Interaction between Firm-level Variables and Stock Betas: a South African Perspective

Mini Dissertation by
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Abstract

This paper aims to determine the existence of the interaction between firm-level variables and stock betas in the South African equity market and if existent, use this relationship to aid market participants in the investment process.

This paper looks at the use of Kalman filter in estimating stock betas which vary over time. A brief overview of the Kalman filter method is provided. In particular, this paper examines the impact of sub-sector betas and firm-specific variables on stock betas over the full period under study and over two market regimes to determine if the impact is dependent on the direction of the market.

The paper also continues to explore the uses of this relationship between the stock betas and firm-level variables in the stock selection and portfolio management processes by constructing two portfolios based on two trading strategies. In conclusion, the paper provides comments on the performances of the two trading strategies and the relevance of the stock beta regression analysis in portfolio management.

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1. Introduction

1.1 Background of the Project

Beta — not only is it the heart of many a financial research, it is also one of the most fundamental concepts in finance that permeates across daily investment decisions and portfolio management. For instance, the popular defensive equity investment strategy is based on adjusting the beta of securities of one's portfolio in order to adjust the amount of risks one is exposed to during different phases of the business cycle.

Sharpe (1964) defined beta as the predicted response of an asset's return to changes in the return of an efficient combination of assets and is a measure of the systematic risk of that asset. The combination of assets is efficient in the way that it offers the optimal risk and return trade-off (Markowitz, 1991). This definition of beta is not restrictive such that it can be applied to any asset and the "efficient combination of assets" is often assumed to be any suitable benchmark portfolio. An asset which has a market beta that is greater than one implies the asset's return will tend to move more in percentage terms than that of the market. This asset will be favourable during periods of the market rallies as it gives investors the opportunity to outperform the market. Assets with market betas that are less than one are considered defensive as they lower investors' loss relative to the market when crises or recessions take place.

1.2 Rationale and Research Objectives

The mathematical formula for beta is defined as the ratio of the covariance of an asset's return with its benchmark's return over the variance of the benchmark's return (Sharpe, 1964). As a measure of sensitivity to market movements and systematic risk of an asset,

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1.2 Rationale and Research Objectives

The mathematical formula for beta is defined as the ratio of the covariance of an asset's return with its benchmark's return over the variance of the benchmark's return (Sharpe, 1964). As a measure of sensitivity to market movements and systematic risk of an asset, beta varies over time due to the interaction between these two variables which is dependent on the changing economic conditions and the risk characteristics of the asset. Therefore the point-estimate of beta provided by the ordinary least squares (OLS) estimation is usually inefficient as it overlooks the behaviour of beta over time. With advanced computing power, more superior and complex methods such as the Kalman filter estimation become effortless once the underlying dynamics of the procedures are well understood.

Many international studies have concluded that beta of a stock depends on the industry in which the company functions, and the financial- and operating leverages which change over time (DeJong and Collins, 1985; Galai and Masulis, 1976; Hong and Sarkar, 2007; Panattoni, 2009; Rosenberg and Guy, 1976 and Turnbull, 1977). However, we did not find interesting research papers in South Africa that involve the interaction between various firm-level variables and the stock beta.

The objective of this paper is to investigate the explanatory power of various firm-level and sector variables in capturing the variability of stock betas over time from a South African perspective. They include providing readers with an introduction and a mathematical derivation of the Kalman filter algorithm and using the Kalman filter method to estimate the betas of the sub-sectors and the selected stocks listed on the Johannesburg Securities Exchange (JSE). In addition, OLS regressions of the stock betas against the proposed firm-level variables over two non-overlapping periods are performed; thereby examining the sensitivities of the stock betas to these factors and investigating the use of such information in the stock selection and portfolio management process.

1.3 Plan of Development

A literature review concerning the interaction of stock betas with firm-level variables and the Kalman filter method is followed by a brief theory on the Kalman filter algorithm for readers that are unfamiliar with the estimation method. Those who are familiar with the Kalman filter method may go straight into section four which describes the data and the methodology used in this paper. Section five will present the empirical results which will be followed by section six that concludes this study. The appendices contain additional tables and charts that relate to the topics discussed in the paper.

2. Literature Review

Beta has always been of interest to financial research especially around issues such as the breakdown of portfolio returns into the alpha and beta components in the past few years, ultimately questioning the worthy practice of active management. Waring and Siegel (2006, p.16) defined alpha as "the return generated over and above" a suitable benchmark and beta as the return arising from the exposure to the total market return. Roncalli and Teiletche (2008) also used the Kalman filter method to model the alternative beta component in the hedge fund performance. The interest of this paper, however, goes back to the definition of beta and looks at the factors that drive it.

According to Sharpe (1964) and Bodie, Kane & Marcus (2008), beta is not any measure of risk; it measures the systematic risk of an asset. In finance, total risk of any company and ultimately its stocks, is composed of the market/systematic risk and the firm-specific risk. Market risk is not diversifiable because all firms are exposed to some degree of uncertainties in the macroeconomic conditions. On the other hand, firm-specific risk relates to issues such as capital structure and productivity, which is usually considered diversifiable if investors spread their investments across assets with very different return and risk characteristics. In essence, beta only measures the risk added by an asset to a well diversified portfolio (Damodaran, n.d.).

Since beta only accounts for the systematic risk of a firm and its stocks, one would expect that beta has nothing to do with firm-level variables. However, some firm specific risks accounted by firm-level variables are correlated with market movements and are thus non-diversifiable and systematic (Cho, 1997). Modigliani and Miller (1963) recognized two such non-diversifiable firm-specific risks, namely: business risk and financial risk. These conform to Damordaran's conclusion in his study that the determinants of a stock's beta are the type of business, the degree of operating leverage and the degree of financial leverage. Works by Booth (1991), Conine and Tamarkin (1985) and Mandelker and Rhee (1984) also highlighted the important roles played by financial and operating leverages in managing a company's total risk and determining its cost of capital.

One would expect that companies and their stocks in the same industry should have a similar degree of business risk, excluding those conglomerate companies which may be exposed to risks of other industries. Financial risk is dependent on the amount of long-term debt the company takes and is non-diversifiable as it is subjecting to the impacts of changing interest rates and credit access. It is also firm-specific because capital structure is a corporate decision and interest payments directly affect the earnings of a company. The degree of operating leverage of a company is dependent on its capital asset decisions and is a trade-off between two costs: fixed costs and variable costs (Cho, 1997). During an economic recession, a labour intensive company with a high level of variable costs will show more stable earnings than a capital intensive company with a high level of fixed costs. To summarise, although financial and operating risks are measured by firm-level variables, they account for both firm-specific and systematic risks. The total systematic risk of a company depends on the general market conditions and its management decisions.

There are some international studies done on the decomposition of stock beta into several firm-specific and macroeconomic variables. Galai and Masulis (1976), Hong and Sarkar (2007) and Turnbull (1977) all showed that a stock beta is an increasing function of leverage ratios. The results of Hong and Sarkar (2007) are consistent with Turnbull (1977) that beta is also a decreasing function of earnings growth rate if no expansion takes place. DeJong and Collins (1985) showed empirically that betas are more volatile for highly leveraged companies and during times of large interest-rate changes. In addition, Rosenberg and Guy (1976) have also established the explanatory power of the variance of cash flows in modelling beta. Panattoni (2009) criticised the Capital Asset Pricing Model (CAPM) for ignoring the impacts of firm strategies and industry types on systematic risk and thus beta. The author conducted tests exploring the cross-sectional determinants of betas and found that turnover, earnings and bid-ask spread were among some of the most significant factors. In all, these studies suggested that stock betas are related to firm-level variables.

It is important to understand the interaction between beta and these firm-level variables because, by neglecting such a relationship, one may overstate the explanatory power of these proposed factors in some multifactor models (Panattoni, 2009). One of the most well-known multifactor models is the Fama and French model (Fama and French, 1993). Moreover, Panattoni (2009) suggested that by recognizing the determinants of beta, one may also be able to update and adjust empirical estimates of beta.

Different industries and its composite stocks tend to have different long term average beta values due to their product demands; some studies suggested that the use of the defensive equity investment strategy by switching between high and low beta sectors in expectations of different market conditions are highly profitable (Bernstein, 1995 and Stovall, 1996). Davis and Philips (2007) have defined defensive equity sectors as those that consist of companies that "produce goods and services with relatively inelastic demand curves". Their findings have also shown that although utility, consumer staples and health care sectors had betas below one during the period from 1963 to 2006 in the U.S., the defensive strategy had not generated better returns than a simple buy and hold strategy. They partly attribute the underperformance to the changing betas over time.

In this study, the beta of each selected stock, estimated by the Kalman filter method, is regressed against the proposed firm-level variables over non-overlapping periods to establish whether the sensitivities of the stock beta to these factors and the overall fit of the model may be dependent on the direction of the market. Stock and sub-sector betas are not observable in the market, thus the beta modelling begins with estimating the betas for the selected stocks and sub-sectors.

As mentioned in the introduction, OLS beta estimates do not capture the behaviours of stock betas over time. Other methods such as the rolling window regression, the recursive least squares regression and the Kalman filter method all produce a series of the beta estimates which fit in with the purpose of this paper. However, the recursive least squares regression suffers from the possibility of non-stationary coefficients (Strang, 1986). And rolling window regression results are sensitive to the choices of the window size and the step size (Swinkels and Sluis, 2002). To overcome these issues, the Kalman filter method is used. Kalman filter is a recursive estimation procedure that models the time variations of the coefficients directly as more data become available (Hamilton, 1994). Studies done by and Choudhry and Wu (2009) and Swinkels and Sluis (2002) have suggested the superiority of the Kalman filter method in estimating betas over GARCH models and rolling window regressions respectively.

3. Theory on the Kalman Filter

3.1 Basics of the State Space Models

Kalman filter has a wide range of applications in the financial world; however, before examining the empirical examples, a good understanding behind the dynamics of the Kalman filter is essential.

Any dynamic system can be expressed in a general form called the state space representation which may be summarised by two equations. The representation used here is based on Harvey (1991).

$$y_t = c_t'\beta_t + \varepsilon_t \tag{3.1}$$

$$\beta_t = A_t\beta_{t-1} + Z_t + R_t\eta_t \tag{3.2}$$

The details and dimensions of the variables are listed in the table below:

Table 1 List of variables in the state space model and their dimensions

Variable	Dimension	Description
y_t	Nx1	vector of observable variables at time t
β_t	mx1	state vector of unobservable variables at time t
c_t	mxN	matrix
A_t	mxm	matrix
Z_t	mx1	deterministic vector
ε_t	Nx1	measurement equation disturbance vector
η_t	gx1	state equation disturbance vector
R_t	mxg	matrix

Equation (3.1) is known as the measurement equation which describes the relationship between the observable variables $\{y\}_{t=1}^{T}$ and the unobservable state variables $\{\beta\}_{t=1}^{T}$. Equation (3.2) is known as the state equation which describes the changing dynamics of the unobservable state variables $\{\beta\}_{t=1}^{T}$. Since the unobservable state variables $\{\beta\}_{t=1}^{T}$ are associated with the observable variables $\{y\}_{t=1}^{T}$, the aim of the state space modelling is thus to determine the state of the system by the observable time series.

Disturbances in the measurement and state equations are assumed to be white noises with mean zero and covariance matrix N_t and M_t respectively. ε_t and η_t are uncorrelated. The disturbances are also uncorrelated with the initial state vector β_0:

$$\begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix} \sim WN\left(0, \begin{pmatrix} N_t & 0 \\ 0 & M_t \end{pmatrix}\right)$$
$$E[\beta_0 \varepsilon_t{}'] = E[\beta_0 \eta_t{}'] = 0$$

WN stands for white noise.

If further assumed that ε_t and η_t are normally distributed, then the above model is called the linear Gaussian state space model (Durbin and Koopman, 2001).

3.2 Derivation of the Kalman Filter

Kalman filter is one of the techniques that can be used to determine the unobservable state variables $\{\beta\}_{t=1}^{T}$. It is a recursive algorithm which provides optimal estimates of the state variable at time t considering all the past and current observations (Durbin and Koopman, 2001). The works of Hamilton (1994), Harvey (1990) and Durbin and Koopman (2001) are used in collaboration for this section to provide a reasonably brief and straightforward derivation of the dynamics behind the Kalman filter.

Recall the general state space model in section 3.1:

$$y_t = c_t'\beta_t + \varepsilon_t$$

$$(Nx1)=(Nxm)(mx1)+(Nx1)+(Nx1)$$

$$\beta_t = A_t\beta_{t-1} + Z_t + R_t\eta_t$$

$$(mx1)=(mxm)(mx1)+(mx1)+(mxg)(gx1)$$

for $t = 1, \ldots\ldots, T$.

Assume Gaussian disturbances:

$$\varepsilon_t \sim N(0, N_t)$$

$$\eta_t \sim N(0, M_t)$$

$$E[\beta_0 \varepsilon_t'] = 0$$

$$E[\beta_0 \eta_t'] = 0$$

$$E[\varepsilon_t \eta_t'] = 0$$

And further assume the initial state of the system is $\beta_0 \sim N(b_0, \Sigma_0)$ where b_0 is the initial mean and Σ_0 is the initial variance. In order to make the derivation simpler, focusing on the dynamics rather than letting the mathematics obscure the core focus in this section, the following assumptions are made:

1) $Z_t = 0$ *(Zero vector)*

2) $R_t = I$ *(Identity matrix)*

Equation 3.1 and 3.2 thus become:

$$y_t = c_t'\beta_t + \varepsilon_t \tag{3.3}$$

$$\beta_t = A_t\beta_{t-1} + \eta_t \tag{3.4}$$

Let $\hat{\beta}_{t|t-1} = E[\beta_t | y_0, \dots \dots, y_{t-1}]$ and $\hat{\beta}_{t|t} = E[\beta_t | y_0, \dots \dots, y_t]$. The hat notation here reminds the reader that $\beta_t \neq E[\beta_t | y_0, \dots \dots, y_t]$. The information of the observable variables $y_0, \dots \dots, y_t$ at time t is used to estimate the values of the unobservable state variables at time t based on the model. β_t is reserved as the vector of actual state variables at time t.

There are three steps in the Kalman filter algorithm and the derivations that follow from page 11 to page 15 are mainly based on Durbin and Koopman (2001):

Step 1: Estimate the value of the next state and its associated variance at time t given all the currently available information at time t –1:

$$
\begin{aligned}
\hat{\boldsymbol{\beta}}_{t|t-1} &= E[\beta_t | y_0, \dots \dots, y_{t-1}] \\
&= A_t E[\beta_{t-1} | y_0, \dots \dots, y_{t-1}] + E[\eta_t | y_0, \dots \dots, y_{t-1}] \\
&= \boldsymbol{A_t \hat{\beta}_{t-1|t-1}} \qquad (3.5)
\end{aligned}
$$

$$
\begin{aligned}
\hat{\Sigma}_{t|t-1} &= Var[\beta_t | y_0, \dots \dots, y_{t-1}] \\
&= E[(\beta_t - E[\beta_t | y_0, \dots \dots, y_{t-1}])\,(\beta_t - E[\beta_t | y_0, \dots \dots, y_{t-1}])'] \\
&= E[\,(\beta_t - \hat{\beta}_{t|t-1})\,(\beta_t - \hat{\beta}_{t|t-1})']
\end{aligned}
$$

Substitute in (3.4) and (3.5):

$$
\begin{aligned}
&= E[\,(A_t\beta_{t-1} + \eta_t - A_t\hat{\beta}_{t-1|t-1})\,(A_t\beta_{t-1} + \eta_t - A_t\hat{\beta}_{t-1|t-1})'\,] \\
&= E[\,(A_t(\beta_{t-1} - \hat{\beta}_{t-1|t-1}) + \eta_t)\,(A_t(\beta_{t-1} - \hat{\beta}_{t-1|t-1}) + \eta_t)'\,]
\end{aligned}
$$

Multiply terms out:

$$= A_t E[(\beta_{t-1} - \hat{\beta}_{t-1|t-1})\,(\beta_{t-1} - \hat{\beta}_{t-1|t-1})']A_t' + A_t E[\,(\beta_{t-1} - \hat{\beta}_{t-1|t-1})\eta_t'] +$$

$$E[\eta_t\,(\beta_{t-1} - \hat{\beta}_{t-1|t-1})']A_t' + E[\eta_t\eta_t']$$

Since $E[\eta_t] = 0$, $Var[\eta_t] = M_t$ and η_t is a white noise process resulting all the cross terms equal to zero:

$$\widehat{\boldsymbol{\Sigma}}_{t|t-1} = \boldsymbol{A}_t\widehat{\boldsymbol{\Sigma}}_{t-1|t-1}\boldsymbol{A}_t' + \boldsymbol{M}_t \tag{3.6}$$

Step 2: Forecast the observable variable at time t and then determine the prediction error:

$$\begin{aligned} E[y_t|y_0, \dots\dots, y_{t-1}] &= E[c_t'\beta_t + \varepsilon_t\,|y_0, \dots\dots, y_{t-1}] \\ &= c_t'E[\beta_t|y_0, \dots\dots, y_{t-1}] + E[\varepsilon_t\,|y_0, \dots\dots, y_{t-1}] \end{aligned}$$

Since ε_t is a white noise process and $E[\varepsilon_t] = 0$: $E[y_t|y_0, \dots\dots, y_{t-1}] = c_t'\hat{\beta}_{t|t-1}$

Now let ν_t be the one-step ahead prediction error:

$$\boldsymbol{\nu}_t = y_t - E[y_t|y_0, \dots\dots, y_{t-1}] = \boldsymbol{y}_t - \widehat{\boldsymbol{y}}_{t|t-1} = \boldsymbol{y}_t - \boldsymbol{c}_t'\widehat{\boldsymbol{\beta}}_{t|t-1} \tag{3.7}$$

Step 3: Once the value of the observable variable at time t is available, use that to update the estimate of the state variable and its corresponding variance at time t:

Two statistics are required to be evaluated prior to the updating equations: F_t, the variance of the one-step head prediction error and the covariance between β_t and ν_t.

$$
\begin{aligned}
F_t &= Var(v_t) \\
&= Var\left(y_t - c_t'\hat{\beta}_{t|t-1}\right) \\
&= Var\left(c_t'\beta_t + \varepsilon_t - c_t'\hat{\beta}_{t|t-1}\right) \\
&= Var\left(c_t'\left(\beta_t - \hat{\beta}_{t|t-1}\right) + \varepsilon_t\right) \\
&= E\Big[\Big(c_t'\left(\beta_t - \hat{\beta}_{t|t-1}\right) \\
&\qquad + \varepsilon_t - E\left[c_t'\left(\beta_t - \hat{\beta}_{t|t-1}\right)\right]\Big)\Big(c_t'\left(\beta_t - \hat{\beta}_{t|t-1}\right) + \varepsilon_t - E\left[c_t'\left(\beta_t - \hat{\beta}_{t|t-1}\right)\right]\Big)'\Big] \\
&= E\left[\left(c_t'\left(\beta_t - \hat{\beta}_{t|t-1} - E\left[\beta_t - \hat{\beta}_{t|t-1}\right]\right) + \varepsilon_t\right)\left(c_t'\left(\beta_t - \hat{\beta}_{t|t-1} - E\left[\beta_t - \hat{\beta}_{t|t-1}\right]\right) + \varepsilon_t\right)'\right]
\end{aligned}
$$

Note: $E\left[\beta_t - \hat{\beta}_{t|t-1}\right] = E\left[\beta_t - E[\beta_t | y_0, \dots \dots, y_{t-1}]\right]$

$$
\begin{aligned}
&= E[\beta_t] - E\left[E[\beta_t | y_0, \dots \dots, y_{t-1}]\right] \\
&= E[\beta_t] - E[\beta_t] = 0
\end{aligned}
$$

Therefore:

$$
\begin{aligned}
\boldsymbol{F_t} &= E\left[\left(c_t'\left(\beta_t - \hat{\beta}_{t|t-1}\right) + \varepsilon_t\right)\left(c_t'\left(\beta_t - \hat{\beta}_{t|t-1}\right) + \varepsilon_t\right)'\right] \\
&= c_t' E\left[\left(\beta_t - \hat{\beta}_{t|t-1}\right)\left(\beta_t - \hat{\beta}_{t|t-1}\right)'\right] c_t + E[\varepsilon_t \varepsilon_t'] \quad \text{(all cross terms equal to zero)} \\
&= \boldsymbol{c_t'\widehat{\Sigma}_{t|t-1}c_t + N_t} \qquad (3.8)
\end{aligned}
$$

Note: $E[v_t] = E\left[y_t - c_t'\hat{\beta}_{t|t-1}\right]$

$$
\begin{aligned}
&= E\left[c_t'\beta_t + \varepsilon_t - c_t'\hat{\beta}_{t|t-1}\right] \\
&= c_t'E[\beta_t] + E[\varepsilon_t] - c_t'E\left[E[\beta_t | y_0, \dots \dots, y_{t-1}]\right] \\
&= c_t'E[\beta_t] + E[\varepsilon_t] - c_t'E[\beta_t] = 0
\end{aligned}
$$

Covariance between β_t and v_t also needs to be calculated:

$\boldsymbol{Cov(\beta_t, v_t)}$

$= E[\beta_t v_t] - E[\beta_t]E[v_t]$ substitute in (3.7) and $E[v_t] = 0$

$= E[\beta_t (y_t - c_t'\hat{\beta}_{t|t-1})']$ substitute in (3.3)

$= E\left[\beta_t\left(c_t'\beta_t + \varepsilon_t - c_t'\hat{\beta}_{t|t-1}\right)'\right]$

$= E\left[E[\beta_t\left(c_t'\beta_t + \varepsilon_t - c_t'\hat{\beta}_{t|t-1}\right)' | y_0, \dots \dots, y_{t-1}]\right]$ (by law of conditional expectation)

$= E[E[\beta_t (\beta_t - \hat{\beta}_{t|t-1})' c_t | y_0, \dots \dots, y_{t-1}]]$

$$= \boldsymbol{\hat{\Sigma}_{t|t-1} c_t} \tag{3.9}$$

Now the updated state estimate and its variance may be derived:

$\boldsymbol{\hat{\beta}_{t|t}} = E[\beta_t | y_0, \dots \dots, y_t]$

$= E\left[\beta_t \middle| y_0, \dots \dots, y_{t-1}, v_t\right]$ (since if v_t is known, y_t is also known given $y_0, \dots \dots, y_{t-1}$)

$= E[\beta_t | y_0, \dots \dots, y_{t-1}] + Cov(\beta_t, v_t) Var[v_t]^{-1} v_t$ (by the regression lemma[1])

$$= \boldsymbol{\hat{\beta}_{t|t-1} + \hat{\Sigma}_{t|t-1} c_t [c_t' \hat{\Sigma}_{t|t-1} c_t + N_t]^{-1} v_t} \quad \text{(assume } F_t \text{ is non-singular)} \tag{3.10}$$

Similarly, using the regression lemma:

---

[1] The regression lemma used here refers to Chapter 2 p37 in Durbin and Koopman (2001): For detailed proof please refer to the full text:

$$E[x|y,z] = E(x|y) + \Sigma_{xz}\Sigma_{zz}^{-1}z$$
$$Var[x|y,z] = Var(x|y) - \Sigma_{xz}\Sigma_{zz}^{-1}\Sigma_{xz}'$$

Provided that x, y and z are random vectors of arbitrary orders that are jointly normally distributed with means μ_p and covariance matrices $\Sigma_{pq} = E\left[(p - \mu_p)(q - \mu_q)'\right]$ for p, q = x, y and z with $\mu_z = 0$ and $\Sigma_{yz} = 0$. In this case, the mean of v_t is proved to be zero and it can also be proved that the covariance between v_t and each of $\{y_0, \dots\dots, y_{t-1}\}$ is zero i.e. they are exclusive of each other.

$$\hat{\boldsymbol{\Sigma}}_{t|t} = Var[\beta_t | y_0, \dots\dots, y_t]$$

$$= Var[\beta_t | y_0, \dots\dots, y_{t-1,} v_t]$$

$$= Var[\beta_t | y_0, \dots\dots, y_{t-1}] - Cov(\beta_t, v_t)\, Var[v_t]^{-1} Cov(\beta_t, v_t)'$$

$$= \hat{\boldsymbol{\Sigma}}_{t|t-1} - \hat{\boldsymbol{\Sigma}}_{t|t-1} \boldsymbol{c}_t [\boldsymbol{c}_t' \hat{\boldsymbol{\Sigma}}_{t|t-1} \boldsymbol{c}_t + \boldsymbol{N}_t]^{-1} \boldsymbol{c}_t' \hat{\boldsymbol{\Sigma}}_{t|t-1}' \tag{3.11}$$

To summarise: the Kalman filter algorithm starts with some initial state vector and variance $\beta_0 \sim N(b_0, \Sigma_0)$, then use that to forecast the one step ahead state vector and its variance matrix $\hat{\beta}_{1|0}$ and $\hat{\Sigma}_{1|0}$. When the current value of the observable variable y_1 is available, it is used to update the model's estimate of the state vector and its variance matrix $\hat{\beta}_{1|1}$ and $\hat{\Sigma}_{1|1}$. The process carries on by using these updated values to forecast the state vector at the next period and its variance $\hat{\beta}_{2|1}$ and $\hat{\Sigma}_{2|1}$ and so on.

Any unknown parameters in the model such as the variance matrices of the disturbances N_t and M_t may be estimated using maximum likelihood technique by maximising the log-likelihood function of the form suggested by Fusai and Roncoroni (2008) or any other appropriate estimation methods:

$$L_t = -\frac{T}{2} 2\pi - \frac{1}{2} \sum_{t=1}^{T} ln|F_t| - \frac{1}{2} \sum_{t=1}^{T} v_t' F_t^{-1} v_t \tag{3.12}$$

The basic dynamics behind the Kalman Filter have been introduced; the detailed plan of the methodology and the data used in this report may now be described.

4. Data and Methodology

4.1 Data Requirements

Data limitation is a serious obstacle in carrying out the stock beta decomposition test in South Africa. And as a result, the firm-level factors and stocks are chosen based on the availability of the return and financial statement data over the specified period.

The monthly total return data of 17 stocks listed on the JSE, its 9 sub-sectors and the FTSE/JSE All Share Index (J203) during the period from December 1999 to May 2010 are obtained from I-Net Bridge. The monthly cash rate over the same period is also obtained from the same source. The total debt-to-equity ratios, the trading turnover (in Rand) and the daily return data of the chosen stocks are obtained from Bloomberg. The financial statement data are provided by QuickVal[2]. Descriptive summary statistics of the data are available in Appendix A grouped by stocks. In this study, the local monthly cash rate is assumed to be the risk free rate. The excess returns of various stocks and the sub-sectors are calculated by subtracting the corresponding risk free rate from the total return numbers over the nine and half year period.

A stock beta regression analysis was performed prior to this study which spliced the data into five phases of the South African business cycle according to South African Reserve Bank's Quarterly Bulletin (September 2009). However, because there is a limited period of data that is available, the data for this study are spliced into two non-overlapping periods namely the "Good" and the "Bad" periods according to the proprietary model provided by Peregrine Securities Research Unit[3].

[2] QuickVal: free-cash-flow equity research. Website: http://www.quickval.co.za
[3] Peregrine Securities Research, Dr Gareth Witten: garethwitten@gmail.com, Tel: +27 21 670 5265

The "Good" period refers to times of persistent economic growth and where assets' risk and return characteristics are consistent with their long term averages and theoretical assumptions. The "Bad" period is where there is a consecutive contraction in the economy and returns, risk and correlations among assets are behaving adversely for the market participants. The "Good" and the "Bad" periods may also be called the "bull market" and the "bear market" respectively. There are in total 116 data points, 76 of which are grouped as the "Good" period while the "Bad" period consists of the other 40 data points. Software used in this study includes MS Excel, EView 7 and RATS.

4.2 Detailed Plan of the Methodology

4.2.1 Use Kalman Filter to Estimate Sub-sector and Stock Betas

Betas of sub-sectors and stocks estimated in the study are based on the single factor market model. The FTSE/JSE All Share Index is used as the market proxy. Although it has the problem of high concentration, it is still one of the most commonly used market proxies in South Africa. Let R_{it} be the excess return of sub-sector i or stock i at time t and let R_{mt} be the excess return of the market portfolio (FTSE/JSE All Share Index) at time t. The state space model is defined as follows:

$$R_{it} = \alpha_{it} + \beta_{it} R_{mt} + \varepsilon_{it} \tag{4.1}$$

$$\alpha_{it} = \alpha_{it-1} + \xi_{it} \tag{4.2}$$

$$\beta_{it} = \beta_{it-1} + \eta_{it} \tag{4.3}$$

The disturbances are assumed to be Gaussian and the measurement equation disturbance ε_{it} is independent of the state equation disturbances ξ_{it} and η_{it}:

$$\varepsilon_{it} \sim N(0, P)$$

$$\xi_{it} \sim N(0, Q_1)$$

$$\eta_{it} \sim N(0, Q_2)$$

The initial conditions are obtained from ordinary least squares regressions:

$$\alpha_0 \sim N(a_0, \Pi_0)$$

$$\beta_0 \sim N(b_0, \Omega_0)$$

There are many forms of state space models. Many beta estimation studies such as those of Choudhry and Wu (2009), Gastaldi and Nardecchia (2003), He and Kryzanowski (2008) and Mergner (2009) have utilized the random walk model. Therefore, in this study, it also assumes that the unobserved state variables $\{\alpha_{it}\}_{t=1}^{T}$ and $\{\beta_{it}\}_{t=1}^{T}$ for each stock i follow a random walk (i.e. equation 4.2 and 4.3).

The Kalman filter estimation is carried out using the statistical software programme RATS, using the monthly excess return data during the period December 1999 to May 2010. To reduce the noises in the tails, approximately 5% of the left and right tails of the estimation outputs are discarded, only the monthly beta estimates from May 2000 to December 2009 are carried forward to the stock beta analysis. The results of the sub-sector and stock betas estimation using the Kalman filter method are presented in section five.

4.2.2 Linear Interpolation of Annual Financial Statement Data

The beta estimates of the sub-sectors (CoreBeta) are used to capture the industry effect to avoid the relatively higher noises in the return series. Cash conversion ratio (CCR), dividend yield (DY), EBITA margin (EBITA (M)) and return-on-equity ratio (ROE) are used to account for the operating leverage effects on the stock beta. The total debt-to-equity ratio (DE) is used as a measure of the company's financial leverage. An illiquidity measure named ILLIQ is used to capture the impact of trading liquidity on the stock beta (Amihud, 2002).

We are only able to source annual data for the following fundamental variables such as the CCR, DY, DE, EBITA (M) and ROE. In order to obtain the monthly data series, simple linear interpolation is performed which aims to capture the overall trend of each variable.

4.2.3 Computation of the Illiquidity Measure

The measure of trading illiquidity ILLIQ in this study is recommended by Amihud (2002). It has some distinctive advantages over other measures of illiquidity such as the bid-ask spread and the probability of information-based trading. Benefits such as being the finer measure of illiquidity, overcoming the absence of high frequency data in many stock markets and enabling one to construct long time illiquidity series suit the purpose of this study where data scarcity is the greatest concern and challenge.

Amihud (2002, p.34) defined ILLIQ as "the average ratio of the daily absolute return to the (dollar) trading volume on that day". In this study, the trading volume will be in Rand and instead of computing the annual average, monthly illiquidity measure is calculated based on the same but modified mathematical formula:

$$ILLIQ_{imy} = \frac{1}{D_{imy}} \sum_{t=1}^{D_{im}} \frac{|R_{imyd}|}{VOLD_{imyd}} \times 10^6 \tag{4.4}$$

where

$ILLIQ_{imy}$ is the illiquidity measure of stock i in month m and year y

D_{imy} is the number of days for which data are available for stock i in month m and year y

$|R_{imyd}|$ is the daily absolute return on stock i on day d of month m and year y

$VOLD_{imd}$ is the daily volume in Rand on stock i on day d of month m and year y

4.2.4 OLS Regression of Stock Betas against Firm-level Variables

Once all the estimated sub-sector and stock betas and the associated firm-level variables are spliced into the "Good" and the "Bad" periods respectively, the next step of the study is to perform OLS regressions of the stock beta against the proposed regressors over the two periods for each stock.

The OLS regression will be of the form below:

$$\beta_i = c_1\beta_{CoreBeta} + c_2CCR + c_3DE + c_4DY + c_5EBITA(M) + c_6ILLIQ + c_7ROE + \epsilon \quad (4.5)$$

where β_i is the stock beta estimate and $\beta_{CoreBeta}$ is the corresponding sub-sector beta estimate.

There will be measurement or estimation errors in the Kalman filter stock and sub-sector beta estimates which may interact with the regression error in equation (4.5). However, the aim of this study is not interrogating the superiority of the Kalman filter beta estimates – the assumption of small and reasonable estimation errors in the Kalman filter beta estimates will be made.

4.2.5 Portfolio Strategies Based on the Regression Results

The stock beta regression results are useful in enabling the investors to have a deeper understanding behind the dynamics of the stock beta movements and may improve their return estimation models. However, if these results cannot be used in assisting portfolio managers in their regular stock selection process and other investment decisions, they have no direct value contribution. The third part of the study in this paper is thus to investigate the practical usefulness of the stock beta regressions by constructing portfolios with two different portfolio or trading strategies.

a) Methodology of Strategy 1:

An equally weighted portfolio, diversified across five sub-sectors, consisting of 6 of the 17 selected stocks is formed upfront. Because the resources sector forms a larger proportion of the total market capitalisation of the JSE, 2 stocks are chosen randomly from the basic materials sub-sector, and then one each from the consumer goods, consumer services, financials and industrials sub-sectors.

Strategy 1 is based on the idea of defensive equity investment mentioned by Davis and Philips (2007). It assumes perfect foresight of at least one-month ahead or has some reasonable confidence in predicting the direction of the market in the following month. Strategy 1 focuses on the relative stock beta estimates where the 3 stocks of the portfolio with highest beta estimates will have maximum active weights in the "Good" period. In the "Bad" period, the 3 stocks with lowest beta estimates will have maximum active weights. We chose a maximum of 10% proportionate increase in the active weights.

For instance, if the investor is bullish about the next month, he or she will want to increase the market exposure of the portfolio by selecting 3 stocks that have the highest Kalman filter beta estimates in the current month and then increase each of these stock weights proportionally by 10%. The active weight of each of the other stocks in the portfolio will be decreased proportionally by 10%. On the other hand, if the investor is bearish about the following month, he or she will want to reduce the portfolio's market exposure by selecting 3 stocks that have the lowest filtered beta estimates in the current month and then increase each of these stock weights proportionally by 10% and decrease each of the other stock weights proportionally by 10%.

The main reason for using this relative beta trading strategy is that sub-sector and stock betas do vary over time; it is not ideal to assume that a sub-sector or stock with higher or lower market betas will tend to do so in the future. This study assumes no transaction costs to make results comparable. It is also assumed that during periods of consecutive "Good" or "Bad" periods, the active weight of each stock remains unchanged.

b) Methodology of Strategy 2:

This portfolio strategy is an extension of Strategy 1 by incorporating the stock beta regression results into the investment decisions. The demonstration of Strategy 2 begins with the same equally weighted portfolio and follows the same decision-making process as Strategy 1. In addition, trends of the firm-level variables obtained earlier are also computed for each company and compared with the respective regression coefficients. Depending on the anticipation of a "Good" or a "Bad" period, 3 stocks with relatively higher or lower beta estimates will be considered favourable. However, stock betas do change over time. Therefore, if the combination of the trend of the firm-level variable and its regression coefficient is such that the stock beta will move in the desired direction, this indicates the sustainability of a high or a low stock beta, making investment in this stock justified. We chose to increase the active weight of the most preferable stock by 20% proportionately and increase each of the other two relatively less preferable stocks' active weights by 5% proportionately. The other stocks in the portfolio will bear a 10% proportionate reduction in each of their active weights.

For example, suppose the investor is bullish about the near future, he or she will want to increase his or her portfolio's market exposure thus preferring higher beta stocks. We assume the regression coefficients for all the firm-level variables are significant to simplify the process. Each of the 3 favourable stocks gets a tick if the trend of the firm-level variable is up and its regression coefficient is positive or if the trend of the firm-level variable is down and its regression coefficient is negative. These combinations imply the stock's beta will continue in its upward direction. Vice versa occurs if the next period is expected to be "Bad".

The stock which has the highest number of ticks is ranked most preferable, and the other 2 stocks are ranked relatively less preferable. If two stocks have the same number of the ticks, the standard errors of the regressors will be examined.

5. Results

5.1 Behaviours of FTSE/JSE All Share Index Sub-sector and Selected Stock Betas over Time

Kalman filter is used to estimate the 9 sub-sector betas and the 17 selected stock betas listed on the JSE during the period from May 2000 to December 2009. From Figures 1 to 3, it is clear to see that subsector and stock beta estimates do vary over time. Resources sub-sectors (oil & gas and basic materials) have beta estimates above one whereas the health care sub-sector persistently has the lowest beta estimate among all sub-sectors. Consumer goods, consumer services, financials, industrials and health care all had beta estimates below one over the entire sample period which partly correspond to the findings of Davis and Philips (2007). Their trends and behaviours are also similar, for instance, during the global financial crisis in late 2008, most of these sub-sector betas had declined. Thus, if defensive equity investment strategy is defined as switching to low beta sub-sectors during the economic downturn and recession, these five sub-sectors may be attractive to investors in reducing the market risk in their portfolios. However, most investors have to comply with their investment mandates and may be forbidden to drastically alter their equity holdings and only invest in one sub-sector or cash when market conditions change. They may, however, change their positions in stocks within each sub-sector.

Stock betas have also changed over time and some displayed more variability than others as observed in Figure 3. Table 2 explains the codes of the selected stocks and the sub-sectors to which they belong. GFI and HAR are resource stocks, yet their beta estimates varies above and below one. Therefore, defensive stocks must be those that have betas not only below one but persistently below one and low relative to other stock betas. Financial stocks such as ASA and SBK, consumer services stock TFG and industrial stock BAW all showed more stable betas over time. There is a possibility of large market capitalisation bias in this study since the data for the large and liquid companies are more often available. From Table 2, one can see that most of the stocks are ranked in the top 100 by market capitalisation in the FTSE/JSE All Share Index. Active managers should not only consider the value of a stock's beta estimate at a single point in time but rather its values over time and the causes behind the significant changes to avoid myopic investment decisions.

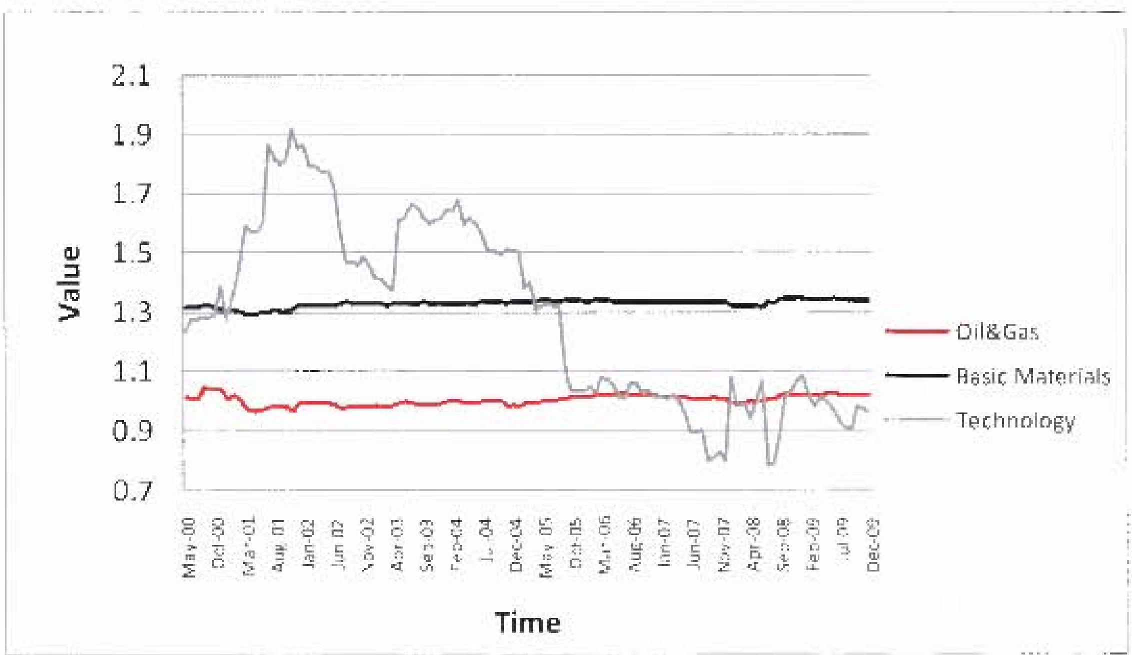

Figure 1 Beta estimates of sub-sectors that have exceeded one: May 2000 to December 2009

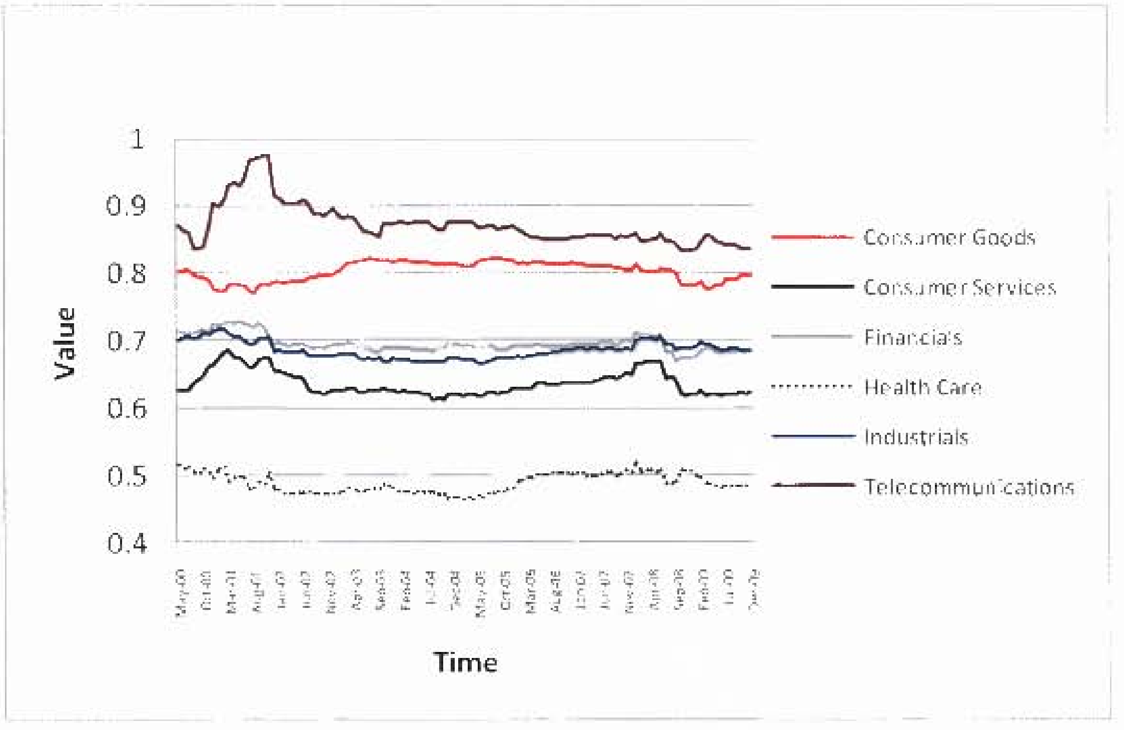

Figure 2 Beta estimates of sub-sectors that have not exceeded one: May 2000 to December 2009

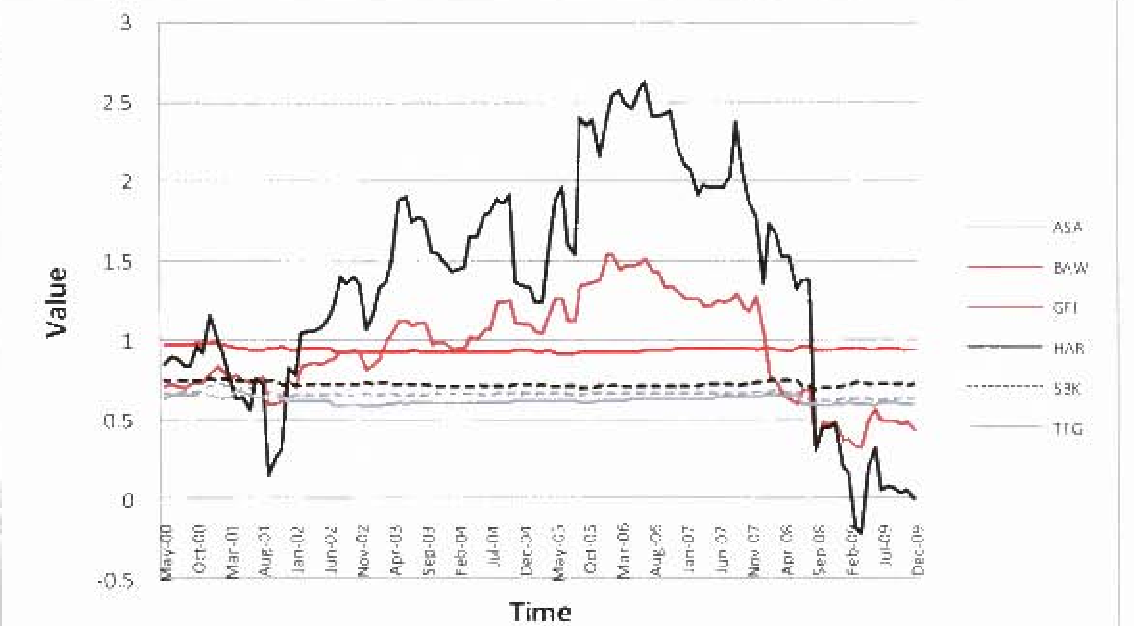

Figure 3 Beta estimates of some stocks listed on JSE: May 2000 to December 2009

Table 2 Brief description of stock codes

Code	Company Name	Sector and Sub-sector	Market Capitalisation Rank as at 4 May 2010
AFE	AECI Ltd.	Basic Materials - Chemicals	77
AMS	Anglo Platinum Ltd.	Basic Materials - Mining	4
ANG	AngloGold Ashanti Ltd.	Basic Materials - Mining	11
ASA	Absa Group Ltd.	Financials - Banks	14
BAW	Barloworld Ltd.	Industrials - General Industrials	62
CLH	City Lodge Hotels Ltd.	Consumer Services - Travel and Leisure	108
CLS	Clicks Group Ltd.	Consumer Services - Food and Drug Retailers	69
GFI	Gold Fields Ltd.	Basic Materials - Mining	17
GRF	Group Five Ltd.	Industrials - Construction and Materials	98
HAR	Harmony Gold Mining Company Ltd.	Basic Materials - Mining	31
HDC	Hudaco Industries Ltd.	Industrials - Industrial Engineering	117
NED	Nedbank Group Ltd.	Financials - Banks	18
RBW	Rainbow Chicken Ltd.	Consumer Goods - Food Producers	93
RLO	Reunert Ltd.	Industrials - Electronic & Electrical Equipment	61
SBK	Standard Bank Group Ltd.	Financials - Banks	7
TBS	Tiger Brands Ltd.	Consumer Goods - Food Producers	29
TFG	The Foschini Group	Consumer Services - General Retailers	52

Source: Oldert, 2010.

5.2 Stock Beta Regressions

The regressors used here are the sub-sector beta (CoreBeta), cash conversion ratio (CCR), dividend yield (DY), debt-to-equity ratio (DE), earnings before interest tax and amortisations margin (EBITA (M)), illiquidity measure (ILLIQ) and return on equity (ROE).

Recall equation 4.5:

$$\beta_i = c_1\beta_{CoreBeta} + c_2CCR + c_3DE + c_4DY + c_5EBITA\ (M) + c_6ILLIQ + c_7ROE + \epsilon \quad (4.5)$$

where β_i is the stock beta estimate and $\beta_{CoreBeta}$ is the corresponding sub-sector beta estimate

The coefficient c_1 measures the sensitivity of a stock's beta to its sub-sector beta which represents the change in the stock's beta that is due to the industry effect. It is expected that c_1 should be significant most of the time since business risk is a major determinant of stock betas.

According to the QuickVal methodology, CCR is defined as the ratio of a company's free cash flow (FCF) over its net operating profit before amortisations and tax (NOPAT). Companies with large and sufficient cash reserves at hand are in a better position to weather out liquidity issues, tighten credit access, pay off expensive debt and even survive a profitable buy-out when crisis strikes. Thus a company with a large FCF would be expected to have a lower beta relative to those companies with a lower FCF. CCR not only measures the free cash flows of a company or the amount of its earnings but also the quality of its profits and how effective the company is at converting its profits to cash. If a company's NOPAT grows at a faster rate than its FCF, the CCR would drop. The higher the CCR, the healthier the company and thus it is expected that on average, stock betas are inversely related to CCR. Similarly, DE is included in the regression to account for the degree of financial leverage and it is expected that a company's stock beta is positively related to this ratio.

Companies paying out stable dividends provide investors with more stable returns and also show the promising performances of the companies. Therefore stock betas should be negatively related to its DY. However, if the investors believe the company only increases its dividends to disguise certain issues and attempt to restore investor confidence, the coefficient of this factor may be positive. Dividend yield data are not provided by QuickVal directly, but are computed via dividing the dividend paid during the year by the stock price at year end and then perform linear interpolation to obtain the approximate monthly DY values.

EBITA (M) is included in this study to partially verify the findings of Panattoni (2009) who suggested earnings and turnover are some of the significant factors in beta decomposition.

Intuitively, companies with higher EBITA are more profitable and financially healthy which is expected to lead to a lower equity beta. But EBITA (M) is defined as the ratio of EBITA and turnover, thus is a measure of the cost structure of the company and its operating efficiency.

Stocks that are infrequently traded subject to higher liquidity premiums than those that are frequently traded due to higher bid-ask spreads and other transaction costs. Investors bear the risk of not being able to disinvest in time when needed. Thus the stock beta is expected to be positively related to the illiquidity measure ILLIQ as by definition: when the trading volume increases, ILLIQ decreases.

ROE further examines how effective the company is at using the shareholders' funds invested in generating profits (Watson and Kew, 2010). Stock betas should decrease with a higher ROE, which is a positive sign of companies' profitability.

When interpreting the regression results, it is important to keep in mind that the CCR, DE, DY, EBITA (M) and ROE are measured in percentage terms. ILLIQ is measured in percentage return per Rand trading volume.

5.2.1 Stock Beta Regressions over the Full Period

The beta estimates of the 17 selected stocks are regressed against the 7 proposed regressors using data from May 2000 to December 2009. The detailed regression outputs are available in Appendix B. Figure 4 gives the adjusted R-squared values for the 17 stock beta regressions.

The R-squared value measures the proportion of variation of the dependent variable, stock beta estimate, explained by the model (Upton and Cook, 2006). By adding more variables in the model, R-squared value will usually increase. But the adjusted R-squared values will penalise the model for adding regressors that do not contribute to the explanatory power of the model and thus is a superior measure of goodness-of-fit of the model.

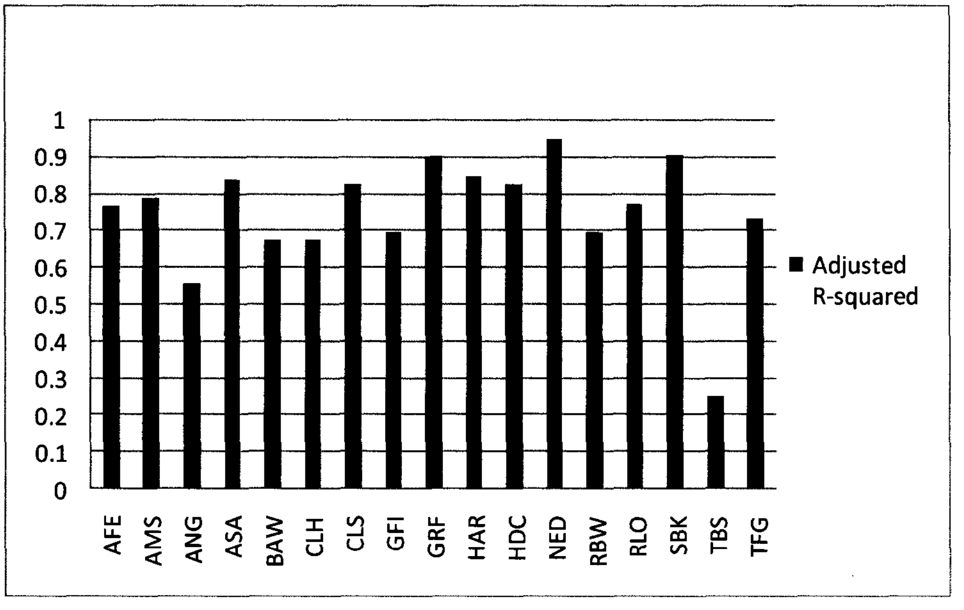

Figure 4 Adjusted R-squared values for the 17 stock beta regressions

From Figure 4, it is observed that the proposed model captured on average more than 50% of the stock beta variation over the specified period with exception of TBS where the adjusted R-squared value is 0.25. CoreBeta is significant in all 17 regressions and the least significant factor is ILLIQ as seen from Appendix B. This may suggest that the industry effect has the most impact and the trading liquidity has the least impact on the movements of stock betas during the period from May 2000 to December 2009. The signs and magnitudes of the regression coefficients are different for each stock. The next step is to investigate whether the explanatory power of this model and the relationship between the firm-level variables and the stock betas are dependent on the direction of the market.

5.2.2 Stock Beta Regressions over the Two Market Regimes

There are 17 stocks but the data have been spliced into two periods, namely the "Good" and the "Bad" periods, thus in total there are 34 regressions performed.

The average adjusted R-squared for all 34 regressions is 0.75 and the average adjusted R-squared values for the "Good" and the "Bad" periods are 0.74 and 0.78 respectively. Overall, the model explains on average 75% of the variations in stock beta over the 34 regressions. The model seems to capture 4% more variations in stock betas during the "Bad" period than the "Good" period. As observed from Table 3, out of the five sub-sectors considered, the consumer goods and the financials sub-sectors are the sub-sectors where the model in the "Good" period outperformed the "Bad" period on average. The maximum adjusted R-squared values in both the "Good" and the "Bad" periods lie in the financial and industrial stocks respectively whereas the model still performed poorly on TBS stock beta during both periods.

Table 3 Average adjusted R-squared values for the five sub-sectors

	Average Adjusted R-squared Values	
Sub-sectors	"Bad" Period	"Good" Period
Basic Materials	0.79	0.71
Consumer Goods	0.51	0.53
Consumer Services	0.81	0.73
Financials	0.90	0.91
Industrials	0.80	0.77

CoreBeta is significant in most regressions except for the stock HAR in the "Bad" period or the bearish market regime. The degree of significance of other regressors is rather mixed for this study. From Table 4, the two most significant factors in the "Bad" period are CoreBeta and DY. The three most significant factors in the "Good" period are CoreBeta, CCR, DY and EBITA (M). The least significant factor suggested by the regression results is the

ILLIQ with approximately 12% of the times for which it is significant. These findings are different from those by Panattoni (2009), suggesting a difference between the U.S. and the South African stock markets. The industry effect captured by the CoreBeta seems to be the most significant factor. As observed earlier, the model in the "Bad" period outperforms the "Good" period by 4% on average, yet the number of times that each factor is significant in the "Good" period exceeds that of the "Bad" period (see Table 4). This suggests that for factors that are significant during the "Bad" period, they may have increasing explanatory power.

Table 4 Number of times a factor is insignificant in the regressions

Number of Regressions Where the Factor is Insignificant		
Factor	**"Bad" Period**	**"Good" Period**
CoreBeta	1	0
CCR	9	3
DE	11	8
DY	7	5
EBITA (M)	11	7
ILLIQ	14	10
ROE	12	8

The next step is to explore each sub-sector, examine whether the relationship between the firm-level variables and the stock betas is different in different market regimes. We will compare the basic materials sub-sector with the financial sub-sector in detail using the CoreBeta and DY regression coefficients. For more details on the regression coefficients and standard errors, individual stock beta regression results can be found in Appendix C.

There are five resource stocks that belong to the basic materials sub-sector included in this study, namely AFE, AMS, ANG, GFI and HAR. There are also three stocks that belong to the financial sub-sector included in this study: ASA, NED and SBK. Since it is suggested by the regression outputs that CoreBeta and DY are two of the most significant factors of stock beta decomposition, Figures 5 to 8 indicate a comparison of the regression coefficients of CoreBeta and DY in the "Good" and the "Bad" periods for these eight stocks. Graphs of the remaining factors' regression coefficients for these stocks and graphs for other stocks are available in Appendix D.

The regression coefficients of the firm-level variables do change between the two market regimes as observed from Figures 5 to 8. For most of the five resource stocks, the regression coefficients of CoreBeta are relatively greater in the "Good" period than those in the "Bad" period, whereas the DY regression coefficients are smaller in the "Good" period than those in the "Bad" period. The results of the three financial stock beta regressions however, are the opposite of those of the resource stocks. The CoreBeta regression coefficients in the "Good" period are less than those in the "Bad" period but the DY regression coefficients in the "Good" period are greater than those in the "Bad" period. These observations have practical implications for resource stocks as their stock betas will increase more or decrease less in the "Good" period than the "Bad" period if their CoreBeta values increase and all else remains constant. When looking at the regression results from an absolute value point of view, the sensitivities of the stock betas to changes in the proposed factors vary between different market regimes and different stocks.

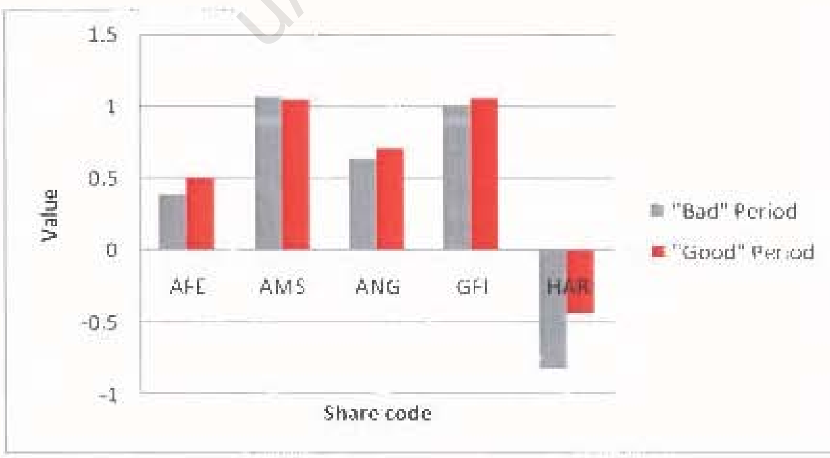

Figure 5 CoreBeta regression coefficients for the five resource stocks

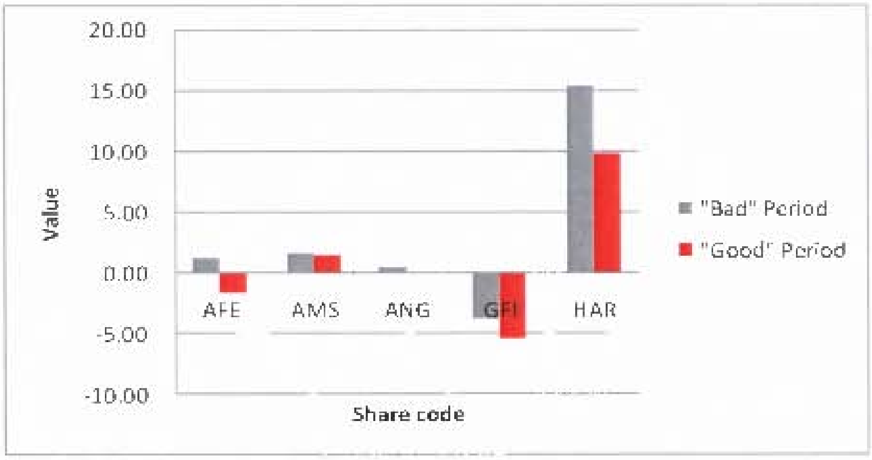

Figure 6 Dividend yield regression coefficients for the five resource stocks

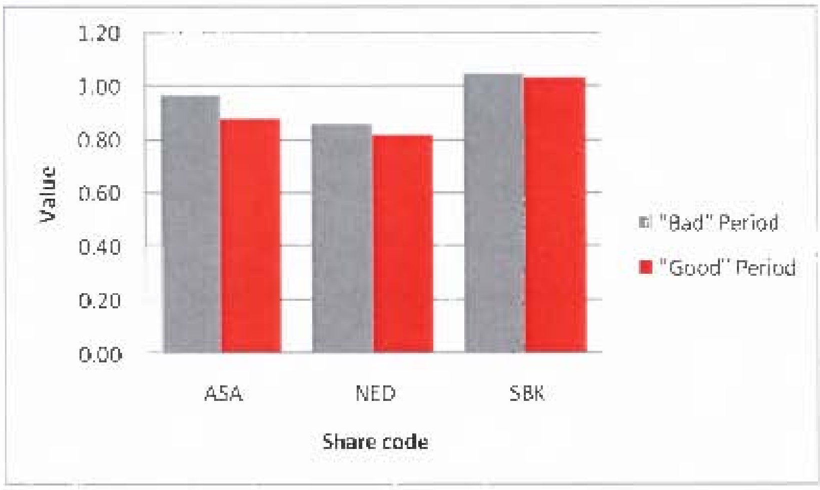

Figure 7 CoreBeta regression coefficients for the three financial stocks

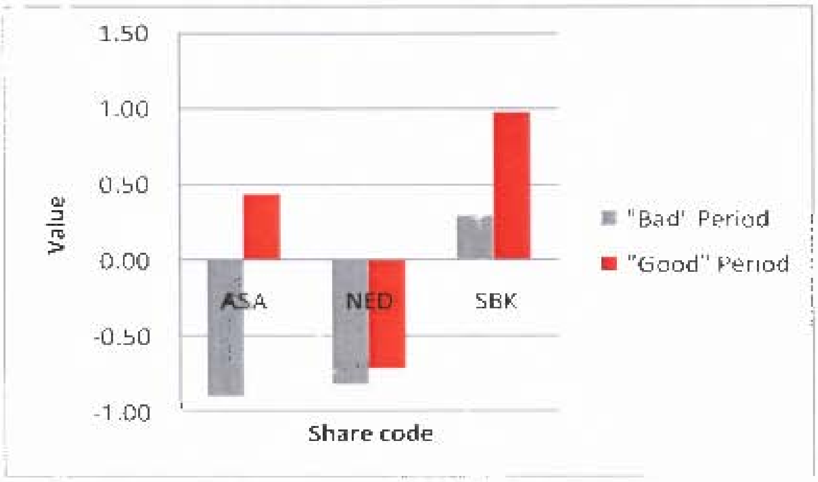

Figure 8 Dividend yield regression coefficients for the three financial stocks

There are some other findings that are worth highlighting. The results of the resource stocks may differ from stocks in other sub-sectors because the performances of these commodity stocks are usually highly dependent on the gold price and the rand/dollar exchange rate. In contrast to stock RBW, which is also a consumer goods stock, beta estimates of stock TBS were poorly fitted. In the "Bad" period, the model captures merely 24% of the variations in the stock beta of TBS and the only significant factor is CoreBeta. This suggests that there must be other factors that affect the movements in the stock beta. In particular, the poor fit of the model may be contributed to the Tiger Brands price-fixing scandal in late 2007 which subjected the company to a R98.8-million fine (Monteiro, 2007). The company's free cash flow shrank by 51% in 2008 but it nevertheless still paid out attractive dividends in that year.

The findings of sections 5.1 and 5.2 indicate the variability of sub-sector and stock betas over time and the changing sensitivities of stock betas to the changes of firm-level variables in different market regimes. They further indicate that in some instances, market capitalisation and firm-specific corporate activities may also have impacts on a stock beta. Further investigations into the company's capital structure, market activities and business decisions are necessary to find the optimal model that explains the variations of a stock beta.

5.3 Performances of the Two Portfolio Strategies

The six stocks which are chosen for this empirical example are: AFE, BAW, HAR, CLH, NED and RBW. Excess stock returns are used in computing the portfolio returns. The performances of various strategies are summarised in Table 5 and graphically presented in Figure 9 (based to 100).

The results show that the equally weighted portfolio outperformed the others with the highest excess return per unit of risk. Strategy 1 outperformed Strategy 2 with the second highest return per unit of risk value. Strategy 2 is based on Strategy 1 but overweighs one of the preferred stocks heavily relative to the other two stocks when the investor anticipates a direction change in the market. Therefore, Strategy 2's portfolio is less diversified than Strategy 1's portfolio with a higher annualized return but also a higher annualized standard deviation during the period from May 2000 to December 2009. Strategy 2 outperformed Strategy 1 by 65 out of the 116 months, equivalent to 56% of the time. Assuming no transaction costs, all three portfolios outperformed the market proxy FTSE/JSE All Share Index (J203).

It can be concluded here that using the stock beta regression results may not necessarily improve the performance of a portfolio. This result may be contributed to the implicit assumption of the derived model, consequently a potential limitation on the portfolio strategy, that historical betas do have some explanatory power concerning future betas. In addition, only one example is back-tested in this study and the regression outputs may still add value by providing investors an extra dimension in making their investment decisions, particularly when they have to choose between some stocks. For instance, if an investor is interested in two high beta stocks, he or she will choose the stock that is expected to have a sustainable and high beta value in the future using the information provided by the stock beta regressions and the forecasted trends of the firm-level variables because beta changes over time.

Table 5 Performances of the four portfolios

Performance of the Four Portfolios					
	Max. Return	Min. Return	Annualised Return	Annualised Std.Deviation	Return Per Unit of Risk
Equally Weighted	13.49%	-12.70%	13.89%	17.76%	0.78
J203	12.59%	-14.59%	6.97%	19.65%	0.35
Strategy 1	13.97%	-11.83%	13.09%	18.04%	0.73
Strategy 2	14.03%	-15.31%	13.41%	21.59%	0.62

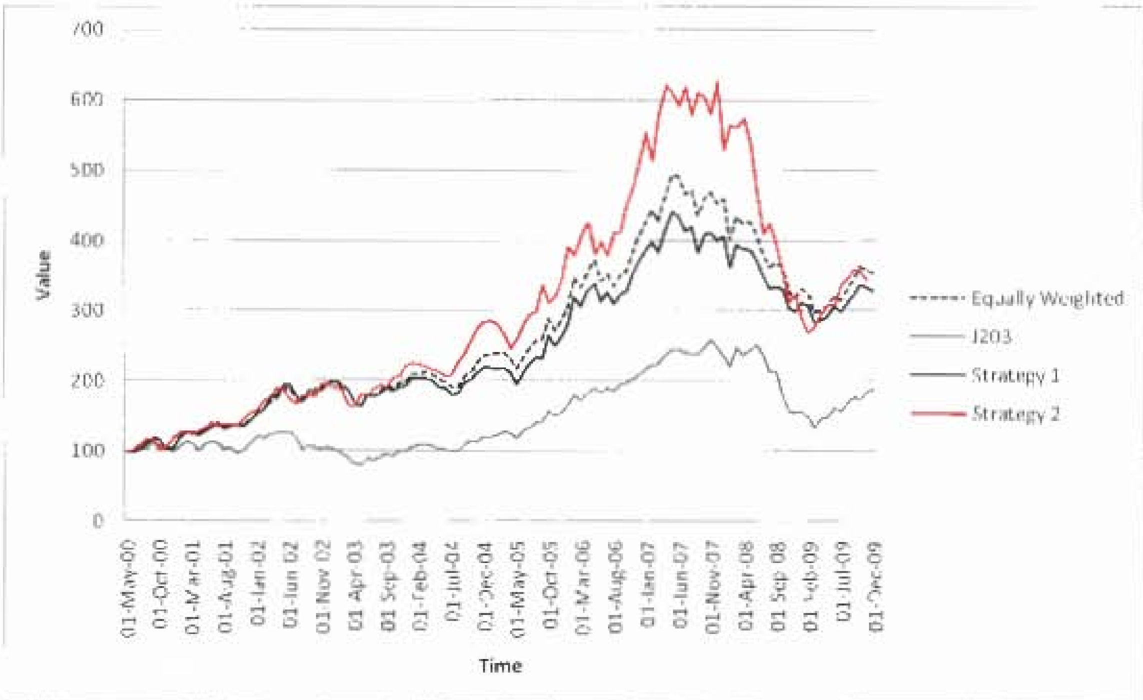

Figure 9 Cumulative returns of the four portfolios: May 2000 to December 2009

6. Conclusions and Recommendations

In view of the findings of this report, the following conclusions about the beta estimation and decomposition in the South Africa equity market may be drawn.

Kalman filter is used to estimate the 9 sub-sector betas and the 17 selected stock betas listed on the JSE during the period from May 2000 to December 2009. The results show that sub-sector and stock beta estimates do vary over time with some stock beta estimates displaying more variability than others. Defensive stocks must be those that have betas not only below one but persistently below one and in relative rather than absolute terms. Market participants must take into account the variability of the stock betas over time when making investment decisions to avoid over reliance on point beta estimates.

The stock beta regression results are mixed and different for stocks within the same sub-sector and are dependent on the market regimes. The beta estimates of stock TBS experienced the poorest fit by the model. For the "Bad" period, CoreBeta and DY are the two most significant factors. CoreBeta, CCR, DY and EBITA (M) are the significant factors in modelling stock beta during the "Good" period. In contrast to the findings of Panattoni (2009), trading liquidity of a stock fails to explain the variations of its beta more than 88% of the time, which may be because the stocks selected for this study are generally quite liquid. The results of the regressions in this study do conform to what was proposed by Damodaran (n.d.), namely that industry effect, operating leverage and financial leverage are the three determinants of equity beta. The measures used to capture these effects are, however, different to his suggestions due to the consideration of the trade-off between interpretation and model fit.

Overall, the model explains on average 75% of the variations in stock beta over 34 regressions. The goodness-of-fit of the model in the "Bad" period outperforms that in the "Good" period by 4% on average.

The use of stock beta regression outputs in Strategy 2 fails to improve Strategy 1's relative beta defensive equity investment scheme. Deviation of Strategy 2's performance from that of Strategy 1 is explained by three factors:

1) Higher proportionate increase in the active weight of the most favourable stock
2) Accuracy of the regression coefficients
3) Accuracy of the estimation of the trend of the firm-level variable

The first factor suggests that Strategy 2 is more aggressive which leads to reduced portfolio diversification relative to Strategy 1. As observed in Figure 9, the derived model and consequently the strategy (Strategy 2) appear to work reasonably well in the "Good" period but failed to achieve desired result in the "Bad" period. This phenomenon may be contributed to the estimation error in the trends of the firm-level variables and the accuracy of the regression coefficients. Estimation of the trends of the firm-level variables is not the focus of this study; however, errors in the regression coefficients may suggest that the model breaks down in the "Bad" period. In the "Bad" period, stock betas tend to change drastically and market participants struggle to price assets fairly. Market may move from equilibrium to disequilibrium. By equilibrium, we mean that there are willing buyers and willing sellers. Disequilibrium is where there are forced transactions such as panic sale, driven by irrationality. The potential failure of the model in the "Bad" period may thus be partly explained by the behavioural aspect of the market participants.

The equally weighted portfolio in the example outperformed these two strategies and the market proxy. However, the attempt of relating stock beta to firm-level variables may add another dimension to the investment decision making process of the market participants. Some market participants may be faced with a dilemma when choosing between two stocks. The combination of the coefficients of the firm-level variables and the forecasted trends of these variables may determine which of the stocks' beta levels is sustainable and will continue to move in the direction preferred by the investor.

The main shortcoming of the study is the shortage of data which prevents out-of-sample testing of the model presented. There are only 116 data points from May 2000 to Dec 2009, of which 76 data points are grouped as the "Good" period and the others are grouped as the "Bad" period. The study requires at least one full business cycle in order to examine the effects of the bull and bear markets on the model. There may be overlaps in certain phases; however, the periods are too short if they are not spliced.

The following recommendations regarding future beta regression studies in South Africa are made.

Availability of the data is always going to be a major constraint in the developing economies. If longer periods of data are made available, one may look at the behaviour of stock betas over different phases of the country's business cycle in addition to the two different market regimes. Out-of-sample testing of the derived model may be performed to add practical values and reduce the risk of the over fitting of data presented in this study. There is the possibility of large capitalization bias in this study since small cap stocks suffer more from the data limitations and only the stocks with obtainable data are included. Therefore the study may only shed some light on the beta decomposition analysis in the South African equity market. Nevertheless, the use of estimation techniques such as the

Kalman filter and further research on the beta decomposition model and its applications in terms of trading strategies must be promoted.

More extensive research in beta decomposition and modelling in South Africa are required as it enables the market participants to have a better understanding of the equity market dynamics, assists in constructing better return models, more accurate stock beta estimates and offer more varieties of investment strategies.

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Appendix A – Summary statistics

The tables show the summary statistics of the sub-sector beta, firm-level variables and the stock beta for each stock included in this study.

			AFE			
Variable	**Mean**	**Standard Deviation**	**Kurtosis**	**Skewness**	**Minimum**	**Maximum**
CCR	0.5718	0.9432	4.4248	1.0639	-1.6855	4.6488
DE	0.4983	0.1268	-1.5293	0.2508	0.3407	0.7062
DY	0.0391	0.0108	-0.1761	0.6338	0.0145	0.0626
EBITA (M)	0.0888	0.0128	-0.1895	0.5732	0.0641	0.1207
ILLIQ	0.0079	0.0101	21.6565	3.7859	0.0005	0.0788
ROE	0.1478	0.0430	-0.4154	0.5645	0.0802	0.2576
StockBeta	0.5434	0.0216	-1.1606	0.4707	0.5112	0.5925
CoreBeta	1.3271	0.0119	0.6919	-1.0322	1.2947	1.3457

			AMS			
Variable	**Mean**	**Standard Deviation**	**Kurtosis**	**Skewness**	**Minimum**	**Maximum**
CCR	-0.8323	3.6102	11.6596	-3.4364	-18.5472	0.8045
DE	0.2550	0.2342	-1.0632	0.5148	0.0000	0.7087
DY	0.0452	0.0146	-0.3332	-0.6780	0.0000	0.0676
EBITA (M)	0.3575	0.1487	-0.7107	0.1590	0.0161	0.6323
ILLIQ	0.0002	0.0003	89.9715	8.9472	0.0000	0.0036
ROE	0.3625	0.1633	-1.1939	-0.1066	0.0219	0.6310
StockBeta	1.6738	0.0310	1.0333	-1.0073	1.5799	1.7260
CoreBeta	1.3271	0.0119	0.6919	-1.0322	1.2947	1.3457

			ANG			
Variable	**Mean**	**Standard Deviation**	**Kurtosis**	**Skewness**	**Minimum**	**Maximum**
CCR	-7.4878	15.9886	4.1045	-2.2728	-65.7808	2.1565
DE	0.6779	0.0924	-0.7484	-0.0297	0.4864	0.8614
DY	0.0241	0.0199	-0.9553	0.7053	0.0040	0.0633
EBITA (M)	0.1825	0.1010	-1.0201	0.4518	0.0212	0.3852
ILLIQ	0.0004	0.0007	70.4015	7.6817	0.0000	0.0071
ROE	0.0166	0.1791	-1.3267	-0.3113	-0.3150	0.2770
StockBeta	0.8731	0.0370	-0.5379	-0.2651	0.7873	0.9315
CoreBeta	1.3271	0.0119	0.6919	-1.0322	1.2947	1.3457

			ASA			
Variable	**Mean**	**Standard Deviation**	**Kurtosis**	**Skewness**	**Minimum**	**Maximum**
CCR	0.2525	0.1806	-1.1199	-0.0062	-0.0637	0.6829
DE	1.9977	1.5755	-0.8257	0.8065	0.2333	5.2727
DY	0.0421	0.0064	-0.6454	0.0953	0.0301	0.0550
EBITA (M)	0.1649	0.0566	-1.4941	-0.1111	0.0756	0.2421
ILLIQ	0.0007	0.0043	114.8775	10.6936	0.0000	0.0460
ROE	0.2082	0.0352	-0.7707	-0.6556	0.1237	0.2505
StockBeta	0.6563	0.0202	1.1049	0.0494	0.6136	0.7184
CoreBeta	0.6950	0.0130	0.4534	0.9848	0.6675	0.7279

			BAW			
Variable	**Mean**	**Standard Deviation**	**Kurtosis**	**Skewness**	**Minimum**	**Maximum**
CCR	0.3652	1.0763	-0.7743	0.3721	-1.3129	2.9328
DE	1.3420	0.6028	-0.3502	0.4490	0.3580	2.8563
DY	0.0402	0.0070	0.3889	-0.8801	0.0208	0.0511
EBITA (M)	0.0669	0.0151	-0.5832	0.6890	0.0416	0.0995
ILLIQ	0.0006	0.0007	32.0032	4.5142	0.0001	0.0060
ROE	0.1162	0.0235	0.1672	-0.0140	0.0562	0.1603
StockBeta	0.9448	0.0155	0.6377	0.9040	0.9191	0.9879
CoreBeta	0.6853	0.0127	-0.3680	0.6196	0.6653	0.7179

CLH						
Variable	**Mean**	**Standard Deviation**	**Kurtosis**	**Skewness**	**Minimum**	**Maximum**
CCR	0.5358	0.2705	-0.7362	-0.1167	-0.0358	1.0962
DE	0.3212	0.2874	-0.4088	1.0752	0.0638	0.9758
DY	0.0585	0.0113	-1.0843	-0.0061	0.0366	0.0772
EBITA (M)	0.4529	0.0482	-1.1244	-0.4244	0.3731	0.5191
ILLIQ	0.2847	0.5812	22.2490	3.9009	0.0010	4.4327
ROE	0.2683	0.0700	-1.2319	-0.3665	0.1540	0.3614
StockBeta	0.4431	0.0230	-0.8281	0.0274	0.3952	0.4946
CoreBeta	0.6364	0.0181	-0.0612	1.0060	0.6125	0.6850

CLS						
Variable	**Mean**	**Standard Deviation**	**Kurtosis**	**Skewness**	**Minimum**	**Maximum**
CCR	0.3633	0.8835	0.4181	0.9820	-0.6921	3.0007
DE	0.2183	0.0673	-0.3814	-0.8322	0.0598	0.3001
DY	0.0342	0.0079	0.3090	-1.0748	0.0150	0.0455
EBITA (M)	0.0520	0.0069	-0.8091	-0.5268	0.0378	0.0617
ILLIQ	0.0101	0.0159	34.1573	5.0419	0.0007	0.1356
ROE	0.2155	0.0910	0.5550	1.3488	0.1304	0.4679
StockBeta	0.6646	0.0271	0.4162	1.2306	0.6338	0.7410
CoreBeta	0.6364	0.0181	-0.0612	1.0060	0.6125	0.6850

GFI						
Variable	**Mean**	**Standard Deviation**	**Kurtosis**	**Skewness**	**Minimum**	**Maximum**
CCR	-0.6749	2.0734	2.1814	-1.6601	-7.4320	1.8042
DE	0.1241	0.0582	-0.7123	-0.4462	0.0000	0.2103
DY	0.0280	0.0306	2.9690	2.0321	0.0092	0.1318
EBITA (M)	0.1904	0.0659	-1.0660	-0.3855	0.0658	0.3038
ILLIQ	0.0004	0.0010	79.2309	8.3218	0.0000	0.0103
ROE	0.1045	0.0706	0.1556	1.1717	0.0153	0.2807
StockBeta	0.9465	0.3146	-0.8951	-0.0679	0.3221	1.5355
CoreBeta	1.3271	0.0119	0.6919	-1.0322	1.2947	1.3457

GRF						
Variable	**Mean**	**Standard Deviation**	**Kurtosis**	**Skewness**	**Minimum**	**Maximum**
CCR	0.8398	2.0986	2.3381	-1.5350	-6.4435	3.7458
DE	0.1803	0.0840	-0.6783	-0.3644	0.0123	0.3002
DY	0.0374	0.0153	-1.2341	0.1275	0.0132	0.0704
EBITA (M)	0.0421	0.0159	-0.8541	0.5059	0.0165	0.0710
ILLIQ	0.5997	2.4976	45.9864	6.4920	0.0007	21.0518
ROE	0.2006	0.0415	-0.0957	-0.9044	0.0970	0.2551
StockBeta	0.6871	0.0413	0.1487	-0.1552	0.5821	0.7748
CoreBeta	0.6853	0.0127	-0.3680	0.6196	0.6653	0.7179

HAR						
Variable	**Mean**	**Standard Deviation**	**Kurtosis**	**Skewness**	**Minimum**	**Maximum**
CCR	-4.9739	8.5919	3.6332	-2.0871	-35.9810	2.7639
DE	0.1803	0.0840	-0.6783	-0.3644	0.0123	0.3002
DY	0.0117	0.0124	-1.2700	0.6072	0.0000	0.0352
EBITA (M)	0.0978	0.0855	-0.3266	0.3080	-0.0506	0.2925
ILLIQ	0.0011	0.0024	13.2745	3.4650	0.0001	0.0152
ROE	0.0495	0.0925	-0.3661	0.7911	-0.0579	0.2789
StockBeta	1.3550	0.7290	-0.7323	-0.2617	-0.2172	2.6291
CoreBeta	1.3271	0.0119	0.6919	-1.0322	1.2947	1.3457

HDC						
Variable	**Mean**	**Standard Deviation**	**Kurtosis**	**Skewness**	**Minimum**	**Maximum**
CCR	0.6433	0.3997	-0.6560	0.2086	-0.1646	1.5513
DE	0.6716	0.8869	-0.6240	1.0987	0.0751	2.6107
DY	0.0518	0.0147	-1.1502	0.2564	0.0306	0.0814
EBITA (M)	0.1174	0.0211	-0.9467	0.0128	0.0811	0.1555
ILLIQ	0.8168	4.1986	101.7809	9.8320	0.0005	44.2377
ROE	0.2235	0.0365	-0.3038	0.4879	0.1543	0.3023
StockBeta	0.5430	0.0297	-0.5241	0.7160	0.5002	0.6189
CoreBeta	0.6853	0.0127	-0.3680	0.6196	0.6653	0.7179

NED						
Variable	Mean	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum
CCR	-4.1709	10.3249	4.4937	-2.3706	-42.5564	2.3894
DE	0.6136	0.5304	2.8512	1.9226	0.1401	2.4254
DY	0.0378	0.0118	-0.5568	0.2147	0.0154	0.0649
EBITA (M)	0.1337	0.0519	-0.6769	-0.6544	0.0160	0.2065
ILLIQ	0.0003	0.0004	83.3972	8.5114	0.0001	0.0046
ROE	0.1540	0.0590	-0.1292	-0.6363	0.0045	0.2565
StockBeta	0.5630	0.0320	-0.7191	0.4885	0.5092	0.6325
CoreBeta	0.6950	0.0130	0.4534	0.9848	0.6675	0.7279

RBW						
Variable	Mean	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum
CCR	0.4961	0.6176	1.2228	-0.5914	-1.3465	1.8796
DE	0.0053	0.0135	22.2532	4.5829	0.0000	0.0890
DY	0.0443	0.0185	1.1623	-1.2930	0.0000	0.0738
EBITA (M)	0.0849	0.0349	-1.1535	0.4515	0.0276	0.1414
ILLIQ	0.3224	0.6351	32.3251	4.9640	0.0009	5.2099
ROE	0.1826	0.0460	0.1204	-0.4854	0.0463	0.2528
StockBeta	0.4527	0.0193	-0.0382	0.7646	0.4187	0.5030
CoreBeta	0.8029	0.0143	-1.0845	-0.5154	0.7718	0.8219

RLO						
Variable	Mean	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum
CCR	0.7947	0.6794	0.8419	0.6781	-0.6607	2.6030
DE	0.2601	0.2538	-1.1048	0.5445	0.0024	0.7736
DY	0.0578	0.0174	22.7151	4.1467	0.0401	0.1734
EBITA (M)	0.1175	0.0207	-1.0690	-0.1924	0.0766	0.1544
ILLIQ	0.0074	0.0310	96.4823	9.5140	0.0001	0.3233
ROE	0.3854	0.0820	-0.8780	-0.1366	0.2165	0.5160
StockBeta	0.5674	0.0155	0.0635	0.6711	0.5375	0.6192
CoreBeta	0.6853	0.0127	-0.3680	0.6196	0.6653	0.7179

SBK						
Variable	Mean	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum
CCR	0.2004	0.4557	-0.6778	-0.5217	-0.9883	0.9509
DE	1.2971	0.2975	-0.9116	0.5964	0.9737	2.0366
DY	0.0364	0.0045	-0.0467	-0.0827	0.0271	0.0465
EBITA (M)	0.2233	0.0357	-0.8881	-0.3086	0.1459	0.2747
ILLIQ	0.0002	0.0004	88.0153	8.8502	0.0000	0.0042
ROE	0.2136	0.0363	-0.3194	0.0959	0.1339	0.2937
StockBeta	0.7214	0.0162	-0.2652	0.7364	0.6823	0.7611
CoreBeta	0.6950	0.0130	0.4534	0.9848	0.6675	0.7279

TBS						
Variable	Mean	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum
CCR	0.6905	0.4337	0.2911	-0.8863	-0.5848	1.3074
DE	1.0255	1.0879	1.0179	1.4437	0.0689	4.2110
DY	0.0409	0.0055	1.0371	1.3212	0.0340	0.0572
EBITA (M)	0.1220	0.0233	-1.5560	-0.0964	0.0833	0.1572
ILLIQ	0.0007	0.0014	78.8424	8.2157	0.0001	0.0140
ROE	0.4797	0.2638	3.6342	2.0764	0.2387	1.4120
StockBeta	0.5377	0.0215	-1.4817	0.3156	0.5067	0.5778
CoreBeta	0.8029	0.0143	-1.0845	-0.5154	0.7718	0.8219

TFG						
Variable	Mean	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum
CCR	-0.9899	3.3702	4.5337	-2.3771	-13.5410	0.7248
DE	0.2756	0.1039	-0.5951	0.7674	0.1338	0.4828
DY	0.0480	0.0111	-0.1053	0.7024	0.0275	0.0740
EBITA (M)	0.1886	0.0657	-1.2445	-0.5932	0.0635	0.2580
ILLIQ	0.0266	0.1976	113.5085	10.6039	0.0001	2.1251
ROE	0.2206	0.0803	-1.1487	-0.5957	0.0685	0.3159
StockBeta	0.6167	0.0222	-0.5567	0.3770	0.5801	0.6736
CoreBeta	0.6364	0.0181	-0.0612	1.0060	0.6125	0.6850

Appendix B – Regression results: May 2000 to December 2009

The tables include results of the 17 stock beta regressions for the following regression using data from the full period (May 2000 to December 2009):

$$\beta_i = c_1\beta_{CoreBeta} + c_2CCR + c_3DE + c_4DY + c_5EBITA(M) + c_6ILLIQ + c_7ROE + \epsilon$$

The individual stock beta regression results are presented with each share code is followed by the sub-sector name and the red colour indicates insignificant coefficients at the 5% significance level.

AFE-Basic Materials			
Variable	Coefficient	Standard Error	t-Statistic
COREBETA	0.5295	0.0232	22.8606
CCR	-0.0107	0.0013	-8.2032
DE	0.0316	0.0160	-1.9679
DY	0.4710	0.1222	3.8554
EBITA (M)	-1.6458	0.4030	-4.2624
ILLIQ	-0.2537	0.1224	-2.0732
ROE	0.0650	0.1102	0.5901
R-squared	0.777331	Adjusted R-squared	0.765074

ANG-Basic Materials			
Variable	Coefficient	Standard Error	t-Statistic
COREBETA	0.7016	0.0146	48.0414
CCR	-0.0008	0.0002	-3.3030
DE	-0.0863	0.0297	2.9052
DY	1.0666	0.2900	-3.6777
EBITA (M)	0.1053	0.0619	1.7005
ILLIQ	0.0471	3.8551	0.0122
ROE	0.0284	0.0424	0.6702
R-squared	0.576372	Adjusted R-squared	0.555163

BAW-Industrials			
Variable	Coefficient	Standard Error	t-Statistic
COREBETA	1.3599	0.0105	129.8718
CCR	0.0024	0.0010	2.4679
DE	0.0041	0.0020	-2.0820
DY	0.0573	0.1605	0.3575
EBITA (M)	0.1151	0.0861	1.3305
ILLIQ	0.7238	1.4975	0.4834
ROE	0.0603	0.0510	1.1818
R-squared	0.689521	Adjusted R-squared	0.672530

CLS-Consumer Services			
Variable	Coefficient	Standard Error	t-Statistic
COREBETA	1.0146	0.0157	51.4442
CCR	-0.0075	0.0016	-4.7608
DE	0.2317	0.0483	4.8001
DY	-1.0616	0.1412	-7.5500
EBITA (M)	-0.6014	0.2602	-2.3111
ILLIQ	0.0387	0.0688	0.5620
ROE	0.1789	0.0390	4.6133
R-squared	0.834718	Adjusted R-squared	0.82562

GRF-Industrials			
Variable	Coefficient	Standard Error	t-Statistic
COREBETA	1.2331	0.0258	47.7408
CCR	-0.0002	0.0007	-0.2942
DE	-0.5244	0.0396	13.2544
DY	0.1365	0.1170	1.1667
EBITA (M)	-0.2489	0.2144	1.1609
ILLIQ	0.0004	0.0006	0.7064
ROE	-0.2887	0.0360	-8.0538
R-squared	0.904568	Adjusted R-squared	0.899336

AMS-Basic Materials			
Variable	Coefficient	Standard Error	t-Statistic
COREBETA	1.0611	0.0171	62.2258
CCR	0.0078	0.0009	-8.5676
DE	0.2104	0.0169	12.4628
DY	4.4646	0.4411	10.1225
EBITA (M)	1.3743	0.1089	12.6153
ILLIQ	-4.5073	4.2359	1.0630
ROE	-1.3425	0.1072	-12.5106
R-squared	0.79620	Adjusted R-squared	0.786045

ASA-Financials			
Variable	Coefficient	Standard Error	t-Statistic
COREBETA	0.9252	0.0094	96.7562
CCR	0.0154	0.0048	-3.2308
DE	-0.0030	0.0008	-3.8524
DY	-0.3475	0.1621	2.1438
EBITA (M)	-0.0515	0.0238	-2.1607
ILLIQ	0.2270	0.1884	1.2050
ROE	0.2224	0.0353	6.2997
R-squared	0.843544	Adjusted R-squared	0.835237

CLH-Consumer Services			
Variable	Coefficient	Standard Error	t-Statistic
COREBETA	0.6142	0.0848	7.2447
CCR	0.0129	0.0090	1.4273
DE	0.0680	0.0071	9.6251
DY	-0.6403	0.3265	-1.9612
EBITA (M)	0.2066	0.2766	0.7469
ILLIQ	0.0047	0.0030	-1.5488
ROE	-0.1168	0.2273	-0.5142
R-squared	0.689944	Adjusted R-squared	0.672877

GFI-Basic Materials			
Variable	Coefficient	Standard Error	t-Statistic
COREBETA	1.1121	0.0493	22.5348
CCR	-0.1319	0.0105	-12.5186
DE	0.5749	0.5577	1.0309
DY	1.6600	0.0285	-2.6412
EBITA (M)	-5.0256	0.5857	-9.6046
ILLIQ	-6.8635	19.4916	-0.3521
ROE	4.1178	0.5629	7.3150
R-squared	0.709906	Adjusted R-squared	0.693937

HAR-Basic Materials			
Variable	Coefficient	Standard Error	t-Statistic
COREBETA	0.3909	0.1326	-2.9715
CCR	0.0467	0.0050	9.7017
DE	10.7631	0.5129	20.9846
DY	15.1562	10.7194	1.4139
EBITA (M)	9.4901	1.7030	5.5778
ILLIQ	-39.2359	15.0583	-2.5988
ROE	17.8010	2.5010	-6.9750
R-squared	0.853360	Adjusted R-squared	0.845310

HDC-Industrials			
Variable	Coefficient	Standard Error	t-Statistic
COREBETA	0.5337	0.0330	19.1049
CCR	0.0100	0.0034	2.9754
DE	-0.0003	0.0027	-0.1048
DY	1.7665	0.1455	12.1472
EBITA (M)	1.1625	0.1890	6.1512
ILLIQ	0.0003	0.0003	1.0751
ROE	0.5633	0.0795	-7.0818
R-squared	0.839927	Adjusted R-squared	0.824785

RBW-Consumer Goods			
Variable	Coefficient	Standard Error	t-Statistic
COREBETA	0.6275	0.0084	74.8577
CCR	0.0149	0.0020	7.4660
DE	-0.6945	0.1066	6.5203
DY	1.1076	0.0692	16.0116
EBITA (M)	0.0366	0.0591	0.6194
ILLIQ	0.0021	0.0017	1.2212
ROE	-0.0531	0.0522	-1.0164
R-squared	0.711500	Adjusted R-squared	0.69562

SBK-Financials			
Variable	Coefficient	Standard Error	t-Statistic
COREBETA	1.0486	0.0103	101.8311
CCR	0.0030	0.0015	1.9624
DE	0.0050	0.0034	1.4463
DY	0.4035	0.1043	3.8675
EBITA (M)	-0.1375	0.0275	-4.9903
ILLIQ	1.4357	1.3272	1.0853
ROE	-0.0107	0.0309	-0.3451
R-squared	0.909810	Adjusted R-squared	0.904641

TFG-Consumer Services			
Variable	Coefficient	Standard Error	t-Statistic
COREBETA	0.9895	0.0141	70.1564
CCR	-0.0000	0.0002	-1.1669
DE	0.0194	0.0258	0.7505
DY	-0.8724	0.1895	-4.6027
EBITA (M)	-0.0005	0.1079	-0.0049
ILLIQ	-0.0010	0.0059	0.1711
ROE	0.1026	0.0745	1.3773
R-squared	0.744305	Adjusted R-squared	0.73023

NED-Financials			
Variable	Coefficient	Standard Error	t-Statistic
COREBETA	0.8358	0.0071	118.1401
CCR	0.0018	0.0001	17.2550
DE	0.0041	0.0016	2.4887
DY	-0.9680	0.0855	-11.3237
EBITA (M)	-0.6656	0.0483	-13.5805
ILLIQ	-0.1079	1.7566	-0.0614
ROE	0.7219	0.0428	16.8457
R-squared	0.944609	Adjusted R-squared	0.943955

RLO-Industrials			
Variable	Coefficient	Standard Error	t-Statistic
COREBETA	0.9013	0.0144	62.6173
CCR	-0.0082	0.0015	5.3975
DE	-0.0082	0.0068	-1.2020
DY	-0.1166	0.0755	-1.5446
EBITA (M)	-0.5305	0.0687	-7.7237
ILLIQ	-0.0362	0.0331	-1.0930
ROE	0.0720	0.0127	5.6615
R-squared	0.781321	Adjusted R-squared	0.768294

TBS-Consumer Goods			
Variable	Coefficient	Std. Error	t-Statistic
COREBETA	0.5951	0.0238	24.9701
CCR	-0.0192	0.0050	-3.8340
DE	0.0111	0.0048	2.3004
DY	-0.4295	0.3539	-1.2137
EBITA (M)	0.5502	0.1145	5.6799
ILLIQ	0.2253	1.5340	0.1468
ROE	0.0082	0.0148	0.5507
R-squared	0.290058	Adjusted R-squared	0.250678

Appendix C – Regression results: the "Good" and the "Bad" periods

The tables include results of the 17 stock beta regressions for the following regression using data from two spliced periods namely, the "Good" period and the "Bad" period:

$$\beta_i = c_1\beta_{CoreBeta} + c_2CCR + c_3DE + c_4DY + c_5EBITA(M) + c_6ILLIQ + c_7ROE + \epsilon$$

The results over the two periods are grouped in sub-sectors and the red colour indicates insignificant coefficients at the 5% significance level.

Basic Materials

AFE				
	"Bad" Period		"Good" Period	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
CoreBeta	0.3998	[illegible]	0.5006	[illegible]
CCR	-0.0126	0.0023	-0.0075	0.0020
DE	0.0680	0.0792	-0.0071	0.0156
DY	0.5392	0.2330	0.5779	0.1649
EBITA (M)	[illegible]2067	2.0188	-1.6849	0.4775
ILLIQ	-0.1516	0.1597	0.4587	0.2308
ROE	-0.9008	0.6375	-0.0845	0.1223
R-squared	0.7439		0.7821	
Adj R-squared	0.5374		0.7601	

AMS				
	"Bad" Period		"Good" Period	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
CoreBeta	1.0706	0.0338	1.0530	[illegible]
CCR	-0.0092	0.0021	0.0073	0.0005
DE	0.1842	0.0399	0.2017	0.0150
DY	6.2492	0.9872	4.8738	0.4157
EBITA (M)	1.6235	0.2359	[illegible]	0.1049
ILLIQ	40.6701	[illegible]	-7.0724	3.2762
ROE	-1.8146	0.2382	-1.3308	0.1042
R-squared	0.8676		0.8431	
Adj R-squared	0.8435		0.8252	

ANG				
	"Bad" Period		"Good" Period	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
CoreBeta	0.6355	0.0336	0.7173	0.0152
CCR	-0.0129	0.0014	0.0062	0.0005
DE	-0.0124	0.0306	-0.0720	0.0398
DY	-2.2945	0.4565	0.8969	0.4043
EBITA (M)	0.4024	0.1969	0.0456	0.0759
ILLIQ	2.5553	10.3481	-1.5906	3.9281
ROE	0.0571	[illegible]	0.0814	0.0462
R-squared	0.8578		0.5772	
Adj R-squared	0.8378		0.5561	

GFI				
	"Bad" Period		"Good" Period	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
CoreBeta	1.0156	0.2009	1.0607	0.0404
CCR	-0.1364	[illegible]	-0.1191	0.0146
DE	0.9252	0.6915	1.1445	0.9051
DY	0.5212	0.5413	-2.9620	1.0301
EBITA (M)	3.7967	1.7338	5.4185	0.8955
ILLIQ	-114.0786	70.3964	[illegible]	23.5903
ROE	2.9351	1.0074	4.0752	0.9035
R-squared	0.7487		0.6363	
Adj R-squared	0.7031		0.6047	

HAR				
	"Bad" Period		"Good" Period	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
CoreBeta	-0.8268	0.5157	[illegible]	[illegible]
CCR	0.0366	0.0101	0.0563	0.0078
DE	9.8660	0.7615	10.9308	0.7042
DY	20.3727	47.1782	[illegible]	12.8963
EBITA (M)	15.4834	9.8584	9.0457	2.0375
ILLIQ	-5.9085	25.2745	[illegible]	30.1671
ROE	21.4846	11.7635	-18.9979	2.9969
R-squared	0.8666		0.0292	
Adj R-squared	0.8446		0.8143	

Consumer Goods

RBW				
	"Bad" Period		"Good" Period	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
CoreBeta	0.6854	0.0153	0.6136	0.0108
CCR	[illegible]	0.0072	0.0163	0.0015
DE	-0.4760	0.1549	-0.8168	0.1332
DY	-1.2714	0.1065	-1.1779	0.0697
EBITA (M)	-0.0297	0.1135	[illegible]	0.0044
ILLIQ	0.0011	0.0019	[illegible]	0.0036
ROE	-0.0460	0.0743	0.0642	0.0618
R-squared	0.9224		0.7374	
Adj R-squared	0.7931		0.7148	

TBS				
	"Bad" Period		"Good" Period	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
CoreBeta	0.6396	0.0482	0.5584	0.0372
CCR	-0.0010	0.0102	-0.0226	0.0052
DE	0.0062	0.0174	0.0125	0.0066
DY	-2.4550	1.6241	0.0456	[illegible]
EBITA (M)	1.1172	0.6488	0.6321	[illegible]
ILLIQ	1.6736	6.3034	1.4444	1.7180
ROE	-0.0174	0.0219	0.0325	0.0210
R-squared	0.3544		0.3650	
Adj R-squared	0.2270		0.3411	

Consumer Services

CLH				
	"Bad" Period		"Good" Period	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Constant	0.7570	0.1712	0.4786	0.3948
CCR	0.0171	0.0256	-0.0032	0.0383
DE	0.0027	0.2154	0.0536	0.0314
DY	-1.4251	0.9195	2.5095	0.3344
EBITA (M)	0.0487	0.0377	0.4765	0.3109
ILLIQ	0.0076	0.0074	2.1048	0.3330
ROE	-0.0890	0.5209	-0.7428	0.2547
R-squared	0.8006		0.6847	
Adj R-squared	0.7662		0.6577	

CLS				
	"Bad" Period		"Good" Period	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Constant	3.9735	0.1571	[illegible]	0.3166
CCR	0.0032	0.0035	0.0009	0.0018
DE	0.1036	0.2177	0.2881	0.0570
DY	-1.4579	0.3025	1.1420	0.1016
EBITA (M)	0.3798	0.6036	-0.8032	0.1229
ILLIQ	0.0764	0.1773	0.0507	0.0704
ROE	0.1520	0.1537	0.2513	0.0497
R-squared	0.8766		0.8124	
Adj R-squared	0.8565		0.7066	

TFG				
	"Bad" Period		"Good" Period	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Constant	1.0514	0.3338	0.9663	0.3141
CCR	0.0003	0.0012	0.0026	0.0010
DE	0.0887	0.0517	-0.3195	0.0969
DY	-2.5816	0.5338	-0.4816	0.2034
EBITA (M)	-0.1695	0.2336	-0.0657	0.1076
ILLIQ	-0.0429	0.5874	0.0005	0.0051
ROE	0.4624	0.2024	0.0746	0.0711
R-squared	0.6311		0.7495	
Adj R-squared	0.6004		0.7277	

Financials

ASA				
	"Bad" Period		"Good" Period	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Constant	0.9666	0.0241	[illegible]	[illegible]
CCR	-0.0183	0.0152	-0.0100	0.0030
DE	-0.0058	0.0044	-0.0042	0.0007
DY	-0.8959	0.3842	0.4410	0.1729
EBITA (M)	0.0144	0.1221	0.0056	0.0217
ILLIQ	-10.6806	6.5710	0.5489	0.1340
ROE	0.2157	0.0761	0.1904	[illegible]
R-squared	0.9763		0.8775	
Adj R-squared	0.9545		0.8607	

NED				
	"Bad" Period		"Good" Period	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Constant	0.8862	0.0113	0.9194	0.0101
CCR	-0.0132	0.0031	0.0018	0.0001
DE	0.0141	0.0027	0.0009	0.0021
DY	-0.0224	0.1179	-0.7127	0.1441
EBITA (M)	-0.1831	0.1169	-0.0762	0.0593
ILLIQ	7.7281	9.6784	1.1707	1.6564
ROE	0.1832	0.1195	0.7484	0.0932
R-squared	0.9635		0.9542	
Adj R-squared	0.9558		0.9500	

SBK				
	"Bad" Period		"Good" Period	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Constant	1.7613	0.0527	1.0314	[illegible]
CCR	0.0000	0.0046	-0.0045	0.0017
DE	0.0013	0.0117	-0.0012	0.0008
DY	0.7002	0.2547	0.9812	0.1585
EBITA (M)	-0.1284	0.0932	-0.1149	0.0240
ILLIQ	-6.4200	11.0775	3.2935	1.0206
ROE	0.0570	0.3850	0.0171	0.0253
R-squared	0.9119		0.9393	
Adj R-squared	0.8959		0.9340	

Industrials

BAW				
	"Bad" Period		"Good" Period	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Constant	1.3206	0.0166	1.3771	0.0122
CCR	0.0045	0.0022	0.0024	0.0014
DE	-0.0013	0.0051	-0.0099	0.0040
DY	0.5595	0.4761	-3.0552	0.1813
EBITA (M)	1.4036	1.7025	0.1215	0.1001
ILLIQ	6.4214	3.6611	1.7288	1.5782
ROE	-0.9903	0.5055	0.2759	0.0497
R-squared	0.7530		0.9862	
Adj R-squared	0.6541		0.9798	

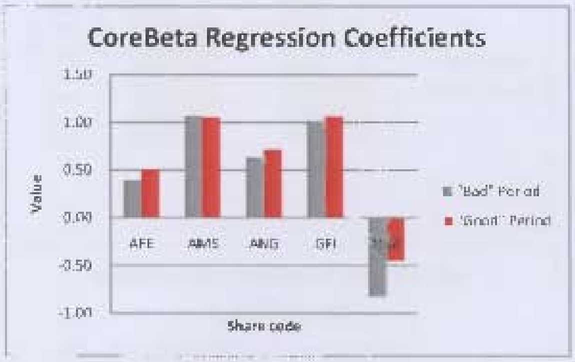
GRF				
	"Bad" Period		"Good" Period	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Constant	1.4634	0.0785	1.1342	0.0386
CCR	-0.0009	0.0014	0.0002	0.0009
DE	-0.7549	0.0862	-0.4107	0.0552
DY	-1.0456	0.4607	0.1409	0.1514
EBITA (M)	-2.4152	0.9474	0.2496	0.2700
ILLIQ	0.0001	0.0006	0.0019	0.0012
ROE	-0.1718	0.1058	-0.1810	0.0011
R-squared	0.9850		0.8470	
Adj R-squared	0.9527		0.8330	

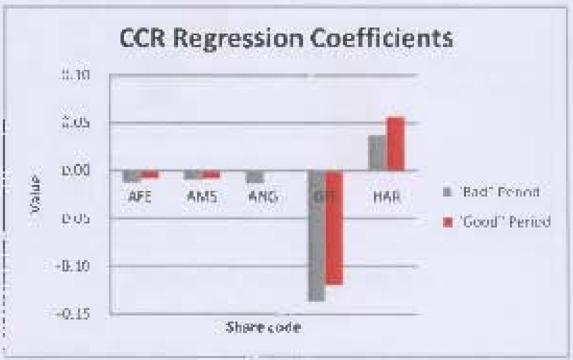
HDC				
	"Bad" Period		"Good" Period	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Constant	0.9664	0.1511	0.7033	0.0565
CGR	[illegible]	0.1996	0.0886	0.0037
DL	-0.3341	0.3021	0.0023	0.0137
DY	0.6646	0.4062	1.4478	0.2524
EBITDA/M	4.2615	1.1315	0.7387	0.2913
ILTO	-0.3079	0.3017	0.0003	0.0063
ROE	-2.5726	0.7912	-0.4649	0.0851
R-squared	0.8037		0.7732	
Adj R-squared	0.6755		0.7534	

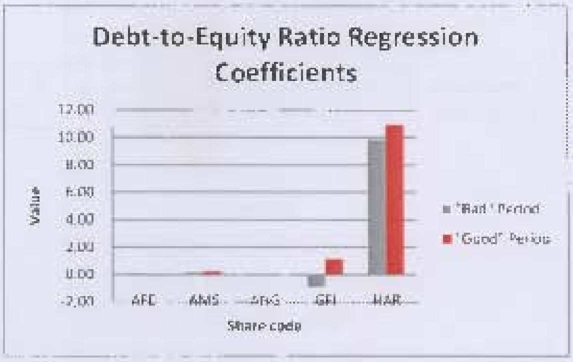
RLD				
	"Bad" Period		"Good" Period	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Constant	-1.0653	[illegible]	0.9132	0.0170
CGR	-0.0743	0.0035	-0.1467	[illegible]
DL	0.3150	0.0257	-0.0147	0.0073
DY	0.0171	0.2169	0.2187	0.0652
EBITDA/M	-0.7170	0.1473	-0.6268	0.1322
ILTO	0.0546	0.0758	[illegible]	0.1713
ROE	-0.1184	0.1524	0.0026	0.0143
R-squared	0.7200		[illegible]	
Adj R-squared	0.3352		0.9084	

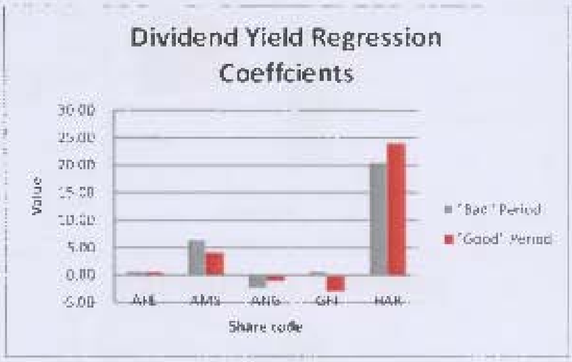
Appendix D – Graphical presentation of the regression coefficients as in Appendix C

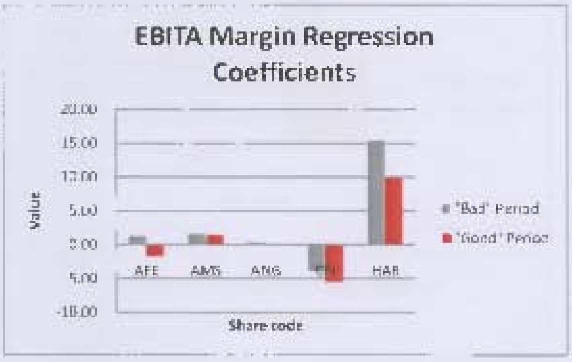
Basic Materials

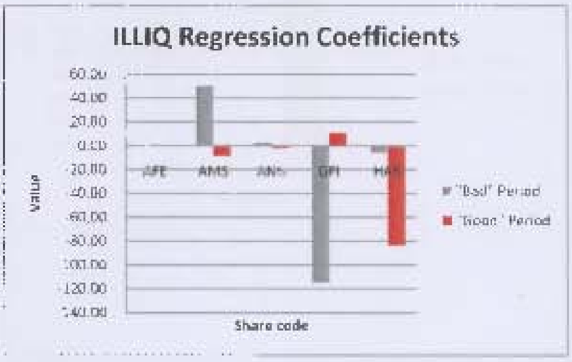


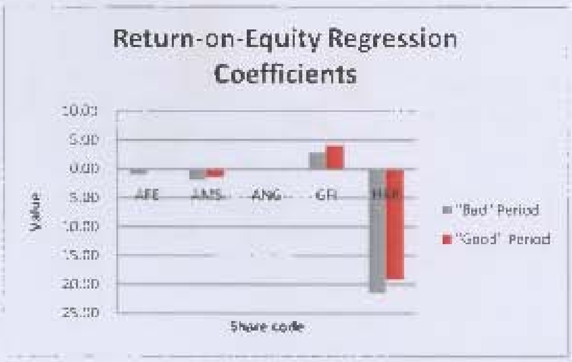




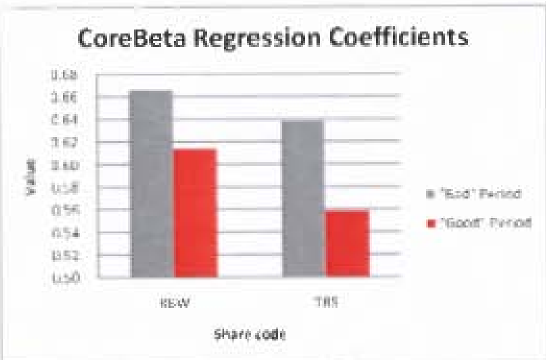


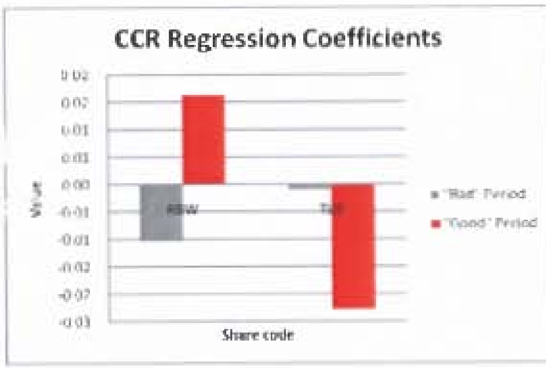


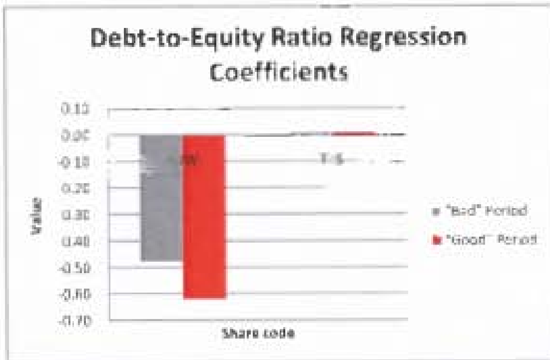


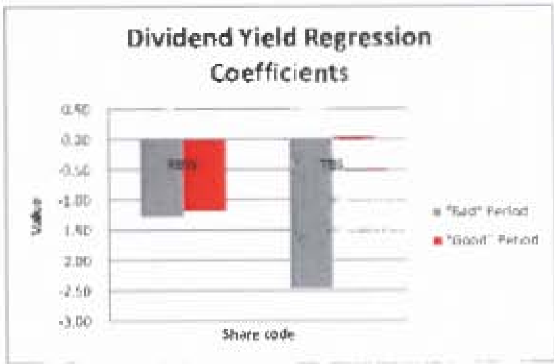


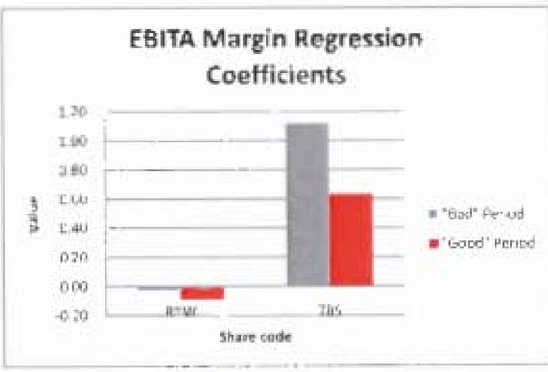
Consumer Goods

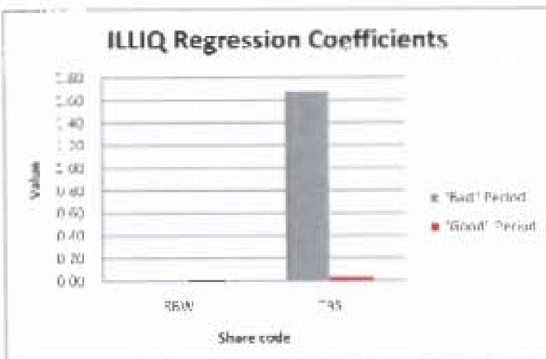


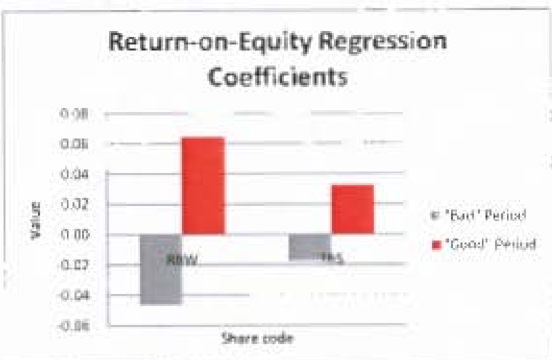




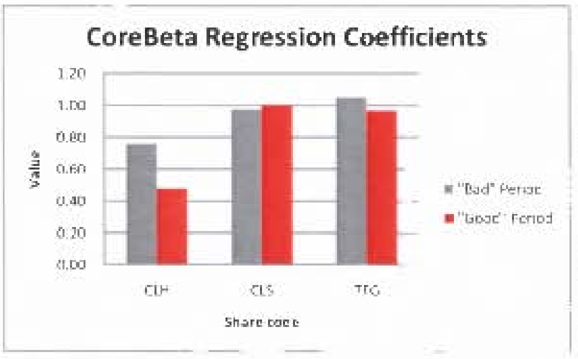


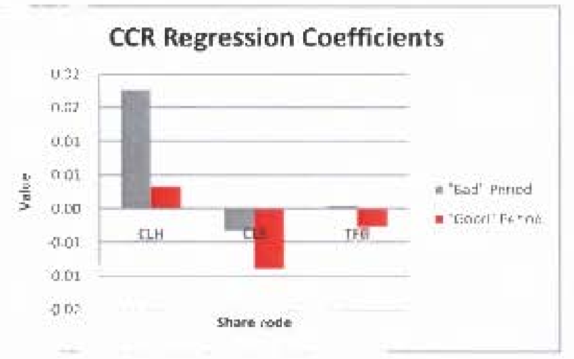


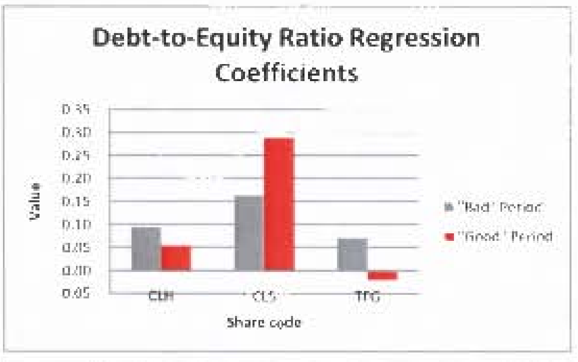


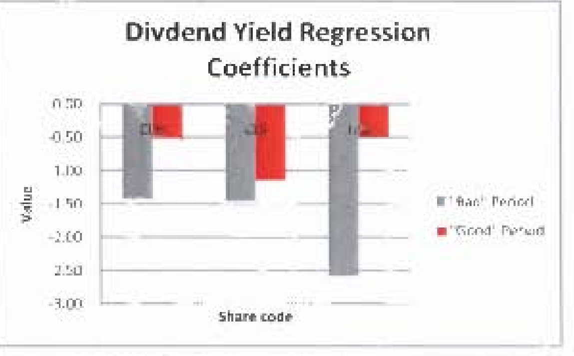


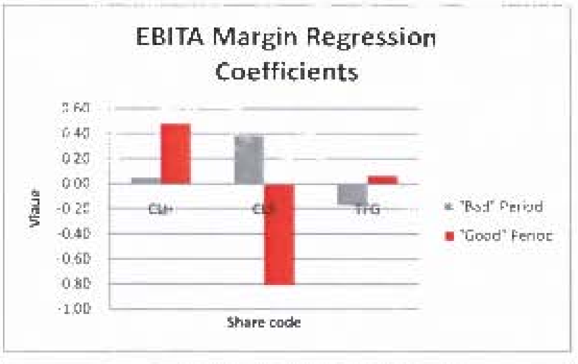
Consumer Services

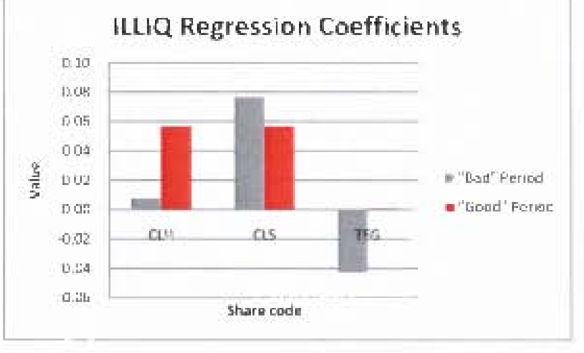


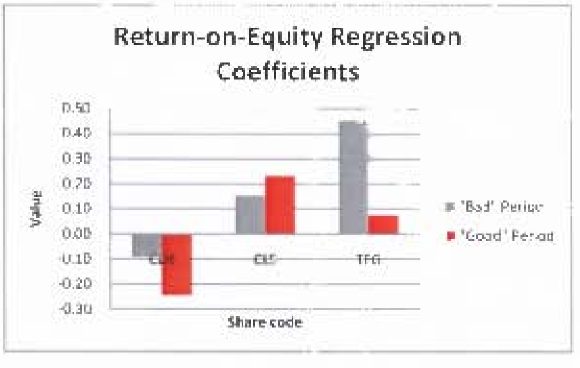




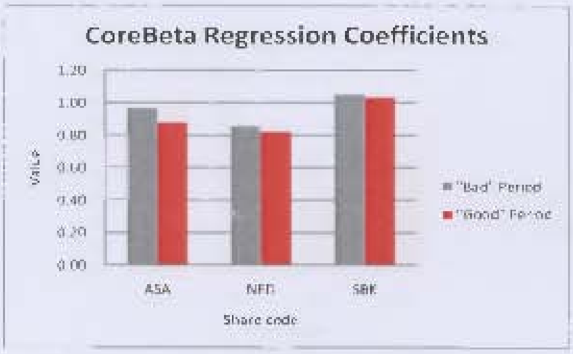








Financials


CoreBeta Regression Coefficients
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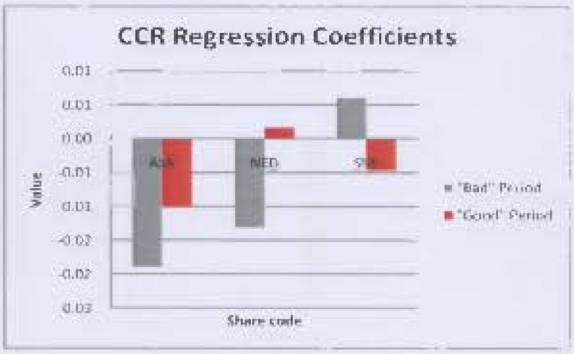
1.00
0.80
0.60
0.40
0.20
0.00
Value
ASA
NED
SBK
Share code
"Bad" Period
"Good" Period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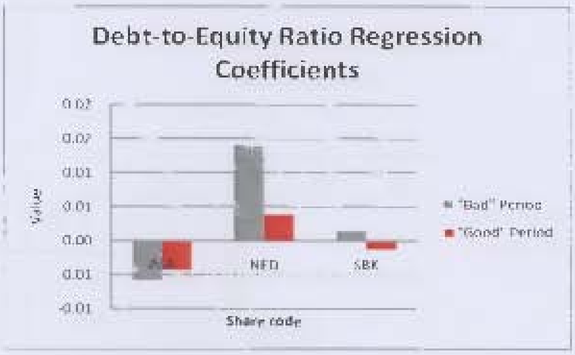
Debt-to-Equity Ratio Regression Coefficients
Value
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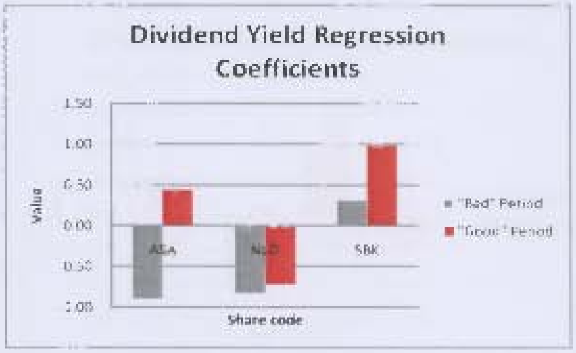
Share code
"Bad" Period
"Good" Period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Value
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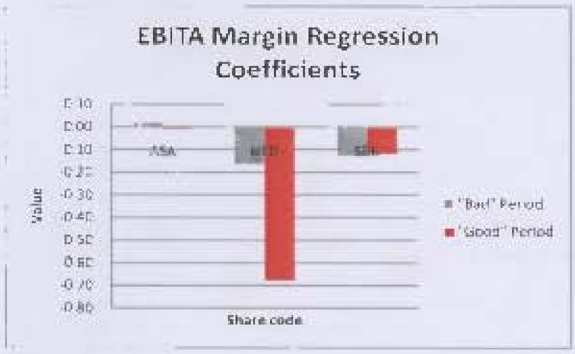
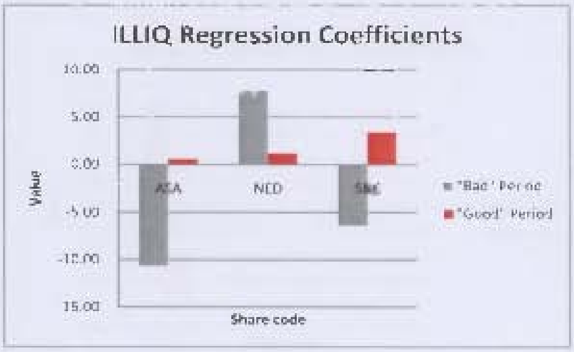
NED
SBK
Share code
"Bad" Period
"Good" Period


EBITA Margin Regression Coefficients
Value
ASA
NED
SBK
Share code
"Bad" Period
"Good" Period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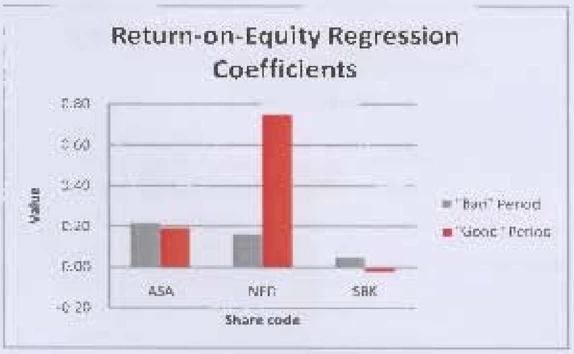
Value
ASA
NED
SBK
Share code
"Bad" Period
"Good" Period


Return-on-Equity Regression Coefficients
Value
ASA
NED
SBK
Share code
"Bad" Period
"Good" Period

Industrials