A comparison of the forecasting accuracy of the Downside Beta and Beta on the JSE Top 40 for the period 2001-2011

Research Report submitted in partial fulfillment of the requirements for the Degree of Master of Commerce

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Date: 26 March 2013

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Declaration

I hereby declare that this research report is my own unaided work. It is submitted in partial fulfillment of the degree of Masters of Commerce by Coursework and Research Report at the University of the Witwatersrand, Johannesburg. It has not been submitted elsewhere for the purpose of being awarded another degree or for examination purposes at any other university. Where other sources of information have been used, they have been acknowledged.

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6 October 2013

Abstract

The purpose of this research report is to determine whether the use of a Downside risk variable – the D-Beta – is more appropriate in the emerging market of South Africa than the regular Beta used in the CAPM model. The prior research upon which this report expands, performed by Estrada (1999; 2002; 2005), focuses on using Downside risk models mainly at an overall country (market) level. This report focuses exclusively on South Africa, but could be applicable to various other emerging markets. The reason for researching this topic is simple: Investors – not just in South Africa, but all across the world – think of risk differently to the way that it is defined in terms of modern portfolio theory. Beta measures risk by giving equal weight to both Upside and Downside volatility, while in reality, investors are a lot more sensitive to Downside fluctuations.

The Downside Beta takes into account only returns which are below a certain benchmark, thereby allowing investors to determine a share's Downside volatility. When the Downside Beta is included as the primary measure of systematic risk in an asset pricing model (such as the D-CAPM), the result is a model which can be used to determine cost of equity, and make forecasts about share returns. The results of this research indicate that using the D-CAPM to forecast returns results in improved accuracy when compared to using the CAPM. However, when comparing goodness of fit, the CAPM and the D-CAPM are not significantly different. Even with this conflicting result, this research shows that there is indeed value in using the D-Beta in South Africa, especially during times of economic downturn.

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Table of Abbreviations

Abbreviation	Meaning
ALSI	All Share Index
CAPM	Capital Asset Pricing Model
CML	Capital Market Line
D-CAPM	Downside Capital Asset Pricing Model
E-S	Expected value-Semivariance
ES-CAPM	Expected value-Semivariance Capital Asset Pricing Model
JSE	Johannesburg Securities Exchange
MAR	Minimum Acceptable Return
MLPM	Mean-Lower Partial Moment
MSB	Mean-Semivariance Behaviour
MVB	Mean-Variance Behaviour

Chapter I: Introduction

There is significant debate about the correct definition of 'risk' in both developed and emerging markets. In developed markets, the Capital Asset Pricing Model (CAPM) is widely used by practitioners, notwithstanding the numerous theoretical and practical difficulties it presents (Estrada, 1999). Roll and Ross (1994) indicate that several decades of empirical studies have reported little evidence of a significant cross-sectional relation between average returns and Betas, even in developed markets, which would be expected to provide the best environments for such studies. In emerging markets, where the assumptions upon which the CAPM are based do not necessarily hold, it is even more important to attempt to find alternative models to measure risk and return (Estrada, 1999).

This is especially important given the continued and widespread use of the CAPM in numerous spheres of finance: It is taught on virtually every finance course at universities and business schools around the world, it is found in all finance textbooks, and it is used regularly in the financial services industry to evaluate different projects and perform discounted cash flow valuations of businesses (Ward and Muller, 2012). This is in spite of the fact that over thirty years of academic debate has not settled the matter of whether beta (and therefore the CAPM) is the most appropriate measure of risk (Estrada, 1999). Collins and Abrahamson (2006) suggest that in order to mitigate some of these shortcomings and increase the robustness of the cost of equity calculations, numerous different methods should be applied – one of which is the Downside Beta.

The definition of risk as used in modern portfolio theory (and hence the CAPM) clashes with most investors' views on risk: investors do not generally associate risk with uncertain positive returns or returns above their expectations. Rather, most investors associate risk with negative outcomes, or returns below their expectations (Estrada, 2006). In emerging markets, it has been suggested that a model which only takes into account Downside risk (the risk of earning a return on investment which is lower than a certain benchmark) would be more appropriate.

Traditional asset pricing models assume, amongst other things, that equity returns are log-normally distributed. That is to say, the distribution can be described fully by two variables: the normalized arithmetic mean and the normalized standard deviation (which represents risk). This technique is appropriate in developed markets, as the assumptions on which the CAPM are based (homogeneous expectations, rationality, efficient markets) are met in these markets. Because South Africa is an emerging market, however, the distribution of returns on the Johannesburg Securities Exchange (JSE) is not normally distributed (Jefferis and Smith, 2004; Mamoghli and Daboussi, 2010). As a result, it may not be appropriate to use traditional techniques when forecasting returns for JSE shares. Furthermore, the CAPM is not an appropriate measure of systematic risk in emerging markets because emerging markets are not completely integrated (Estrada, 1999). Market integration implies that assets with the same risk must have the same expected return regardless of where they trade, a condition which does not necessarily exist in emerging markets (Estrada, 1999). Estrada (2002) finds that in emerging markets, the average Downside Beta is 50% larger than the average Beta, which means that emerging markets exhibit relatively more Downside volatility than total volatility. It may therefore be more appropriate to use models which take into account Downside risk measures when determining the cost of capital for emerging markets.

Purpose and Significance of the study

The purpose of this paper is to consider whether the use of a down-side risk model such as the D-CAPM (Downside Capital Asset Pricing Model) of Estrada (2002) is more appropriate for use in an emerging market such as South Africa than the traditional CAPM. Even though formal definitions of Downside risk are just as old as formal definitions of risk, the use thereof has only recently become more widely accepted by practitioners and academics (Estrada, 2006).

One of the main uses of the CAPM is calculating the cost of equity of a firm (Estrada, 1999). If the D-CAPM is found to be more appropriate, it would indicate that financial managers should be calculating their cost of capital using the D-CAPM return on equity rather than that of the CAPM. Prior research has already shown that the use of the D-CAPM could result in a difference of as much as 6% to the firm's cost of capital (Estrada, 2002). With the average cost of equity in South Africa being 11.67% (Collins and Abrahamson, 2006), this difference is too large to ignore. The importance of using the correct cost of equity is especially evident when the uses of the CAPM are considered: the acceptance or rejection of new projects by financial managers using the CAPM as the hurdle rate could have a significant impact on country-wide growth rates and unemployment rates (Collins and Abrahamson, 2006).

The semideviation, which is the predecessor of the Downside Beta, is also frequently reported on by financial institutions as a means of comparing the Downside risk exhibited by various equity instruments. A 1999 *Forbes* article argued that many funds use semideviation to calculate risk-adjusted returns and include this measure of risk in annual reports; in addition, Morningstar also uses semideviation to create its star ratings, which are used and relied upon by investors globally (Estrada, 2006). It seems imperative therefore that further research is performed on this topic in the South African market.

Research question

Is the Downside Beta model a better approximation of expected returns on the Top 40 equities on the JSE than the traditional CAPM for the period 2001-2011?

In order to answer this question, two quantitative statistical methods will be used, each with their own hypotheses. Therefore, the above research question can be split into two sub-questions.

1. *Is the forecasting error of the D-CAPM smaller than that of the CAPM?*

The method will be to calculate an error term ( ) for each model, which is defined as the difference between the actual return observed and the expected return generated by the model. A matched-pairs t-test will then be used to determine whether the Downside risk measure (the D-CAPM) results in a smaller error term. More precisely, the following hypothesis will be tested:

2. *Does the D-CAPM Beta explain more of the share price movements than the CAPM Beta?*

The second approach will be to compare the strength of the relationship between average return and the two risk variables, Beta and Downside Beta, respectively. The R-squared statistic, which measures the explanatory power of the independent variable, will be used in this test. A Wilcoxon signed-rank test will then be used to determine whether the Downside risk measure (D-CAPM) results in a larger R-squared term. Therefore, the following hypothesis will be tested:

Where represents the R-squared statistic obtained from Ordinary Least Squares regression using the CAPM Beta as the independent variable, and represents the R-squared statistic using the D-CAPM Beta as the independent variable.

In the next chapter – the Literature Review – the history of Downside Risk measures is introduced and explored by examining the contributions made by each of the leading thinkers in the field. The path from traditional risk measures to Downside Risk measures shall now be examined – from standard deviation to the semideviation, to eventually the Downside Beta proposed by Estrada.

Chapter II: Literature review

The Mean-Lower Partial Moment

Downside risk measures have been used and developed since the early 1950's, when Markowitz published his ground-breaking paper on Portfolio Theory (Markowitz, 1952). In the period from 1952 until 1975, various different Downside risk models were produced, some of which will be explored in more detail in this report. However, it was not until Bawa and Lindenberg (1977) developed their theory on the Mean-Lower Partial Moment (MLPM) that all the preceding Downside risk models were able to be generalized within one model. Indeed, the MLPM is defined as a generalized formulation of the previous Downside risk models.

In its first iteration, the MLPM allowed the user to specify an attitude towards risk: i.e. risk-neutral, risk-loving or risk-averse (Nawrocki, 1999). The model also allowed for increased flexibility within these three broad groups, as the variable which represents risk appetite did not have to be a whole number. The MLPM also supported the use of several different Von Neumann-Morgenstern utility functions. Harlow and Rao (1989) then expanded the MLPM – where the target rate of return was fixed as the risk-free rate – by allowing the user to specify the target 'benchmark' rate of return in addition to specifying risk appetite. By specifying certain values for the input variables, this Mean-Lower Partial Moment (MLPM) model can be shown to be identical to the CAPM as well as other Downside risk models which focus exclusively on the semivariance. Empirical testing has shown that the MLPM cannot be rejected as a reliable pricing model, while the CAPM can be rejected (Harlow and Rao, 1989).

The Development of the Semivariance

The CAPM developed by Sharpe (1964), Lintner (1965) and Mossin (1966) has been in use for the last 40 years, with a broad range of uses, from corporate finance applications to investor utility theory. While the purpose of this paper is not to explore the theoretical soundness (or lack thereof) of the CAPM, some background information is required in order to identify what distinguishes the CAPM from the D-CAPM. The CAPM is built around the assumption that investors subscribe to the idea of Mean-Variance Behaviour (MVB).

Mean-Variance Behaviour (also referred to as the expected value-volatility (E-V) model) was first proposed by Markowitz in his paper on Portfolio Selection (Markowitz, 1952). Under the Mean-Variance Behaviour model, investors seek to maximize a utility function – which is simply a way of measuring an investor's sensitivity to changing wealth and risk (Nawrocki, 1999)– which depends on the mean and the variance of their portfolio. This theory provided the groundwork for modern portfolio theory, and led to the formulation of the efficient portfolio set – different combinations of securities which allow the investor to maximize return for a given level of risk, or minimize risk for a given level of return (Markowitz, 1952). This is the cornerstone of modern portfolio theory, and it remains valid to this day.

As with all groundbreaking discoveries, however, there is a constant need for revision and refinement. Even in the early 1950s, Markowitz identified that the standard model of Mean-Variance Behaviour might not be the most appropriate model to use in all situations – especially if the distribution of the share returns is non-normal. He noted that in situations where the distribution of share returns is significantly skewed, a Downside risk model may be more appropriate. He had already been considering the use of a Downside risk measure which could be used to represent the volatility of a security: the semivariance would capture all of the Downside risk that an investor is exposed to, without being tainted by the upside volatility. It is called a *semi*variance because it considers only a portion of the underlying return distribution – the negative returns (or returns below a certain pre-defined benchmark). In the same way that the standard deviation is calculated as the square root of the variance, the semideviation is the square root of the semivariance, i.e.:

Markowitz showed that "the semideviation produces efficient portfolios somewhat preferable to those of the standard deviation" (Markowitz, 1952 cited in Estrada, 1999, p.5). This suggests that the semivariance is in fact a more useful measure of risk than the variance. The question then becomes: if Markowitz had decided that the semivariance was a more appropriate risk measure than the variance, then why did he continue using and promoting the latter? There are a couple of reasons why Markowitz did not continue using the semivariance as his risk measure.

Firstly, calculating efficient portfolios based on a semivariance was significantly more expensive than using variance, due to the complexity of the calculations which were necessary, and the lack of available computing power at the time. The cosemivariance optimization models needed twice the number of data inputs (Nawrocki, 1999), which significantly increased the cost of the calculations, both financially and in terms of the time required to process the data.

Secondly, semivariance as a measure of risk was relatively unknown in 1952 – the date of Markowitz' paper (Estrada, 1999). With the amount of research done on Downside risk and the level of technological progress achieved in the last 50 years, neither of these two reasons is valid today.

At the same time as Markowitz' research, Roy was also investigating Downside risk measures (Nawrocki, 1999). Roy's 'safety first technique' states that investors will set some minimum acceptable return at which his capital will be preserved. This minimum return level is called the disaster level return, *d*.

According to the theory, investors will choose the portfolio which has the lowest probability of going below the disaster level, given a certain mean return (*r*) and standard deviation (*s*).

More precisely: ——

In general terms, this represents a reward to variability ratio, the most well-known of which is the Sharpe ratio. Roy's concept of an investor preferring safety of principal first when dealing with risk was instrumental in the development of Downside risk measures – the reward to variability ratio allows the investor to minimize the probability of his portfolio falling below the disaster level (Nawrocki, 1999). Markowitz recognized the importance of this idea, suggesting that investors would be interested in minimizing Downside risk for two reasons: Firstly, only Downside risk or 'safety first' is relevant to an investor and secondly, security distributions may not be normally distributed (Nawrocki, 1999). Markowitz showed that when security distributions are normally distributed, both the semivariance and the variance produce the correct result – this is intuitive since a normal distribution implies that negative returns are equally as likely as positive returns, therefore the solution provided by the semivariance based on the *negative* returns is equally as applicable to the *positive* returns. However, if security distributions are not normally distributed, only the semivariance provides the correct answer (Nawrocki, 1999). The implication here is that if returns in South Africa are negatively skewed, then using the semivariance in a Downside risk model should provide more accurate forecasts in the South African market.

Markowitz suggested two different versions of the semivariance: one computed using the mean of the returns as the benchmark ("below-mean semivariance"), and one computed using a target rate of return ("below-target semivariance") (Nawrocki, 1999). Each of these variations has proponents: Harlow and Rao (1989) tested the significance of these two measures, and concluded that the most appropriate benchmark to use in computing the semivariance is the mean of the returns. They found that market participants appear to characterize risk as Downside deviations below a target that is related to equity market mean returns rather than to the risk-free rate. On the other hand, Klemkosky (1973) and Ang and Chua (1979) both found that the below-target semivariance is superior. Hogan and Warren (1974) compute the semivariance using a risk-free rate as the benchmark return in the model. Estrada (2006) concurs: in order to promote comparability between different stocks, a common reference point should be used. Whichever return is used as the benchmark, this way of thinking about Downside risk can provide investors with more information than a traditional model such as the CAPM.

The semideviation of an asset is best used in two contexts: one is in relation to the standard deviation of the *same asset* and the other is in relation to the semideviation of *other assets*. Comparing the semideviation to the standard deviation of an asset provides insight into how much of the total volatility is occurring below the specified benchmark. When comparing different assets, the semideviations will indicate which of the assets exhibits greater Downside volatility. It is of course always necessary to consider risk in the context of expected return, therefore no analysis of the Downside risk of an asset is complete without also considering some sort of reward to variability ratio, such as the Treynor Index.

One such ratio was developed by Mamoghli and Daboussi (2010): they proposed an index called the Adjusted Treynor Index, which is based on the same reward to variability concept as the original Treynor index, but which uses the Downside Beta of Estrada (2002) as its risk measure. It is described as follows:

Where is the return of the portfolio, MAR is the minimum acceptable return (this could be the mean return of the portfolio, or the risk-free rate, for example) and is the Estrada Downside Beta of the portfolio with respect to the same MAR used in the numerator. In this ratio, the excess return over and above the minimum acceptable return is divided by the Downside risk in order to provide a meaningful way to compare the relative reward-to-Downside risk of various portfolios.

Mamoghli and Daboussi (2010) also used the Downside Beta of Estrada (2002) in another performance measure – the calculation of alpha. By substituting the traditional Beta for the Downside Beta, this measure calculates the excess return of a share (or portfolio of shares) over and above its required rate of return as calculated by the D-CAPM.

Downside risk measures have also historically been used to calculate skewness statistics. Skewness is a measure of the symmetry of the distribution (Nawrocki, 1999). If one divides the variance of a distribution by its semivariance, the resultant figure is a measure of skewness. For symmetrical distributions, the result should be equal to two, since the semivariance would be exactly half the variance. If the result is not two, then it means that the distribution is asymmetric: gains and losses do not occur with equal probabilities. A positively skewed distribution implies that when losses occur, they will be of a smaller magnitude, while gains will be larger when they occur. A negatively skewed distribution obviously implies the opposite. Rational investors would therefore require a premium for investing in securities whose distributions are negatively skewed. Co-skewness has also been investigated as a measure of Downside risk; however the scope of this research paper is not broad enough to explore this idea in any further detail.

The Cosemivariance

Hogan and Warren (1974) extended the body of research on Downside risk techniques by developing a new model called the expected value-semivariance model, or E-S model (also referred to as the Mean Semivariance Behaviour 'MSB' model). Using a semivariance statistic very similar to that proposed by Markowitz, they developed their ES-CAPM model, which substitutes Beta with their version of a Downside Beta based on the semivariance. They argue that rational investors would choose portfolios which minimize the semivariance for a given expected return, or maximize the expected return for a given semivariance. By definition, the minimization of the semivariance is analogous to the minimization of expected losses. This is in contrast to the variance which, when minimized, does not differentiate between extreme gains and extreme losses. The result of minimizing the variance is paradoxical: extreme gains (which investors want) would *increase* the variance, which may *dissuade* risk-averse investors from investing in the asset. This is sub-optimal, since no rational investor would choose to limit his upside volatility. The ES-CAPM model therefore allows the investor to structure his portfolio in such a way that only Downside risk is minimized.

In order for the E-S model to be used as an alternative to the E-V model, it must be at least as useful for establishing a framework of risk and return. Hogan and Warren (1974) show that this is the case by proving that the Capital Market Line (CML) can also be derived using the E-S model. The CML is the graphical depiction of the linear relationship between risk and return. That is, an investor would expect a higher return in exchange for taking on more risk. In this case, the measure of risk is the semideviation, not the standard deviation. When combining the CML with an investor's utility functions, the efficient frontier can be developed. The efficient frontier is the myriad of portfolios which would maximize the utility of the investor.

The E-S model also needed to be useful when determining the marginal risk and return that a new stock would add to a portfolio. Under the Mean-Variance Behaviour model, the correct measure of risk to consider when introducing an individual asset into a portfolio is that asset's *covariance* with the other assets in the portfolio (Markowitz 1952). The covariance is simply a measure of how two assets move with each other (Hogan and Warren, 1974). Analogously, under the E-S model the appropriate measure of risk is the *cosemivariance*. The expected return on a security is therefore a function of its cosemivariance with the given portfolio. The cosemivariance is defined by Hogan and Warren (1974) as follows:

Where E( ) is the required return on asset i, is the risk-free rate, E( ) is the required return on the market, and Min is the minimum operator, which chooses the lower of the two numbers.

As already stated, Hogan and Warren (1974) chose the risk-free rate as the default benchmark return. In situations where purchasing power is important, for example pension funds which are investing on behalf of retirees, using the risk-free rate as the benchmark rate of return makes intuitive sense. This is because the biggest risk is that the investments do not at least provide compensation for the loss of purchasing power due to inflation.

The most significant issue with the definition of the cosemivariance presented by Hogan and Warren (1974) is that it is asymmetrical. That is, the cosemivariance of asset i with asset j is different to that of asset j with asset i, i.e.: . As a result, it is far from clear how the contribution of each of these 2 assets to cosemivariance risk should be interpreted.

Estrada (2002) expanded upon this work and developed a Downside risk model which does not suffer from this weakness. This model is called the D-CAPM, which shall now be examined.

The Downside Beta model

Estrada (1999) was concerned with the inappropriateness of using the CAPM to estimate cost of equity, specifically in emerging markets where the underlying security distributions cannot be assumed to be normal. Without a widely-accepted definition of risk in emerging markets, investors and companies do not have a reliable way to calculate appropriate discount rates and required returns (Estrada, 1999). Several attempts have been made at modifying the CAPM for use in emerging markets, such as the research performed by Godfrey and Espinosa (1996), who adjusted both the risk-free rate and the Beta; Erb, Harvey, and Viskanta (1995, 1996a), who related stock returns to the country's credit rating; and Bekaert and Harvey (1995), who incorporated a time-varying measure of market integration (Estrada, 1999). Estrada's goal was to develop a more appropriate model for use in emerging markets which took into account the critically important Downside risk which is inherent in these markets (Estrada, 2002), while still maintaining the simplicity of the traditional CAPM.

Estrada (1999) used data collected from the Morgan Stanley Capital Indices (MSCI) of emerging markets, which covers 28 countries (including South Africa) over different time periods. The data showed that emerging markets exhibit high volatility and a low correlation to the world market – results which confirm findings of other studies (Estrada, 1999). This low correlation to the world markets implies that there is substantial diversification potential in emerging markets: more developed economies are able to reduce their overall investment risk by investing in these markets. In addition, the low correlation to the world market confirms that emerging markets are not completely integrated, thus strengthening the arguments against using the CAPM in these markets. Furthermore, the data confirmed the existence of significant departures from symmetry in most distributions of returns, further justifying the use of a Downside risk model in emerging markets.

In order to develop the model, Estrada (1999) identified and calculated several different risk variables for each of the 28 emerging markets: The first is systematic risk (this is the risk which is not able to be mitigated through diversification), measured by Beta; the second is total risk, measured by the standard deviation of returns; the third is idiosyncratic risk, measured by the variability of returns not explained by Beta; the fourth is size, measured by market capitalization; and the fifth is Downside risk as measured by five different variables. Three of these Downside risk variables are based on the semideviation, each with a different benchmark: the mean, the risk-free rate and zero. The last two Downside risk variables are the Downside Beta and the Value at Risk (VAR). Estrada (1999) justified the inclusion of each of these variables. Systematic risk for being the most widely-used measure of risk, total risk for being the appropriate measure of risk in segmented markets, idiosyncratic risk in order to assess the impact of diversifiable risk on returns, size in order to test for the well-known size effect, and Downside risk for the numerous reasons discussed above (Estrada, 1999).

Estrada (1999) then ran regression analysis to determine which of the nine risk variables were significantly related to stock returns. The results indicated that only total risk, systematic risk and three of the Downside risk variables were significant: the semideviation with respect to the mean, the Downside Beta and VAR. Of these three Downside risk variables, Estrada (1999) then chose to use only the semideviation with respect to the mean in the continued analysis, not only because it was the most significant of the three, but also due to Markowitz' preference for the mean. These three variables were then used to forecast costs of equity for each of the 28 countries.

In all but one of the markets, the cost of equity based on Downside risk fell in between those based on systematic risk and those based on total risk. This is intuitively pleasing, since in fully integrated markets the correct risk measure is Beta (systematic), and in fully segmented markets the correct measure is the standard deviation (total). Due to the fact that most emerging markets are only partially integrated, it makes intuitive sense that the cost of equity should lie somewhere between the forecasts based on systematic risk and total risk.

Based on the success of his prior work, and having recognizing the need for a new asset pricing model, Estrada (2002) expanded on his previous work in the Downside risk environment by developing a new model similar to that of Hogan and Warren (1974). Four risk variables were identified as potential determinants of return. Two of these variables, the standard deviation and Beta, are derived from the Mean-Variance Behaviour framework. The other two are derived from the Mean Semivariance Behaviour framework, namely the semideviation and the Downside Beta. Having performed simple regression on each of these variables, he found that the two Downside risk measures were the best performers, with the Downside Beta having the highest R-squared statistic (0.55). When all four variables were jointly considered in a multiple regression, he found that only the Downside Beta was significant in explaining the mean returns. Estrada (2002) concluded that returns in emerging markets are much more sensitive to the Downside Beta than to ‘normal’ Beta, and therefore the D-CAPM is a more appropriate model to use in emerging markets.

The author cites three reasons why the Downside Beta is a better measure of risk than the Beta. First, there is an asymmetry in investors’ attitude towards volatility. Naturally, investors do not dislike upside volatility, they only dislike Downside volatility. Second, the semivariance is more appropriate than the variance in a situation of asymmetric distributions of returns, as is the case in South Africa (Mamoghli and Daboussi, 2010). Moreover, it is equally appropriate as the variance when the distribution is symmetric – this is because the semivariance looks at one half of the distribution, and if the two halves are symmetric, then the second half is the same as the first half. Third, the semivariance is useful because it combines two relevant statistics – variance and skewness – into one variable. This facilitates the use of a one-factor model, a desirable characteristic when compared to the complexity of multi-factor models.

The version of the cosemivariance as developed by Estrada (2002) is as follows:

Where µ represents the arithmetic mean of the distribution, E( ) is the required return on asset i, E( ) is the required return on the market, and Min is the minimum operator, which chooses the lower of the two numbers.

This formulation of the cosemivariance does not suffer from the same drawback of asymmetry as the previous models. This is because in Estrada's formulation, the Minimum operator applies to both the excess returns of the individual share as well as the market portfolio. When the cosemivariance is divided by the semivariance of returns of the market portfolio, the result is the Downside Beta:

This Downside Beta represents the systematic Downside risk of an asset in Estrada's D-CAPM formulation:

$$E(\quad) = R_F + \quad (E(R_M) - R_F)$$

Estrada (2002) attempts to justify the plausibility of his finding that the Downside Beta explains more of the cross section of returns than the Beta: First, investors do not dislike volatility *per se*, they only dislike

Downside volatility. Second, aversion to the Downside is consistent with models put forward by proponents of behavioural finance, such as the S-shaped utility function developed by Kahneman and Tversky (1979). In this model, the slope of the utility curve is steeper on the Downside than on the upside, implying that losses of a given magnitude loom larger than gains of the same magnitude (Estrada, 2002). Finally, the superiority of the Downside Beta may be related to the contagion effect in financial markets, which suggests that markets are more integrated on the Downside than on the upside – an idea which is supported by most data (Estrada, 2002). For example, the failure of a major bank may result in a 'domino effect' such that other banks are also put under strain.

In the next section of this research report, the research methodology will be introduced and explained.

Chapter III: Methodology

Is the Downside Beta model a better approximation of expected returns on the Top 40 equities on the JSE than the traditional CAPM for the period 2001-2011?

Data

The chosen methodology was data driven. In order to answer the research question, a quantitative statistical approach was taken. The data was collected using McGregor BFA, DataStream, and ShareMagic Pro. These facilities were easily accessible via the Commerce Library at the University of the Witwatersrand. As this is a local study, only South African company data was used. More specifically, only companies which are publically traded on the JSE were used.

The selected companies were the largest 40 companies on the JSE, ranked by market capitalization as per 31 January 2011. Once the companies were chosen, no changes were made. Based on an examination of the composition of the Top 40 over the period to be examined, no significant movements were identified. The choice of only 40 companies is appropriate, as they form more than 87% of the total market capitalization of the JSE (see Appendix I). It is submitted that other companies which are smaller, may not be sufficiently liquid to provide any meaningful contributions towards the study.

The time period for the data collection is 2001 – 2011. The reason for this time period is simple: for this study to be as relevant as possible, the time period must be as recent as possible. The choice of ten years' worth of data is simply for ease of data collection. Some of the companies were not listed on the JSE as far back as 2001; therefore the largest 40 companies for which a complete data set was available were used in the study. Between late 2007 and 2010, South Africa experienced a bear market due to the global financial crisis (Te Velde, 2008). The results of the analysis were interpreted taking this into account. It may be the case that the Downside Beta model is actually a better model to use in times of economic recession, due to the fact that it only takes into account Downside risk (Estrada, 2002).

Data was also collected for the market portfolio. The market portfolio is, by definition, the weighted sum of *all* assets available in the market, in the same proportion as they exist in the market (Strong, 1992). It is therefore not possible to calculate the return on the true market portfolio. As a substitute, the JSE's All Share Index was used as a proxy for the market portfolio. This is preferable to using the Top 40 index as the market proxy, as the All Share Index represents a much larger proportion of the total market than the Top 40 Index. This is consistent with similar research which has been performed in South Africa: see (Van Rensburg and Robertson, 2003) and Ward and Muller (2012). This index tracks the performance of the largest 160 companies on the JSE, which together account for 99% of the total market capitalization (Ward and Muller, 2012).

Biases in the data

As a result of choosing the 40 largest companies by market capitalization, it is obvious that there will be a size bias in the data. This means that the results of the study may not be generalizable to smaller companies. In addition, an industry bias may exist as a result of the composition of the companies within the top 40 group. Specifically, the financial services and resource industries make up a large proportion of these companies (Ward and Muller, 2012); therefore the results may only be appropriately generalized within these industries.

Limitations

Due to the difficulty surrounding data availability, the possible introduction of a survivorship bias may be unavoidable. This is not seen to be a significant issue in this study however, as the purpose of this study is not to identify any causal relationship between the CAPM or D-CAPM and company longevity.

Data Analysis

Usually studies of this type adopt the approach developed by Fama and MacBeth (1973), where the companies are assigned to various portfolios. Risk estimation is thought to be more precise within a portfolio than when examining an individual security (Fama and French, 2004). However, this technique requires a substantial amount of data over a long time-frame in order to be effective (Galagedera and Brooks, 2007). This is difficult to accomplish in an emerging market such as South Africa due to a lack of available data. Furthermore, grouping the individual companies into portfolios would reduce the degrees of freedom, which would hamper the ability of the analyses to identify significant differences between the models (Comiskey et al., 1986). Lastly, since only the Top 40 companies have been examined, the benefits of portfolio analysis would be minimal, as the necessary level of diversification would not be achieved. Obviously then, portfolio re-balancing is not an issue, as the stocks have not been allocated to portfolios. Re-balancing of the Top 40 stocks would have been required if the All Share Top 40 Index had been used as the proxy for the market portfolio, however due to the complete All

Share Index being used (comprising the top 160 stocks), this is not an issue, as all 40 stocks are included in the top 160 at all times. Instead, this study used a similar technique to that used by Galagedera and Brooks (2007) and Estrada (2002). The testing of the hypotheses was based on the results of all 40 companies in the study. By doing so, an acceptable level of diversification was achieved. This technique is mathematically sound, as portfolio return and portfolio Beta are both simply weighted averages of the individual securities.

The individual share returns were calculated monthly as the difference between two consecutive log prices. This is consistent with prior studies performed on the Downside risk framework by Galagedera and Brooks (2007) and Estrada (2002). This does not represent the total return to shareholder however, as there may have been dividends which were declared during the period in question. The pricing models which were used in this study to make forecasts do not differentiate between the dividend portion of the return and the capital appreciation portion; therefore to compare like with like, it was necessary to adjust the total return to include the effect of the dividend.

The monthly data from 2001 – 2006 was used to calculate two different proxies for systematic risk for each individual company: the traditional Beta as used in the CAPM, and the Downside Beta, as proposed by Estrada (2002) and used in the D-CAPM. The choice of using the most recent 60 months of share data to determine these risk variable is in line with a similar South African study performed recently (Ward and Muller, 2012). The fear is that using price data which is older than 60 months may taint the results. The Beta ( ) and the Downside Beta ( ) can be calculated using two approaches, which should provide the same result. The first technique is to use simple linear regression in Excel, specifically the 'Linest' function, with the intercept term set equal to zero[1]. This is the method used by Estrada (2006), and the method adopted in this study. This is accomplished by regressing the individual company data on the

[1] There is a technical mathematical reason for setting the intercept equal to zero, as described in Estrada (2002).

market return for the period 2001 – 2006. The coefficient of the independent variable (the market return) represents the risk variable in question. To calculate , each monthly return will be included in the analysis. To calculate , only monthly returns lower than the benchmark are included in the analysis. Each monthly return higher than the benchmark will be replaced by zero, thus ensuring that only Downside movements are being captured in the risk variable.The second approach to calculating these risk variables is to use the following equations, as developed and presented in Estrada (2002):

Where "R" represents the actual observed return, " " represents the mean return, "Min" represents the Minimum function, "i" indexes the individual companies, and "M" indexes the market.

One advantage of the first approach to calculating the risk variables is that a scatter-diagram can be used to identify any outliers, which could potentially distort the results of the survey. These outliers could then be removed from the sample data. To add robustness to the results, and to determine which statistical techniques are appropriate, the data will be tested for normality using the Jarque-Bera test, which is a joint test of the skewness and kurtosis of the distribution.

Testing the hypotheses

First test:

The two risk variables, and , were then used in each of the two models (CAPM and D-CAPM) to forecast expected returns for each individual share for the period 2006 – 2011. The following equations were used:

CAPM: E( ) = R_F + (E(R_M) – R_F)

D-CAPM: E( ) = R_F + (E(R_M) – R_F)

Where:

- E(R) represents expected return using the CAPM model
- E(R_D) represents expected return using the D-CAPM model
- R_F is the risk-free rate applicable in South Africa (see below).
- and are defined as above
- E(R_M) represents the return on the All Share index, which is the proxy for the market return

The risk-free rate used was the yield from South African government bonds with 10 years to maturity. The choice of the risk-free rate was largely based on the time horizon of the study, and is supported by other research, where the 10 year US Treasury Bond rate is used in an emerging market study with a time horizon of 10 years (Galagedera and Brooks, 2007).

The expected returns as generated by the CAPM and D-CAPM were then compared to the actual returns as observed over the same 5 year period. The difference between the expected return and the actual return ” ” was then calculated for both the CAPM and the D-CAPM. More precisely:

Where represents the actual return observed for company *i*. The smaller the error, the better the model is at predicting returns.

40 pairs of errors (and for each company) were then calculated. In order to perform statistical analysis on this data, it was necessary to test the assumptions which must be met in order for a matched-pairs t-test to be performed. The assumptions for a matched pairs t-test are as follows (Cochran, 1947):

- Each of the two populations being compared should follow a normal distribution
- The two populations being compared should have the same variance

As these assumptions were both met (refer to Chapter IV: Results), it was determined that the matched-pairs t-test was appropriate. The purpose of the test was to indicate whether the population of errors was significantly different between the models.

The hypotheses which were tested are as follows:

Second test:

As a second means of testing the research question, the explanatory power of each of the risk variables was tested using regression: The calculation involved regressing the average actual individual company return for all 40 companies over the period 2006 – 2011 on each of the risk variables individually, using simple Ordinary Least Squares linear regression.

The formulae for the regressions are as follows:

Where is the mean return of all the companies over the 5 year period, and are the intercept and sensitivity of the return to the risk variable respectively, and are calculated as above, and is an error term. The output of this analysis will be an and an for each of the 5 years which were examined: 2006, 2007, 2008, 2009 and 2010.

These 5 pairs of data were then statistically tested using a Wilcoxon Signed-Rank Test in order to determine whether they are significantly different. The sample size was too small to use parametric tests. The higher the R-squared, the better the explanatory power of the independent variable. The hypotheses which were tested are as follows:

Where represents the coefficient of determination.

Validity

Internal validity

Internal validity is the extent to which the design of the report allows the researcher to draw meaningful causal relationships from the data (Leedy and Ormrod, 2010). In designing a research report, one of the objectives should be to minimize the possibility that the data can be explained by some other relationship between the variables. The higher the degree of control achieved in the study, the higher the internal consistency will be. (Ryan et al., 2002) Internal validity should not be an issue. The methodology is sound, and the statistical techniques to be used are appropriate for their intended uses. The assumptions underlying the statistical tests used were all tested before the test was used.

The data were collected from reputable sources which guarantee its reliability, and several robustness checks were performed to ensure the validity of the results. These include tests for normality and equal variance.

External validity

External validity is the extent to which the results obtained in a study can be generalized (Leedy and Ormrod, 2010). This study uses solely South African data. Furthermore, the data relates to the 40 largest, multinational companies which are listed on the JSE. It may not be possible, therefore, to generalize the results across the South African equity market as a whole, due to size and industry biases in the data.

Assumptions

The following assumption has been made in this study:

Both the CAPM and the D-CAPM were developed based on an assumption that all investors are rational utility maximizers. In order to use these models in this study, the same assumption must be made.

Chapter IV: Results

General Observations

Table 1 (see Appendix II) lists all 40 shares which formed the sample for this study. For each share, four different proxies for systematic risk were calculated: the Beta, which represents total systematic risk, and three Downside Betas, each calculated with respect to a different benchmark. The second column – D-Beta with respect to the mean – was calculated using the arithmetic mean of the share over the period 2001-2006 as the benchmark return. The Downside Betas in columns three and four have as their benchmarks the risk-free rate and zero respectively. The average result is presented in the last row of the table.

At first glance, it is evident that on average, all three of the Downside Betas are larger than Beta. This indicates that the Top 40 shares exhibit relatively more Downside risk than total systematic risk. This should not be surprising, as Estrada (2002) showed the same results in his analysis of emerging markets. As South Africa is an emerging market, it stands to reason that the Top 40 South African shares should exhibit similar characteristics. When examining the three Downside measures, the Downside Beta with respect to the mean comes out as the largest, on average. There is also a direct relationship between the magnitude of the benchmark and the result: a benchmark return of zero yields the lowest of the Downside measures, with an average of 0.8. This result should be interpreted as follows: When the market falls by 1%, the average share will fall by 0.8%, thus mitigating some of the decrease in value.

As the benchmark return increases, the average Downside Beta increases: using a risk-free rate of just over 7% slightly increases the average to 0.82. When the mean is used as the benchmark, the average Downside Beta increases to 0.9, which should be expected due to the average mean returns for all the shares (24%) being significantly greater than zero, or even the risk-free rate. This is intuitive, since the higher the benchmark, the higher the proportion of returns which will be lower than this benchmark, and therefore the higher the degree of Downside risk. It is worth noting that the difference between using zero and the risk free rate as the benchmark is almost insignificant, however using the mean as the benchmark provides a substantially different result. Again, this is mostly due to the mean return being significantly higher than zero and the risk-free rate. The remainder of the analysis will use the Downside Beta with respect to the mean as the relevant measure of Downside risk.

It is also interesting to view the results by sector: the top 40 shares on the JSE generally fall into three different sectors: the Financial sector, represented by companies like Old Mutual and ABSA; the Resource/Mineral sector, represented by companies like Anglo American and BHP Billiton, and Other sectors, which encompass the rest of the companies. Table 2 below illustrates the average Betas and Downside Betas for the respective sectors on the JSE:

Table 2: Comparison of Beta to Downside Betas by Sector

	Beta	**D-Beta with respect to:**			**Sector**
		Mean	R_F	**Zero**	
Financial Sector	**0.62**	**0.82**	**0.80**	**0.79**	**Financial**
Other Sectors	**0.55**	**0.75**	**0.65**	**0.63**	**Other**
Resource/Mineral Sector	**1.14**	**1.20**	**1.08**	**1.08**	**Resource**

If one stratifies the top 40 companies across the different sectors, another interesting result becomes apparent. For both “Financial” and “Other” shares, all three of the Downside Beta measures are higher than Beta. However for Resource shares, only the Downside Beta with respect to the mean is greater than Beta - the Downside Betas with respect to the risk free rate and zero are both slightly lower than Beta. At this point it is worth noting that the average Beta for the Resource sector (1.14) is much higher than that of the Financial (0.62) and Other (0.55) sectors. This illustrates that Resource shares are much more volatile on the whole than other shares. Importantly, this high volatility is across the entire spectrum of returns – it is not limited to only Downside returns. The fact that Resource shares have a much larger Beta than other shares also makes sense in the South African market, as the All Share Index (which is used as the proxy for the market in this study) is heavily weighted towards Resource stocks. Therefore the ALSI would be expected to move in accordance with its biggest contributors – being the Resource stocks. If one recalls that Beta is simply a measure of covariance (or cosemivariance in the case of Downside Beta) between a share and the market, this result makes intuitive sense.

The remainder of the analysis will focus on testing the hypotheses in order to answer the research question: ***Is the Downside Beta model a better approximation of expected returns on the Top 40 equities on the JSE than the traditional CAPM for the period 2001-2011?***

First test

Recall the sub-question associated with the first section of the testing: *Is the forecasting error of the D-CAPM smaller than that of the CAPM?*

Having calculated the two risk variables, and for each of the 40 shares, these risk variables were then used in each of the two models (CAPM and D-CAPM) to forecast expected returns for each individual share for the period 2006 – 2011. The following equations were used:

CAPM: E( ) = R_F + (E(R_M) – R_F)

D-CAPM: E( ) = R_F + (E(R_M) – R_F)

The risk-free rate used was the yield from South African government bonds with 10 years to maturity, yielding 7.3% per annum (BusinessReport, 2013; Ward and Muller, 2012). The expected returns as generated by the CAPM and D-CAPM were then compared to the actual returns as observed over the period 2006 - 2011. The difference between the expected return and the actual return " " was then calculated for both the CAPM and the D-CAPM. More precisely:

Where represents the actual return observed for company *i* and represents the expected return for company *i*.

40 pairs of errors (and for each company) were then calculated. The results of these calculations can be found in Appendix III. A matched-pairs t-test was then performed in order to determine whether the errors were significantly different between the models. The smaller the error, the better the model is at predicting returns.

The use of the t-test was based upon the results of test of normality which was performed on the pairs of errors. Normality was tested using two techniques, first graphically by plotting the frequency of the errors using a histogram and fitting a 2-period moving average trend-line, and secondly using the Jarque-Bera test for normality, which is a joint test of the skewness and kurtosis of the distribution. If the data do come from a normal distribution, the expected skewness and excess kurtosis are both zero, which implies that if they are non-zero, then the data are not normally distributed. The test statistic, JB, is calculated as follows:

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right)$$

where *n* is the number of observations; *S* is the sample skewness, and *K* is the sample kurtosis.

$$S = \frac{\hat{\mu}_3}{\hat{\sigma}^3} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^3}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2\right)^{3/2}}$$
$$K = \frac{\hat{\mu}_4}{\hat{\sigma}^4} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2\right)^{2}},$$

where $\hat{\mu}_3$ and $\hat{\mu}_4$ are the estimates of third and fourth central moments, respectively, $\bar{x}$ is the sample mean, and $\hat{\sigma}^2$ is the estimate of the second central moment, the variance.

The JB test statistic follows a chi-squared distribution with 2 degrees of freedom, therefore a p-value can be obtained. The null hypothesis states that the data are normally distributed. The alternate hypothesis states that the data are not normally distributed.

Both techniques resulted in the same conclusion – that the 40 pairs of errors followed a normal distribution.

Table 3: Jarque-Bera test for normality (Significance level = 5%)

	BETA	DOWNSIDE BETA
Error test for normality		
Average error	2.5332%	1.4636%
S numerator	0.001076223	0.00101336
S denominator	0.004415223	0.004222457
K numerator	0.002844685	0.0026701
K denominator	0.000724331	0.000682475
S	0.243752933	0.239992981
K	3.927330472	3.912374575
JB Test stat	0.003391978	0.00400655
Chi-Sq	0.499152724	0.498999365
	Accept Normal	**Accept Normal**

Figure 1

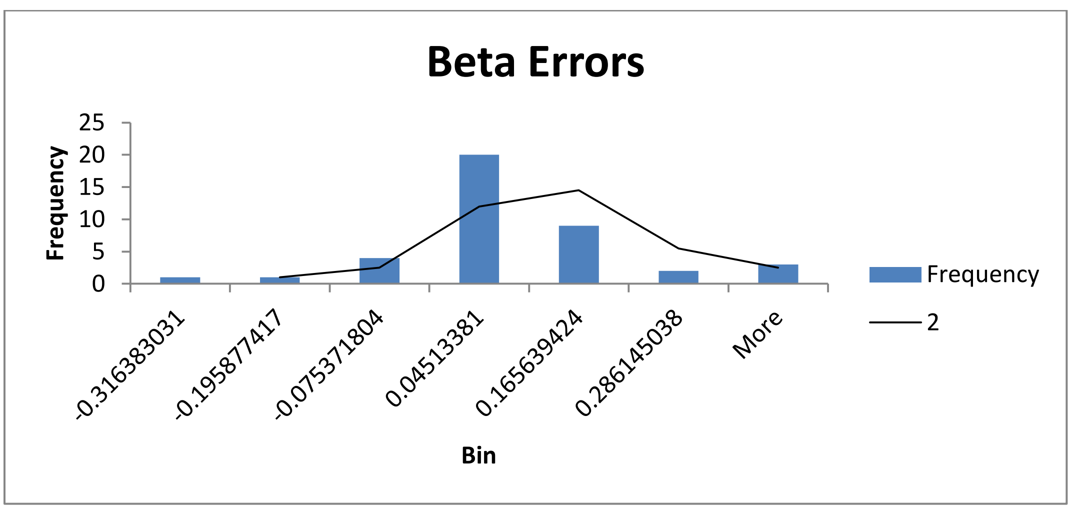
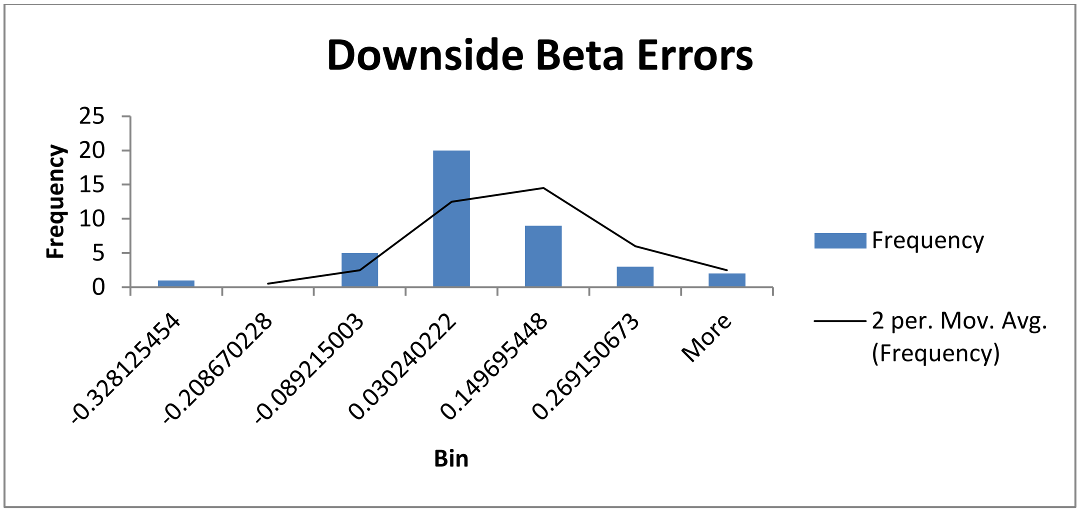


Figure 2



From the two Figures above, the familiar Bell-shaped curve is evident.

In addition to testing that the two populations follow a normal distribution, it was also necessary to test whether the two populations have the same variance. An F-Test was performed in Excel in order to determine this. Refer to Table 4 below for the results of this test:

Table 4: F-Test

F-Test Two-Sample for Variances		
	Beta Error	*D-Beta Error*
Mean	0.025331605	0.014636419
Variance	0.01740622	0.017112268
Observations	40	40
Df	39	39
F	1.017177863	
P(F<=f) one-tail	0.478928789	
F Critical one-tail	1.704465067	

Note: The significance level is 5%

The null hypothesis related to the F-Test states that the variances of the two populations are equal. The alternative hypothesis states that one of the variances is greater than the other. In order to disprove the null hypothesis, the test statistic, F, should be greater than the critical value for F. Note that the F-Test is directional; therefore the one-tailed critical value is the relevant benchmark to use. In this case, the F statistic (1.02) is smaller than the critical value of F (1.7); therefore it is not possible to reject the null hypothesis. The p-value (0.479) provides very little evidence to reject the null hypothesis. It can therefore be concluded that the two populations do not have different variances. The use of the matched-pairs t-test is therefore justified.

The hypothesis which was tested using the matched-pairs t-test was as follows:

That is, the null hypothesis states that the errors produced by the D-CAPM are equal to the errors produced by the CAPM. The alternate hypothesis states that the errors produced by the D-CAPM are smaller than the errors produced by the CAPM. This is the implicit expectation of this study.

A matched-pairs t-test was performed on the data, the results of which are as follows:

Table 5: t-Test

t-Test: Paired Two Sample for Means		
	Beta Error	*D-Beta Error*
Mean	0.025331605	0.014636419
Variance	0.01740622	0.017112268
Observations	40	40
Pearson Correlation	0.996122791	
Hypothesized Mean Difference	0	
df	39	
t Stat	5.819950768	
P(T<=t) one-tail	4.60603E-07	
t Critical one-tail	1.684875122	
P(T<=t) two-tail	9.21206E-07	
t Critical two-tail	2.02269092	

As can be seen from the above table, the critical value for a one-tailed test (as was performed here) is 1.68. In order to reject the null hypothesis – that is, there is no difference between the errors generated by the two models – the calculated t-statistic needs to be higher than the critical value. In this case, the t-statistic is 5.82, which is significantly higher than the critical value of 1.68. In addition, the p-value is very close to zero, which means that there is overwhelming evidence to suggest that there is a difference between the errors. From the above table it is also possible to determine which of the models produces smaller errors on average: The mean error using the Beta model is 0.025, while the mean error using the D-Beta model is 0.015, 42% smaller. The total errors observed under each model were totaled, with the following results:

Total error	
Beta	**Downside Beta**
101.33%	58.55%

It is clear from the above results that the Downside Beta model resulted in a much smaller total error than the Beta model. Based on all of the above results, there is sufficient evidence to reject the null hypothesis. It is now possible to answer the sub-question related to the second part of the testing in this study: *Is the forecasting error of the D-CAPM smaller than that of the CAPM?*

The data suggest that the answer to this question is: Yes. It appears that the use of the D-CAPM does result in a significantly smaller forecasting error than the CAPM.

The second part of the testing will be discussed in the following section.

Second Test

Recall the sub-question associated with the second section of the testing: *Does the D-CAPM Beta explain more of the share price movements than the CAPM Beta?*

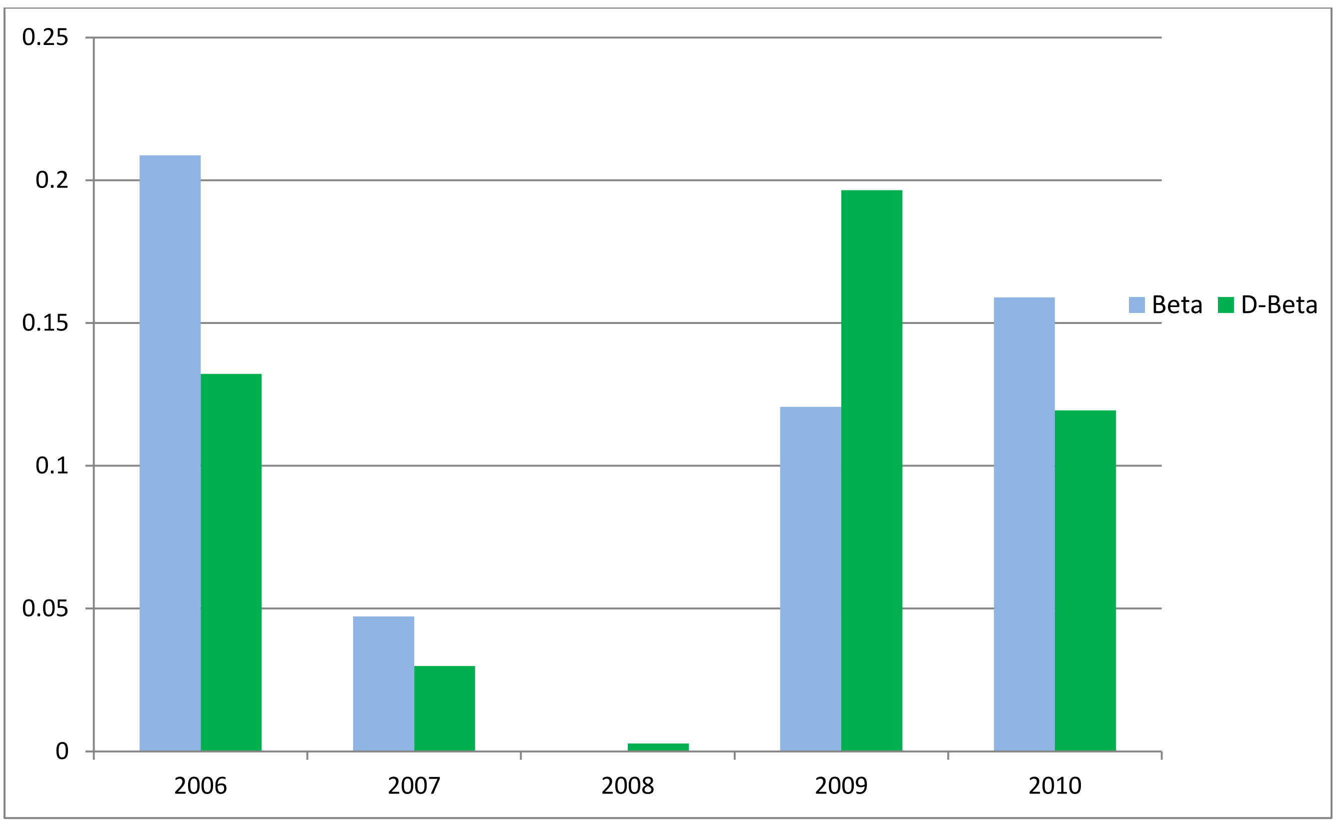
Formally, the hypothesis which was tested is as follows:

The actual average return for each company was calculated for the years 2006, 2007, 2008, 2009 and 2010. For each year, two regressions were run, one using Beta as the independent variable, and the second using Downside Beta as the independent variable. The dependent variable in each regression was the array of 40 average returns in that particular year. See Appendix IV for the full results of these regressions. For each year, two statistics were obtained, one from the Beta model, and one from the Downside Beta model. In total, 5 pairs of were obtained, as shown in the table below:

Table 6: R-squared Results

Results	Beta Model	D-Beta Model	Larger?
2006	0.208732485	0.132166545	Beta
2007	0.047263605	0.029836539	Beta
2008	1.79818E-05	0.002738709	D-Beta
2009	0.120653704	0.196483328	D-Beta
2010	0.158958087	0.119382179	Beta

Figure 3: R-Squared Results



General Observations

In general, the results are all very low, a finding which supports that of Estrada (1999): that in emerging markets, Betas and stock returns are largely uncorrelated. The highest R^2 obtained was in 2006 – 21% – using the Beta model. The lowest result – from the Beta model in 2008 – is almost zero. These results, although very low, are not entirely surprising. It is widely known and accepted that the CAPM is not a good predictor of share returns: Fama and French (1992) resurrect an old finding that there is virtually no detectable cross-sectional Beta-mean return relation. Roll and Ross (1994) suggest that the reason for this is not necessarily due to the failures of the model itself, but rather due to the inputs used in the model – specifically the choice of the market proxy. They argue that ordinary least squares regression relation is very sensitive to the choice of the index and that various indices can be quite close to each other and to the efficient frontier and yet still produce significantly different relationships between expected return and Beta. This same argument applies to the D-CAPM as well, and explains why the results obtained in the testing are so low.

As is evident from the above illustrations, the Beta model produces a higher R^2 than the D-Beta model in three out of the five years: 2006, 2007 and 2010. An interesting finding presents itself here: the two years in which South Africa was most badly affected by the global financial crisis – 2008 (where the number of positive annual returns across the sample was only nine out of forty) and 2009 – are the two years in which the Downside Beta model provides the better fit. In 2009 especially, the difference between the two models is significant – almost 8%. This finding supports the idea that Downside risk measures are more accurate than traditional methods during times of significant market downturn. Another possible explanation for this result is the increased number of observations in a recessionary environment, considering that upwards movements are effectively removed. This in turn suggests that one would expect the Downside Beta model to provide a better fit during adverse trading conditions.

It is worth noting that the results obtained in this section of the testing do not tie in with the results obtained by Estrada (2002) when he examined emerging markets as a whole – where he found that Downside Beta explained a substantial 55% of the variability of returns. The results obtained in this study are far lower than this. The most obvious reason for this is that Estrada used for his data set the entire Morgan Stanley Capital Indices of emerging markets, over a significantly different period. Whereas Estrada's study included data from 1988 through to 2002, this study has focused on a very different time period. Notable differences in these periods, in a South African context, include the abolishment of apartheid as well as a global financial crisis. It is therefore understandable that significantly different results were obtained, as these events, amongst others, had significant effects on the financial market in South Africa.

In order to perform a statistical analysis on these results, a non-parametric test of location was used in order to determine whether or not the R^2 generated by the CAPM Beta are significantly larger than the R^2 generated by the Downside Beta. The test which was selected for this analysis is called the Wilcoxon Signed-Rank Test. This is an appropriate test to use in this situation as the sample size is small – there are only five pairs of data which are being examined. It is therefore not appropriate to use parametric tests in this situation. This test is based solely on the order in which the observations from the two samples fall. The assumptions underlying the Wilcoxon Signed-Rank Test are:

- Data are paired and come from the same population
- Each pair is chosen randomly and independently
- The data are measured on an interval scale

All these assumptions have been met: The pairs of data each come from one particular year (2006 – 2010), each pair was randomly and independently chosen, and the data are measured on an interval scale.

The procedure of the test is as follows: First, calculate the difference between the two observations in each pair. Second, note the sign of the difference (1 for positive differences, -1 for negative differences). Third, calculate the absolute value of the difference. Fourth, rank the pairs in ascending order according to the absolute value of the differences. The smallest difference is assigned a rank of 1, and the largest is assigned a rank of 5 in this case. As none of the differences are the same in this case, no sharing of ranks is necessary. Fifth, obtain the signed rank by multiplying the rank by the sign of the original difference. Sixth, calculate the test statistic, W, by summing the signed ranks. The results of this test are presented in the table below:

Table 7: Wilcoxon Signed-Rank Test

Wilcoxon Signed-Rank Test						
Beta	**D-Beta**	**Diff**	**Abs (Diff)**	**Sign**	**Rank**	**Sign * Rank**
1.79818E-05	0.002738709	-0.002720727	0.002720727	-1	1	-1
0.047263605	0.029836539	0.017427066	0.017427066	1	2	2
0.158958087	0.119382179	0.039575907	0.039575907	1	3	3
0.120653704	0.196483328	-0.075829623	0.075829623	-1	4	-4
0.208732485	0.132166545	0.07656594	0.07656594	1	5	5
AVERAGE R^2:	AVERAGE R^2:					
0.107125173	0.09612146					
					W	5
					Critical W (α = 0.05)	15

When the sample size is smaller than 10, the critical value of W can be taken from a chart. For a one-tailed test (as was performed here), the critical value of W at a significance level of 5% is 15, as per the table below:

Table 8: Critical values for Wilcoxon Signed-Rank Test

Critical Values of ±W for Small Samples:

	Level of Significance for a Directional Test			
	.05	.025	.01	.005
	Non-Directional Test			
N	--	.05	.02	.01
5	15	--	--	--
6	17	21	--	--
7	22	24	28	--
8	26	30	34	36
9	29	35	39	43

Table obtained from http://vassarstats.net/textbook/ch12a.html

In order to reject the null hypothesis – that the R^2 generated by the CAPM Beta is equal to the R^2 generated by the Downside Beta – the test statistic needs to be larger than the critical value. In this case, the test statistic (5) is smaller than the critical value of W (15); therefore it is not possible to reject the null hypothesis. The results indicate that there is no significant difference between the R^2 generated by the CAPM Beta and that generated by the Downside Beta. This is confirmed by a trivial comparison of the average R^2 generated: the difference between them is only 1.1%.

It is now possible to answer the sub-question related to the second part of the testing in this study: *Does the D-CAPM Beta explain more of the share price movements than the CAPM Beta?*

The data suggest that the answer to this question is: No. It does not appear that there is any significant difference between using Beta or Downside Beta as the predictor of share returns.

Summary

The following table summarises the results obtained from the two sections of testing:

Table 7: Summarised Results

Sub-Question	Answer	Conclusion
Is the forecasting error of the D-CAPM smaller than that of the CAPM?	Yes	D-Beta is a more accurate predictor of share returns.
Does the D-CAPM Beta explain more of the share price movements than the CAPM Beta?	No	Neither model is significantly better than the other in predicting share returns.

It is clear from the above table that the results of the study are conflicting. These results will now be analysed in further detail in the final section of the report – Chapter V: Conclusions and Recommendations

Chapter V: Conclusions and Recommendations

The purpose of this research report was to determine whether the use of a Downside risk model – the D-CAPM – presents a viable alternative to the use of the CAPM in the emerging market of South Africa. The prior research upon which this report expands, performed by Estrada (1999; 2002; 2005), focused on using Downside risk models at an overall country (market) level. This report focuses exclusively on South Africa, but could be applicable to various other emerging markets. The reason for researching this topic is simple: Investors – not just in South Africa, but all across the world – think of risk differently to the way that it is defined in terms of modern portfolio theory. Beta measures risk by giving equal weight to both upside and Downside volatility, while in reality, investors are a lot more sensitive to Downside fluctuations. The S-shaped utility curve developed by Kahneman and Tversky (1979) provides evidence that investors associate a higher level of dissatisfaction with losing a given return than the satisfaction they associate with gaining the same return. It therefore seems logical that Downside risk measures should, in theory, be able to provide useful information to investors which they cannot currently obtain using more traditional risk measures.

There does not seem to be a clear answer to the question of which model is better at predicting share returns. The results from the first section of testing indicate that using the D-CAPM to predict share returns on the top 40 shares on the JSE produces results which are significantly more accurate than those obtained when using the CAPM. The average error produced by the D-CAPM is 42% smaller than that produced by the CAPM. These results support the use of a Downside risk model such as the D-CAPM in an emerging market such as South Africa.

The findings of Estrada (2002) – that emerging markets display relatively more Downside risk than total risk – are supported here: The average Downside Beta is 40% higher than the average Beta in the South African market. This means that the top 40 shares on the JSE in South Africa display relatively more

Downside volatility than total volatility. This has significant real-life implications: One of the most common uses of the CAPM model is to determine cost of equity for use in cost of capital calculations. The cost of capital is critical for project evaluation, firm valuation, mergers and acquisitions, and capital structure considerations, therefore it is imperative to have the most accurate cost of capital possible. With the Downside Beta in South Africa being, on average, 40% higher than the average Beta, the effect on companies' cost of capital calculations is significant. This could have far-reaching implications for South Africa, as new project acceptance and expansion has the potential to greatly affect the labour force and industry as a whole.

After examining the results from the first section of testing, it seems to be obvious that the Downside Beta model has significant advantages over the CAPM Beta. However, when comparing goodness of fit across the two models in the second section of testing, the Downside Beta turns out to be a better predictor of share returns only during periods of significant market downturn. In 2008 and 2009, when South Africa was feeling the worst effects of the global financial crisis, the Downside Beta model resulted in R-squared figures which were significantly larger than those generated by the Beta model. This supports Estrada's (2002) suggestion that the Downside Beta model is a better model to use in times of economic recession, due to the fact that it only takes into account Downside risk.

When one examines the results from the other three years in the study – 2006, 2007 and 2010 – the results clearly show that the Beta model provides the better fit, with the average R^2 result being 40% larger than the results obtained using the Downside Beta model. For the five years which were examined, therefore, it appears that the Beta model is more appropriate.

There are several possible reasons which may explain the conflicting results obtained in this report. In the first section of testing, the time period which was used to calculate the Betas was 2001- 2005, a consistently bullish period for the South African market where the All Share Index approximately doubled its value[2]. This is in contrast to the second section of testing, where for each year, new Betas were calculated based on the prior five years. The drastic changes in the overall South African market across the period 2006-2010 means that the Betas calculated during those periods could be significantly different to Betas calculated using periods of relative stability.

The first section of testing used parametric statistical techniques, while the results obtained from the second section of testing were derived from non-parametric tests. Non-parametric tests are less powerful because they use less information in their calculations. It may be possible that if a sufficiently large data set was obtained to facilitate the use of parametric tests, the results of the second section of testing may be different.

If one considers the results of the two sections of testing together, there is evidence to suggest that the Downside Beta model is better, while there is no evidence to suggest that the Beta model is better.

The Downside Beta appears to be an appropriate model to use during times of economic depression. In periods of expected downturn, the use of the Downside Beta in cost of capital calculations is justified by the results.

This research report represents one of the first investigations into using Downside risk models in South Africa. While the D-Beta does appear to be valuable in certain situations, further research is required in this area in order to fully understand the topic, and to take advantage of the benefits which a model like the D-CAPM can provide. Further research in this field could include the comparison of the D-CAPM to a different benchmark, such as the APT model.

[2] ALSI level: 31/01/2001: 9072; 30/12/2005: 18096.

Acknowledgements

I would like to thank every person who contributed to this report, especially my supervisor, Kwasi Okyere-Boakye. I would also like to thank my friends and family for their endless support. Any mistakes which were made in this report are my own.

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Appendices

Appendix I

Top 40 share data: Market capitalization presented in final column

Symbol	Shortname	Description	Sector	Close (c)	Prev Close (c)	% Day's Move	Mrkt Cap (ZARm)
BTI	BATS	British American Tobacco plc	Tobacco	45 487.00	44 484.00	2.25	921 682
SAB	SABMILLER	SABMiller plc	Beverages	37 600.00	37 351.00	0.67	626 497
BIL	BHPBILL	BHP Billiton Plc	Mining	26 398.00	26 284.00	0.43	563 910
AGL	ANGLO	Anglo American plc	Mining	24 970.00	24 684.00	1.16	350 943
MTN	MTN GROUP	MTN Group Ltd.	Mobile Telecommunications	15 500.00	15 475.00	0.16	292 173
CFR	RICHEMONT	Compagnie Financi�re Richemont SA	Personal Goods	5 322.00	5 226.00	1.84	277 808
SOL	SASOL	Sasol Ltd.	Oil & Gas Producers	37 005.00	36 805.00	0.54	238 871
NPN	NASPERS-N	Naspers Ltd.	Media	54 026.00	53 199.00	1.55	222 772
SBK	STANBANK	Standard Bank Group Ltd.	Banks	10 420.00	10 480.00	-0.57	167 270
FSR	FIRSTRAND	FirstRand Ltd.	Banks	2 842.00	2 830.00	0.42	160 230
KIO	KUMBA	Kumba Iron Ore Ltd.	Industrial Metals & Mining	48 000.00	47 791.00	0.44	154 588
VOD	VODACOM	Vodacom Group Ltd.	Mobile Telecommunications	10 155.00	10 300.00	-1.41	151 102
OML	OLDMUTUAL	Old Mutual plc	Life Insurance	2 422.00	2 385.00	1.55	117 979
ANG	ANGGOLD	AngloGold Ashanti Ltd.	Mining	28 462.00	28 508.00	-0.16	109 029
AMS	AMPLATS	Anglo American Platinum Ltd.	Mining	39 425.00	39 500.00	-0.19	106 322
ASA	ABSA	Absa Group Ltd.	Banks	14 151.00	13 950.00	1.44	101 634
SHP	SHOPRIT	Shoprite Holdings Ltd.	Food & Drug Retailers	17 029.00	17 335.00	-1.77	97 164
NED	NEDBANK	Nedbank Group Ltd.	Banks	18 431.00	18 410.00	0.11	93 539
IMP	IMPLATS	Impala Platinum Holdings Ltd.	Mining	13 528.00	13 760.00	-1.69	85 458
SLM	SANLAM	Sanlam Ltd.	Life Insurance	3 822.00	3 800.00	0.58	80 262
GFI	GFIELDS	Gold Fields Ltd.	Mining	10 456.00	10 563.00	-1.01	76 277
REM	REMGRO	Remgro Ltd.	General Industrials	14 370.00	14 483.00	-0.78	69 135
BVT	BIDVEST	The Bidvest Group Ltd.	General Industrials	20 505.00	20 630.00	-0.61	67 202
APN	ASPEN	Aspen Pharmacare Holdings Ltd.	Pharmaceuticals & Biotechnology	14 472.00	14 515.00	-0.30	65 896
EXX	EXXARO	Exxaro Resources Ltd.	Mining	16 023.00	15 840.00	1.16	57 310
RMH	RMBH	RMB Holdings Ltd.	Banks	3 770.00	3 753.00	0.45	53 221
WHL	WOOLIES	Woolworths Holdings Ltd.	General Retailers	6 250.00	6 365.00	-1.81	52 437
TBS	TIGBRANDS	Tiger Brands Ltd.	Food Producers	27 118.00	27 553.00	-1.58	51 830
SHF	STEINHOFF	Steinhoff International Holdings Ltd.	Household Goods & Home Construction	2 694.00	2 655.00	1.47	47 676
ASR	ASSORE	Assore Ltd.	Mining	33 000.00	32 705.00	0.90	46 070
TRU	TRUWTHS	Truworths International Ltd.	General Retailers	9 799.00	9 760.00	0.40	45 253
GRT	GROWPNT	Growthpoint Properties Ltd.	Real Estate Investment & Services	2 495.00	2 495.00	0.00	44 102
CSO	CAPSHOP	Capital Shopping Centres Group PLC	Real Estate Investment Trusts	4 660.00	4 561.00	2.17	40 319
IPL	IMPERIAL	Imperial Holdings Ltd.	Industrial Transportation	17 801.00	18 525.00	-3.91	37 556
MSM	MASSMART	Massmart Holdings Ltd.	General Retailers	16 800.00	16 687.00	0.68	36 323
MDC	MEDCLIN	Mediclinic International Ltd.	Health Care Equipment & Services	4 349.00	4 320.00	0.67	35 964
ARI	ARM	African Rainbow Minerals Ltd.	Mining	15 801.00	15 687.00	0.73	33 986
DSY	DISCOVERY	Discovery Holdings Ltd.	Life Insurance	5 684.00	5 601.00	1.48	33 642
RMI	RMIH	Rand Merchant Insurance Holdings Ltd.	Equity Investment Instruments	2 255.00	2 245.00	0.45	33 502
MPC	MRPRICE	Mr Price Group Ltd.	General Retailers	13 250.00	13 400.00	-1.12	33 224

	ZAR M's
Top 40 Market Cap	5880158
JSE Market Cap	6785600
% of JSE captured by Top 40	0.866564
	87%

Share price data obtained using ShareMagic Pro, accessed on 19 October 2012

JSE Market Capitalisation data obtained from the JSE market profile: March 2011

Appendix II

Table 1: Share Betas and Downside Betas

Share Code	Share Name	Mean Return	Beta	D-Beta with respect to: Mean	Rf	Zero	Sector
CFR	COMPAGNIE FINANCIERE RICHEMONT SA	10%	1.13	1.26	1.32	1.35	Financial
SBK	STANDARD BANK GROUP LIMITED	24%	0.58	0.76	0.66	0.64	Financial
FSR	FIRSTRAND LIMITED	23%	0.67	0.84	0.75	0.73	Financial
ASA	ABSA GROUP LIMITED	31%	0.53	0.71	0.61	0.60	Financial
OML	OLD MUTUAL PLC	5%	0.64	0.88	0.96	0.95	Financial
NED	NEDBANK GROUP LIMITED	-5%	0.42	0.72	0.89	0.87	Financial
SLM	SANLAM LIMITED	17%	0.65	0.86	0.82	0.80	Financial
RMH	RMB HOLDINGS LIMITED	25%	0.70	0.83	0.71	0.69	Financial
ABL	AFRICAN BANK INVESTMENTS LIMITED	26%	0.51	0.80	0.69	0.67	Financial
LBH	LIBERTY HOLDINGS LIMITED	0%	0.36	0.53	0.62	0.59	Financial
SAB	SABMILLER PLC	21%	0.83	0.87	0.81	0.82	Other
MTN	MTN GROUP LIMITED	26%	0.91	1.24	1.15	1.15	Other
NPN	NASPERS LIMITED	33%	1.09	1.54	1.44	1.50	Other
REM	REMGRO LIMITED	20%	0.59	0.59	0.51	0.48	Other
BVT	THE BIDVEST GROUP LIMITED	20%	0.50	0.64	0.56	0.53	Other
SHP	SHOPRITE HOLDINGS LIMITED	25%	0.24	0.67	0.55	0.52	Other
APN	ASPEN PHARMACARE HOLDINGS LIMITED	44%	0.38	0.64	0.37	0.33	Other
CSO	CAPITAL SHOPPING CENTRES GROUP PLC	18%	0.61	0.49	0.40	0.34	Other
SHF	STEINHOFF INTERNATIONAL HOLDINGS LD	25%	0.91	0.89	0.76	0.73	Other
TBS	TIGER BRANDS LIMITED	19%	0.59	0.77	0.70	0.67	Other
TRU	TRUWORTHS INTERNATIONAL LIMITED	41%	0.23	0.45	0.22	0.17	Other
MSM	MASSMART HOLDINGS LIMITED	41%	0.26	0.42	0.24	0.19	Other
GRT	GROWTHPOINT PROPERTIES LIMITED	33%	0.27	0.44	0.27	0.23	Other
MMI	MMI HOLDINGS LIMITED	3%	0.58	0.93	1.05	1.08	Other
IPL	IMPERIAL HOLDINGS LIMITED	23%	0.74	0.99	0.92	0.93	Other
DSY	DISCOVERY HOLDINGS LIMITED	14%	0.38	0.73	0.73	0.74	Other
NTC	NETCARE LIMITED	36%	0.38	0.62	0.48	0.48	Other
PIK	PICK N PAY STORES LIMITED	16%	0.35	0.57	0.53	0.50	Other
BIL	BHP BILLITON PLC	32%	1.15	0.96	0.75	0.71	Resource
AGL	ANGLO AMERICAN PLC	20%	1.44	1.31	1.26	1.28	Resource

SOL	SASOL LIMITED	37%	1.01	0.96	0.72	0.68	Resource
AMS	ANGLO PLATINUM LIMITED	20%	1.87	1.75	1.74	1.80	Resource
IMP	IMPALA PLATINUM HOLDINGS LIMITED	35%	1.74	1.74	1.59	1.65	Resource
ANG	ANGLOGOLD ASHANTI LIMITED	31%	1.09	1.25	1.11	1.11	Resource
GFI	GOLD FIELDS LIMITED	39%	1.11	1.23	1.01	0.99	Resource
ARI	AFRICAN RAINBOW MINERALS LIMITED	14%	0.82	0.81	0.78	0.75	Resource
LON	LONMIN PLC	8%	1.38	1.31	1.40	1.43	Resource
ACL	ARCELORMITTAL SOUTH AFRICA LIMITED	26%	0.47	1.08	1.01	1.02	Resource
HAR	HARMONY GOLD MINING COMPANY LIMITED	35%	1.45	1.54	1.36	1.35	Resource
ASR	ASSORE LIMITED	37%	0.13	0.40	0.21	0.15	Resource
Average		24%	0.74	0.90	0.82	0.80	

Appendix III

First section of testing: Errors produced using the Beta CAPM and the Downside CAPM

Company	Actual Return	Beta	CAPM	Beta Error	D-Beta	D-CAPM	D-Beta Error
BHPBILL	26.35%	1.145505	15.0256%	**11.3289%**	0.959753409	13.7728%	**12.5816%**
ANGLO	18.62%	1.438313	17.0003%	**1.6243%**	1.312800133	16.1539%	**2.4708%**
SAB	18.19%	0.830547	12.9014%	**5.2923%**	0.868065366	13.1545%	**5.0393%**
MTN GROUP	18.74%	0.90866	13.4282%	**5.3073%**	1.241479331	15.6729%	**3.0627%**
SASOL	15.04%	1.01457	14.1425%	**0.9001%**	0.956039668	13.7478%	**1.2948%**
RICHEMONT	13.74%	1.13262	14.9387%	**-1.1948%**	1.257943911	15.7839%	**-2.0400%**
ANGLOPLAT	21.75%	1.871822	19.9241%	**1.8257%**	1.747765309	19.0874%	**2.6624%**
STANBANK	13.98%	0.578921	11.2044%	**2.7778%**	0.763830944	12.4515%	**1.5307%**
NASPERS	28.83%	1.08681	14.6297%	**14.1965%**	1.540201243	17.6875%	**11.1387%**
IMPLATS	24.58%	1.742038	19.0488%	**5.5351%**	1.741771645	19.0470%	**5.5369%**
ANGGOLD	6.43%	1.094965	14.6847%	**-8.2547%**	1.252483726	15.7471%	**-9.3171%**
FIRSTRAND	13.59%	0.666407	11.7944%	**1.7909%**	0.841933391	12.9782%	**0.6071%**
ABSA	12.94%	0.526168	10.8486%	**2.0962%**	0.71203421	12.1021%	**0.8426%**
GFIELDS	7.37%	1.112588	14.8036%	**-7.4380%**	1.233319984	15.6178%	**-8.2522%**
OLDMUTUAL	4.19%	0.639028	11.6098%	**-7.4168%**	0.880801234	13.2403%	**-9.0474%**
NEDBANK1	12.66%	0.4233	10.1548%	**2.5060%**	0.723886281	12.1821%	**0.4788%**
SANLAM	18.32%	0.646209	11.6582%	**6.6630%**	0.859401454	13.0960%	**5.2251%**
REMGRO2	7.72%	0.587279	11.2608%	**-3.5390%**	0.589008502	11.2724%	**-3.5506%**
BIDVEST	15.82%	0.500571	10.6760%	**5.1435%**	0.637349951	11.5985%	**4.2210%**
SHOPRIT2	37.61%	0.242058	8.9325%	**28.6727%**	0.666580604	11.7956%	**25.8097%**
RMBH	14.50%	0.702044	12.0348%	**2.4647%**	0.828813715	12.8897%	**1.6098%**
ARM	43.29%	0.822026	12.8440%	**30.4443%**	0.814463581	12.7930%	**30.4953%**
LONMIN	-3.46%	1.382721	16.6254%	**-20.0851%**	1.312171123	16.1496%	**-19.6092%**
ASPEN	24.40%	0.383081	9.8836%	**14.5115%**	0.641307732	11.6251%	**12.7699%**
ARCMITTAL	2.91%	0.46656	10.4466%	**-7.5376%**	1.084072512	14.6113%	**-11.7023%**
CAPSHOP	-5.06%	0.613824	11.4398%	**-16.5003%**	0.487263419	10.5862%	**-15.6467%**
STEINHOFF	13.46%	0.909826	13.4361%	**0.0246%**	0.889653616	13.3001%	**0.1607%**
TIGBRANDS	9.57%	0.586402	11.2548%	**-1.6846%**	0.772531203	12.5101%	**-2.9399%**
HARMONY	9.14%	1.445677	17.0500%	**-7.9101%**	1.543384022	17.7090%	**-8.5690%**
ABIL	5.04%	0.510909	10.7457%	**-5.7061%**	0.798148965	12.6829%	**-7.6433%**
TRUWTHS	27.59%	0.233833	8.8770%	**18.7154%**	0.452373272	10.3509%	**17.2415%**
MASSMART	28.72%	0.262709	9.0718%	**19.6469%**	0.420947383	10.1390%	**18.5797%**
ASSORE	48.83%	0.128626	8.1675%	**40.6651%**	0.396183371	9.9720%	**38.8606%**

GROWPNT	18.64%	0.266648	9.0983%	**9.5439%**	0.437434926	10.2502%	**8.3920%**
MMI HLDGS	4.80%	0.576124	11.1855%	**-6.3844%**	0.933311462	13.5945%	**-8.7934%**
IMPERIAL2	10.49%	0.737354	12.2729%	**-1.7834%**	0.986922198	13.9561%	**-3.4666%**
DISCOVERY	8.30%	0.377941	9.8489%	**-1.5529%**	0.725588685	12.1936%	**-3.8976%**
NETCARE	11.36%	0.383989	9.8897%	**1.4659%**	0.61941815	11.4775%	**-0.1219%**
LIB HOLD	-21.94%	0.355764	9.6994%	**-31.6383%**	0.529873863	10.8736%	**-32.8125%**
PICKNPAY	6.48%	0.351879	9.6732%	**-3.1899%**	0.569290105	11.1394%	**-4.6561%**

Appendix IV

2006

BETA SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.4568725
R Square	0.2087325
Adjusted R Square	0.1879097
Standard Error	0.0151885
Observations	40

ANOVA

	df	SS	MS	F	ignificance F
Regression	1	0.0023125	0.00231	10.0242	0.0030413
Residual	38	0.0087662	0.00023		
Total	39	0.0110787			

	Coefficients	andard Errc	t Stat	P-value	Lower 95%	pper 95%	wer 95.0%	Jpper 95.0%
Intercept	0.0156488	0.0048854	3.2032	0.00275	0.0057589	0.0255	0.00576	0.0255386
X Variable 1	0.0181494	0.0057324	3.1661	0.00304	0.0065447	0.0298	0.00654	0.029754

D-BETA SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.3635472
R Square	0.1321665
Adjusted R Square	0.1093288
Standard Error	0.0159064
Observations	40

ANOVA

	df	SS	MS	F	ignificance F
Regression	1	0.0014642	0.00146	5.7872	0.0211167
Residual	38	0.0096145	0.00025		
Total	39	0.0110787			

	Coefficients	andard Errc	t Stat	P-value	Lower 95%	pper 95%	wer 95.0%	Jpper 95.0%
Intercept	0.013645	0.0069063	1.97572	0.05548	-0.000336	0.0276	-0.0003	0.0276261
X Variable 1	0.0171786	0.0071409	2.40566	0.02112	0.0027226	0.0316	0.00272	0.0316347

2007

BETA SUMMARY OUTPUT

Regression Statistics	
Multiple F	0.217402
R Square	0.047264
Adjusted I	0.022192
Standard E	0.023015
Observati	40

ANOVA

	df	*SS*	*MS*	*F*	*gnificance F*
Regressio	1	0.000999	0.000999	1.885114	0.177802
Residual	38	0.020128	0.00053		
Total	39	0.021126			

	Coefficients	*andard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
Intercept	0.020837	0.008685	2.399343	0.021434	0.003256	0.038418	0.003256	0.038418
X Variable	-0.01272	0.009264	-1.37299	0.177802	-0.03147	0.006035	-0.03147	0.006035

D-BETA SUMMARY OUTPUT

Regression Statistics	
Multiple F	0.172733
R Square	0.029837
Adjusted I	0.004306
Standard E	0.023224
Observati	40

ANOVA

	df	*SS*	*MS*	*F*	*gnificance F*
Regressio	1	0.00063	0.00063	1.168657	0.286491
Residual	38	0.020496	0.000539		
Total	39	0.021126			

	Coefficients	*andard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
Intercept	0.021487	0.011234	1.912797	0.063332	-0.00125	0.044229	-0.00125	0.044229
X Variable	-0.01161	0.01074	-1.08104	0.286491	-0.03335	0.010131	-0.03335	0.010131

2008

BETA SUMMARY OUTPUT

Regression Statistics	
Multiple F	0.00424
R Square	1.8E-05
Adjusted I	-0.0263
Standard E	0.031715
Observati	40

ANOVA

	df	SS	MS	F	gnificance F
Regressio	1	6.87E-07	6.87E-07	0.000683	0.979282
Residual	38	0.038222	0.001006		
Total	39	0.038223			

	Coefficient	andard Err	t Stat	P-value	Lower 95%	Upper 95%	ower 95.0%	pper 95.0%
Intercept	-0.01527	0.011853	-1.28803	0.205523	-0.03926	0.008728	-0.03926	0.008728
X Variable	-0.00031	0.011832	-0.02614	0.979282	-0.02426	0.023643	-0.02426	0.023643

D-BETA SUMMARY OUTPUT

Regression Statistics	
Multiple F	0.052333
R Square	0.002739
Adjusted I	-0.02351
Standard E	0.031672
Observati	40

ANOVA

	df	SS	MS	F	gnificance F
Regressio	1	0.000105	0.000105	0.104357	0.748434
Residual	38	0.038118	0.001003		
Total	39	0.038223			

	Coefficient	andard Err	t Stat	P-value	Lower 95%	Upper 95%	ower 95.0%	pper 95.0%
Intercept	-0.0207	0.016715	-1.23833	0.223188	-0.05454	0.013139	-0.05454	0.013139
X Variable	0.004922	0.015236	0.323043	0.748434	-0.02592	0.035765	-0.02592	0.035765

2009

BETA SUMMARY OUTPUT

Regression Statistics	
Multiple F	0.347352
R Square	0.120654
Adjusted I	0.097513
Standard E	0.016543
Observati	40

ANOVA

	df	SS	MS	F	gnificance F
Regressio	1	0.001427	0.001427	5.213919	0.028087
Residual	38	0.0104	0.000274		
Total	39	0.011827			

	Coefficients	andard Err	t Stat	P-value	Lower 95%	Upper 95%	ower 95.0%	pper 95.0%
Intercept	0.015265	0.005659	2.69743	0.010362	0.003809	0.026722	0.003809	0.026722
X Variable	0.013487	0.005906	2.283401	0.028087	0.00153	0.025444	0.00153	0.025444

D-BETA SUMMARY OUTPUT

Regression Statistics	
Multiple F	0.443264
R Square	0.196483
Adjusted I	0.175338
Standard E	0.015814
Observati	40

ANOVA

	df	SS	MS	F	gnificance F
Regressio	1	0.002324	0.002324	9.292111	0.004175
Residual	38	0.009503	0.00025		
Total	39	0.011827			

	Coefficients	andard Err	t Stat	P-value	Lower 95%	Upper 95%	ower 95.0%	pper 95.0%
Intercept	0.010575	0.005858	1.805171	0.078976	-0.00128	0.022434	-0.00128	0.022434
X Variable	0.016347	0.005363	3.048296	0.004175	0.005491	0.027203	0.005491	0.027203

2010

BETA SUMMARY OUTPUT

Regression Statistics	
Multiple F	0.398695
R Square	0.158958
Adjusted I	0.136825
Standard E	0.013379
Observati	40

ANOVA

	df	*SS*	*MS*	*F*	*ignificance F*
Regressio	1	0.001286	0.001286	7.182053	0.010826
Residual	38	0.006802	0.000179		
Total	39	0.008088			

	Coefficients	*andard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
Intercept	0.029056	0.004854	5.985904	5.95E-07	0.01923	0.038883	0.01923	0.038883
X Variable	-0.01386	0.005171	-2.67994	0.010826	-0.02433	-0.00339	-0.02433	-0.00339

D-BETA SUMMARY OUTPUT

Regression Statistics	
Multiple F	0.345517
R Square	0.119382
Adjusted I	0.096208
Standard E	0.01369
Observati	40

ANOVA

	df	*SS*	*MS*	*F*	*ignificance F*
Regressio	1	0.000966	0.000966	5.151523	0.028985
Residual	38	0.007122	0.000187		
Total	39	0.008088			

	Coefficients	*andard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
Intercept	0.028687	0.005445	5.268893	5.72E-06	0.017665	0.039709	0.017665	0.039709
X Variable	-0.0116	0.005109	-2.2697	0.028985	-0.02194	-0.00125	-0.02194	-0.00125