UNIVERSITY OF WESTERN CAPE

RESEARCH PROJECT

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Title of the Research Project:

The Time-Series Approaches in Forecasting One-Step-Ahead Cash-Flow Data of Mining Companies Listed on the Johannesburg Stock Exchange

A research project (60 Credit Units) in partial fulfillment of the requirements for the degree of Master of Commerce
Faculty of Economic and Management Sciences
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Supervisor: Professor Sulaiman Gool

Date: 15th, November, 2007

DECLARATION:

I declare that

"THE TIME-SERIES APPROACHES IN FORECASTING

ONE-STEP-AHEAD CASH-FLOW DATA OF MINING COMPANIES

LISTED ON THE JOHANNESBURG STOCK EXCHANGE"

is my own work, which has not been submitted before

for any degree or examination in any other university, and that all the

sources I have used or quoted have been indicated and acknowledged by

means of complete references.

Yang Li

Signature: ……………

November 15th, 2007

To My Parents

Acknowledgments

I wish to acknowledge and thank the following individuals for their help and support during the course of my research.

Firstly, I want to thank my supervisor, Professor Sulaiman Gool for his mentorship and guidance through the entire research, without whom the research could not have been completed. I am especially appreciative of the help and guidance of Professor Chris Koen who has given me very valuable suggestions with the statistical analyses; Professor Robert Madsen from University of Missouri assisted me in using SAS programme for the data analyses. I am also grateful to Mr Rashied Small, Mr Andre Stoltz and many other staff members who have continuously supported me during my research.

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ABSTRACT

Background:

Previous research pertaining to the financial aspect of the mining industry has focused predominantly on mining products' values and the companies' sensitivity to exchange rates. There has been very little empirical research carried out in the field of the statistical behavior of mining companies' cash flow data, specifically in relation to the weak form market hypothesis which theorizes that company's share price reflects all the market information.

Objectives:

This paper aims to study the time-series behaviour of the cash flow data series of JSE listed mining companies. In addition, it estimates forecasting models and evaluates the fitness of these models.

Research Methodology:

Two data series were used: Cash Flow from Operations (CFO) and Cash Flow from Operations Deflated by Number of Shares Issued (CFO_DFL). Three steps of data transformation were performed due to the large fluctuation observed in sequence plots. Cluster analysis was employed to group the companies that showed similar variance. Stepwise regression analysis was performed to select appropriate models for each group of data.

Research Findings:

No significant result was obtained on the auto-correlation function for cash-flow series. For Cash Flow from Operations (CFO) data series, two groups were tested and both obtained some significant cross-correlation results with p-values less than 0.05 ($p<0.05$), while for others there were no significant cross-correlation results. For series Cash Flow from Operations Deflated by Number of Shares (CFO_DFL) data series, one group was tested and shown to have strong cross-correlation amongst all pairs at time 0 with p-value less than 0.05 ($p<0.05$). However, cross-correlation results provided little predictive value. Linear models were found to fit two groups of data (Group 1 of CFO series and Group 1 of CFO_DFL series), while the quadratic model fitted one of the CFO group series (Group 2 of CFO series). Only the linear model for CFO_Gr1 data series was found to exhibit a good fit, though strong significances ($p<0.001$) were observed for all three models.

Key Words:

Cash flow from operations, Cash flow from operations deflated by number of shares issued, mining companies, Johannesburg Stock Exchange, time-series analysis, data transformation, cross-correlation, curve estimation, one-step-ahead cash-flow, model evaluation

Glossary of Terms and Acronyms

ACF: Auto-Correlation Function, it describes the evolution of a data series through time and is a univariate study.

AR: Auto-Regression Model

ARIMA: Auto-Regression Integrated Moving-Average Model

ARMA: Auto-Regression Moving-Average Model

Bivariate Analysis: it explores the association between two variables.

CCF: Cross-Correlation Function, it describes the evolution of two data series through time and is a bivariate study.

CFO: Cash Flow from Operations

CFO_DFL: Cash Flow from Operations Deflated by Number of Shares

CFO $_t$**:** Cash Flow from Operations at Time t

Cluster Analysis: To group the objects into a number of classes so that objects within classes are similar in some respect and unlike those from other classes.

ΔY_t **:** The difference between current year's CFO (or CFO_DFL) data and previous year's CFO (or CFO_DFL) data.

Durbin-Watson statistic: To determine whether there is evidence of first-order auto-correlation exists between consecutive residuals.

EMH: Efficient Market Hypothesis

ε_t **:** Same as ΔY_t **,** is equal to $Y_t - Y_{t-1}$

$f_{i(t)}$ **:** is the natural logarithm value of $\varepsilon_{(t)}{}^2$.

F-statistic: a measurement of the relationship between dependent and independent variables of a linear model.

MA: Moving-Average Model

R-squared: The statistical measure of how well a regression line approximates real data points; an r-squared value of 1.0 indicates a perfect fit.

Stepwise Regression: An iterative procedure that adds and deletes one independent variable at a time. The decision to add or delete a variable is made on the basis of whether that variable improves the model.

$Var(\varepsilon_t)$ **:** The squared value of CFO differencing ($\Delta Y_t = \varepsilon_t = Y_t - Y_{t-1}$ **).** It is the variance of CFO (or CFO_DFL) series over time.

Y_t **:** Current year's CFO data (or CFO_DFL data)

Y_{t-1} **:** Previous year's CFO data (or CFO_DFL data)

Univariate Analysis: is concerned with the description or summarization of individual variables in a given data set.

$V_{i(t)}$: is the natural logarithm value of squared differencing ($\varepsilon_{(t)}{}^{2}$) of company i divided by the average of natural logarithm value of squared differencing $\varepsilon_{(t)}{}^{2}$ of the group that company i is in.

White Noise: a data series that is a sequence of mutually independent variable.

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Chapter 1 INTRODUCTION

1.1 Background

Past research on the mining industry has focused mainly on mining products' values and the companies' sensitivity to exchange rates. There has been very little research carried out in the field of statistical behaviour of the mining companies' cash flow data, especially in relation to the weak-form market hypothesis which states that company's share price should reflect all the market information. This paper aims to study the time-series behaviour of the CFO data series of JSE listed mining companies. It also estimates forecasting models and evaluates the fitness of the models. The research is experimental and can be considered to be seminal in many aspects.

1.2 Rationale of the Study

Like many other empirical financial research, this paper follows a weak form efficient market hypothesis (EMH), which assumes current share prices fully reflect all market information (Reilly and Brown, 2002:178). Some earning forecasting research utilizes companies' earning data, such as Levi (1989:185) and Fairfield, et al (1996:354). However, some researchers argue that such forecasting power is limited and less accurate in predicting future profitability (e.g. Finger, 1994:220). Other researchers provided evidence for the strong positive correlation between earnings per share and company cash flows (Dechow et al, 1988:163-166). This will be reviewed later in Chapter 2. Studying the statistical behaviour of company cash-flow data is thus important, as the trend of cash flow data is a predictor of future earnings.

The accounting rationale of this research also follows the weak form EMH. The Classical Theory developed by White et al (2003:164-165) assumes that the financial statements not only reflect a company's operating, financing and investment decisions, but also have included the impact of market information.

Two cash-flow data series were used in this paper: cash flow from operations and cash flow from operations deflated by the number of shares issued. The construct of cash flow from operations, as opposed to just earnings, was used to predict the future profitability of the company.

The selection of forecasting tools should consider the capital-intensive nature of the mining industry. Mining companies usually require large amounts of capital to maintain operations. The replacement of assets usually happens after a certain period, as in the case of mining machines that generally have to be replaced periodically. This implies that company's financial statements will be impacted on in a cyclical manner. It may therefore be useful to utilize a time-series methodology to capture all these industry specific expenditure and therefore better predict future profitability.

1.3 The Aims of the Research

The aims of the research are:

1. To study the past cash flow data of JSE mining companies, in particular, the Cash Flow from Operations (CFO) and Cash Flow from Operations Deflated by Number of Shares (CFO_DFL).
2. To study the time-series attributes of the selected mining companies' cash-flow data.
3. To select an appropriate forecasting model for each cluster of cash flow data based on statistical fit.
4. By using the selected model, to estimate the one-year-ahead cash-flow data using CFO and CFO_DFL.
5. To evaluate the fitness of each forecasting model using R-squared results and Durbin-Watson statistic results.

1.4 Research Problem Statement

In order to meet the research objectives, the following research questions were to be addressed:

1. Do the selected companies' cash-flow data series possess time-series attributes?
2. Are there any significant auto-correlation test results for the cash-flow series?
3. Which of the models are most appropriate for each cluster of cash flow data?

1.5 Research Hypothesis

Historically, future cash flow data was estimated using the ARMA model and without testing whether there was significant auto-correlation. However, when large volatility exists in cash flow data series, auto-correlation results may be insignificant, and therefore the validity of using the ARMA model is doubtful (Chatfield, 1980:50). Once the data is normalized, and the companies are clustered according to how their cash flows fluctuate, the research essentially becomes a study of the cash flow data's variance behaviour. This simplifies the data series, suggesting that the equations for these curves may not be complicated and relative to the quadratic and cubic models, the linear model may be more appropriate. We therefore hypothesize thus:

H_0: The linear model is the appropriate model to forecast future cash flow.

H_1: The linear model is not an appropriate model to forecast future cash flow.

1.6 Significance of the Study

This study can make a significant contribution to the prediction of profitability of mining companies by utilizing the time-series attributes of the cash flow data. This will assist in building cash flow forecasting models for listed mining companies even when large volatility exist in data series.

1.7 Report Outline

This research report comprises 5 chapters. Chapter 1 introduces the research area and provides a background to the study. Chapter 2 is a literature review of the different types of financial modeling and its application to the mining industry. Chapter 3 presents the research methodology, while the findings are discussed in Chapter 4. The results are discussed, and recommendations for future research are made in Chapter 5.

Chapter 2 LITERATURE REVIEW

2.1 Approaches in Analyzing Mining Sector

Traditionally, mining companies were valued mostly according to the market price of their products. Dan diBartolomeo (1993:1) and Tufano (1998:1015) based their research on market value approaches in studying mining companies. They both examined how gold mining firms were affected once exposed to the changes of gold prices, especially how the behavior of gold mining equities changed in relation to the gold price. Davis (2002), on the other hand, linked mineral asset valuation and mineral firm equity valuation.

Previous research compared the gold mining companies across countries. Adamson (1999:3) researched the gold premium by comparing gold producers across Northern and the Southern hemisphere. He studied the market value per ounce of the companies' reserves, as well as the market value of the company versus the net present value of the company. He used price to earning ratios and price to cash flow ratios indexed against those of non-gold mining companies. He then compared North American with the Southern hemisphere using these parameters. Adamson provided evidence that a group of South African mining companies were undervalued compared to the major mining companies in other countries. He also argued that only a small group of mining companies in the Northern hemisphere operated with lower costs and obtained higher gold premiums, compared to the mining companies in South Africa. Faff and Hillier (2004:473) conducted similar research but focused more on how differently the factors affected conditional gold betas in the Australian and South African (Southern Hemisphere) gold sectors. They compared this to North American companies, and concluded that the factors that determined gold betas in the Southern Hemisphere were different from those in the Northern Hemisphere.

Other researchers investigated the high capital requirements of mining companies. Nichole (1987:114) discussed the capital-intensive attribute of the mining sector from an operating cost perspective. However, he did not investigate the cash flow from operations. Cahill (2003:4) addressed the importance of looking at the cash flow data when valuing a company, especially when the company is capital-intensive. According to his description, the mining industry can be characterized as a capital-intensive sector as large amounts of capital are required to maintain operations. Although much previous research has investigated the use of cash flow data to predict company's profitability, there is a paucity of research using this approach to predict the profitability of mining companies.

2.2 The Predictive Attributes of Accounting Data and Associated Researches

There is abundant research that focuses on forecasting earnings using share price and earnings. Ball and Brown (1968:161) were one of the first to test the relationship between security prices and the announcement of income. They provided evidence that there was significant correlation between interim income and share price. Based on this study, Cornell and Landsman (1989:680) provided further evidence of significant correlation between the return of securities and other market information. Foster (1977:17) estimated future quarterly earnings using time-series models. However, in Lev's (1989:185) research, he found there was a weak and unstable correlation between stock returns and earnings, and argued that the utility of earnings as a base for forecasting is limited.

Altman (1968:589) was amongst the earliest researchers who extended the utility of financial ratios from simply assessing company performances to predicting company bankruptcy. A more extensive study by Ou and Penman (1989:307) used the multivariate LOGIT model to explore the utility of financial ratios. Later, Ou (1990:161) again used empirical evidence to prove that a firm's non-earnings annual report numbers contain information concerning the direction of its future earnings.

Researches have subsequently moved the focus from simply taking the announced earning to construct their own earning data based on cash flow from operations. Bowen et al (1986:713) researched the predictive attributes of two cash flow measurements. They used a traditional concept of cash flow from operation (net income before depreciation) and the adjusted cash flow from operations (the cash flow from operations adjusted by accruals). They found that both cash flow series contained signals that were associated with forecasting future earnings. These findings addressed the importance of cash flow forecasting.

Rayburn (1986:131) investigated the association between operating cash flow, accruals and abnormal returns. By using Pearson correlation statistic test and multivatiate time-series models, he argued that the association between accruals and abnormal returns were not significant. Barth et al (1999: 222-223) provided evidence on the predictive values of cash flow components of earnings in forecasting future returns.

Lorek and Willinger (1996:85) used the adjusted cash flow from operations. They used various ARMA and ARIMA models, and a multivariate time-series model, and proved that the multivariate time-series model performed best in forecasting future cash flow. Krishnan and Largay (2000:221-223) used a multivariate time-series model to test the performance using the direct method cash flow construct and indirect method cash flow construct in forecasting future cash flow. However, many of them skipped the pre-step of testing for auto-correlation. If the auto-correlation is insignificant, the ARMA models selected are not very meaningful. There is lack of thorough time-series analysis regarding cash flow data forecasting (Pankratz, 1983:46).

It is difficult to make inferences from the above approaches as the forecasting was done at different time horizons, in different stock exchange markets, and across different industrial sectors.

2.3 Time-Series Model Estimation

Several researches studied the time-series attributes of companies' quarterly stock earning and other accounting data, and estimated forecasting models (Brown and Rozeff, 1979:182; Maines and Hand, 1996:317). However, not all the researches followed the correct steps in time-series models estimation. Pankratz, (1983:46) suggests that the steps to be followed in conducting a time-series analysis should normally include:

(1) Plot the data series and observing whether there is cyclical behavior or outliers;

(2) If there is cyclical behavior, auto-correlation should be tested. Based on this, decide whether it is auto-regressive (AR) or a moving-average (MA) model, or whether it is the combination of the two models (ARMA).

2.4 Cross-Correlation Function

Another common test in time-series is the cross-correlation function test. It tests the relationship of two series when they exist on an equal footing (Chatfield, 1980:169). It is a bivariate study, and is an alternative when the univariate model estimation cannot be implemented.

The question arises as to which pairs should be tested, because the sequences of some companies' vary significantly from that of other companies. There is therefore no point in finding a correlation between a smoother curve and a widely fluctuated curve, and as a consequence Cluster Analysis was considered (Everitt, 1980:2).

2.5 Cluster Analysis

The purpose of clustering is to divide the objects into a number of classes so that various objects within groups are similar (Everitt, 1980:1). However, the number of groups and the attributes of each group must be defined.

There are different ways in grouping data series. Since the emphasis in studying the cash-flow series becomes a variance study, hierarchy cluster technique is considered.

The hierarchy cluster analysis first separates the series into a few large groups. Each of the groups is further divided into smaller groups. Each of these further divided and so on until the defined number of groups is formed (Everitt, 1980:24).

2.6 Curve Estimation and Evaluation

The ultimate goal of this study is forecasting. When the curve estimation process is introduced, the problem is then how to estimate the curve. There is a great deal of literature written on curve estimation and especially in recent decades (Tarter and Lock, 1993:36), mathematical and statistical simulation packages have been introduced for complicated curve estimation.

The evaluation of the fitness of curves generally uses the R-squared results which explain the percentage accuracy of the forecasting (Keller and Warrack, 2003:621). In addition, the Durbin-Watson statistic can be used to evaluate a model by examining its residuals (Keller and Warrack, 2003:688).

Chapter 3 Research Methodology

3.1 Data Collection

The data was accessed from McGregor's BFA database as it provides annual financial statements as far back as 1980 for most companies.

The companies used in the sample included 21 major mining companies operating in South Africa that were listed on the Johannesburg Stock Exchange. Companies such as Eland Platinum Holding Ltd with limited years of financial data due to short time of establishment were excluded. Companies (e.g. AngloGold Ashanti Ltd) who had gone through mergers and acquisitions were also excluded. 16 companies out of the pool were selected for the research. The companies (and their JSE codes) are: African Rainbow Mineral Limited (ARI), Anglo American Plc (ANL), Anglo Platinum Limited (AMS), Barplats Investments Limited (BPL), BHP Billiton Plc (BIL), DRDGOLD Limited (DRD), GoldFields Limited(GFI), Harmony Gold Mining Company Limited (HAR), Impala Platinum Holding Limited (IMP), Merafe Resources Limited (MRF), Metorex Limited (MTX), Mvelaphanada Resources Limited (MVL), Northam Platinum Limited (NHM), Scharring Mining Limited (SCN), Trans Hex Group Limited (TSX), and Western Areas Limited (WAR).

3.2 Data Normalization

Of the 16 companies, 5 had missing data for a particular financial year. Letters requesting for missing financial data were sent to the five companies (see Appendix A). Responses showed that these companies went through major internal reconstruction in particular years even though they have recorded financial statements since 1980's. Data for the missing months were estimated using weighted-average method, based on the assumption that the activities of the company in each month reflected on the accounting record were identical.

For historical reasons, some mining companies had developed their own ways of recording their financial data. One common example is that many companies' financial years started and ended at different months. As this study entailed analyzing cash flow data from many companies, it was also necessary to match the financial year endings. All the 16 companies' financial years were made to end at March, using weighted-average methodology. Company Anglo America's data from 1999 onwards was recorded in US Dollar term, and was converted into South Africa Rand based on the annual Rand/USD average spot rate.

3.3 Cash-flow Data Construction

Two data series were used for this research, namely cash flow from operations (CFO) and cash flow from operations deflated by number of shares (CFO_DFL). According to the accounting data provided by the database, the constructs of the two data series were as follows:

1. Cash Flow from Operations (CFO) = Operating Income before Depreciation (a)

– Interest Expense (b)

– Tax expense (c)

– Increase in Net Working Capital (d)

(a) Operating Income before Depreciation = Profit before interest & tax

+ Depreciation of Land & Building

+ Depreciation of other Fixed Assets

(b) Interest Expense = Total Interest Paid

(c) Tax Expense = Total Tax Paid

(d) Increase in Net Working Capital = $NWC_n - NWC_{n-1}$

2. Cash Flow from Operations Deflated by the Number of Shares (CFO_DFL) is calculated as CFO divided by Number of Ordinary Shares Issued per year.

3.4 Data Analysis

Excel, SPSS and SAS programmes were used for data analysis in this research. Data analysis followed a multi-step approach. Firstly, the data series were plotted and this was followed by auto-correlation function test for each series.

Secondly, three steps of data transformation were done to normalize the data series as they both appeared to be very volatile and little time-series attributes were observed. The transformations are:

1. Differencing

$$\Delta Y_t = Y_t - Y_{t-1} = \varepsilon_t \quad \text{(Equation 3.1)}$$

– t stands for current year;

– $t-1$stands for previous year.

2. Square the Differencing

$$Var(\varepsilon_t) = \varepsilon_{(t)}{}^2 \quad \text{(Equation 3.2)}$$

3. Logarithm of the Squared Differencing

$$f_{i(t)} = Ln[\varepsilon_{(t)}{}^2] = Ln\left[Y_t - Y_{t-1}\right] \quad \text{(Equation 3.3)}$$

Thirdly, cluster companies according to the volatility of cash-flow data.

Fourthly, do cross-correlation test for each pair of companies within one particular group based on the cluster analysis results.

$$V_{i(t)} = \frac{Ln[\varepsilon_{i(t)}{}^2]}{\sum Ln[\varepsilon_{i(t)}{}^2] / n} \quad \text{(Equation 3.4)}$$

- i refer to a company's name in a particular group;

- n is the number of companies in a particular group.

One company's $V_{i(t)}$ value was then cross-correlated with another company's $V_{i(t)}$ value within its group.

Fifthly, fit a model for each cluster of companies. Given the limited data points for this research project, the literature which deals with complicated models does not have much value. Three simple models were considered, the linear model, the quadratic model and the cubic model.

Linear model:

$$f(t) = b_0 + b_1 \times t \quad \text{(Equation 3.5)}$$

Quadratic model:

$$f(t) = b_0 + b_1 \times t + b_2 \times t^2 \quad \text{(Equation 3.6)}$$

Cubic model:

$$f(t) = b_0 + b_1 \times t + b_2 \times t^2 + b_3 \times t^3 \quad \text{(Equation 3.7)}$$

The curve estimation employed stepwise regression analysis, assigning time t, and its quadratic value t^2 and cubic value t^3 as three independent variables.

Lastly, the fitness of each model was evaluated using R-squared and Durbin-Watson statistics. R-squared value is usually used to assess the validity of linear models (Keller and Warrack, 2003:622). Durbin-Watson statistics was used to test whether there were any first-order auto-correlation between residuals in the estimated models (Keller and Warrack, 2003:681). F-statistics was used to measure how strongly the dependent variable and independent variable were related for a particular model by measuring the variance level of the model (Keller and Warrack, 2003:477).

Chapter 4 Results and Discussion

4.1 Auto-correlation function results

From the sequence plot (Figure 4.1, Figure 4.2) of both cash-flow series, no time-series attributes were captured. Huge volatility exists in many companies' cash-flow data series, which indicates that the variances for many cash-flow series are not constant. In addition, no significant results were obtained from the auto-correlation tests either. Large volatility also suggests that an estimation of the auto-regression model is not very meaningful without any time-series attributes observed because significant lags or leads in auto-correlation tests tell us when a data series resembles itself. In general, auto-regressive moving-average models (ARMA models) or auto-regression integrated moving-average models (ARIMA models) will not be suitable for the forecasting of future cash-flow data.

Figure 4.1: Sequence Plot of CFO Data Series– before data transformation

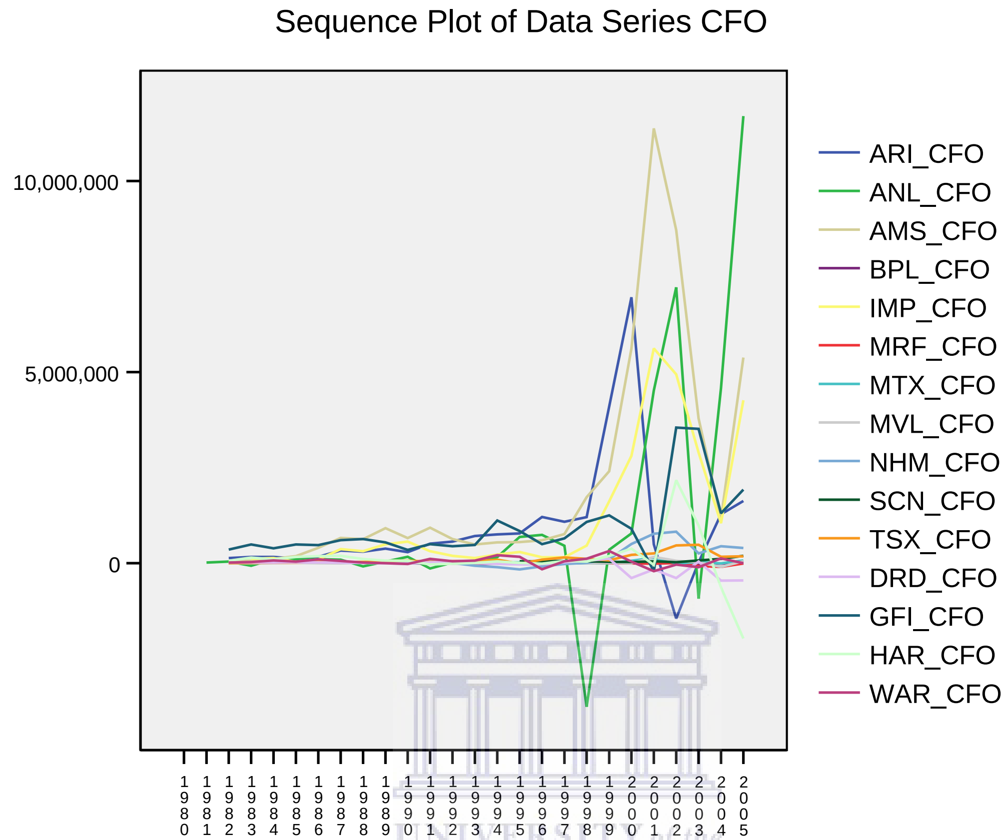
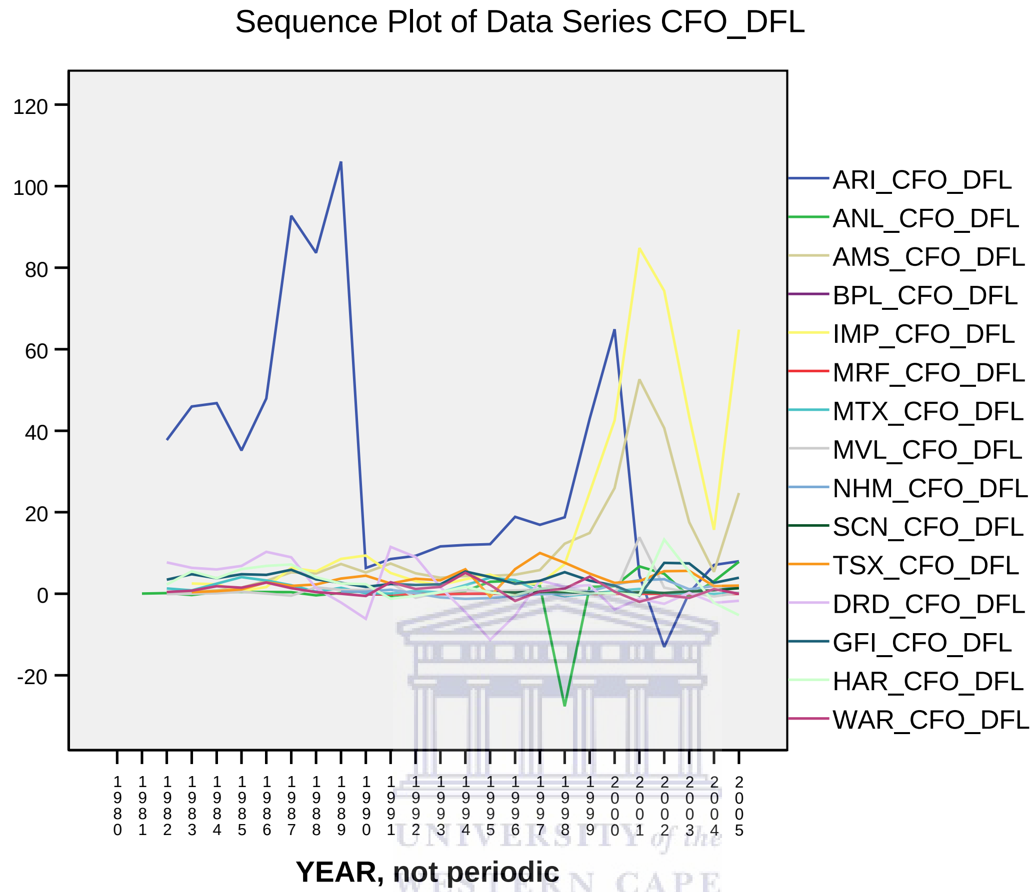


Figure 4.2: Sequence Plot of CFO_DFL Data Series – before data transformation



4.2 Sequence plot of Cash-flow data series transformed

The volatility is reduced after the logarithmic transformation, and the data series appear to be at similar scales, but the data series lie at different levels (Figure 4.3, Figure 4.4). The research becomes a study of the cash flow data series' variance over time. Cluster analysis is then introduced to classify the companies whose cash flow data behave most likely in terms of fluctuation, and the forecast is based on the mean value of cash-flow data of each cluster instead of individual companies.

Figure 4.3: Sequence Plot of CFO Data Series– after data transformation

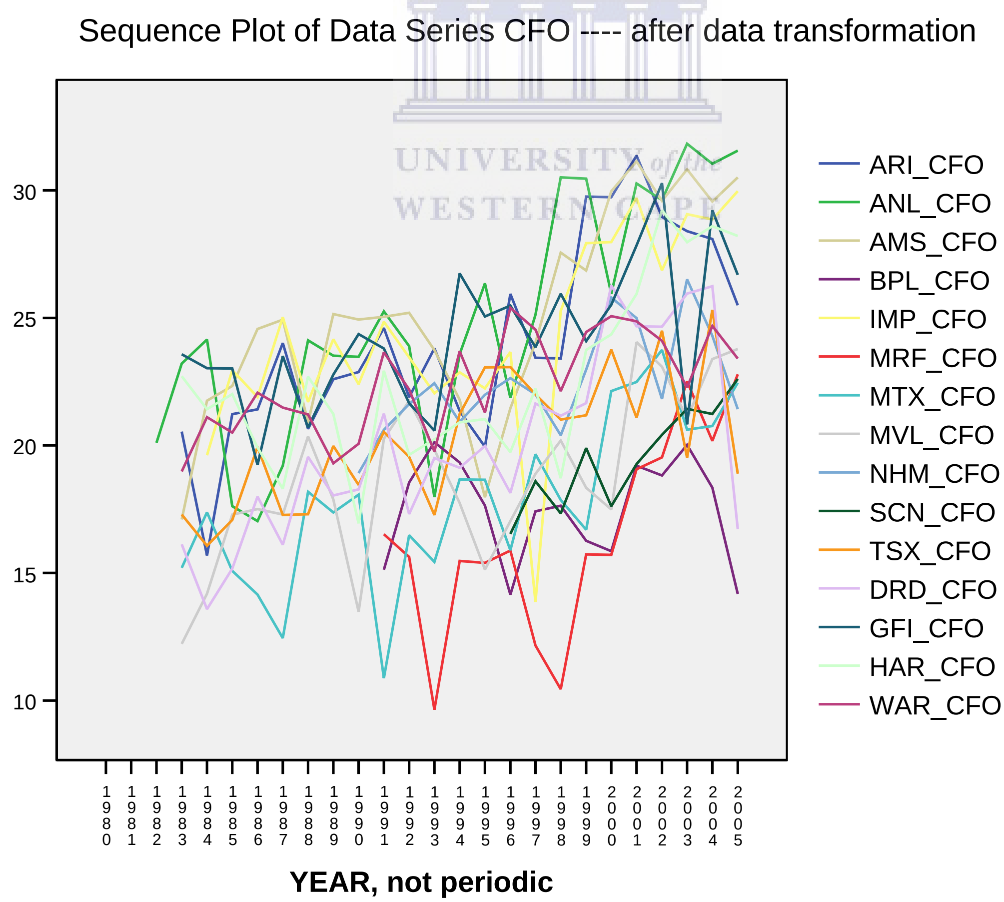
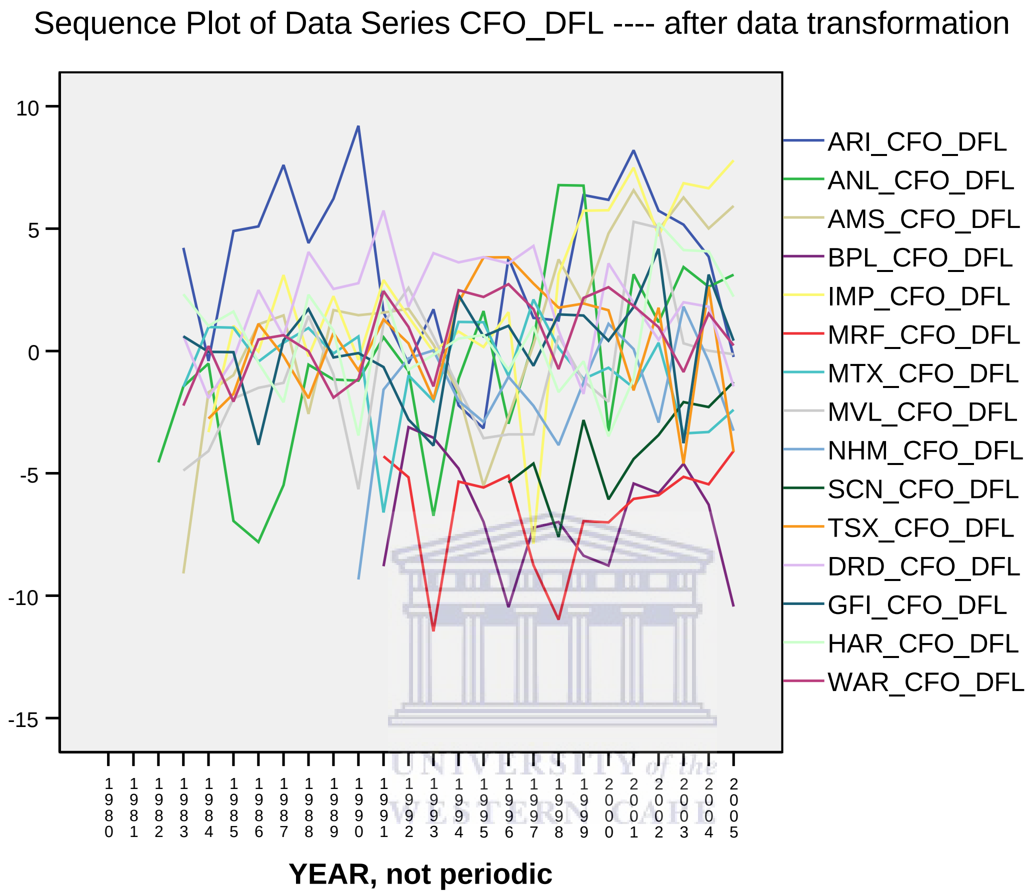


Figure 4.4: Sequence Plot of CFO_DFL Data Series – after data transformation



4.3 Cluster Analysis

There are many ways of doing cluster analysis. Hierarchy cluster analysis is used because it can better capture the fluctuation behaviours of the data series in this research. Everitt (1980:24) characterised hierarchy cluster analysis to partition the series until the classes cannot be further subdivided. Given the small number of data series, three clusters were selected for each. SAS program matched all the data series to the data series with the shortest time period, thus companies (BHP, BPL, MRF, NHM and SCN) with less data were excluded. Cluster analysis was conducted within 11 companies.

For data series CFO, companies were divided into the following 3 groups according to their variance behaviour (see Figure 4.3):

- Group 1: DRD, MTX, MVL, TSX;
- Group 2: AMS, ARI, GFI, HAR, IMP, WAR;
- Group 3: ANL.

Company ANL was eliminated from the study, because it could not cross correlate with another company.

For data series CFO_DFL, companies were divided into 3 groups as follows according to the variance behaviour of their cash flow data (see Figure 4.4):

- Group 1: AMS, DRD, GFI, HAR, IMP, MTX, MVL, TSX, WAR;
- Group 2: ANL;
- Group 3: ARI.

Both group 2 and group 3 only have one company, thus companies ANL and ARI were eliminated from the analysis.

4.4 Cross-correlation test results

Cross-correlation function (CCF) tests how pairs of data correlate. However, it is not meaningful if the variances of the paired data are very different. Hence, cluster analysis is performed before cross-correlation to classify cash flow data according to their variance pattern.

The cross-correlation tests were calculated according to Equation 3.4 (in Chapter 3), and the significant results ($p<0.05$) are summarized in Table 4.1, Table 4.2 and Table 4.3 (complete cross-correlation results see Appendix D).

Table 4.1: Cross-Correlation Results Summary for Group 1 of Data Series CFO

	DRD	MTX	MVL	TSX
DRD	1	-0	W/N	-lag2; (lead4)
MTX		1	-0; (lag4)	W/N
MVL			1	-0; (lead4)
TSX				1

The interpretation for the tables below is as follows: direction of correlation, significant lags or leads observed. More specifically:

- "+" stands for a positive correlation;
- "-" stands for a negative correlation;
- "0" means the significance is observed at time 0;
- W/N stands for Pure White Noise (Chatfield, 1980:39), meaning there is no significance obtained from the test.
- the brackets with lags (leads) indicate insignificant significances at relatively far distance.

As illustrated in Table 4.1 above, for CFO data series Group 1, four significant results were obtained out of six tests. Three pairs of cash flow data are negatively correlated at time 0. They are company DRD and MTX, MTX and MVL, and MVL and TSX. Company DRD and TSX's cash-flow data are negatively correlated at Lag 2.

The cash flow data of DRD's is negatively correlated with the cash flow data of MTX's, MVL's cash flow data is negatively correlated with both MTX's and TSX's. However, it doesn't mean that the variance of company DRD and MVL's cash flow data are likely to behave in similar manner, or the variance of company MTX and TSX's cash flow data are likely to behave in similar manner. There is no significant correlation between these companies, thus such inference about the variance behaviour is wrong.

The only inference that can be made is that DRD's cash flow data will respond to TSX's cash flow data at lag 2 in a negative direction. This result is not explainable unless there is a connection between at the two companies, and such connection made DRD respond to TSX's change after 2 years' time. In this case, the predictive value is again doubtful.

Table 4.2: Cross-Correlation Results Summary for Group 2 of Data Series CFO

	ARI	AMS	IMP	GFI	HAR	WAR
ARI	1	W/N	W/N	-0	-0;(lag6)	-lag2
AMS		1	+lag2	-0	W/N	-0, -lag1
IMP			1	W/N, (lag6)	W/N	-0
GFI				1	W/N	+lag1, +lag2, +lag3
HAR					1	W/N
WAR						1

For CFO data series Group 2 (Table 4.2), eight significant results were obtained out of fifteen tests. Company ARI and AMS are both negatively correlated with company GFI at time 0. Company AMS is negatively correlated with company HAR and WAR at time 0. Company WAR is negatively correlated with company AMS and IMP at time 0. Company AMS and IMP's cash flow data are positively correlated at lag 2.

According to Table 4.2 above, AMS will respond positively at lag 2 to IMP's cash flow variance, WAR's cash flow variance is an indicator for ARI at lag 2 (negatively), for AMS at lag 1 (negatively), and for GFI at lag 1, 2 and 3 (positively).

These results also provide little predictive values. The explanation for this is similar to that for the cross-correlation results for the companies in Group 1 of CFO data series.

Table 4.3: Cross-Correlation Results Summary for Group 1 of Data Series CFO_DFL

	AMS	IMP	MTX	MVL	TSX	DRD	GFI	HAR	WAR
AMS	1	+lag2	-lag2	-0; +lag2	-lag2	+0; -lag2	-0; +lag2	-lag2	-lag2
IMP		1	-0	+0	-0	-0	+0	-0	-0
MTX			1	-0	+0	+0	-0	+0	+0
MVL				1	-0	-0	+0	-0	-0
TSX					1	+0	-0	+0	+0
DRD						1	-0	+0	+0
GFI							1	-0	-0
HAR								1	+0
WAR									1

Three important results are found in the cross-correlation tests for Group 1 of the CFO_DFL series illustrated in Table 4.3 above. Firstly, company AMS is significantly correlated with all other companies at lag 2. It is positively correlated with company IMP, MVL, and GFI, while it is negatively correlated with company MTX, TSX, DRD, HAR and WAR. In addition, AMS is also significantly correlated with company MVL, GFI (both negatively) and DRD (positively) at time 0. Secondly, apart from AMS, all other companies are significantly correlated at time 0. Lastly, no pure white noise was found in the cross-correlation tests for this group.

One can also conclude that there are little predictive values as in the case the cross-correlation results in Table 4.1 and Table 4.2. In addition, too many significant results suggest that a multiple hypothesis test should be performed to examine the trueness of the significances (Sawyer, 1984:424).

4.5 Curve Estimation

The stepwise regression method was used for curve estimation in this research, by using time values t , t^2 and t^3 as different variables. For each model estimated, only one variable was entered.

Table 4.4: Model selection

Dependent Variable	Independent Variables Entered	Model	Method
CFO Group1	t	Linear	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
CFO Group2	t^2	Quadratic	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
CFO_DFL Group1	t	Linear	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).

Table 4.4 above, summarises the models selected for each cluster. For CFO Series Group 1 data, variable t is entered, meaning the model is linear. For CFO Series Group 2 data, variable t^2 is selected, meaning Quadratic Model fits the curve. For CFO_DFL Series Group 1 data, variable t is entered, meaning the model is also linear. The plots of estimated curves see Appendix E.

4.6 Forecasts

Table 4.5: Parameters for Selected Models

CF Data Group	Model	df1	df2	Sig.	Parameter Estimates		
Dependent Variable	Description				Constant	b1	b2
CFO_Gr1	Linear	1	20	0.000	15.5	0.338	N/A
CFO_Gr2	Quadratic	2	19	0.000	21.346	0.015	0.000001410
CFO_DFL_Gr1	Linear	1	20	0.000	-0.633	0.114	N/A

N.B.: The time period t is adjusted according to the series with the shortest length (see Appendix C), thus for the forecast of 2006, t is equal to 23.

Based on the parameters provided in Table 4.5 above, the following forecasts were performed.

Forecast mean value of CFO Group 1 in 2006:

The Equation is (consult Equation 3.5):

$$Y = b_0 + b_1 t$$

Thus:

$$Y_{(2006)} = 15.55 + 0.338 \times 23 = 23.324$$

Description: the mean value of variance for CFO_Gr1 data series in 2005 is 20.46 (see Appendix C, Table C-1), thus in 2006, the variance will increase.

Forecast mean value of CFO Group 2 in 2006:

The equation is (consult Equation 3.6):

$$Y = b_0 + b_1 t + b_2 t^2$$

Thus:

$$Y_{(2006)} = 21.346 + 0.015 \times 23 + 0.00000141 \times 23^2 = 21.692$$

Description: the mean value of variance for CFO_Gr2 data series in 2005 is 27.38 (see Appendix C, Table C-1), thus in 2006, the variance will decrease.

<u>Forecast mean value of CFO_DFL Group 1 in 2006:</u>

The equation is (consult Equation 3.5):

$$Y = b_0 + b_1 t$$

Thus:

$$Y_{(2006)} = -0.633 + 0.114 \times 23 = 1.989$$

Description: the mean value of variance for CFO__DFL_Gr1 data series in 2005 is 0.94 (see Appendix C, Table C-1), thus in 2006, the variance will increase.

4.7 Evaluation of Models

Table 4.6: R-squared value and Durbin-Watson Statistic

CF Data Group Dependent Variable	Model Description	R	R - Squared	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
CFO_Gr1	Linear	0.887	0.787	0.776	1.172	2.012
CFO_Gr2	Quadratic	0.884	0.782	0.771	1.261	1.439
CFO_DFL_Gr1	Linear	0.719	0.517	0.492	0.734	2.180

According to the R-Squared results (Table 5.1), the linear model for CFO_Gr1 data series can predict future cash flow variance at accuracy of 78.7%. Durbin-Watson statistic exceeds 1.648, meaning that there is no first-order correlation between residuals (Keller and Warrack, 2003:681). Therefore, the linear model fits well for CFO_Gr1 data series.

However, the other two models do not fit well for the other two series. The Durbin-Watson statistic for the quadratic model of CFO_Gr2 data series lies in the range of 1 to 1.648, meaning that the forecasting result is inconclusive (Keller and Warrack, 2003:683). The poor R-squared value for the linear model of CFO_DFL_Gr1 data series suggests that the accuracy of forecasting is unreliable (Keller and Warrack, 2003:622).

Table 4.7: F-statistics

Data Series	Model		Sum of Squares	df	Mean Square	F	Sig.
CFO_Gr1	Linear	Regression	117.837	1	117.837	89.969	0.000
		Residual	27.505	21	1.31		
		Total	145.342	22			
CFO_Gr2	Quadratic	Regression	104.845	1	104.845	51.382	0.000
		Residual	40.81	20	2.041		
		Total	145.655	21			
CFO_DFL_Gr1	Linear	Regression	11.536	1	11.536	21.425	0.000
		Residual	10.769	20	0.538		
		Total	22.305	21			

F-statistics explains how strongly the dependent variable (cash-flow data) and the independent variable (time t) are related, and a higher F-statistic shows a stronger relationship (Keller and Warrack, 2003:477). According to table 4.7, the linear model for series CFO_Gr1 shows strongest relationship between variables than the other two models. This result is consistent with the r-squared fitness.

4.8 Hypothesis Testing

The Null Hypothesis was that the linear model is the appropriate model to forecast future cash flow.

The Null Hypothesis is accepted for the data series CFO_Gr1. The linear model is an appropriate model to forecast future cash flows using CFO_Gr1 data series.

The Null Hypothesis is rejected for the data series CFO_Gr2 and CFO_DFL_Gr1. The linear model is an inappropriate model to forecast future cash flows using CFO_Gr2 and CFO_DFL_Gr1 data series.

Chapter 5 Conclusion and Recommendation

5.1 Conclusion

This research has thoroughly gone through the time-series approaches in studying the cash flow data of the selected mining companies. The research finding proves that ARMA models are not applicable due to large volatility exists in data series. It also provided evidence that other time-series approaches, such as cross-correlation test, have limited predictive value. Furthermore, the candidate models are not as ideal as expected, because of the poor R-squared value and a Durbin-Watson statistic which suggests inconclusiveness of the forecasting result.

As far as the implication for industry is concerned, when people make investment decisions on the companies in Group 1 (DRD, MTX, MVL and TSX), they can consult the forecast on variance. However, they should not rely on it. Fundamental analysis is suggested in this case. More importantly, many assumptions have been made when normalizing data for forecasting purposes in this research (see Chapter 3). In reality, companies and investors should consult the particular company's financial statements' ending when they adopt the same forecasting model introduced in this research. Otherwise, the validity of the application will be questionable.

The mining companies being researched are South African based companies. Many accounting items are different from those of the United States based companies being researched in the literature, thus the accounting items used have been adjusted for the cash-flow constructs. In the American literature, quarterly accounting data were used, and those data exhibited cyclical behaviour. This finding is consistent with Ball and Brown's (1968:724), and with Bowen and Rozeff's (1979:187), that the quarterly and interim accounting reports are more appropriate for forecasting, as investors act more promptly to these information than the annual reports.

Since the sequence plots of both series do not show any cyclical behavior, three steps of transformation were used to normalize the data. Errors are accumulated during this process and these can reduce the accuracy of the forecasting models. Thus, one-step-ahead forecasting is reasonable, but forecasting for more than one year is not meaningful.

5.2 Recommendations for Future Study

1. Results from this study suggest that researchers should obtain quarterly data or data covering a longer period.
2. Different cash-flow data construction can be attempted, or even different accounting items can be used. For instance, research mining companies' quarterly earnings. It may show some cyclical behavior and data transformation would not be necessary, which will make the forecasting more accurate and the study more practical.
3. This study has included mining companies that produce different products. In the future, studies can also classify these companies according to their major product and then research the cash-flow data' attributes.
4. Multiple hypothesis test is suggested so as to eliminate the false significances.

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APPENDIX A: The Letters to Mining Companies Requesting for Missing Data

University of Western Cape

Department of Management
Tel: +27 21 9592595
Fax: +27 21 9591518
Email: Sgool@uwc.ac.za

P Bag X17 Bellville
7530
South Africa

1st February, 2007

Mr I. Graulich
Investor Relations
DRD Gold Limited
P.O. Box 309,
Maraisburg, 1700

Dear Mr Graulich:

Re: Request for Information – Research Masters thesis

I am a Masters' student in finance at the University of the Western Cape; I am currently working on my Masters thesis with regard to the major SA mining companies' Cash Flows. I obtained the financial statements of DRD Gold Limited from McGregor's' BFA database, from 1980 to 2005. However, the data for **1995** are **missing**. Would you please kindly assist me with getting the missing data for 1995 strictly for research purpose, including balance sheet, income statement and cash flow statement.
The data can be sent to the following email addresses:
sgool@uwc.ac.za (my thesis supervisor's email address)
2441134@uwc.ac.za (my student email address)

Your effort and support will be acknowledged in my final paper!
With kind regards!

Thesis Supervisor: Professor Sulaiman Gool Signature: …………………

Student: Yang Li Signature: …………………

University of Western Cape

Department of Management
Tel: +27 21 9592595
Fax: +27 21 9591518
Email: Sgool@uwc.ac.za

P Bag X17 Bellville
7530
South Africa

1st February, 2007

Mr Barnard Jacobs Mellet
Investor Relations
Metorex Limited
P.O. Box 62200,
Marshalltown, 2107,
Johannesburg

Dear Mr Mellet:

Re: Request for Information – Research Masters thesis

I am a Masters' student in finance from the University of the Western Cape, currently working on my Masters thesis with regard to major SA mining companies' Cash-Flow data. I obtained MTX's financial data from McGregor's BFA database; I have from 1980 till 2005. However, the whole set of data for **1984** are **missing**. Would you kindly assist me in getting the missing data for 1984 strictly for research purpose, including balance sheet, income statement and cash flow statement.
The data can be sent to the following email addresses:
sgool@uwc.ac.za (my thesis supervisor's email address)
2441134@uwc.ac.za (my student email address)
Your effort and support will be acknowledged in my final paper!
With kind regards!

Thesis Supervisor: Professor Sulaiman Gool Signature: …………………

Student: Yang Li Signature: …………………

University of Western Cape

Department of Management
Tel: +27 21 9592595
Fax: +27 21 9591518
Email: Sgool@uwc.ac.za

P Bag X17 Bellville
7530
South Africa

1st February, 2007

Mr James Wellsted
Investor Relations
Mvelaphanda Resources Limited
P.O. Box 413420,
Craighall, 2024

Dear Mr Wellsted:

Re: Request for Information – Research Masters thesis

I am a Master's student in finance at university of Western Cape; I am working on my master's thesis on SA mining companies' Cash Flows. I obtained MVL's financial data from McGregor's' BFA database, from year 1980 to 2005. However, the data for **1986** are all **missing** from the spreadsheet. Would you kindly assist me in getting the data for 1986, including the balance sheet, income statement and the cash flow statement, strictly for research purpose? In addition, the data for two particular accounting items are also not very good from the spreadsheet from 1980 to 2005, they are: depreciation for other fixed assets & depreciation for land and building.

The data can be sent to the following email addresses:
sgool@uwc.ac.za (my thesis supervisor's email address)
2441134@uwc.ac.za (my student email address)
Your effort and support will be acknowledged in my final paper!
With kind regards!

Thesis Supervisor: Professor Sulaiman Gool Signature: …………………

Student: Yang Li Signature: …………………

University of Western Cape

Department of Management
Tel: +27 21 9592595
Fax: +27 21 9591518
Email: Sgool@uwc.ac.za

P Bag X17 Bellville
7530
South Africa

1st February, 2007

Mr Jason Holland
Financial Director)
Scharrig Mining Limited
P. O. Box 30193,
Jet Park 1469

Dear Mr Holland:

Re: Request for Information – Research Masters thesis

I am a Master's student in finance at University of Western Cape; I am currently busy with my Master's thesis on SA mining companies' Cash Flows. I obtained the financial statements for SCN from McGregor's' BFA database, from 1993 to 2005. However, the data for **1997** are **missing**. Would you please kindly assist me in getting the missing data for on 1997 strictly for research purpose, including balance sheet, income statement and cash flow statement?

The data can be sent to the following email addresses:
sgool@uwc.ac.za (my thesis supervisor's email address)
2441134@uwc.ac.za (my student email address)

Your effort and support will be acknowledged in my final paper!

With kind regards

Thesis Supervisor: Professor Sulaiman Gool Signature: …………………

Student: Yang Li Signature: …………………

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Tel: +27 21 9592595
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Email: Sgool@uwc.ac.za

P Bag X17 Bellville
7530
South Africa

1st February, 2007

Mr Steve Levitt
Financial Director
Western Areas Limited
P.O. Box 61719, Marshalltown, 2107

Dear Mr Levitt:

Re: Request for Information – Research Masters thesis

I am a Masters' student in finance at the University of the Western Cape; I am currently busy with my Master's thesis on major SA mining companies' Cash Flows. I obtained the financial statements for WAR from Mcgregors' BFA database, from 1980 to 2005. However, the data for **1984** are **missing**. Would you please kindly assist me in getting the missing data on 1997 strictly for research purpose, including balance sheet, income statement and cash flow statement?

The data can be sent to the following email addresses:
sgool@uwc.ac.za (my thesis supervisor's email address)
2441134@uwc.ac.za (my student email address)

Your effort and support will be acknowledged in my final paper!

With kind regards!

Thesis Supervisor: Professor Sulaiman Gool Signature: …………………

Student: Yang Li Signature: …………………

APPENDIX B:

The Returned Emails Regarding Missing Financial Data

From:	"Ilja.Graulich" <ilja.graulich@za.drdgold.com>	Monday - February 19, 2007 11:06 AM
To:	<2441134@uwc.ac.za>	
Subject:	letter 1 Feb 2007	
Attachments:	Mime.822 (10363 bytes)	[View] [Save As]

Hi

With reference to your letter of 1 Feb. 2007, looking for data for 1995, I am sorry, but we are unable to assist you in getting this data.

The entire management team here is post 1995, which is also post major restructuring and corporate governance changes that the company went through and we are unable to locate any 1995 annual report data.

kind regards

IDG

Ilja Graulich (Mr.)
Strategic Development Officer

DRDGOLD Limited

Tel: +27 11 219 8700
Direct: +27 11 219 8707
Fax: +27 11 476 2637
Mobile: +27 83 604 0820
ilja.graulich@za.drdgold.com
www.drdgold.com <http://www.drdgold.com/>

From:	"Pieter Henning" <phenning@wal.co.za>	Monday - February 26, 2007 10:14 AM
To:	<sgool@uwc.ac.za>, <2441134@uwc.ac.za>	
Subject:	Western Areas Ltd	

Attachments: Mime.822 (3910 bytes) [View] [Save As]

Dear Prof Gool / Yang

I refer to your letter dated 1 February 2007 requesting the financial information of Western Areas Limited for 1984.

The year-end was changed from December to June in that period thus there is no financial statements for 1984 per se. The financials of 1985 is for 18 months from 1 January 1984 to 30 June 1985 and the comparatives are as at 31 December 1983.

Yang, Good luck with your research.

Regards

Pieter Henning
Chief Financial Officer
Western Areas Ltd
Tel: +27 11 688 5065
Fax: +27 11 834 9195 or +27 11 836 7111
E-mail: phenning@wal.co.za

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No virus found in this outgoing message.
Checked by AVG Free Edition
Version: 7.1.412 / Virus Database: 268.18.4/702 - Release Date: 2007/02/25

APPENDIX C: The Mean Value of Different Groups of Data Series after Transformation

Table C-1: The Mean Value of Different Groups of Data Series after Transformation

Year	Original t (Independent variables)			Adjusted t (Independent variables)			CFO_Gr1	CFO_Gr2	CFO_DFL_Gr1
	t	t^2	t^3	t	t^2	t^3	Mean	Mean	Mean
1980	1	1	1						
1981	2	4	8						
1982	3	9	27						
1983	4	16	64				15.21		
1984	5	25	125	1	1	1	15.3	20.43	-1.29
1985	6	36	216	2	4	8	16.15	22.01	-0.39
1986	7	49	343	3	9	27	17.4	21.52	-0.12
1987	8	64	512	4	16	64	15.78	22.88	0.33
1988	9	81	729	5	25	125	18.85	21.31	0.63
1989	10	100	1000	6	36	216	18.32	22.54	0.53
1990	11	121	1331	7	49	343	17.07	21.93	-0.74
1991	12	144	1728	8	64	512	18.23	24.15	1.15
1992	13	169	2197	9	81	729	18.77	22.34	0.47
1993	14	196	2744	10	100	1000	18.01	21.69	-0.52
1994	15	225	3375	11	121	1331	19.19	22.89	1.08
1995	16	256	4096	12	144	1728	19.21	21.25	0.37
1996	17	289	4913	13	169	2197	18.53	23.61	0.54
1997	18	324	5832	14	196	2744	20.55	21.99	0.02
1998	19	361	6859	15	225	3375	20.06	23.84	1.03
1999	20	400	8000	16	256	4096	19.47	26.14	0.96
2000	21	441	9261	17	289	4913	22.41	27.1	1.4
2001	22	484	10648	18	324	5832	23.07	28.47	2.3
2002	23	529	12167	19	361	6859	24	28.17	3.07
2003	24	576	13824	20	400	8000	21.79	26.56	0.78
2004	25	625	15625	21	441	9261	23.93	28.17	2.39
2005	26	676	17576	22	484	10648	20.46	27.38	0.94

APPENDIX D: CROSS-CORRELATION TEST RESULTS

Table D-1: Complete Cross-correlation tests results of data pairs – data series CFO Group 1

	Lag	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7
DRD& MTX	Cross Correlation	0.047	0.07	-0.035	-0.242	0.097	-0.124	0.158	-0.439	0.039	0.354	0.082	0.058	-0.038	0.095	0.305
	Std. Error(a)	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.209	0.213	0.218	0.224	0.229	0.236	0.243	0.25
DRD & MVL	Cross Correlation	-0.068	0.135	0.051	-0.245	-0.188	0.194	-0.068	-0.337	0.073	0.114	-0.083	-0.116	0.16	0.136	-0.178
	Std. Error(a)	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.209	0.213	0.218	0.224	0.229	0.236	0.243	0.25
DRD & TSX	Cross Correlation	0.123	-0.058	0.132	0.552	-0.013	0.032	-0.12	-0.012	-0.152	-0.462	-0.129	0.012	-0.005	-0.091	-0.057
	Std. Error(a)	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.209	0.213	0.218	0.224	0.229	0.236	0.243	0.25
MTX & MVL	Cross Correlation	-0.089	-0.242	-0.28	0.019	0.093	0.055	0.021	-0.389	-0.212	-0.024	0.403	0.459	-0.138	-0.307	-0.016
	Std. Error(a)	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.209	0.213	0.218	0.224	0.229	0.236	0.243	0.25
MTX & TSX	Cross Correlation	0.025	0.108	-0.021	-0.135	0.174	-0.312	-0.035	-0.31	0.147	0.266	-0.24	-0.404	-0.208	0.217	0.187
	Std. Error(a)	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.209	0.213	0.218	0.224	0.229	0.236	0.243	0.25
MVL & TSX	Cross Correlation	0.152	0.098	-0.09	-0.433	-0.117	0.211	-0.039	-0.467	-0.19	0.033	0.374	0.244	0.196	0.018	0.134
	Std. Error(a)	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.209	0.213	0.218	0.224	0.229	0.236	0.243	0.25

a. Based on the assumption that the series are not cross-correlated and that one of the series is white noise.

Note: Series Pair: LnSqCompanyCode_CFO_1_DividedBy_MeanGr1_CFO Correlated with LnSqCompanyCode_CFO_1_DividedBy_MeanGr1_CFO

Table D-2: Complete Cross-correlation tests results of data pairs – data series CFO Group 2

	Lag	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7
ARI & AMS	Cross Correlation	0.018	-0.13	-0.44	-0.18	0.007	-0.24	0.013	0.15	0.25	-0.03	-0.08	0.226	-0.1	-0.11	0.144
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
ARI & IMP	Cross Correlation	0.01	-0.16	-0.06	-0.13	-0.2	-0.27	0.15	-0.02	-0.28	0.292	0.059	-0.14	0.02	0.02	-0.07
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
ARI & GFI	Cross Correlation	-0.01	0.311	0.223	0.037	0.157	0.287	-0.03	-0.46	-0.03	0.023	-0.18	-0.12	0.159	-0.27	-0.06
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
ARI & HAR	Cross Correlation	-0.09	-0.14	0.086	-0	-0.31	0.007	-0.25	-0.37	0.003	0.189	0.284	0.127	0.086	0.466	0.024
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
ARI & WAR	Cross Correlation	0.086	0.148	0.374	0.201	0.245	0.215	-0.03	-0.21	-0.04	-0.58	-0.26	-0.17	-0.01	-0.08	-0.03
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
AMS & IMP	Cross Correlation	-0.06	-0.29	0.039	-0.07	-0.11	0.14	-0.24	0.05	0.398	0.549	0.25	-0.27	-0.16	0.129	-0.15
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
AMS & GFI	Cross Correlation	0.097	0.003	-0.03	-0.1	0.267	0.072	-0.35	-0.53	-0.19	-0.32	-0.11	0.354	0.206	0.01	0.062
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
AMS & HAR	Cross Correlation	-0.23	0.107	0.127	0.144	-0.01	-0.01	0.25	-0.18	-0.06	0.382	0.098	0.163	0.29	-0.12	-0.18
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
AMS & WAR	Cross Correlation	0.111	0.439	0.084	-0	-0.04	-0.09	-0.13	-0.43	-0.5	-0.34	-0.23	0.086	0.208	0.203	0.345
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
IMP & GFI	Cross Correlation	-0.19	0.02	0.164	0.143	-0.21	-0.38	-0.11	-0.33	-0.15	0.165	0.227	0.016	-0.11	0.481	0.056
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
IMP & HAR	Cross Correlation	0.273	0.022	-0.02	0.11	0.098	-0.11	0.314	-0.23	0.276	0.104	0.051	0.099	-0.21	-0.17	-0.2
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
IMP & WAR	Cross Correlation	0.183	-0.04	-0.13	0.154	-0.14	-0.18	-0.26	-0.59	0.049	-0.07	0.028	0.109	0.305	0.256	0.246
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
GFI & HAR	Cross Correlation	0.149	0.002	0.099	-0.22	-0	-0	-0	-0.17	0.036	-0.37	-0.26	-0.07	-0.02	-0.07	0.249

	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
GFI & WAR	Cross Correlation	-0.23	-0.24	-0.18	-0.02	0.05	0.108	0.31	0.406	0.397	0.518	0.136	-0.03	-0.19	-0.2	-0.13
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
HAR & WAR	Cross Correlation	0.233	-0.01	0.087	-0.33	-0.22	-0.39	-0.29	-0.09	-0.34	0.028	0.15	-0	-0.12	0.062	-0.05
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258

a. Based on the assumption that the series are not cross-correlated and that one of the series is white noise.

Note: Series Pair: LnSqCompanyCode_CFO_1_DividedBy_MeanGr2_CFO Correlated with LnSqCompanyCode_CFO_1_DividedBy_MeanGr2_CFO

Table D-3: Complete Cross-correlation tests results of data pairs – data series CFO_DFL Group 1

	Lag	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7
AMS & IMP	Cross Correlation	-0.032	-0.281	-0.003	-0.072	-0.088	-0.036	-0.103	-0.361	0.221	0.64	0.074	0.029	-0.141	-0.047	0.086
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
AMS & MTX	Cross Correlation	0.003	0.259	0.035	0.128	0.113	0.008	0.082	0.314	-0.216	-0.642	-0.073	-0.033	0.143	0.047	-0.11
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
AMS & MVL	Cross Correlation	-0.028	-0.277	-0.05	-0.11	-0.121	-0.087	-0.093	-0.364	0.291	0.597	0.086	0.015	-0.115	-0.072	0.087
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
AMS & TSX	Cross Correlation	0.083	0.28	0.024	0.095	0.086	0.07	0.077	0.327	-0.274	-0.63	-0.091	-0.042	0.114	0.04	-0.087
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
AMS & DRD	Cross Correlation	0.011	0.264	0.028	0.054	0.094	0.112	0.088	0.388	-0.276	-0.636	-0.071	-0.014	0.131	0.042	-0.069
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
AMS & GFI	Cross Correlation	-0.082	-0.095	-0.021	0.01	0.082	-0.278	0.019	-0.612	0.205	0.394	0.02	0.069	-0.115	0.013	0.034
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
AMS & HAR	Cross Correlation	-0.009	0.243	-0.123	0.015	0.135	0.036	0.187	0.299	-0.131	-0.617	-0.049	-0.013	0.199	0.139	-0.114
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
AMS & WAR	Cross Correlation	0.084	0.332	0.018	0.1	0.056	0.08	0.068	0.338	-0.278	-0.624	-0.036	-0.046	0.112	0.036	-0.081
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
IMP & MTX	Cross Correlation	0.067	0.144	0.076	0.008	0.042	0.018	0.068	-0.993	0.043	0.053	0.047	0.047	0.049	0.105	0.064
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
IMP & MVL	Cross Correlation	-0.111	-0.08	-0.089	-0.045	-0.041	0.014	0.003	0.986	-0.05	-0.032	-0.037	-0.064	-0.07	-0.063	-0.058
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
IMP & TSX	Cross Correlation	0.065	0.08	0.06	0.036	0.051	-0.023	-0.008	-0.988	0.041	0.03	0.046	0.063	0.064	0.125	0.057
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
IMP & DRD	Cross Correlation	0.089	0.052	0.036	0.107	0.041	0.007	0.014	-0.986	0.051	0.059	0.042	0.053	0.067	0.051	0.06
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
IMP & GFI	Cross Correlation	0.016	0.031	0.175	-0.163	-0.024	-0.035	-0.011	0.634	-0.025	-0.012	-0.018	-0.025	-0.052	0.113	-0.037
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
IMP & HAR	Cross Correlation	-0.05	0.029	0.09	0.046	0.046	0.022	0.098	-0.953	0.102	0.074	0.122	0.082	0.033	-0.052	0.027
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
IMP & WAR	Cross Correlation	0.06	0.069	0.044	0.039	0.041	-0.007	-0.009	-0.988	0.08	0.025	0.041	0.056	0.074	0.099	0.07
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
MTX & MVL	Cross Correlation	0.122	0.097	0.081	0.045	0.042	-0.011	-0.008	-0.983	0.058	-0.004	0.028	0.031	0.093	0.126	0.067

	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
MTX & TSX	Cross Correlation	-0.081	-0.106	-0.051	-0.032	-0.045	0.025	0.012	0.981	-0.053	0.008	-0.035	-0.028	-0.088	-0.187	-0.067
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
MTX & DRD	Cross Correlation	-0.103	-0.072	-0.024	-0.104	-0.04	-0.011	-0.01	0.974	-0.06	-0.017	-0.033	-0.018	-0.088	-0.117	-0.074
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
MTX & GFI	Cross Correlation	0.024	-0.027	-0.218	0.152	0.015	0.046	0.032	-0.585	0.018	-0.021	0.002	-0.004	0.057	-0.071	0.059
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
MTX & HAR	Cross Correlation	0.05	-0.053	-0.077	-0.033	-0.042	-0.032	-0.103	0.944	-0.122	-0.029	-0.113	-0.039	-0.058	-0.016	-0.038
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
MTX & WAR	Cross Correlation	-0.071	-0.096	-0.036	-0.041	-0.035	0.013	0.017	0.978	-0.092	0.009	-0.034	-0.017	-0.098	-0.161	-0.078
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
MVL & TSX	Cross Correlation	0.07	0.062	0.075	0.041	0.037	-0.048	-0.004	-0.991	-0.017	-0.043	0.038	0.058	0.103	0.127	0.116
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
MVL & DRD	Cross Correlation	0.089	0.034	0.051	0.112	0.032	-0.013	0.019	-0.992	-0.009	-0.009	0.036	0.048	0.102	0.058	0.11
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
MVL & GFI	Cross Correlation	0.014	0.065	0.171	-0.116	-0.024	-0.012	-0.058	0.685	0.038	0.039	0.001	-0.025	-0.064	0.087	-0.062
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
MVL & HAR	Cross Correlation	-0.052	0.008	0.087	0.069	0.027	0.016	0.077	-0.93	0.041	0.01	0.114	0.085	0.082	-0.056	0.071
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
MVL & WAR	Cross Correlation	0.068	0.053	0.063	0.043	0.027	-0.035	-0.007	-0.988	0.023	-0.039	0.028	0.048	0.11	0.103	0.128
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
TSX & DRD	Cross Correlation	-0.09	-0.099	-0.047	-0.115	-0.039	0.017	-0.001	0.989	0.004	0.016	-0.045	-0.036	-0.071	-0.055	-0.064
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
TSX & GFI	Cross Correlation	-0.007	-0.007	-0.169	0.153	0.023	0.009	0.012	-0.685	0.003	-0.028	0.02	0.022	0.045	-0.097	0.015
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
TSX v.s. HAR	Cross Correlation	0.057	-0.068	-0.083	-0.058	-0.035	-0.006	-0.071	0.919	-0.039	-0.019	-0.131	-0.076	-0.046	0.057	-0.028
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
TSX & WAR	Cross Correlation	-0.069	-0.12	-0.053	-0.05	-0.036	0.038	0.016	0.994	-0.017	0.052	-0.035	-0.042	-0.082	-0.102	-0.084
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
DRD & GFI	Cross Correlation	-0.053	-0.039	-0.156	0.132	0.031	0.062	0.046	-0.732	-0.008	-0.014	0.004	0.065	0.044	-0.1	0.04
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
DRD & HAR	Cross Correlation	0.038	0.01	-0.098	-0.06	-0.041	-0.033	-0.075	0.931	-0.049	-0.032	-0.114	-0.152	-0.026	0.082	-0.049
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
DRD & WAR	Cross Correlation	-0.062	-0.046	-0.058	-0.033	-0.036	0.002	0.005	0.986	-0.045	0.018	-0.025	-0.108	-0.055	-0.077	-0.103
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258

GFI & HAR	Cross Correlation	0.015	-0.159	0.126	0.036	0.031	-0.03	-0.066	-0.565	-0.062	0.086	0.08	0.238	-0.165	-0.146	-0.043
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
GFI & WAR	Cross Correlation	0.012	-0.104	0.039	0.006	0.028	-0.037	0.026	-0.679	0.05	0.007	-0.033	0.152	-0.159	-0.006	-0.002
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258
HAR & WAR	Cross Correlation	-0.025	0.062	-0.032	-0.079	-0.106	-0.037	-0.04	0.919	-0.115	0.014	-0.038	-0.043	-0.096	-0.042	0.036
	Std. Error(a)	0.258	0.25	0.243	0.236	0.229	0.224	0.218	0.213	0.218	0.224	0.229	0.236	0.243	0.25	0.258

a. Based on the assumption that the series are not cross-correlated and that one of the series is white noise.
Note: Series Pair: LnSqCompanyCode_CFO_DFL_1_DividedBy_MeanGr1_CFO_DFL Correlated with LnSqCompanyCode_CFO_DFL_1_DividedBy_MeanGr1_CFO_DFL

APPENDIX E: Plots of Estimated Curve

Figure E-1: Linear Curve Plot for CFO_Gr1 Data Series

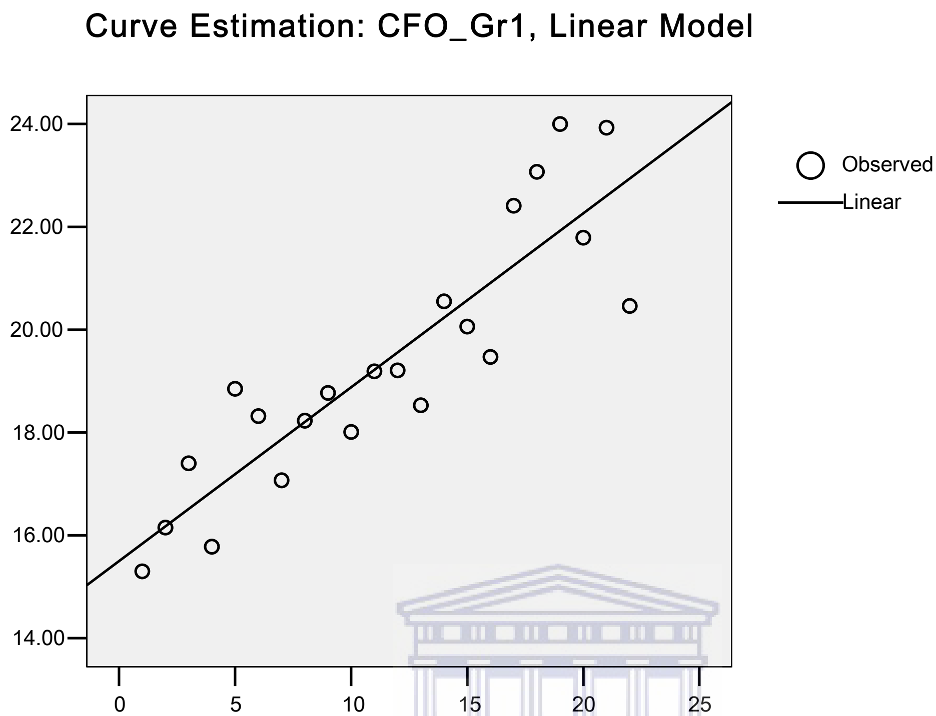

Figure E-2: Quadratic Curve Plot for CFO_Gr2 Data Series

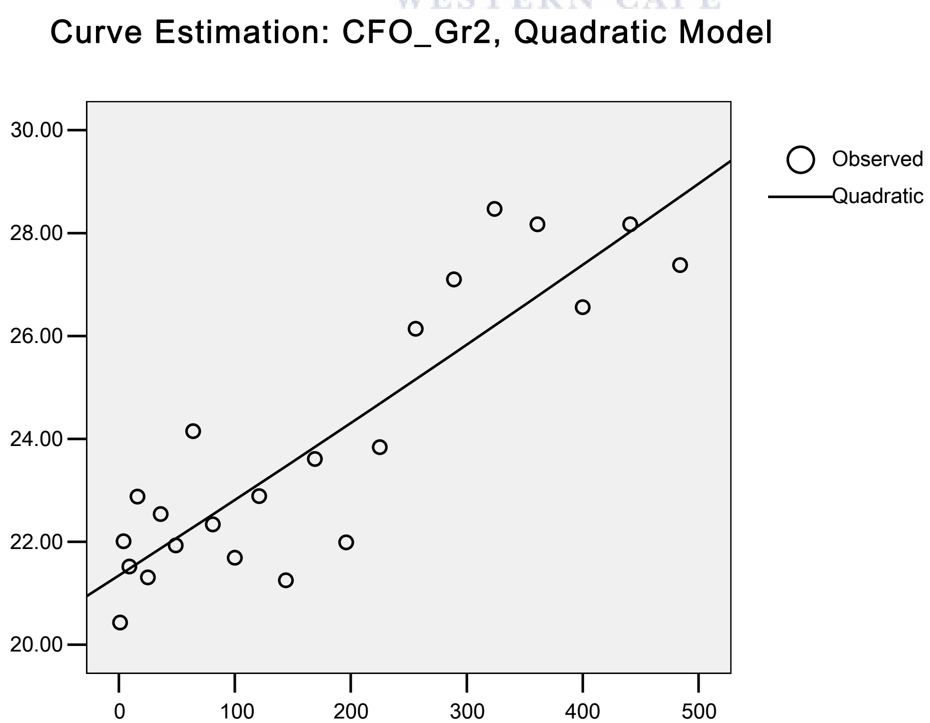

Figure E-3: Linear Curve Plot for CFO__DFL_Gr1 Data Series