Abstract

The paper examines the applicability of two different modelling techniques: CBSEM and PLS on the data set collected to investigate small and medium sized firm growth in the ICT industry in Australia and Hungary. The two analytical techniques are evaluated based on the research objectives and the conceptual model proposed by the authors. The data is tested for basic assumptions of CFA and CBSEM, as well as PLS. The results of CFA are discussed and the reliability indicators of the scales are presented. In reflection to the findings, PLS is the recommended technique for further analysis.

1. INTRODUCTION

Small and medium sized firms are sources of growth in modern economies, especially in areas like the Silicon Valley in the USA (Audretsch 2003) and the Blue Banana in the EU (Koski, Rouvinen & Ylä-Anttila 2002). In these areas, information communication technology (ICT) developed quickly during the last three decades and many small firms were founded. Developments such as these are seen as possibilities in within Australia (ACS 2008) and the accession countries of the EU in the Central European region (Pakucs & Papanek 2007).

The relevance small and medium sized enterprise (SME) growth in entrepreneurship research has been pointed out by a series of publications, e.g. Lester, Parnell & Carraher (2003), Massey et al. (2006) and McMahon (2001). Papers discussing the topic have been presented and recognized as leading papers in the field at conferences, e.g.: Fitzsimmons, Steffens & Douglas (2005) and Steffens, Fitzsimmons & Davidsson (2006). Books have discussed and analysed the impact of SMEs on economic performance (Storey 1994) and conceptual as well as practical issues of research (Davidsson 2005).

The firm life cycle theory can be used as an integrating framework to conceptualize the factors influencing firm growth. The life cycle phenomenon has been found meaningful by SME owner managers (Massey et al. 2006). Evidence has been provided for the sequential nature of firm life cycle stages (Lester, Parnell & Carraher 2003). The linear nature of life cycle models can be strongly criticised. Inconsistency has been recognized in the life cycle theory by Churchill and Lewis (1983) and Hanks et al. (1993) and empirical evidence approves of the existence of life cycle stages that represent a dead end in terms of firm growth (McMahon 2001).

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Literature review (Davidsson, Delmar & Wiklund 2006) suggests that a very broad range of factors affect firm growth such as resources (Wiklund & Shepherd 2003), firm development stage (McMahon 2001)
and growth intentions (Churchill & Lewis 1983; Hanks et al. 1993). An alternative conceptual model for researching SME growth through a life cycle perspective can be defined.

The authors have developed a conceptual framework (Figure 1) to assess the influence of potential factors on small firm growth in the ICT sector (Perényi, Selvarajah & Muthaly 2008) based on a comprehensive review of firm life cycle theory literature (Perényi, Selvarajah & Muthaly 2007) to represent the evolutionary approach to firm development (Penrose 1952), the resource based firm theory to represent the contractarian approach to firms (Hodgson 1998) and the theory of planned behaviour (Ajzen 1991) to incorporate the growth intentions of small businesses into the model.

**Figure 1: Conceptual framework of SME growth in the ICT sector**

Lester et al. (2003) provide an empirical scale for assessing the firm life cycle construct. The measurement of firm resources from the resource heterogeneity angle (Newbert 2007) was constructed based on the resource based approach of Barney (1991) and Wernerfelt (1984) and expanded by Wade and Hulland (2004) and Gottschalk (2007). The measurement of growth intentions was conducted by assessing the expansion plans of the companies (Ajzen 1991; Kozan, Öskoy & Özsoy 2006) based on Pistrui (2003). Firm growth was measured following the conceptualization of Davidsson et al. (2006).

Bartelsman et al. (2004) points out that firm behaviour has been tested in individual countries and specific industries, but empirical literature lacks cross-country comparison and analysis. The study was based into an international context to cover this empirical gap.

As part of a research project on the growth of SMEs in the ICT sector in Australia and Hungary at Swinburne University of Technology, quantitative data has been collected using survey methodology. This paper aims at determining whether a covariance-based or a variance-based SEM approach is more feasible and suitable to analyse the data and thus demonstrate a practical example of the choice between these two different modelling approaches. This choice can also be interesting to the broader academic community, as Henseler, Ringle & Sinkovics (2009, p. 294.) point out that “literature on formal comparison of CBSEM and PLS is rare”.

The data set has been entered, controlled, treated for missing data and outliers before being applied in this paper. 282 responses were identified usable, 148 from Australia and 134 from Hungary. 101 variables were selected for further analysis.

2. SEM METHODOLOGY OVERVIEW
Structural Equation Modelling (SEM) enables researchers to examine multiple relationships between variables simultaneously and allow the test of an entire model or theory (Streiner 2006). This extends the ability of statistical methods dealing with relationships between dependent and independent variables one at a time (Chin 1998; Hair et al. 2006). SEM has become generally accepted practice for validating research instruments and testing links between constructs (Reisinger & Mavondo 2006).

In preparation for undertaking SEM, confirmatory factor analysis (CFA) needs to be performed to assess construct validity. CFA is used when variables can be grouped into constructs during the research design based on prior research. CFA can also be used to assess translated scales, by comparing factor structures between the data collected in the different languages (Streiner 2006). However it may be difficult to isolate the impact of language on the factor structure from the impact of the different characteristics of the respondents from the different countries.

The clear advantage of SEM compared to the first generation statistical techniques is the greater flexibility it provides researchers to connect theory with data. It allows the assessment of relationships between multiple variables, through the construction of unobservable variables, while addressing the measurement error of these latent variables. SEM can test theoretically based assumptions on measurement as well as conceptual relationships between constructs (Chin 1998; Chin & Newsted 1999).

Henseler, Ringle & Sinkovics (2009, p. 296.) defines covariance-fitting-based SEM (CBSEM) and variance-based SEM (PLS) approaches as being “complementary rather than competitive.” CBSEM is better suitable for theory testing and development, whereas PLS path modelling is more suited to predictive modelling, with research situations of “high complexity but low theoretical information” (Henseler, Ringle & Sinkovics 2009, p. 296.). Reisinger & Mavondo (2006) also consider CBSEM to have potential in both theory testing and development. CBSEM and PLS are two techniques used to analyse data under different conditions, in different models and for different research objectives (Chin & Newsted 1999). PLS can be used for theory confirmation as well as testing the existence of relationships between constructs (Chin 1998; Henseler, Ringle & Sinkovics 2009). Table 1 summarizes the most important distinctions between PLS and CBSEM.

### Table 1: Comparison of PLS and CBSEM

<table>
<thead>
<tr>
<th>Criterion</th>
<th>PLS</th>
<th>CBSEM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Objective</td>
<td>Prediction oriented</td>
<td>Parameter oriented</td>
</tr>
<tr>
<td>Approach</td>
<td>Variance based</td>
<td>Covariance based</td>
</tr>
<tr>
<td>Assumptions</td>
<td>Predictor specification (nonparametric)</td>
<td>Typically multivariate normal distribution and independent observations (parametric)</td>
</tr>
<tr>
<td>Parameter estimates</td>
<td>Consistent as indicators and sample size increase (i.e., consistency at large)</td>
<td>Consistent</td>
</tr>
<tr>
<td>Latent variable (LV) scores</td>
<td>Explicitly estimated</td>
<td>Indeterminate</td>
</tr>
<tr>
<td>Epistemic relationship between LVs and its measures</td>
<td>Can be modelled in either formative or relative mode</td>
<td>Typically only with reflective indicators</td>
</tr>
<tr>
<td>Implications</td>
<td>Optimal prediction accuracy</td>
<td>Optimal parameter accuracy</td>
</tr>
<tr>
<td>Model complexity</td>
<td>Large complexity (e.g. 100 constructs and 1000 indicators)</td>
<td>Small to moderate model complexity (e.g. less than 100 indicators)</td>
</tr>
<tr>
<td>Sample size</td>
<td>Power analysis based on the portion of the model with the largest number of predictors. Minimal recommendations range from 30 to 100 cases.</td>
<td>Ideally based on power analysis of specific model. Minimal recommendations range from 200 to 800.</td>
</tr>
</tbody>
</table>

Source: Chin & Newsted (1999, p. 314.)

Three distinct modelling approaches can be taken when applying SEM: confirmatory; model development and alternative model testing approach (Reisinger & Mavondo 2006). Hair et al. (2006) refer to these as modelling strategies: confirmatory; competing models; and model development strategy.
While a confirmatory modelling strategy or approach aims at assessing the fitness of a particular model, the other two aim at coming up with an adjusted or alternative model that fits the data the best. The main difference between the latter two is that while competing or alternative modelling approaches start assessing the fitness of the data with pre-defined models, the developmental strategy gradually adjusts the starting model with an iterative approach (Hair et al. 2006; Reisinger & Mavondo 2006). Both PLS and CBSEM require firm conceptual support and can be equally applicable. The project used as an example in this paper is intended to apply a confirmatory strategy.

2.1. Requirements for CBSEM

Methodology books such as Hair et al. (2006) point out the necessity of testing different characteristics of the data analysed. Both separate variables and the multivariate model have to be tested for these statistical assumptions. Some analytical techniques are more robust against the violations of these statistical assumptions. Hair et al. (2006) points out, that CBSEM is not very sensitive to the violation of assumptions.

There are some general statistical assumptions regarding multivariate techniques. The four major statistical assumptions are: normality (no skewness, kurtosis, multivariate normality), homoscedasticity, linearity and absence of correlated errors. The implications of the variations from these assumptions can be severe, or minimal (Hair et al. 2006). Further assumptions of CBSEM can be listed, such as: no extreme cases or outliers; data measured on interval or ratio scale; a sample size of between 100 and 400, with a minimum ratio of 5:1 between cases and variables; discriminant validity of measures; and randomness of sampling (Reisinger & Mavondo 2006). There are also specific statistical issues attributed to SEM in particular, and CFA as a required step towards SEM. Multicollinearity within the constructs and a minimum of 5-10 cases per variable (with a minimum of 50 cases) is required for CFA, the lack of multicollinearity between the constructs is required by CBSEM (Hair et al. 2006).

Normality (the correspondence of variables to normal distribution) is required for conducting F and t statistical tests on the data. If the variation from normal distribution is too big, these statistical tests become invalid. Both normality at univariate and multivariate levels needs to be satisfied, where multivariate normality means that both the individual variables and their combination is normally distributed. Non-normality can have severe effects on small samples below 50 cases, but when the sample size reaches 200, the effect usually diminishes (Hair et al. 2006).

Homoscedasticity means that the dependent variables show equal variance across the range of independent variables. This is important as it ensures that a wide range of independent variables have influence on the dependent variables. Heteroscedasticity causes predictions to be better at some levels of the independent variables, than others. Heteroscedasticity is usually the effect of non-normality, so it may be necessary to normalize the sample due to heteroscedasticity rather than for the sake of normality (Hair et al. 2006).

The assumption of linearity is necessary for all multivariate statistical techniques, including factor analysis and structural equation modelling. Its importance is due to the nature of correlation, and its capability to only represent linear relationships. The lack of linearity needs to be addressed either with the transformation of the data so it reflects a linear relationship, or the implementation of non-linear models (Hair et al. 2006).

The presence of correlated errors shows that systematic relationship exists between the dependent and the independent variables that have not been covered in the model. This is the most commonly violated assumption of the four, and can be corrected by including the additional causal factors of the phenomenon (Hair et al. 2006).

Extreme cases or outliers are eliminated during the initial process of data preparation, and sample size minimum requirements need to be judged in reflection to the required Alpha, statistical power and the expected effect size in the research. According to Hair et al. (2006, p. 10.), Alpha— or type I error — is “the probability of rejecting the null hypothesis when actually true;” statistical power is “the probability of correctly rejecting the null hypothesis when it should be rejected;” effect size is “the actual magnitude of the effect of interest.”
A minimum ratio of 5:1 between cases and variables (Reisinger & Mavondo 2006) represents an inherent limitation to the complexity of the measurement model, as well as a strict requirement for sample size. Hair et al. (2006) prescribe guidelines for factor analysis with a requirement of between 5 and 10 observations per variable with a minimum of 50 observations.

The necessity of the data being measured on interval or ratio scales can be derived from the covariance based calculation methods. Although some alternative methods exist for handling non-parametric data, these are mostly not applicable to SEM. Thus another issue needs to be addressed at a theoretical level: whether variables measured on a Likert scale can be considered interval for the nature of SEM, or they should be treated as ordinal (as the nature of the Likert scale would suggest). As often as Likert (1932)’s original paper is referred to, it may occur to a thorough researcher, that that paper is very difficult to access. (The inter library loan specialist of Swinburne University Library has not been able to locate an accessible copy of the paper for over two months at the time of writing this paper in Australia or overseas.) Luckily, specialists of quantitative methodology as well as applied researchers from different disciplines have investigated this issue. Carifio & Perla (2007) discuss the confusion in terminology and application and state that the Likert response format and the Likert scale variables are substantially different. “The Likert response format is only a problem… [if researchers analyse] … each individual item on a scale or questionnaire separately.” In fact, “a single item is not a scale in the sense of a measurement scale” (Carifio & Perla 2007, p. 110.). Thus they conclude that treating a set of Likert scale variables as ordinal measures is not appropriate.

Empirical evidence has also been presented, that for instance F-tests are fairly robust against the violation of the interval data assumption for 5 to 7 point Likert type scales. In conclusion, Carifio & Perla (2007) state that at a scale level – if the measure is constructed appropriately (Lyons 1998) – it is fine to treat 5 to 7 point Likert type scale questions as interval scale variables for parametric testing. Furthermore, several studies show that it is acceptable to treat Likert scale responses or the sum of these as interval level data and analyse them univariately and multivariately (Carifio & Perla 2008). Even promoters of the ordinal interpretation of Likert scale data acknowledge that parametric statistics are widely used to analyse this type of data (Gob, McCollin & Ramalhoto 2007; Liu & Agresti 2005). Scaling methodology books, such as Dunn-Rankin (2004) also prescribe parametric treatment for summed Likert scale data. Thus the authors see it appropriate to apply parametric methods to the exemplary data set mainly consisting of variables measured on a Likert scale.

Assessing the discriminant validity of measures comes down to the actual analytical process (exploratory or confirmatory factor analysis), rather being an explicit prior requirement to conduct SEM (Hair et al. 2006). After conducting CFA, implications can be drawn on the applicability of the modelling technique.

Randomness of sampling is a research design and execution parameter, which in practice can be heavily constrained by the researchers’ possibilities to conduct data collection as well as whether the underlying factors of responsiveness are actually related to the measured characteristics of the population. Statistical methodology (Hair et al. 2006) does not suggest tests to confirm such randomness.

A certain level of multicollinearity is required for the CFA, providing the basis of CBSEM, as this allows the grouping of variables into factors. However as it increases, it becomes more and more difficult for CBSEM to identify the individual effect of construct (Hair et al. 2006).

2.2. Requirements for PLS

PLS gives an alternative to CBSEM shifting the focus from model or theory testing to prediction. It imposes minimal demands on measurement scales, sample size, residual (error term) distributions and independence of observations (Chin 1998; Chin & Newsted 1999). Henseler, Ringle & Sinkovics (2009, p. 284.) point out the ability of PLS to analyse “high dimensional data in a low-structure environment.”

PLS starts with a different objective: to calculate latent variable scores, and uses an estimation algorithm with three stages (Chin 1998). The PLS path model is described by two distinct set of linear equations. The inner model is the actual conceptual model, in other words the relationship between the latent variables representing the constructs. The outer model specifies the measurement model of the constructs involved in the inner model (Henseler, Ringle & Sinkovics 2009). Unlike CBSEM, PLS estimates the loadings and weights within the model through an iterative process starting with an initial outside
approximation, than the inner approximation and finally the outside approximation. This also means that there is no overall goodness-of-fit measure (Chin 1998; Chin & Newsted 1999; Henseler, Ringle & Sinkovics 2009). The inner and the outer models need to be assessed separately using different, variance based indicators – as covariance based indicators would be inappropriate due to the lack of distributional assumptions (Chin & Newsted 1999).

Another nouvelle feature of PLS based SEM is the way it handles formative measures and is able to incorporate both formative and reflective measures within one model without great difficulty (Chin & Newsted 1999). As formative indicators represent an identification problem in CBSEM and also need to be treated differently during the CFA (Hair et al. 2006), it is easier to use PLS for frameworks incorporating formative measures (Chin 1998).

Nevertheless, there are minimum sample size requirements to PLS modelling as well. Based on the inside and the outside approximation, and the multiple regression method used by PLS, it is advised to use at least ten times as many indicators, as either the largest number of formative indicators leading into one construct, or the largest number of independent latent variables influencing a dependent latent variable (Chin 1998; Chin & Newsted 1999; Henseler, Ringle & Sinkovics 2009).

Henseler, Ringle & Sinkovics (2009) point out however, that a lesser sample size requirement does not mean that PLS is advantageous in detecting statistical significance in small sample sizes. In fact, the only relative advantage seems to be, that while goodness-of-fit indicators of CBSEM models decline with the increase of model complexity, for PLS increasing sample size actually means better convergence.

Independence of observations is not required for PLS modelling – which can be interpreted as the randomness of sampling requirement in CBSEM is waived (Chin 1998).

PLS is not resistant to multicollinearity, but shows more favourable characteristics than CBSEM. This means, that factor cross-loadings will still impose a difficulty although mathematically it does not present a problem (Henseler, Ringle & Sinkovics 2009).

PLS is a distribution-free method, thus does not allow distribution dependent statistical testing. However with different strategies, such as bootstrapping and jackknife, distribution-dependent tests can still be performed (Henseler, Ringle & Sinkovics 2009).

As PLS relies on linear regression, the assumptions about the data on regression need to be observed. (Hair et al. 2006) recommends a minimum sample size of 50-100 for multiple regression on order to maintain power at a 0.8 level and a minimum ratio of 5:1 between observations and variables. Linearity, homoscedasticity, independence of error terms and a normality of error term distribution is assumed when running multiple regression (Hair et al. 2006). These assumptions overlap with the assumptions examined generally for the CBSEM.

3. EXAMINATION OF THE RESEARCH SCENARIO AND MODELLING REQUIREMENTS

3.1. General assessment of the research project

In reflection to Table 1, the general objectives of the research project need to be examined to feed into the choice between the CBSEM and PLS methods. The research project, whose conceptual framework is displayed in Figure 1 aims at assessing the importance of the effect of different factors on firm growth. The main research question is: “What makes SMEs in the ICT sector grow?” This can be decomposed into three sub-questions that relate to both the nature of the observation and the structure of the conceptual model. The first question is related to the validity of the topic of investigation: “Do SMEs in the ICT sector grow?”

This suggests however, that the distribution of the responses to the questionnaire items assessing the perception of the respondent on firm growth will be skewed (as the target of the project is to assess growing SMEs in the ICT sector.) This already indicates the possibility of non-normal distribution in some of the variables.
The central theme of the research suggests the second research question: “Which factors influence the growth of SMEs in the ICT sector and to what extent?” Translated to the conceptual framework, this question requires the assessment of the data and the model to identify which elements of the proposed framework actually fit the model and thus is useful in explaining firm growth. In other words, a model confirmatory or development strategy needs to be followed in order to assess the measurement model, the interactions between the examined constructs and whether the Expansion plans construct is an independent or mediating construct. The third question relates to the international scope of the data collection: “Are the discovered factors of growth country specific?” Data has been collected from Australia and Hungary, and it can be tested whether the Country of origin serves as a moderating variable.

The Objective of the project (in line with Table 1) is to assess the parameters in order to explain firm growth better. The Implications of the choice regarding the accuracy of the results is similar to the objective related considerations of the methodology choice. The project itself is aiming at predicting the dependent construct (Firm growth) in retrospect, thus a parameter orientation can be identified, suggesting the application of CBSEM.

As the model only consists of reflective indicators, the epistemology of measurement is not really an issue (both PLS and CBSEM can handle reflective measures) making both techniques appropriate. The clear advantage of PLS for calculating latent variable scores is not really needed to answer the research questions either, thus not making a difference for the applicability of the methods.

Model complexity – as well as modelling approach – does seem to be making a difference in choosing between the two modelling techniques. The case of this research with 101 indicators is on the borderline to be too complex for CBSEM. However CFA may force the researchers to rule out some indicators reducing the complexity of the measurement model. Applying the thresholds provided in Table 1, the model is of moderate-high complexity, thus suggesting PLS to be more applicable for the analysis. Further requirements will be discussed respectively to the particular methods.

3.2. Evaluation of data related assumptions

Hair et al. (2006) and Reisinger & Mavondo (2006) have identified several assumptions, which need to be made before proceeding with CBSEM modelling. These assumptions ensure that the statistical tests CBSEM uses as well as the statistical tests required for testing hypotheses after establishing the model work properly.

Both Kolmogorov-Smirnov and Shapiro-Wilk tests of normality show a $p=0.000$ (df=282) significance level of normality of every variable, meaning that none of the variables are normally distributed. This can be confirmed by looking at the histograms drawn based on the individual variables and comparing them to the fitted normal distribution curve (Hair et al. 2006). 42 out of 101 variables can be considered not skewed at a $p=0.05$ significance level. 25 variables are positively, 34 are negatively skewed. 26 out of 101 variables have a close to normal kurtosis at a $p=0.05$ significance level. 13 variables are leptokurtic (peaked), 62 variables are platykurtic (flat). Only 4 variables out of 101 do not have a significantly different skewness or kurtosis from the normal distribution. However, as indicated by the Kolmogorov-Smirnov and Shapiro-Wilk tests, their distribution still cannot be significantly identified with the normal distribution. On the construct level of raw summated scales (before CFA and reliability testing), the measures associated to the firm life cycle construct have proven to be of normal distribution, the raw summated scale of firm growth is close to normality, and the others are significantly different from normal distribution. In other words, normality cannot be assumed on the construct level, not to speak of the level of individual variables.

Table 2: Heteroscedasticity in the sample

<table>
<thead>
<tr>
<th>Raw summed independent construct measures</th>
<th>Count of dependent measures showing heteroscedasticity at a $p=0.05$ significance level according to Levene’s test.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm life cycle (present)</td>
<td>8 out of 18 variables</td>
</tr>
<tr>
<td>Firm life cycle (past)</td>
<td>2 out of 18 variables</td>
</tr>
<tr>
<td>Resources</td>
<td>12 out of 18 variables</td>
</tr>
<tr>
<td>Expansion plans</td>
<td>2 out of 18 variables</td>
</tr>
</tbody>
</table>
Using Levene’s test (Hair et al. 2006) in SPSS, across all four raw summated scales of all three independent constructs, some heteroscedasticity can be found in the data (also probably due to the large proportion of non-normally distributed variables).

Table 2 shows that the dependent variables are mostly homoscedastic over the past indicated raw summated values of the Firm life cycle construct and the Expansion plans, but are rather heteroscedastic over the raw summated construct scores of resources and the current indicated score of firm life cycle.

Hair et al. (2006) suggests several ways of testing the assumption of linearity: examining scatterplots, the residuals of a linear regression analysis, or testing an explicitly non-linear model as a modelling alternative. Having a large number of variables, examining the (over 1000) scatterplots would present itself as a less favourable alternative. Alternative non-linear model testing is not feasible at this stage of the analysis, as starting modelling would need the assumptions tested and approved in the first case.

Running linear regression analysis on all 18 dependent variables separately, 3 regressions presented an R value between 0.5-0.6, 9 regressions presented an R value between 0.7-0.8 and a further 6 have a result for the R value between 0.6-0.7. This confirms the existence of some linear relationship between the dependent and the independent variables. This relationship will hopefully be amplified after the exclusion of the unreliable measures. However, this can only be treated as a preliminary indication, as the models do not fulfil the recommended 5:1 ratio between independent variables and observations (84 independent variables, including country of origin have been used, and the sample size is only 282). (Hair et al. 2006)

Multicollinearity can be examined alongside with linearity testing. There has been some indication of multicollinearity using the VIF indicator (Hair et al. 2006), but much of this multicollinearity is expected to be between the variables contributing to individual factors and disappear within the factor scores.

Correlated errors may be due to relationships or factors not included in the model. In this study, there are some potential variables, which may show some influence on the dependent variables. Such variables were identified in the profile building section of the survey, and involve firm location, industry classification of activities, legal format, gender of respondents and which batch of invitations the respondent comes from. Using Pearson’s Chi-square test, relationships between categorical variables can be identified. Cross-testing the variables of the study with the multiple response set of industry classification (using SPSS), the majority of valid Chi-square results indicate the independence of the variable values from the industry involvement indicated by the respondent at a p=0.05 significance level. Most of the valid test results between respondent gender and the variables of the study also indicate independence at a p=0.05 significance level. The results indicated as possibly not valid by SPSS (due to low case count) are also in line with the independence situation indicated above. Further analysis would require the ANOVA technique, but as the variables have proven not to be normal, that would breach the assumptions ANOVA makes about the data (Lind, Marchal & Mason 2002). Extending from this, it is difficult to provide statistical test results for the randomness of sampling using the collected data. Indications of randomness can be derived from details of the data collection process. The data collection was conducted in waves of invitations, and it is difficult to cross-check response times with response characteristics, mainly due to the small number of observations in each batch.

Univariate outliers can be generated by the regression based imputation method applied in this project, as its outcomes may end outside the allowed range of the variables. (Hair et al. 2006) The regression based imputation resulted in no invalid values. It may happen, that running the regression based imputation with a random element comes up with substitution values outside the valid variable range. The authors decided to refrain from adding the random elements to the imputed values to eliminate this problem.

According to Hair et al. (2006), univariate outliers in samples larger than 80 observations are values falling outside a threshold of up to 4 times the standard deviation around the variable mean. After checking the imputed dataset, two variables displayed values outside the acceptable interval, identifying 9 cases, out of which 4 were outliers within both variables. These cases will need to be considered before entering them into the analysis.

Bivariate outlier detection was not performed on the data. There are 83 independent and 18 dependent variables initially identified in the model, which would require the pairwise comparison would require the examination of 1494 scatterplots to start with. This step is therefore not pursued, in line with the recommendations of Hair et al. (2006).
The Mahalanobis $D^2$ measure can be used to indicate outliers at a multivariate level (Hair et al. 2006). Although Dasgupta (1995) suggests that the $D^2$ follows a Chi-square distribution, and Rightmire (1969) also supports the statement, it is also pointed out that there is no established support for this claim. Mukhopadhyay (2008) suggests, that although the Chi-square distribution is appropriate, the Hotelling's T-square statistic is more justified (which is a generalization of the t-statistic). This is in line with the recommendation of Hair et al. (2006) for using the t-statistic to assess the significance level of $D^2$. Observations having a $D^2/df$ value of greater then 2.5 for small samples and 3 or 4 in large samples can be considered as multivariate outliers. When applying the Chi-square statistic, significance levels of 0.001 or less can indicate outliers, which seems to be a more rigorous assessment of the $D^2$ values. If the recommendation of (Hair et al. 2006) is followed, no multivariate outliers can be identified. The Chi-square statistic would suggest 13 outlier cases (6 Australian and 7 Hungarian) three of which overlap with the univariate outlier cases. These cases will require further investigation.

3.3. Sample size requirements

Sample size requirements of CBSEM include 5 cases per variables for CFA (Hair et al. 2006; Reisinger & Mavondo 2006). There are 4 constructs in the conceptual model. The firm life cycle is measured by 21 Likert scale variables, however its contemporary values as well as its retrospective values are measured. There is an additional variable, which has been transformed to a 5 point scale as well, measuring firm age. So the construct contains 43 variables, essentially two sets of 21 plus one measures. 18 variables are associated to the dependent construct, 12 out of which measure firm growth, and 6 measure the change of firm growth. 18 variables measure the resource attributes construct and 22 variables are used to measure the growth intentions and expansion plans construct. Applying the 5:1 principle, $5 \times 43 = 215$ is the minimum amount of cases for conducting a CFA. This is achievable for this project, but the target number can not only be met with the total sample, not within the two major sub-samples (Australia and Hungary) with 148 and 134 respondents respectively.

Hair et al. (2006) recommends determining the required sample size in relation the effect size, alpha and power. Choosing these parameters can be based on common practice of the academic field. Hair et al. (2006, p. 12.) provides a diagram for assessing sample size requirements at a medium effect size (0.35) and also suggests a power level of 0.8 to be achieved. At an alpha level of 0.01, approximately 190 responses are required, while the alpha level of 0.05 can already be satisfied with approximately 130 responses. This suggests that with the current sample, a combined analysis of 282 responses would allow a stringent analysis (significance levels of 0.01) with high power expected, but the separate analysis of the sub-samples could only be conducted at a less stringent significance level of 0.05. The possible moderating nature of the Country of origin requires the separate analysis of the sub-groups thus restricts the analysis to the alpha level of 0.05. As there are 148 cases from Australia and 134 cases from Hungary, both sub-group fulfil the sample size requirement at an alpha level of 0.05. This alpha level is still acceptable for the discipline (Hair et al. 2006).

Sample size requirement for PLS is a lot less stringent, but still need to be considered. As the measurement model only contains reflective measures, the required sample size is ten times the largest number of independent latent variables influencing a single latent variable. According to Figure 1, this is 30.

3.4. Statistical methodology choice in reflection to the data

Evaluation of the assumptions and requirements of the different statistical techniques is described in Table 3. Although in terms of the research objective, CBSEM may seem more suitable, the model and the data parameters suggest the more successful applicability of PLS.
### Table 3: Evaluation of the applicability of statistical methods for the examined case

<table>
<thead>
<tr>
<th>Assumptions, requirements</th>
<th>PLS</th>
<th>CBSEM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Objective of the research project</td>
<td>The project primarily aims at determining the model parameters, although predictive applications of the model can be considered useful for businesses.</td>
<td>CBSEM modelling is suitable for the research objective.</td>
</tr>
<tr>
<td>Model complexity</td>
<td>PLS can deal with higher model complexity, so can be considered more suitable for this research.</td>
<td>The complexity of the model is at the top range manageable by CBSEM. The risk is that the model will not find significant relationships.</td>
</tr>
<tr>
<td>Normality</td>
<td>This assumption needs to be rejected based on the data, making PLS more the suitable technique for the analysis. Analysing sub-samples would not provide a high-enough sample size for CBSEM to be robust against normality assumption violations.</td>
<td></td>
</tr>
<tr>
<td>Homoscedasticity</td>
<td>Some level of heteroscedasticity can be identified within the data.</td>
<td>To some extent, CBSEM modelling assumptions are violated due to the presence of some heteroscedasticity.</td>
</tr>
<tr>
<td>Linearity</td>
<td>Linearity can be assumed for the data, thus both modelling requirements are fulfilled.</td>
<td></td>
</tr>
<tr>
<td>Multicollinearity</td>
<td>Some multicollinearity can be identified within the data.</td>
<td>It can only be identified after CFA to what extent this multicollinearity actually breaches the modelling requirements.</td>
</tr>
<tr>
<td>Correlated errors</td>
<td>Not required for PLS.</td>
<td>The lack of correlations in errors is required for CBSEM modelling, however it is difficult to test without an establishment of the model. It may need to be judged in retrospect. Cross-examining the variables with different elements of firm profile has shown no significant influence.</td>
</tr>
<tr>
<td>Outliers</td>
<td>Outliers would be significant distorting factors in both cases. Multivariate outlier detection has not shown significant outliers (although a more rigorous evaluation suggested 11 cases to be different) and the univariate outliers are also very few in number. No outlier involves more than 2 variables.</td>
<td></td>
</tr>
<tr>
<td>Measurement requirements</td>
<td>A minimum of interval scale measurement is required for both modelling techniques. As a common practice, factor scores can be calculated from the individual Likert scale variables and considered as interval scale variable for the purposes of modelling.</td>
<td></td>
</tr>
<tr>
<td>Randomness of sampling</td>
<td>Independence of observations not required for PLS.</td>
<td>Difficult to give statistical evidence based on the data.</td>
</tr>
</tbody>
</table>

Further exploring the data, and conducting CFA using SPSS, some of the constructs did not show the expected factor structure. The construct Resources – which has shown the highest level of heteroscedasticity – has not reflected the expected factor structure. The other two independent constructs (Firm life cycle and Expansion plans) have to some extent delivered factors along the theoretical background. Several variables were excluded during the CFA process. The dependent construct (Firm growth) has also delivered a different factor solution from expected, although no variables needed to be excluded. The difference in CFA outcomes and the necessity of excluding variables during the process on one hand suggests, that the data-characteristics are not really suitable for CBSEM, on the other hand, that the project drifts away from confirmatory research to some extent in the direction of model improvement. This also supports the choice of PLS for further analysis.
3.5. Initial CFA and scale reliability assessment

CFA was performed on the data using SPSS, to determine the underlying factors within the constructs. The data has been entered into SmartPLS (Ringle, Wende & Will 2005) and the conceptual model displayed in Figure 1 has been implemented on the data. Table 4 summarizes the results of the CFA and the reliability tests of the measures before and after the factor analysis.

### Table 4: Reliability of measures

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Number of variables</th>
<th>Cronbach’s Alpha</th>
<th>Dillon-Goldstein’s Rho</th>
</tr>
</thead>
<tbody>
<tr>
<td>All variables</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm life cycle</td>
<td>43</td>
<td>0.654</td>
<td>0.5233</td>
</tr>
<tr>
<td>Resources</td>
<td>18</td>
<td>0.627</td>
<td>0.6025</td>
</tr>
<tr>
<td>Expansion plans</td>
<td>22</td>
<td>0.821</td>
<td>0.8483</td>
</tr>
<tr>
<td>Firm growth</td>
<td>12</td>
<td>0.562</td>
<td>0.6565</td>
</tr>
<tr>
<td>CFA selected variables</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm life cycle</td>
<td>30</td>
<td>0.802</td>
<td>0.7203</td>
</tr>
<tr>
<td>Resources</td>
<td>13</td>
<td>0.865</td>
<td>0.7139</td>
</tr>
<tr>
<td>Expansion plans</td>
<td>14</td>
<td>0.774</td>
<td>0.7836</td>
</tr>
<tr>
<td>Firm growth</td>
<td>12</td>
<td>0.781</td>
<td>0.6545</td>
</tr>
</tbody>
</table>

The Cronbach’s Alpha scores were generated using SPSS, Dillon-Goldstein’s Rho scores were calculated using the SmartPLS software (Ringle, Wende & Will 2005). The reliability indicators were significantly improved by the CFA, and pushed up to the acceptable level of 0.7 (Hair et al. 2006). However the composite reliability (Dillon-Goldstein’s Rho) figures were calculated by SmartPLS, with the iterative process of optimizing the external and the internal models. The internal model features had some influence on the reliability scores of the indicators applied in the external model. As the composite reliability figures are mostly lower than the Cronbach’s Alpha figures, indicators retained during the CFA may not be optimal for PLS modelling. The appropriate indicators should thus be selected examining indicator reliability and average variance extracted (AVE) commonly applied in the PLS technique (Fornell & Larcker 1981).

4. CONCLUSIONS

Comparing the applicability of CBSEM and PLS based on the general description of the nature of the research project, or basic statistical assumptions made about the data is only the first step of choosing the appropriate technique. Although researchers have presented CBSEM and PLS as not competing analytical techniques, it is relatively difficult to make such a choice before the actual data has been collected and examined.

The nature of the research (whether the confirmatory or exploratory nature is more dominant) may change in reflection to the actual data collected. As the CFA has shown, the measurement model has already suggested questioning the factors behind the constructs included in the model (or at least the measures applied to collect information on them).

Having examined the model and sample characteristics, PLS has proven to be the more appropriate modelling technique. Not only for the lack of the data fulfilling the assumptions needed to conduct CBSEM, but also due to the CFA results in the model. PLS provides a possibility of broader inclusion of variables into the model.

It can be said in conclusion, that a case based comparison of the applicability of the two different modelling techniques requires not only the assessment of the underlying statistical assumptions, but also an investigation into the measurement models. So, compelling argumentation on which one is the more appropriate method requires significant progress into building up the model, and a lot of statistical testing. For this particular project, it can be determined, that PLS is not only the better choice for the reasons of multiple violations against the underlying assumptions of CBSEM, but also promises to deliver a better measurement and more inclusive conceptual model. The analysis of the model on this dataset will continue using PLS.
5. REFERENCES


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Perényi, Á, Selvarajah, C & Muthaly, S 2007, 'A review of the firm life cycle theory and its applicability to small and medium sized enterprises' Student Research Conference, Hamilton, New Zealand, The University of Waikato