.8879</td>
<td>0.9018</td>
<td>NAB</td>
<td>2009</td>
<td>0.9963</td>
<td>0.9879</td>
<td>0.9751</td>
<td>0.9956</td>
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<tr>
<td>BEN</td>
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<td>0.9725</td>
<td>0.9660</td>
<td>0.9591</td>
<td>0.9719</td>
<td>NAB</td>
<td>2010</td>
<td>1</td>
<td>0.9829</td>
<td>0.9600</td>
<td>0.9994</td>
</tr>
<tr>
<td>BEN</td>
<td>2011</td>
<td>0.9713</td>
<td>0.9657</td>
<td>0.9596</td>
<td>0.9708</td>
<td>NAB</td>
<td>2011</td>
<td>1</td>
<td>0.9856</td>
<td>0.9715</td>
<td>0.9994</td>
</tr>
<tr>
<td>BEN</td>
<td>2012</td>
<td>0.9529</td>
<td>0.9478</td>
<td>0.9422</td>
<td>0.9524</td>
<td>NAB</td>
<td>2012</td>
<td>1</td>
<td>0.9919</td>
<td>0.9810</td>
<td>0.9993</td>
</tr>
<tr>
<td>BOQ</td>
<td>2006</td>
<td>1</td>
<td>0.9756</td>
<td>0.9070</td>
<td>0.9994</td>
<td>SUN</td>
<td>2006</td>
<td>1</td>
<td>0.9822</td>
<td>0.9456</td>
<td>0.9995</td>
</tr>
<tr>
<td>BOQ</td>
<td>2007</td>
<td>1</td>
<td>0.9757</td>
<td>0.9231</td>
<td>0.9995</td>
<td>SUN</td>
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<td>1</td>
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<tr>
<td>BOQ</td>
<td>2008</td>
<td>1</td>
<td>0.9752</td>
<td>0.9161</td>
<td>0.9994</td>
<td>SUN</td>
<td>2008</td>
<td>0.9186</td>
<td>0.9100</td>
<td>0.8989</td>
<td>0.9179</td>
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<tr>
<td>BOQ</td>
<td>2009</td>
<td>0.9770</td>
<td>0.9669</td>
<td>0.9481</td>
<td>0.9763</td>
<td>SUN</td>
<td>2009</td>
<td>0.9517</td>
<td>0.9437</td>
<td>0.9324</td>
<td>0.9510</td>
</tr>
<tr>
<td>BOQ</td>
<td>2010</td>
<td>1</td>
<td>0.9856</td>
<td>0.9609</td>
<td>0.9992</td>
<td>SUN</td>
<td>2010</td>
<td>1</td>
<td>0.9860</td>
<td>0.9616</td>
<td>0.9993</td>
</tr>
<tr>
<td>BOQ</td>
<td>2011</td>
<td>0.9631</td>
<td>0.9547</td>
<td>0.9398</td>
<td>0.9625</td>
<td>SUN</td>
<td>2011</td>
<td>1</td>
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<td>0.9071</td>
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</tr>
<tr>
<td>BOQ</td>
<td>2012</td>
<td>0.8937</td>
<td>0.8882</td>
<td>0.8815</td>
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<td>SUN</td>
<td>2012</td>
<td>1</td>
<td>0.9871</td>
<td>0.9629</td>
<td>0.9996</td>
</tr>
</tbody>
</table>
As discussed before, two banks which do not seem to be homogeneous with other banks are removed to mitigate their effects in efficiency results. Accordingly, Macquarie and Suncorp are eliminated from the sample and the re-examined results for the six remaining banks are illustrated in Table 6-4. Interestingly, no significant difference is observed in the original results between the two samples of six and eight banks which implies that the frontier function has not changed. Thus, removing the two banks from the sample seems unnecessary and does not affect the efficiency result of other banks. However, a negligible difference can be seen in the bootstrap results.

Table 6-4: Bootstrapped Pure Technical Efficiency of Six Australian Banks (2006-2012)

<table>
<thead>
<tr>
<th>Bank</th>
<th>Year</th>
<th>Original</th>
<th>Bootstrap</th>
<th>Lower bound</th>
<th>Upper bound</th>
<th>Bank</th>
<th>Year</th>
<th>Original</th>
<th>Bootstrap</th>
<th>Lower bound</th>
<th>Upper bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBA</td>
<td>2006</td>
<td>1</td>
<td>0.9876</td>
<td>0.9719</td>
<td>0.9993</td>
<td>CBA</td>
<td>2006</td>
<td>1</td>
<td>0.9933</td>
<td>0.9920</td>
<td>0.9837</td>
</tr>
<tr>
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<td>0.9368</td>
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<td>0.9889</td>
<td>0.9623</td>
</tr>
<tr>
<td>CBA</td>
<td>2008</td>
<td>0.9908</td>
<td>0.9781</td>
<td>0.9480</td>
<td>0.9991</td>
<td>WBC</td>
<td>2008</td>
<td>1</td>
<td>0.9880</td>
<td>0.9598</td>
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</tr>
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<td>WBC</td>
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<td>0.9755</td>
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</tr>
<tr>
<td>CBA</td>
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<td>0.9482</td>
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<td>2010</td>
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</tr>
<tr>
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<td>0.9995</td>
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<tr>
<td>CBA</td>
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<td>0.9590</td>
<td>0.9995</td>
<td>WBC</td>
<td>2012</td>
<td>1</td>
<td>0.9886</td>
<td>0.9737</td>
<td>0.9992</td>
</tr>
</tbody>
</table>

As discussed before, two banks which do not seem to be homogeneous with other banks are removed to mitigate their effects in efficiency results. Accordingly, Macquarie and Suncorp are eliminated from the sample and the re-examined results for the six remaining banks are illustrated in Table 6-4. Interestingly, no significant difference is observed in the original results between the two samples of six and eight banks which implies that the frontier function has not changed. Thus, removing the two banks from the sample seems unnecessary and does not affect the efficiency result of other banks. However, a negligible difference can be seen in the bootstrap results.

Table 6-4: Bootstrapped Pure Technical Efficiency of Six Australian Banks (2006-2012)

<table>
<thead>
<tr>
<th>Year</th>
<th>Original</th>
<th>Bootstrap</th>
<th>Lower bound</th>
<th>Upper bound</th>
<th>Bank</th>
<th>Year</th>
<th>Original</th>
<th>Bootstrap</th>
<th>Lower bound</th>
<th>Upper bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>0.9900</td>
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<td>2007</td>
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<td>2008</td>
<td>0.9331</td>
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<tr>
<td>2009</td>
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The trends of bias corrected (bootstrapped) efficiency scores for the three categories of small, medium and large banks are illustrated in Figure 6-1. Overall, a decline can be seen in the efficiency level of all banks regardless of their size during the financial crisis. The effect of the global financial crisis on efficiency scores appears in either 2008 or 2009, as the Australian banks follow different financial years. Figure 6-1 (a) shows the trend of pure technical efficiency of Bendigo and Adelaide Bank, and Bank of Queensland, the two small sized banks. Although, both banks experienced a decline in pure technical efficiency in 2009, this decline was very sharp for Bendigo and Adelaide Bank. Figure 6-1 (b) indicates the efficiency trend of Macquarie and Sucorp, the two medium sized banks. As shown in Figure 6-1 (b), the impact of the global financial crisis on pure technical efficiency of Suncorp and Macquarie can be seen in 2008 and 2009 respectively. In contrast, Figure 6-1 (c) indicates the pure technical efficiency trend for four major banks. Similar to the other groups of small and medium sized banks, larger banks have been affected by the global financial crisis. Specifically, as shown in Figure 6-1 (c) a decline can be seen in pure technical efficiency of ANZ and NAB in 2008 while the impact of the global financial crisis on pure technical efficiency of Commonwealth and Westpac is notable in 2009.

Figure 6-1: Trend of Bias Corrected Pure Technical Efficiency (2006-2012)

Bootstrap efficiency scores (bias corrected) offer more accurate measures than original scores by considering measurement errors and sample variations. However, to provide a more realistic view on the efficiency level of the observations, it is necessary to look at the confidence intervals of the efficiency
estimates. The role of confidence intervals in efficiency comparisons also becomes more important when efficiency scores are equal or close. For example, efficiency scores in the case of National Australia Bank are very close during the study period and it is difficult to make a distinction between efficiency scores over the years. To address this issue, Figure 6-2 illustrates confidence intervals for all eight banks over the seven years study period in separate box plots. It is shown that although some efficiency scores are very close and it is not possible to find the most efficient bank, confidence intervals provide useful information to make a distinction between the efficiency scores.

Figure 6-2 reveals that while the confidence interval is quite wide for some banks (Bendigo and Adelaide in 2006 or Macquarie and NAB in 2008), it is relatively narrow for some other bank-year samples (Bendigo and Adelaide, and Bank of Queensland in 2012 or Westpac in 2006). Thus, it is crucial to consider the confidence intervals along with efficiency scores in any comparisons. For instance, while the bias corrected efficiency scores for ANZ Bank in 2011 and 2012 are almost equal, the confidence intervals indicate that the efficiency level is higher in 2011. Similarly, we can conclude that Westpac performs more efficiently in 2006 than 2007.

Figure 6-2: Box Plots of Bootstrapped Pure Technical Efficiency of Banks (2006-2012)
As discussed in the previous chapter any comparison which is only based on the original results can be misleading due to lack of statistical precision. In addition, it is not possible to distinguish between the efficiency levels of fully efficient banks.
which can be a considerable number of banks when the sample size is small. For instance, in this study, the original results show that 31 out of 56 observations contribute to construct the frontier and are fully pure technical efficient. In other words, it is not possible to make comparisons between efficiency levels of the majority of bank-year observations based on the original results. Figure 6-3, by providing the confidence intervals of all fully pure technical efficiency banks based on original estimates in a box plot, facilitates making comparisons between efficient bank/year observations. As shown in Figure 6-2, the confidence intervals are quite wide for a number of bank-year observations and rather narrow for some others.

Figure 6-4 shows the number of fully efficient banks prior, during and post global financial crisis. It is shown that the number of efficient banks has dropped which indicates the adverse effect of the recent financial crisis on the pure technical efficiency of all banks.

**Figure 6-3: Differences between Efficient Banks using Bootstrap Method (2006-2012)**
Figure 6-4 also shows that no bank is operating efficiently in 2009 and the recovery process is continuing while the pure technical efficiency level is still below the pre-crisis level. In addition, looking at the confidence intervals of efficient banks illustrated in Figure 6-3 indicates that the best performers in terms of pure technical efficiency are operating in 2006 and 2012. Specifically, National Australia Bank and Westpac in 2012, and two other major banks, ANZ and Commonwealth in 2006 seem to be more pure technical efficient than other counterparts due to exhibiting narrower confidence intervals.

Figure 6-4: Number of Efficient Banks Prior, During and Post Financial Crisis

The original results presented in Table 6-3 show all banks contributed in constructing the frontier and could be fully pure technical efficient regardless of their size. However, the number of years that banks have been efficient varies. While Bendigo and Adelaide Bank is fully pure technical efficient only in 2006, National Australia Bank is pure technical efficient in all years except in 2009. However, as emphasised before, looking at bootstrap results shows that there are different levels of efficiency between these efficient banks. For instance, National Australia Bank seems fully efficient in almost all years but wide confidence intervals in most years except 2012 imply that its level of efficiency is less than many other bank-year observations in the sample. Although all 31 bank-year samples presented in Figure 6-3 are equally fully pure technical efficient, National
Australia Bank in 2008 exhibits a wider confidence interval than a number of observations like ANZ in 2012, Bank of Queensland in 2010, Macquarie in 2006 and Westpac in 2008. Thus, when making efficiency comparisons between individual banks consideration of confidence intervals is essential.

Pure technical efficiency provides information on how efficiently business units convert inputs to outputs by removing the effect of size. In other words, in pure technical efficiency the effect of scale is ignored and business units only are compared with units of similar size instead of the whole sample. Scale efficiency fills this gap by measuring the effect of size and the extent to which a business unit deviates from the optimal scale. Thus, focusing only on pure technical efficiency provides only a partial view on efficiency while decision makers and managers need to know the effect of size on efficiency in order to plan for the optimal scale. This issue is crucial in a competitive sector like banking where different size categories are evident.

As detailed in the previous chapter, obtaining the statistical properties of scale efficiency is important because relying only on original results can be misleading. Table 6-5 presents scale efficiency results from both the original and bootstrap methods. Based on original results, 44.6% of bank-year observations are scale efficient and 55.4% are scale inefficient. Among scale inefficient observations, almost half are operating under Increasing Return to Scale (IRS) and the other half under Decreasing Return to Scale (DRS). In contrast, using the bootstrap method detailed in Chapter 4 shows that about 71% of observations are scale efficient and 18% and 11% are operating in the IRS and DRS regions respectively. The existence of large differences between original and bootstrap results implies the necessity of applying statistical based techniques in such studies to account for measurement errors and sample variations.

In respect to scale efficiency distribution by size, the bootstrapped results show that 29% of observations related to small banks are scale efficient and the rest are operating under increasing returns to scale. Interestingly, all medium sized banks
are found to be scale efficient over the 7 years period. In contrast, 79% of observations for major banks operate at optimal scale and the remaining 21% of observations operate under decreasing returns to scale. This important finding indicates that the optimum scale belongs to the medium sized banks, while small banks suffer highly from scale inefficiency and the majority of large banks operate under optimal scale.

Table 6-5: Comparison of Scale Efficiency of Banks using Original DEA vs. Bootstrap DEA (2006-2012)

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<th>VRS</th>
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6.3.2 Efficiency Matrix

Technical efficiency can be decomposed to pure technical and scale efficiency. This decomposition provides useful information regarding the source of inefficiency and helps managers and decision makers find opportunities for improvement. The technical efficiency matrix proposed in Chapter 4 illustrates visually the sources of technical inefficiency and facilitates any comparisons among observations. Similar to the previous chapter, due to wide confidence intervals for some observations and to avoid interference of drawn ellipses in this matrix, we present only 90% of confidence intervals for both the scale and pure technical efficiencies. The median of pure technical and scale efficiency is used to draw the border zones. Figure 6-5 consists of eight matrixes that show technical efficiency decomposition for each bank over the period 2006-2012.

As shown in Figure 6-5 observations related to two small banks, Bendigo and Adelaide Bank and Bank of Queensland, are mostly in the zone with low pure technical and scale efficiency. This means Bendigo and Adelaide Bank is both pure technical and scale inefficient in most of the examined years. Nevertheless, as a result of mergers and acquisitions, the scale efficiency level has improved over the years while the pure technical efficiency remains low. It is also clear from Figure 6-5, that due to the global financial crisis pure technical efficiency has considerably declined in 2009. Bank of Queensland seems scale inefficient in the early study period but its scale efficiency considerably improves toward the end of study period possibly due to recent acquisitions such as St Andrew's Insurance and CTI Group Australia. Although, the Bank of Queensland performed better in terms of efficiency than its other small counterpart during the global financial crisis, its efficiency level deteriorated significantly in 2012 due to troubled property loans in the Gold Coast region.

Overall, in contrast to the results of the previous chapter, the magnitude of scale efficiency is improving for small banks possibly due to recent mergers and acquisitions. However, small sized banks still seem to be less scale efficient than other banks and mostly operate under increasing returns to scale. Additionally,
consistent with our findings in Chapter 5, the decline in pure technical efficiency during and post global financial crisis has offset the improvement in scale efficiency. Hence, it may be concluded that on average the technical efficiency of small sized banks has deteriorated.

Looking at medium sized banks, pure technical efficiencies of both Macquarie and Suncorp decline during the financial crisis and reach their lowest point in 2009 and 2008 respectively. However, it seems Suncorp’s pure technical efficiency has considerably improved during the post financial crisis while Macquarie is still struggling and no sign of improvement can be seen. On the other hand, Suncorp and Macquarie are quite stable in terms of scale efficiency, operating under the optimal scale throughout the entire period. Overall, the results suggest that medium sized banks in our sample have different levels of pure technical efficiency but both are operating at the optimal scale.

As shown in Figure 6-5, among the major banks, ANZ is the only one found to be fully scale efficient during the entire period. It also shows a high level of pure technical efficiency except during the global financial crisis in 2008 and 2009. The second scale efficient major bank is the Commonwealth which is only scale inefficient in 2008 and operates under decreasing returns to scale. However, similar to ANZ it performs relatively well in terms of pure technical efficiency except during the financial crisis. National Australia Bank experiences the highest level of scale inefficiency among the big four and operates under decreasing returns to scale in 2008, 2009 and 2012. Although National Australia Bank has been pure technical efficient based on original results in almost all years (except in 2008), wide confidence intervals in some years imply that this major bank has less pure technical efficiency in 2006, 2007, 2008 and 2010 than 2012. Westpac Bank also performs well in terms of pure technical efficiency during the study period except in 2009. However, it suffers from scale inefficiency and operates under decreasing returns to scale in 2008 and 2009 possibly due the merger with St. George Bank in 2008
Our findings are consistent with those of discussed in Chapter 5 that larger banks are more likely to operate under decreasing returns to scale. Interestingly, the high level of scale inefficiency can be seen during the financial crisis. For instance, both Westpac and National Australia Bank operate under decreasing returns to scale in 2008 and 2009. Similarly, the Commonwealth Bank also operates under decreasing returns to scale in 2008. This might be due to a high increase in banks’ expenses (such as the costs of bad loans) during the global financial crisis. In addition, some mergers and acquisitions which were completed in 2008 and 2009 may have contributed to an increase in scale inefficiency of major banks. It is not surprising that the financial crisis had an adverse effect on pure technical efficiency of all major banks as their lowest level of pure technical efficiency can be seen in either 2008 or 2009.

Finally, from the estimated results it is clear that the efficiency level of all Australian banks has been affected by the global financial crisis. Nevertheless, the severity of the impact was not equal among banks. While some banks like Macquarie were affected severely, the impact of the financial crisis was moderate on some others. Additionally, the global financial crisis had an adverse impact on the scale efficiency of major banks and increased their expenses. As shown in Figure 6-5, small sized banks still suffer from scale inefficiency and operate under increasing returns to scale despite mergers and acquisitions in recent years. This makes them vulnerable in a tough competitive environment. Existence of scale inefficiency among major banks also implies that any merger between the big four banks may increase the scale inefficiency and the government four pillars policy seems a proper decision not only to control scale inefficiency but also to maintain a strong competitive environment and avoid monopoly.
Figure 6-5: Technical Efficiency Matrix, a Graphical Illustration of Technical and Scale Efficiencies (2006-2012)
6.3.3 Efficiency Improvement

Although, measuring the efficiency level of banks is of interest to managers and decision makers, they are more interested in assessing the areas of possible efficiency improvements. Fortunately, by using DEA it is very straightforward to estimate the amount of reduction or increase needed in inputs (expenses) or outputs (incomes) for each bank to be fully efficient. However, the effect of slacks can be prominent in some cases and this needs to be taken into consideration in planning for efficiency improvements. For the sake of brevity, methods for measuring the slacks have not been discussed here and interested readers can refer to Cooper et al. (2011a).

Table 6-6 presents the level of cost reductions in 2012 which the sample banks needed in order to be fully pure technical efficient based on bootstrap results. The first column shows the bank names abbreviation and the other columns present the amount of reductions for interest expenses and non-interest expenses for each bank to be pure technical efficient. Using the bootstrap results and confidence intervals of efficiency estimates it is possible to obtain a cost reduction plan. This approach provides different scenarios to improve efficiency levels. For instance, it shows that by reducing $245bn and $129bn in interest expenses and non-interest expenses respectively, it was very likely that ANZ could be fully pure technical efficient in 2012. Based on the confidence intervals, it is also shown that using the upper bound of the confidence interval which assumes ANZ was almost fully efficient, ANZ still needed at least $13bn and $7bn reduction in interest expenses and non-interest expenses to be fully pure technical efficient in 2012. In contrast, in a worst case scenario and taking the lower bound of the confidence interval which assumes ANZ is considerably less efficient than what the original results show, this bank needed a huge saving to be fully pure technical efficient in 2012. It is worth mentioning that where the difference between the confidence interval is narrow then the minimum and maximum cost reductions are getting closer. For instance, due to the existence of a narrow confidence interval for pure technical efficiency for the Bank of Queensland, the proposed reductions in interest expenses range between $208bn and $230bn.
All figures illustrated in Table 6-6 are based on bootstrap results without considering the effect of slacks obtained from DEA models. However, as mentioned above, the role of slacks in providing efficiency improvement solutions should not be ignored as it can be significant in some cases. Surprisingly, for 2012 all slacks are zero except the slacks for non-interest income of two small sized banks (Bendigo and Adelaide Bank, and Bank of Queensland which are $174bn and $176bn respectively). It means along with the above proposed reductions in expenses, these two banks should increase their non-interest incomes to be fully pure technical efficient.

### Table 6-6: Cost Reduction Options for 2012

<table>
<thead>
<tr>
<th>Banks</th>
<th>Interest Expense Reduction $m</th>
<th>Non-Interest Expense Reduction $m</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Based on Bootstrap Min Max</td>
<td>Based on Confidence Intervals Min Max</td>
</tr>
<tr>
<td>ANZ</td>
<td>245 13553</td>
<td>129 7 291</td>
</tr>
<tr>
<td>BEN</td>
<td>130 144</td>
<td>46 42 51</td>
</tr>
<tr>
<td>BOQ</td>
<td>217 230</td>
<td>92 88 98</td>
</tr>
<tr>
<td>CBA</td>
<td>363 1,030</td>
<td>148 6 422</td>
</tr>
<tr>
<td>MQG</td>
<td>443 494</td>
<td>649 603 725</td>
</tr>
<tr>
<td>NAB</td>
<td>173 404</td>
<td>94 8 219</td>
</tr>
<tr>
<td>SUN</td>
<td>40 117</td>
<td>153 5 442</td>
</tr>
<tr>
<td>WBC</td>
<td>277 642</td>
<td>104 7 240</td>
</tr>
</tbody>
</table>

As emphasised in this chapter, looking at only pure technical efficiency provides only a partial picture of technical efficiency. A full picture requires analysing scale efficiency along with pure technical efficiency. Examining scale efficiency results presented in Table 6-5 indicates that that majority of banks were scale efficient. However, we found that the National Australia Bank, Bendigo and Adelaide Bank, and Bank of Queensland suffer from scale inefficiency in 2012. Bias corrected scale efficiency results show that while National Australia Bank needed around 2.7% reduction in the size of its operation, the other two banks on
the contrary needed a larger scale of about 2.7% and 4.2% respectively to be fully scale efficient in 2012. It should be noted that this increase or decrease needed to be made on both expenses and incomes at the same rate. For instance, National Australia Bank needed a 2.7% reduction in the size of its operation by cutting $569bn and $308bn in interest expenses and non-interest expenses respectively while relinquishing $922bn and $119bn from its interest income and non-interest income respectively to operate at the optimum scale.

6.4 Summary and Conclusion

This chapter examined both pure technical and scale efficiency of eight Australian banks using the bootstrap DEA method developed and detailed in Chapter 4 over the period 2006-2012. To the best of our knowledge it is the first study that investigates the Australian banking efficiency level using bootstrap DEA for the given time period which covers the period prior, during and post the global financial crisis. The core profit efficiency approach was used in choosing input and output variables in the DEA based models. Additionally, similar to Chapter 5, particular attention is given to data visualization using efficiency matrix and box plots to facilitate the efficiency analysis of the sample banks.

Comparing the original and bootstrapped results indicates the need for combining statistical approaches with non-parametric methods to overcome measurement errors and sample variations in such studies. For instance, the original estimates revealed that 55% of bank-year observations were fully pure technical efficient while the bootstrapped results provided considerable distinctions between the efficiency levels of these observations by calculating the confidence intervals of the efficiency estimates. It was also shown that the bootstrap results can be employed to develop different scenarios for improving efficiency levels.

Looking at the impact of the global financial crisis on the efficiency level of Australian banking, the original estimates show that the number of pure technical efficient banks dropped considerably during the global financial crisis and no
bank in the sample was pure technical efficient in 2009. It was also shown that the number of pure technical efficient bank-year observations were at their highest point prior to the global financial crisis in 2006 and the recovery process has been continuing during the post crisis period. It was also found that all major banks were efficient with narrow confidence intervals in 2012 while other banks are still suffering from low levels of pure technical efficiency after the crisis. That is, the pure technical efficiency of major banks is returning to the level that existed prior to the financial crisis while it seems other banks face significant challenges in a tough business environment after the crisis.

Focusing only on pure technical efficiency provides only a partial view of efficiency and ignores the effect of size on technical efficiency. To address this issue, the bootstrapped method developed in Chapter 4 was employed to examine the returns to scale in the sample banks over the study period. It was found that small sized banks suffer from scale inefficiency in most years and operate under increasing returns to scale. This implies that recent mergers and acquisitions by regional banks were not sufficient and should be continued to achieve the optimal scale. In contrast, all medium sized banks were scale efficient while the larger banks were suffering from scale inefficiency and operated under decreasing returns to scale in some years mostly during the global financial crisis. This was possibly due to increasing expenses such as bad loan charges and growing household deposits.

Consistent with our findings in Chapter 5, it can be argued that the “Too big to fail” argument may be applied to the case of the Australian banking industry as the three major banks experienced scale inefficiency in some years and operated under decreasing returns to scale specially in 2008 and 2009 when a number of mergers and acquisitions were completed. Thus, our results in this chapter are in line with our findings in Chapter 5 and support the continuation of the four pillars policy to prevent mergers among major banks. This will not only prevent an adverse effect on scale efficiency but also would protect competition and customer bargaining power. Finally, similar to our conclusion in the previous
chapter, to avoid further scale inefficiency in the industry and improve scale efficiency levels, mergers between the small sized banks or other financial institutions such as building societies or credit unions should be further pursued.
Chapter Seven: Conclusions, Recommendations and Policy Implications

7.1 Introduction
This study introduces a bootstrap procedure to estimate scale efficiency and the nature of returns to scale. It also introduces the efficiency matrix which illustrates the confidence intervals of both pure technical and scale efficiency of business units in the sample. The applications of the methods developed in Chapter 4 are presented in Chapter 5 and Chapter 6 for Australian banks. Given the importance of the Australian banking industry, efficiency analysis of this sector is a crucial research stream that draws considerable attention from academics and policy makers. However, earlier studies that employed non-parametric methods suffer from statistical deficiencies and problems in variable selection (e.g., Avkiran, 2000, Avkiran, 2004, Paul and Kourouche, 2008, Sathye, 2002). To address the above issues, this study improves the choice of variables in the core profit efficiency models and provides statistical properties of both pure technical and scale efficiency of Australian banks for the first time using bootstrap DEA techniques.

The rest of the chapter is organised as follows: Section 7.2 reviews the methodological contributions of this study. Section 7.3 provides a summary of the empirical Australian banking efficiency results for the two study periods 1997-2005 and 2006-2012. Policy implications are presented in Section 7.4. This section discusses the four pillars policy, impact of the financial crisis on banks, the future of small banks and competition, technology and innovation. Finally,
Section 7.5 identifies limitations of this study along with possible future research areas.

7.2 Methodological Contributions

This study makes three methodological contributions in the area of efficiency analysis using DEA methods. Firstly, it provides a statistical procedure based on the bootstrap DEA method to determine the nature of returns to scale of business units. Secondly, it proposes the efficiency matrix to visualize statistical properties of both pure technical and scale efficiency. Thirdly, it improves the discriminatory power of efficiency estimates by correcting the choice of variables in the core profit efficiency models in the context of Australian banking. A summary of these contributions is presented below.

The DEA method is a deterministic technique which has not been able to provide statistical properties of efficiency estimates. The bootstrap procedure suggested by Simar and Wilson (1998a) opened a new insight in efficiency analysis using non-parametric methods by providing statistical precision of efficiency estimates. Recently, Simar and Wilson’s bootstrap DEA approach has become popular in estimating pure technical efficiency of business units. Using their procedure researchers not only can utilize all the advantages of the DEA method but also they can provide statistical properties of efficiency estimates such as confidence intervals and bias. Pure technical efficiency only provides a partial view on technical efficiency of business units. The examination of scale efficiency as the other component of technical efficiency is necessary in order to provide a full picture of efficiency levels. Unfortunately, despite the importance of scale efficiency and returns to scale in efficiency analysis, bootstrap procedures recently introduced to offer statistical properties of scale efficiency estimates are inconsistent or are not suitable for estimating scale efficiency for individual business units (e.g., Lothgren and Tambour, 1999b, Simar and Wilson, 2002). This study fills this gap by proposing a bootstrap DEA procedure to estimate scale efficiency and relevant statistical hypothesis testings as detailed in Chapter 4.
Managers and policy makers usually are interested in visual tools which simplify the results of complex techniques and methods in easily understandable and comparable ways. The efficiency matrix proposed in this study is able to present the decomposition of technical efficiency to pure technical and scale efficiency by portraying confidence intervals in a matrix with four zones. Each zone defines the level of both pure technical and scale efficiencies. For instance, observations located in zone 1 have a low level of both pure technical and scale efficiency. On the contrary, those located in zone 3 experience high levels of pure technical and scale efficiency. This matrix not only shows the results of the bootstrap method in an easily understandable way but also it is very useful for comparison purposes or for presentation of the findings. The efficiency matrix and its application is presented in Chapter 4.

The core profit efficiency approach is the most employed approach in choosing variables for DEA models in Australian banking efficiency studies. Unfortunately, selecting the net interest income as one of the output variables confounds the efficiency estimates as detailed in Avkiran and Thoraneenitiyan (2010). This study addresses this issue and improves the choice of variables by replacing net interest income by interest income. Re-examining the pure technical and scale efficiency estimates shows that the discriminatory power of the efficiency scores significantly improved in comparison with the recent study by Paul and Kourouche (2008) as detailed in Chapter 5.

### 7.3 Summary of Empirical Findings

This study investigates pure technical and scale efficiency of Australian banks using the bootstrap DEA method in the periods 1997-2005 and 2006-2012. In the first period, statistical properties of efficiency estimates for 10 Australian banks during the post-Wallis period are examined. As discussed in Chapter 5 and Chapter 6 using statistical approaches when using non-parametric methods is necessary due to measurement errors associated with such studies. This issue has been neglected in the earlier Australian banking literature. In the second period,
the impact of the global financial crisis on technical efficiency of 8 Australian banks is examined during the periods before, during and post the financial crisis. As shown in Chapter 6 the global financial crisis had an adverse effect on the efficiency level of all Australian banks and the severity of this effect varies among individual banks. The mean overall pure technical efficiency of the sample banks for the first period between 1997 and 2005 is found to be 93.9%. This result indicates that small banks were suffering from pure technical inefficiency more than other two groups of medium and large sized banks during the post-Wallis period. In contrast, major banks exhibit a higher growth in pure technical efficiency while medium sized banks demonstrate mixed results of ascending, descending and flat trends. Looking at scale efficiency results suggests that 50% of bank-year observations are inefficient. Similar to the results for pure technical efficiency, the scale inefficiency level of small sized banks is higher than the other two groups. About 92.6% of observations related to small banks are scale inefficient while medium sized banks experience a higher level of scale efficiency than major banks. Specifically, 81.5% of scale efficient bank/year observations belong to medium sized banks while this rate is only 58.3% for large banks. All scale inefficient small banks operate under increasing returns to scale and scale inefficient large banks operate under decreasing returns to scale. That is, while small banks need to increase their size of operation to achieve the optimal scale, some major banks suffer from the large scale of operation.

Pure technical efficiency of all small banks significantly declined during the period 1997-2005. The bootstrap results indicate that the pure technical efficiency scores of Adelaide Bank, Bendigo Bank and Bank of Queensland decrease from 95.7%, 96.4% and 97.1% in 1997 to 89.4%, 87.1% and 87.7% in 2005 respectively. On the contrary, scale efficiency scores of small banks improve from 95.8%, 87.9% and 91% in 1997 to 98.5%, 98% and 97.4% in 2005. Despite this improvement, statistical hypothesis testing indicates all small banks still suffer from scale inefficiency and operate under increasing returns to scale in 2005.
Among medium sized banks, on average, Macquarie has the highest level of pure technical efficiency at 95.3% followed by St. George 93.3% and Suncorp 92.4%. While pure technical efficiency of Macquarie declines considerably from 98.2% in 1997 to 89.8% in 2002, Suncorp experiences significant improvement from 89% in 1997 to 96.5% in 2002. In terms of scale efficiency, while St. George is almost scale efficient through the entire period, Macquarie experiences scale inefficiency in the early study period from 1997 to 2000. Suncorp also operates at optimum scale in all years except 1997 where it operates under increasing returns to scale.

On average, pure technical efficiency of the four major banks improves from 91.7% in 1997 to 95.1% in 2005. ANZ seems to be the main contributor to this increase as its pure technical efficiency improves from its lowest 86.6% in 1997 to 95.7% in 2005. In contrast, other major banks operate differently and some fluctuations can be seen in their pure technical efficiency during the study period. On average, Commonwealth has the highest level of pure technical efficiency of 96.1%, followed by National Australia Bank, ANZ and Westpac with mean efficiency scores of 95.3%, 93.4% and 93.1%. In terms of returns to scale, ANZ is the most scale efficient major bank with an average score of 99.5% followed by Westpac (98.9%). In contrast Commonwealth and National Australia Bank suffer from scale inefficiency in most of the years and their bootstrapped scale efficiency scores are 95.8% and 93.7% respectively.

The results from the second period indicate that the mean overall pure technical efficiency of the sample banks between 2006 and 2012 is 96.6%. The results show that medium sized banks suffer more from pure technical inefficiency than small and large banks. It is also shown that although the recent global financial crisis had an adverse effect on the efficiency of all banks in the sample, pure technical efficiency of large banks was affected less than the other two groups during the financial crisis. Specifically, while the mean pure technical efficiency score of large banks was 95.7% in 2009, medium and small sized banks experience their lowest mean pure technical efficiency of about 91.4% and 93.1% respectively.
Looking at scale efficiency results suggests that 71% of bank-year observations are inefficient. Similar to the results from the first period, small sized banks have a higher level of scale inefficiency than medium and large sized banks. Specifically, 71% of observations related to small banks are scale inefficient and operate under increasing returns to scale. Three out of four major banks also suffer from scale inefficiency in some years and 21% of bank/year observations of this group are scale inefficient and operate under decreasing return to scale. Thus, similar to the first period while small banks require up-scaling strategies, some large banks may need to decrease their size of operation to be scale efficient.

The bootstrap results indicate that pure technical efficiency of Bendigo and Adelaide Bank as one of the small sized banks declines considerably from 97.5% in 2006 to its lowest point at 89.7% in 2009. This implies that the global financial crisis had a severe effect on pure technical efficiency of Bendigo and Adelaide Bank. On the contrary, pure technical efficiency of the Bank of Queensland, the other small sized bank, decreased slightly from 97.5% in 2006 to 96.7% in 2009 which suggests a relatively small effect of the global financial crisis on pure technical efficiency of this bank. Bank of Queensland experienced a sharp decline in its pure technical efficiency to the lowest rate of 88.8% in 2012 due to difficult economic conditions after the crisis and bad loan charges in the Gold Coast area. In terms of scale efficiency, although both small sized banks are equally scale inefficient and operate under increasing returns to scale prior to the global financial crisis, Bank of Queensland shows a better performance during and after the crisis except in 2012 where it suffers seriously from both pure technical and scale inefficiency.

Among medium sized banks, Macquarie suffers more during the financial crisis than Suncorp and its pure technical efficiency falls from 98.5% in 2006 to 88.4% in 2008. Contrary to Suncorp, which improves its pure technical efficiency from the lowest point at 90.9% during the global financial crisis to 98.7% in 2012, pure technical efficiency of Macquarie has not improved after the financial crisis and still remains around 89% in 2012. Despite different results in terms of pure
technical efficiency, both medium sized banks operate under the optimal scale of operation throughout the entire period.

Similar to other bank groups, pure technical efficiency of major banks declines during the global financial crisis. This effect is not identical for each of the major banks. While ANZ and Commonwealth experience more than 6% decline in their pure technical efficiency, Westpac and National Australia Bank experience declines of less than 2% and 1% respectively in pure technical efficiency. Contrary to other banks in the sample, all major banks could achieve the same level of pure technical efficiency that they had before the recent financial crisis. In terms of returns to scale, ANZ is the only major bank operating at optimal returns to scale throughout the entire period while National Australia Bank is the least efficient one. It is also found that mergers and acquisitions during the global financial crisis had an adverse effect on the scale efficiency of major banks. For instance, scale inefficiency of Westpac in 2008 and 2009 may have been due to increasing its size of operation through the acquisition of St. George in 2008. Similarly, acquisitions of Aviva and Goldman Sachs JBWere by National Australia Bank to develop its wealth management division during the global financial crisis may have contributed to its scale inefficiency in 2008 and 2009.

Overall, comparing the results of the two periods shows that on average both pure technical and scale efficiency have improved which may imply an increasing level of competition in the Australian banking sector. Specifically, mean pure technical efficiency improved from 94% in the first period to 96.6% in the second period. Similarly, mean scale efficiency increases from 96.9% to 98.3%. It is also shown that on average pure technical efficiency is slightly lower than scale efficiency and small sized banks suffer more than other banks from pure technical inefficiency. Looking at scale efficiency, medium sized banks are the most scale efficient banks while small banks suffer from a high level of scale inefficiency in comparison with medium and large sized banks and operate mostly under increasing returns to scale in both periods.
7.4 Policy Implications

There are several policy implications that can be drawn from the results of this study. This section discusses key issues in the Australian banking industry such as the four pillars policy, the impact of the financial crisis, the future of small banks and competition, technology and innovation.

7.4.1 Four Pillars Policy

In response to the Wallis Inquiry recommendations, the Australian government amended the six pillars policy to the four pillars policy in 1997 to prevent mergers between the major four banks in order to protect the competitive environment. Although, this policy was introduced by a liberal government, the labour government continued to support it despite recent discussions regarding the abolition of the policy. Opponents believe that the four pillars policy is anti-competitive because it ensures that a major bank cannot be taken over by other major counterparts and reduces their incentives to be more internationally competitive. On the contrary, our results support the government’s policy and indicate that high competition among the four major banks exists. For instance, looking at pure technical efficiency results during the period 2006-2012 show that the difference between the mean pure technical efficiency score of the major banks is only 1.6% which implies the existence of high competition among the big four banks. Moreover, according to the current regulations major banks can be taken over by foreign banks which protect competition and forces major banks to be efficient. Thus, the four pillars policy has not been anti-competitive as claimed by opponents.

Our results also suggest that all major banks operate at optimal scale or decreasing returns to scale which imply further mergers may intensify the scale inefficiency level of the banking industry in Australia. Furthermore, recent mergers during the global financial crisis show an adverse effect on the scale efficiency of the major banks. Specifically, following the acquisition of St. George by Westpac in 2008, Westpac became scale inefficient in 2008 and 2009 and was operating under
decreasing returns to scale. Similarly, acquisitions of Aviva and Goldman Sachs JBWere by National Australia Bank seem to be one of the major drivers of scale inefficiency during the global financial crisis. Thus, our results suggest that any merger between the four big banks has the potential to intensify scale inefficiency of the banking sector in Australia and can lead to the “too big to fail” problem in Australian banking. Moreover, the recent financial crisis shows that large banks’ failure can cause massive losses by increasing the systematic risk (Cejn, 2009). Finally, as reported by KPMG (2012) solid performance of big four banks during the global financial crisis and rankings in the top 25 global banks by market capitalisation proves that the Australian major banks are successful in the global market. Thus, it can be concluded that contrary to the arguments made by opponents of the four pillars policy, Australia’s major banks do not need further mergers to perform well internationally.

7.4.2 Financial Crisis

The recent global financial crisis was the most significant event in the post-war period (Edey, 2009). Australian banking can be considered a well-regulated and stable banking system and its solid performance during the global financial crisis is an indication of this. The positive performance of the Australian banks during the recent financial crisis may be explained by their high level of efficiency. As emphasised by Blejer (2006), efficient banking systems lead to financial stability during crises. Our results confirm the above observation and indicate the existence of a high level of technical efficiency for Australian banks during the pre-crisis period. Our results also show that despite the severity of the global financial crisis and its profound effect on the global banking industry, the recovery process has been completed for some Australian banks.

Despite strong economic performance, some business analysts warn that the ending of the mining boom, economic slowdown in China, the high Australian dollar and the possibility of another shock in the world economy raise concerns on the future of the Australian economy. Australian regulatory bodies aim to raise
trust and protect financial stability by establishing tougher lending standards and reducing the risk of banking failure by bank liquidity. Our results show that along with regulations to manage risk in the banking sector, the efficiency level of banks can be monitored regularly to establish effective policies and regulations. Regulatory bodies can use advanced, reliable and accurate benchmarking tools introduced in this study to monitor the efficiency of the banking industry in Australia and use the results as inputs to policy making and strategic planning aimed at improving the overall efficiency level of the banking sector.

7.4.3 Small Banks Future

The results of this study suggest that small banks in Australia are suffering from both pure technical and scale inefficiency which is consistent with the earlier Australian efficiency studies (e.g., Kirkwood and Nahm, 2006, Paul and Kourouche, 2008). Furthermore, looking at other performance measures such as ROA and ROE indicates that these banks are significantly less profitable than their major counterparts. The reduction in the number of regional banks during the last two decades and poor performance of existing small banks imply that remaining regional banks in Australia are facing serious challenges. It is worth mentioning that some government’s policies and the global financial crisis have intensified these problems. The ban on mortgage exit fees on new loans by the federal government can disadvantage small banks as mortgage exit fees of these banks are higher than the major banks (Lee, 2013). Increasing impaired loans as a result of the recent global financial crisis and high funding costs due to the lower credit rating of regional banks in comparison with the major competitors are other critical issues for regional banks.

Our efficiency results and the above challenges raise some concern regarding the viability of the regional banks in the future. Operating under increasing returns to scale implies that the regional banks need to increase their scale of operation by further mergers and acquisitions. Colombo and Turati (2011) argue that the economic and social environment are more hospitable to larger firms and markets.
which in turn result in the appearance of larger banks. Banks can obtain cost advantages by expanding their size of operation. Thus, it is not surprising that the majority of regional banks have been taken over by major rivals. The approval by Australian regulators of recent acquisitions and mergers during the recent global financial crisis such as the acquisition of St. George by Westpac or Bankwest by Commonwealth implies that the regulators’ priority is on protecting financial stability rather than competition.

The inefficiency and low profitability of small banks along with issues discussed above lead us to the conclusion that current small banks may be the next take-over targets by the major banks. However, due to increasing the level of concentration and lowering competition intensity in Australian banking, the regulators may not accept such further mergers. The alternative choice then is a merger between these two small banks and the formation of a larger bank to improve scale efficiency. Our findings suggest that while the regulators need to maintain the four pillars policy to protect competition in the market, they must also allow the major banks to take over inefficient regional banks or facilitate mergers between small banks and building societies and credit unions to protect financial stability and improve the performance of the banking sector.

Despite the concerns of opponents to further mergers in the Australian banking industry, this study suggests that protecting regional banks from being taken over by the major banks not only will not be an effective policy to protect competition due to their small market share but also will intensify the inefficiency and instability of the Australian financial system. Instead, to increase competition, entry barriers in the banking industry should be reduced and the government should facilitate the entrance of foreign banks and their operations in Australia. As establishing branches is the most costly part of setting up a new bank, using the successful experience of establishing Kiwi Bank in New Zealand which uses post offices seems a good benchmark for the Australian banking industry. Finally, while mergers among regional banks or take-overs by the major banks would
improve the efficiency level of the banking sector in Australia, more debate is required on the overall benefits to society arising from such actions.

7.4.4 Competition, Technology and Innovation

Our efficiency analysis results show that there is high competition among Australian banks. To succeed in such a competitive market, Australian banks need to constantly monitor and improve their efficiency level. To do so, they need to find efficiencies through cost management, product and service innovation, improving risk management and technology improvement.

As shown in this study, pure technical efficiency analysis indicates that banks can reduce their expenses by reducing both interest expenses and non-interest expenses in order to be fully efficient. As interest expense is the largest cost of commercial banks, the cost of funding is the main concern for the majority of banks especially after the global financial crisis when the cost of funding grew substantially. Consequently, banks should rely more on retail deposits as a replacement for wholesale funding. Furthermore, outsourcing and joint ventures allow banks to reduce their costs and expand their distribution channels.

Product and service innovation is critical for the Australian banks to boost their profitability and efficiency in such a competitive market. For instance, using cross-selling products, banks can sell low profit services along with more profitable products in order to stay competitive. Other good examples of innovation in the Australian banking industry include the launching of a branchless bank by National Australia Bank in 2008. UBank as a branchless bank operates under NAB's banking licence and appears to be successful. NAB claims in its 2009 annual report that almost 10,000 new customers in a month had signed up to use the services of UBank. Overall, the importance of innovation is greater than ever before due to increasing levels of competition among banks.
The increasing level of bad loans during the global financial crisis shows the importance of improving the risk management in the Australian banking industry. Banks need to establish more conservative risk management policies to protect themselves during future financial market turmoils. Technology is another driver of efficiency and allows banks to deliver better services at lower costs. For instance, mobile banking technology is growing very fast and becoming more popular.

7.5 Limitations and Suggestions for Future Research

This study introduces several methodological contributions such as a bootstrap procedure to estimate scale efficiency as detailed in Chapter 4 and also provides a number of contributions to the limited literature on the efficiency analysis of the Australian banking sector. Similar to other studies, this study has a number of limitations. First, the sample includes only 10 Australian domestic banks due to lack of data for foreign banks operating in Australia. Second, due to the small sample size the recent bootstrap methods that have been developed to examine the relationship between efficiency estimates and environmental variables cannot be used (technical limitation).

This study also suggests several possible future research areas to deepen the understanding of Australian banking efficiency. First, this study focuses only on non-parametric methods. Comparing the results with other frontier methods like parametric models can be the aim of the future research. Second, this study only uses the core profit efficiency approach in choosing input and output variables of the model, One possibility for future research is the use of other models such as the intermediation and production approach. Third, it would be interesting to compare the efficiency level of the Australian banks with banks in other developed countries such as UK, Canada and the US especially during the recent financial crisis.
8 References


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