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Predicting corporate turnaround of listed companies in South Africa

Author: Mr Chu-kuo Chin (University of Cape Town)

Supervisor: Mr Darron West (University of Cape Town)

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Department of Finance and Tax

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Plagiarism Declaration

I, Chu-kuo Chin, hereby declare that the work of this dissertation is my own work and that to the best of my knowledge in contains no material previously published or written by another person, or substantial proportions of material which have been accepted for the award of any other degree or diploma at any educational institution, except where due acknowledgement is made in this dissertation. Furthermore, any contribution made to the research by others is explicitly acknowledged and referenced in this dissertation. I also declare that the intellectual content of this dissertation is the product of my own work, except to the extent acknowledged.

Name: Chu-kuo Chin

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Abstract

Corporate turnaround, in comparison to financial distress, is not substantially researched either internationally or locally in South Africa. This study attempts to explore this area of research by developing models that identify financially distressed companies with a potential for turnaround. This analysis examines listed companies on both the JSE Securities Exchange ('JSE') and Alternative Exchange ('AltX') for the period 2007 to 2014 by using available data from iNet BFA. The financial distress model, Taffler's Z-score, is used to identify companies that fall within the sample. Multiple linear discriminant models with interaction variables are used as part of the process to derive the turnaround models. The first model shows that efficiency is a key driver for a successful turnaround. The second model reveals that JSE-listed companies are more likely to survive than AltX companies. This study contributes to the existing research by identifying significant factors for corporate turnaround and summarizing its findings in a practical manner.

Key words

Corporate turnaround, financial distress, JSE, AltX.

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Introduction

A significant amount of research has been done on predicting corporate bankruptcy. These prediction models have provided useful information for auditors, lenders and insurers (Poston, Harmon & Gramlich, 1994). Auditors are able to use bankruptcy models to determine whether companies are able to operate in the near future and, therefore, assist the audit partners in assessing the applicability of the going concern assumption for the preparation of financial statements. Lenders and insurers are able to use the information to determine if companies are able to fulfil their obligations to repay debts or whether there is to be a positive investment return.

Corporate bankruptcy attempts to predict the negative outcome for companies, but often companies are subject to the economic cycles or possible temporary underperformance; thus, using a bankruptcy model may limit the opportunity to allow good companies to turn around after being classified as bankrupt. A turnaround model may act as a secondary confirmation of the results of the bankruptcy models. It may provide further insight and distinguish successful and unsuccessful turnaround strategies, thus providing useful information to management.

Given the practice of predicting bankruptcy, it has been an area of significant attention for both international and local academics. The turnaround landscape is relatively unexplored, possibly due to the lack of data or interest from the public. This has certainly provided an opportunity for further research in finance literature.

This paper is a replication of research by Smith and Graves (2005) in corporate turnaround and financial distress, but in a South African context. Smith and Graves (2005) identified distressed UK listed companies that have turnaround potential by means of predicting a discriminant turnaround model. This paper attempts to answer the same research question as Smith and Graves (2005), but for JSE Securities Exchange ('JSE') and Alternative Exchange ('AltX') companies.

Smith and Graves (2005) used the Z-score developed by Taffler (1983) to identify distressed companies, and hypothesized their own independent variables for the turnaround model. This paper will follow the same approach and methodology.

The layout of this paper is as follows: Section 2 will review the literature in the areas of bankruptcy and turnaround models. Section 3 sets out the methodology and variables used to address the research question. Section 4 sets out the analysis of data and turnaround models. Section 5 is the discussion of results. Section 6 will be the conclusion with Section 7 making recommendations for further research.

Literature review

2.1 Bankruptcy

The earliest bankruptcy studies dated back to the 1930s, with Paul FitzPatrick being the pioneer in this field (Bellovary, Giacomino & Akers, 2007). Earlier research focused predominantly on univariate analysis with Beaver (1966) as a commonly cited author. A univariate analysis estimates an optimal cut-off point for classification of failed and non-failed companies. It is a simple technique and no in-depth statistical knowledge is required (Balcaen & Ooghe, 2006).

Two years after Beaver's (1966) paper, Altman published a multivariate study in his 1968 paper, which remains well-cited literature today (Altman, 1968).

Many of the concepts in Altman (1968) remain key in the research of corporate bankruptcy. This includes the use of multiple discriminant analysis, the significant indicators of profitability, liquidity and solvency as ratios, and a focus on manufacturing sectors only (Altman, 1968). The result was the Z-score, which Altman (1968) termed the overall index. Since its creation 40 years ago, the Z-score still remains a commonly referenced calculation in bankruptcy literature.

Altman, Haldeman and Narayanan (1977) published an updated Z-score called the ZETA model. The ZETA model took into account retail companies which had never been modelled previously and also took into account the change in accounting practices. Specific adjustments were made to the accounting data (for example, the capitalization of operation leases and the elimination of goodwill from total assets). The updated ZETA model has two ranges which classify the firm as either bankrupt or non-bankrupt. The model has also increased from the previous five-variable model to a seven-variable model (Altman, Haldeman & Narayanan, 1977).

In an updated study by Altman (1999), both the Z-score and the ZETA model were revisited. The multiple discriminant analysis remained as the primary statistical technique used, but elimination of both very large and very small firms was done and a revised Z-score was presented in evaluating private companies, where market value is substituted for book value of equity (Altman, 2000).

Besides the univariate analysis and multiple discriminant analysis, there are three further statistical methods commonly used in corporate failure predictions, namely: the risk index model, conditional probability model and neural network model.

The earliest risk index model for forecasting bankruptcy appeared in 1966, whereby Tamari (1966) calculated an overall index ratio based on a set of financial ratios. The argument was that an analyst should not rely on one single ratio in measuring the degree of risk. This reliance would be mitigated by using an average of all significant ratios. The potential downside is that the allocation of the weights is subjective in nature (Tamari, 1996). This was followed by work presented by Moses and Liao (1987), where each ratio is assigned a dichotomous variable based on an optimal cut-off point. The risk index is simply the sum of the dichotomous variables (Balcaen & Ooghe, 2006).

The conditional probability model can take on different forms based on the assumed probability distribution. For example, a logistic model assumes a logistic distribution, a probit model assumes a cumulative normal distribution, and a linear probability model assumes a linear distribution. The most common conditional probability model is the logistic model (Balcaen & Ooghe, 2006). The logistic model implies that the failure probability follows a logistic distribution in that a healthy company must have a larger deterioration in its variables in order to decrease its bankruptcy score (Balcaen & Ooghe, 2006). The conditional probability model was first introduced by Ohlson (1980).

The last commonly used model to forecast bankruptcy is the neural network model. The neural network model was first developed to replicate the processes of the brain (Brockett et al, 2006). It intends to provide algorithmic structures that can interact like the human brain, based on artificial intelligence which includes learning from experience, generalizing and abstracting relevant information (Brockett et al, 1994). This type of modelling was possible due to the development of technology in the late 1980's.

The different methods of prediction of corporate bankruptcy have experienced varying degrees of popularity over time. According to Bellovary et al (2007) (in a review of bankruptcy studies from 1930 to 2007), the most accurate method of predicting bankruptcy in the 1960's was the univariate analysis followed by the multiple discriminant analysis in the next two decades. Thereafter, it was overtaken by the neural networks. Table 1 shows the predictive abilities by method and decade, according to Bellovary et al (2007).

Table 1: Predictive ability by decade and method

Decade	Lowest accuracy	Highest accuracy	Method(s) used to obtain highest accuracy
1960's	79%	92%	Univariate analysis
1970's	56%	100%	Multiple discriminant analysis
1980's	20%	100%	Multiple discriminant analysis, Neural networks
1990's	27%	100%	Neural networks
2000's	27%	100%	Multiple discriminant analysis

Another interesting conclusion reached by Bellovary et al (2007) is that models were able to predict at maximum accuracy as they evolved. The predictive ability by method shows that multiple discriminant analysis and neural networks are the most promising methods. Table 2 presents the predictive ability by method as summarized by Bellovary et al (2007).

Table 2: Predictive ability by method

Method	Lowest accuracy	Highest accuracy
Multiple discriminant analysis	32%	100%
Logistic analysis	20%	98%
Probit analysis	20%	84%
Neural networks	71%	100%

Aziz and Dar (2006) presented a review on bankruptcy literature, in which they found multiple discriminant analysis and logistic models as the dominant research methodologies, with neural networks in third place. Table 3 shows the top three methods used in all studies as presented by Aziz and Dar (2006).

Table 3: Top 3 methods employed by past international studies

Method	No. of employing studies
Multiple discriminant analysis	30.3%
Logistic analysis	21.3%
Neural networks	9%

Bellovary, Giacomino & Akers (2007) did not reach a firm conclusion on a superior method. This is consistent with Aziz & Dar (2006) and Balcaen & Ooghe (2005). Two further international studies comparing methods also indicated that there are no statistically significant differences between the results of the various methods: Laitinen & Kankaanpaa (1999) examined the predictive accuracy based on Finnish data, and Pompe & Feelders (1997) did the same using Belgian data. The argument presented by Balcaen and Ooghe (2005) is that it is impossible to determine a superior method by examining a large selection of studies without any scientific tool of comparison. However, Balcaen and Ooghe (2005) noted that the more complicated methods do not necessarily result in a significant marginal improvement in accuracy. In spite of different academics across different countries examining more than 35 years of bankruptcy literature, there is no consensus as to which method is superior. It is largely left to the researchers to select the method.

For the purposes of this study, Taffler's Z-score is used as the bankruptcy model which is consistent with Smith & Graves' (2005) original study. Smith & Liou (2007) also examined the Taffler's Z-scores of companies for a period of twenty years by looking at its predictive ability between period 1 (1981 - 1987) and period 2 (1988 - 1994). The authors found that Taffler's Z-score had remained robust across the period with the same variables and weights as the model developed by Taffler in 1983. Sudarsanam & Lai (2001) also made use of the Taffler's Z-score in identifying financially distressed companies in their empirical analysis.

The nature and derivation of Taffler's Z-score lies in the initial Z-score model developed by Altman in 1968. The two models share many of the same characteristics and remain popular and relevant in the present day, hence, the Z-score is a reliable measure of bankruptcy.

In the South African context, there is some existing literature on the application of bankruptcy models, but they are not as well-researched as they are internationally. The earliest work on bankruptcy models was mainly by academics at the University of Witwaterstrand in the 1970s (Arron & Sandler, 1994). As mentioned in Arron & Sandler (1994), there were two studies that mirrored Beaver's (1966) univariate and Altman's (1968) multiple discriminant models. The accuracy of the early South African studies mirrors the success achieved by international research. The result of the South African studies and the corresponding international counterpart are presented in table 4.

Table 4: Early studies of South African bankruptcy models and their international bases

Author(s) and year	Method	Accuracy of model in SA study	International Author(s)	Accuracy of model in international study
Strebel & Andrews (1977)	Univariate analysis	90%	Beaver (1966)	87%
Amiras, Aston & Cohen (1978)	Multiple discriminant analysis	88.5%	Altman (1968)	95%

In more recent times, Arron & Sandler (1994) compared the predictability of multiple discriminant analysis, logistic analysis and neural networks on listed companies on the JSE and concurred with international studies that there is no significant statistical difference between the three methodologies. Court & Radloff (1990) showed that there is not sufficient evidence to accept that multiple discriminant analysis is superior to logic analysis. A follow-up study by Court (1991) concluded that the inclusion of non-financial variables, such as the delay in publishing results, and changes in directors and directors' shareholding, does enhance the predictive ability of the bankruptcy model. Court's (1991) tested sample resulted in 100% predictive accuracy.

More recently, Naidoo & Du Toit (2007) tested JSE data (up to 1999) using all international and South African models and demonstrated that the results across the different methods are equally favourable. Hence, there is no strong case for a superior method. Appendix A presents a summary of relevant South African literature since 1990.

It is interesting to note that in all South African literature examined, companies listed on AltX were excluded. This may be partly due to the limited data on AltX, as it was only established in 2006 and the bulk of the listing consists of smaller companies with less trading liquidity. Given that the majority of the bankruptcy models comprise of financial ratios as independent variables, the examination of the bankruptcy model on AltX shares remains feasible. This is certainly an area for future research. A recent study by Coelho, Correia and West (2014) applied the Altman Z-score to AltX companies; however, since that study examined the application of the Z-score result during the 2008 economic crisis, it offered no conclusion on the predictive ability of the model. All recent South African studies have examined the entire JSE market, except for Muller, Steyn-Bruwer & Hamman (2009) who excluded the mining, financial and property sectors from their sample. This is a shift away from initial bankruptcy studies which tended to be limited to a single industry.

A South African study (Garbers & Uliana, 1994) that involved the comparison of univariate and multiple discriminate models to a local bank's ability to detect distress in privately owned firms revealed that both models are superior to the local bank's internal evaluation. Hence, bankruptcy models seem valid for both listed and unlisted companies.

It is evident from the examination of Appendix A and by a review of South African literature that there is no superior model for predicting bankruptcy in South Africa.

2.2 Turnaround

Literature on the turnaround phenomenon gained momentum in the 1980s. This was not only as a result of an increase in business failures during the same period, but it also coincided with an increase in bankruptcy literature over the same period (Solnet, Paulsen & Copper, 2010). The driver of turnaround literature has its root in America's manufacturing and financial services industries. During the period 1979 to 1985, the index of net business formation declined by 14 percent due to offshore competition in the steel and automobile industries. The financial sector also experienced a similar downturn in that the number of bank failures between 1980 and 1985 exceeded the total bankruptcy of the previous 40 years (Cameron, Sutton & Whetton, 1988). The increase in business bankruptcies due to the state of the economy had caught the attention of academics and created a niche for research.

Literature on turnarounds may be broadly classified into two major categories: empirical quantitative research (which involves the analysis of large data samples), or empirical qualitative research (which uses a case study approach involving smaller sample sizes) (Solnet, Paulsen & Cooper, 2010). Most literature, both quantitative and qualitative, views turnaround as a stage-based process. Cater & Schwab (2008) differentiate turnaround strategies into stage 1 and stage 2, where stage 1 focuses more on organizational stabilization and stage 2 involves organizational changes. It is further argued that stage 1 involves the following strategies: (1) top-management change, (2) external management expertise, and (3) organizational retrenchment. A similar argument is presented by Solnet, Paulsen & Cooper (2010), which summarizes strategic approaches to turnaround in the following three themes: (1) senior management team replacement, (2) strategic reorientation and (3) retrenchment/cost-cutting. These two studies shared a common theme as both external management expertise and strategic reorientation involve the altering of firm strategy. This is consistent with Smith & Graves (2005), where two stages in the turnaround process were identified: decline stemming (stability) and recovery strategies (growth-oriented). Other writers supporting the two-stage process include Bibeault (1982), Pearce & Robbins (1992), Sudarsanam & Lai (2001), Arogyaswamy et al (1995) and Tangpong, Abebe & Li (2015). The focus of this study is primarily on modelling stage 1 of the process.

2.2.1 The role of an efficiency-orientated approach

The objective of efficiency is characterized by either an asset reduction or a cost reduction. The purpose of the down-size is to allow companies to limit cash outflows for immediate survival (Balgobin & Pandit, 2001). The firms are able to achieve some stability and allow management to focus on areas of concern. These strategies are mentioned frequently in turnaround literature and often are a necessity for managing turnaround businesses (Pearce & Robbins, 1993; Hofer, 1980; D'Aveni, 1989; Hambrick & Schecter, 1983; Schmitt & Raisch, 2013; Solnet, Paulsen & Cooper, 2010).

Two key studies examining the efficiency-orientated approach are Hambrick & Schecter (1983) and O'Neill (1986). With the use of multiple regression analysis, Hambrick & Schecter (1983) found that efficiency measures (cost cutting and asset reduction) were the key to an improved return on investment in mature industries. O'Neill (1986) examined the relationship between four specific factors in a turnaround strategy, namely: management, cutbacks, growth and restructuring. O'Neill (1986) concluded that cutbacks are successful in achieving turnaround in firms with a weak market position. These studies were important as it was the first time quantitative research provided positive findings to support the efficiency-orientated approach to turnaround.

In a recent publication, Tangpong, Abebe & Li (2015) investigated the temporal approach of retrenchment in successful turnaround. The finding indicates that firms with early divestment and geographical market exits have a higher chance of turnaround. Hence, the efficiency-orientated approach remains applicable in the current environment. It is also noted that the efficiency-orientated approach tends to be favoured by CEOs who are not replaced in the turnaround process at the outset (O'Kane & Cunningham, 2012).The potential morale and internal climate change as the result of the cost reduction should also be taken into account, especially if the cost reduction is staff-related in a service industry (Solnet, Paulsen & Cooper, 2010). The social and economic costs may filter down to the firm's customers (Khandwalla, 2001).

A study on the Nairobi Securities Exchange in Kenya shows that employee layoff and asset restructuring are the most preferred turnaround strategies (Mbogo & Waweru, 2014). Another study, focused on financially distressed Finnish companies that were ordered by Court to implement restructuring, concluded that cost-cutting and retrenchment are important in successful turnarounds (Collett, Pandit & Saarikko, 2014). Evans, Chitnomrath & Christopher (2013) found that distressed firms in Thailand use multiple methods of restructuring with cost and expense deduction as the most common operational restructuring, together with company size reduction and disposal of non-core assets as the primary strategies for a successful turnaround. It follows that the major themes in turnaround strategy research seem universally applicable.

Panicker & Manimala (2015) performed a qualitative investigation on published case studies and ranked all factors contributing towards a successful turnaround on a scale ranging from 1 to 3. Statistical examination of the ranking concluded that cost management was one of the significant factors. This is clear theoretical research that shows that cost reduction plays a vital role in turnaround.

Arogyaswamy & Yasai-Ardekani (1997) attempted to distinguish between cutbacks and efficiency improvements, as the authors argued that cutbacks do not necessarily imply an increase in efficiency, owing to the negative effects mentioned above. The measures for cutbacks were number of employees, cost of sales and generally selling expenses, whereas the measures for efficiency were revenue over employees, revenue over receivables and revenue over inventories. The conclusion reached was that cutbacks may aid turnaround, but increased efficiency is also important for turnaround. The nub of Arogyaswamy & Yasai-Ardekani's (1997) research is that cutbacks and efficiency are so closely related that the two variables would result in multicollinearity.

2.2.2 The role of company size

The existing literature shows mixed findings regarding the relationship between a company's size and ability to turn around. According to the resource-based theory, large companies have more stability and resources at their disposal, which include the ability to raise additional funding to overcome adverse economic situations (Smith & Graves, 2005). At the same time, the complex structure and multiple relationships with stakeholders may potentially act as a barrier to a quick response. In contrast, small companies with less complex organizational structures may allow changes to be implemented faster (Francis & Desai, 2005). The publicity and reputation of large companies may also work in their favour, as the potential losses to the stakeholders are greater and the higher publicity may result in more willingness from stakeholders to keep the companies alive (Smith & Graves, 2005).

In Korea, company size is an indicator of the level of protection received from the state. The rule of the bankruptcy court states that when a company with less than US$ 25 million in assets files for bankruptcy, it should be liquidated (Kim,Kim & McNiel, 2008). Hence, Kim, Kim & McNiel found that firm size is an important variable in predicting bankruptcy. The same protection might not be evident in South Africa, but there is certainly a social benefit of protecting large companies due to potential large-scale layoffs.

2.2.3 The role of senior management turnover

A number of researchers have found that a change in senior management is a prerequisite for a successful turnaround effort (Bibeault, 1982; Hofer, 1980; Solnet, Paulsen & Cooper, 2010; Arogyaswamy, Barker & Yasai-Ardekani, 1995; Castrogiovanni, Baliga & Kidwell, 1992; Smith & Graves, 2005; O'Kane & Cunningham, 2012; Sudarsanam & Lai, 2001). One argument is that a change in the senior management team is a means of restoring stakeholders' confidence in the firm (Smith & Graves, 2005). In a case study interview conducted in Ireland, it was noted that CEOs find it challenging to persuade stakeholders, including financers, to support a change in strategy without a change in personnel (O'Kane & Cunningham, 2012). Other advantages to consider in bringing in new management include the ability to provide fresh perspective and knowledge (Castrogiovanni, Baliga & Kidwell, 1992; Cater & Schwab, 2008), to retain stakeholders' support (Barker & Patterson, 1996; Cater & Schwab, 2008; Sudarsanam & Lai, 2001) and an indication of the attitude towards turning around the firm (O'Neill, 1986).

The concept of escalating commitment was introduced by Kesner & Dalton (1994), where existing management would be inclined to increase spending on existing projects such that it may put further pressure on the firm and its resources. Another concept, called trapped administrators, refers to people that are so closely affiliated to the project that they cannot provide an honest evaluation, which also results in negative consequences for the firm (Kesner & Dalton, 1994).

A change in senior management often presents more challenges than expected, and some authors argue against the effect of a change in senior management in turnaround effort (Hofer, 1980; Robbins & Pearce, 1992), since most organizations have a core aspect of their business and the current management team would have good insight into it. A new management team may not have that core insight, which is vital in pressurized periods of operation. On a social level, a study has shown that the new management is required and expected to introduce a more interpersonal and employee-focused approach to emphasize the shared responsibility of a successful turnaround challenge, besides the normal transitional challenges faced by management. Hence, it is imperative for senior management to have self-awareness and emotional intelligence (Higgs & Rowland, 2005).

The related empirical studies seem to have support for and against change in senior management which may be due to the unique nature or characteristics of each successful turnaround (Sudarsanam & Lai, 2001; Trahms, Ndofor & Sirmon, 2013; Kesner & Dalton, 1994). For example, Arogyaswamy, Barker & Yasai-Ardekani (1995) pointed out that a change in top management is only effective if the existing top management loses credibility with stakeholders. What is evident is that a change in senior management increases value by creating new expectations (O'Kane & Cunningham, 2012) and, irrespective of whether there is a change in senior management, a successful turnaround requires management's support (Arogyaswamy, Barker & Yasai-Ardekani, 1995).

2.2.4 The role of free assets

Very little existing research concentrates on this area, possibly due to the difficulty in defining and obtaining the data to measure free assets. Nevertheless, both Kim, Kim & McNiel (2008) and Routledge & Gadenne (2000) define free assets as assets that are not pledged as collateral to borrowings. This is in line with the definition presented in Smith & Graves (2005). It is argued that a firm with larger free assets is able to obtain additional financing and does not run the risk of creditors exercising covenant.

The pioneers of free assets in turnaround process, White (1989) and Casey, McGee & Stickney (1986), using the non-collateralized tangible assets over total tangible assets as proxy for free assets, found that free assets is a statistically significant variable for turnaround firms.

2.2.5 The role of severity of distressed state

Smith & Graves (2005) defined severity as the ability of the firm to enact a recovery whereas Francis & Desai (2005) and Arogyaswamy, Barker & Yasai-Ardekani (1995) defined it as the magnitude of decline. The difference is a reflection of the turnaround process as a continuum with no distinction between stage 1 (stability) and stage 2 (recovery) which is evident in Smith & Graves (2005).

Hofer (1980), in a qualitative research, made the first attempt to link severity of distress with the degree of asset and cost reduction. It is argued that more severely distressed positions require more drastic asset and cost reductions, and make it more difficult to achieve a turnaround (Hofer, 1980; Bibeault, 1982; Robbins & Pearce, 1992; Pearce & Robbins, 1993; Francis & Desai, 2005). Pearce & Robbins (1993) further argued that the asset reduction is expected to be more drastic than cost reduction. Management in a severely distressed firm is also likely to have a shorter timeframe to respond and implement strategies, hence the expectation that severity is negatively related to turnaround outcome (Pearce & Robins, 1993; Francis & Desai, 2005).

Methodology and variable definition

For the purposes of this study, a multiple discriminant analysis model (Taffler's Z-score) will be used to identify financially distressed companies. The same methodology is used in Smith and Graves (2005), which is the original paper this study is replicating in a South African context. The Taffler's Z-score was derived through the use of a stepwise multiple linear discriminant package by running 80 potentially useful ratios identified by all previous bankruptcy model literature (Taffler, 1983). The actual Taffler's Z-score (Agarwal & Taffler, 2003) is set out below:

$Z = 3.2 + (12.18) X_1 + (2.5) X_2 - (10.68) X_3 + (0.0289) X_4$

Where X_1 = profit before tax (PBT)/average current liabilities (ACL)

X_2 = current assets (CA)/total liabilities (TL)

X_3 = current liabilities (CL)/total assets (TA)

X_4 = no-credit interval (NCI)

The no-credit interval is defined as the number of days the company may continue to operate without generating revenue, and is calculated as follows:

NCI= (CA - inventory - current liabilities) / (Sales - PBT + depreciation) $\times$ 365 days

An adjustment of 7:1 was made by Taffler to ensure that Taffler's Z-score has a zero cut-off (in comparison to Altman's Z-score), which implies that if the computed Z-score is positive, the firm is unlikely to fail within the next year. Taffler's Z-score was initially applied to manufacturing and construction firms only in the original 1983 study (Taffler, 1983), but an updated version of the paper was published, which evaluated Taffler's Z-score for all non-financial firms listed on the London Stock Exchange in the period 1979 to 2003 (Agarwal & Taffler, 2007). The result reached from the updated paper showed that Taffler's Z-score has maintained its clear predictive ability over the recent time period (Agarwal & Taffler, 2007). It was also concluded that a higher Z-score may be viewed as better performance, but does not mean it has a linear relationship (Taffler, 1983).

Smith & Liou (2007) examined the Taffler's Z-scores of companies for a period of twenty years by looking at its predictive ability between period 1 (1981 - 1987) and period 2 (1988 - 1994). The authors found that Taffler's Z-score had remained robust across the period with the same variables and weights as the model developed by Taffler in 1983. Sudarsanam & Lai (2001) also made use of the Taffler's Z-score in identifying financially distressed companies in their empirical analysis.

The nature and derivation of Taffler's Z-score lies in the initial Z-score model developed by Altman in 1968. The two models share many of the same characteristics and remain popular and relevant in the present day, hence, the Z-score is a reliable indicator of likely bankruptcy within a certain period.

The length of the turnaround cycle has to be defined in order to determine the sample of firms to be included in the study. Two common turnaround cycles are used in literature, which are the four-year cycle (two down years and two up years) and the eight-year cycle (four down years and four up years) respectively. Baker & Mone (1994), Smith & Graves (2005), Mbogo & Waweru (2014), O'Kane & Cunningham (2014), Tangpong, Abebe & Li (2015) all used the four-year cycle, while Bibeault (1982) and Arogyaswamy & Yasai-Ardkani (1997) used the eight-year cycle. For this study, the four-year turnaround cycle is used, which is consistent with Smith & Graves (2005). Due to the limited number of listed firms on the JSE and AltX, the eight-year cycle will reduce the sample size significantly. A four-year cycle is also regarded as sufficient time to observe a successful turnaround (Smith & Graves, 2005).

Based on the four-year cycle, a successful turnaround company is defined as having two consecutive years of negative Taffler's Z-score (financial distress) followed by two consecutive years of positive Taffler's Z-score (healthy/turnaround). The combination of a successful turnaround is as follows: $--++$. An unsuccessful turnaround is defined as having two consecutive years of negative Taffler's Z-score followed by one negative Taffler's Z-score within the next two years. The possible combinations for an unsuccessful turnaround are as follows: $--+-, ---+, ----$.

3.1 Efficiency measure

Based on previous studies, efficiency may be achieved through either an asset reduction or cost reduction. The use of cost reduction as a measure of efficiency may be unreliable due to the difficulty in calculating costs saved from the financial statements. On the other hand, asset reduction may be calculated as the change of asset value from one year to the next, as the asset value is disclosed in the financial statements and is readily available to users. Hambrick & Schecter (1983), O'Neill (1986) and Tangpong, Abebe & Li (2015) have also all found that asset reduction has a positive impact on companies' ability to turn around. Hence, the efficiency measure in Smith & Graves (2005) and Francis & Desai (2005) is used, which is measured as follows:

{Tangible assets (t)-Tangible assets (t-1)}/Tangible assets (t-1)

Efficiency measure is denoted as "Downsizing" in Table 5.

3.2 Size measure

There are many measurements for size based on information disclosed in the financial statements. Revenue is a good indicator, but the revenue figure may be misleading when the company is in financial distress. Nevertheless, Francis & Desai (2005) and Chenchehene & Mensah (2014) used revenue as the proxy for size in their studies. Chancharat et al (2010) went a step further by introducing the square of revenue to accommodate any non-linear relationships. This study involves multiple linear discriminant analysis and non-linear relationship measures will not be considered. The number of employees may also be a good proxy for size, but due to the nature of this study, which involves companies across all industries, there may be potential for distortion. For example, a technology company is expected to have a smaller workforce than a retailer. Asset value is another option, as a large company is expected to hold more assets for its operation. Asset value as a measure for company size is used in Hotchkiss (1995), Campbell (1996) and Routledge & Gadenne (2000).

As it is observed in Smith & Graves (2005), both revenue and total assets are used as measures of company size. The natural log of revenue and total tangible assets are used to remove any skewness and for ease of interpretation and comparison of results. The natural log of revenue and natural log of total tangible assets are denoted as "LN(Rev)" and "LN(TTA)" in Table 5.

3.3 Free assets measure

In Routledge & Gadenne (2000), free assets are measured as total liabilities over total assets. Casey, McGee & Stickney (1986) considered only tangible assets as free assets. Campbell (1996) and Kim, Kim & McNiel (2008) used the non-pledged asset as a proxy for free assets. A combination of Routledge & Gadenne (2000) and Campbell (1996) is used in this study, and free assets is defined as:

(Total tangible assets-Secured loans)/Total tangible assets

The numerator represents the non-pledged assets while the denominator converts it to a ratio for modelling purposes. The same ratio is used in Casey, McGee & Stickney (1986), Smith & Graves (2005) and Chenchehene & Mensah (2014).

Free assets measure is denoted as “Free assets” in Table 5.

3.4 Senior management change measure

Kesner & Dalton (1994) made a clear distinction between CEO and top management, whereby top management is defined as all corporate officers with the title of vice-president or above for US companies. O’Kane & Cunningham (2012) defined leadership change as change of CEOs, but did acknowledge that leadership change may also be interpreted as changes in other members of the top management team. Due to the limited available data on JSE and AltX companies, only CEO changes are considered for the measurement of senior management change. This is consistent with Smith & Graves (2005).

Senior management change measure is denoted as “CEO turnover” in Table 5. CEO change measure takes on either the value of one (change in CEO) or zero (no change in CEO).

3.5 Severity measure

Severity of decline is often measured by Altman Z-score in literature (Francis & Desai, 2005). The severity measure in this study is the Taffler’s Z-score and the severity of decline is measured by the change in Taffler’s Z-score from one year to the next. Hence, Taffler’s Z-scores were calculated in year 2 and year 1. The change in Z-score (Zchange) is calculated as the difference between year 2 and year 1. Z2 represents the calculated Taffler’s Z-score in year 2 of the analysis. The components of Taffler’s Z-score, which are the financial ratios, are calculated and presented as part of the analysis of data (Table 5).

These financial ratios are: profitability ratio (PBT/CL), working capital ratio (CA/TL), risk ratio (CL/TA) and liquidity ratio (NCI).

Severity measure is denoted as “Zchange” in Table 5.

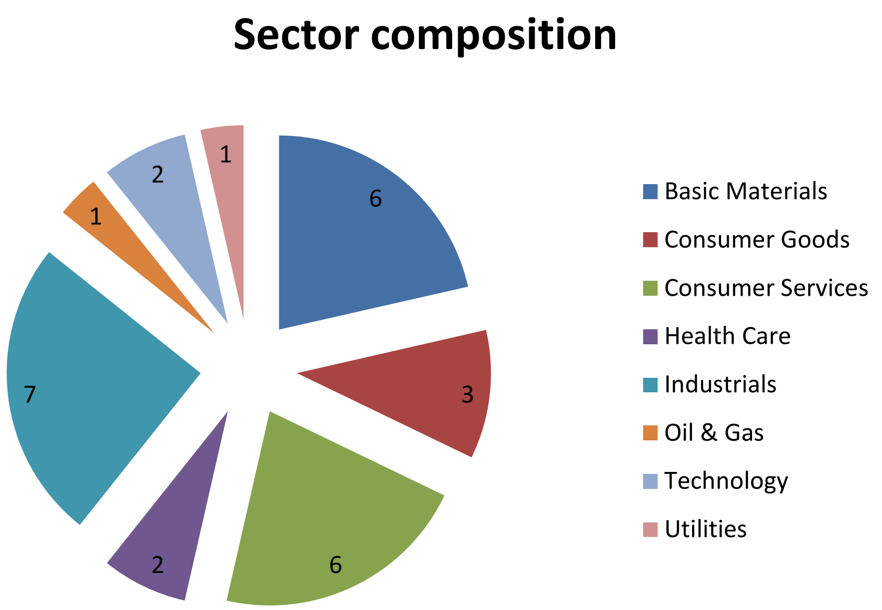
3.6 Sample selection

The sample for this study is based on data collected from iNet BFA for the period 2007 to 2014, with the exception of CEO turnover. CEO turnover data was collected manually from the companies’ published annual financial reports. The actual data was extracted on 7 July 2015 as it is anticipated that all listed companies would have published and finalized their annual reports six months after year end as according to JSE Listing Requirements Section 19.20 (d). The above date would accommodate the inclusion of all companies’ data for the 2014 financial year as the last possible year end date is the 31 December 2014. Companies with 31 December year end would have published their annual financial reports by 30 June 2015. Newly listed companies with less than four years of financial results were excluded from the sample as the turnaround cycle defined above is four-years. Both the JSE-listed and AltX companies are included in the data, but financial sector companies are excluded because Taffler's Z-score is designed for manufacturing companies which have a completely different characteristic to the financial sector. This is consistent with sample selection employed by Chen (2014).

The total number of successful turnaround companies in the sample is eleven. The number of unsuccessful turnaround companies is eighteen. The turnaround companies and non-turnaround companies form the two distinct sets of sample for statistical analysis in this study. Therefore the total sample for this study is twenty-nine companies. Note that the same company may not appear in both sets of sample. If a company meets the turnaround criteria by exhibiting the pattern of $- -$ $+ +$ in its Taffler's Z-scores in earlier years, it is classified as a turnaround company. Graph 1 is a summary plot of all companies in the sample selection with their Z-scores at year 2. The red points represent non-turnaround companies, while green points represent turnaround companies. A list of the sample companies is included in Appendix B.

A sector analysis on the sample companies indicates that the three largest sectors in the sample are: industrial (7), consumer services (6) and basic materials (6). Graph 1 sets out the sample spread across sectors.

Graph 1: JSE sector of sample companies



Analysis of data and turnaround models

The dependent variable used to model the turnaround is a dichotomous variable which takes on either a value of one (turnaround) or zero (non-turnaround). The dependent variable is regressed against potentially influential independent variables based on the significance level of the individual t-test for each independent variable (Table 5).This approach is consistent with Smith & Graves (2005).

As part of the process in determining the appropriate t-test, an F-test is performed on the two sets of sample (turnaround and non-turnaround companies) and the result is included in Appendix C. The F-test shows that the variables Zchange, PBT/CL, NCI and downsizing have unequal variances, while the variables Z2, CA/TL, CL/TA, LN (rev), LN (TTA), free assets and CEO turnover have equal variances based on a 5% significant level used.

Different Student's t-tests are performed on variables based on their F-test classification. The t-test results indicate that none of the variables are significant at a 5% level. The most significant variable, Z2, has a p-value of 0.21. This observation is different to Smith & Graves (2005), whereby Zchange, PBT/CL, NCI and revenue were found to be statistically significant between the two sets of sample (turnaround and non-turnaround companies). The results of the t-test are included in Appendix D with a summary presented in Table 5.

Table 5 presents the descriptive statistics in year two for each of the variables included in the study. The first column represents all the possible independent variables. The Mean (turnaround) column is the equally-weighted average of each independent variable within the turnaround set of sample at year two. The Mean (non-turnaround) represents the equally-weighted average of each independent variable within the non-turnaround set of sample at year two. The values of the independent variables in year two are used as part of the analysis to determine whether there is a statistically significant relationship between the two data sets. This approach is consistent with Smith & Graves (2005). Student's t-test is presented to determine whether the two sets of data are significantly different, hence, there is merit in including it in the turnaround model. Pearson's correlation coefficient is also included to investigate whether there is a linear correlation between the two sets of variables.

Table 5: Summary of significance tests for year two

	Mean (turnaround)	Mean (non-turnaround)	F-test	Significance	t-test	Significance
Z2	-1.150	-2.199	0.6801	0.2712	1.2814	0.2110
Zchange (Z2-Z1)	0.284	0.710	0.3392	0.0430	-0.3355	0.7398
PBT/CL	-0.791	-2.167	0.1037	0.0004	0.8341	0.4132
CA/TL	0.766	0.615	1.1852	0.3643	1.0423	0.3065
CL/TA	0.471	0.505	0.9770	0.5035	-0.3307	0.7434
NCI	-0.224	0.171	0.0432	0.0000	-0.9231	0.3675
LN(rev)	10.870	12.901	0.9342	0.4725	-0.9152	0.3682
LN(TTA)	12.294	13.422	0.5577	0.1745	-1.0224	0.3157
Free assets	0.737	0.729	0.6000	0.2070	0.0585	0.9538
Downsizing	-0.139	8.480	0.0000	0.0000	-1.0091	0.3271
CEO turnover	0.364	0.278	1.1983	0.3570	0.4698	0.6423

Since the t-test shows that a few variables may have some predictive ability due to their p-values being in the range of 0.2 to 0.35, an alternative analysis is introduced by looking at the interaction effect between variables within this range. Hence, linear interaction variables are introduced to examine whether interaction variables may be statistically significant. The following variables are subject to linear interaction modelling (based on their resulting p-values): “Z2”, “CA/TL”, “LN(TTA)” and “downsizing”. The statistical freeware, R, is used to determine the best-fit model with interaction variables which is denoted as Model One below:

$$\mathrm{Z} = 0.560 + 0.897(\mathrm{downsizing}) - 0.001\mathrm{LN(TTA)} - 0.180(\mathrm{Z2}) + 0.1007(\mathrm{CA/TL}) + 0.024\,(\mathrm{LN(TTA)} \times \mathrm{Z2}) - 2.517(\mathrm{downsizing} \times \mathrm{CA/TL}) \tag{1}$$

The output from R is included in Appendix E. Both the downsizing and the “downsizing x CA/TL” interaction variable are statistically significant at a 5% level. “LN(TTA)”, “Z2” and “downsizing x CA/TL” contribute negatively towards the success of business turnaround “Downsizing”, “CA/TL” and “LN(TTA) x Z2” contribute positively to turnaround success It is evident from the above model that efficiency, which is measured by downsizing, is the key to business turnaround success.

One of the additional advantages of utilizing R is the ability to categorize a single variable into sub-categories. Since the sample data includes both JSE and AltX companies, there may be merit in examining whether JSE and AltX companies have different turnaround success rates. An additional variable called “main1”, which either takes a value of 1 if listed on the main board or 0 if listed on AltX, is introduced in the modelling. This variable, together with the four variables used to examine potential interaction, is used to formulate the best-fit interaction model in R which is denoted as Model Two below:

$$\mathrm{Z} = -1.972 + 4.068(\mathrm{main1}) + 0.208\mathrm{LN(TTA)} - 0.622(\mathrm{CA/TL}) - 0.222(\mathrm{downsizing}) + 0.002(\mathrm{Z2}) + 0.100(\mathrm{LN(TTA)} \times \mathrm{CA/TL}) - 0.519(\mathrm{downsizing} \times Z2) - 2.080\,(\mathrm{CA/TL} \times \mathrm{downsizing}) - 0.372(\mathrm{main1} \times \mathrm{LN(TTA)}) \tag{2}$$

The output from R is included in Appendix F. Note that the Factor Function in R is used to convert the variable “main1” into a relative measure which has a different interpretation to the conventional dummy variable. This is denoted as “main1” in the model above. The Factor Function eliminates the need of introducing two dummy variables (one for JSE and one for AltX). The result of the best-fit model tells a different story in that the variable “main1” plays a significant role in the determination of business turnaround success. Both “main1” and the interaction variable “main1 x LN(TTA)” are statistically significantly at the 1% level. This is clearly an indication that JSE and AltX companies do have distinct characteristics which would result in different turnaround success rates. The “main1” variable is a relative measure in that it should be compared to the base which is AltX companies. Since all companies in the sample are listed, they have to either belong to the JSE exchange or the AltX exchange. Hence, the use of Factor Function is appropriate due to mutually exclusive classification. AltX companies would take up a value of zero for the variable “main1”. The positive coefficient of “main1” implies that companies listed on the JSE are more likely to survive in comparison to AltX. The coefficient of the interaction variable “main1 x LN(TTA)” implies that JSE companies with a large tangible asset base are less likely to turnaround than AltX companies, *ceteris paribus*.

“LN(TTA)” and “CA/TL x downsizing” are both significant but only at the 10% level. “CA/TL” represents the risk measure in Taffler’s Z-score. Due to the negative coefficient of “CA/TL x downsizing", it implies that turnaround is harder to achieve for companies with higher liquidity risk or less efficient operations.

Discussion of results

The individual t-test indicates that there is no one independent variable included in this study that is able to predict the success of corporate turnaround. This is not a setback for the research as those independent variables may exhibit interaction effects that may be statistically significant in predicting turnaround. This is consistent with the research concept introduced by Francis & Desai (2005), whereby the authors examined the integrated actions as they often impact each other in the turnaround process. Hence, the four most significant independent variables are selected to examine for interaction effect, which is the basis for Model One developed above. The result indicates that "efficiency", which is represented by the downsizing variable, is statistically significant. Therefore the model suggests that an increase in "efficiency" would increase the success of turnaround. It is also observed that liquidity risk, in combination with "efficiency", is negatively related to the possibility of a successful turnaround (i.e. higher risk equates to lower possibility of turnaround).

The above finding on the "efficiency" indicator contradicts Smith & Graves (2005), but confirms the findings in Robbins & Pearce (1992) and Francis & Desai (2005). "Efficiency" driven strategy is suggested to be key in the turnaround process and South African companies show no deviation from the norm. This study further contributes towards existing research by presenting a case for the significant effect of existing liquidity risk on the success of companies recovering in an "efficiency" driven strategy.

Model Two provides evidence that JSE-listed companies are more likely to experience a successful turnaround than their counterparts, AltX companies. The distinction between the JSE and AltX is important for practical purposes, which is supported by the empirical evidence obtained from Model Two. This observation has significant implications in that there is a distinct advantage for companies on the JSE. As suggested in Scholtz & Smit (2013), AltX is geared towards attracting new small and medium-sized companies that would like to raise funds for expansions and acquisitions without necessarily having the resources available to be listed on the JSE. The nature of the AltX companies implies that a distinct relationship for this part of the market is not unusual. The finding that JSE companies are more likely to survive a turnaround than AltX companies endorses the current market interpreters' view. As indicated in Correia & Holman (2008), the AltX companies are relatively small and hence greater risks are involved which should be compensated for by greater returns.

As discussed in the introductory section of this study, the models may assist stakeholders in the determination of a successful turnaround. The auditing profession may use the models as guidelines in formulating the going concern opinion of the business. There are certainly risks involved in issuing the incorrect audit opinion due to the financial statements being widely used by different stakeholders. Bankers and lenders are able to use the models to determine the risk in investing or providing facilities to the companies. These models may present a primary source of evidence in supporting the viewpoint of the stakeholders. Management may also apply the models in improving efficiency and productivity in a turnaround by assigning resources to key areas so that the possibility of turnaround is improved.

Conclusions

This study has contributed towards existing business failure and corporate turnaround literature by investigating empirical models for turnaround and by discussing key indicators for turnaround success. The examination of both JSE and AltX companies shares further insight into the two unique sets of listed markets. Based on the research principles presented in Smith & Graves (2005), the study replicates a similar investigation in the South African context. The findings indicate the unique nature of the South African stock market, as results were different to Smith & Graves' conclusion. Deviation from the original paper was considered by looking at interaction effects due to ideas leveraged from Francis & Desai (2005). The outcome of this method of examination may play a key role in deriving value-added facts to existing literature in corporate turnaround.

Two turnaround models were derived, each with a different focus in mind. Model One is derived by examining variables that have an indication of significance based on the individual t-test result. Model Two focused on the distinction between JSE and AltX companies with the introduction of a factor variable. Both models have shared insight into the ability of companies to turnaround. Model One shows that "efficiency", which is measured by downsizing, is a key strategy for a successful turnaround. Model Two indicates that JSE companies have a higher turnaround potential than their AltX counterparts.

In closing, corporate turnaround literature is in its infancy in South Africa, and this may be due to the relatively smaller listed market, which certainly limits the data available for financial modelling. Nevertheless, this study attempts to fill the existing gap in literature and hopes to be the catalyst for further future research in this field.

Future research and recommendations

There are many potential areas for future research deriving from this study. The study has focused on all JSE and AltX companies, excluding financial services companies. An area of significant interest in the international literature is examining sector-specific turnaround. This would almost certainly improve the effectiveness of the models, and detailed insight into each sector may be built onto existing literature. This study utilizes the multiple linear discriminant analysis as its primary form of analysis in deriving the turnaround models. Other forms of methodologies, such as probit analysis, logistic analysis or neural networks, may be used instead on the same set of sample. A four-year turnaround period is used as part of the sample selection, but a further area of research may involve using an eight-year turnaround period.

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Appendix A: Summary of SA literature on failure prediction models

Author(s)	Year published	Model	Overall accuracy	Sample size	Independent variables	Market	Sample year(s)	Company industry
Court & Radloff	1990	MDA	81%	52	FR	SA (JSE)	1965-1986	All
Court & Radloff	1990	LA	88%	52	FR	SA (JSE)	1965-1986	All
Court	1991	LA	100%	52	Mix	SA (JSE)	1965-1986	All
Arron & Sandler	1994	NN	88%	68	FR	SA (JSE)	1966-1976	All
Arron & Sandler	1994	LA	87%	68	FR	SA (JSE)	1966-1976	All
Arron & Sandler	1994	MDA	83%	68	FR	SA (JSE)	1966-1976	All
Kidane	2004	MDA	79%	86	Mix	SA (JSE)	1999-2003	All
Steyn-Bruwer & Hamman	2006	RP	NA	NA	FR	SA (JSE)	1997-2002	Industrial companies only
Naidoo & Du Toit	2007	Univariate	87%	42	FR	SA (JSE)	1970 - 1999	All
Naidoo & Du Toit	2007	MDA	95%	42	Mix	SA (JSE)	1970 - 1999	All
Naidoo & Du Toit	2007	LA	82%	42	FR	SA (JSE)	1970 - 1999	All
Muller, Steyn-Bruwer & Hamman	2009	MDA	74%	239	Mix	SA (JSE)	1997-2002	All (ex. Mining, financial and property)
Muller, Steyn-Bruwer & Hamman	2009	LA	87%	239	Mix	SA (JSE)	1997-2002	All (ex. Mining, financial and property)
Muller, Steyn-Bruwer & Hamman	2009	RP	80%	239	Mix	SA (JSE)	1997-2002	All (ex. Mining, financial and property)
Muller, Steyn-Bruwer & Hamman	2009	NN	87%	239	Mix	SA (JSE)	1997-2002	All (ex. Mining, financial and property)
Mazaba	2010	MDA	95%	229	All	SA (JSE)	2001-2009	All
Kruger & Maeteletsa	2011	MDA	81%	71	FR	SA (JSE)	1998-2007	All
Marais , Soni & Chitakunye	2014	MDA	95%	13	Mix	SA (JSE)	2006-2012	Industrial sector (J257)

Appendix B: Sample companies

Ticker	Company Name (Turnaround)	Ticker	Company Name (Non-turnaround)
AHL	AH-VEST LIMITED	**1TM**	1TIME HOLDINGS LIMITED
APN	ASPEN PHARMACARE HOLDINGS LIMITED	**BIO**	BIOSCIENCE BRANDS LIMITED
BDM	BUILDMAX LIMITED	**CLS**	CLICKS GROUP LIMITED
CRD	CENTRAL RAND GOLD LIMITED	**FRT**	FARITEC HOLDINGS LIMITED
CSP	CHEMICAL SPECIALITIES LIMITED	**GRF**	GROUP FIVE LIMITED
DRN	DELRAND RESOURCES LIMITED	**IPS**	IPSA GROUP PLC
ILE	IMBALIE BEAUTY LIMITED	**MMH**	MIRANDA MINERAL HOLDINGS LIMITED
MML	METMAR LIMITED	**MSM**	MASSMART HOLDINGS LIMITED
NUT	NUTRITIONAL HOLDINGS LIMITED	**OAO**	OANDO PLC
WBO	WILSON BAYLY HOLMES-OVCON LIMITED	**PIK**	PICK N PAY STORES LIMITED
WEA	W G WEARNE LIMITED	**PLL**	PLATFIELDS LIMITED
		PWK	PICK N PAY HOLDINGS LIMITED
		SHB	SHERBOURNE CAPITAL LIMITED
		SKY	SEA KAY HOLDINGS LIMITED
		SNV	SANTOVA LIMITED
		SPP	THE SPAR GROUP LIMITED
		SSK	STEFANUTTI STOCKS HOLDINGS LTD
		TCS	TOTAL CLIENT SERVICES LIMITED

Appendix C: F-test output

F-Test Two-Sample for Z2 Variances		
	Variable 1	*Variable 2*
Mean	-1.14996937	-2.199077628
Variance	3.530950355	5.192099213
Observations	11	18
df	10	17
F	0.680062189	
P(F<=f) one-tail	0.271157264	
F Critical one-tail	0.355617887	

F-Test Two-Sample for Zchange Variances		
	Variable 1	*Variable 2*
Mean	0.284225909	0.710181989
Variance	6.32801273	18.65300522
Observations	11	18
df	10	17
F	0.339248966	
P(F<=f) one-tail	0.043070676	
F Critical one-tail	0.355617887	

F-Test Two-Sample for PBT/CL Variances		
	Variable 1	*Variable 2*
Mean	-0.791016628	-2.166547148
Variance	4.338397507	41.85117647
Observations	11	18
df	10	17
F	0.103662498	
P(F<=f) one-tail	0.000441578	
F Critical one-tail	0.355617887	

F-Test Two-Sample for CA/TL Variances		
	Variable 1	*Variable 2*
Mean	0.766376554	0.615074423
Variance	0.159569563	0.134637608
Observations	11	18
df	10	17
F	1.185178243	
P(F<=f) one-tail	0.364308746	
F Critical one-tail	2.4499155	

F-Test Two-Sample for CL/TA Variances		
	Variable 1	*Variable 2*
Mean	0.471475389	0.50509929
Variance	0.069549684	0.071189205
Observations	11	18
df	10	17
F	0.976969536	
P(F<=f) one-tail	0.503468344	
F Critical one-tail	0.355617887	

F-Test Two-Sample for NCI Variances		
	Variable 1	*Variable 2*
Mean	-0.223827251	0.170784096
Variance	0.132765845	3.072285875
Observations	11	18
df	10	17
F	0.043214027	
P(F<=f) one-tail	8.13338E-06	
F Critical one-tail	0.355617887	

F-Test Two-Sample for LN(rev) Variances		
	Variable 1	*Variable 2*
Mean	10.87036832	12.90071158
Variance	32.17696904	34.44455993
Observations	11	18
df	10	17
F	0.934166937	
P(F<=f) one-tail	0.472502683	
F Critical one-tail	0.355617887	

F-Test Two-Sample for LN(TTA) Variances		
	Variable 1	*Variable 2*
Mean	12.29467536	13.42172342
Variance	5.533371283	9.921596939
Observations	11	18
df	10	17
F	0.557709743	
P(F<=f) one-tail	0.174487643	
F Critical one-tail	0.355617887	

F-Test Two-Sample for Free assets Variances		
	Variable 1	*Variable 2*
Mean	0.736598176	0.728527861
Variance	0.091412234	0.152328473
Observations	11	18
df	10	17
F	0.600099459	
P(F<=f) one-tail	0.207045654	
F Critical one-tail	0.355617887	

F-Test Two-Sample for downsizing Variances		
	Variable 1	*Variable 2*
Mean	-0.139196993	8.480109834
Variance	0.019617221	1313.206242
Observations	11	18
df	10	17
F	1.49384E-05	
P(F<=f) one-tail	0	
F Critical one-tail	0.355617887	

F-Test Two-Sample for CEO turnover Variances

	Variable 1	*Variable 2*
Mean	0.363636364	0.277777778
Variance	0.254545455	0.212418301
Observations	11	18
df	10	17
F	1.198321678	
P(F<=f) one-tail	0.357025493	
F Critical one-tail	2.4499155	

Appendix D: t-test output

t-Test: Two-Sample Assuming Equal Variances (Z2)		
	Variable 1	*Variable 2*
Mean	-1.14996937	-2.199077628
Variance	3.530950355	5.192099213
Observations	11	18
Pooled Variance	4.576858895	
Hypothesized Mean Difference	0	
df	27	
t Stat	1.281356984	
P(T<=t) one-tail	0.105482117	
t Critical one-tail	1.703288446	
P(T<=t) two-tail	0.210964235	
t Critical two-tail	2.051830516	

t-Test: Two-Sample Assuming Unequal Variances (Zchange)		
	Variable 1	*Variable 2*
Mean	0.284225909	0.710181989
Variance	6.32801273	18.65300522
Observations	11	18
Hypothesized Mean Difference	0	
df	27	
t Stat	-0.335538738	
P(T<=t) one-tail	0.369906029	
t Critical one-tail	1.703288446	
P(T<=t) two-tail	0.739812058	
t Critical two-tail	2.051830516	

t-Test: Two-Sample Assuming Unequal Variances (PBT/CL)		
	Variable 1	*Variable 2*
Mean	-0.791016628	-2.166547148
Variance	4.338397507	41.85117647
Observations	11	18
Hypothesized Mean Difference	0	
df	22	
t Stat	0.834119902	
P(T<=t) one-tail	0.206589574	
t Critical one-tail	1.717144374	
P(T<=t) two-tail	0.413179147	
t Critical two-tail	2.073873068	

t-Test: Two-Sample Assuming Equal Variances (CA/TL)		
	Variable 1	*Variable 2*
Mean	0.766376554	0.615074423
Variance	0.159569563	0.134637608
Observations	11	18
Pooled Variance	0.143871665	
Hypothesized Mean Difference	0	
df	27	
t Stat	1.042295844	
P(T<=t) one-tail	0.153258939	
t Critical one-tail	1.703288446	
P(T<=t) two-tail	0.306517877	
t Critical two-tail	2.051830516	

t-Test: Two-Sample Assuming Equal Variances (CL/TA)		
	Variable 1	*Variable 2*
Mean	0.471475389	0.50509929
Variance	0.069549684	0.071189205
Observations	11	18
Pooled Variance	0.070581975	
Hypothesized Mean Difference	0	
df	27	
t Stat	-0.330700455	
P(T<=t) one-tail	0.371711717	
t Critical one-tail	1.703288446	
P(T<=t) two-tail	0.743423435	
t Critical two-tail	2.051830516	

t-Test: Two-Sample Assuming Unequal Variances (NCI)		
	Variable 1	*Variable 2*
Mean	-0.223827251	0.170784096
Variance	0.132765845	3.072285875
Observations	11	18
Hypothesized Mean Difference	0	
df	19	
t Stat	-0.92307778	
P(T<=t) one-tail	0.183770623	
t Critical one-tail	1.729132812	
P(T<=t) two-tail	0.367541247	
t Critical two-tail	2.093024054	

t-Test: Two-Sample Assuming Equal Variances (LN(rev))		
	Variable 1	*Variable 2*
Mean	10.87036832	12.90071158
Variance	32.17696904	34.44455993
Observations	11	18
Pooled Variance	33.60471145	
Hypothesized Mean Difference	0	
df	27	
t Stat	-0.91517254	
P(T<=t) one-tail	0.18410129	
t Critical one-tail	1.703288446	
P(T<=t) two-tail	0.368202581	
t Critical two-tail	2.051830516	

t-Test: Two-Sample Assuming Equal Variances (LN(TTA))		
	Variable 1	*Variable 2*
Mean	12.29467536	13.42172342
Variance	5.533371283	9.921596939
Observations	11	18
Pooled Variance	8.296328177	
Hypothesized Mean Difference	0	
df	27	
t Stat	-1.022428797	
P(T<=t) one-tail	0.157826021	
t Critical one-tail	1.703288446	
P(T<=t) two-tail	0.315652042	
t Critical two-tail	2.051830516	

t-Test: Two-Sample Assuming Equal Variances (Free assets)		
	Variable 1	*Variable 2*
Mean	0.736598176	0.728527861
Variance	0.091412234	0.152328473
Observations	11	18
Pooled Variance	0.129766903	
Hypothesized Mean Difference	0	
df	27	
t Stat	0.058538571	
P(T<=t) one-tail	0.476875375	
t Critical one-tail	1.703288446	
P(T<=t) two-tail	0.95375075	
t Critical two-tail	2.051830516	

t-Test: Two-Sample Assuming Unequal Variances (downsizing)		
	Variable 1	*Variable 2*
Mean	-0.139196993	8.480109834
Variance	0.019617221	1313.206242
Observations	11	18
Hypothesized Mean Difference	0	
df	17	
t Stat	-1.009106064	
P(T<=t) one-tail	0.163535965	
t Critical one-tail	1.739606726	
P(T<=t) two-tail	0.327071931	
t Critical two-tail	2.109815578	

t-Test: Two-Sample Assuming Equal Variances (CEO turnover)		
	Variable 1	*Variable 2*
Mean	0.363636364	0.277777778
Variance	0.254545455	0.212418301
Observations	11	18
Pooled Variance	0.22802095	
Hypothesized Mean Difference	0	
df	27	
t Stat	0.469818324	
P(T<=t) one-tail	0.321128658	
t Critical one-tail	1.703288446	
P(T<=t) two-tail	0.642257316	
t Critical two-tail	2.051830516	

Appendix E: Output from R for Model One

```
Call:
glm(formula = Turnover ~ Downsizing + LN.TTA. * Z2 + Downsizing *
    CA.TL, data = data1)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.71159  -0.31227  -0.00388   0.35473   0.72985

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)       0.5602518  0.6452133   0.868   0.3946
Downsizing        0.8968947  0.3716352   2.413   0.0246 *
LN.TTA.          -0.0008355  0.0577675  -0.014   0.9886
Z2               -0.1804275  0.3521757  -0.512   0.6135
CA.TL             0.1007414  0.2820017   0.357   0.7243
LN.TTA.:Z2        0.0236403  0.0325570   0.726   0.4754
Downsizing:CA.TL -2.5167880  1.0441371  -2.410   0.0247 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.2052621)

    Null deviance: 6.8276  on 28  degrees of freedom
Residual deviance: 4.5158  on 22  degrees of freedom
AIC: 44.367

Number of Fisher Scoring iterations: 2
```

Appendix F: Output from R for Model Two

```
Call:
glm(formula = Turnover ~ Main + LN.TTA. + LN.TTA. * CA.TL + Downsizing *
    Z2 + Downsizing * CA.TL + Main * LN.TTA., data = data1)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.64628  -0.17834  -0.02237   0.11251   0.90973

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)      -1.971690   1.264596  -1.559  0.13546
Main1             4.068270   1.350468   3.012  0.00716 **
LN.TTA.           0.208090   0.104278   1.996  0.06052 .
CA.TL            -0.622280   1.463905  -0.425  0.67555
Downsizing       -0.221910   1.089369  -0.204  0.84075
Z2                0.002077   0.084306   0.025  0.98060
LN.TTA.:CA.TL     0.100046   0.121327   0.825  0.41984
Downsizing:Z2    -0.519384   0.517841  -1.003  0.32847
CA.TL:Downsizing -2.079966   1.032228  -2.015  0.05827 .
Main1:LN.TTA.    -0.371614   0.118577  -3.134  0.00547 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.15841)

    Null deviance: 6.8276  on 28  degrees of freedom
Residual deviance: 3.0098  on 19  degrees of freedom
AIC: 38.601

Number of Fisher Scoring iterations: 2
```