Cost of financial distress model for JSE listed companies: A Case of South Africa

By

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i. Abstract

The idea behind the study was to answer the question: how costly is financial distress and what is an appropriate model in quantifying these costs for JSE listed entities? The objective was to find a sample of companies that were purely financially distressed on the bases of interest coverage and then to follow those through the resolution of the distress, to see what happened to them and to quantify how costly those factors were. The analysis was conducted through a robust regression exercise and a time series investigation. Quality control was done through outlier investigations and Benford law distribution to determine human influence on the financial statements. It was found that the average costs of financial distress for JSE listed companies is approximately 16.7% market value per annum. The South African appropriate model for JSE listed companies resulted in the cost of financial distress being inversely related to the change in investment policy, holding of liquid assets, size of an entity and Tobin's Q ratio, but directly related to the economic effect, probability of financial distress and change in employment policy.

ii. Keywords

Costs of Financial Distress

Bendford Law

Probability of Financial distress

iii. Declaration

I declare that this research project is my own work. It is submitted in partial fulfillment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorization and consent to carry out this research.

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ii. Abbreviations

JSE	Johannesburg Stock Exchange
CFD	Cost of Financial Distress
NPV	Net Present Value
MDA	Multiple Discriminant Analysis
L	Logit
NN	Neutral Network
LA	Liquid Assets
STATSA	Statistics South Africa
NCSS	Number Cruncher Statistical Software
GAAP	Generally Accepted Accounting Principles
IQR	Interquartile range
SD	Standard Deviation
CV	Coefficient of Variance

1 Problem Definition

1.1 Research Title

Cost of financial distress (CFD) model for JSE listed companies: A case study of South Africa.

1.2 Research problem

Recently coming from a global recession, most organizations have experienced that the economic consequences of corporate failure is enormous, especially among public companies or enterprises. To avoid such a failure in the future, organizations have embarked on establishing and use a capital structure model that accurately estimate the value of an organization. This is conducted through optimizing the risks of and returns from acquiring debt through a tradeoff between tax benefits and financial distress costs such as bankruptcy costs. De Wet (2006) is one of the South African researchers that adopted a trade-off model incorporating taxes and financial distress costs to determine the optimal capital structure for three companies listed on the Johannesburg Stock Exchange (JSE) of South Africa.

Korteweg (2007) stated that when the costs of financial distress (CFD) outweigh the tax benefits of debt, a company is worth less with debt in its capital structure than it is worth without debt, thus leading to organizational failure. Such a situation reflects that there is a downside to debt and questions surface on quantifying the magnitude of CFD due to its influence on the tax benefit of debt. Determining CFD then arise as an important subject because it has an impact on lending decisions and profitability of financial institutions (Hua *et al*., 2007).

The significance of costs of financial distress in influencing the optimal capital structure has stimulated a considerable number of studies on the subject. Researchers divide the study into direct and indirect CFD. In this regard, academic investigations have been skewed to the study of direct CFD which primarily includes administrative costs, unpaid taxes/employee compensation (Yen and Yen, 2008). On the other hand indirect CFD involves the deterioration of asset value and loss in profitable opportunities (Yen and Yen, 2008). Direct CFD have shown to have less influence on the optimal capital structure (Elkamhi, Ericsson and Parsons, 2009).

Studies illustrates that estimates of the direct and indirect CFD are widespread (Branch, 2002). Cited from Yen and Yen (2008), Warner (1977) reported that direct bankruptcy costs are 4% of market value one year prior to bankruptcy, while Altman (1984) found that direct costs are 4.3% for 11 retailers and seven industrial firms with indirect costs being 4.5% for retailers and 10.5% for industrial firms. Kaplan (1994) even claims that a bankruptcy process may produce a net gain from a bankruptcy-induced financial restructuring process.

In a sample of 31 high-leveraged transactions (HLTs), Andrade and Kaplan (1998) isolated the effect of economic distress from financial distress and estimated financial distress cost to range from 10% to 20% of firm value. As cited by Purnanandam (2008), Asquith, Gertner and Scharfstein (1994) demonstrated that on average, financially distressed firms sell 12% of their assets as part of their restructuring plans. Chen and Merville (1999) pointed out that companies with a distinctive pattern of increasing financial distress over time, may have an average annual loss expressed as a percentage of market value as high as 10.3%.

From the study of Yen and Yen (2008), 104 financially distressed companies in the Taiwan Security Exchange (TSE) during the period of 1998-2004 were studied and found that they embodied an average of 62.99% reduction in shareholder wealth and reached 0.01 significance level 20 days after announcing the distressed condition. Of the companies investigated in this study (Yen and Yen, 2008), it was observed that three groups: delisting group generated the greatest loss estimated at 86.93%, while suspended trading and maintaining normal trading groups had a loss of about 76.95 and 27.94%, respectively. These empirical findings show there are indirect costs of financial distress involved that are indeed substantially underreported. This finding is strongly supported by Pindado and Rodrigues (2005) who also noted less attention is paid to the measures of indirect costs of financial distress mainly due to the difficulty in quantifying them. In the United States, several studies have been conducted in depth to measure indirect costs of financial distress (Elkamhi *et al.,* 2009; Andrade and Kaplan, 1998; Molina, 2005; Hennessy & Whited, 2005; Almeida & Philippon, 2007). In order to resolve this problem, Pindado and Rodrigues (2005) went a step further and formulated a model that incorporates the indirect costs of financial distress with variables from prediction models.

The determination of costs of financial distress in South Africa for JSE listed companies has been offset by the prediction of financial distress models (Kidane, 2004; Muller, 2009). With no published research conducted to measure indirect cost of financial distress, South African companies financing decisions will be heavily biased to the tax benefits side of the scale.

Due to indirect CFD that are indeed substantially under reported worldwide, there is thus the need for further review. As for South African companies, there is a need to investigate all costs that are directly and indirectly incurred due to financial distress and an appropriate model formulated in this regard.

1.3 Research Aim

The aims of this study are to:

- Determine the cost of financial distress of South African JSE listed companies that have undergone this mishap in the past 20 years (1990 to 2010).
- Formulate an appropriate model for determining the costs of financial distress for South African JSE listed companies.

1.4 Research Purpose

The research purpose is to assist shareholders and managers in determining accurately, the costs of financial distress that will help in determining an appropriate optimal capital structure model for their organizations.

2 Theory and Literature Review

2.1 Introduction

CFD are an important component of the Trade-off theory of optimal capital structure (Korteweg, 2007). According to the trade-off theory, value-maximizing organizations choose the level of debt by balancing tax benefits of debt against the costs associated with debt such as bankruptcy and agency costs (Gwatidzo and Ojah, 2009).

A company can be decomposed as a portfolio of the assets of the unlevered organization and a security whose value represents the effects of debt financing (Korteweg, 2007). This is illustrated by Korteweg (2007) as $V_t^L = V_t^U - C_t$; whereby, $V_t^U$is the market value of the unlevered company, V_t^L is the market value of the levered company and the difference between the two market values is a fictitious security, C_t, defined as the expected present value at time t of lost future cash flows due to past financing decisions, minus the present value of the interest tax shield. Accordingly, a positive C_t means that the costs of financial distress outweigh the tax benefits of debt, and a company is worthless with debt in its capital structure than it is worth without debt. C_t Includes the direct and indirect CFD that are realized both before and after default, and is on an ex-ante basis because the market discounts all expected future CFD (Korteweg, 2007).

2.2 Definition and concept of financial distress

Literature on costs of financial distress explores two types of financial distress viz: direct and indirect costs of financial distress. Direct costs are a vastly investigated finance stream that can be explained as the total loss incurred by a company filing for bankruptcy (Pindado, 2005). Administrative and legal costs of bankruptcy process constitute this loss. Conversely, indirect financial distress costs are costs borne by all companies that can no longer meet their financial obligations when they become due (Pindado, 2005). Direct distress costs are easy to quantify when compared to indirect costs. For the purpose of this research, indirect costs of financial distress will be investigated.

According to Elloumi and Gueyie (2001), financial distress is defined by an organisation's business deteriorating to the point where it cannot meet its financial obligations. Entry into financial distress can be defined as the first year in which cash flows are less than current maturities' long-term debt (Elloumi & Gueyie, 2001). Purnanandam (2008) defines financial distress as a low cash-flow state in which the firm incurs losses without being insolvent. This definition reflects that financial distress differs from insolvency.

Pindado and Rodrigues (2005) applied Opler and Titman (1994) definition of financial distress in formulating an inclusive model for costs of financial distress. Here, financial distress is defined as the non-sporadic situation where an organization can no longer meet their liabilities when they become due, and then break their commitments with creditors or face them with severe difficulties.

This definition was also adopted by Wruck (1990), Asquith et al. (1994), Andrade and Kaplan (1998) and Whitaker (1999) in characterizing the critical point when an organization reaches a financial distress situation (Pindado & Rodrigues, 2005). One can conclude that financial distress is an analogue for economic distress. Andrade (2003) differentiated economic distress from financial distress by stating that economic distress, in some sense, is a loss of value due to weakness in fundamental business.

In this regard, a business is economically distressed if its own viability is in question, whereas financial distress is distress or problems that arise due to the inability to repay debt obligations (Andrade, 2003). Obviously these two are not totally distinct. Clearly, it is possible for an organization to be financially distressed because it is also economically distressed and therefore does not have the profits to pay its debts. But organizations can also be financially distressed, even if their fundamental business is healthy, just because they have too much debt.

2.3 Effects of the Costs of Financial Distress

There are three important effects of financial distress costs. Firstly, according to Titman (1994), a financially distressed firm may lose customers, valuable suppliers, and key employees provide empirical evidence that financially distressed firms lose significant market share to healthy counterparts in industry downturns. This means that debt weakens the competitive position of a firm. Secondly, a financially distressed firm is more likely to violate its debt covenants or miss coupon/principal payments without being insolvent (Purnanandam, 2008). These violations lead to deadweight losses in the form of financial penalties, accelerated debt repayment, operational inflexibility and managerial time and resources spent on negotiations with the lenders.

Finally, a financially distressed firm may have to forgo positive NPV projects due to costly external financing. These characteristics lead us to the various definitions of financial distress as previously stated in Section 2.2. The effects of CFD on the company value have been widely studied. Branch (2002) in his review article writes "Clearly we have a wide range of estimates for financial distress costs."

2.4 Variables for predicting financial distress

Historically, variables for determining the cost of financial distress originated from the following models: Multiple Discriminant Analysis (MDA), Logit (L) and Neural Networks (NN) prediction models which were able to predict corporate bankruptcy on 28 "failed" and 40 "non-failed" companies listed on the JSE between 1966 and 1993 (Muller, 2008). The combined predictive accuracy of these three techniques were 83,2%, 86,8% and 87,8% for MDA, LA and NN, respectively. Common variables used in these predictions were working capital/total assets, retained earnings/ total assets, earnings before interest and tax/total assets, market value of equity/book value of total liabilities and sales/total assets (Ko, Blocher and Lin, 2006). It is imperative to discuss on each of these variables in isolation.

2.4.1 Working Capital/Total Assets (WC/TA)

The working capital/total assets ratio is a measure of the net liquid assets of the firm relative to the total capitalization (Altman, 2000). A company experiencing consistent operating losses will have shrinking current assets in relation to total assets.

2.4.2 Retained Earnings/Total Assets (RE/TA)

Retained earnings, report the total amount of reinvested earnings and/or losses of a firm over its entire life. This is subject to "manipulation" via corporate quasi-reorganizations and stock dividend declarations. Hence when employing it, one needs to note the bias created by a substantial reorganization or stock dividend and appropriate readjustments made to the accounts (Ko *et al.,* 2006). Retained earnings are a measure of cumulative profitability over time (Pindado et al, 2008.) Companies with high RE relative to TA, have financed their assets through retention of profits and have not utilized as much debt as possible.

2.4.3 Earnings Before Interest and Taxes/Total Assets (EBIT/TA)

The EBIT/TA ratio is a measure of the true productivity of the firm's assets, independent of any tax or leverage factors. Pindado, Rodrigues, and de la Torre (2008) applied this ratio as a variable for financial distress likelihood model. This is because a company's ultimate existence is based on the earning power of its assets. This ratio appears to be particularly appropriate for studies dealing with corporate failures.

2.4.4 Market Value of Equity/Book Value of Total Liabilities (MVE/TL).

Equity is measured by the combined market value of all shares of stock, preferred and common, while liabilities include both current and long term liabilities. According to Altman (2000) and Muller (2008), the measure shows how much the firm's assets can decline in value (measured by market value of equity plus debt) before the liabilities exceed the assets and the company becomes insolvent.

More recent models are essentially based on the market value of equity and its volatility (Altman, 2000).

2.4.5 Sales/Total Assets (S/TA)

The capital-turnover ratio is a standard financial ratio illustrating the sales generating ability of the firm's assets. According to Altman (2000), this ratio is one measure of management's capacity in dealing with competitive conditions. According to Ko *et al. (*2006), this ratio is quite important because it is the least significant ratio on an individual basis.

2.4.6 Financial expenses (FE/RTA)

Pindado et al (2008) in their prediction model replaced debt stock ratios with financial expenses because the latter seem to lose explanatory power when compared to the chosen flow variable. Pindado et al. (2008) revealed the advantages of using a variable that considers the flow of financial expenses instead of the stock of debt. Since the revision of the Z-score carried out by Altman (2000), many other subsequent studies point out that debt variables have less power in explaining financial distress than variables of financial expense (Pindado *et al.,*2008).

Apart from the common variables, Ohlson (1980) concluded that four main factors that were statistically significant in predicting the probability of failure within one year. These factors include the size of the company, measures of financial structure, performance and current liquidity. Laitinen (1991) attempted to predict and quantify the different processes of financial failure of 40 small or middle-sized Finnish companies.

Accordingly, a theoretical model was developed which showed that determinants including profitability, growth, capital intensiveness, loan taking intensiveness and debt financing should be considered:. A decade later, Kuruppu, Laswad and Oyelere (2003) argued that liquidation was a better proxy for assessing the validity of a going concern assumption. Beaver, McNichols and Rhie (2005) used hazard analysis to predict profitability of assets, proxy for cash flow to service principal and interest payments and leverage were the most significant predictor variables.

By using Panel Data Least Square Regression Model, Pranowo *et al.* (2010) found that financial variables which significantly influence the corporate financial distress are:

- Current ratio: Current Assets to current liabilities
- Efficiency: EBITDA to total assets
- Leverage: Due date account payable to fund availability
- Equity: Paid in capital (capital at book value)

South African research on financial distress dates back to the 1990, where Court and Radloff (1990) used MDA and LRA to predict corporate failure on 26 matched companies listed on the JSE between 1965 and 1986. The findings show that the overall predictive accuracy of MDA and LRA was 78,5% and 84,6%, respectively. More recently, Kidane (2004) used Altman and Springate models to predict financial distress for IT companies, while Muller (2008) used MDA, RP, LA and NN to determine an appropriate model for the prediction of financial distress of JSE listed companies.

Using the financial distress predictive variables in a Logit regression exercise, Pindado (2009) inferred the determinants of costs of financial distress as follows: the company's holding of liquid assets, change in the company's investment policies, change in employment policies, company's Tobin's q adjusted to its sector, average profitability of the company's sector, logarithm of the company's sales, probability of financial distress, company's leverage adjusted to its sector which he adapted from different prediction models. Using these factors, it was concluded that the cost of financial distress is positively related to the probability of default (Pindado, 2009). CFD exhibited a negative relationship with leverage which supports the benefit of leverage in increasing performance and reducing financial distress.

Pindado's (2009) model also reflects a negative relationship that exists between the cost of financial distress and the holding of liquid assets, which implies that insolvent companies can take advantage of holding larger stocks of this kind of assets. For a change in investment policy this model exhibits a negative relationship with the cost of financial distress. According to Pindado (2009), this means that divesture increase the cost of financial distress and concluded that underinvestment has a stronger effect than overinvestment in financial policies.

Regarding the change in employment policy Pindado (2009) confirmed that the relationship depends on the institutional context. The Tobin Q variable is used to reinforce the need to control investment decisions and the sector variable used with the intention to capture the effect of the industry on the individual performance. Size reflected a negative relationship with financial distress, showing that larger firms deal easily with financial distress than smaller ones.

Iwarere and Akinleye (2010) stated that bankruptcy costs are relatively higher for smaller firms because larger firms tend to be more diversified. To standardize this unbalance effect one can measure the size of an entity as the natural logarithm of net sales or alternatively, one could use the natural logarithm of total assets (Iwarere & Akinleye, 2010). Iwarere and Akinleye (2010) think that net sales is a better proxy for size because many firms attempt to keep their reported size of assets as small as possible, for example, by using lease contracts.

2.5 Methods for determining costs of ex-ante financial distress

The general formula according to Elkamhi *et al.* (2009) in determining the costs of ex-ante financial distress is given by:

Where, CFD is the cost of financial distress, q_j the risk-adjusted probability of defaulting in year j, LGD_j the value loss given default in year j, and r_j the risk-free rate from year t to year j. The most standard variation of calculating ex-ante distress costs is to find the product of Andrade and Kaplan (1998) that estimates the ex-post costs and the historical probabilities of default (Molina, 2005). The main draw-back of using this method is that it ignores capitalization and discounting. Other variations are structural in nature.

They simply assume either risk-neutral measure (Leland and Toft, 1996) or risk neutrality and discount the costs of financial distress by the risk-free rate (Hennessy and Whited, 2005). In either case according to Almeida and Philippon (2007), they do not emphasize the difference between objective and risk-adjusted probabilities of distress.

Almeida and Philippon (2007) employed a similar approach as Molina (2005) of multiplying the estimates of ex-post costs and probabilities of default of Andrade and Kaplan (1998). Instead of using historical probabilities of default, Almeida and Philippon (2007) used a risk-adjusted distress probability from credit spreads. This risk-adjusted distress probability is given by Almeida and Philippon (2007) as $q_j = \frac{y-r_j}{(1+y)(1-\rho)}$, where q_j is the risk-adjusted probability of defaulting in year j, r_j the risk-free rate from year t to year j, y the bond yield and ρ the bond recovery rate.

This estimate suggests that risk-adjusted probabilities of default and consequently, the risk-adjusted NPV of distress costs, are considerably larger than historical default probabilities and the nonrisk-adjusted NPV of distress, respectively. This large difference between historical and risk-adjusted probabilities translates into a substantial difference in the NPVs of distress costs.

The discovery of Almeida and Philippon (2007) fueled some skepticisms by Elkamhi *et al.* (2009) who argued that in recent applications, estimates of the value losses due to financial distress are substantially inflated because they consider economic shocks that are unrelated to an organization's financial position.

These recent estimates appear to be able to offset the substantial tax benefits (Elkamhi *et al.*, 2009) that could shed new light in the trade-off between tax benefits and costs of financial distress of capital structure could be reached. Unfortunately, calculation of Almeida and Philippon (2007) overstates ex-ante financial distress costs, because it does not properly filter out economic shocks that could lead the firm to become distressed as stated by Elkamhi *et al.* (2009).

According to Korteweg (2007), it is important to separate economic and financial distress because only the costs of financial distress matter for optimal capital structure. To verify this fact, Elkamhi *et al.* (2009) calculated ex-ante distress costs through first determining the risk-adjusted probabilities and corresponding default thresholds using the model of Leland and Toft (1996), which assumes that default is endogenous. The findings showed that risk-adjusted default probabilities matched quite closely to those reported by Almeida and Philippon (2007). However, when Almeida and Philippon (2007) calculated ex-ante financial distress costs, it was found that for most organisations, the costs were quite modest; less than 1% of current value that is less than the 4-5% provided by Almeida and Philippon (2007). This showed that economic shock has great influence on the costs of financial distress.

From the above-mentioned evidence, it can be concluded as the case may be for Elkamhi *et al.* (2009) that, to calculate ex-ante distress costs, one needs to determine the value losses given distress, multiply this by the objective and risk-adjusted distress probability of becoming distressed, factor in the economic shock and then discount to present value. This finding leads to the question of what is then an appropriate model for South African companies to be used in determining the costs of financial distress considering risk adjustment probabilities and economic shock.

Pindado (2009) formulated a holistic approach in his international model of determining costs of financial distress by combining the probability of financial distress and economic effects. The model is based on merging the school of determining the cost of financial distress and that of formulating prediction model of financial distress. The variables employed herein have been previously discussed in Section 2.4.

2.6 Measures Management conduct in relieving financial distress

When management realizes that its company is under financial distress, they mitigate the effects of the position through restructuring either by reducing headcount or by abandoning business lines. This is evident through the change in employment policy or investment policy (Pindado, 2009). As mentioned by Andrade (2003) a company might have a hard time retaining key employees, or management might flee. The organization might also suffer investment cuts. For example, a research-and-development (R&D)-intensive or an investment-intensive company might have to decide whether to use cash flows to pay off debt or to fund ongoing investment projects. During the period of distress there is a diversion of managerial time and effort that is put into restructuring (Andrade, 2003).

Also common in this situation are asset fire sales. A company might have to sell some assets and, particularly if the situation of distress is well known in the market, it might be forced to sell at a price below market (Andrade, 2003). Couple of other things that companies do not usually consider is delays in renegotiation because of strategic bargaining by investors.

If parties with conflicting interests are bargaining at a distressed table, this can delay the process unnecessarily and cause excess cost to the company. In addition to all the difficult states a company in distress can incur, there is also an incentive for management of companies in distress to gamble. Management or stockholders of a company on the verge of going into bankruptcy have some incentive to want the company to gamble on high-risk projects Andrade (2003). At best, they will pay off, and the company will avoid distress. Most likely they will not but if the company was going bankrupt anyway, management might want to take that chance to gamble.

2.7 Conclusions

From the review of related literature discussed herein, one can conclude that it is possible to determine a cost of distress model by combining independent variables from financial distress models and methods of calculating costs of distress. Literature also leaves us with the question of what is an appropriate model for South African companies to be used in determining the costs of financial distress considering risk adjustment probabilities and economic shock. Due to Pindado model's variables having an impact on the efficiency and accuracy of the model (Muller, 2008) and its holistic approach, this study intends to adopt the model.

3 Research Hypothesis

Similar to Pindado's (2009) model, a model is proposed in which financial distress is explained by the probability of financial distress occurring and ex-post distress costs controlling for economic shock and size of the company. Given the premise the financial distress model is given by the following null ($H1_o$) and alternative ($H1_A$) hypotheses:

$H1_0$: $CFD_P = \beta_0 + \beta_1 PROB + \beta_2 LEV + \beta_3 LA + \beta_4 \Delta\ INV + \beta_5\ \Delta\ EMP + \beta_6 Q + \beta_7 GDP + \beta_8 SIZE$

$H1_A$: $CFD_P \neq \beta_0 + \beta_1 PROB + \beta_2 LEV + \beta_3 LA + \beta_4 \Delta\ INV + \beta_5\ \Delta\ EMP + \beta_6 Q + \beta_7 GDP + \beta_8 SIZE$

Where CFD_P is the cost of financial distress expressed by the difference in growth rate (GDP) of the country and that of the company; PROB the probability of financial z-score; LEV the company's leverage given in terms of the debt ratio (long term debt)/(long term debt +market capitalization); LA reflecting the organisation's holding of liquid assets expressed by the cash flows/current asset ratio; Δ INV change in organisation's investment policies stated as the year on year change in reinvestment rate in terms of retained earnings; Δ EMP the change in the company's employment policies expressed as the year on year change in employee retention rate; Q the Tobin's q adjust expressed as the market value/replacement value (Mcgregor BFA); GDP the average profitability of country given by the gross domestic product; and SIZE the logarithm of firm's sales.

This model differs from Pindado's model in that:

- The model employs GDP of the country instead of sector growth rate used in Pindado's model due to unavailability of sectorial GDP's prior to 1993 from Statistics South Africa (STATSA).
- The model applies z-score instead of Pindado's likelihood method (Pindado et al., 2008). The z-score employed is formulated for South African companies by Dr J H de la Rey at the Bureau of Financial Analysis in Pretoria (1981). The Pindado likelihood method gives correct classifications of mean values of 83%, while de la Ray's have a 96% success rate in classifying South African as either financially failed or financially sound.
- Holding of liquid assets uses cash flow data instead of balance sheet variables. This is due to the fact that a company under distress will utilize cash to try to mitigate the distress effect.
- Change in reinvestment rate was employed instead of change in investment rate. Reinvestment rate considers investment based on retained earning which shows the cumulative effect of profitability and the organisation's ability to fuel itself instead of a global investment ratio that considers external investing options.

4 Research Methodology

4.1 Research Design

To conduct the research, a descriptive research design of a quantitative nature was employed. A design was chosen to elaborate the characteristics of the cost of financial distress as suggested by Zikmund's definition of descriptive research (Zikmund, 2003). This research design was selected because; variables can be implemented to formulate those for the financial distress model.

A quantitative approach was used due to the intensive calculations needed to reach the research goals. This research approach has previously been employed to investigate costs of financial distress by Elkamhi *et al.* (2009), Korteweg (2007), Pindado and Rodrigues (2005) and Almeida and Philippon (2007).

4.2 Sampling Population

The target sampling population for the research was all companies listed on the Johannesburg Securities Exchange (JSE) as of the time of sampling, while those that were de-listed from the JSE at the time of sampling were excluded. Companies that were listed on the JSE within the last 20 years (between 1990 till date) were excluded to avoid limitation comparisons between companies across a time series.

4.3 Unit of Analysis

The unit of analysis will be a single JSE listed company.

4.4 Size and Nature of the Sample

The sampling method for the research was non-probability sampling of a judgmental nature. Zikmund (2003) suggested its use to fulfill a certain purpose. In the case of this research, the aim was to determine the costs of financial distress.

This led to a sample of the JSE listed companies that have shown evidence of financial distress between1990 to 2009. Companies were selected across different industrial sectors within the main board of the JSE including Oil and Gas, Basic Materials with the exception of Mining companies, Industrials, Consumer Goods, Health Care, Consumer Services and Telecommunications and Technology.

The financial sector was excluded from the research because it is regulated, which limits its involvement in taking up more debt (Ratshikuni, 2009). The regulatory environment for financial institutions limits them from fully participating in a perfect free market. Mining companies are excluded because they constitute about 40% of the industry, thus giving bias in results of the total population.

A company was assumed to be financially distressed if it exhibited a negative cash flow interest coverage ratio for the past 3 or more successive years. On the third year, the company was regarded as distressed. Out of 399 companies in the JSE, 84 companies were sampled as distressed in the past 20 years (Appendix A). Companies in basic resources and utilities sector and telecommunication did not meet the above-mentioned requirement.

4.5 Instruments

Microsoft EXCEL was employed for data capturing and processing. NCSS statistical package was employed to conduct evaluations of relationships using more complex algorithms.

4.6 Data Collection

Secondary data was used for model building according to Zikmund (2003) because the process is less expensive and comprehensive than attaining the information from the individual companies.

Industry data was obtained from Mcgregor BFA research domain's electronic database (Table 1). This source is credible because it provides a large sample data points and follow the GAAP reporting procedure with common definitions of terms. The source was also selected because they are consistent with the research needs and the data time period is consistent with the population of interest.

Table 1: Type of data and database sources

Data Type	**Database Sources**
Income statement data	McGregor BFA
Balance sheet data	McGregor BFA
Cashflow statement data	McGregor BFA
Market capitalization data	McGregor BFA
Probability of Financial Distress	McGregor BFA
Tobin's Q ratio	McGregor BFA

From the raw data selected, the processes of data screening for outliers and human influence were conducted. From the screened data, probability values were determined and then ex-post variables were calculated, after which time, a regression was conducted to establish a relationship. Quality control was conducted through tolerance level investigations.

4.7 Data Analysis

Firstly, the sample was screened for quality control using T-bar for outliers and Bedford law for human influence in financial statements. Secondly, data was then tested for statistical significance using robust regression, which was benchmarked by the standard regression results.

Thirdly, the robust regression was used to determine the cross-sectional explanation of CFD. Lastly, a time Series investigation was conducted to reinforce cross-sectional findings.

4.7.1 Data screening

Data was screened for outliers that might influence the results using NCSS statistical software 2007. Companies were also screened based on a forensic statistical method that was used to analyze the possible effect of human endeavors on the financial statements.

This was to reinforce the reliance of the financial statements. This forensic method is called the Benford's Law which relies on the observation that certain digits appear more than others (Durtschi *et al*, 2004). According to Durtschi (2004), this law shows that in a database, the probability of first place digits is around 30% of numbers 1, 18% with a 2 and 4.6%with the number 9. Table 2 reflects the distribution of expected frequency of occurrence. The first digit frequencies were used for sampling distressed companies in this research. Benford law was employed using the following variables: sales, ebit, debtors, creditors, interest, taxation, disbursements, expenses and costs of sales.

Table 2: Expected frequencies based on Benford's law

(Source: Durtschi, 2004)

Digit	1st place	2nd place	3rd place	4th place
0		0.11968	0.10178	0.10018
1	0.30103	0.11389	0.10138	0.10014
2	0.17609	0.19882	0.10097	0.1001
3	0.12494	0.10433	0.10057	0.10006
4	0.09691	0.10031	0.10018	0.10002
5	0.07918	0.09668	0.09979	0.09998
6	0.06695	0.09337	0.0994	0.09994
7	0.05799	0.09035	0.09902	0.0999
8	0.05115	0.08757	0.09864	0.09986
9	0.04576	0.08500	0.09872	0.09982

4.7.2 Probability of Financial Distress: Z-score

This method involves a linear discriminant analysis introduced by Altman in 1968 (Altman, 2000). McGregor's financial distressed model developed by Dr J H de la Rey was run to establish the probability of financial distress. Financial Data from 1999 to 2009 was screened for distressed based on the following algorithm:

k = 0.01662a + 0.0111b + 0.0529c + 0.086d + 0.0174e + 0.01071f - 0.0688811

Where:

A is (total profit outside financing / total assets) x 100% and

B is (profit before interest and tax / average total assets) x 100%.

C is (total current assets + listed investments) / total current liabilities.

D is (profit after tax / average total assets at book value) x 100%.

E is cash flow profit after tax / (inflation-adjusted total assets at market value).

F is (total inventory / inflation-adjusted total assets) x 100%.

4.7.3 Variables

To calculate the financial distress costs based on Pindado and Rodrigues (2005) we measure the difference between the growth rate of the sales of the sector and the growth rate of the sales of the firm. $CFD = \left(\frac{Sales_{it} - Sales_{it-1}}{Sales_{it-1}}\right)_{\text{sector}} - \left(\frac{Sales_{it} - Sales_{it-1}}{Sales_{it-1}}\right)$

Where $Sales_{it}$ denotes the company's turnover as measured by the gross sales reduced by cash discounts, trade discounts, returned sales excise taxes and value-added taxes; and LEV the company's leverage given in terms of the debt ratio

Where LEV the company's leverage given in terms of the debt ratio

$$LEV = \frac{Long\ Term\ Debt}{Long\ Term\ Debt + Market\ Capitalisation};$$

Where LA reflecting the organisation's holding of liquid assets expressed by the current ratio,

$$LA = \frac{Cash\ Flow}{Current\ Assets};$$

Δ INV change in organisation's investment policies stated as the year on year change in reinvestment rate in terms of retained earnings,

$$\Delta INV = \left(\frac{Net\ Retained\ Cash}{Fixed\ Assets + Intangible\ Assets + Current\ Assets}\right) X100;$$

Δ EMP the change in the company's employment policies expressed as the year on year change in employee retention rate,

$$\Delta EMP = \left(\frac{Number\ of\ employees_t - Number\ of\ employees_{t-1}}{Number\ of\ employees_{t-1}}\right) X\ 100;$$

Tobin's Q-ratio can be described as the market value of the enterprise's equity plus the book value of interest-bearing debt to the replacement cost of its fixed assets,

$$Q = \frac{Market\,Value\ of\ Equity + Book\,Debt}{Assets}$$ (Mcgregor BFA);

SECTOR the average profitability of country given by the gross domestic product less the Sector GDP; and

SIZE the logarithm of firm's sales, $SIZE = \ln Sales$.

4.7.4 Regression

The method used for analysis of the variables was a robust regression analysis chosen because it reduces the effect of outliers. The robust regression was employed to determine which variables are likely to explain the cost of financial distress at different confidence levels (70%, 80%, 90% and 95%). When the variables were selected, a relationship analysis was conducted to investigate the negative or positive impact of the variables on the costs of financial distress.

4.8 Potential Research Limitations

Potential limitations of the research were generated by:

- The bias of the definition of financial distress which might make the sample unrepresentative of the industries,
- Results conclusions were only based on the sample and no generalization was made,
- Systematic rounding errors when conducting calculations,
- Financial data reporting on a year on year bases, which led to missing successive data for some entities
- Bias of outliers in relationship investigations,
- Focus on only the linear relationship of variables and not non-linear, and
- Limitations inherent of the software’s employed for analysis

5 Results

5.1 Sample description

Of the 399 listed JSE companies, 77 companies were found to not meet their financial obligations by reflecting a negative interest coverage for 3 or more successive years. Of the 77 companies 14 companies were from the consumer goods industry, 21 from the consumer service industry, 8 companies were from the health care industry, 4 from the oil and gas industry, 11 organizations from the technology industry, and 19 from the Industrial industry. 84 observations were obtained from companies with negative interest cover for 3 successive years, 33 observations were obtained from 4 successive years, 18 from 5 years, 10 from 6 years3 and only observations from companies with negative interest coverage for 7 successive years (Table 3).

Table 3: Summary of number of observations

	3 years	4 years	5 years	6 years	7 years	Total observations/variables
Number of observations	84	33	18	10	3	313

In total there were 313 observations initially quality control was conducted. Companies in basic resources and utilities sector and telecommunication did not meet the sampling requirements.

Table 4, summarizes the descriptive statistics of the observations with CFD representing the cost of financial distress, Delta INV the change in reinvestment rate, LA the holding of liquid assets, Size the size of the entity, Q represents Tobin's Q ratio, Lev represents the leverage, PROB the probability of financial distress expressed as a z-score, GDP represents the economic effect and DeltaEMP represent the retention rate (change in employment rate). The table illustrates the number of observations per variable, median, mean, standard deviation, range, minimum value, maximum value, and the upper and lower confidence level.

Table 4: Descriptive Statistics Summary

Variable	Count	Median	Mean	Standard Deviation	Standard Error	Minimum	Maximum	Range	95% LCL	95% UCL
CFD	117	2.86%	2.86%	22.30%	2.06%	-48.34%	47.32%	95.66%	-1.23%	6.94%
DeltaINV	112	0.53	2.51	15.42	1.46	-38.61	53.75	92.36	-0.37	5.40
LA	120	-11.61	-15.67	16.63	1.52	-81.11	9.05	90.16	217.78	362.78
Size	148	10.52	7.94	5.89	0.48	0.00	16.32	16.32	6.98	8.90
Q	145	0.79	1.32	1.89	0.16	0.16	17.64	17.48	1.01	1.63
LEV	148	7.56%	22.27%	28.29%	2.33%	0.00%	100.00%	100.00%	17.67%	26.86%
PROB	129	-0.58	-1.47	3.37	0.30	-8.82	6.60	15.43	-2.05	-0.88
GDP	148	3.68%	3.32%	1.80%	0.15%	-1.78%	8.56%	10.34%	3.02%	3.61%
DeltaEMP	65	14.62%	14.41%	43.62%	5.41%	-96.37%	97.49%	193.86%	3.60%	25.22%

The data reflects CFD with a mean value of 2.86% at a standard deviation of 22.30% and a range of 95.66%; DeltaINV of a mean value of 2.51% at a 15.42% standard deviation and a range of 92.36%; LA of a mean value -15.67 and a standard deviation of 16.63 and a spread 90.16; SIZE show a central tendency of 7.94 at a standard deviation of 5.89 and a range of 16.32; Q show a central tendency of 1.32 at a standard deviation of 1.89 and a spread of 17.48; LEV exhibits a mean value of 22.27% at a standard deviation of 28.29% and arrange of 100%; PROB exhibits a central tendency of -1.47 at a standard deviation of 3.37 and a spread of 15.43; GDP shows a mean value of 3.32% and a standard deviation of 1.80% with a range of 10.84%; and DeltaEMP shows a mean value of 14.41% at a standard deviation of 43.62% and a spread of 193.86%.

Histograms were produced to demonstrate the distribution of the observations per variable (Appendix A). CFD and DeltaINV exhibit a normal distribution of data, while LA, PROB, GDP and DeltaEMP are skewed to the right, and Q and LEV are skewed to the left; and SIZE that shows a bimodal distribution.

5.2 Scatter Plots

Figure 1, Figure 2, Figure 3, Figure 4, Figure 5, Figure 6, Figure 7 and Figure 8, represents scatter plots for the change in investment policy, holding of liquid assets, size of the entity, Tobin Q ratio, leverage, probability of financial distress, economic effect and change in employment policy respectively against CFD. The scatter plots reflect the entire population without accounting for outliers. Based on the scatter plots CFD is negatively related to change in investment policy, holding of LA, leverage and change in employment, and positively related to size, Tobin Q ratio, probability of financial distress and economic effect. Corresponding relationships are explained by linear equations in each figure (1, 2, 3, 4, 5, 6, 7 and 8).

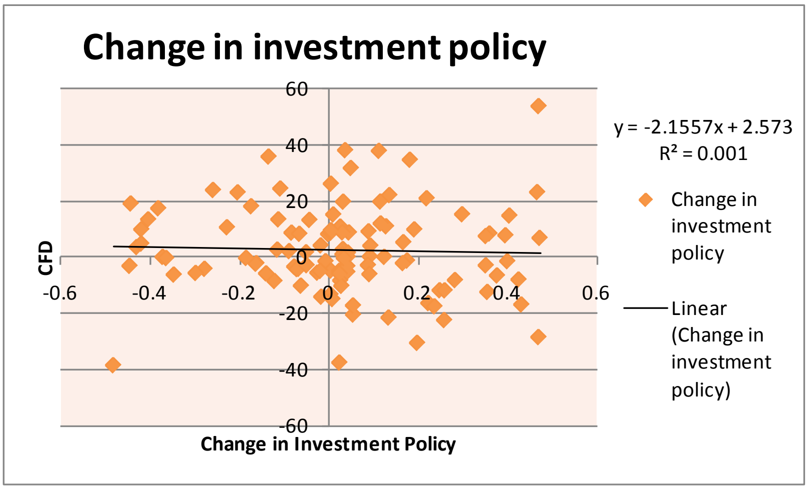


Figure 1: Scatter plot representing the relationship between CFD and the change in investment policy

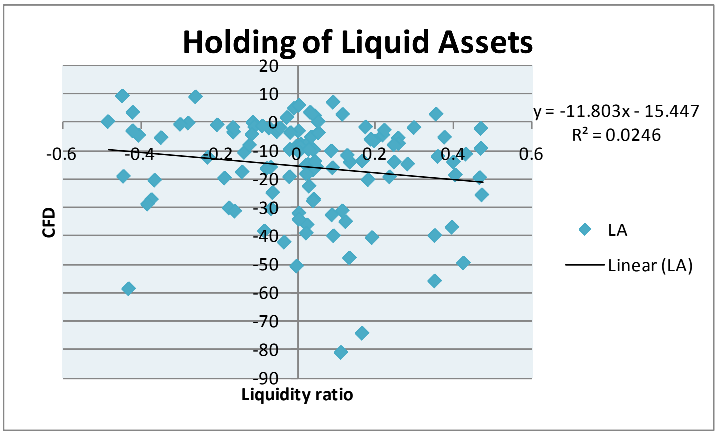


Figure 2: Scatter plot representing the relationship between CFD and holding of liquid assets

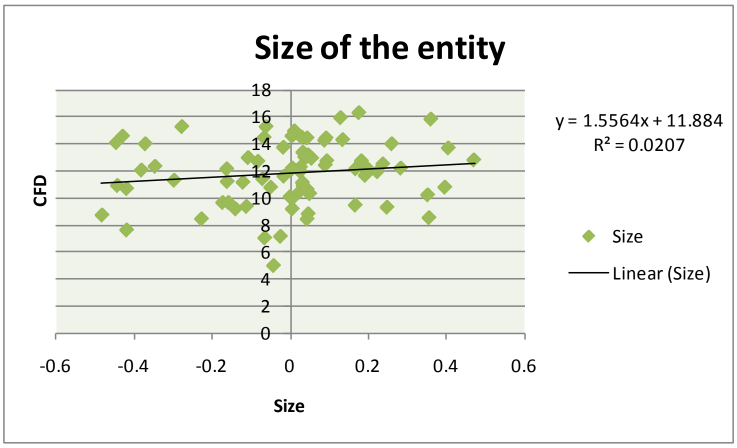


Figure 3: Scatter plot representing the relationship between CFD and the size of the entity

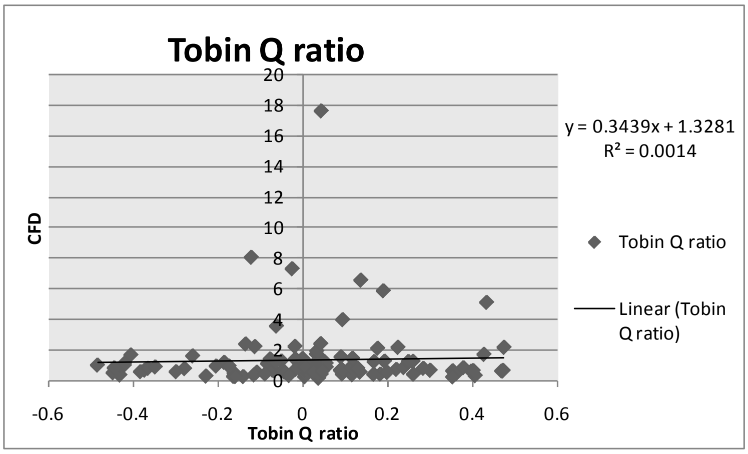


Figure 4: Scatter plot representing the relationship between CFD and Tobin's Q ratio

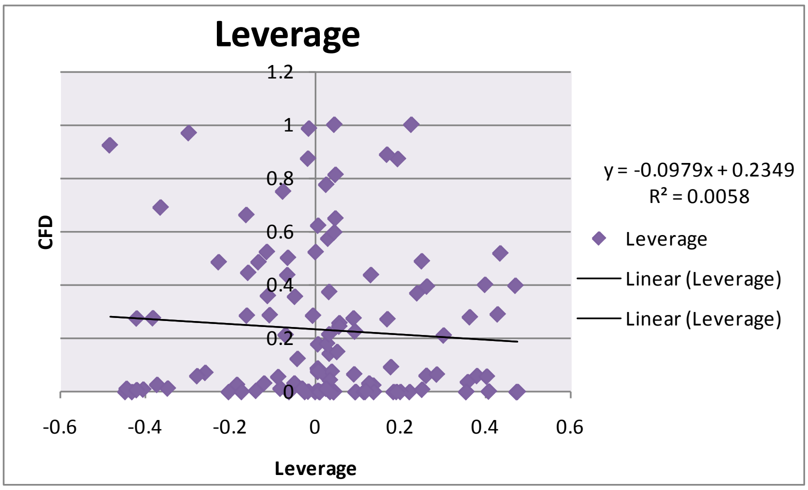


Figure 5: Scatter plot representing the relationship between CFD and leverage

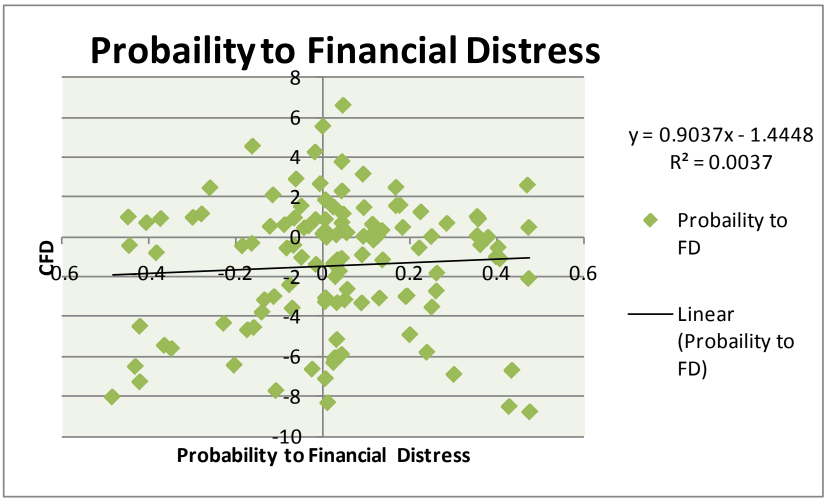


Figure 6: Scatter plot representing the relationship between CFD and probability of financial distress

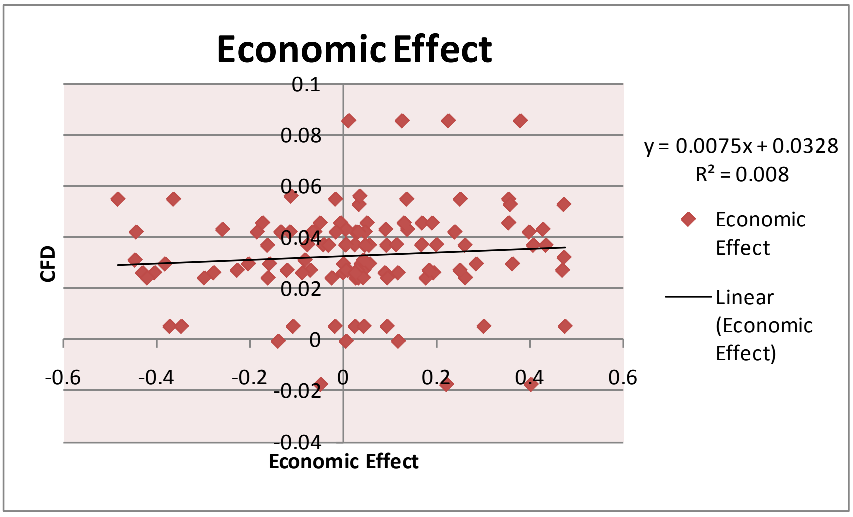


Figure 7: Scatter plot representing the relationship between CFD and economic effect

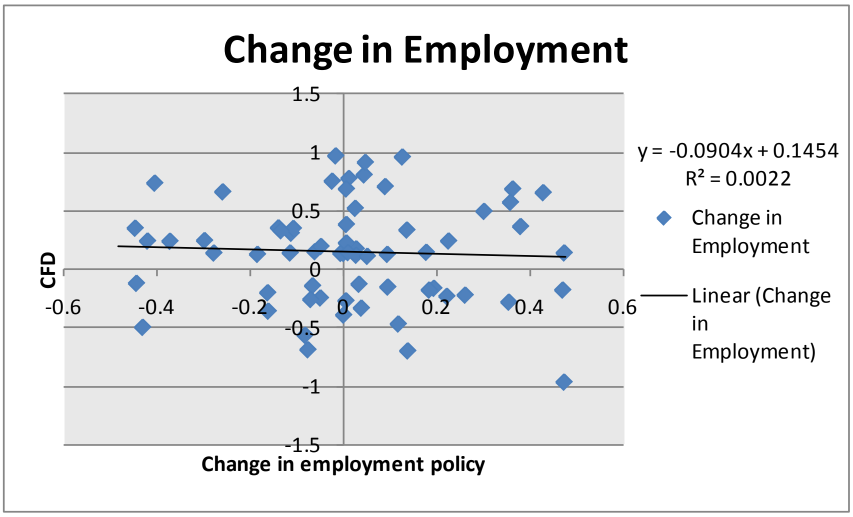


Figure 8: Scatter plot representing the relationship between CFD and the change in employment policy

5.3 Quality Control

For quality control, data was screened for outliers and tolerance level determined.

5.3.1 Outliers (NCSS)

Outliers were screened over three interquantile ranges (IQR). Box plots in figure 9 gives an overview of the outliers per variable. CFD has 9 observable outliers, change in employment rate 1, GDP 8 outliers, change in investment rate 9 outliers, leverage consists of 11 outliers, LA show 6 observation outside the 75% interquantile range, probability 7, Tobin Q 7 and observation under size exhibit no outliers. Appendix B, reflects the results for the tolerance levels using Tbar plots.

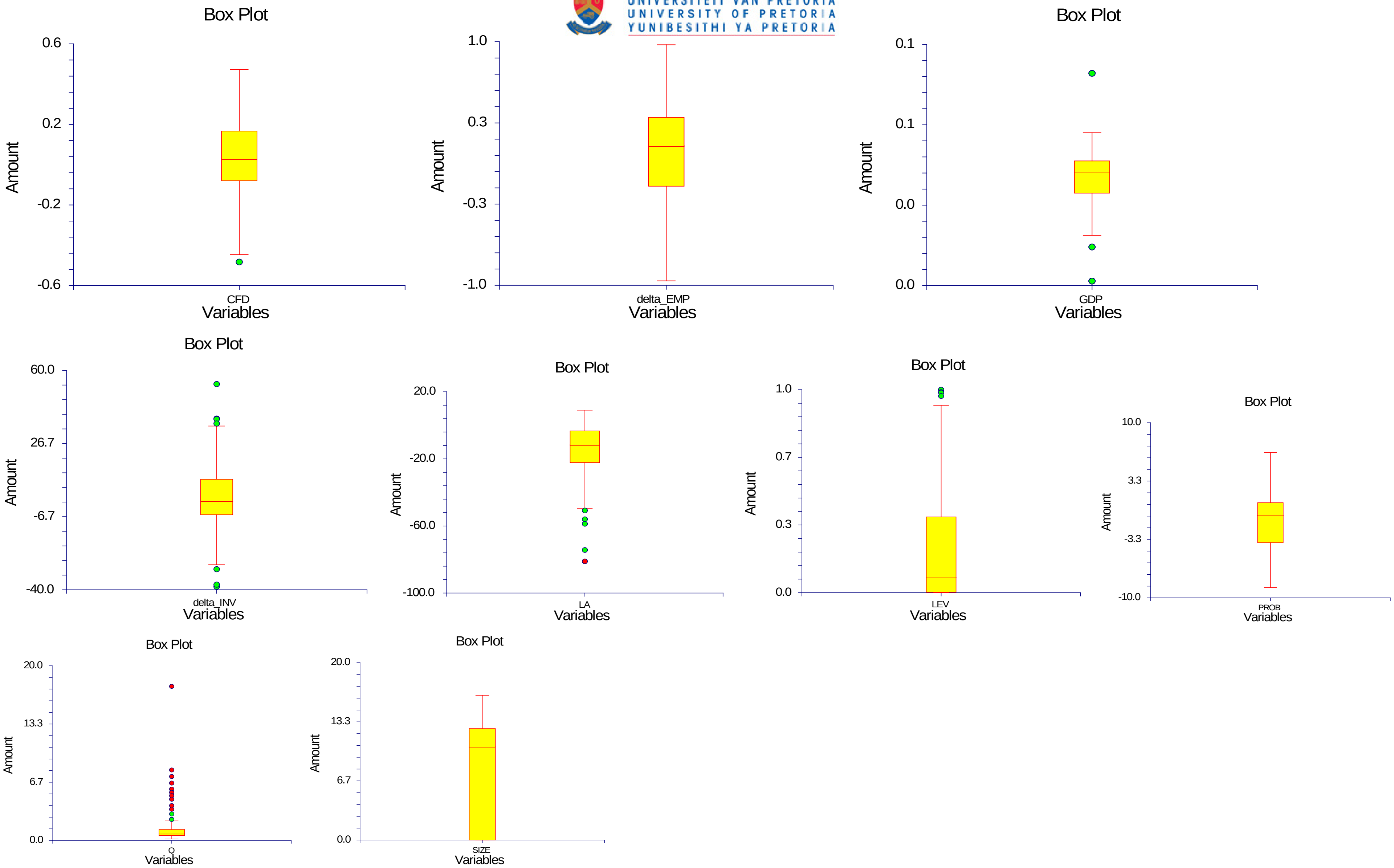
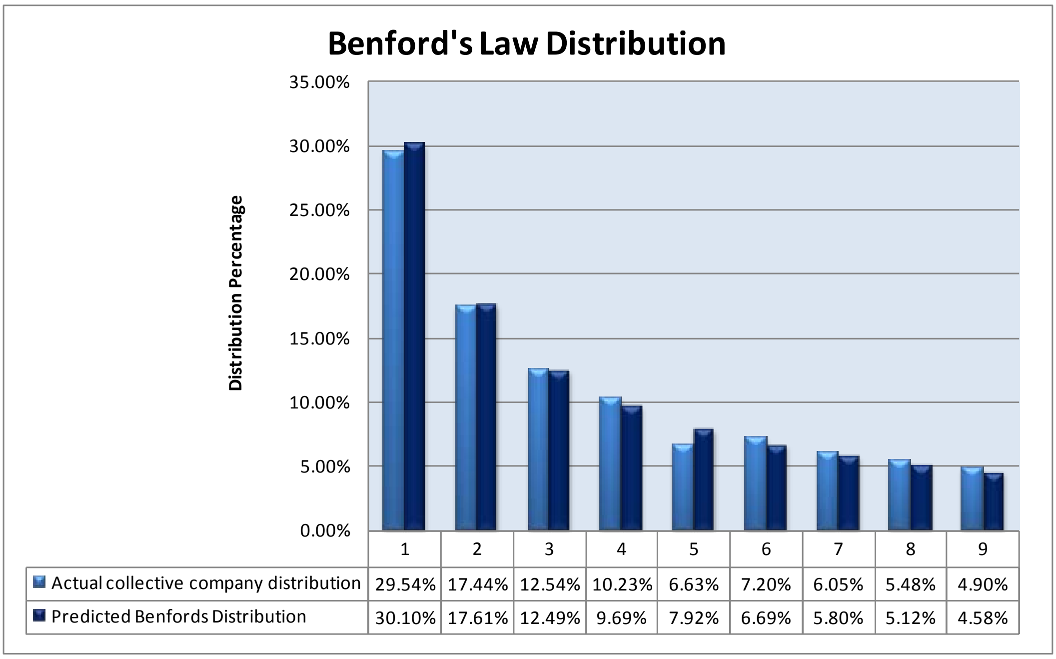


Figure 9: Box Plots illustrating outliers per variable

5.3.2 Bendford Law Distribution



	1	2	3	4	5	6	7	8	9
Actual collective company distribution	29.54%	17.44%	12.54%	10.23%	6.63%	7.20%	6.05%	5.48%	4.90%
Predicted Benfords Distribution	30.10%	17.61%	12.49%	9.69%	7.92%	6.69%	5.80%	5.12%	4.58%

Figure 10: A collective distribution of distressed company verses the Benford law distribution.

From a global perspective, figure 10 represents a distribution of first digits of variables in financial statements that are difficult to manipulate verses Benford’s law distribution of statistical occurrence of digits to determine reliability of the financial statements. The companies’ distributions reflect that there has been minimal human tempering with the financial data with the exception of an overstatement of the digit 6 by a 0.51% noticeable difference. This interference led 0.5% decrease in the number of ones and a 1.29% decrease in the number of fives in the data. But from a company individual view, human influence is of concern (Table 5 and Appendix C).

Table 5: Summary distressed companies' first digit distribution

	Digits	Ideal count	Rounted Ideal count	0	1	2	3	4	5	6	7	8
Ones	Count	3.01	3	5	17	22	11	15	5	2	0	2
	Percent			6.33	21.52	27.85	13.92	18.99	6.33	2.53	0	2.53
Twos	Count	1.76	2	19	22	20	12	3	1	1		
	Percent			24.36	28.21	25.64	15.38	3.85	1.28	1.28		
Threes	Count	1.25	1	27	24	20	5	2				
	Percent			34.62	30.77	25.64	6.41	2.56				
Fours	Count	0.97	1	33	23	18	4					
	Percent			42.31	29.49	23.08	5.13					
Fives	Count	0.79	1	40	30	8						
	Percent			51.28	38.46	10.26						
Sixes	Count	0.67	1	38	31	8	1					
	Percent			48.72	39.74	10.26	1.28					
Sevens	Count	0.58	1	46	23	8	1					
	Percent			58.97	29.49	10.26	1.28					
Eights	Count	0.51	1	49	20	9						
	Percent			62.82	25.64	11.54						
Nines	Count	0.46	0	50	23	4	1					
	Percent			64.1	29.49	5.13	1.28					

Instead of reflecting 3 number ones as first digits, the companies' reflects 55.7% of the first digits being less than 3 ones, thus is an understatement of the ones in the first digit place. The First digit distribution also reflects a 30.8% overstatement of ones in the first digit place. The bias of the number of ones is towards an understatement of values which reflects how other digits replaced the spot for ones. Only 13.92% companies followed the Benford law distribution. For the number of twos in the first digit distribution it was found that 25.64% of the organizations' were within the Benford law distribution but 52.57% understated and 47.43% overstated the number of twos in the first digit place. For the rest of the numbers in the first digit distribution screening of data resulted in weights of 30.77%, 29. 49%, 38.46%, 39.74%, 29.49% of the numbers three, four, five, six, seven, and eights in the first digit place respectively. This led to companies reflecting an average 32.2% of overstatement of first digits, which mirrors the understatement of ones and twos.

5.4 Regression Analysis Model: Cross sectional

5.4.1 Summary Section

The regression analysis performed was to formulate a cost of financial distress model through a cross-sectional linear relationship between CFD, the dependent explanatory and 8 independent variables: change in employment rate, change in reinvestment rate, holding of liquid assets, leverage, probability, Tobin Q and economic shock. From the processed 148 observations per variable, 82 were missing thus only 66 observations per variable were utilized for the regression estimation. The model exhibits a low coefficient of determination (R^2) of 0.1298, thus a more non-linear relationship of the dependent variable with the independent variable. The coefficient of variation is 9.4345.

The regression model exhibits a mean value of 74.06 % for the change in employment rate with a standard deviation of 446.21%. The range of the observations is 3722.95% with -96.37% as the minimum and 3626.58% as the maximum change in employment rate.

The model also reflects a central tendency of the change in reinvestment rate through a mean value of 350.92% at a standard deviation of 1503.46% and a range of 9142% with -3767% as the minimum value and 5375% as the maximum value. The economic effect is explicated by a mean value of 3.33% at a standard deviation of 2.07% and a range of 10.34% with -1.78% as the minimum value and 8.56% as the maximum value.

The holding of liquid assets is explained by a mean value of -14.25 at a standard deviation of 15.94 and a spread of 67.79 with -58.74 as the minimum value and 9.05 as the maximum value.

The leverage shows a mean value of 0.204 at a standard deviation of 0.267 and a range of 1 with 0 as the minimum value and 1 as the maximum value. The model elucidates the probability of financial distress by a mean value of -0.921 at a standard deviation of 3.22 and a range of 15.15 with -8.55 as the minimum value and 6.603 as the maximum value. The model explains the Tobin Q by a mean value of 1.49 at a standard deviation of 2.36 and a spread of 17.48 with 0.16 as the minimum value and 17.64 as the maximum value. The model details the size of the entity by a mean value of 8.189 at a standard deviation of 5.82 and a range of 16.31 with 0 as the minimum value and 16.318 as the maximum value. The cost of financial distress is explained by the mean value of 2.03% at a standard deviation of 19.23% and a range of 91.76% with -44.67% as the minimum value and 47.09% as the maximum value.

5.4.2 Coefficients and Regression Equation

Table 6, summarizes the coefficients from the robust regression and the standard regression including their standard error. The robust regression generated lower values compared to the standard regression. Under the robust regression, the economic effect exhibits the highest coefficient value of 2 and the rest of the variables reflect a value close to 0. The probability of financial distress, change in employment rate and the economic effect details a positive relationship with the dependent variable (CFD), while the change in reinvestment rate, holding of liquid assets, leverage, Tobin Q and the entity's size.

Table 6: List of robust regression and standard regression coefficient

Independent Variable	Robust Regression Coefficient	Standard Error	Standardized Regression Coefficient
Intercept	-0.0054	0.0672	0
delta_EMP	0.0031	0.0107	0.0725
delta_INV	-0.0003	0.0016	-0.0243
GDP	2.0042	1.1737	0.2153
LA	-0.002	0.0015	-0.1681
LEV	-0.0675	0.0974	-0.0936
PROB	0.0025	0.0076	0.0413
Q	-0.0027	0.0193	-0.0335
SIZE	-0.0068	0.0041	-0.2051

As illustrated in the robust model equation below:

$$CFD = 0.0031\ \Delta EMP - 0.0003\Delta INV + 2.0042\ GDP - 0.002LA - 0.0675LEV + 0.0025PROB - 0.0027Q - 0.0068SIZE - 0.0054$$

For 1% increase in employment policy there is a 0.0031% increase in the cost of financial distress while for a 1% increase in the change in reinvestment rate, there is a corresponding 0.0003% decrease in the cost of financial distress. For holding liquid assets and leverage, the robust model reflects a decrease of 0.002% and 0.0675% respectively in the cost of financial distress for every 1 unit increase in liquid assets and leverage. The probability to financial distress exhibits a 0.0025% decrease in financial distress costs for every 1unit increase.

The reaction variables: economic effect, Tobin's Q ratio and entity size, demonstrates an increase of 2.0042% in CFD for every 1% increase in economic effect, a decrease of 0.0027% in CFD for 1 unit increase in Tobin's ratio, and a decrease of 0.006% in CFD for every 1 unit increase in the entity's size.

5.4.3 Statistical significance of the variables

Table 7 and Appendix D, summarizes the results of the t-test of statistical significance. The slopes of variables in the investigation was conducted at decreasing confidence level: alpha 5%, alpha 10%, alpha 20% and alpha 30% that is 95% confidence level, 90% confidence level, 80% confidence level, and 70% confidence level respectively.

The power of the test increases with a decrease in confidence level. The table also states the probability levels, t-value and the power of the test. Evidence show probability levels of the slope of the variables in the model being greater than zero, thus the model is appropriate in determining significance levels of each variable.

Table 7: Regression significance level t-test results

Independent Variable	Regression Coefficient b(i)	Standard Error Sb(i)	T-Value to test H0:B(i)=0	Prob Level	At alpha= 5%		At alpha=10%		At alpha= 20%		At alpha=30%	
					Reject H0	Power of Test	Reject H0	Power of Test	Reject H0	Power of Test	Reject H0	Power of Test
Intercept	-0.0054	0.0672	-0.081	0.936	No	0.0507	No	0.1011	No	0.2014	No	0.3016
delta_EMP	0.0031	0.0107	0.292	0.7713	No	0.0595	No	0.1141	No	0.2187	No	0.3201
delta_INV	-0.0003	0.0016	-0.194	0.847	No	0.0542	No	0.1062	No	0.2083	No	0.3089
GDP	2.0042	1.1737	1.708	0.0932	No	0.3894	Yes	0.5173	Yes	0.6619	Yes	0.7494
LA	-0.002	0.0015	-1.332	0.1881	No	0.2583	No	0.3728	Yes	0.5209	Yes	0.6229
LEV	-0.0675	0.0974	-0.693	0.4914	No	0.1046	No	0.1783	No	0.3007	No	0.4065
PROB	0.0025	0.0076	0.325	0.7463	No	0.0618	No	0.1175	No	0.2232	No	0.3249
Q	-0.0027	0.0193	-0.141	0.8881	No	0.0522	No	0.1033	No	0.2044	No	0.3048
SIZE	-0.0068	0.0041	-1.649	0.1046	No	0.3677	No	0.4945	Yes	0.6408	Yes	0.7311

The intercept, change in the employment rate, change in reinvestment rate, leverage, probability of financial distress and Tobin Q result in a low statistically significant level at all investigated levels of confidence, thus the linear relationship with the cost of financial distress is questionable. Probability levels of variables with a questionable linear relationship with CFD ranges from 0.74 to 0.88. The economic effect independent variable details a statistical significance level that is rejected at 95% confidence level but not rejected at confidence levels 90%, 80% and 70%, thus the variable has a linear influence on the cost of financial distress. The holding of liquid asset and the entity's size variables elucidates linearity at 80% and 70% confidence level. Leverage even though not shown above, demonstrates a linear relationship confidence level 50%.

5.4.4 Statistical significance of the Model

Results from the analysis of variance of the regression model summarized in Table 8, illustrates a model where the variation of the explained observation is larger than the unexplained observations by a value of 1.063 F-ratio, which is subjectively low. This was consistent at different confidence levels. The probability of the slope of the model being equal to zero is rejected because the probability of the slope is 0.4015, which is greater than zero. Thus the model is significant in explaining the financial distress cost through the variables: change in the employment rate, change in reinvestment rate, leverage, and probability of financial distress, Tobin Q, size and economic effect.

Table 8: Analysis of variance regression model summary

Analysis of Variance Section										
Source	DF	R 2	Sum of Squares	Mean Square	F-Ratio	Prob Level	Power -5%	Power -10%	Power -20%	Power -30%
Intercept	1		0.0250	0.0250						
Model	8	0.1298	0.3122	0.0390	1.063	0.4015	0.4452	0.5827	0.7334	0.8208
Error	57	0.8702	2.0922	0.0367						
Total(Adjusted)	65	1	2.4044	0.0370						

5.5 Time Series

From a time series perspective data was investigated from the first year the company could not meet their financial obligations.

Figure 11, illustrates the general behavioural trend of the costs of financial distress as decreasing with time. This trend can be explained by a linear relationship of y= -0.0486 +0.0289 with a negative gradient and R-squared equal to 0.1164. The costs of financial distress start out at 17% on the first year the company cannot meet its financial obligations, they then decrease to second year to 5.7%. On the third year CFD increases exponentially to 23.6%. From year three throughout to year six most companies listed in the JSE show recovery through reduction in financial distress costs. If a company experience distress for more than 6 years, figure 1 demonstrates a rapid increase in CFD by 81.3%.

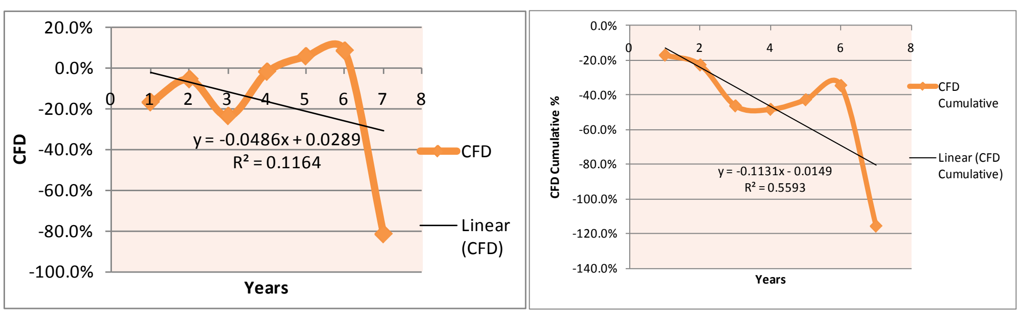


Figure 11: Time series trend and cumulative CFD through time

Figure 12, demonstrates a general increased reinvestment rate of companies under stress. This trend is elucidated by a linear relationship y= 5.0256x – 42.66 with a positive gradient and an R squared value of 0.7103. JSE listed companies in financial distress demonstrate negative liquid ratios. The first year a company cannot meet its financial dues, the entity reflect poor reinvestment rate of -31%.

From year 2 to year 4, this value decreases from -32% to -37% with year 3 showing an anomaly of -27% reinvestment rate. From year 5 to year 7, the reinvestment rate shows a positive turn of -17.7% in year 5 to -4.16% in year 7. The cost of financial distress leads the change in reinvestment rate and CFD is inversely proportional to the .change in reinvestment rate.

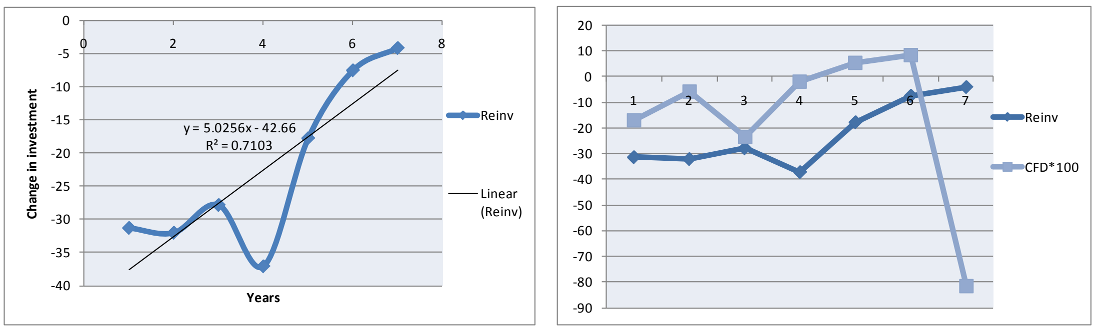


Figure 12: Change in reinvestment policy time series trend

Figure 13 exhibits a generally positive trend of a distressed entity with holding liquid assets, thus the company's ability to meet its short term obligation deteriorates with time. This trend is summarized by the linear relationship y=4.0098X- 73.806 at an r-squared value of 0.1036. The holding of liquid assets leads the CFD. From year 1 to 5, the holding of liquid assets increases at an average value of –55.40% and then decreases from year 5 to 7 at an average value of -63.64%.

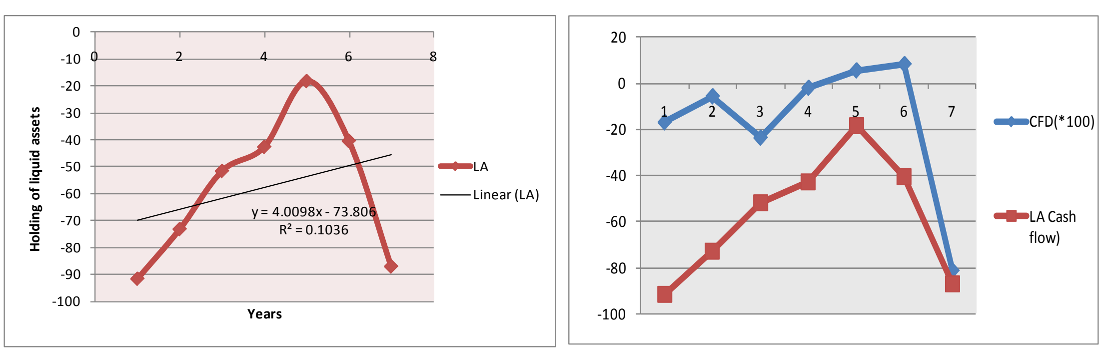


Figure 13: Effect of the holding of LA time series investigation

Figure 14 details the shrinking in the company's size as the company goes through a financial distress period. The tendency is summarized by the linear relationship y=-0.386x + 8.6717 at an r-squared value of 0.1925. From year 1 to year 5, there is a gradual increase in the size of the company in distress. With this increase the rate at which the size of a JSE listed company in distress changes is -0.37% in the first three years in distress and then it increases to 10.78% in year 4 and slows down to 7.80% in year 5. From year 5 to 7, an entity's size rapidly decreases at a rate of 22.72% in year 6 and 42.46% in year 7 respectively. The gradual increase in size for the first 5 years before a drastic decrease in entity size shows that size lags the other effects of financial distress.

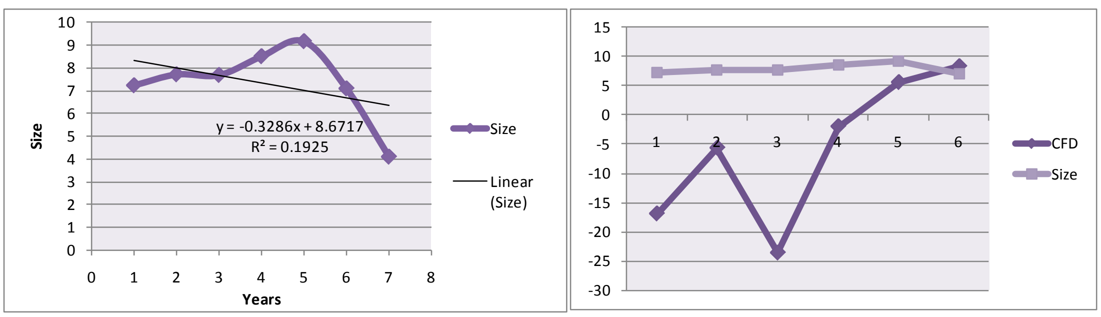


Figure 14: Effect of the size of an entity time series investigation

Figure 15 demonstrates a gradual decreased in the Tobin Q value within the distressed period. This trend is elucidated by a linear relationship y= -1.979x +17.039 and an R squared value of 0.1002. The Tobin value is generally stable between 0 and 5 within the 7 years of distress with the exception of the anomaly in year 3 were it shoots up to 38. Tobin's Q ratio is consistent with CFD in real time and inversely proportional to CFD. As the Tobin ratio increases the cost of financial distress decreases and vice versa.

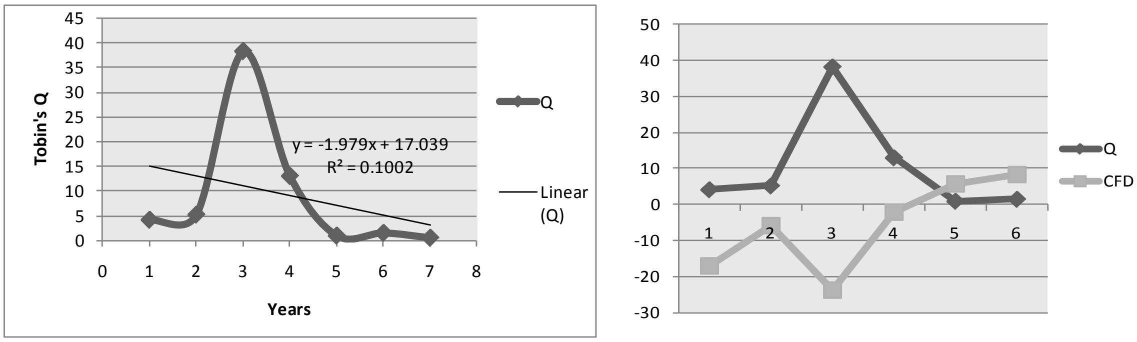


Figure 15: Tobin's Q ratio time series investigation

Figure 16, illustrates the general behavioural trend of leverage as decreasing with time. This trend can be explained by a linear relationship of y= -0.0089x +0.1864 with a negative gradient and R-squared equal to 0.0557. The first year the company cannot meet its financial obligation the company's leverage is 0.19 and it increases slightly to 0.224 in year 2. The company remains at this stable leverage value until year four. In year 5, the leverage values decrease slightly to 20 and steeply decrease to 0.09 in year 6 before increasing to 37 in year 7, thus increasing the debt. Figure 8, also reflects that leverage leads CFD by two to three years.

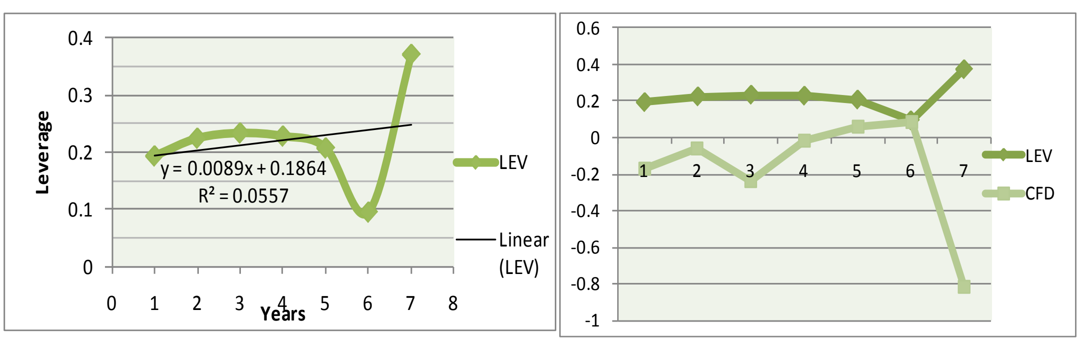


Figure 16: Effect of the leverage through the period of financial distress

Figure 17, reflects the general inclination of the probability is decreasing with the time spend in distress without getting bankrupt. This trend can be explained by a linear relationship of y= 1.1506x -8.6979 with a positive gradient and R-squared equal to 0.6303. In year one, the entity shows a z-score value of -9.75 which steeply increases to -7.15, -2.90, -2.11 and 1.36 in years two, three, four and five respectively. There is then an increase in the probability of default through a decrease of the z-score in year 6. In year 7 the company either defaults or recovers through an increase in the z-score to -2.10.

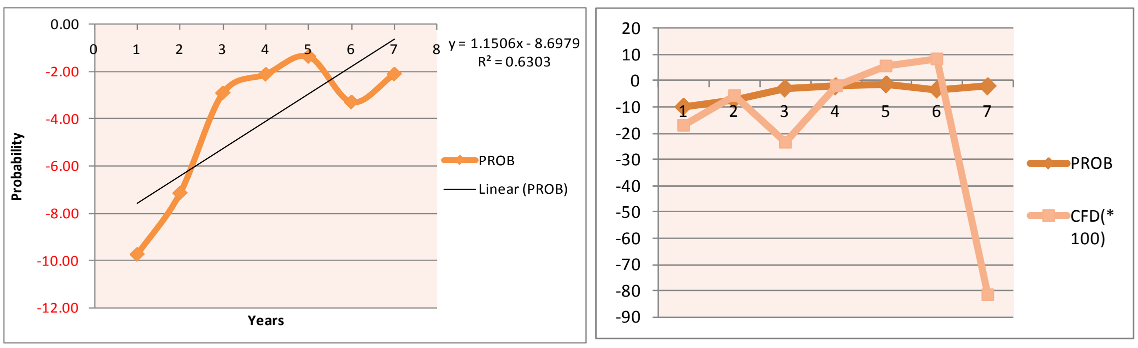


Figure 17: Effect of the probability of financial distress for the period of financial distress

Figure 18, exhibits the general behavioural movement of the economic effect as increasing during the distress period. The movement shows a gentle slope at a value of 0.03. This trend can be explained by a linear relationship of y= 0.0012 +0.0285 with a negative gradient and R-squared equal to 0.3715. GDP lags the cost of final distress.

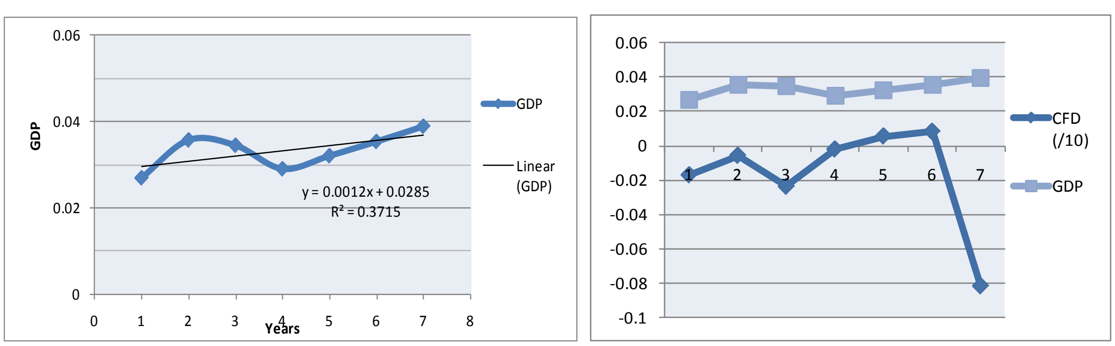


Figure 18: Effect economic activity of a company under financial distress

Figure 19, demonstrates a generally decreased change in employment rate of entities under financial distress. This trend is elucidated by a linear relationship y= 0.0892x + 0.5887 with a negative gradient and an R squared value of 0.3221. The first year the company cannot meet its financial dues, the entity reflects a high retention level of 88.6%. In year two the retention of employees decreases to 13.36% and then increase to 37.7% in year 3. From year 4 to year 6, retention becomes negative, there is a decrease in the number of employees. In year 7, the employee retention rate increases to 33.52%. The cost of financial distress is inversely proportional to financial distress.

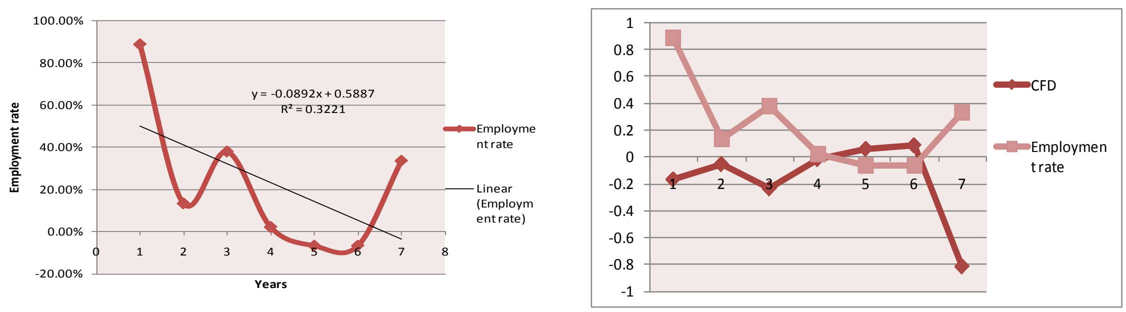


Figure 19: Effect of the change in employment policy time series investigations

6 Discussion

The cumulative trend in figure 11, reflects how the costs of financial distress of JSE listed companies accumulate through time before liquidation takes place. This trend provides empirical evidence that financially distressed firms lose significant market share to their healthy counterparts in industry downturns. The average costs of financial distress amounts to 16.7% annual loss as percentage of market value. This annual loss is similar to Chen and Merville (1999) distinctive pattern of an average annual loss as a percentage of market value of 10.3% in Taiwan. Sanz and Ayca (2006) also concluded that a company's value decreased by 25% to 26% in the total period in distress.

Andrade and Kaplan (1998) results on 31 highly leveraged transactions demonstrated that indirect financial distress costs may be in the range of 10–17% which is also in the range of the JSE listed company findings. The average loss in market value in South African JSE listed distress companies is an overestimate compared to Elkamhi *et al.*(2009) findings of less than 1% and Almeida and Philippon (2007) risk-adjusted CFD value of 4-5% market value in the United States of America. The difference might be due to the geographic location, government regulations, and growth rate or development stages in a country. The anomaly in figure 11 on the seventh year of distress of the value (81% loss in market value), eludes to the fact that the companies that are still in distress after these 7 years are heading for bankruptcy and recovery will be impossible, thus the period one stays in distress influences the total CFD. The anomaly echoes the findings by Yen and Yens' (2008) study of 104 financially distressed companies in the Taiwan Security Exchange during the period from 1998 to 2004 companies that have registered an average of 62.99% reduction in shareholder wealth at a 0.01 significance level 20 days after announcing the distressed condition.

Of the companies investigated by Yen and Yen (2008), it was observed that the 81% loss in JSE listed companies correspond to the third group in their results. This group is a category of delisting companies that registered the largest loss of 86.93% market value. The other two groups of companies: those who have suspended trading and those maintaining normal trading registered a loss of 76.95% and 27.94%. From the above market share losses, the disruption caused by the financial distress generally have an adverse effect on the organisation's ability to compete in the marketplace. Its customers, suppliers, and others will be less inclined to do business with a distressed company. It also confirms that one can indeed state that indirect costs of financial distress are substantially underreported and not understood. Development stages in a country have a quantifiable effect on the cost of financial distress, thus costs of emerging countries and third world countries differ greatly from developed countries.

It also shows that employing developed country models and findings as proxy of South African companies is not an appropriate technique. The negative increased CFD confirms Sanz and Ayca (2006) conclusion that distress costs grows faster as the crisis worsened in their Venezuelan investigation of CFD.

The model results that contributes to the indirect costs of financial distress is described below:

6.1 Investment Policy

The negative relationship as illustrated in the regression cross-sectional results and the time series between CFD and the reinvestment rate confirms that JSE listed companies underinvestment have a stronger effect than overinvestment in financial policies.

As reflected in figure 12, the period from 1 to year 4 exhibits a decrease in reinvestment rate will be due to the minimal availability of earnings to redistribute at the end of the financial year, or the company continues paying shareholders dividends as a camouflage of the distressed state. From year 5 to 7, a change in dividend policy might have occurred and more earnings being reinvested into the company, or on the other hand the company might be showing signs of recovery. The anomaly in year 3 of -27% reinvestment rate gives evidence of managerial response to mitigating the distressed state through an increase in reinvestment rate. This attempt was temporal as the decrease in reinvestment rate continued into year 4.

On average the reinvestment rate of JSE listed companies in the stressed state is -37% in the first four years after they cannot meet their financial obligations and -9.8% in the last three years of distress, provided they are in the state of distresses for a period of 7 years. From a cross-sectional view for every 1% decrease in reinvestment rate there is a corresponding 0.0003% increase in reinvestment rate at a probability level of 0.847 employing the robust regression and a 0.0243% increase in reinvestment rate employing the standard regression. This is negligible compare to the 1.728%, 1.71192% and 2.445% increase in CFD in the USA, United Kingdom and Germany (Pindado, 2009). This difference might be due to the difference in the variable definition of the change in investment policy.

JSE listed distressed companies show another different relationship characteristic compared to international findings conducted in USA, UK and Germany (Pindado, 2009). JSE listed companies in distress show a in lag reinvestment rate compared to CFD. This relationship reflects that managerial decisions on investment are a response of the effect or increase in financial is distress, thus increase in CFD encourage divesture instead of vice versa as stated by Pindado (2009).

With this evidence in light, reinvestment is not necessarily a suitable variable in calculating financial distress cost due to the one year lag. This is reinforced by the result that the change in investment policy is not statistically significant to predict CFD in South African JSE listed companies. With that noted, the change in investment rate can be used as a reaction variable in calculating the cost of financial distress.

6.2 Holding of Liquid Assets

The holding of liquid assets ratio leads the CFD trends, hence it is an appreciate variable in determining the cost of financial distress. The evidence is supported by robust regression results that gave the holding of liquid assets a positive significance test at confidence level 70% and 80%. The inverse relationship that resulted from the model demonstrates that as an organization continues in a distressed state managerial decisions lead to a global decrease in liquid assets. This confirms Pindado (2009) findings that the holding of liquid assets are negatively related to the cost of financial distress, which implies that insolvent companies can take advantage of holding larger stocks of this kind of assets.

JSE listed companies in financial distress demonstration of negative liquid ratios reflects negative working capital in an organization. At face value one might think that a company's efficiency is extremely high, but for a company to have a negative working capital and be very efficient it needs to generate cash quickly in such a way that products are delivered and sold to customers before the company pays for them. The above is highly unlikely, thus the negative liquid ratio illustrated by the JSE distressed companies is a sign that bankruptcy is looming. The increase in liquid assets from year 1 to 5 (figure 13), demonstrates how companies tend to increase their cash component of their balance sheet to fund capex or through the reduction of current liabilities, this does not seem probable because at this point the company cannot pay its financial obligations.

The cash component is utilized to assist the company mitigate the effect of financial distress. The increase in cash flow suggests that the organization is forced to focus on short term goals. In increasing the liquid assets and an increased CFD reflects how organizations usually waste their liquid assets to covering losses, instead of allocating them to profitable projects, thus leading to organizations bearing an opportunity cost due to the lower return on these kinds of assets. The decrease in the liquid assets ratio from year 5 to 7 suggests that the cash either runs off or the company has no more property to sell. Either way, this proves that the financial health of the company gets worse the longer the company stays in distress. Compared to Pindado (2005) liquid ratio coefficient of -1.0255, JSE listed companies in distress resulted in coefficient magnitudes of -0.002 at a probability value of 0.1881for the robust regression and -0.1681 for the standard regression is extremely low. The low coefficient number in South Africa indicates that most of account receivable of the companies is not liquid. From the Indonesian Stock Exchange financial distressed model the liquidity ratio was found to have a positive coefficient of 0.001831 at a probability level of 0.0201(Pranowo et al., 2010), which is similar to the JSE listed companies magnitude but different in sign. The fundamental difference in these coefficients might be due to the economic standing of developed and developing countries.

6.3 Size of Entity

Even though the coefficient of size in the robust regression exercise, exhibits a low value of -0.0068 at a low probability value of -0.1046, size was found statistically significant in the model estimates at confidence levels 70% and 80% showing the influence of size on CFD. Due to the significance of size in the model, one should control for it during determining CFD. The low magnitude of the coefficient infers that distressed JSE listed companies experience low revenue levels during the distress period.

From an African perspective Iwarere and Akinlenye (2010) in Nigeria determined the mean value of the company's size to be 4.12 compared to the 7.94 mean value of JSE listed companies. This shows that the revenue of JSE listed companies is greater than that of Nigerian listed companies during the distressed period.

Size reflected a negative relationship with CFD, showing that larger firms deal easily with financial distress than smaller ones. As reflected in figure 14, the slowdown in the rate increase in company size in year 1 to three reflects the impact of CFD on the entity. When managers recognize this they tend to react in increase in sales, thus the increase in the rate of an entity's size. From year 5 to 7, the company can no longer resist the impact of financial distress thus the company size decrease exponentially and the rate of that decrease is enormous (22.7% and 42.46%).

6.4 Tobin's Q Ratio

Tobin Q which was employed to reinforce the need to control investment decisions exhibits a negative relationship with the cost of financial distress. In figure 20, Tobin Q ratio leads the change in investment policy and is inversely proportional to the reinvestment policy. This makes it a good proxy in reinforcing the reinvestment rate relationship with CFD. Similar to the reinvestment rate, Tobin Q ratio exhibits a low significance level.

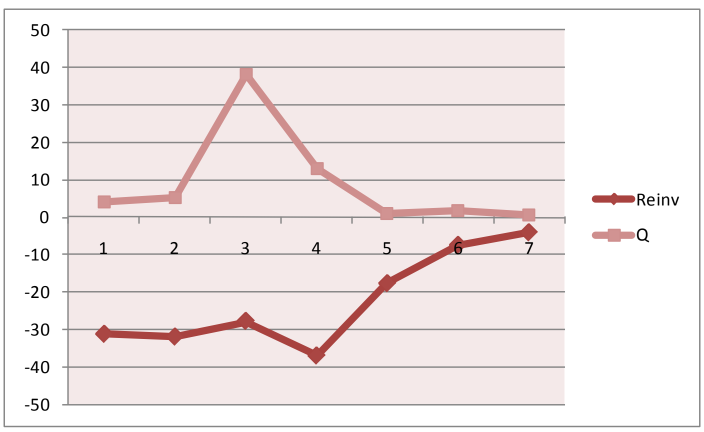


Figure 20: Change in reinvestment policy verses Tobin Q

In figure 15 Tobin Q ratio's response mirrors that of CFD, showing a direct relationship between CFD and Tobin Q. As the market value added by a distressed entity increases during the financially distressed period the reinvestment rate of an entity decreases and hence the CFD also increases. This shows that companies' market value added in the distressed period is short lived as a vicious cycle arises.

From the robust regression Tobin Q ratio resulted in a coefficient value of -0.0027 and -0.0335 from the standard regression results. The magnitude of the standard regression results is similar to the findings of Pindado (2008), of the coefficient value of -0.04511. The negative sign of the coefficients illustrates that the existence of good investment opportunities mitigates the effects of CFD.

6.5 Leverage

In the both the regression and time series report, CFD exhibits a negative relationship with the coefficient of leverage. This relationship supports the benefit of leverage in increasing performance and reducing financial distress, thus leverage is a significant variable for calculating CFD. The statistical significance is also illustrated by the t-test for statistical significance that recommends leverage as linearly related to CFD at 50% confidence level. This is a low confidence level, and might be due to South African JSE companies having a low sample of distressed companies in the past twenty years. The significance of the variable reinforces the use of highly leveraged companies in determining CFD by Halpern et al. (2009) and Kaplan (1998).

From figure 16, in the first 5 years the company tends to freeze the leverage level. Leverage then eventually decreases because the entity avoids undertaking most long-term opportunities and focus on fulfilling previous commitments that are not already inescapable.

This reinforces George and Hwang's (2007) findings in the study of capital structure that organizations choose less leverage if their operations expose them to high financial distress costs.

This reduction in debt might be due to funders not encouraged fund distressed companies since their interest cover ratio is negative. The company might fund itself using equity, this results in the lowering of the leverage ratio as reflected in year 6. The entity then gains capacity to approach funders, which lead to an increase in debt and thus the leverage as illustrated in year 7. The acts of immediate funding after one period of decreased leverage becomes suicide for an entity and thus enter a delisting or liquidation phase. This reflects the costs of debt instead of its benefit as generally accepted in financial literature. Figure 8, show that leverage leads CFD by two to three years. This shows the lagging effect of the CFD which is not recognized easily by the time delay. From the results, funding institutes are cautioned to investigate the sudden lowering of leverage as well as the funding history of an entity. On an entity level, a South African company is advised not to enter debt obligations straight after a stressed period since they are not certain if they are completely out of financial distress.

6.6 Probability of Financial Distress

The resultant cost of financial distress model reflect a positive relationship between the cost of financial distress and the probability of distress, that is, the higher the probability of distress, the higher the CFD. Through the distressed period the longer a company stays listed in the JSE, the lower the probability of distress. The former is displayed in figure 17, were the average probability of distress is -4.09. This means that the company that experiences distress has a 400% chance of incurring financial distress costs.

From the regression results the coefficients determined are low (0.0025 from the robust regression and 0.0413 from the standard regression) compared to 0.5 from Pindado's model (Pindado, 2008). This difference might be due to the methodology in determining the probability of financial distress, where this research employed a South African orientated model, Pindado (2008) applied a customized personal version. The significance level of this variable reflects concern due to its common use in the research by Elkamhi *et al.* (2009), Molina (2005), Almeida & Philippon (2007), Pindado (2009) and Leland & Toft model (1996).

6.7 Economic Effect

The effect of the economy on the individual performance lags the cost of financial distress, thus an appropriate reaction variable for CFD model.

Its selection as a reaction variable is reinforced by its coefficient's positive statistical significance level at 90%, 80%, and 70% confidence level. This also reflects the effect of economic shock on the cost of financial distress. And due to this high significance level one need to adjust for it as Elkamhi *et al.*(2009) attempted to do in their risk adjusted model. This brings one to conclude that Almeida and Philippon (2007) risk adjusted model without economic shock accounted for is invalid for South African listed companies.

6.8 Employment Policy

The probability of financial distress cost from a cross sectional view exhibits a positive relationship with CFD. This is different from Pindado's (2009) finding in the USA but the same as in UK and Germany. The positive relationship also differs from the time series findings of a general decrease in employment rate through time. This ambiguity is a result of employment policy dependence on the institutional context. The statistical insignificance of the coefficient of the variable might be due to this ambiguity.

The decrease in the net number of employees (negative employee retention) in figure 19 reflects a restructuring exercise. The negative trend reflects that employees and potential employees feel less secure working for it because a company in distress is less likely to be able to honor its commitments. This reality makes others less inclined to rely upon its promises.

Thus the distress company's ability to attract and hold the most suitable employees declines as the distressed condition worsens and the CFD increases. Titman (1994) alludes to these results by stating that a financially distressed firm may lose customers, valuable suppliers, and key employees. In year 7, the retention rate of employees increases hence a probable sign of financial recovery by the entity.

7 Conclusions and Recommendations

The idea behind the study was to answer the question: how costly is financial distress and what is an appropriate model in quantifying these costs? The objective was to find a sample of companies that were purely financially distressed and then to follow those through the resolution of the distress, to see what happened to them and to quantify how costly those things were. The exercise led to the conclusion, that the average costs of financial distress for JSE listed companies is approximately 16.7% of the entity's market value per annum.

Government regulations, growth rate or development stages in a country also affects the annual financial loss per annum, with developed countries exhibiting lower financial distress costs than developing countries due to legal assistance in this regard. The longer an entity stays in distress the greater the annual CFD, which can amount to 81% in magnitude.

South African CFD results of JSE listed companies confirm that one can indeed state that indirect costs of financial distress are substantially underreported and not understood. Most managerial interference to minimize the CFD often worsens the distress state. The financial health of the company gets worse the longer the company stays in distress.

Based on the probability of financial distress occurring and ex-post distress costs controlling for economic shock and size of the company a South African specific model was formulated that illustrates:

- A negative insignificant relationship with the reinvestment rate of -37% annually and the reinvestment rate lags the CFD.
- A negative significant relationship of a low coefficient value with the holding of liquid assets, whereby the liquidity ratios are negative within the distressed period.

- An inverse significant relationship with size, concluding that size is an appropriate reaction factor in the CFD. The effect of size is not immediate but can be realized 3 years into the distressed period.

- Tobin Q ratio in inversely related to reinvestment policy and CFD. Tobin Q ratio is a good proxy in reinforcing the effect of the investment policy decisions. Tobin Q ratio also illustrated that a good investment opportunities mitigates the effects

- A negative significant relationship with the coefficient of leverage. The relationship with leverage demonstrates the benefits of leverage to a certain point before creating an irreversible liquidity dilemma.

- A positive relationship with the probability of distress, whereby the probability of distress averages -4.09 for a South African publicly listed company in distress.

- A positive significant relationship with economic shock. This brings one to conclude that in calculating the CFD, one needs to factor in economic shock.

- A positive relationship with employment policy; the higher the CFD the higher the loss in employee. South African listed company's employment policy was found to be entity specific.

The model can be explained by the equation

$$CFD = 0.0031\,\Delta EMP - 0.0003\Delta INV + 2.0042\,GDP - 0.002LA - 0.0675LEV +$$

$$0.0025PROB - 0.0027Q - 0.0068SIZE - 0.0054$$

Where ΔEMP is the change in the employment policy, ΔINV is the change in investment policy, GDP is the economic effect, LA is the holding of liquid assets, Lev is the leverage, PROB is the probability of financial distress, Q is the Tobin's Q ratio and SIZE the entity's size.

From the research conducted it is recommended that one examines the influence of cash flow ratios in the model as companies' burn out cash to fund their mitigation solutions. Due to the model only focused on a linear relationship, one can conduct a non-linear regression to explore possible relationships that could not have surfaced in a linear situation. It is recommended that one can expand the focus of the research to be industry specific as this might have an effect on the economic effect on the model.

To expand the academic investigations on CFD, researcher can focus on investigating the effect of human influence on financial statement of financial distressed entities, looking at the distribution of the first three digits. This will also assist in determining fraudulent entity's who overstate or understate their financial standing. Another future study can be on the influence of a country's legal system on the cost of financial distress, a research focusing on an optimal trade-off between the tax benefit of debt and CFD, thus enhancing the understanding of the optimal capital structure.

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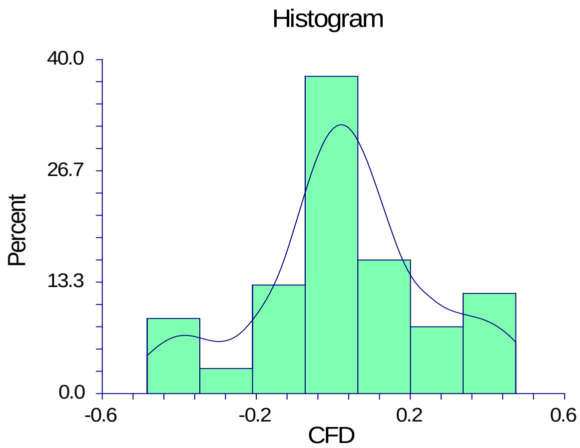
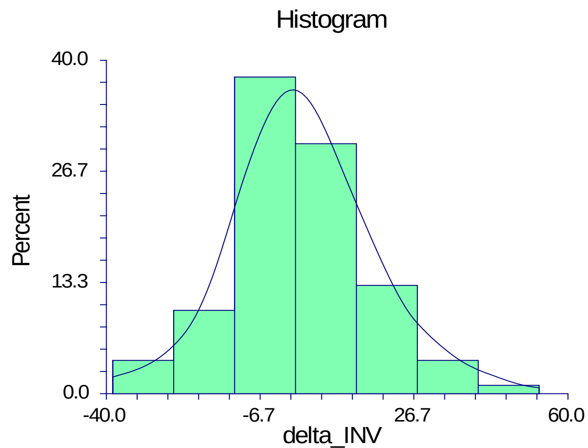
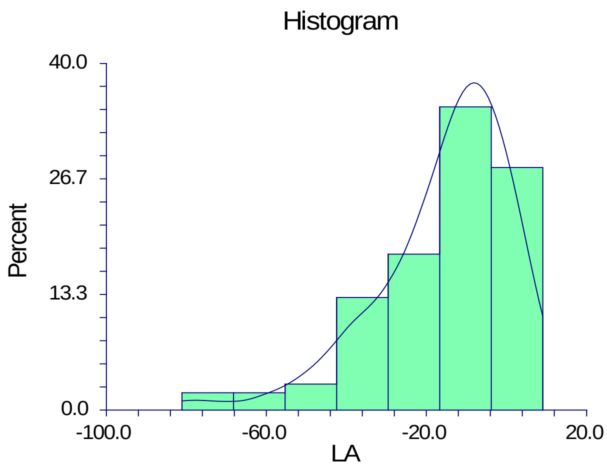
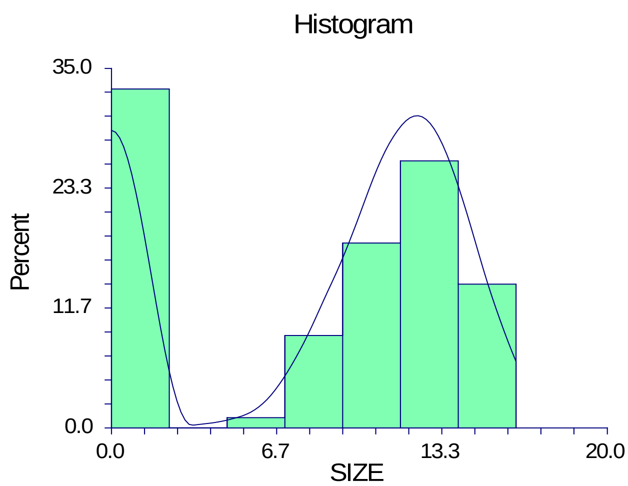
9 Appendices

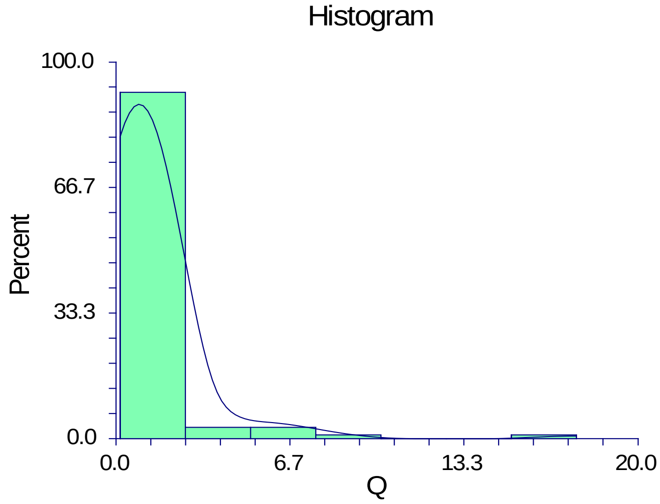
9.1 Appendix A: Histograms

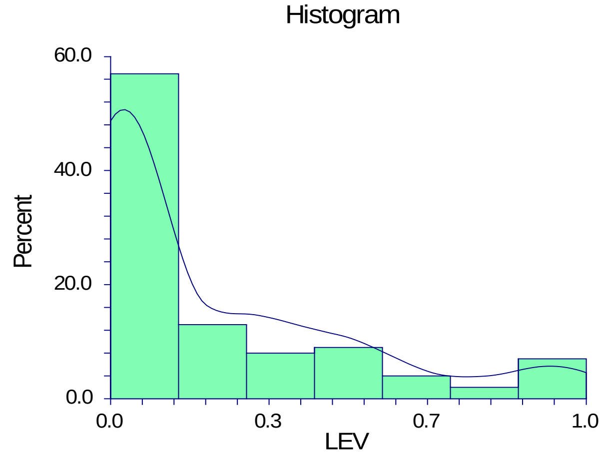


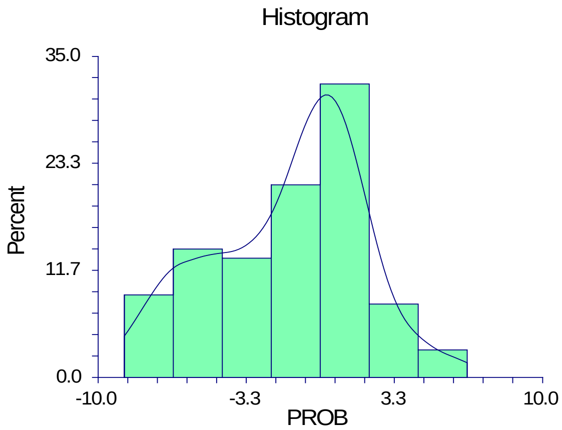








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11.7
0.0
Percent
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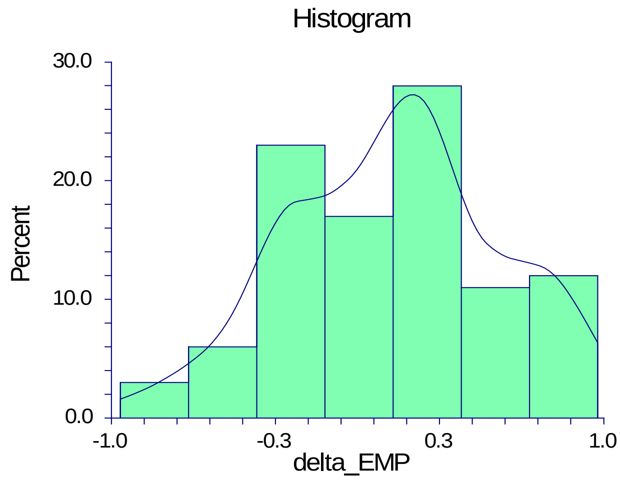
-3.3
3.3
10.0
PROB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0.0
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-0.3
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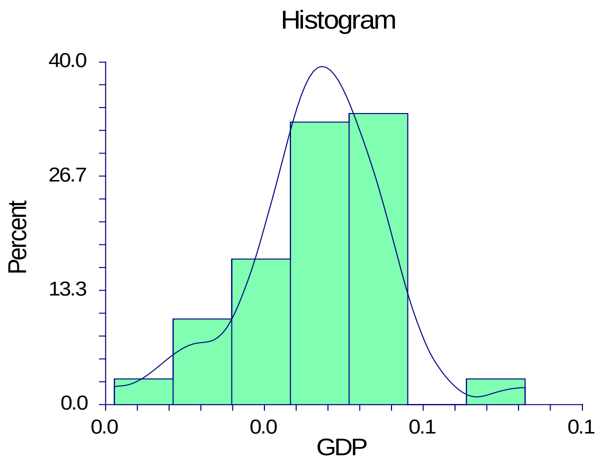
1.0
delta_EMP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0.0
Percent
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0.0
0.1
0.1
GDP

9.2 Appendix B: Tbar summary

XBar-R Chart Report
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Database
Variables CFD

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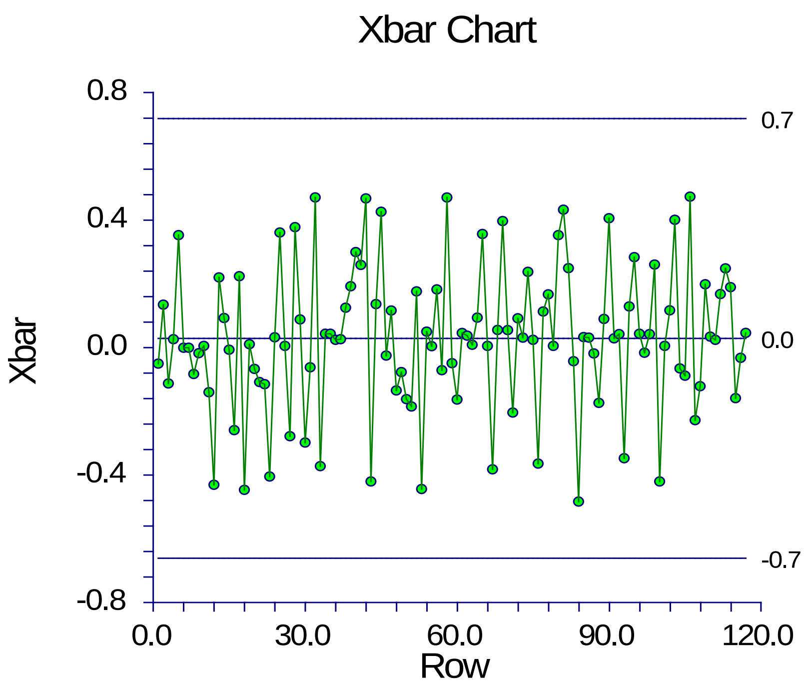

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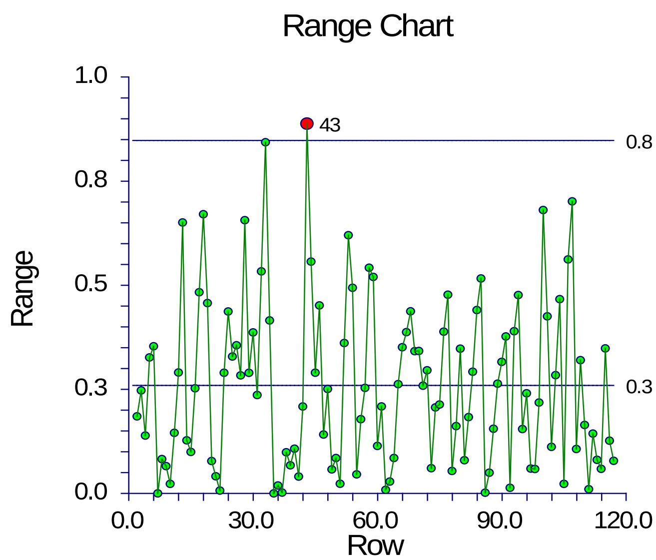

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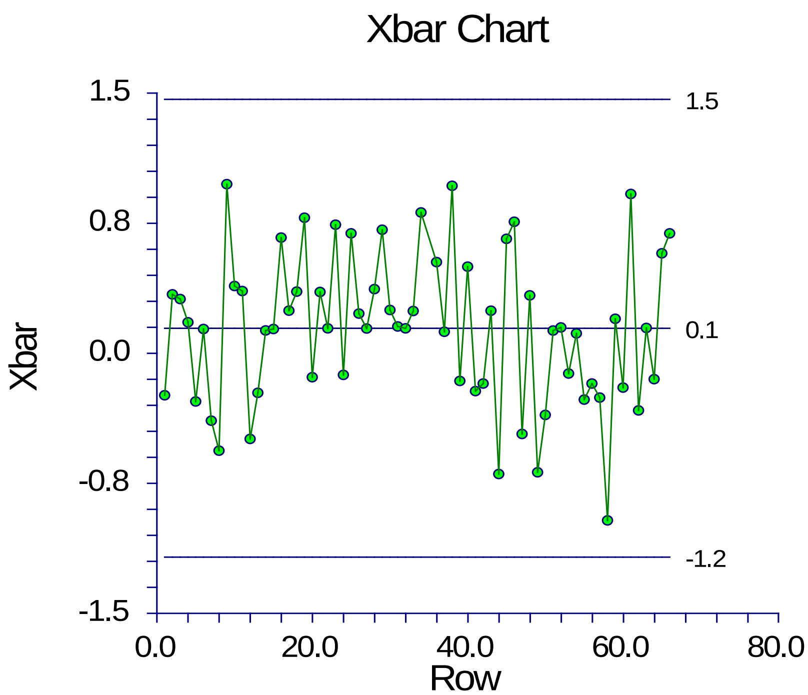

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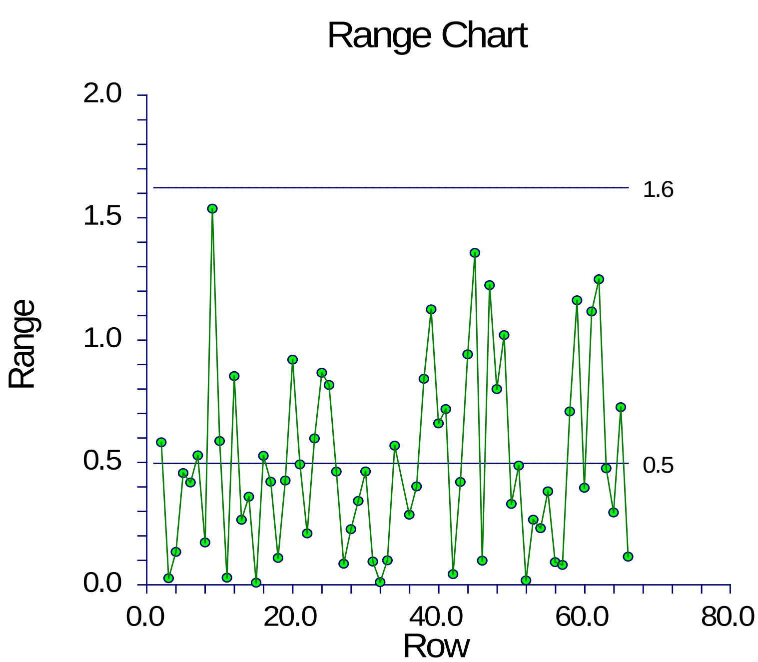

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Database
Variables GDP

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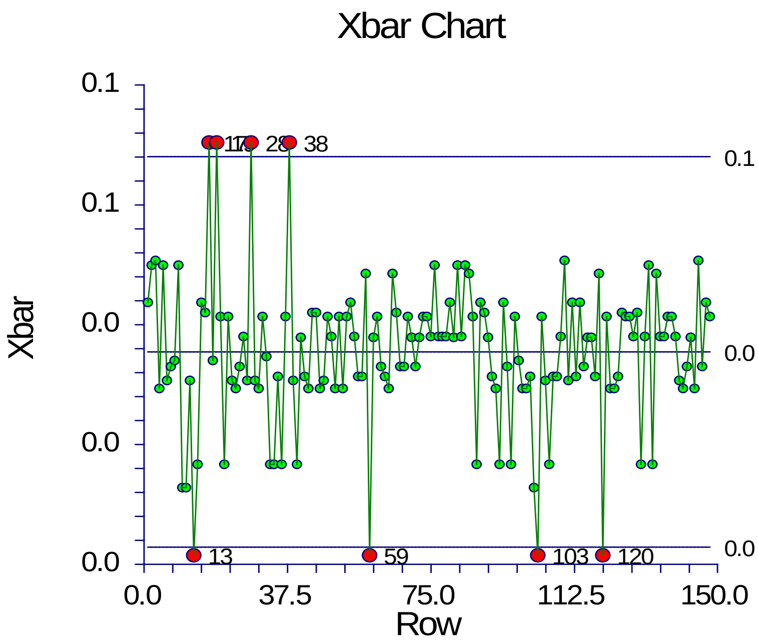

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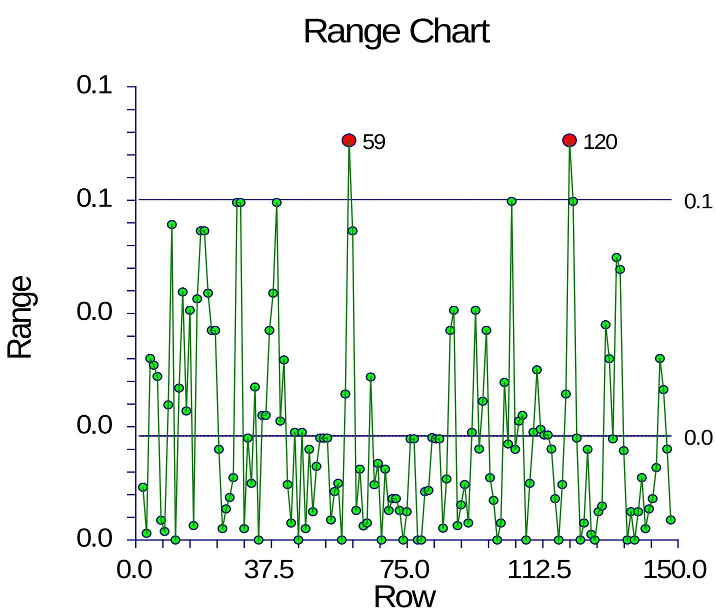
Database
Variables GDP



XBar-R Chart Report

Page/Date/Time 4 27/10/2010 20:42:55
Database
Variables GDP

Histogram Section for Rows 1-148

XBar-R Chart Report
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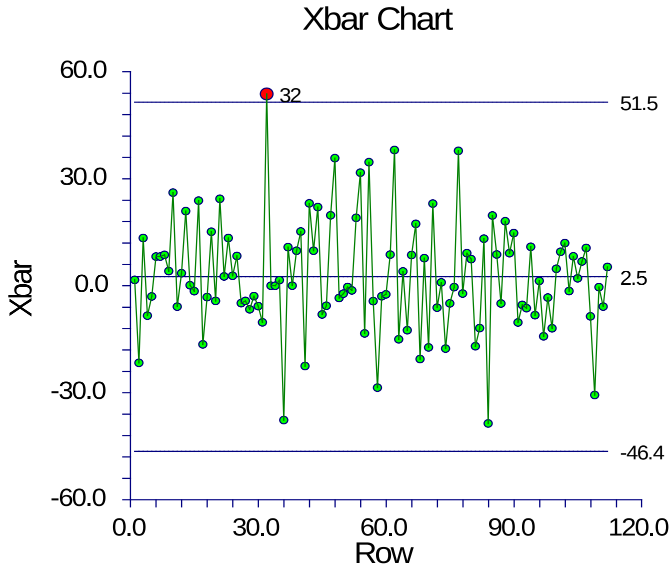
Database
Variables delta_INV

Chart Section for Rows 1 - 112



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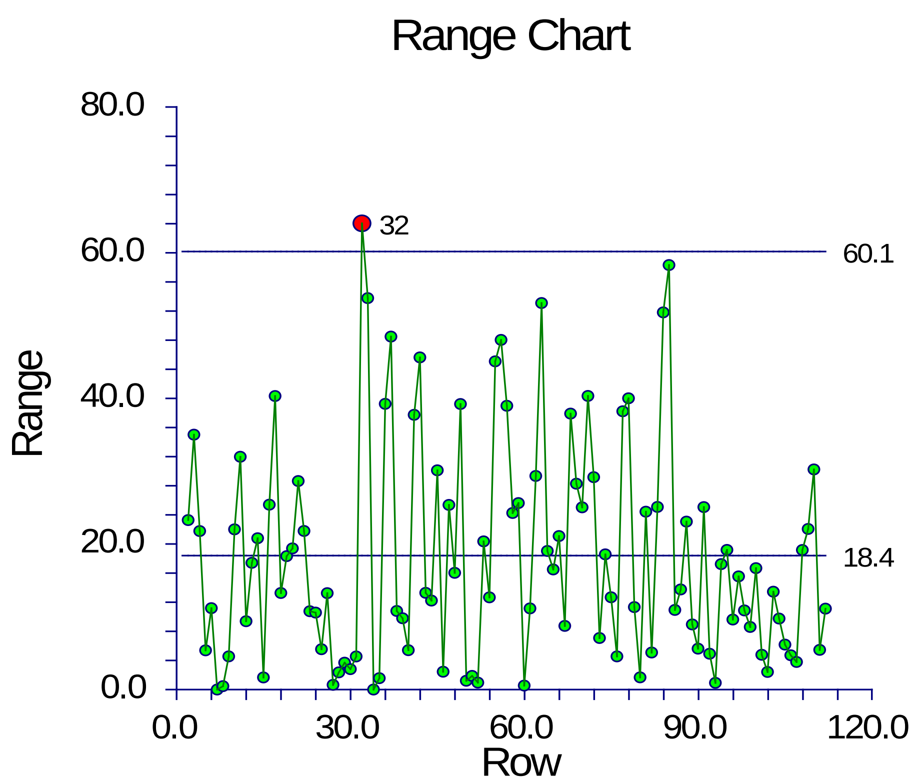

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Database

Variables LA

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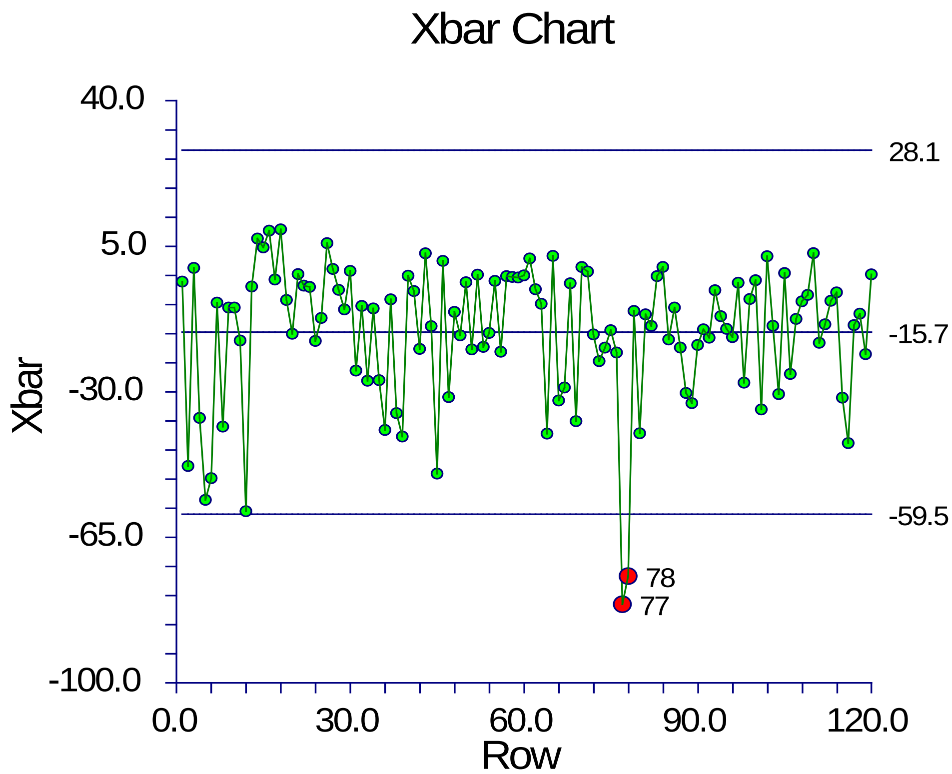

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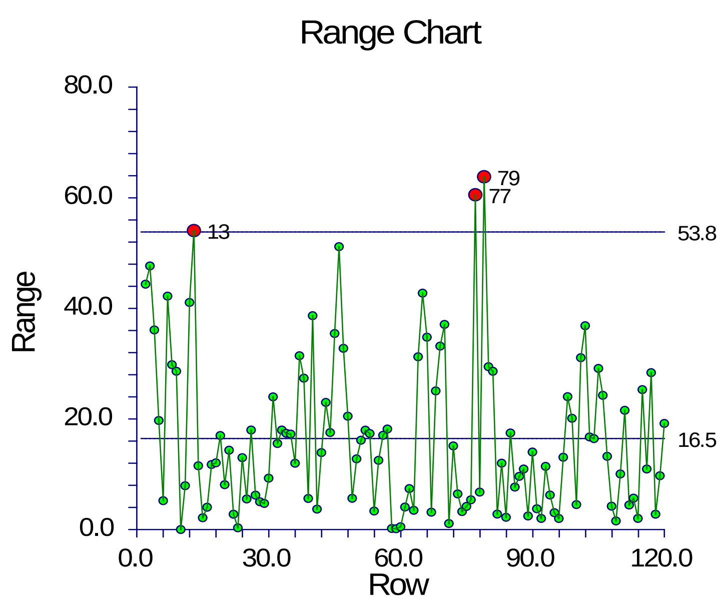
Variables LA



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Variables LEV

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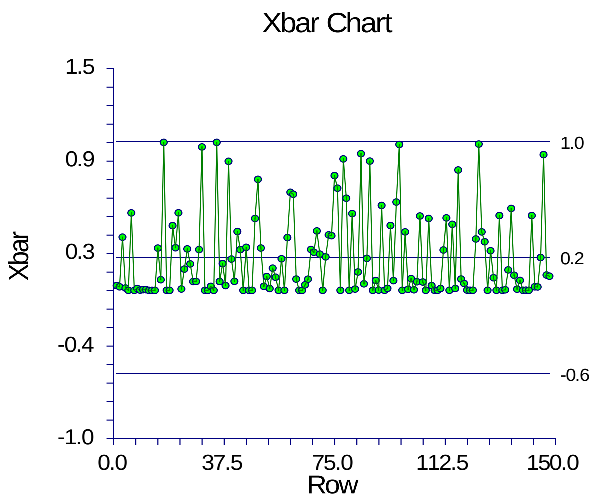

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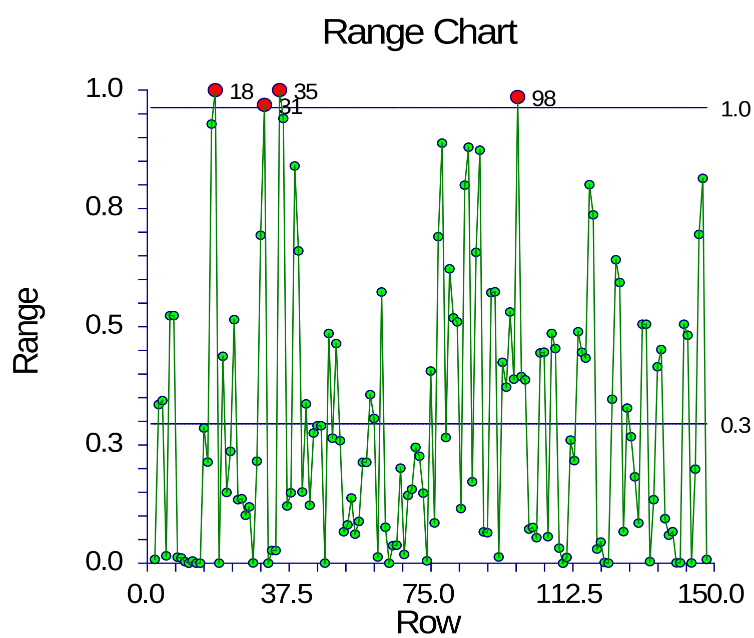

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Variables PROB

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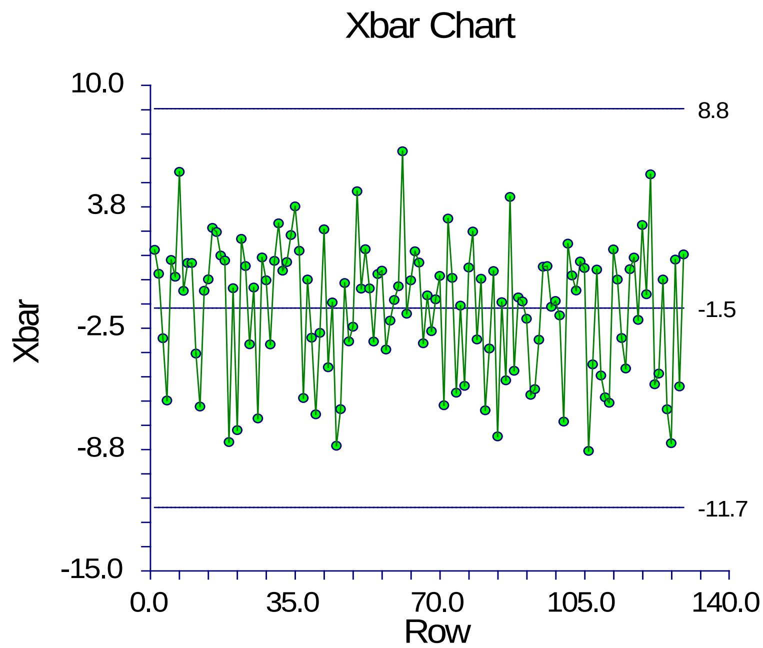

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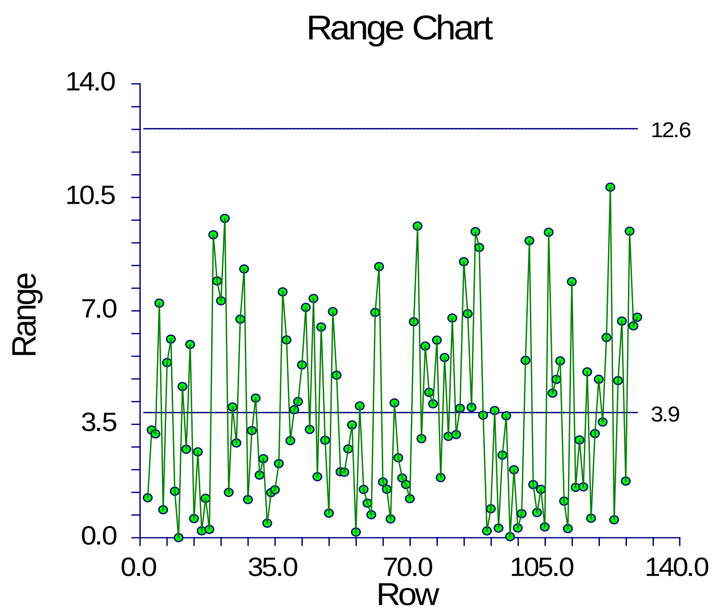
Variables PROB



XBar-R Chart Report

Page/Date/Time 4 27/10/2010 20:42:39
Database
Variables PROB

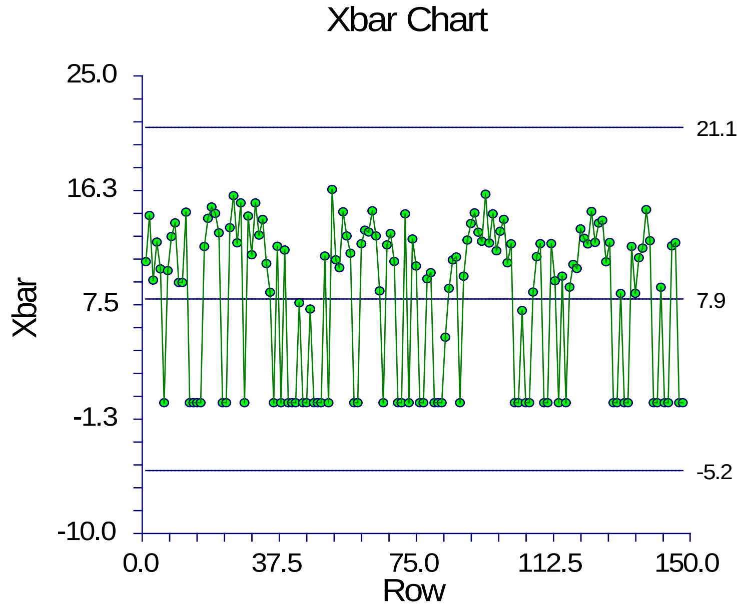
Histogram Section for Rows 1-129

XBar-R Chart Report

Page/Date/Time 1 27/10/2010 20:41:39
Database

Variables SIZE

Chart Section for Rows 1 – 148



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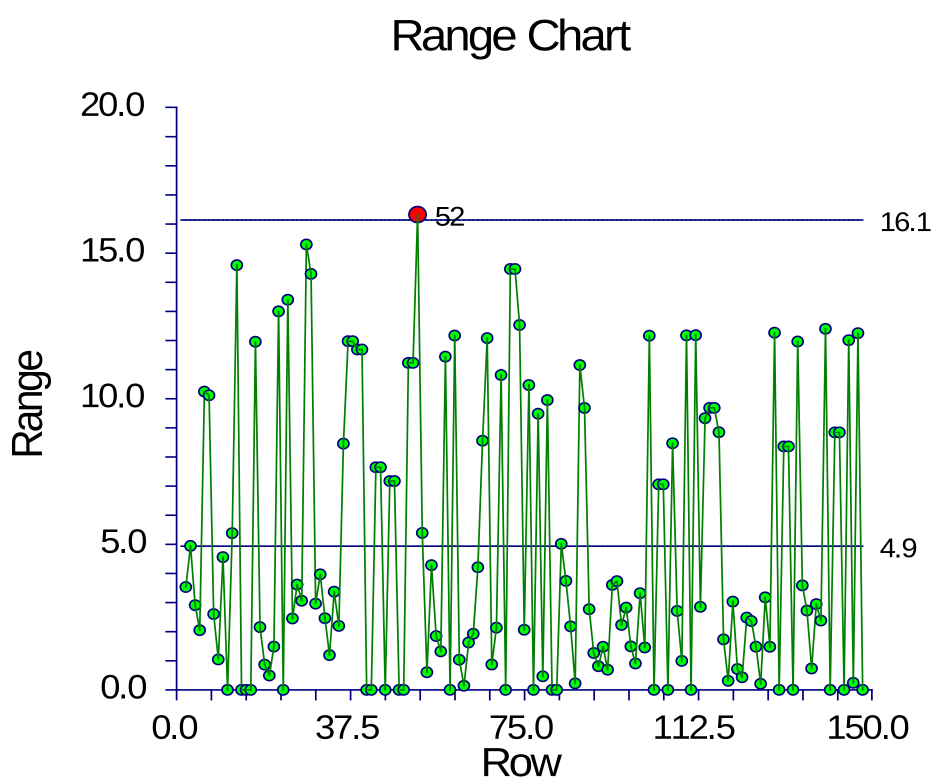
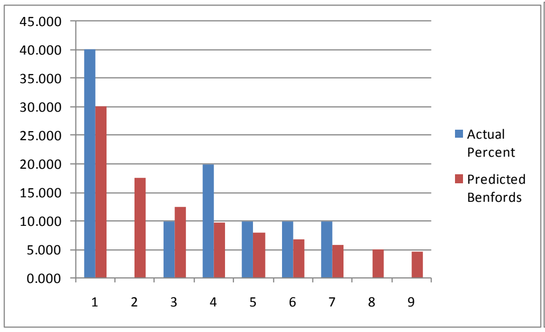
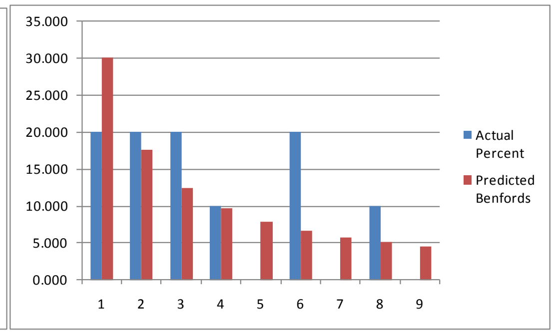
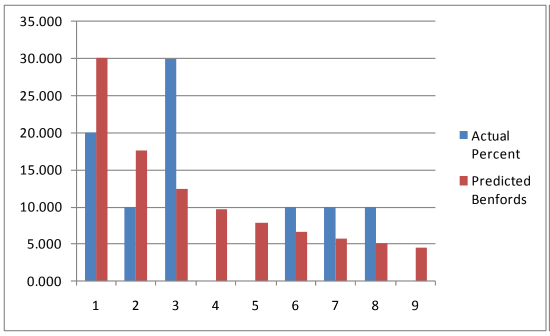
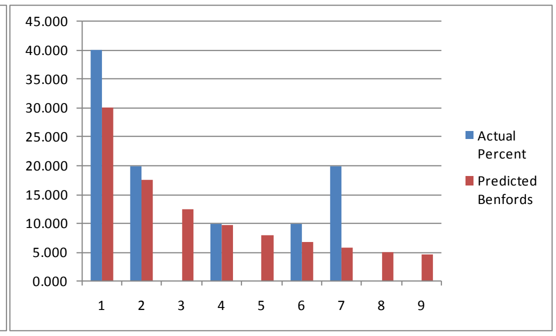


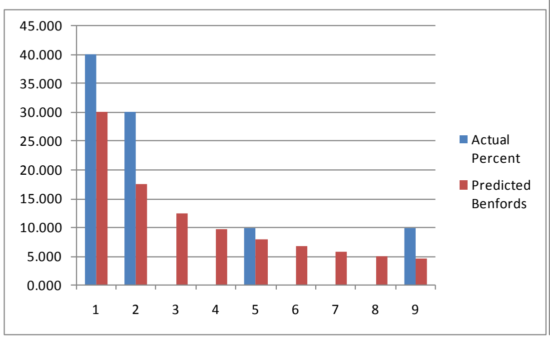
9.3 Appendix C: Bedford Law Results

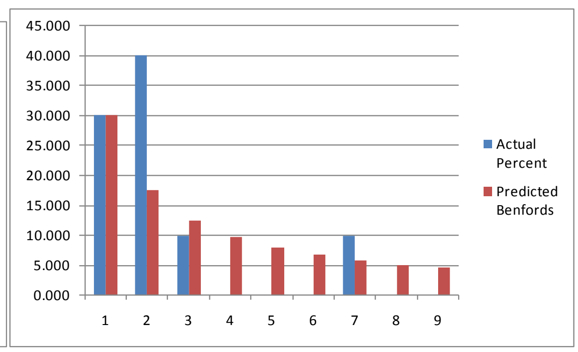


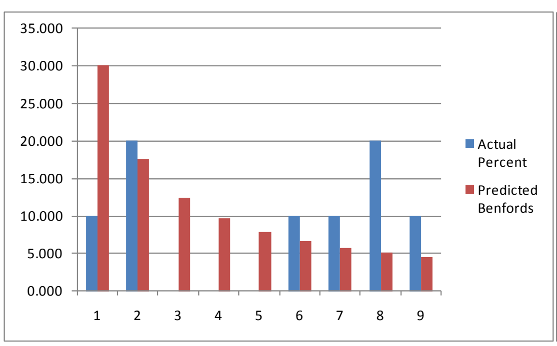


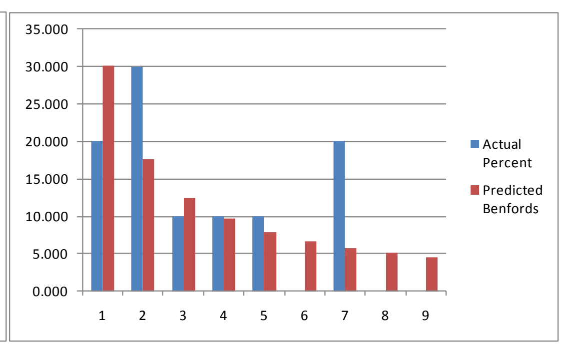


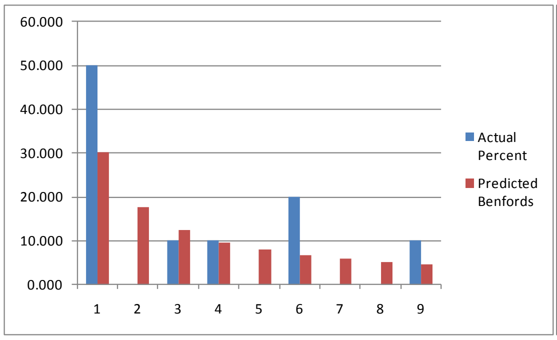








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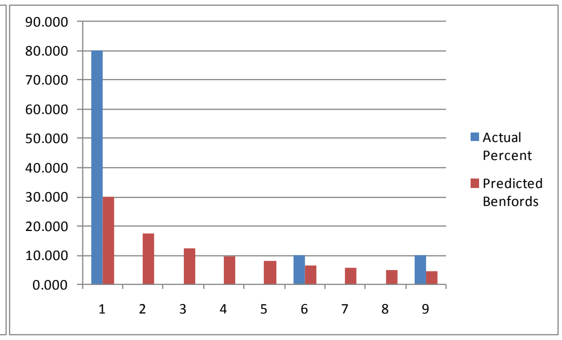
30.000
20.000
10.000
0.000
1 2 3 4 5 6 7 8 9
Actual Percent
Predicted Benfords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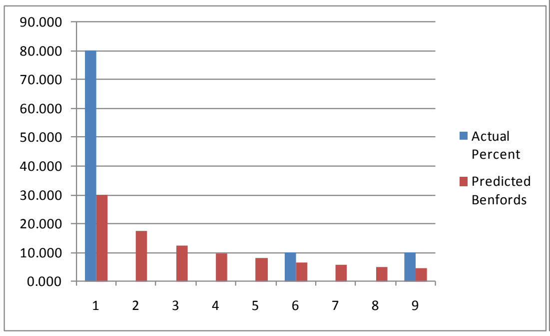
Actual Percent
Predicted Benfords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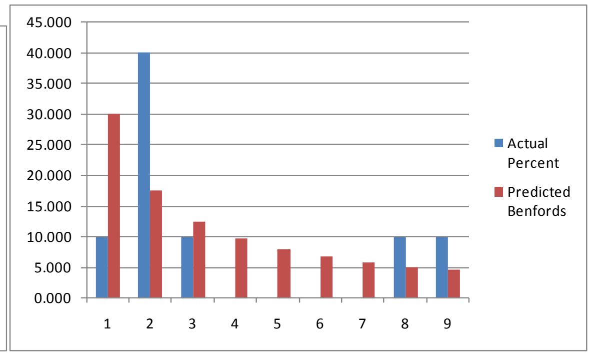
Actual Percent
Predicted Benfords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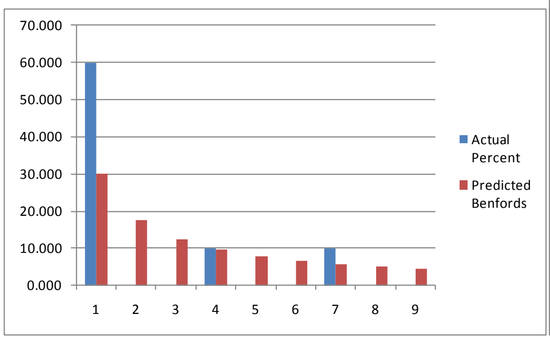
Actual Percent
Predicted Benfords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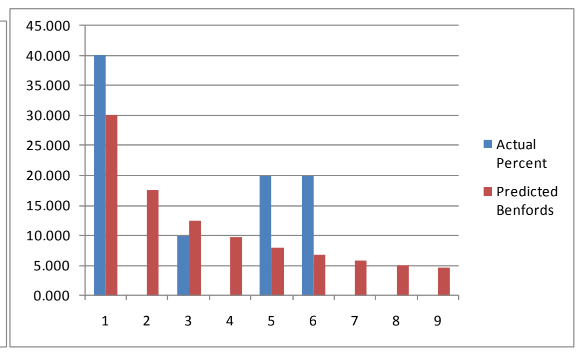
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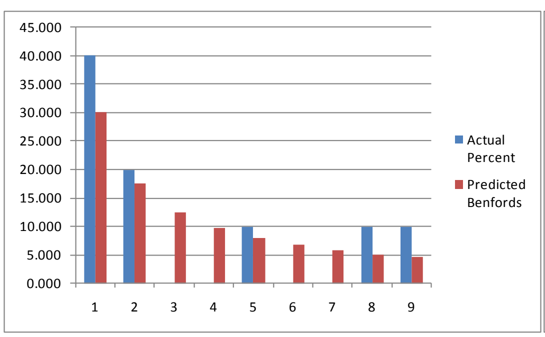
Actual Percent
Predicted Benfords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1 2 3 4 5 6 7 8 9
Actual Percent
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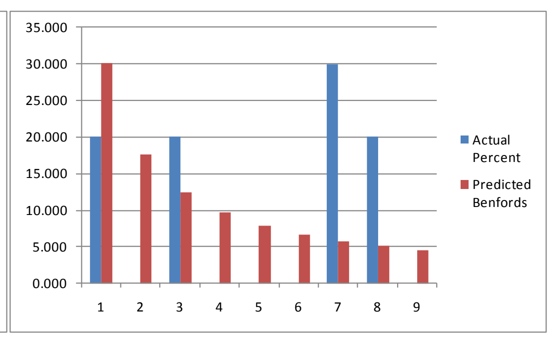
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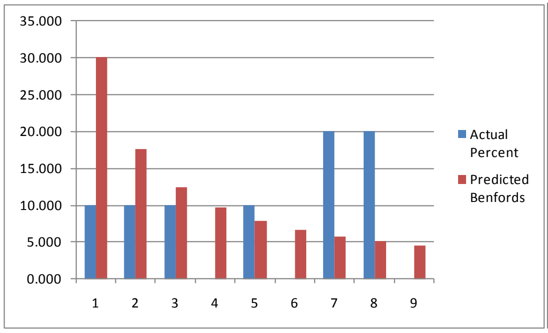
Actual Percent
Predicted Benfords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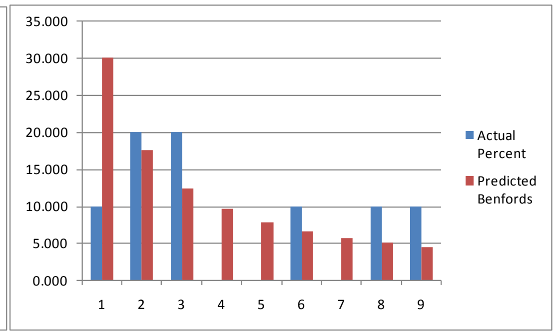
Actual Percent
Predicted Benfords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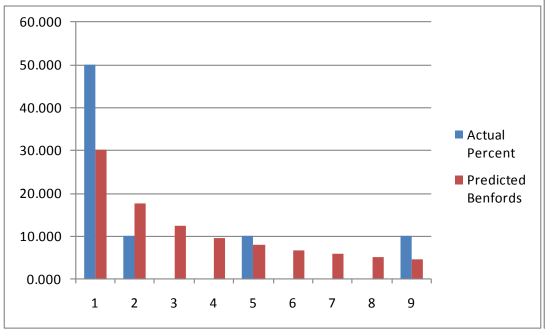
Actual Percent
Predicted Benfords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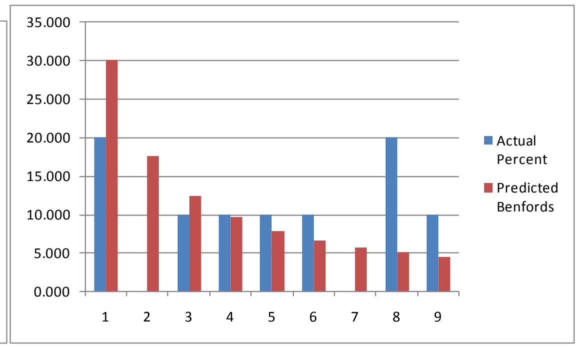
Actual Percent
Predicted Benfords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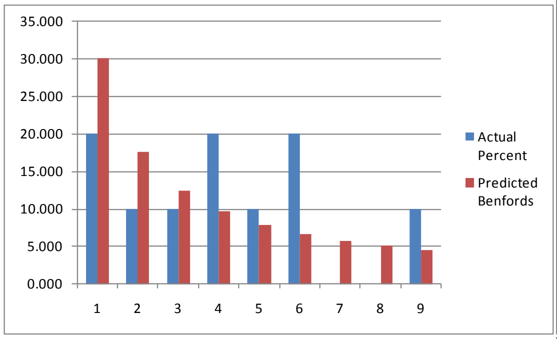
Actual Percent
Predicted Benfords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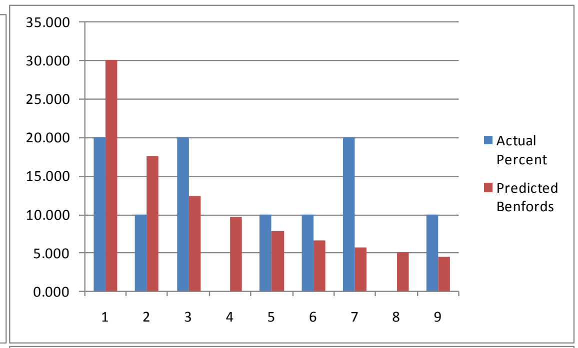
Actual Percent
Predicted Benfords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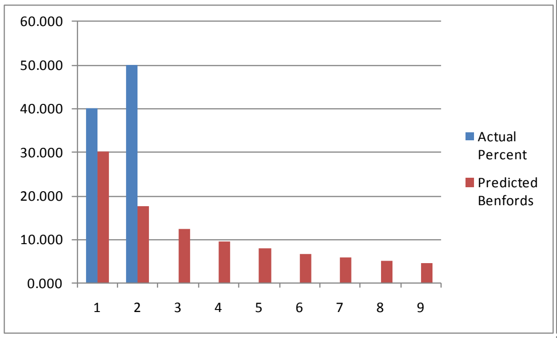
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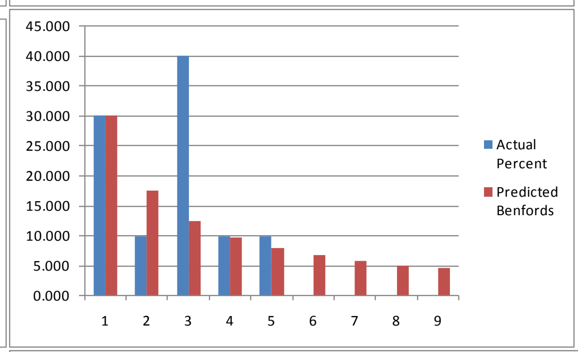
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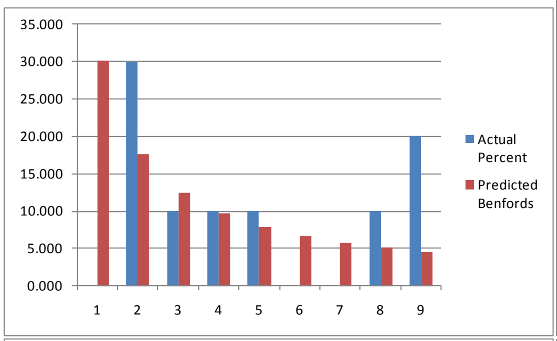
Actual Percent
Predicted Benfords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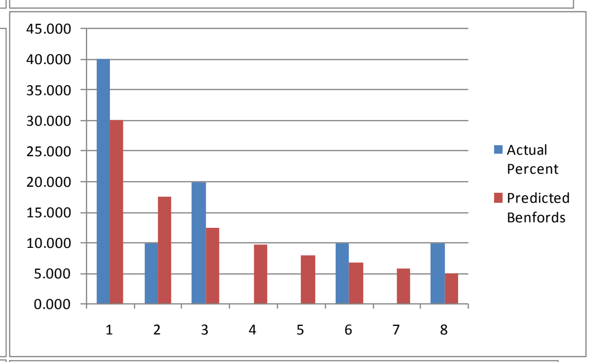
Actual Percent
Predicted Benfords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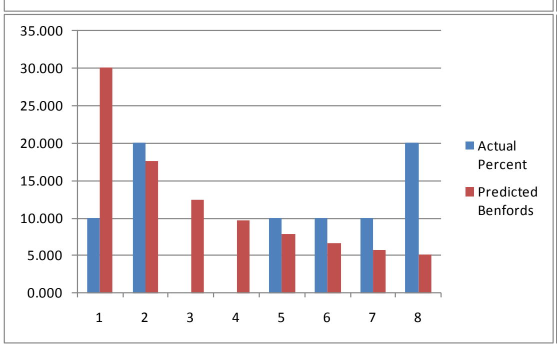
Actual Percent
Predicted Benfords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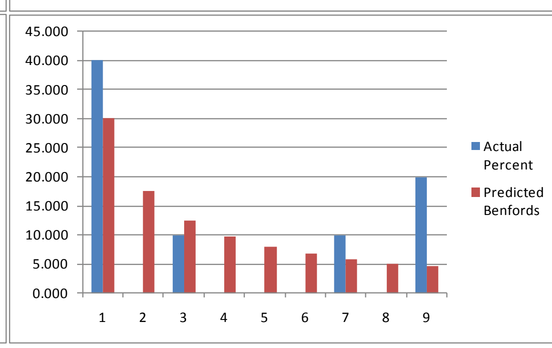
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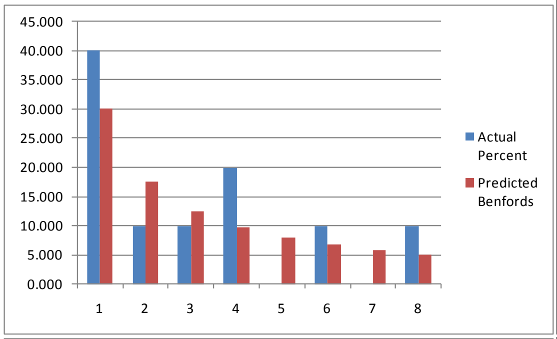
Actual Percent
Predicted Benfords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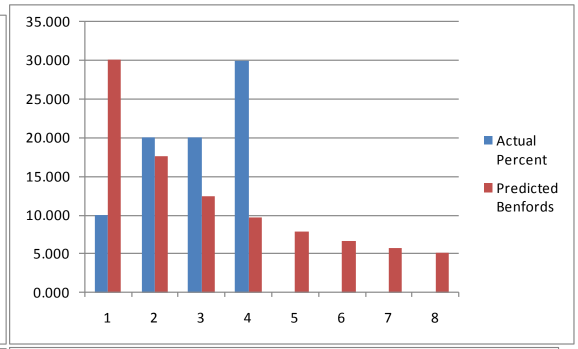
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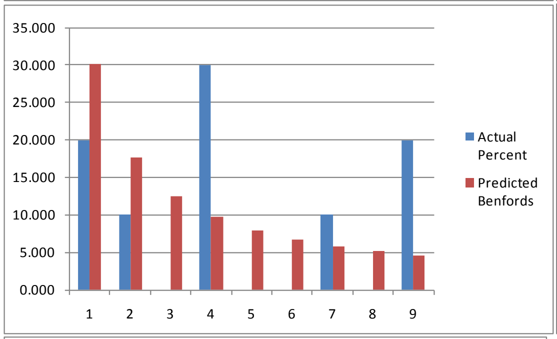
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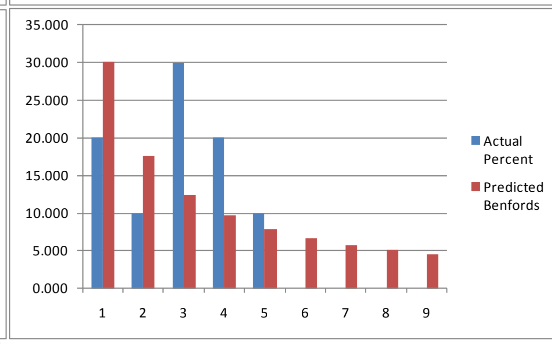
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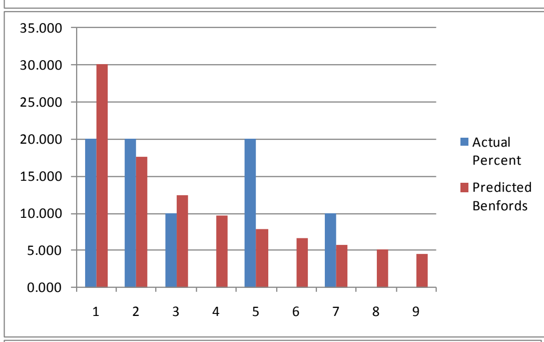
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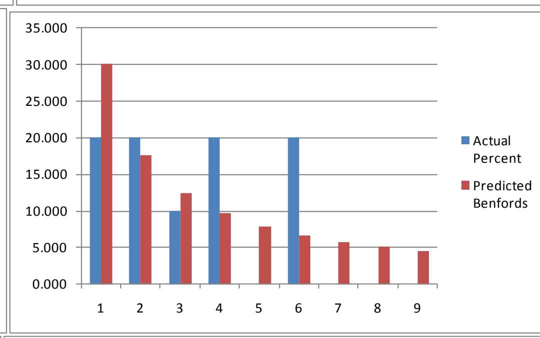
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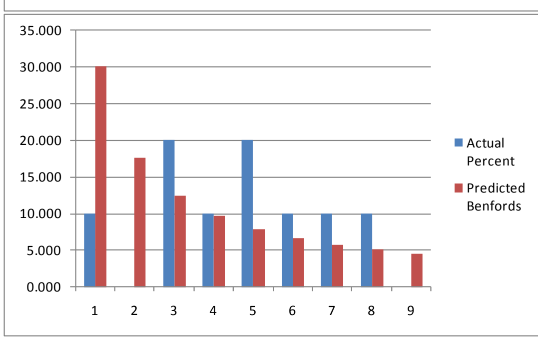
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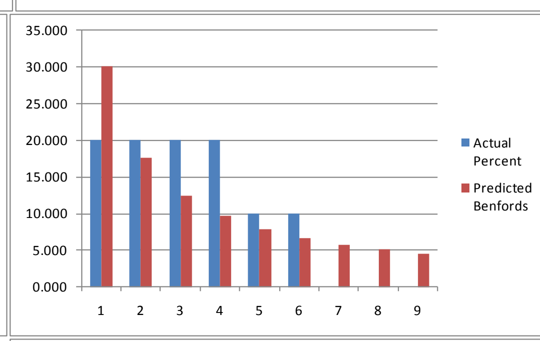
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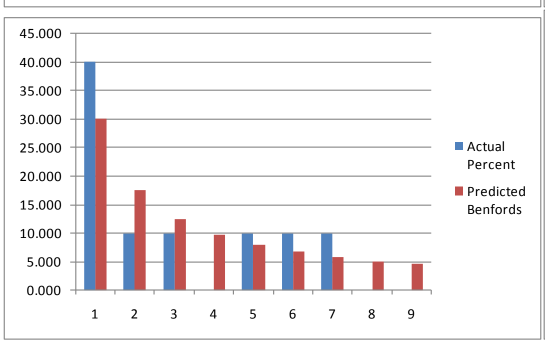
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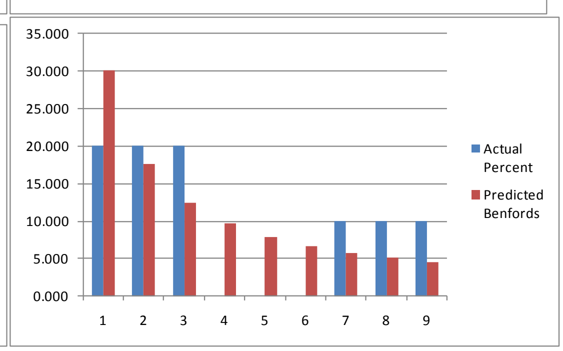
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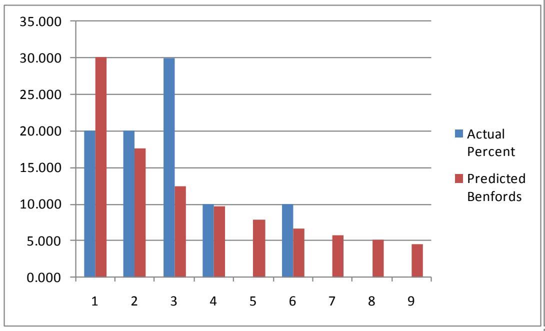
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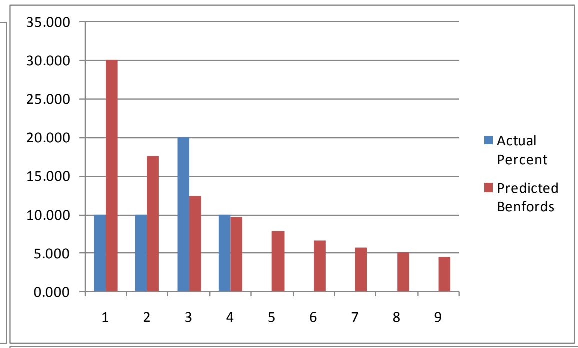
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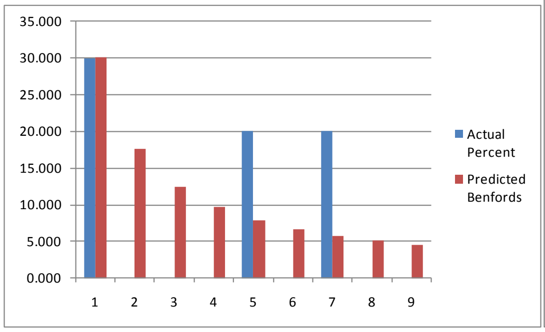
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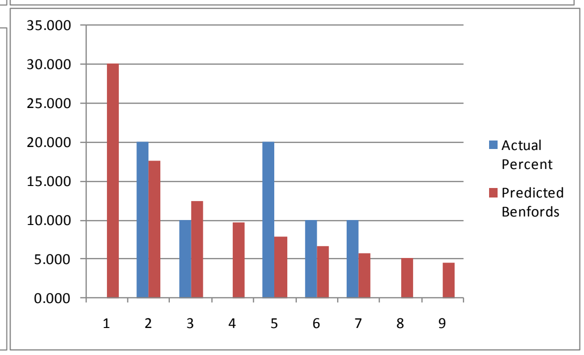
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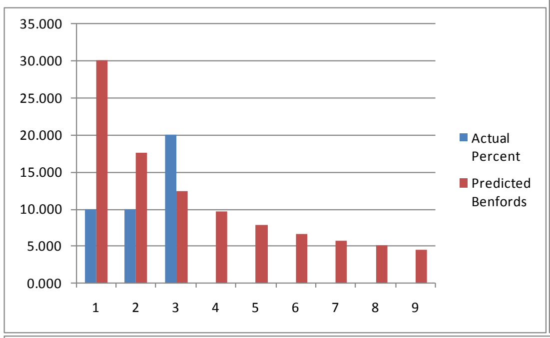
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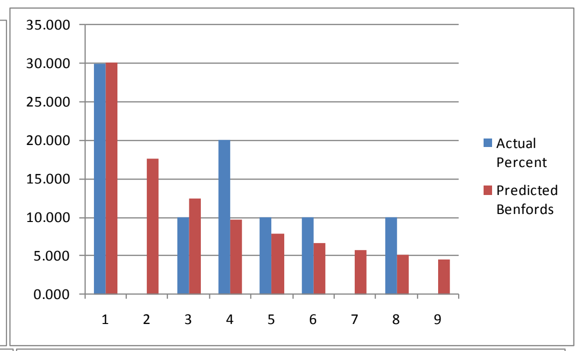
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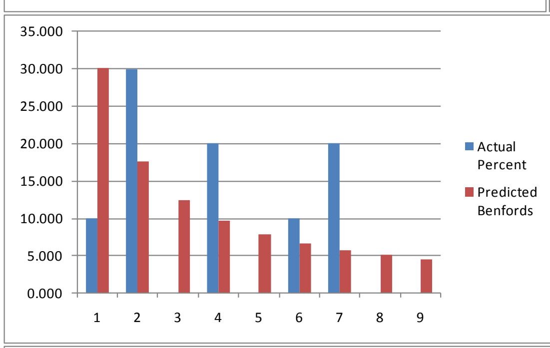
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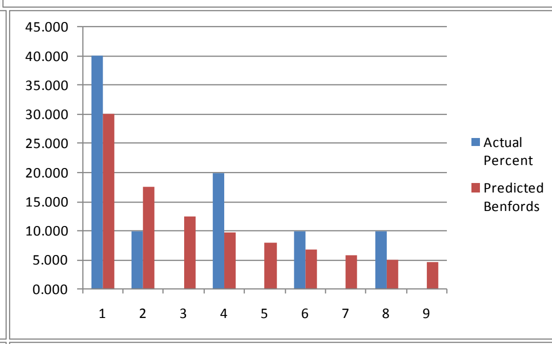
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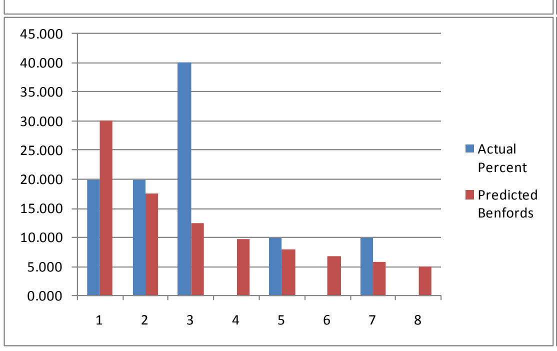
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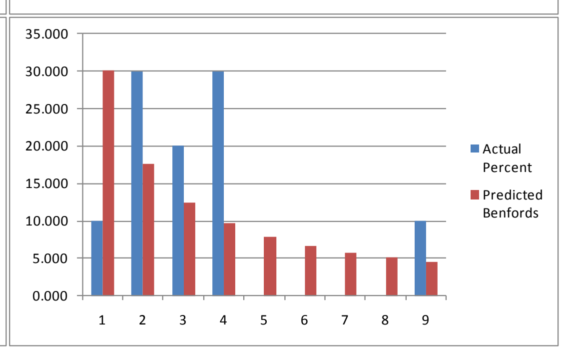
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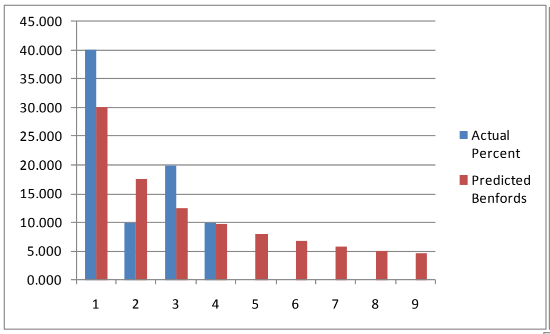
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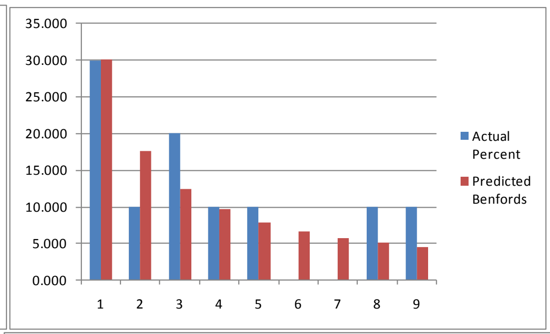
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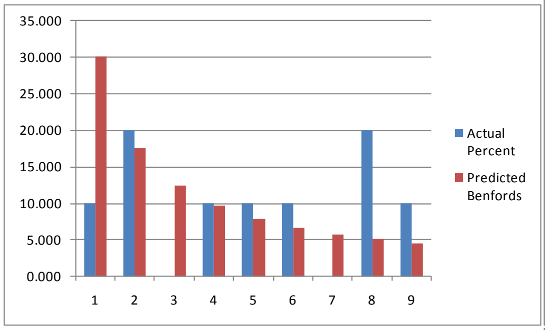
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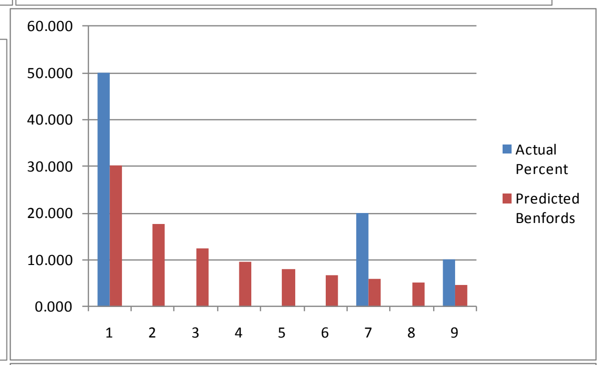
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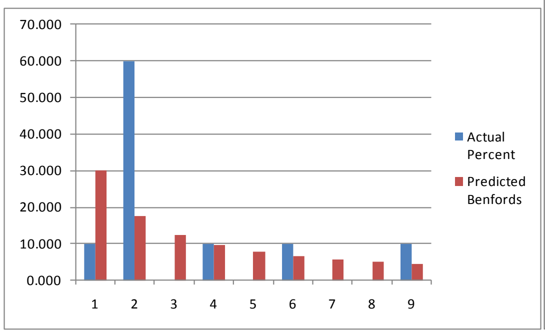
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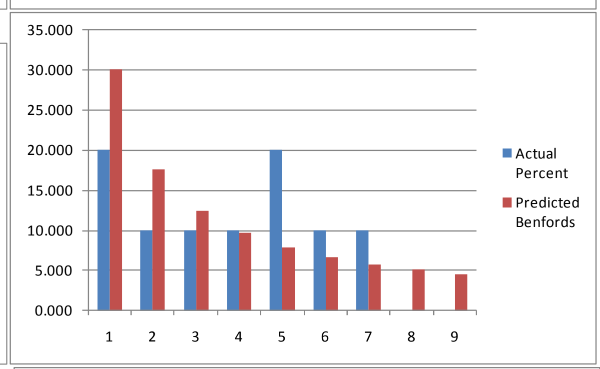
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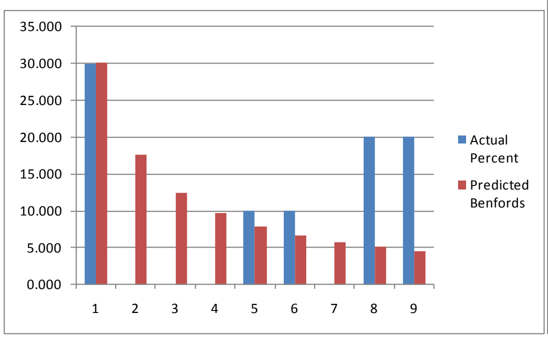
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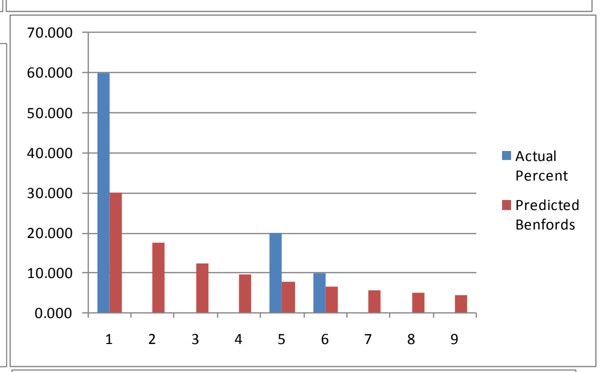
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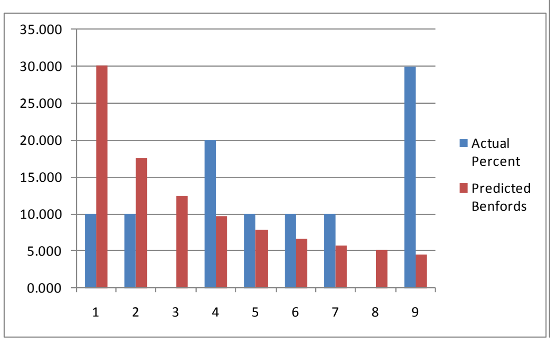
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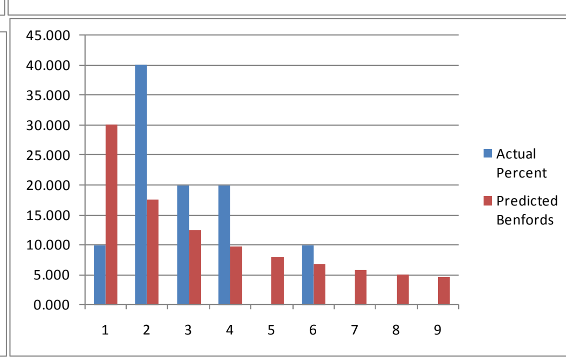
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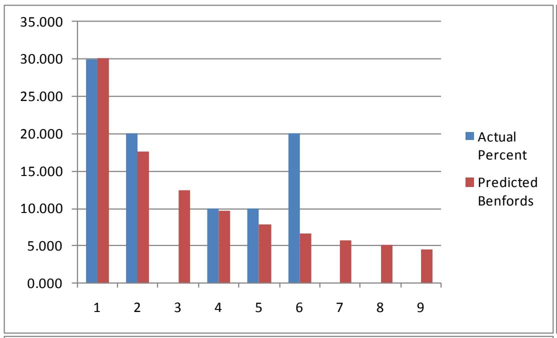
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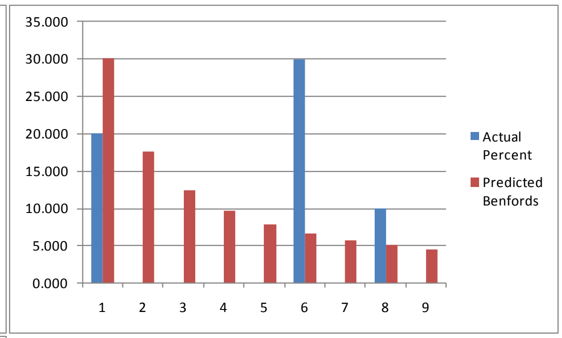
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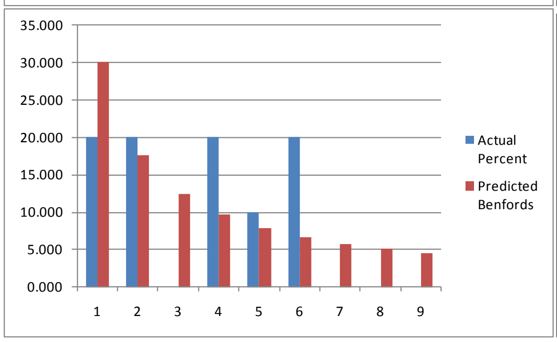
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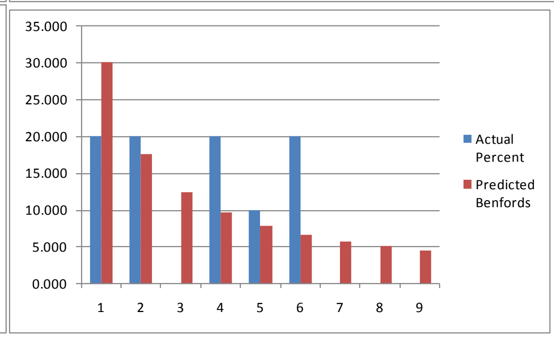
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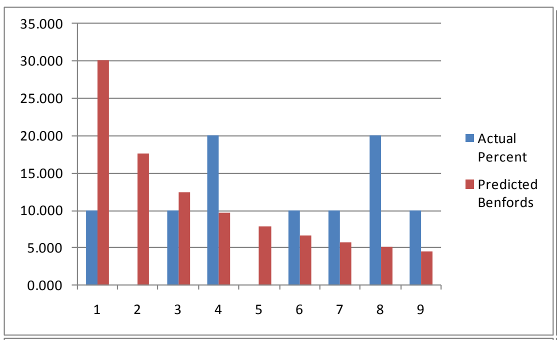
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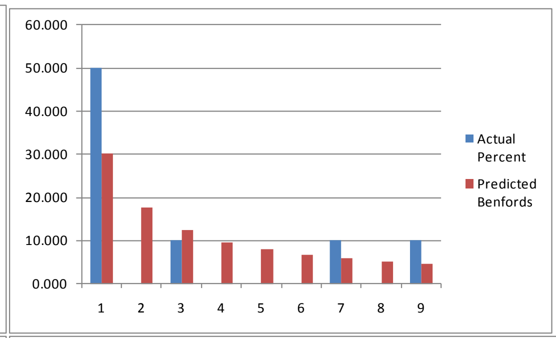
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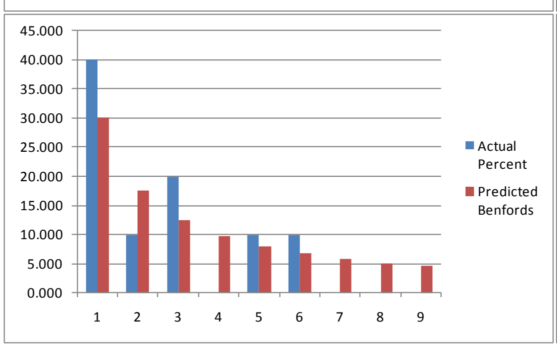
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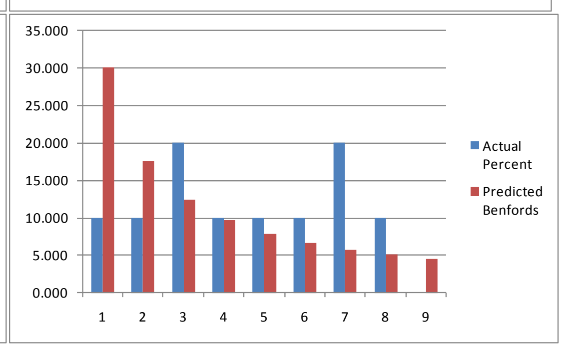
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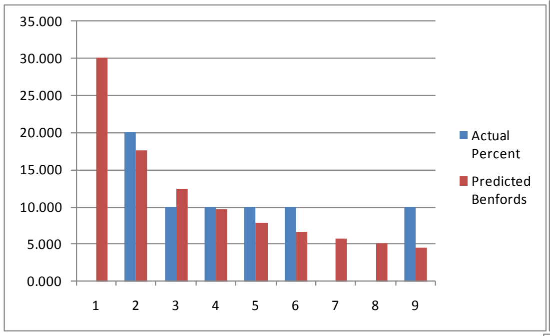
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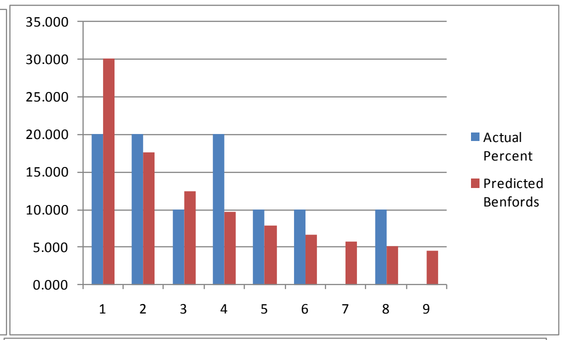
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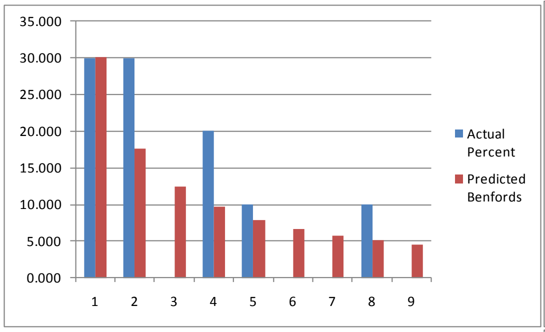
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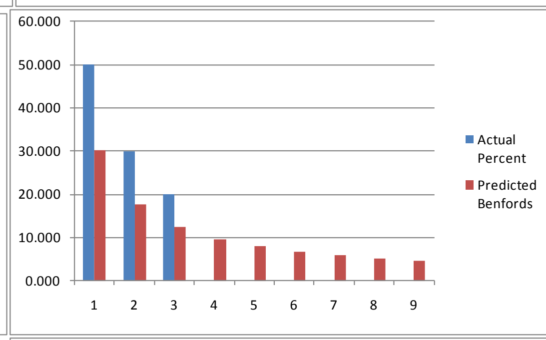
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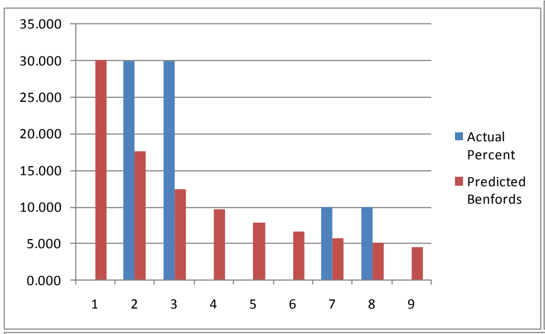
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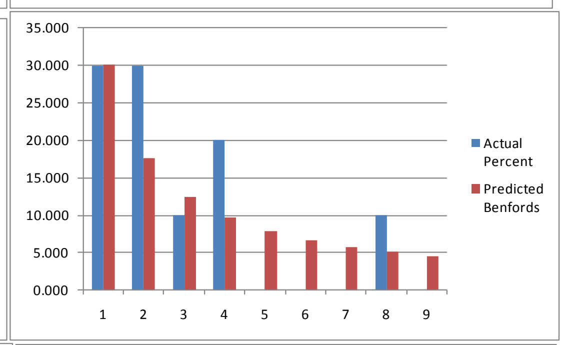
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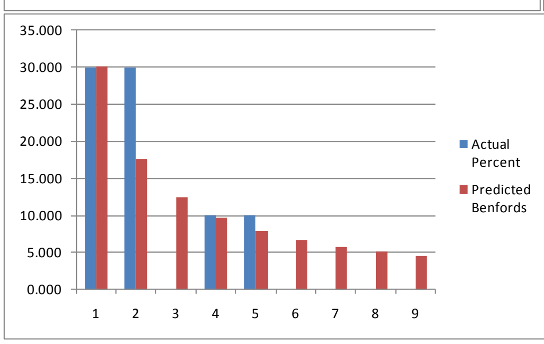
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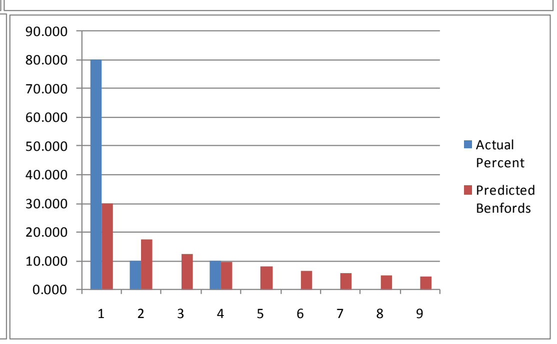
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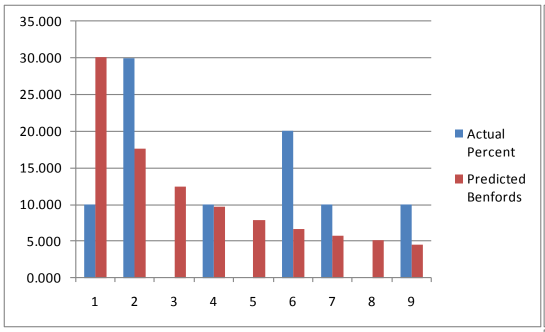
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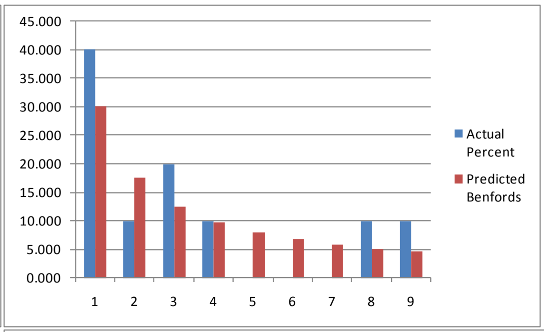
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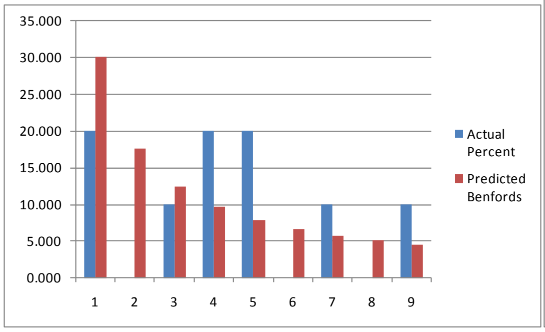
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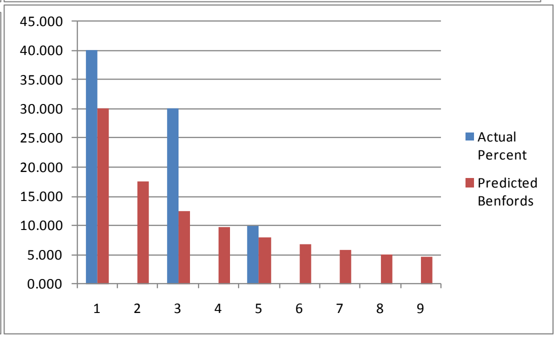
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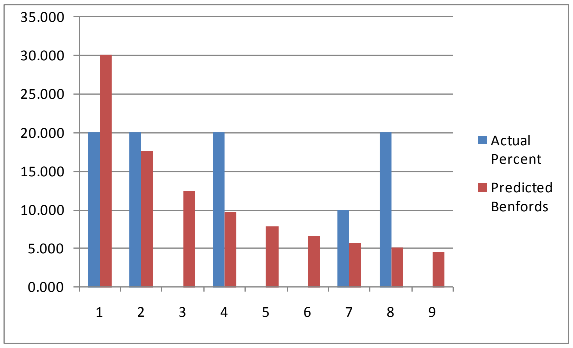
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Actual Percent
Predicted Benfords

9.4 Appendix D: Regression Results

Robust Multiple Regression Using Huber's Method (C=1.345)

Page/Date/Time	1 27/10/2010 20:12:04
Database	
Dependent	CFD

Run Summary Section

Parameter	Value	Parameter	Value
Dependent Variable	CFD	Rows Processed	148
Number Ind. Variables	8	Rows Filtered Out	0
Weight Variable	None	Rows with X's Missing	82
R2	0.1298	Rows with Weight Missing	0
Adj R2	0.0077	Rows with Y Missing	0
Coefficient of Variation	9.4345	Rows Used in Estimation	66
Mean Square Error	0.0367052	Sum of Weights	60.636
Square Root of MSE	0.191586	Completion Status	Normal Completion
Ave Abs Pct Error	437.852		

Descriptive Statistics Section

Variable	Count	Mean	Standard Deviation	Minimum	Maximum
delta_EMP	66	0.7406288	4.462143	-0.9636679	36.26579
delta_INV	66	3.509186	15.03464	-37.67	53.75
GDP	66	3.329322E-02	2.065815E-02	-1.777839E-02	8.557288E-02
LA	66	-14.25594	15.94636	-58.74	9.05
LEV	66	0.2049206	0.2669157	0	1
PROB	66	0.9214215	3.223322	-8.555	6.603
Q	66	1.49551	2.368494	0.16	17.64
SIZE	66	8.189043	5.821412	0	16.31834
CFD	66	2.030702E-02	0.1923301	-0.4466857	0.4709118

Regression Equation Section

Independent Variabe	Regression Coefficient b(i)	Standard Error Sb(i)	T-Value to test H0:B(i)=0	Prob Level	Reject H0 at 5%?	Power of Test at 5%
intercept	-0.0054	0.0672	-0.081	0.9360	No	0.0507
delta_EMP	0.0031	0.0107	0.292	0.7713	No	0.0595
delta_INV	-0.0003	0.0016	-0.194	0.8470	No	0.0542
GDP	2.0042	1.1737	1.708	0.0932	No	0.3894
LA	-0.0020	0.0015	-1.332	0.1881	No	0.2583
LEV	-0.0675	0.0974	-0.693	0.4914	No	0.1046
PROB	0.0025	0.0076	0.325	0.7463	No	0.0618
Q	-0.0027	0.0193	-0.141	0.8881	No	0.0522
SIZE	-0.0068	0.0041	-1.649	0.1046	No	0.3677

Estimated Model

-5.4206219543403E-03+ 3.12606011595479E-03*delta_EMP-3.11249424566263E-04*delta_INV+ 2.00416675938841*GDP-2.02730951712804E-03*LA-6.74786217056617E-02*LEV+2.46477418478162E-03*PROB-2.72163089715429E-03*Q-6.77672120731327E-03*SIZE

Robust Multiple Regression Using Huber's Method (C=1.345)

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Database	
Dependent	CFD

Run Summary Section

Parameter	Value	Parameter	Value
Dependent Variable	CFD	Rows Processed	148
Number Ind. Variables	8	Rows Filtered Out	0

Weight Variable	None	Rows with X's Missing	82
R2	0.1298	Rows with Weight Missing	0
Adj R2	0.0077	Rows with Y Missing	0
Coefficient of Variation	9.4345	Rows Used in Estimation	66
Mean Square Error	0.0367052	Sum of Weights	60.636
Square Root of MSE	0.191586	Completion Status	Normal Completion
Ave Abs Pct Error	437.852		

Descriptive Statistics Section

Variable	Count	Mean	Standard Deviation	Minimum	Maximum
delta_EMP	66	0.7406288	4.462143	-0.9636679	36.26579
delta_INV	66	3.509186	15.03464	-37.67	53.75
GDP	66	3.329322E-02	2.065815E-02	-1.777839E-02	8.557288E-02
LA	66	-14.25594	15.94636	-58.74	9.05
LEV	66	0.2049206	0.2669157	0	1
PROB	66	0.9214215	3.223322	-8.555	6.603
Q	66	1.49551	2.368494	0.16	17.64
SIZE	66	8.189043	5.821412	0	16.31834
CFD	66	2.030702E-02	0.1923301	-0.4466857	0.4709118

Regression Equation Section

Independent Variable	Regression Coefficient b(i)	Standard Error Sb(i)	T-Value to test H0:B(i)=0	Prob Level	Reject H0 at 10%?	Power of Test at 10%
Intercept	-0.0054	0.0672	-0.081	0.9360	No	0.1011
delta_EMP	0.0031	0.0107	0.292	0.7713	No	0.1141
delta_INV	-0.0003	0.0016	-0.194	0.8470	No	0.1062
GDP	2.0042	1.1737	1.708	0.0932	Yes	0.5173
LA	-0.0020	0.0015	-1.332	0.1881	No	0.3728
LEV	-0.0675	0.0974	-0.693	0.4914	No	0.1783
PROB	0.0025	0.0076	0.325	0.7463	No	0.1175
Q	-0.0027	0.0193	-0.141	0.8881	No	0.1033
SIZE	-0.0068	0.0041	-1.649	0.1046	No	0.4945

Estimated Model

-5.4206219543403E-03+ 3.12606011595479E-03*delta_EMP-3.11249424566263E-04*delta_INV+ 2.00416675938841*GDP-2.02730951712804E-03*LA-6.74786217056617E-02*LEV+2.46477418478162E-03*PROB-2.72163089715429E-03*Q-6.77672120731327E-03*SIZE

Robust Multiple Regression Using Huber's Method (C=1.345)

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Database	
Dependent	CFD

Run Summary Section

Parameter	Value	Parameter	Value
Dependent Variable	CFD	Rows Processed	148
Number Ind. Variables	8	Rows Filtered Out	0
Weight Variable	None	Rows with X's Missing	82
R2	0.1298	Rows with Weight Missing	0
Adj R2	0.0077	Rows with Y Missing	0
Coefficient of Variation	9.4345	Rows Used in Estimation	66
Mean Square Error	0.0367052	Sum of Weights	60.636
Square Root of MSE	0.191586	Completion Status	Normal Completion
Ave Abs Pct Error	437.852		

Descriptive Statistics Section

Variable	Count	Mean	Standard Deviation	Minimum	Maximum

delta_EMP	66	0.7406288	4.462143	-0.9636679	36.26579
delta_INV	66	3.509186	15.03464	-37.67	53.75
GDP	66	3.329322E-02	2.065815E-02	-1.777839E-02	8.557288E-02
LA	66	-14.25594	15.94636	-58.74	9.05
LEV	66	0.2049206	0.2669157	0	1
PROB	66	0.9214215	3.223322	-8.555	6.603
Q	66	1.49551	2.368494	0.16	17.64
SIZE	66	8.189043	5.821412	0	16.31834
CFD	66	2.030702E-02	0.1923301	-0.4466857	0.4709118

Regression Equation Section

Independent Variable	Regression Coefficient b(i)	Standard Error Sb(i)	T-Value to test H0:B(i)=0	Prob Level	Reject H0 at 20%?	Power of Test at 20%
Intercept	-0.0054	0.0672	-0.081	0.9360	No	0.2014
delta_EMP	0.0031	0.0107	0.292	0.7713	No	0.2187
delta_INV	-0.0003	0.0016	-0.194	0.8470	No	0.2083
GDP	2.0042	1.1737	1.708	0.0932	Yes	0.6619
LA	-0.0020	0.0015	-1.332	0.1881	Yes	0.5209
LEV	-0.0675	0.0974	-0.693	0.4914	No	0.3007
PROB	0.0025	0.0076	-0.325	0.7463	No	0.2232
Q	-0.0027	0.0193	-0.141	0.8881	No	0.2044
SIZE	-0.0068	0.0041	-1.649	0.1046	Yes	0.6408

Estimated Model

5.4206219543403E-03+ 3.12606011595479E-03*delta_EMP-3.11249424566263E-04*delta_INV+ 2.00416675938841*GDP-2.02730951712804E-03*LA-6.74786217056617E-02*LEV+2.46477418478162E-03*PROB-2.72163089715429E-03*Q-6.77672120731327E-03*SIZE

Robust Multiple Regression Using Huber's Method (C=1.345)

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Database		
Dependent	CFD	

Run Summary Section

Parameter	Value	Parameter	Value
Dependent Variable	CFD	Rows Processed	148
Number Ind. Variables	8	Rows Filtered Out	0
Weight Variable	None	Rows with X's Missing	82
R2	0.1298	Rows with Weight Missing	0
Adj R2	0.0077	Rows with Y Missing	0
Coefficient of Variation	9.4345	Rows Used in Estimation	66
Mean Square Error	0.0367052	Sum of Weights	60.636
Square Root of MSE	0.191586	Completion Status	Normal Completion
Ave Abs Pct Error	437.852		

Descriptive Statistics Section

Variable	Count	Mean	Standard Deviation	Minimum	Maximum
delta_EMP	66	0.7406288	4.462143	-0.9636679	36.26579
delta_INV	66	3.509186	15.03464	-37.67	53.75
GDP	66	3.329322E-02	2.065815E-02	-1.777839E-02	8.557288E-02
LA	66	-14.25594	15.94636	-58.74	9.05
LEV	66	0.2049206	0.2669157	0	1
PROB	66	0.9214215	3.223322	-8.555	6.603
Q	66	1.49551	2.368494	0.16	17.64
SIZE	66	8.189043	5.821412	0	16.31834
CFD	66	2.030702E-02	0.1923301	-0.4466857	0.4709118

Regression Equation Section

Independent Variable	Regression Coefficient b(i)	Standard Error Sb(i)	T-Value to test H0:B(i)=0	Prob Level	Reject H0 at 30%?	Power of Test at 30%
Intercept	-0.0054	0.0672	-0.081	0.9360	No	0.3016
delta_EMP	0.0031	0.0107	0.292	0.7713	No	0.3201
delta_INV	-0.0003	0.0016	-0.194	0.8470	No	0.3089
GDP	2.0042	1.1737	1.708	0.0932	Yes	0.7494
LA	-0.0020	0.0015	-1.332	0.1881	Yes	0.6229
LEV	-0.0675	0.0974	-0.693	0.4914	No	0.4065
PROB	0.0025	0.0076	-0.325	0.7463	No	0.3249
Q	-0.0027	0.0193	-0.141	0.8881	No	0.3048
SIZE	-0.0068	0.0041	-1.649	0.1046	Yes	0.7311

Estimated Model

-5.4206219543403E-03+ 3.12606011595479E-03*delta_EMP-3.11249424566263E-04*delta_INV+ 2.00416675938841*GDP-2.02730951712804E-03*LA-6.74786217056617E-02*LEV+2.46477418478162E-03*PROB-2.72163089715429E-03*Q-6.77672120731327E-03*SIZE