An empirical investigation into cross-sectional return dispersion on the South African equity market

by
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DECLARATION REGARDING PLAGIARISM

By submitting this thesis, I, the undersigned, hereby declare that the work contained therein is my own original work and that I have not previously in its entirety or in part submitted it at any university for a degree.

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ABSTRACT

This study examines the role of cross-sectional return dispersion in portfolio management by examining two topics. To begin with, the study considers why return dispersion changes over time. Given the influence of return dispersion on active portfolio return opportunity, it is important for managers to understand why return dispersion changes over time. For a sample of South African listed shares over the period June 1996 to December 2011, univariate time-series analysis reveals significant serial correlation in return dispersion which may be modelled using ARMA (1, 1) and GARCH (1, 1) processes. Further analysis within a rational economic framework reveals that return dispersion is countercyclical to aggregate economic activity and related to both local and foreign economic uncertainty.

The study then considers the relationship between return dispersion and the return to investment strategies. If substantial association between return dispersion and any investment strategy exists, then it is possible for managers and fund sponsors to augment an understanding of when active return opportunity is high with strategies for exploiting return opportunities. Continuing within the rational economic framework, the study uses Spearman's rank correlation coefficients to show a significant positive relationship between return dispersion and the value premium. In aggregate, these findings suggest that it is possible for South African investors to understand why return dispersion changes over time, as well as how to take advantage of changes in return dispersion.

OPSOMMING

Hierdie studie ondersoek die rol van opbrengsverspreiding oor die kruissnit van ‘n mark in portefeuljebestuur deur twee onderwerpe te bestudeer. Eerstens bestudeer die studie hoekom opbrengsverspreiding oor tyd verander. Gegewe die invloed van opbrengsverspreiding op aktiewe beleggingsgeleentheid is dit belangrik vir bestuurders om te verstaan hoekom opbrengsverspreiding oor tyd verander. Vir ‘n steekproef van Suid Afrikaanse aandele oor die periode Julie 1996 tot Desember 2011 dui enkelvoudige tydreeks analise aan dat opbrengsverspreiding beduidende outokorrelasie het, waar die outokorrelasie beskryf word deur ARMA (1, 1) en GARCH (1, 1) prosesse. Verdere analise binne ‘n rasionele ekonomiese raamwerk dui daarop dat opbrengsverspreiding kontra-siklies aan makro-ekonomiese aktiwiteit is en verwant is aan beide plaaslike en buitelandse ekonomiese onsekerheid.

Die studies ondersoek daarna die verhouding tussen opbrengsverspreiding en die opbrengs van beleggings strategieë. Indien daar ‘n noemenswaardige verhouding is tussen opbrengsverspreiding en enige beleggings strategie, dan kan bestuurders beter oordeel watter strategieë hoë opbrengste lewer wanneer beleggingsgeleenthede hoog is. Die studie hou binne ‘n rasionele ekonomiese raamwerk en gebruik Spearman se rang-orde korrelasie koeffisiënte om ‘n beduidende positiewe verwantskap tussen opbrengsverspreiding en die opbrengs van die waardepremie aan te dui. As ‘n geheel dui hierdie bevindinge daarop aan dat dit moontlik is vir Suid-Afrikaanse beleggers om te verstaan hoekom opbrengsverspreiding oor tyd verander asook hoe om voordeel uit die verwantskappe te trek.

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AN EMPIRICAL INVESTIGATION INTO CROSS-SECTIONAL RETURN DISPERSION ON THE SOUTH AFRICAN EQUITY MARKET

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CHAPTER ONE
INTRODUCTION

1.1 RESEARCH SETTING

The aim of this study is to examine the practical use of return dispersion in active portfolio management. Return dispersion, or the cross-sectional standard deviation of asset returns around the market mean (Chadha and Satchell, 2008: 4) plays an important role in investment management. De Silva, Sapra and Thorley (2001) show that the difference in returns between the best and worst performing active equity managers is a uniform function of return dispersion. Numerous papers use the findings of De Silva et al. (2001) to develop the thesis that return dispersion and managerial talent combine to explain most of active portfolio management performance. In this role as a proxy for active risk taking opportunity, variation in return dispersion determines the degree to which active bets can outperform the market, if at all.

Despite the obvious importance of return dispersion, little research considers why return dispersion changes over time, or how it relates to the conditional distribution of asset returns[1]. Both of these research questions have important implications for strategic investment decisions. First, since investment decisions are inherently forward-looking (Laopodis, 2013: 420), benefitting from changes in investment opportunity presupposes that investors are able to anticipate changes in return dispersion. Second, if return dispersion correlates with the conditional distribution of returns for any asset class, it is possible to understand if certain shares perform better when risk-taking opportunity is high and exploit these changes in an active investment management context.

The question of why return dispersion changes over time, as well as how it relates to the conditional distribution of asset returns are the guiding research questions of this thesis. This thesis argues that it is possible for investors to understand why return dispersion changes over time, as well as how to take advantage of variation in return dispersion. As a result, it should be possible for investors to exploit changes in return dispersion in a manner that improves investment performance. The remainder of this chapter provides a broad overview of this thesis' approach to examining this position.

[1] That is, the distribution of asset returns as it varies over time.

1.2 RESEARCH OBJECTIVES

The study uses the two research questions to formulate two research objectives. The first research objective is to examine why return dispersion changes over time. By characterising changes in return dispersion, the study aims to provide a platform for forming ex-ante expectations of return dispersion. Given the forward-looking nature of investment management, the ability to form ex-ante expectations of return dispersion is useful in a variety of situations, including manager selection and determining optimal active strategies. To illustrate, a fund sponsor may use ex-ante expectations to determine how to allocate funds across active or passive managers, while an active manager may use ex-ante expectations to determine the right time for implementing active bets.

The second research objective is to examine if any asset allocation strategy varies predictably with changes in return dispersion. By focussing on the research problem at an asset allocation level, the study controls for the effect of managerial talent in determining how to take advantage of changes in return dispersion. Following Gorman, Sapra and Weigand (2010b), evaluating active performance strategies needs to consider both investment opportunity and managerial skill. If there is a reliable link between return dispersion and the conditional distribution of returns, it is possible to exploit the relationship in asset allocation decisions by changing allocations as the expected return distribution changes. Returning to the previous illustration, an active manager may supplement information on when to implement active bets with information on what kind of active bets to make.

1.3 RESEARCH DESIGN

This study pursues its research objectives using a statistical modelling approach. Statistical modelling seeks “to capture the essence of a process by identifying key variables and creating a representation of it” (Hofstee, 2006: 129). With application to this study, the statistical modelling approach seeks, in the first place, to identify independent variables associated with changes in return dispersion, after which it examines whether return dispersion in itself is a key variable related to changes in the conditional returns of any asset allocation strategies.

A statistical modelling approach has both advantages and disadvantages. Mandel (1984) relates the advantages and disadvantages to a trade-off between objectivity and accuracy on the one hand and the problem of inductive inference on the other. Statistical analysis reduces relationships to objective, quantifiable amounts, which is of great potential benefit in an industry such as investment management. By applying statistical modelling, it is possible to form exact expectations of return dispersion, instead of relying on rules-of-thumb.

While statistical modelling reduces relationships to exact equations, it is vulnerable to a variety of potential shortcomings. Most importantly, there is a close link between statistical modelling and the problem of inductive reasoning, or moving from the particular to the general (Mandel, 1984). There is, of course, no guarantee that inferences drawn from any sample are universally valid. The nature of statistical modelling compounds this problem by making assumptions at both theoretical and modelling levels (Hofstee, 2010). As a result, relationships between variables may vary from sample to sample, or even within a sample depending on the statistical model employed.

Fortunately, there are methods for limiting the shortcomings of statistical modelling. First, basing candidate variables for a model on sound economic theory reduces the problem of inductive inference. If there is strong theoretical support for an empirical relationship between two variables, there is less chance of the result disappearing out-of-sample (Cochrane, 2008: 243). Second, a careful delineation of the theoretical and modelling assumptions reduces potential errors by clarifying the extent to which modelled results can be generalised to the real world. These issues are considered in the scope and limitations.

1.4 SCOPE AND LIMITATIONS

In order to address the issue of inductive reasoning, this study places itself in a theoretical context by characterising the time-variation in return dispersion and its relationship to asset allocation strategies from a rational economic perspective. In particular, the study makes use of a stock market modelling approach similar to Chen, Roll and Ross (1986) in order to characterise some of the changes in return dispersion over time. The stock market modelling approach makes use of both the efficient market hypothesis (EMH) and discounted cash flow (DCF) analysis.

Although a characterisation of time-variation in return dispersion and its relationship to asset allocation strategies is possible from a behavioural perspective, this study favours a rational economic approach for three reasons. First, following Cochrane (2008), by relating changes in return dispersion to rational economic factors, there is less chance of relationships disappearing out-of-sample as investors correct possible behavioural biases. Second, quantifying behavioural biases is a potentially difficult and possibly subjective exercise compared to a quantification of rational economic factors. Third, a variety of literature supports a rational interpretation of both return dispersion (Gomes, Kogan and Zhang, 2003; Jiang, 2010) and asset allocation strategies such as the value premium (Gomes et al., 2003; Petkova, 2006). Based on these considerations, this study argues that there is sufficient motivation for studying the research objectives from a rational economic perspective.

By assuming a rational economic framework, the study also makes an important assumption at a modelling level, namely that return dispersion is dependent on changes in the real economy. While the assumption that changes in the economy cause changes in the stock market is commonplace in studies (e.g. Chen et al. 1986; Schwert, 1989), there is evidence that stocks markets may influence the real economy (Patrick, 1966). In light of evidence that there is a two-way relationship between financial markets and the real economy, generalising results to infer causality should be treated with care. As a result, this study focusses on relationships between variables without inferring causality in its conclusions.

1.5 OVERVIEW OF THE REMAINDER OF THE STUDY

The remainder of the study is outlined as follows. Chapter 2 defines return dispersion and reviews literature related to the variable. The aim of the chapter is to provide a thorough grounding of what is meant by return dispersion, as well as to understand where the variable fits into literature. Chapter 3 presents the research method, first deriving research hypotheses, then defining variables for empirical purposes and outlining the statistical approach. Chapter 4 presents the main empirical findings and analysis. Chapter 5 concludes the study.

CHAPTER TWO
BACKGROUND AND RELATED LITERATURE

2.1 INTRODUCTION

This chapter provides a backdrop for the empirical work that follows in chapters 3 and 4. The aim of the chapter is twofold. First, the chapter defines the concept 'cross-sectional return dispersion'. A thorough explanation of what is meant by return dispersion is important given its central role in the thesis. Second, the chapter reviews literature related to return dispersion. The literature review provides context and justification for the two research questions examined in this study. Section 2.2 defines cross-sectional return dispersion, while section 2.3 reviews literature related to return dispersion.

2.2 CROSS-SECTIONAL RETURN DISPERSION

This section defines cross-sectional return dispersion using the cross-sectional and time-series expectations framework of Hwang and Satchell (2001). The expectations framework provides a useful method of defining cross-sectional return dispersion and drawing a distinction between cross-sectional return dispersion and time-series volatility. In addition, the framework clarifies what is meant by the term 'the time-series of return dispersion', which is frequently referred to in the empirical section of this paper.

A definition of cross-sectional return dispersion within the expectations framework begins with a delineation of time-series and cross-sectional expectations, from which the mean, variance, skewness and kurtosis of returns may be calculated from a time-series or cross-sectional perspective. First, for a market consisting of $i = 1, 2, \dots, N$ assets measured over $t = 1, 2, \dots, T$ time periods, the time-series expectation of asset x is:

$$E_{TS}\ x_{i,t}\ = \frac{1}{T}\ {}_{t=1}^{T} x_{i,t}\quad for\ i = 1, 2, \dots, N \tag{2.1}$$

Second, for the same market of $i = 1, 2, \dots, N$ assets measured over $t = 1, 2, \dots, N$ time periods, the cross-sectional expectation of assets is:

$$E_{CS}\ x_{i,t}\ =\ {}_{i=1}^{N} w_{i,t} x_{i,t}\quad for\ t = 1, 2, \dots, T \tag{2.2}$$

Where $w_{i,t}$ is a suitable weight for asset i at time t. A 'suitable weight' may be a probability (in which case $w_{i,t} \geq 0$ and $\sum_{i=1}^{N}(w_{i,t}) = 1$) or any other arbitrary weight, such as market capitalisation.

Equations (2.1) and (2.2) imply that it is possible to calculate the mean, variance, skewness and kurtosis from either a time-series or a cross-sectional perspective. An application of this concept to the variance of returns leads to a definition of time-series volatility and cross-sectional return dispersion. In both cases, the calculation of an expected mean precedes the calculation of variance. First, in a time-series setting, a mean return (or expected return) is calculated using a univariate model of returns, such as a first-order autoregressive process[2]:

$$r_{i,t} = \gamma_0 + \gamma_1 r_{i,t-1} + \varepsilon_{i,t} \tag{2.3}$$

Where γ_0 is an intercept term, γ_1 is a slope term and $\varepsilon_{i,t}$ is an error term at time t. Using (2.3), the variance of returns in each period t is expressed as $\varepsilon_{i,t}^2$.

Second, in a cross-sectional setting, the mean return is calculated as a weighted average of cross-sectional observations; using ex-ante return observations and a market capitalisation weighting implies that the mean can only be calculated using two or more asset returns in each time period:

$$r_{m,t} = \sum_{i=1}^{N} w_{i,t} r_{i,t} \tag{2.3}$$

Where $r_{m,t}$ is the average return across the N assets in the market. The variance in each period t is then expressed as $\sigma_{m,t}^2$, where:

$$\sigma_{m,t} = \sqrt{\sum_{i=1}^{N} w_{i,t}\left(r_{i,t} - r_{m,t}\right)^2} \tag{2.4}$$

Literature (e.g. Stivers, 2003; Chadha and Satchell, 2008) refers to equation (2.4) as cross-sectional return dispersion. This is the definition of cross-sectional return dispersion that is followed throughout the rest of the study; from this definition, the time-series of cross-

[2] A first-order autoregressive process, or AR (1) process, models the expected value of a variable in each time period as a function of its observed value in the previous time period.

sectional return dispersion refers to a series of periodical observations of cross-sectional return dispersion.

2.3 LITERATURE REVIEW

The remainder of the chapter focusses on a literature review of cross-sectional return dispersion, with a view to providing a background for the empirical work in this study. The section divides the literature into three subsections covering the use of cross-sectional return dispersion in three topics related to finance as a field of study. The three topics are (i) portfolio management, (ii) risk management and (iii) asset pricing. The literature review covers each topic by means of a non-exhaustive review of financial literature from books, journal articles and working papers. The review excludes literature from promotional research (i.e. in-house investment management research), due to the tendency of promotional research to focus on historical movements in return dispersion, complex mathematical extensions of return dispersion and the application of return dispersion in proprietary models.

2.3.1 RETURN DISPERSION IN PORTFOLIO MANAGEMENT

The use of cross-sectional return dispersion in the field of portfolio management springs from two sources, namely: (i) its use as an instantaneous measure of market correlation and (ii) its use as a proxy for active risk taking opportunity. First, Solnik and Roulet (2000) introduce the possibility of cross-sectional return dispersion serving as an instantaneous measure of correlation, citing the short estimation window of cross-sectional return dispersion (the authors cite a one month window versus the five years of data ordinarily used for correlation estimates) as the primary advantage of their method. The short estimation period of cross-sectional return dispersion leads Solnik and Roulet (2000) to derive a cross-sectional correlation measure, which they put forth as a useful alternative to traditional correlation estimates.

Second, De Silva, Sapra and Thorley (2001) introduce the possibility of cross-sectional return dispersion serving as a proxy for active risk taking opportunity through a combination of theoretical and empirical proof. First, the authors use the Capital Asset Pricing Model (CAPM) to demonstrate an analytical link between cross-sectional return dispersion and the spread in active returns across investment managers. The essence of De Silva et al. (2001)'s analytical proof is easily explained using a more intuitive approach. Consider table 2.1, which presents two return scenarios for a market containing three shares.

TABLE 2.1

TWO RETURN SCENARIOS

This table presents two scenarios for a market of three shares; for each scenario, the table reports share returns, market returns and cross-sectional return dispersion (CSRD). The cross-sectional return dispersion is calculated using equation (2.4).

	Share 1	**Share 2**	**Share 3**	**Average**	**CSRD**
Weight	15%	35%	50%	n.a.	n.a.
Return					
Scenario 1	13%	13%	13%	13%	0%
Scenario 2	24%	13%	9.7%	13%	4.86%

Source: Researcher's own data

A comparison of scenario 1 and scenario 2 presents a natural illustration of the association between return dispersion and the range of active opportunity. In scenario 1, all three shares earn 13%; as a result, market return is 13% and using equation (2.4) yields a return dispersion value of zero. In scenario 2, share 1 earns 24%, share 2 earns 13% and share 3 earns 9.7%; as a result, market return is still 13%, but in this instance, return dispersion is 4.86%. For a long-only active manager, scenario 1 presents no opportunity to outperform the market, since any combination of the shares yields the market return. By contrast, scenario 2 presents a long-only active manager an opportunity to earn up to 11% or lose up to 3.3% relative to the market. Intuitively, there is a direct link between the magnitude of active opportunity and the level of return dispersion.

A range of empirical literature supports the theoretical link between cross-sectional return dispersion and the range of active management outcomes. De Silva et al. (2001) confirm their own model by documenting a positive relationship between return dispersion and the spread between top- and bottom performing non-indexed U.S. mutual funds on Morningstar's database over the period 1981-2000. Ankrim and Ding (2002) extend the result of De Silva et al. (2001) by mitigating the possibility of sample-specific evidence along two dimensions. First, the authors find out-of-sample evidence of an association between return dispersion and the spread in performance across active managers in the United Kingdom and Japan, indicating that the result is not limited to the United States[3]. Second, the authors find that the

[3] Raubenheimer (2012) presents similar evidence for a sample of South African equity managers.

result holds for both small capitalisation and large capitalisation active managers, suggesting the result is not limited to any category of active manager[4]. The empirical evidence provided by De Silva et al. (2001) and Ankrim and Ding (2002) present robust support for the use of cross-sectional return dispersion as a proxy for active investment opportunity.

The evidence for using cross-sectional return dispersion as a proxy for active investment management leads to several theoretical papers documenting the use of return dispersion in portfolio management. These theoretical papers cover a broad choice of topics. De Silva et al. (2001) build upon their findings by developing an ex-post performance evaluation measure corrected for variation in return dispersion. Yu and Sharaiha (2007) derive a theoretical factor decomposition of return dispersion to identify 'alpha granularity', or the spread of active return opportunities across asset allocation styles and stock picking approaches. Chadha and Sacthell (2008) develop a mathematical model for quantifying the effect of return dispersion on various aspects of Grinold and Kahn's (1999) Active Investment framework. Gorman, Sapra and Weigand (2010a; 2010b) study the implications of return dispersion in Modern Portfolio Theory and Active Portfolio Management contexts[5] – motivating their work on the thesis that managerial talent and return dispersion serve as the primary determinants of active investment performance.

Gorman et al. (2010b) use their theoretical work to derive several interesting results. First, they demonstrate that cross-sectional return dispersion is related to time-series volatility and average market correlation in the form $\sigma_{cs,t} = \sigma_{ts,t} \ 1 - \rho \ ^{1/2}$, where $\sigma_{cs,t}$ is return dispersion, $\sigma_{ts,t}$ is time-series volatility and ρ is the average market correlation. By implication, return dispersion is a positive function of time-series volatility and a negative function of average market correlation. As a result, cross-sectional volatility may increase with either a jump in volatility or a decrease in correlation, but not necessarily with a simultaneous jump in both volatility and correlation. As such, time-series volatility, which is a feature of traditional active management frameworks (Gorman et al., 2010b) may be an inadequate measure in situations where changing market correlation causes its value to diverge from the level of return dispersion.

[4] Connor and Li (2009) provide additional support by documenting a positive relationship between return dispersion and the spread in U.S. hedge fund returns.

[5] Modern Portfolio Theory refers to the mean-variance optimisation framework of Markowitz (1959), while Active Portfolio Management refers to the framework of Grinold and Kahn (1999).

Second, total, systematic and idiosyncratic measures of portfolio risk are a positive function of return dispersion. The positive association between return dispersion and idiosyncratic risk allows a cross-sectional interpretation of Modern Portfolio Theory's diversification argument. In a time-series context, diversification reduces idiosyncratic risk by reducing the effect of idiosyncratic risk in constituent shares. In a cross-sectional context, diversification reduces the contribution of return dispersion to idiosyncratic risk: increasing the amount of shares in a portfolio reduces the risk of misidentifying future 'winner' and 'loser' shares. In this context, it is evident that the level of return dispersion plays some role in determining the optimal number of shares for diversification benefits.

Third, there is a linear relationship between cross-sectional return dispersion and both the level of active returns and the level of active risk, or tracking error. As a result, there are three important implications for benchmark relative investors. First, benchmark relative managers mandated to follow a certain level of tracking error need to form ex-ante expectations of return dispersion in order to align ex-ante and ex-post levels of tracking error. Second, investors within an information ratio framework will not benefit from timing strategies aimed at exploiting return dispersion, since the linear relationship of return dispersion to both active risk and active return implies a constant information ratio irrespective of the level of return dispersion. This limitation does not extend to absolute return investors. Third, to compound the second point, benchmark relative investors should be averse to increases in return dispersion. This result arises from a trade-off between increasing utility from higher active return and decreasing utility from higher tracking error, which results in a decreasing vector of active weights in Gorman et al.'s (2010b) theoretical framework.

An important thread in Gorman et al.'s (2010a; 2010b) theoretical models is the importance of variation in cross-sectional return dispersion over time, which influences the optimal number of shares for diversification, the divergence of ex-ante and ex-post tracking error levels and informs possible timing strategies for absolute return investors. The postulated relationship between return dispersion and traditional risk measures is also an important facet of their work. The relationship between return dispersion and a class of traditional risk measures, namely conditional heteroscedasticity models, is the topic of a concurrent body of literature; section 2.3.2 considers this literature.

2.3.2 RETURN DISPERSION IN VOLATILITY MODELLING

The use of cross-sectional return dispersion in risk management rests largely on its ability to improve volatility forecasts in variants of the autoregressive conditional heteroscedasticity models of Engle (1982) and Bollerslev (1986). This section documents a significant body of evidence that shows that return dispersion does improve autoregressive conditional heteroscedasticity estimates. The empirical evidence is defended along both statistical and economic grounds, although there is no conclusive consensus over the reason for return dispersion improving volatility estimates.

This section reviews empirical literature pertaining to the use of return dispersion in autoregressive conditional heteroscedasticity estimates. The section includes a brief discussion of the theoretical justification of empirical results in literature. Given the broad scope of economic and statistical theory in time-series volatility, some of which is evidenced in return dispersion literature, this section limits its discussion of the theoretical explanations to fairly simplistic and non-technical explanations.

From a statistical point of view, it is possible to separate volatility into market, common factor and firm-specific components (e.g. Campbell, Lettau, Malkiel and Xu, 2001; Connor Korajczyk and Linton, 2006). Most studies aimed at evaluating the role of return dispersion in volatility estimates argue that return dispersion captures some unobservable part of the market or common factor components of volatility. Hwang and Satchell (2001), for example, argue that return dispersion proxies for the unobservable market component in Campbell et al.'s (2001) volatility framework. Hwang and Satchell's (2001) empirical evidence indicates that return dispersion significantly improves the performance for a special case of Engle, Ng and Rothschild's (1990) multivariate GARCH model fitted to FTSE 350 Index and S & P 500 Index returns from 1989-1999. In addition, the authors find that return dispersion explains around 12-15% of asset specific variance, which they interpret as further support for their theoretical motivation.

Stivers (2003) follows a similar approach to Hwang and Satchell (2001) by suggesting that return dispersion may capture unobservable common factor shocks in the market. For a sample of monthly American Stock Exchange (AMEX) and New York Stock Exchange (NYSE) market returns over the period 1927-2005, Stivers (2003) shows that return dispersion significantly improves the performance of mean and variance components for a

Glosten, Jagannathan and Runkle (1993) asymmetric GARCH model fitted to the data. The result is robust along two dimensions. First, the result is consistent for a variety of alternate GARCH specifications, statistical models and volatility models. Second, the result is robust to the inclusion of both a default yield spread and recessionary factor, which Schwert (1989) demonstrates to be important factors in time-series volatility. Although these findings indicate that return dispersion makes a significant and unique contribution to volatility estimates, Stivers (2003) concedes that there is limited evidence for return dispersion capturing unobservable common factor shocks. Results show that return dispersion is also robust to the inclusion of size, industry and book-to-market factors, which are traditionally considered to be proxies for common factor shocks.

Connolly and Stivers (2006) extend the work of Stivers (2003) by examining whether return dispersion improves volatility estimates at firm and disaggregate portfolio level. For a sample containing daily returns of 1081 NYSE listed shares measured from 1985-1999, the authors find that adding return dispersion significantly improves volatility models using traditional lagged own-firm and market level shocks. The authors show that the result is robust across book-to-market, industry, market capitalisation and market beta levels. As with Stivers (2003), Connolly and Stivers (2006) note that the robustness of return dispersion to size, industry and book-to-market factors weakens the argument that return dispersion captures unobservable market shocks.

Connolly and Stivers (2006) note that, irrespective of evidence against return dispersion capturing unobservable common factor shocks, empirical evidence makes a strong case for return dispersion capturing some unobservable volatility component. Based on the authors' empirical evidence, they present two possible economic interpretations for the result. First, they suggest that return dispersion may capture persistent firm-level information flows, which may influence even index-level volatility, depending on the extent to which information flows are correlated across firms. Second, the authors suggest that return dispersion and volatility may capture dispersion in beliefs across investors and economic uncertainty associated with the current economic state, which could plausibly influence firm and index-level volatility. Connolly and Stivers (2006) find some evidence in favour of the second proposition by documenting that return dispersion and trading turnover are lower during weeks with frequent macroeconomic news updates.

Ratner, Meric and Meric (2006) propose a different economic interpretation by suggesting that return dispersion captures informational asymmetry across sectors as investors fail to follow all sectors equally. Allan and Gayle (1994) find that informational asymmetry leads to higher volatility. Based on the evidence by Allan and Gayle (1994), Ratner et al. (2006) suggest that return dispersion may lead stock market volatility. The authors test for a relationship between return dispersion and both industry and market level volatility using Granger causality tests for S & P 500 Index industry and market data over the period 1974-2003. Their empirical evidence indicates that high return dispersion causes volatility at market and industry level, while low return dispersion does not significantly predict either.

As a whole, volatility modelling literature presents strong evidence in favour of return dispersion improving time-series autoregressive conditional heteroscedasticity estimates. The evidence is robust to a variety of data, model and variables specifications, as well as to a variety of control variables. Despite strong empirical support, the precise statistical and economic interpretation of the evidence remains open to question. Nevertheless, some of the results presented in this section lead to further enquiry surrounding the use of cross-sectional return dispersion in asset pricing settings. The use of cross-sectional return dispersion in asset pricing settings is the topic of the following section.

2.3.3 RETURN DISPERSION IN ASSET PRICING

The use of cross-sectional return dispersion in asset pricing rests on arguments for its function as a countercyclical economic state variable. The concept ‘state variable’ in finance comes from Merton’s (1973) Inter-temporal Capital Asset Pricing Model (I-CAPM), which uses the term ‘state variable’ to refer to priced risk-factors capturing the ‘economic state’ in asset returns. Stivers (2003) first refers to the possibility that cross-sectional return dispersion is a possible state variable inasmuch it captures unobserved common-factor shocks in a market. A few studies examine the implications for asset pricing, namely that return dispersion may be a priced risk-factor in asset returns.

In order to evaluate whether return dispersion is a state variable, it is useful to consider what constitutes a state variable. Cochrane (2008) provides theoretical guidance for the evaluation of state variables by suggesting that they should fulfil two prerequisites. First, state variables should be motivated by economic theory. By grounding state variables in economic theory: (i) the state variables avoid the fishing license argument of Fama (1996)[6] and (ii) the proposed relationship is more likely to continue its existence in out-of-sample empirical work. Second, state variables should affect the conditional distribution of asset returns; that is either the conditional mean or conditional variance of asset returns. Literature on return dispersion defends its use as a state variable for both prerequisites.

First, asset pricing literature defends return dispersion on economic grounds by arguing that return dispersion is a leading countercyclical economic state variable that captures the effect of business cycles and transitions in economic state. Theoretical evidence by Gomes, Kogan and Zhang (2003) and empirical evidence by Christie and Huang (1994) and Campbell et al. (2001) show that return dispersion is higher during periods of economic recession. Based on the evidence, it is accepted that cross-sectional return dispersion is countercyclical. In addition, stock markets are forward-looking, which suggests a market variable such as return dispersion will lead the business cycle.

In addition, there is evidence that the relationship between return dispersion and the economic cycle is not merely a statistical anomaly. Evidence by Lougani, Rush and Tave (1990) indicates that return dispersion leads unemployment, which Stivers (2003) uses to suggest that return dispersion captures the reallocation of economic resources across industries. Connolly and Stivers (2003, 2006) support Stivers (2003)'s point by showing that return dispersion and trading turnover are significantly higher during periods with frequent economic news releases. The relationship between return dispersion, trading turnover and the frequency of news releases suggests that return dispersion captures portfolio reallocations across investors as they update asset allocations to reflect changes in economic state, which in turn suggests that return dispersion is a proxy for transitions in economic state.

Second, a variety of literature supports the ability of return dispersion to capture changes in both the conditional risk and conditional return of assets. Section 2.3.2 documents several papers showing that return dispersion is linked to the future level of share, portfolio and market volatility. Moreover, a variety of papers show that return dispersion is related to time-varying asset returns. Connolly and Stivers (2003), for example, find that share returns exhibit

[6] In light of the recent proliferation of factor-mimicking portfolios in asset pricing models justified as 'state variable', Fama (1996) labels the I-CAPM a 'fishing license', implying the I-CAPM has become a catch-all explanation for otherwise poorly motivated asset pricing models that are potentially only artefacts of data mining.

substantial momentum (reversals) over a two-week period when return dispersion and trading turnover are unexpectedly high (low) in the second week. The result is robust to alternate specifications using equity indices, index futures and individual stock returns.

Jiang (2010) argues that return dispersion captures economic transitions, uncertainty and business cycles arising from technology, policy and taste shocks. These shocks may have either homogenous or heterogeneous effects. Homogeneous shocks refer to business cycle shocks, which affects economic output and generally pulls shares in the same direction as the shock; that is expansionary or recessionary. Heterogeneous shocks refer to shocks that cause economic reallocation across firms, causing competitive advantage to shift across firms and a diverse reaction across firm share prices; as such, these shocks reflect the future output and state of the economy.

Based on the argument that return dispersion captures technology, policy and taste shocks, Jiang (2010) develops a theoretical model of consumption, which shows that share prices are affected by the market portfolio and cross-sectional return dispersion. Empirical tests of the model indicate that shares with higher sensitivity to return dispersion earn a higher risk premium, indicating return dispersion is a positively priced risk-factor. The two-factor model containing the market portfolio and return dispersion significantly outperforms the I-CAPM, Fama-French three factor model and a host of other asset pricing models in explaining returns over 25 portfolios constructed from NYSE and AMEX stock returns over the period 1963-2005. The explanatory power of return dispersion is robust to the inclusion of book-to-market, idiosyncratic volatility, market volatility, momentum and size factors.

Stivers and Sun (2010) take a different approach to Jiang (2010) by examining the effect of return dispersion on the value premium and the momentum premium. Citing theoretical evidence by Gomes et al. (2003) and Johnson (2002), the authors argue that return dispersion may be a leading countercyclical state variable that prices the value and momentum premiums. For a sample of NYSE and AMEX shares over the period 1962-2005, Stivers and Sun's (2010) empirical work indicates that a lagged three-month moving average of return dispersion is positively associated with the subsequent value premium and negatively associated with the subsequent momentum premium. The associations are robust to sub-period analysis, alternate specifications of the key variables and to the inclusion of popular economic state variables.

2.4 SYNTHESIS AND CONCLUSION

This chapter set out to define cross-sectional return dispersion and delineate its position in literature. To begin with, the chapter defined return dispersion within the cross-sectional and time-series expectations framework of Hwang and Satchell (2001). The framework of Hwang and Satchell (2001) provided a method of defining both return dispersion and time-series volatility, as well as drawing a distinction between the two concepts. After defining return dispersion, the chapter proceeded with a review of related literature. A survey of literature revealed that return dispersion features in portfolio management, volatility modelling and asset pricing literature.

Within the field of portfolio management, return dispersion plays an important role as a proxy for the active investment opportunity set. Earlier literature (e.g. De Silva et al., 2001) led to the proposition that return dispersion and managerial talent are the primary factors influencing a manager's active returns. From this proposition, numerous papers (e.g. Gorman et al., 2010a) proceeded to examine the role of return dispersion in active management. The scope of these papers span performance evaluation, market analysis and portfolio construction. Irrespective of their scope, these papers uniformly demonstrated that portfolio managers can only earn active returns to the extent that return dispersion exists in a market.

Although literature highlights the influence of return dispersion on the active opportunity set, there has been no substantial effort at discovering why return dispersion changes over time. A few papers demonstrate that return dispersion increases during recessions, but the relationship probably fails to capture the entirety of variation in return dispersion. Understanding time-variation in return dispersion has many potential uses in portfolio management, which is by its nature forward-looking. To begin with, multi-managers and private investors may use return dispersion to gauge whether a manager has sufficient opportunity to outperform a benchmark, before even considering if the manager has sufficient skill.

Turning from the strategic investment decision, managers themselves may benefit from understanding why return dispersion changes over time. Given theoretical evidence that return dispersion influences the alignment of ex-ante and ex-post tracking error, it is crucial that managers mandated to a certain level of tracking error understand how return dispersion changes over time. In addition, since there is evidence that return dispersion influences the optimal amount of shares for diversification, even passive managers, who may employ sampling techniques to match a benchmark (Ambachtsheer and Ezra, 1998: 71), should understand why return dispersion changes. In all of these applications, understanding why return dispersion changes can assist investors in managing their investments in a proactive manner.

The possible benefits of knowing why return dispersion changes have a recurring theme; investors can smooth investment returns over time by limiting active exposure to periods where the active opportunity set suggests that it is worthwhile. While understanding why return dispersion changes over time has great potential use in this regard, there is a qualification. Since return dispersion is a symmetrical measure, meaning it treats positive and negative returns equally, an increase in return dispersion also increases the likelihood of significantly underperforming a benchmark. In fact, the influence of potential underperformance on traditional risk measures leads theoretical models to suggest that risk-averse managers in a benchmark-relative framework should decrease active positions if the active opportunity set increases.

Although a negative theoretical relationship between the size of active positions and the active opportunity set seems counterintuitive, the link stands up to further inspection. If investors are unable to predict share returns, an increase in the active opportunity set will lead to an equal increase in the probability of active positions to outperform or underperform the market substantially. As a result, the occurrence of positive and negative active returns will average out over the long run, at the cost of higher transaction fees. If returns are random, risk-averse investors operating in a benchmark-relative framework should seek to reduce active positions if return dispersion increases.

At this point, it may seem that understanding the theoretical implication of return dispersion does not help the argument for benchmark relative active management. However, if managers can discover what kind of shares tend to perform well when active opportunity is high, there is still an incentive for active management. Although share returns are generally unpredictable, evidence by Banz (1981), Fama and French (1992) and others indicate that assets with certain characteristics generate reliable risk-adjusted returns over long periods. Returning to the role of return dispersion in asset pricing, which was examined in Section 2.3, there is strong evidence of a link between return dispersion and returns associated with at least a few of these characteristics. If there is a reliable link, it may be possible to smooth investment returns by improving managerial performance through exploiting time-variation in returns to certain investment strategies.

In summary, based on a review of literature, there seems to be sufficient justification for examining two research questions. First, why does return dispersion change over time? Second, is return dispersion related to time-variation in asset anomalies? The remainder of this thesis is an empirical investigation into these two research questions. By answering these two research questions, the study aims to contribute to portfolio management literature and the investment practice. As far as understanding why return dispersion changes over time, the study hopes to break new ground as far as investment literature is concerned. Although there is existing evidence of a relationship between return dispersion and the value premium, this study hopes to contribute by providing out-of-sample evidence for previous studies.

CHAPTER THREE
RESEARCH METHOD

3.1 RESEARCH OBJECTIVES

The previous chapter identified two key questions related to return dispersion. First, why does return dispersion change over time? Second, is return dispersion related to time-variation in any of the asset pricing anomalies? The remainder of this study aims to answer these two questions. In order to set the foundation for the empirical work that follows, this chapter begins by restating the two research questions as research objectives. This study aims to:

(i) Provide a characterisation of time-variation in return dispersion and
(ii) Evaluate the relationship between return dispersion and the value premium.

As mentioned at the close of the previous chapter, the first research objective is motivated, amongst others, by literature (e.g. Gorman et al., 2010b) demonstrating that return dispersion influences the optimal level of shares for diversification and the correspondence between ex-ante and ex-post levels of tracking error. The influence of return dispersion on these variables means managers must form ex-ante expectations of the level of return dispersion in strategic portfolio management decisions. The second research objective is motivated by literature (e.g. Gorman et al., 2010b) demonstrating that absolute return investors may profit from timing changes in return dispersion. Given the narrative of active performance as a function of managerial talent and return dispersion, this objective aims to test whether investors may exploit changes in return dispersion through asset allocation strategies.

The remainder of this chapter is devoted to setting up a method for evaluating the research objectives. The goal of the chapter is to move from the research objectives mentioned above to empirically testable hypotheses and to set up a testing procedure for evaluating the hypotheses. Section 3.2 covers the research design, section 3.3 develops the hypotheses, section 3.4 presents the sample selection, the data and construction of key variables and section 3.5 presents the statistical method. Section 3.6 concludes the chapter.

3.2 RESEARCH DESIGN

This study characterises time-variation in return dispersion from both a univariate time-series and a multivariate econometric perspective. Examining time-variation in return dispersion from a univariate time-series perspective allows a characterisation of return dispersion based only on variation in past observations of its own series, which is useful since it imposes minimal structure to the series (Pindyck and Rubinfeld, 1998: xv). Multivariate econometric models allow a characterisation of return dispersion based on variation in observations of an independent series, which is useful since it allows a method of evaluating possible variation in return dispersion based on the expected variation of other readily observable variables (Pindyck and Rubinfeld, 1998: xv-xvi). Combining the two perspectives should provide a balanced characterisation of return dispersion over time.

As far as a multivariate approach and independent variables are concerned, the study characterises the time-variation in return dispersion and its relationship to the value premium from a rational economic perspective. In particular, the study makes use of the Efficient Market Hypothesis (EMH) and the Discounted Cash Flow model (DCF)[7]. The EMH states that security prices update quickly and without bias[8] to reflect new information (Malkiel, 2003:59; Moolman and du Toit, 2005:80). The DCF model states that security prices equal fundamental value, or the present value of expected future cash flows (Pinto, Henry, Robinson and Stowe 2012: 84). By using the EMH and DCF model, the study places itself in a stock market modelling context similar to Chen et al. (1986) and Schwert (1989).

Although a characterisation of time-variation in return dispersion and its relationship to the value premium is possible from a behavioural finance perspective, this study chooses to focus on a rational economic perspective. There are three reasons for this. First, based on Cochrane (2008), tying changes in return dispersion to rational economic factors reduces the likelihood of results disappearing out of sample as investors correct possible behavioural biases. Second, quantifying behavioural biases is a difficult and possibly subjective exercise compared to a quantification of rational economic factors. Third, a variety of literature supports a rational interpretation of both return dispersion (Gomes et al. 2003; Jiang, 2010) and the value

[7] Mandelbrot (1963), Samuelson (1965) and Fama (1970) demonstrate that the EMH and DCF model are congruent theoretical traditions in the rational economic approach (Moolman and du Toit, 2005: 80).

[8] Unbiased adjustments imply that, while the adjustments are not always correct, over and under-adjustments occur in an unpredictable manner (Moolman and du Toit, 2005: 80).

premium (Gomes et al., 2003; Petkova, 2006; Stivers and Sun, 2010). Based on these considerations, there appears to be sufficient motivation for a rational economic perspective.

Within the rational economic perspective, the study characterises time-variation in return dispersion and its relationship to the value premium in terms of association, or the degree to which the variables ‘move together’. Given the likelihood of exogenous underlying factors, i.e. the technological, policy or taste shocks of Jiang (2010), results are not generalised to infer causal relationships.

3.3 HYPOTHESES

The following five subsections use the two research objectives, namely (i) characterising changes in return dispersion over time and (ii) characterising the relationship between return dispersion and the value premium, in order to develop empirically testable hypotheses. In order to facilitate a characterisation of return dispersion over time, the study suggests four hypotheses:

(i) Cross-sectional return dispersion is related to past observations of its own series.

(ii) Cross-sectional return dispersion is countercyclical to aggregate economic activity.

(iii) Cross-sectional return dispersion is related to domestic economic uncertainty.

(iv) Cross-sectional return dispersion is related to international economic uncertainty.

In order to facilitate an examination of the relationship between cross-sectional return dispersion and the value premium, the study suggests the following hypothesis:

(v) Cross-sectional return dispersion is related to time-variation in the value premium.

The following two sections use a combination of economic and financial theory, as well as empirical evidence, in order to develop the five respective hypotheses. Section 3.3.1 provides a theoretical and empirical foundation for each of the four hypotheses related to characterising change in cross-sectional return dispersion over time, while section 3.3.2 provides a theoretical and empirical foundation for characterising a relationship between cross-sectional return dispersion and the value premium.

3.3.1 DEFINING TIME-SERIES PROPERTIES OF RETURN DISPERSION

Pindyck and Rubinfeld (1998) describe two general approaches to modelling series. First, a time-series approach uses historical values of a series to draw inferences about possible future behaviour. Second, an equation modelling approach defines a series as a linear or nonlinear function of one or more independent variables. Both represent possible approaches to characterising changes in return dispersion over time. The following four subsections develop hypotheses from these two general approaches.

3.3.1.1 Univariate properties

There are three basic univariate stationary time-series models[9]. First, autoregressive (AR) models express the expected value of a series as a function of past observations. For a series x_t, an autoregressive model over *p* lags, or AR (*p*), may be expressed as:

$$x_t = \theta_0 + \sum_{i=1}^{p} \theta_i x_{t-i} + \varepsilon_t \qquad (3.1)$$

Where θ_0 is an intercept term, θ_i is the autoregressive coefficient for the observation x_{t-i} and ε_t is the error term at time t.

Second, moving average (MA) models express the expected value of a series as a function of past deviations from an expected value. For a series x_t, a moving average model over *q* lags, or MA (*q*), may be expressed as:

$$x_t = \delta_0 + \varepsilon_t + \sum_{i=1}^{q} \delta_i \varepsilon_{t-i} \qquad (3.2)$$

Where δ_0 is an intercept term, ε_t is the error term at time t and δ_i is the moving average coefficient for error term ε_{t-i}.

[9] For a more in-depth discussion of the models presented in this section, please refer to Cryer and Chan (2008).

Third, autoregressive moving average (ARMA) models use the output from a MA (q) model as input for an AR (p) model. For a series x_t with moving average output $\nu_t = \delta_0 + \varepsilon_t + \sum_{i=1}^{q} \delta_i \varepsilon_{t-i}$, an ARMA ($p$, q) model may be expressed as:

$$x_t = \theta_0 + \sum_{i=1}^{p} \theta_i x_{t-i} + \nu_t \tag{3.3}$$

Which is an AR (p) model with errors modelled by the output from an MA (q) model.

All of the models assume that the error terms ε_t are white noise with a constant error variance σ_e^2. If the error variance is non-homogeneous and changes over time (i.e. a conditional variance process), then conditional heteroscedastic models on the error terms are appropriate. If series x_t may be specified as output from an AR, MA or ARMA model μ_t, and error term ε_t, then it is possible specify the series as $x_t = \mu_t + \varepsilon_t$, where:

$$\varepsilon_t = \sigma_t . u_t \tag{3.4}$$

Where σ_t is a time-varying standard deviation and u_t is an independent and normally distributed standardised error series with a mean of zero and variance of one. Using equation (3.4), an Engle (1982) ARCH (m) model using the time-varying standard deviation may be defined as:

$$\sigma_t^2 = \varphi_0 + \sum_{i=1}^{m} \varphi_1 \varepsilon_{t-i}^2 \tag{3.5}$$

Where φ_0 and φ_1 are the slope and intercept terms and ε_{t-i}^2 is the squared error term from equation (3.4). Bollerslev's (1986) GARCH (m, s) model generalises (3.5) to:

$$\sigma_t^2 = \varphi_0 + \sum_{i=1}^{m} \varphi_i \varepsilon_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2 \tag{3.6}$$

Where φ_0 is a slope term, φ_i is an intercept term for the squared error term at time $t - i$ and β_j is an intercept term for the conditional variance at time $t - j$.

This study considers whether the three basic stationary time-series models along with the conditional variance models are suitable for the time-series of return dispersion. All three of the basic models assume a degree of serial correlation, or correlation of observations over time. The prerequisite of serial correlation is the starting point for formulating the first hypothesis.

Hypothesis 1: Return dispersion is associated with historical observations of its own series.

Empirical evidence by Hwang and Satchell (2001), Stivers (2003) and Stivers and Sun (2010) indicate significant levels of serial correlation in return dispersion. Serial correlation is a key component of univariate time-series models, since these models assume that historical values of a series may be extrapolated into future time-periods. Based on the empirical evidence by Hwang and Satchell (2001) and others, this study examines the ability of time-series models to characterise return dispersion by proposing that *return dispersion is associated with past observations of its own series* in the South African equity market. In order to test if return dispersion is associated with past observations of its own series, the null-hypothesis is formulated as:

H_{01}: Return dispersion is unrelated to historical observations of its own series.

3.3.1.2 Structural properties

Structural modelling of stock market data often proceeds from the EMH and the DCF model (e.g. Chen et al., 1986; Schwert, 1989). The basic intuition of the EMH and DCF approach easily extends to return dispersion. This section derives the basic stock market modelling approach and extends it to a cross-sectional framework in order to derive hypotheses for structural sources of variation in return dispersion.

To begin with, a single-period DCF model is:

$$p_{i,t} = E_t \;\; x_{i,t+1} \quad E_t \;\; m_{i,t+1} \tag{3.7}$$

Where $p_{i,t}$ is the price of security i at time t, E_t is a time-varying expectations operator, $x_{i,t+1}$ is the expected payoff for security i in time t and $m_{i,t+1}$ is the expected discount rate for security i in time t.

The stock market modelling approach assumes that market-wide economic factors will influence the mean and variance of share returns. Chen et al. (1986) argue that the price of security i at time t in equation (3.7) is only influenced by variation in its expected payoff or expected discount rate. Under the diversification argument of Sharpe (1964), only market-wide systematic factors affect share price; as such, only aggregate economic factors that influence the expected payoff or discount rate of a security may affect security returns. Schwert (1989) extends the argument to time-series volatility by arguing that variance in $p_{i,t}$ reflects variance in aggregate economic factors.

The basic thesis of stock market modelling is easily extended to return dispersion by combining an analytical proof from Cochrane (2008) with evidence from Jiang (2010). First, Cochrane (2008) dissects equation (3.7) into risk-free and risk-bearing components using the definition of covariance and a risk-free rate $r_f = 1 \quad E(m)$[10]:

$$p_{i,t} = E_t \;\; x_{i,t+1} \quad E_t \;\; r_{f,t+1} \quad + cov(x_{i,t+1}, m_{i,t+1}) \tag{3.8}$$

Equation (3.8) states that a security's price is a function of a risk-neutral present value and the covariance of its expected payoff with the expected discount rate. Securities with a higher negative covariance with the discount rate command a higher risk-premium, or equivalently a lower price. From equation (3.8), it is possible to develop three hypotheses regarding time-variation in return dispersion.

Hypothesis 2: Return dispersion is associated with the business cycle

Cochrane (2008) defines the risk-free interest rate as a proxy for growth in the marginal value of wealth. Marginal value of wealth is a measure of 'hunger', since it captures the value of one additional unit of return. From this perspective, the risk premium in equation (3.8) captures the covariance of asset returns with the marginal value of wealth. In particular, shares that are expected to perform poorly when the marginal value of wealth is high will command a higher unconditional risk-premium.

Under the assumption that the marginal value of wealth is related to the business cycle[11], the definition of a risk premium in equation (3.8) may be used to draw business cycle implications for share returns from both time-series and cross-sectional perspectives. From a

[10] See Appendix A for the derivation of (3.8).

[11] Cochrane (2008) states that the marginal value of wealth will be higher during bad times such as recessions.

time-series perspective shares with a high risk premium are expected to perform poorly during recessionary periods (Cochrane, 2001: xiv). From a cross-sectional perspective share returns are expected to diverge during recessions, as the recession forces economic reallocation across industries and firms (Jiang, 2010).

As a result of economic reallocation across firms and an accompanying divergence in share returns, this study attempts a further characterisation of return dispersion by proposing that *return dispersion is countercyclical to the aggregate economy* in the South African market. Theoretical evidence by Gomes et al. (2003) and empirical evidence by Christie and Huang (1994) and Stivers and Sun (2010) support this proposition. In order to test if return dispersion is countercyclical to the aggregate economy, the null-hypothesis is formulated as:

H_{02}: Return dispersion is not associated with the business cycle.

Hypothesis 3: Return dispersion is associated with domestic economic uncertainty

The proposed association between return dispersion and the business cycle refers to mid- to long-term fluctuations in return dispersion. In addition to these long-term fluctuations, it is possible that short-term economic dynamics affect return dispersion. Schwert (1989) suggests that variance in economic factors, which he proposes as a proxy for economic uncertainty, influences share return variance. In a similar vein to the time-series and cross-sectional business cycle characteristics of security returns; if economic shocks have heterogeneous effects across shares, in line with Jiang (2010), then it is possible that return dispersion will fluctuate over the short term in response to economic shocks. Based on this, this study attempts a characterisation of return dispersion by proposing that *return dispersion is related to domestic economic uncertainty* in the South African market. This proposition is tested by formulating the null-hypothesis as:

H_{03}: Return dispersion is not associated with domestic economic uncertainty

Hypothesis 4: Return dispersion is associated with foreign economic uncertainty

The proposed association between return dispersion and economic uncertainty may not be limited to domestic economic effects. South Africa is a small open economy that attracts increasingly large offshore investments. Table 3.1 illustrates the growth in offshore investments over the period 1990-2010. Given the increasing importance of foreign investors, it is possible that return dispersion may be affected by foreign economic dynamics. Based on this, this study attempts a final characterisation of time-variation in return dispersion by proposing that *return dispersion is related to foreign economic uncertainty* in the South African market. This proposition is formally tested by formulating the null-hypothesis as:

H_{04}: Return dispersion is not associated with foreign economic uncertainty

TABLE 3.1

TOTAL PORTFOLIO INFLOWS 1990 – 2010

This table shows portfolio inflows from non-resident investors to the South African market over the period 1990-2010. The table presents the yearly total Rand amount of portfolio inflows, in thousands at four-year intervals over the reported period. The data comes from the South African Reserve Bank.

	1990	**1994**	**1998**	**2002**	**2006**	**2010**
Total (R "000)	21.7	67.3	179.7	308.2	716.2	1192.3

Source: South African Reserve Bank

3.3.2 RETURN DISPERSION AND THE VALUE PREMIUM

Equation (3.8) easily extends to capture time-variation in the value premium. Recall that the definition of the risk-premium in equation (3.8) implies that firms earn a higher unconditional risk-premium if they perform poorly when the marginal value of wealth is high. From this result, it is possible to formulate the last hypothesis.

Hypothesis 5: Return dispersion is associated with the value premium

If the value premium is a rational economic phenomenon, then there is a strong possibility that it reflects the exposure of shares to changes in the marginal value of wealth. By implication, if there is a plausible link between return dispersion and the marginal value of wealth (Jiang, 2010), then the two variables will contain a degree of co-movement. Based on this, this study proposes that *return dispersion is associated with the value premium.* This is formally tested by formulating the null-hypothesis:

H_{05}: Return dispersion is not associated with the value premium.

The five hypotheses should allow a relatively thorough examination of the research objectives. The remainder of the chapter discusses the method applied to testing the hypotheses, covering sample selection, the data and variable construction in section 3.4 and the statistical method in section 3.5.

3.4 DATA AND VARIABLES

3.4.1 SAMPLE

The hypotheses are evaluated using monthly data over the period June 1996 to December 2011. The June 1996 start date allows the dataset to commence after the introduction of the Johannesburg Equities Trading (JET) JET system by the Johannesburg Stock Exchange (JSE) in March 1996. Van Zyl, Botha and Skerrit (2003: 298) show that market turnover increases substantially following the introduction of the JET system. Given evidence by Connolly and Stivers (2003, 2006), who document a positive contemporaneous relationship between turnover and return dispersion, including data prior to March 1996 introduces the possibility of a structural break in return dispersion. December 2011 concludes the last year for which a full year of financial data was available at the time of data collection.

3.4.2 DATA SOURCES

The key variables require data from a variety of sources. McGregor-BFA (M-BFA) provides financial market data, including market value, price and volume data at a monthly frequency, as well as yearly book value per share values at financial year-end. The South African Reserve Bank (SARB) provides monthly observations of industrial production, the coincident economic indicator, various exchange rates (discussed in section 3.4.4.3) and 10- year South African Government bond yields, as well as weekly observations of the 91-day South African Treasury bill yield. Statistics South Africa provides monthly observations of the headline CPI index from which inflation is calculated. The Federal Reserve Bank of St. Louis provides monthly observations of U.S. 91-day Treasury-bill yields and U.S. 10-year Government Bond yields, as well as Moody’s Aaa and Baa Rated Corporate Bond Indices.

3.4.3 A COMMENT ON DATA EDITING AND RELIABILITY

M-BFA’s database yields 958 JSE listed shares for which at least a share code, company name and at least one financial data observation exists over the sample period. The 958 shares serve as a foundation from which to calculate return dispersion and the value premium. For each of the 958 shares, the study conducts a basic data editing procedure, spanning (i) the calculation of share returns and (ii) the editing of outliers. This section considers these two topics.

Share returns

This study calculates returns as follows; for any share i of the 958 available shares, the return in month t is equal to the natural logarithm of the sum of price and dividend in month t over the price in month $t-1$[12]:

$$r_{i,t} = ln \quad p_{i,t} + d_{i,t} \quad p_{i,t-1} \tag{3.9}$$

Where the dividend $d_{i,t}$ is equal to the actual dividend amount in the month when the last day to trade occurs. This method, which assumes the dividend’s last day to trade occurs at month-end, reduces endogenous noise arising from price adjustments when shares go ex-dividend. A slight mismatch between the actual price adjustment and assumed price adjustment occurs if the last day to trade does not occur at month-end. Nevertheless, this method is preferable to alternative methods such as adding one-twelfth of the dividend yield to monthly returns.

Adjustment for outliers

Numerous South African studies (e.g. Bailey and Gilbert, 2007; Gilbert and Strugnell, 2010) note that historical market data drawn from South African databases contain inaccuracies. In particular, these studies draw attention to pricing errors among older data. In addition, exogenous noise arises in price series due to M-BFA’s lack of adjustment for share splits or demergers (McGregor-BFA, 2012). As a result, many of the return series calculated from

[12] The calculation, as well as all subsequent return calculations, uses the closing price on the last trading day of the month.

equation (3.9) contain large fictitious return observations, which introduce substantial noise and clouds statistical analysis.

This study controls for these large fictitious return observations by means of a trimming and winsorisation process. Trimming and winsorisation correct for values in the extreme tails of variable distributions by defining outliers relative to some boundary value. The boundary value is ordinarily a symmetrical measure such as the mean plus or minus a predetermined number of standard deviations. Trimming removes outliers from a series entirely, while winsorisation sets values outside of the boundary value equal to the boundary value.

Although many South African studies (e.g. Van Rensburg, 2001; Bailey and Gilbert, 2007) correct for share events such as demergers or share splits by individually correcting relevant return observations, there are two factors that favour a trimming and winsorisation approach. First, M-BFA appends share series for companies that merge; as a result, some difficulty exists concerning correcting for share events. Second, the dataset is large (99 862 total return observations), which makes trimming and winsorisation a more time-efficient process.

The trimming and winsorisation process itself follows Foster (1978): First, an aggregate mean and standard deviation of share returns is calculated over all 958 shares. Next, observations lying more than five standard deviations from the mean are trimmed from the dataset[13]. Then, the aggregate mean and standard deviation values are recalculated, after which observations lying more than three standard deviations from the mean are set equal to the boundary value of the mean plus or minus three standard deviations. The last step also sets trimmed observations from the second step equal to the boundary value.

Trimming and winsorisation is subject to some criticism in literature. This study calibrates its trimming and winsorisation process in order to address some of these criticisms. First, trimming and winsorisation may result in the misidentification of outliers, which destroys information (Chernobai, Rachev and Fabozzi, 2007) and adversely affects regression estimates (Lien and Balakrishnan, 2005). A three standard deviation boundary rule addresses this issue, since it recodes only 0.005% of the most extreme observations, thereby minimising the likelihood of misidentifying outliers.

[13] Although Foster (1978) uses the median for this step, using log returns yields an approximately normal distribution; for this reason, the study uses a mean value.

Second, a symmetrical trimming and winsorisation rule may bias a non-normally distributed dataset, since it emphasises one side of the variable's distribution (Reifman and Keyton, 2010: 1637). A database of share returns, for example, may be positively skewed, which biases a symmetrical rule to exclude negative return observations. Although this is potentially a strong criticism against the use of trimming and winsorisation for share returns, using lognormal returns calculated from equation (3.9) yields a closer approximation to normally distributed returns, which reduces potential bias.

In order to assess the reliability of the return series after trimming and winsorisation, the study calculates a correlation coefficient between a value-weighted composite return series from the database and actual market returns. Using a composite return series equal to the returns of the top 40 return shares in each year ranked by market value, and actual market returns based on the FTSE/JSE Top 40 Index yields a correlation coefficient of 0.975[14]. This indicates that the return series are nearly perfectly correlated over the sample period. Based on a correlation coefficient of 0.975, the empirical work proceeds under the assumption that the data is reliable.

3.4.4 KEY VARIABLES

3.4.4.1 Return dispersion

The empirical work features two return dispersion measures calculated from an equal-weighted specification of the return dispersion formula presented in equation (2.4):

$$RD_t = \sqrt{\frac{1}{N-1} \cdot \sum_{i=1}^{N} \left(r_{i,t} - r_{m,t}\right)^2} \tag{3.10}$$

An equal-weighted measure is deemed favourable based on the nature of the South African equity market. The Johannesburg Stock Exchange is a highly concentrated market (Raubenheimer, 2011); by specifying an equal-weighted measure, the empirical work attempts to avoid the possibility of a few shares dominating the return dispersion measure. Although an equal-weighted measure is slightly incongruent with the actual situation faced by

[14] Sub-period analysis of the correlation coefficient indicates that the result is equivalent for both back-stated returns prior to the listing of the FTSE/JSE Top 40 index in June 2002 and for actual returns thereafter.

active managers, who typically face evaluation on a value-weighted benchmark, an equal-weighted measure remains highly useful as long as it specifies the 'market' correctly.

The two 'markets' of shares used to calculate return dispersion loosely correspond to the FTSE/JSE Top 40 and FTSE/JSE All-Share Indices. For each month in year t, the return dispersion calculation uses the top 40 or 160 shares ranked by market capitalisation at the end of December of year $t-1$. The FTSE/JSE Top 40 and FTSE/JSE All-Share Indices are usually appropriate benchmarks for South African portfolio managers. This study assumes that the shares in these Indices are generally large enough for an equal-weighted return dispersion measure to remain informative about active investment opportunity[15].

In addition to remaining informative about the active investment opportunity set, Stivers (2003) identifies three reasons for removing smaller shares from the return dispersion measure. First, an equal-weighted return for large shares will remain a good proxy for the overall value-weighted market. Second, removing smaller shares from the return dispersion measure will remove related asynchronous trading and idiosyncratic variance issues associated with smaller shares. Third, Lo and MacKinlay (1990) show that large firm returns tend to lead small firm returns. Based on these arguments, there appears to be a sufficient case for focussing on the top 40 and top 160 shares in the return dispersion calculation[16].

3.4.4.2 The value premium

This study follows a traditional portfolio sorting approach (see, for example, Fama and French, 1992; Jegadeesh and Titman, 1993) by defining the value premium as the return spread between top and bottom tertile[17] portfolios ranked on price-to-book ratios. To control for the effect of share size on returns, shares are ranked into three size segments before constructing price-to-book ratio tertile portfolios. This study follows guidance by Fama and French (2008) and Hoffman (2012) in order to identify appropriate size segments.

[15] This may be a slightly more tenuous assumption for the top 160 shares, for which reason the study uses the top 40 measure as its primary return dispersion measure in Chapter 4.

[16] Please note that, here and throughout the rest of the study, references to uncapitalised "top 40" and "top 160" measures refer to constructed return dispersion measures and not to the FTSE/JSE TOP 40 and FTSE/JSE All-Share Indices upon which they are based.

[17] A tertile refers to three equally sized parts of a distribution.

The remainder of this sub-section devotes itself to a detailed description of the value premium calculation. The method itself is based primarily on the method of Fama and French (1992). A brief synopsis runs as follows; for each year t, the portfolio sorting method ranks eligible shares using market values taken at the end of June of year t. After ranking shares by market value, the portfolio sorting method ranks shares in each size segment using price-to-book values taken at the end of December of year $t - 1$. For each size segment, the portfolio sorting method divides ranked shares into quintile portfolios, for which it then captures portfolio returns from July of year t to June of year $t + 1$. Portfolio returns comprise both equal and value-weighted returns.

The calculation method uses several assumptions at each point in the summary above. These assumptions cover:

(i) The selection of eligible shares,

(ii) The calculation of price-to-book ratios,

(iii) The share ranking and portfolio formation procedure and

(iv) The calculation of portfolio returns.

Eligible shares

Value premium literature presents several prerequisites for eligible shares. First, most South African studies exclude non-financial and non-gold shares (Mutooni and Muller, 2007) in order to minimise potential bias. Financial firms have a unique definition of book value, which complicates comparison with other firms. A strong association between gold share performance and the gold price (De Villiers, Lowing, Petit and Affleck-Graves, 1986) introduces a potential exogenous source of return variation. Second, Hoffman (2012) excludes shares with less than 24 months of return data, in order to minimise possible idiosyncratic effects. Third, many South African studies (e.g. Van Rensburg, 2001; Bailey and Gilbert, 2007) introduce thin trading filters to control for bias from asynchronous trading.

This study follows the guidance found in South African literature by excluding non-financial and non-gold shares, shares listed for less than 24 months and thinly traded shares. In a similar vein to Van Rensburg (2001), this study excludes shares with zero trading volume in any month. Although the 24-month trading rule and thin trading filter introduce potential look-ahead bias, there are important mitigating factors. The crux of these mitigating factors is that an investor mechanically selecting non-financial and non-gold shares from the top 160 shares[18] ranked on the market value would arguably arrive at a very similar universe of shares over the sample period.

First, in the instance of the 24-month trading rule, shares with less than 24 months of listed data are most likely micro capitalisation shares, since very few firms list with a large market capitalisation structure. Although the 24-month minimum listing rule excludes 5% of the shares in the database, these shares are most likely micro capitalisation shares that the average investor would seek to avoid. Second, in the instance of the non-zero trading volume rule, a similar logic applies. Amihud (2013) shows that there is an inverse relationship between market capitalisation and trading volume, which arguably relegates zero trading volume occurrences to micro capitalisation shares once again. Applying the eligibility rules yields an average of 121 shares per year, which will arguably be reasonably close to the FTSE/JSE All-share Index constituents net of financial and gold shares.

The price-to-book ratio

The price-to-book (P/B) ratio for any share i used in the value premium calculation in year t is equal to the quotient of share i's share price at the end of year $t-1$ to its book-value per share at the financial year end of firm i in year $t-1$.

$$P\ B_{i,t} = \frac{Price_{i,Dec\ t-1}}{Book\text{-}value\ per\ share_{i,(fye)\ t-1}} \tag{3.11}$$

Following M-BFA, book-value per share is defined as ordinary shareholders interest at financial year-end (M-BFA line item 0201001) divided by the number of shares in issue at financial year-end (M-BFA line item 01050101). Using the share price at year-end ensures that the book value per share is known to market participants when measuring P/B ratios. In addition to the six-month lag between price-to-book ratio measurement and portfolio measurement, the method of calculating the P/B ratio should ensure that no look-ahead bias exists. Fama and French (1992: 430) show that the measurement date mismatch between book-value and share price does not materially affect empirical evidence for the value premium.

[18] The top 160 shares ranked by market value is a loose approximation of the FTSE/JSE All-Share index.

Share ranking and portfolio formation

In each year t, shares for which a price-to-book ratio exists at the end of year $t-1$ are ranked by market capitalisation in June of year t, after which they are allocated to three market value segments. The breakpoints for market value segments follow Hoffman (2012). Shares in the bottom 3% of aggregate market value are allocated to a *Micro* size segment, shares that make up the fourth to thirteen percentile of aggregate market value are allocated to the *Small* size segment and shares that make up the top 87% of market value are allocated to the *Large* size segment. In addition to the Micro, Small and Large size segments, two aggregate market size segments are calculated, namely a *Market* size segment, which aggregates the Small, Micro and Large size segments and a *Market Less Micro* size segment, which aggregates the Small and Large size segments.

Within each size segment, shares are ranked by P/B ratios and subdivided into tertile portfolios. Following Fama and French (1992), the tertile portfolios exclude negative P/B ratio observations arising from negative ordinary shareholders equity. The tertile portfolio specification allows a reasonable balance between a sufficient spread in P/B ratios and an adequate number of shares in each of the portfolios. This point is demonstrated in table 3.2, which presents summary statistics for each size segment.

TABLE 3.2

SUMMARY OF BREAKPOINTS BY MARKET CAPITALISATION

This table presents summary information for tertile portfolios in each size segment. For each size segment, the table presents the market-value breakpoints, as well as the minimum, maximum and mean number of shares in each size segment. The mean number of shares includes the mean amount per tertile.

Size segment	**Breakpoints (Cum% of market cap)**		**Share count**			
	Bottom	**Top**	**Min**	**Max**	**Mean**	**Tertile**
Micro	0	3	44	91	59	20
Small	3	13	24	38	31	10
Large	13	100	25	41	32	10
Market	0	100	100	155	121	40
Market less micro	3	100	45	75	62	20

Source: Researcher's own data

Tertile portfolios within the Micro size segment contain an average of 20 shares per year, while the quintile portfolios within the small and large size segments each contain an average of ten shares per year. Tertile portfolios within the Market less micro and Market segments contain an average of 20 and 40 shares per year, respectively. This seems reasonably well specified in light of Patterson (1995), who recommends a minimum of ten shares per portfolio in order to generate stable statistical inferences.

Portfolio returns

For each tertile portfolio, returns are calculated from July of year t to June of year $t + 1$. The empirical work in this study features both equal and value-weighted returns for tertile portfolios, using an aggregated version of equation (3.9):

$$r_{p,n}^{EW} = ln\left(1 + \frac{1}{N} \cdot \sum_{i=1}^{N} \frac{P_{i,n} + D_{i,n}}{P_{i,n-1}}\right) \tag{3.12}$$

For equal-weighted returns and

$$r_{p,n}^{VW} = ln\left(1 + \sum_{i=1}^{N} w_{i,t} \frac{P_{i,n} + D_{i,n}}{P_{i,n-1}}\right) \tag{3.13}$$

For value-weighted returns, where N is the number of shares in the quintile, $P_{i,n}$ and $D_{i,n}$ are the closing price and dividend received for tertile constituent share i in month n and $P_{i,n-1}$ is the closing price for tertile constituent share i at the end of month $n - 1$. For equation (3.13), $w_{i,n}$ is the market capitalisation weight of constituent share i in month n relative to the aggregate market capitalisation of all shares within its tertile portfolio.

The return calculation controls for delisted shares by assuming that they are sold at closing price on the last day of the month prior to the month of delisting. Proceeds are reinvested equally among the remaining shares with no taxes or transaction costs. Since the JSE requires companies to seek shareholder approval prior to delisting (JSE, 2011), it is assumed that an investor would be able to anticipate delisting and liquidate holdings in the company in the month prior to delisting. The process of seeking shareholder approval is expected to take at least 30 days, which makes it reasonable that an investor would be able to anticipate delisting in the manner described above.

3.4.4.3 Economic variables

This study selects economic variables based on the taxonomy of Chen et al. (1986). Chen et al. (1986) identify a variety of economic variables that may influence share returns through either expected payoffs or the discount rate. First, the expected payoff may be a function of general economic activity. Second, the discount rate may be influenced by a variety of factors. The discount rate is an average of rates over time; as such, both the level and term structure of interest rates will influence the discount rate (Chen et al., 1986: 385). In addition, the discount rate may be dissected along both real and nominal components and risk-free and risk-bearing components. These components suggest the discount rate consists of a real risk-free component and risk-bearing components covering inflation and other risks such as default risk; all of these components may affect the discount rate.

Real economic variables

This study uses the growth rate of industrial production as its basic indicator of economic activity. Following Chen et al. (1986), the growth rate in industrial production is stated as:

$$G\ \ IP\ \ _t = ln\ \ IP_t\ \ IP_{t-1} \tag{3.14}$$

Where $G\ \ IP\ \ _t$ is the growth rate in industrial production and IP_t is the level of industrial production in month t as indicated by the SARB. Although the monthly series of industrial production does not fully reflect the South African market structure (Boshoff, 2005: 13), the measure reduces potential loss of information compared to quarterly observations of real GDP.

Monetary economic variables

The empirical work in this study features a variety of monetary variables. First, two interest rates, namely the 91-day Treasury bill and 10-year government bond yield serve as proxies for the short and long term South African interest rates respectively. Both interest rates are restated as an effective monthly yield. Following Chen et al. (1986), the term structure of interest rates is captured using the difference between the 10-year government bond yield and the three month Treasury bill yield. Both interest rates are examined in real and nominal forms. Inflation is calculated as the monthly growth in Statistics South Africa (StatsSA)'s official headline CPI series.

The study uses an approximate Fisher equation to derive real interest rates. The approximate Fisher equation takes the form:

$$r = i - \pi \tag{3.15}$$

Where r is the real interest rate, i is the nominal interest rate and π is inflation. In order to form an ex-ante real interest rate, it is necessary to specify how inflation expectations are formed. Following Boshoff (2005), the empirical work in this study assumes that the expected inflation in month t is equal to actual inflation in month $t - 1$ for the purpose of calculating real rates.

In addition to the monetary variables described in the previous paragraph, the empirical work features a risk premium. International variables typically define the risk-premium as the spread between Moody's Baa and Aaa Rated Corporate Bond Indices. Since Moody's does not calculate these indices for the South African market, this study defines the risk-premium as the spread between the OTHI and GOVI South African bond Indices. Although this provides a similar measure to the international convention, the data is only available from June 2004 onwards. As a result, analysis of the relationship between risk premium uncertainty and return dispersion is limited to the period June 2004 to December 2011.

International variables

This study includes a variety of international variables. These variables primarily relate to the foreign exchange market as well as secondary equity and bond markets of the United States. The study uses five exchange rates, namely the real exchange rate and exchange rates for 4 of South Africa's largest trading partners. These trading partners include the European Union, the United States, the United Kingdom and Japan. As with the South African interest rate data, the study uses 91-day U.S. Treasury bill and 10-year U.S. Government bond yield data obtained from the Federal Reserve Board of St. Louis. For the term structure of U.S. interest rates, the study uses a term structure variable similar to the one calculated for the South African market. Lastly, a U.S. risk premium is defined as the spread between Moody's Baa and Aaa Rated Corporate Bond Indices.

Testing the association between return dispersion and the business cycle uses industrial production growth as a proxy for business cycles. Following Schwert (1989) an evaluation of the association between return dispersion and domestic and foreign macroeconomic uncertainty uses the conditional variance of real, monetary and foreign economic variables. The conditional variances of the economic series are determined via univariate modelling of the series using the Box-Jenkins methodology.

3.5 STATISTICAL METHOD

The study evaluates each of the hypotheses using a combination of correlation and regression analysis. Since the hypotheses are formulated as ‘relationships’ between variables, a measure of association such as correlation provides sufficient data from which to assess the null-hypothesis. Regression estimates complement the analysis by capturing incremental links between several variables. As such, a combination of correlation and regression estimates should provide an interesting and robust analysis.

The study determines correlation using Spearman’s rank order correlation coefficients, which is a non-parametric version of the standard Pearson’s coefficient. Spearman’s method transforms raw series by assigning a rank to observations in each series, after which it calculates correlation between ranks using Pearson’s equation. The study uses Spearman’s method based on evidence of significant serial correlation and heteroscedasticity in the key variables, which invalidates Pearson’s assumption of normally distributed data. Spearman’s method overcomes the issue of non-normally distributed data by imposing no specific distribution on the data. Second, the study estimates regression coefficients using least squares. In order to ensure valid inferences from the least squares method, the study controls for serial correlation and heteroscedasticity by using either univariate modelling or Newey and West (1978) robust standard errors where necessary.

3.6 CONCLUSION

This chapter has two main purposes. First, it identifies two research objectives, namely (i) characterising time-variation in return dispersion and (ii) characterising the relationship between return dispersion and the value premium. Second, it goes about developing a strategy for pursuing the research objectives. The objectives are primarily pursued from a rational economic perspective, leading to five main hypotheses. Based on a variety of considerations, the chapter suggests an empirical evaluation of the hypotheses using monthly data over the period June 1996 to December 2011. Thereafter, each variable is defined and a statistical method constructed with due consideration to both practical constraints and theoretical guidance from literature. Chapter Four employs the method for pursuing the research objectives via an empirical analysis.

CHAPTER FOUR
RESULTS

4.1 CHAPTER OVERVIEW

Chapter 3 developed five empirically testable hypotheses aimed at pursuing the research objectives. This chapter proceeds with the actual empirical work. The core of this chapter consists of five sections, each of which considers one of the five hypotheses in turn. To begin with, Section 4.2 considers the univariate properties of return dispersion, with a view to determining if the series is random.

After determining if return dispersion is non-random, the chapter studies the economic properties of return dispersion. Section 4.3 assesses whether the countercyclical relationship between return dispersion and the economic cycle predicted in literature holds in the South African market. Section 4.4 evaluates whether there is a link between return dispersion and domestic economic uncertainty. Section 4.5 builds on Section 4.4 by extending the analysis to foreign economic variables.

Finally, after examining the statistical and economic properties of return dispersion, the chapter turns its attention to the asset pricing characteristics of return dispersion. Section 4.6 evaluates whether the value premium exists in the South African market, before testing whether there is a relationship between return dispersion and the value premium.

Each of the five sections dedicated to evaluating the hypotheses follow a similar structure, first stating if there is sufficient evidence to reject the null-hypothesis, before deriving and discussing the result. After considering each of the five hypotheses, the chapter moves to its conclusion. Section 4.7 provides a robustness analysis of the main findings. Section 4.8 concludes the chapter.

4.2 THE TIME-SERIES OF RETURN DISPERSION

The first null-hypothesis, namely that return dispersion is unrelated to past observations of its own series, is rejected for a sample of South African listed shares over the period June 1996 to December 2011. An examination of the time-series of return dispersion reveals that it is a first-order autoregressive moving average (ARMA (1, 1)) process with GARCH (1, 1) errors.

The presence of statistically significant autoregressive, moving average and autoregressive conditional heteroscedasticity terms indicates that substantial serial correlation exists in return dispersion, and that a univariate approach to modelling return dispersion is feasible in the South African equity market. The remainder of this section derives and discusses this result.

4.2.1 STATIONARITY

The first-step in analysing return dispersion is to establish whether the series is stationary. A series is stationary if it has a constant probability distribution over time (Wooldridge, 2009). Failure to control for non-stationarity yields biased statistical inference; in their 'nonsense regression problem', Granger and Newbold (1974) show the probability of incorrectly rejecting the null-hypothesis increases significantly when the regression uses two non-stationary series. Given the impact of stationary series on reliable inference, it is essential to ensure that data are stationary.

This study follows Campbell et al. (2001) by evaluating stationarity using a combination of visual evidence and unit root testing. First, Figure 4.1 presents the time-series of return dispersion over the period June 1996 to December 2011. Panel A presents the raw series, while Panel B presents a twelve month lagged moving average. Both Panels show recessionary periods shaded in grey, with the recessionary periods based on official SARB recession dates. A comparison of Panel A and Panel B reveals that return dispersion contains a large degree of short-term noise as well as a slower moving component.

The short-term noise appears to correspond somewhat to major political and economic events. Major jumps occur, for example, around the South African general elections in December 2000 and the financial crisis in 2008. By comparison, when comparing the lagged moving average to the recession bars, the slow-moving element appears loosely related to the business cycle. Irrespective of these apparent phenomena, return dispersion shows no discernible trend; over time, the variable appears to revert to its mean level. Consequently, visual inspection appears to show that return dispersion is stationary.

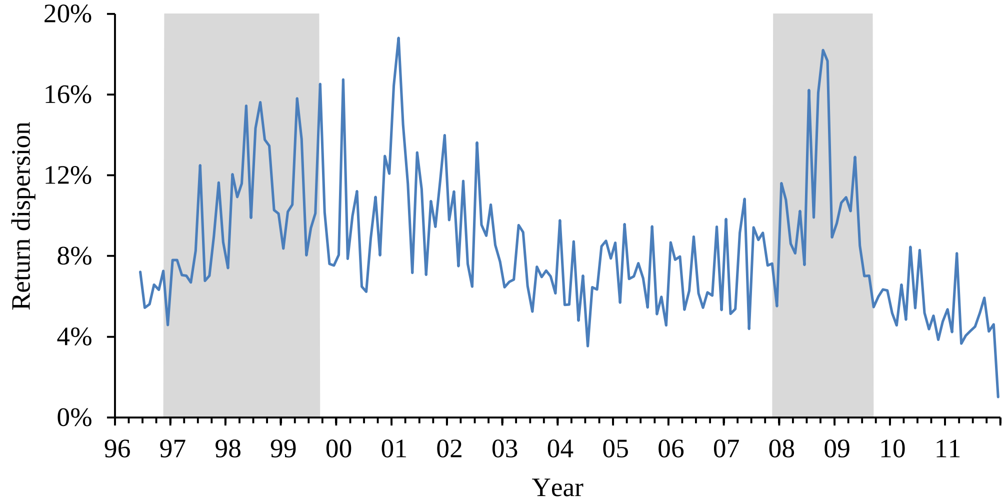
Second, Table 4.1 presents Augmented Dickey-Fuller (ADF) unit root tests for return dispersion. The table presents t-statistics and p-values for all ADF tests using 'intercept' and 'intercept and trend' specifications. The ADF statistics in Table 4.1 indicate that there is sufficient evidence to reject the unit root hypothesis at a 5% level of significance. This result holds irrespective of the test's specification. Taken together with the visual evidence, rejecting the unit root hypothesis presents strong evidence that return dispersion is stationary. Based on this evidence, the remainder of the empirical analysis uses the level of return dispersion.

FIGURE 4.1

TOP 40 RETURN DISPERSION: JUNE 1996 TO DECEMBER 2011

Figure 4.1 presents calculated levels of monthly return dispersion over the period June 1996 to March 2011. The calculation procedure is outlined in section 3.5.1. The y-axis indicates the percentage value of return dispersion. Panel A presents the raw time-series of return dispersion, while Panel B presents a twelve month moving average of return dispersion

PANEL A: RAW SERIES



PANEL B: TWELVE MONTH MOVING AVERAGE

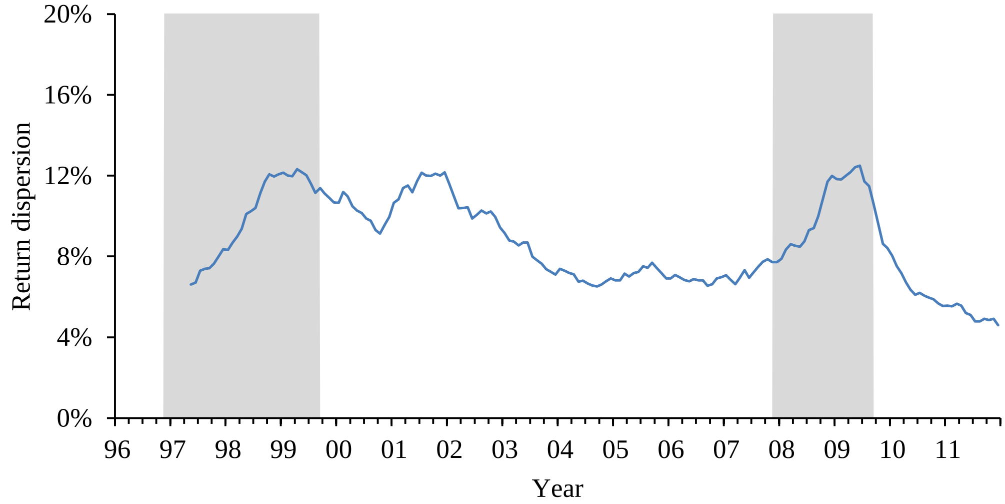


TABLE 4.1

AUGMENTED DICKEY-FULLER TEST STATISTICS: RETURN DISPERSION

This table presents ADF test statistics for return dispersion using both intercept and intercept and trend specifications. The table presents the lag length of the test, as well as the t-statistic and its associated p-value. The lag length is determined by minimising the Schwarz Information Criterion for ADF tests over 1 to 14 lags.

Specification	**Lag length**	**t-statistic**	**p-value**
Intercept	1	-4.52	0.00
Trend and intercept	1	-5.20	0.00

Source: Researcher's own data

4.2.2 SERIAL CORRELATION

Having established that return dispersion is stationary, the empirical work turns its attention to testing the hypothesis that return dispersion is related to past observations of its own series. This section evaluates the hypothesis by considering the serial correlation structure of return dispersion using Ljung-Box Q-Statistics. The Lung-Box Q-statistic tests whether observations are serially correlated against a null-hypothesis of independence.

Table 4.2 presents serial correlation statistics for return dispersion over the period June 1996 to December 2011. The table shows autocorrelation (AC) functions, partial autocorrelation functions and Ljung-Box Q-Statistics with their associated p-values at one, two, three, six and twelve lags. The AC function measures correlation between two observations, while the PAC function measures correlation between the same two observations after controlling for the intervening observations. The Q-Statistic uses AC function observations, which implies that it tests cumulative serial correlation at each lag.

Table 4.2 indicates that there is significant serial correlation in return dispersion. The AC function ranges from 0.5 at one lag to 0.2 at twelve lags, indicating that return dispersion is positively correlated with past observations of its own series. The PAC function shows a similar trend, ranging from 0.5 at one lag to 0.1 at twelve lags. An evaluation of the Q-statistics shows that positive serial correlation from the AC function is statistically significant at all six reported lags. This result indicates that there is strong evidence that return dispersion is related to past observations of its own series, based on which the first null hypothesis may be rejected.

TABLE 4.2

SUMMARY STATISTICS: RETURN DISPERSION

Table 4.2 contains descriptive statistics for cross-sectional return dispersion over the period June 1996 to March 2011. The left-hand side of the table presents basic statistics including the mean, standard deviation, skewness, kurtosis and a MacKinnon (1996) one-sided p-value for the augmented Dickey-Fuller test statistic (ADF). The ADF test-statistic is calculated assuming an intercept and no trend in the data. Alternate specifications using a trend yield the same conclusions. The right-hand side of the table presents autocorrelation and partial autocorrelation values at one, two, three, six and twelve lags.

Basic statistics		**Autocorrelation functions**				
Statistic	**Value**	**Lag**	**AC**	**PAC**	**Q-Stat**	**p-value**
Mean	8.5	1	0.5	0.5	56.9	0.0
St. deviation	7.9	2	0.5	0.3	103.4	0.0
Skewness	0.9	3	0.4	0.1	140.3	0.0
Kurtosis	3.7	6	0.4	0.0	236.4	0.0
ADF	0.0	12	0.2	0.1	332.5	0.0

Source: Researcher's own data

4.2.3 A UNIVARIATE MODEL OF RETURN DISPERSION

The presence of serial correlation indicates the possibility that return dispersion may be modelled using univariate time-series methods. This section uses a modified Box-Jenkins approach that considers the model specification, estimation and model diagnostics. To begin with, a visual inspection of the AC and PAC functions of return dispersion shows that the AC and PAC functions are both greatest at one lag, with a slow subsequent decay towards zero. The slow decay in both AC and PAC functions is consistent with an ARMA (1, 1) process.

Least square estimation confirms that return dispersion is an ARMA (1, 1) process. Table 4.3 presents the estimated output from an ARMA (1, 1) model fitted to return dispersion. Based on initial diagnostic evidence, the ARMA (1, 1) model is updated to include a GARCH (1, 1) variance process. Table 4.3 shows coefficients together with their standard errors and associated p-values, as well as model diagnostics including adjusted R-Squared, Durbin-Watson test statistics and Engle-ARCH test p-values. An evaluation of standard errors reveals that the autoregressive, moving average and GARCH terms are all statistically significant at a 5% level of significance. The diagnostic statistics indicate that the model is well specified; a Durbin-Watson test statistic of 1.90 and Engle-ARCH test statistic p-value of 0.69 indicates that no serial correlation or ARCH effects remain in the error terms after fitting the ARMA (1, 1) and GARCH (1, 1) processes.

TABLE 4.3

A UNIVARIATE MODEL OF TOP 40 RETURN DISPERSION

Table 4.3 presents estimated output for an ARMA (1, 1) process fitted to the time-series of cross-sectional return dispersion using ordinary least squares estimation. The equation takes the form:

$$\sigma_{cs,t} = \gamma_0 + \gamma_1\sigma_{cs,t-1} + \varepsilon_t - \gamma_2\varepsilon_{t-1}$$

Where γ_0 is the constant, γ_1 is the first-order autoregressive coefficient and γ_2 is the first-order moving average coefficient. Based on the ADF test statistic in table 4.1, the equation is estimated using levels of return dispersion. The first two sections present estimated output for the mean and variance equations, while the third section presents diagnostic statistics.

Estimated output			
Variable	**Value**	**Standard error**	**p-value**
Constant	0.08	0.02	0.00
AR(1)	0.96	0.03	0.00
MA(1)	-0.69	0.07	0.00
Variance equation			
Constant	0.00	0.00	0.17
Residual	0.09	0.07	0.15
GARCH	0.84	0.10	0.00
Model diagnostics			
Statistic	**Adj. R-Squared**	**Durbin-Watson**	**Engle-ARCH p-value**
Value	0.40	1.90	0.69

Source: Researcher's own data

The result indicates that it is possible to form an ex-ante expectation of return dispersion by means of a mechanical application of univariate time-series techniques. Taking the estimated output from table 4.3 as an example, the expected level of return dispersion in month t given the level of return dispersion in month $t-1$ is:

$$E_{t-1}\ RD_t \ = 0.96RD_{t-1} - 0.69\epsilon_{t-1} + \epsilon_t \tag{4.1}$$

Where

$$\epsilon_t = \sigma_t u_t \tag{4.2}$$

And

$$E_{t-1}\ \sigma_t^2 \ = 0.00 + 0.09\epsilon_{t-1}^2 + 0.84\sigma_{t-1}^2 \tag{4.3}$$

In equation (4.1), RD_{t-1} is the value of return dispersion in period $t-1$ and ϵ_{t-1} is the divergence of return dispersion in period $t-1$ from its expected value in period $t-2$. The model implies that a one percentage point increase in return dispersion in month $t-1$ will lead to a 0.96 percentage point increase in return dispersion in month t, while a one percentage point divergence in return dispersion in month $t-1$ from its expected value in month $t-2$ will lead to a 0.69 percentage point correction in return dispersion in month t.

Equations (4.2) and (4.3) complement equation (4.1) by demonstrating the influence of volatility on the reliability of ex-ante expectations. Equation (4.2) indicates that the error term ϵ_t in (4.1) consists of a conditional standard deviation term σ_t and a white noise term u_t. Equation (4.3) shows that the conditional variance σ_t^2 may be modelled as a function of past error term observations and past conditional variance observations. A one percentage point increase in the error term in month $t-1$ will lead to a 0.09 percentage point increase in conditional variance in month t, while a one percentage point increase in conditional variance in month $t-1$ will lead to a 0.84 percentage point increase in conditional volatility in month t. Since the error term in (4.1) influences the accuracy of ex-ante expectations, investment managers may use the conditional volatility model in (4.3) to assess the influence of previous divergences from expected values on the accuracy of current expectations. Put differently, if recent return dispersion levels have been volatile, managers may infer that it will remain volatile, thus decreasing the accuracy of expectations formed from (4.1).

In summary, this section demonstrates that return dispersion may be characterised using ARMA (1, 1) and GARCH (1, 1) time-series processes. Applying these processes to return dispersion demonstrates that it is possible for investment managers to form ex-ante expectations of return dispersion using univariate time-series techniques. Overall, the evidence on serial correlation in Section 4.2.2 and univariate time-series evidence in section 4.2.3 present strong evidence in favour of rejecting the null-hypothesis that return dispersion is unrelated to past observations of its own series.

4.3 RETURN DISPERSION AND THE BUSINESS CYCLE

The second null-hypothesis, namely that return dispersion is not associated with the business cycle, is rejected for a sample of South African listed shares over the period June 1996 to December 2011. A regression of the growth rate of industrial production on one and two-month lags of return dispersion reveals a statistically significant negative relationship between return dispersion and the business cycle. The presence of a statistically significant negative relationship between return dispersion and industrial production growth confirms international evidence (Christie and Huang, 1994; Gomes et al., 2003; Stivers and Sun, 2010) documenting a countercyclical trend in return dispersion. The remainder of this section derives and discusses this result.

An initial inspection of the twelve month moving average of return dispersion in Panel B of Figure 4.1 presents some initial evidence of a business cycle component. The apparent association between return dispersion and the economic cycle is formally evaluated by means of a regression of lagged return dispersion on the growth rate in industrial production. Return dispersion is lagged due to the forward-looking nature of stock markets (Schwert, 1989), which means that stock market variables often lead general economic activity (e.g. Auret and Golding, 2012).

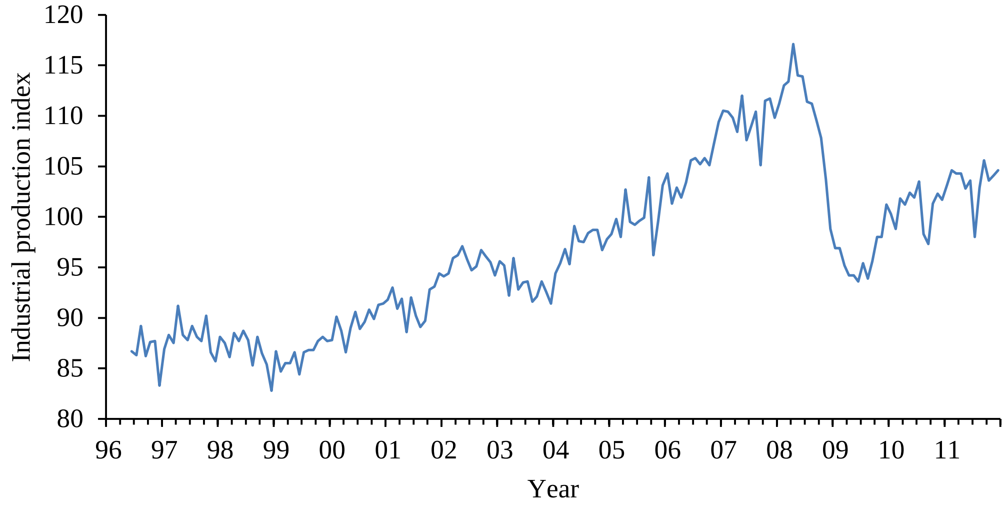
Although the level of industrial production provides an intuitive method of examining cyclical behaviour, there is evidence that the series is non-stationary. Figure 4.2 presents industrial production over the period June 1996 to December 2011. Panel A shows the level of industrial production. Combined with an ADF p-value of 0.56 for the raw series of industrial production, there is clear evidence that the series is non-stationary. As a result, the level of industrial production is transformed to a growth rate by means of the equation $g\ ip = \log(ip_t)\ (ip_{t-1})$. Panel B of Figure 4.2 and an ADF p-value of 0.00 provide strong evidence that the growth rate of industrial production is stationary.

FIGURE 4.2

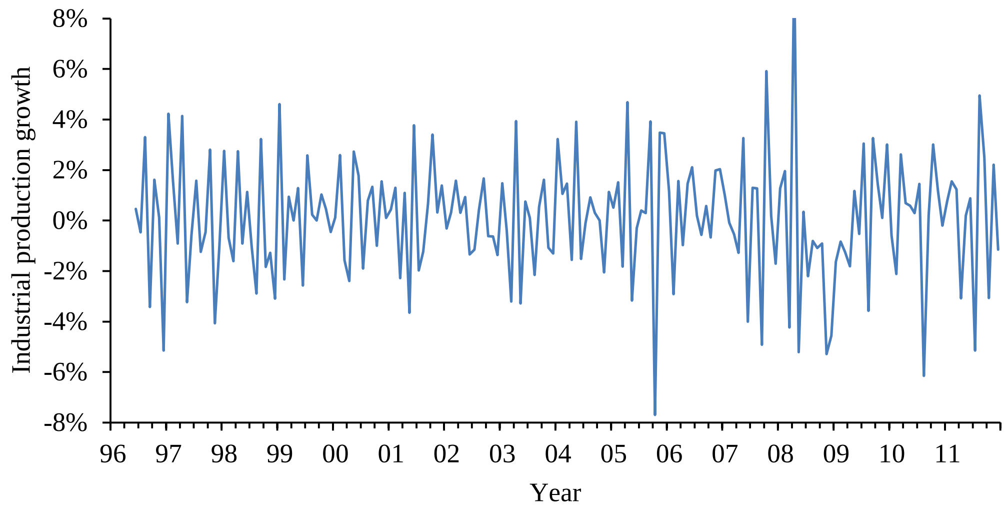
INDUSTRIAL PRODUCTION: JUNE 1996 – DECEMBER 2011

This figure presents the time-series of industrial production and industrial production growth over the period June 1996 to December 2011. Panel A shows the level of industrial production, while Panel B shows the growth rate of industrial production calculated with (3.14).

PANEL A: INDUSTRIAL PRODUCTION



PANEL B: INDUSTRIAL PRODUCTION GROWTH



After ensuring industrial production is stationary, it is possible to calculate valid regression estimates. Table 4.4 presents estimates for a regression of return dispersion on industrial production growth. Since Lougani et al. (1990) and Stivers and Sun (2010) present evidence that return dispersion leads the economic cycle, the original analysis considered zero to six lags of return dispersion. Table 4.4 reports regression estimates at one lag, which represents the lag at which statistical significance is the greatest. Based on the univariate model of return dispersion reported in Section 4.2, the regression estimates control for serial correlation and heteroscedasticity using ARMA (1, 1) and GARCH (1, 1) processes.

TABLE 4.4

ESTIMATED OUTPUT: RETURN DISPERSION AND THE BUSINESS CYCLE

This table presents a regression of return dispersion on industrial production growth using least squares estimation. The equation takes the form:

$$\sigma_{cs,t} = \gamma_0 + \gamma_1 G(IP)_{t+1} + \varepsilon_t$$

Where G(IP) is the lagged industrial production growth. Based on preliminary Spearman's Rank-order correlation coefficient evaluation, the regression leads return dispersion by one month. Given univariate evidence on return dispersion, the study uses ARMA (1, 1) and GARCH (1, 1) processes to control for serial correlation and heteroscedasticity. The first two sections present estimated output for the mean and variance equations, while the third section presents diagnostic statistics.

Estimated output			
Variable	**Value**	**Standard error**	**p-value**
Constant	0.08	0.02	0.00
G(IP)*	-0.15	0.07	0.02
AR(1)	0.96	0.03	0.00
MA(1)	-0.69	0.08	0.00
Variance equation			
Constant	0.00†	0.00†	0.15
Residual	0.12	0.09	0.18
GARCH	0.83	0.11	0.00
Model diagnostics			
Statistic	**Adj. R-Squared**	**Durbin-Watson**	**Engle-ARCH p-value**
Value	0.40	1.93	p = 0.67

*One month lag. † Non-zero value appears as zero due to rounding.

Source: Researcher's own data

An evaluation of the regression estimates reveals a significant negative link between return dispersion and industrial production growth. The estimated output in Table 4.4 shows that a 1% increase in return dispersion leads to a 0.10% decrease in industrial production during the following month. The model diagnostics indicate that the model is well specified, with a Durbin-Watson statistic value of 1.93 and an Engle-ARCH p-value of 0.67. Despite the fact that the model is well specified, the adjusted R-Squared statistic shows that, overall, the model does not perform significantly differently from the univariate return dispersion model.

In summary, there is sufficient evidence in the share sample to reject the null-hypothesis of no association with the economic cycle. Although the result is robust to controlling for serial correlation, the adjusted R-Squared value indicates that the model does not perform significantly better than the univariate return dispersion model in Section 4.2. Nevertheless, there is evidence that return dispersion leads the economic cycle in a countercyclical fashion. This finding confirms empirical evidence by Lougani et al. (1990) and Stivers and Sun (2010).

4.4 RETURN DISPERSION AND LOCAL ECONOMIC UNCERTAINTY

The third null-hypothesis states that return dispersion is unrelated to domestic economic uncertainty. Empirical data in this section indicates that there is sufficient evidence to reject this null-hypothesis for a sample of South African listed shares over the period June 1996 to December 2011. Regressions of return dispersion on local economic uncertainty yield significant links between return dispersion and the uncertainty of both economic production and the risk-premium. The remainder of this section derives and discusses the result.

The analysis conducted in this section follows a similar pattern as the previous section by measuring association using regression analysis. Following Schwert (1989), the analysis uses the conditional variance of selected local state variables to capture domestic economic uncertainty. These variables include industrial production, real 91-day T-Bill and 10-year T-Bond rates, the term yield spread, inflation and the risk-premium. The uncertainty related to each variable is equal to its conditional variance derived from univariate time-series regression analyses[19].

The regressions themselves take the form:

$$RD_t = \beta_0 + \beta_1 EU_t + \varepsilon_t \tag{4.4}$$

Where RD_t is return dispersion and EU_t is economic uncertainty at time t.

[19] The process for deriving conditional variances is detailed in Section A.4 of Appendix A.

Table 4.5 reports estimates for regressions of return dispersion on domestic economic uncertainty[20]. The table reports both estimated output, including coefficients along with their standard errors and p-values, as well as model diagnostics including adjusted R-Squared, Durbin-Watson and Engle-ARCH statistics. As with the previous regressions, these regressions control for serial correlation and heteroscedasticity using ARMA (1, 1) and GARCH (1, 1) processes.

The estimated output in Table 4.5 supports the proposition that short-term variation in return dispersion is related to local economic uncertainty. There are statistically significant slope coefficients for the conditional variances of both industrial production (*IP*) and the risk-premium (*RP*). First, the conditional variance of industrial production (*IP*) has a statistically significant negative coefficient, which indicates that an increase in real economic uncertainty coincides with a decrease in return dispersion. Second, the conditional variance of the risk-premium (*RP*) has a statistically significant positive coefficient, which indicates that an increase in risk-premium uncertainty coincides with an increase in return dispersion.

Although the statistically significant *IP* and *RP* coefficients provide uniform evidence against the null-hypothesis, it is more difficult to provide an economic account for the negative *IP* coefficient than the positive *RP* coefficient. A rational economic view would most likely predict a positive coefficient, since risk-averse rational economic agents would hedge against economic downturns. Using the law of supply and demand, hedging against economic downturn would increase return dispersion, since investors would bid up the price of 'safe' (hedged) shares and sell down the price of 'risky' (exposed) shares. The data, however, contradicts this theoretical prediction.

[20] The research used a headline (or equivalent) inflation rate obtained from Statistics South Africa (www.statssa.gov). The study used the total CPI for all metropolitan areas for the period June 1996 to January 2008. After January 2008, the study changed the CPI index to reflect changes in the SARB's inflation targeting policy and CPI calculation methodology in January 2008 (Statistics South Africa, 2008). The study intended to use total CPI (all items) for all areas, but instead used total CPI (all items) for the Western Cape in error. The results in Table 4.5 use the incorrect inflation series, mainly because the statistical package used for analysis was no longer available when the error was discovered. The error affects the South African inflation, South African real T-Bill and South African real T-Bond rates in this section only; none of the variables are statistically significant in the regression and would therefore not have an important bearing on the overall results of the study. In addition, the correlation between correct and incorrect series is 0.94, based on which the researcher does not expect significant results would have been found if the correct series had been used.

TABLE 4.5

RETURN DISPERSION AND DOMESTIC ECONOMIC UNCERTAINTY

This table shows estimated output for regressions of return dispersion on economic uncertainty. The equation takes the form:

$$RD_t = \beta_0 + \beta_1 EU_t + \varepsilon_t$$

Where RD_t is return dispersion and EU_t is economic uncertainty at time t. Economic uncertainty is derived using the conditional variance of several state variables, including industrial production (*IP*), the real T-Bill rate (*T-Bill**), the real T-Bond rate (*T-Bond**), the nominal term yield spread (*TYS*), inflation (*inflation*) and the risk-premium (*RP*). The conditional variances come from univariate time-series models of the state variables; these are described in Section A.4 of Appendix A. The table itself reports an intercept, slope and slope lag, as well as model diagnostics including the adjusted R-Squared (Adj. RSQ), Durbin-Watson statistic and a p-value for the Engle-Arch statistic. For both the intercept and slope, the table reports the estimated value, standard error (round brackets) and a p-value for t-statistics calculated from the standard errors (square brackets). The slope lag represents a lag in economic data dissemination based on the lags in the SARB's *Monthly Release of Selected Data*.

Estimated output				**Model diagnostics**		
Variable	**Lag**	**Intercept**	**Slope**	**Adj. RSQ**	**Durbin-Watson**	**Engle-ARCH p-value**
IP	2	0.08 (0.02) [0.00]	-5.09 (1.78) [0.00]	0.40	1.92	0.73
*T-Bill**	0	0.08 (0.02) [0.00]	-13.08 (65.97) [0.84]	0.38	1.89	0.67
*T-Bond**	0	0.08 (0.02) [0.00]	19.64 (58.68) [0.74]	0.39	1.90	0.70
TYS	0	0.08 (0.02) [0.00]	-142.36 (5996.58] [0.98]	0.39	1.90	0.67
Inflation	1	0.08 (0.02) [0.00]	45.98 (60.59) [0.45]	0.39	1.91	0.74
RP	0	0.07 (0.03) [0.00]	4053.27 (1503.45) [0.01]	0.39	2.27	0.54

Source: Researcher's own data

While the results dismiss the rational economic argument discussed above, there are several possible alternatives. Given a lack of supporting empirical analysis, these alternatives remain propositions at best. Two of the more compelling arguments are (i) the sample contains an insufficient number of real economic hedges and (ii) *IP* fails as a measure of economic uncertainty. First, if the sample contains an insufficient number of hedges, real economic uncertainty will affect all shares in a uniform manner. If this is true, correlation across shares will increase in times of economic uncertainty. Given the negative relationship between return dispersion and correlation, this would likely decrease return dispersion. Second, if *IP* fails as a measure of economic uncertainty, a positive change in *IP* is analogous to a positive economic shock; if this is the case, then the negative link is equivalent to the countercyclical relationship between return dispersion and economic activity shown in Section 4.2.

Two less compelling arguments for the negative link between return dispersion and *IP* are (i) that the assumption of rational economic agents is invalid and (ii) that the assumption of risk-averse investors is invalid. Both these explanations seem invalid given the positive *RP* coefficient, which is consistent with both rational and risk-averse economic agents. The positive *RP* coefficient indicates that an increase in risk-premium uncertainty coincides with an increase in return dispersion. As before, investors will hedge against adverse movements in the risk-premium, which will increase return dispersion as investors bid up the prices of hedged shares and sell down the prices of exposed shares.

Notwithstanding the slightly confusing negative link between return dispersion and real economic uncertainty, the results indicate that return dispersion has a significant link with at least two economic uncertainty measurements. Based on this, there appears to be sufficient evidence to reject the null-hypothesis in favour of the proposition that return dispersion is related to domestic economic uncertainty. This finding confirms the theoretical model developed in Chapter 3. Of course, if there is a link between return dispersion and local economic uncertainty, there may be a link between return dispersion and foreign economic uncertainty. The following section considers this possibility.

4.5 RETURN DISPERSION AND FOREIGN ECONOMIC UNCERTAINTY

The fourth null-hypothesis states that return dispersion is unrelated to foreign economic uncertainty. Empirical results in this section indicate that there is sufficient evidence to reject this null-hypothesis for a sample of South African listed shares over the period June 1996 to December 2011. Regressions of return dispersion on foreign economic variables reveal significant relationships between return dispersion and the Rand/U.S. Dollar exchange rate, real U.S. interest rates and the U.S. term yield spread. The remainder of this chapter derives and discusses this result; first considering foreign exchange rate uncertainty in Section 4.5.1, before turning attention to U.S. state variable uncertainty in Section 4.5.2.

4.5.1 EXCHANGE RATE UNCERTAINTY

This section's examination of foreign economic uncertainty begins with an inspection of foreign exchange rates. A number of factors influence foreign exchange rates, including the relative economic strength of countries, speculative behaviour by investors, economic or political factors and central bank involvement (Delaney and Whittington, 2010: 132). Given the array of economic factors embodied in exchange rates, their conditional variances may be useful proxies for the general level of international economic uncertainty.

Table 4.6 presents estimated outputs for regressions of return dispersion on exchange rate uncertainty. The regressions consider five exchange rates, namely the real effective exchange rate, as well as the Rand/Euro, Rand/British Pound, Rand/U.S. Dollar and Rand/Japanese Yen exchange rates. The last four exchange rates capture economic ties to South Africa's four largest trading partners[21]. The exchange rates are quoted using the direct quotation method[22]. For each regression, the table presents intercept and slope coefficients, along with their standard errors and p-value. Based on the univariate characteristics of return dispersion, the regressions control for serial correlation and heteroscedasticity using ARMA (1, 1) and GARCH (1, 1) processes.

Table 4.6 shows that the slope coefficients are all positive, indicating that an increase in exchange rate uncertainty coincides with an increase in return dispersion. However, of all the coefficients, only the *Rand/USD* coefficient (p = 0.05) is significant at a 5% level, although *Rand/GBP* (p = 0.08) and *Rand/JPY* (p = 0.06) are close to the 5% threshold. Based on this, there is sufficient initial evidence to indicate a moderate link between return dispersion and foreign economic uncertainty, at least as far as foreign exchange rate uncertainty is concerned.

Since the initial evidence points to a link between return dispersion and foreign exchange rate uncertainty, it is worthwhile considering the economic interpretation. The positive link seems

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[21] The analysis excludes China, which uses a fixed exchange rate system (Morrison, Labonte and Sanford, 2004; Madura, 2011: 183-184) that leads to nearly constant exchange rates.

[22] The direct method implies that the currencies are stated in terms of the amount of domestic currency required to purchase one unit of foreign currency.

TABLE 4.6

RETURN DISPERSION AND FOREIGN EXCHANGE RATE UNCERTAINTY

This table shows estimated output for regressions of return dispersion on foreign exchange rate uncertainty. The equation takes the form:

$$RD_t = \beta_0 + \beta_1 EU_t + \varepsilon_t$$

Where RD_t is return dispersion and EU_t is exchange rate uncertainty at time t. As with the economic uncertainty variables in Section 4.4, this section uses the conditional variances of the regressors as a measure of uncertainty. The univariate time-series regressions used to capture these conditional variances are contained in section A.4 of Appendix A. The regressions consider five exchange rates, namely the Real Effective (*EER*), Rand/Euro (*R/EUR*), Rand/Dollar (*R/USD*), Rand/British Pound (*R/GBP*) and Rand/Japanese Yen (*R/JPY*) exchange rates. All regressions use zero lags for the independent variables. For each regression, the table presents estimated output and model diagnostics. The estimated output includes intercept and slope coefficients along with their standard errors and t-statistic p-values. The model diagnostics include Adjusted R-Squared (Adj. RSQ), Durbin-Watson and Engle-ARCH p-value statistics. All regressions control for serial correlation and heteroscedasticity using ARMA (1, 1) and GARCH (1, 1) processes.

Estimated output				**Model diagnostics**		
Variable	**Lag**	**Intercept**	**Slope**	**Adj. RSQ**	**Durbin-Watson**	**Engle-ARCH p-value**
*EER**	0	0.08 (0.02) [0.00]	1.63 (1.04) [0.12]	0.41	1.93	0.73
R/EUR	0	0.08 (0.02) [0.00]	1.09 (0.90) [0.23]	0.40	1.94	0.72
R/USD	0	0.08 (0.02) [0.00]	1.75 (0.89) [0.05]	0.43	2.00	0.88
R/GBP	0	0.08 (0.02) [0.00]	1.45 (0.84) [0.08]	0.41	1.95	0.78
R/JPY	0	0.08 (0.02) [0.00]	1.15 (0.62) [0.06]	0.42	2.02	0.86

Source: Researcher's own data

plausible within a rational economic framework. To begin with, risk-averse foreign investors will prefer locally listed shares that hedge exchange rates during periods of economic uncertainty. To clarify, if all companies in a market contain some degree of exchange rate exposure, an exchange rate depreciation (from R/USD = 7.00 to R/USD = 7.05, for example) will benefit net exporters and harm net importers[23]. The same depreciation will negatively affect foreign investors, since it incurs a negative return on their investment. As a result, during periods of exchange rate uncertainty, foreign investors will prefer net exporters, since the returns on these shares should hedge possible negative exchange rate movements. Using the same hedging argument as in Section 4.4 will lead return dispersion to increase. As a result, there should be a positive link between return dispersion and foreign exchange rate uncertainty.

4.5.2 STATE VARIABLE UNCERTAINTY

Next, the examination of foreign economic uncertainty turns its attention to the link between return dispersion and foreign economic state variable uncertainty. The analysis focuses on the economy of the United States, using the same state variables as in Section 4.4. Although the study selected U.S. variables prior to the analysis based on data availability, this choice also seems appropriate given the significant link between return dispersion and the Rand/U.S. Dollar exchange rate uncertainty documented in Section 4.5.1.

Table 4.7 presents estimated output for regressions of return dispersion on the U.S. economic uncertainty variables. The regressions use the same basic variables as Section 4.4, namely industrial production, the real T-Bill and T-Bond rates, the term yield spread, inflation and the risk-premium. For each regression, the table presents intercept and slope coefficients along with their standard errors and p-values. Based on the univariate characteristics of return dispersion, the regressions once again control for serial correlation and heteroscedasticity using ARMA (1, 1) and GARCH (1, 1) processes.

Table 4.7 indicates that the slope coefficients of all measurements are positive, although only the *U.S. T-Bill** (p = 0.05), *U.S. T-Bond** (p = 0.05) and *U.S. TYS* (p = 0.00) are significant at a 5% level. The result indicates that an increase in real U.S. T-Bill interest rates or the term yield spread correspond with an increase in return dispersion. The presence of these significant positive coefficients confirms the initial evidence in Section 4.5.1 of a link

[23] Net exporters are companies who export more than they import and net importers are companies who import more than they export. The relation assumes the exports and imports are foreign currency denominated; as a result, currency depreciation will increase the revenue base of exports and the cost base of imports, thereby causing differential costs and benefits to net exporters and net importers.

between return dispersion and foreign economic uncertainty, at least as far as the United States is concerned.

TABLE 4.7

RETURN DISPERSION AND FOREIGN ECONOMIC UNCERTAINTY

This table shows estimated output for regressions of return dispersion on foreign exchange rate uncertainty. The equation takes the form:

$$RD_t = \beta_0 + \beta_1 EU_t + \varepsilon_t$$

Where RD_t is return dispersion and EU_t is economic uncertainty at time t. As with the domestic economic uncertainty variables in Section 4.4, this section uses the conditional variances of the regressors as a measure of uncertainty. The univariate time-series regressions used to capture these conditional variances are contained in Appendix A. The regressions consider U.S. Industrial Production growth (*U.S. IP*), the real U.S. T-Bill (*U.S. T-Bill**) and T-Bond (*U.S. T-Bond**) yields, U.S. nominal term yield spread (*U.S. TYS*), U.S. inflation (*U.S. Inf.*) and the U.S. risk premium (*U.S. RP*). The regressions use the same lag structure assumed for the South African state variables in Section 4.4. For each regression, the table presents estimated output and model diagnostics. The estimated output includes intercept and slope coefficients along with their standard errors and t-statistic p-values. The model diagnostics include Adjusted R-Squared, Durbin-Watson and Engle-ARCH p-value statistics. All regressions control for serial correlation and heteroscedasticity using ARMA (1, 1) and GARCH (1, 1) processes.

Estimated output				**Model diagnostics**		
Variable	**Lag**	**Intercept**	**Slope**	**Adj. RSQ**	**Durbin-Watson**	**Engle-ARCH p-value**
U.S. IP	2	0.08 (0.02) [0.00]	28.11 (17.62) [0.11]	0.40	1.95	0.89
*U.S. T-Bill**	0	0.08 (0.02) [0.00]	262.60 (135.18) [0.05]	0.42	1.94	0.88
*U.S T-Bond**	0	0.08 (0.02) [0.00]	277.89 (143.76) [0.05]	0.42	1.94	0.91
U.S. TYS	0	0.08 (0.02) [0.00]	81899.31 (27651.10) [0.00]	0.40	1.99	0.44
U.S. Inf.	1	0.08 (0.02) [0.00]	253.47 (139.23) [0.06]	0.42	1.95	0.91
U.S. RP	0	0.08 (0.02) [0.00]	0.05 (0.03) [0.15]	0.39	1.92	0.20

Source: Researcher's own data

The link between return dispersion and foreign interest rate variables seems plausible within an interest rate parity framework. Interest rate parity relates domestic and foreign interest rates to the exchange rate by means of an arbitrage argument, under which investors should be indifferent to interest rates in different countries. Formally, the parity condition is:

$$i_t = i_t^f + \ \ ER_{t+1} - ER_t \quad ER_t \tag{4.5}$$

Where i_t is the local interest rate, i_t^f is the foreign interest rate and $ER_{t+1} - ER_t \quad ER_t$ is the depreciation of the domestic currency ER from period t to period $t + 1$.

If equation (4.5) holds, a decrease in domestic interest rates should lead to a depreciation of the local currency. For U.S. investors, this implies that an increase in U.S. T-Bill or T-Bond rates will increase the value of a U.S. Dollar relative to the Rand, thereby incurring a loss on U.S. investors with South African investments (see Section 4.5.1). By extension, uncertainty over the level of U.S. T-Bill or T-Bond rates should cause risk-averse U.S. investors to shift foreign share holdings to exchange rate hedged shares. Using the same hedging argument as in Section 4.5.1, an increase in real T-Bill, T-Bond or term yield spread uncertainty will lead to an increase in domestic return dispersion.

Overall, the results indicate that there is a link between return dispersion and foreign economic uncertainty, although the link appears to be limited to U.S. economic uncertainty. Based on this, there appears to be sufficient evidence to reject the null-hypothesis in favour of the proposition that there is a link between return dispersion and foreign economic uncertainty. This finding confirms the theoretical framework presented in Chapter 3.

4.6 RETURN DISPERSION AND THE VALUE PREMIUM

The fifth null-hypothesis states that return dispersion is unrelated to the value premium. Empirical results in this section indicate that there is sufficient evidence to reject this null-hypothesis for a sample of South African listed shares over the period June 1996 to December 2011. An evaluation of Spearman's ranked correlation coefficients reveals that there is a significantly positive link between return dispersion and seven of the twelve value premium variables. The remainder of the study derives and discusses this result.

4.6.1 SIZE AND VALUE PREMIUMS IN THE SOUTH AFRICAN MARKET

It is important to examine the share sample for evidence of size and value effects. The analysis in this section presupposes that a value premium exists in the South African market. If no value premium exists, the remainder of the analysis become pointless. Similarly, if no size premium exists, controlling for market value in the value calculation is also pointless. This section tests for evidence of size and value effects using simple visual inspection of the size and price-to-book portfolios.

Table 4.8 shows summary statistics for tertile portfolios formed based on size and P/B ratios. The summary statistics include average monthly excess returns, the average standard deviation of excess returns and a Sharpe ratio[24]. Excess returns are equal to tertile portfolio returns less the effective monthly 91-day T-Bill rate. The excess returns calculation uses both equal and value-weighted portfolio returns. Panel A shows evidence for the equal-weighted portfolio returns, while Panel B shows evidence for the value-weighted portfolio returns.

The average excess monthly returns in Table 4.8 confirm Fama and French's (1992, 1993) evidence of a negative link between size and returns and a positive link between BE/ME and returns. First, there is a downward trend in returns across the Micro, Small and Large size segments, which indicates a negative link between size and returns. The link ranges from around 0.70% to 0.65% for equal-weighted returns and 3.36% to 1.43% for value-weighted returns. Second, there is a downward trend in returns across the low, mid and high P/B tertile portfolios, which indicates a negative link between P/B and returns. Since P/B and BE/ME are reciprocal, the negative link between P/B is equivalent to a positive link between BE/ME and returns. The link ranges from around 0.96% to -0.33% for equal-weighted returns and 3.31% to 1.56% for value-weighted returns. Based on this evidence, there is strong support for size and value premiums in the South African equity market.

Although the excess average monthly returns show trends in keeping with other literature, the average standard deviations present two results that are inconsistent with international evidence. First, there is no clear evidence that Micro shares are more risky than Small or Large shares. A simple average of standard deviations for Micro shares is around 6% for equal-weighted shares and 10% for value-weighted shares. These risk levels are not

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[24] The Sharpe ratio is: $R_p - R_b \quad \sigma_b$, where R_p is the portfolio return, R_b is the benchmark return and σ_p is the portfolio standard deviation. In this instance, the benchmark return R_b is set equal to the risk-free rate.

noticeably different from small shares, which have simple average standard deviations of 6% for equal-weighted portfolios and 10% for value-portfolios, or big shares, which have a simple average standard deviation of 7% for equal-weighted portfolios and 12% for value-weighted portfolios.

TABLE 4.8

SUMMARY STATISTICS FOR PORTFOLIOS SORTED ACCORDING TO SIZE AND P/B

This table presents selected summary statistics for the equal and value-weighted tertile portfolio returns. Panels A and B present statistics for the equal and value-weighted returns, respectively. Each panel partitions the summary statistics for each tertile according to the five possible size segments (Market, Micro, Small, Big and Market less micro). For each quintile portfolio in each size segment, the table reports average excess returns, average standard deviation, t-statistics and p-values. The average excess returns are equal to the monthly portfolio return less the effective monthly yield on a 91-day T-Bill.

PANEL A: EQUAL-WEIGHTED RETURNS

	Tertile portfolios		
	Low	**2**	**High**
Market size segment			
Average excess returns	1.02	-0.09	-0.34
Average standard deviation	5.40	5.50	6.10
Sharpe ratio	0.19	-0.02	-0.06
Micro size segment			
Average excess returns	1.11	0.10	-0.51
Average standard deviation	5.71	5.87	6.67
Sharpe ratio	0.19	0.02	-0.08
Small size segment			
Average excess returns	0.94	-0.04	-0.47
Average standard deviation	6.17	6.17	6.31
Sharpe ratio	0.15	-0.01	-0.07
Big size segment			
Average excess returns	0.83	-0.17	-0.01
Average standard deviation	7.19	6.60	6.85
Sharpe ratio	0.12	-0.03	0.00
Market less micro size segment			
Average excess returns	0.87	0.02	-0.27
Average standard deviation	6.17	5.76	6.50
Sharpe ratio	0.14	0.00	-0.14

TABLE 4.8 (CONTINUED)

SUMMARY STATISTICS FOR PORTFOLIOS SORTED ACCORDING TO SIZE AND P/B

PANEL B: VALUE-WEIGHTED RETURNS

	Tertile portfolios		
	Low	**2**	**High**
Market size segment			
Average excess returns	3.04	1.93	1.27
Average standard deviation	12.17	10.45	10.24
Sharpe ratio	0.25	0.18	0.12
Micro size segment			
Average excess returns	4.97	2.61	2.49
Average standard deviation	10.43	9.01	11.01
Sharpe ratio	0.48	0.29	0.23
Small size segment			
Average excess returns	3.02	1.63	1.31
Average standard deviation	9.80	9.75	10.49
Sharpe ratio	0.31	0.17	0.12
Big size segment			
Average excess returns	1.93	1.46	0.89
Average standard deviation	11.26	11.91	11.38
Sharpe ratio	0.17	0.12	0.08
Market less micro size segment			
Average excess returns	0.87	0.02	-0.27
Average standard deviation	6.17	5.76	6.50
Sharpe ratio	0.14	0.00	-0.04

Source: Researcher's own data

Second, low P/B shares are no more risky than growth shares. The simple average standard deviation of low P/B shares across Micro, Small and Large size segments is 6% (10%) for equal (value)-weighted portfolios, compared to 7% (11%) for equal (value)-weighted high P/B shares. This evidence is antithetical to suggestions by Fama and French (1992, 1993), and Gomes et al. (2003) that value shares earn higher returns for carrying more risk.

There are several possible explanations for the conflicting evidence on risk. First, the risk across size segments may be equal due to diversification or thin trading concerns. The Micro segment contains more shares than the Small or Large segments, which may mean that its standard deviation reflects less idiosyncratic risk. Alternatively, the Micro segment may still contain thinly traded shares, which would even out return series and bias downward standard deviations. Second, the risk across P/B portfolios does not have an obvious explanation, although it may point to the failings of standard deviation as a measure of risk. Irrespective of the true reasons for these risk estimates, their existence combined with the size and value effects means that small and low P/B shares have higher Sharpe ratios in this sample.

4.6.2 CORRELATION ANALYSIS

Based on the visual inspection in the previous section, there is sufficient evidence of both size and value premiums in South Africa. Figure 4.3 supports the result with a visual representation of the cumulative spread between low and high price-to-book portfolios in each of the Micro, Small and Large size segments. The cumulative spread is equal to the cumulative sum of the monthly return spread, following Capaul, Rowley and Sharpe (1993).

Figure 4.3 indicates that an investor long on value shares and short on growth shares could have earned substantial returns over the sample period. Nevertheless, the presence of negative slopes in cumulative returns towards the end of the sample period indicates that there were periods where value shares underperformed. Based on this evidence, there is a definite possibility that, if there is a link between return dispersion and the value premium, investors could use a timing strategy with value and growth shares to smooth profits over time. The remainder of this subsection considers this probability.

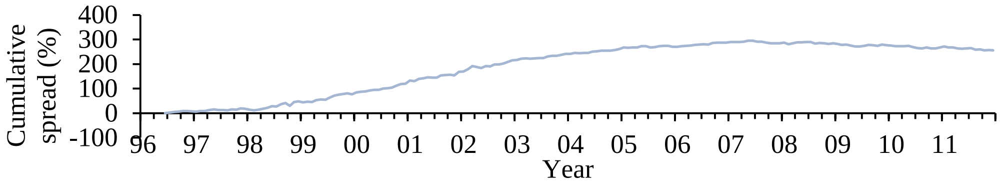
Table 4.9 presents Spearman's rank order correlation coefficients between return dispersion and the value premium. Panel A presents correlation coefficients using equal-weighted value premium returns, while Panel B presents correlation coefficients using value-weighted value premium returns. The value premium measurements are equal to the spread between low and high P/B portfolio returns in each size segment. The table presents pairwise correlation coefficients along with their associated p-values.

FIGURE 4.3

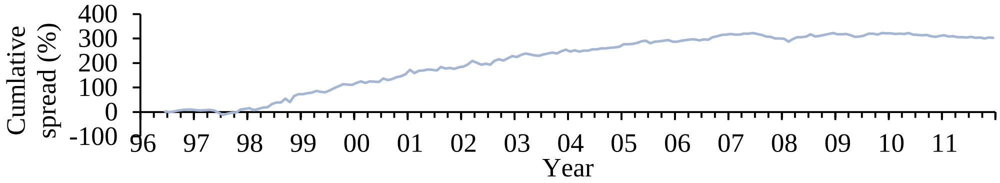
CUMULATIVE PREMIUM PAYOFFS

This figure shows cumulative percentage value spreads for the tertile portfolios in each size segment. The spread is equal to the cumulative sum of return spreads across bottom and top tertile portfolios. Panel A shows the market segment, Panel B the Micro segment, Panel C the Small segment, Panel D the Large segment and Panel E the Market less Micro segment.

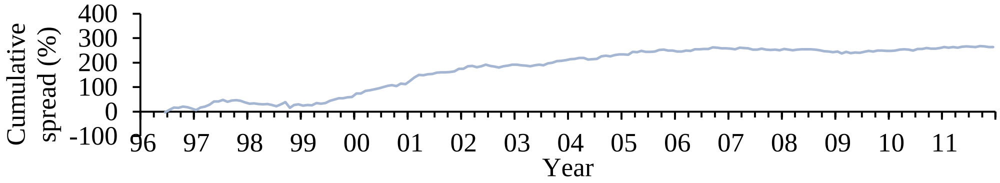
PANEL A: MARKET



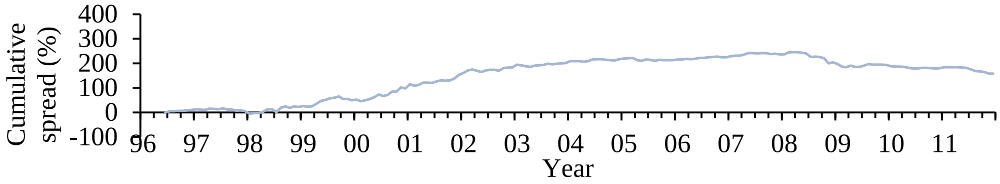
PANEL B: MICRO CAPITALISATION



PANEL C: SMALL CAPITALISATION



PANEL D: LARGE CAPITALISATION



PANEL E: MARKET LESS MICRO CAPITALISATION

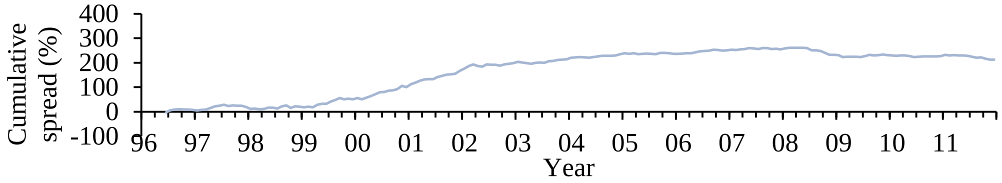


TABLE 4.9

RETURN DISPERSION AND THE VALUE PREMIUM

This table shows Spearman's rank correlation coefficients between return dispersion and the value premium. The value premium measurements consist of return spreads between low and high P/B portfolios in each of the Market, Micro, Small, Big and Market Less Micro segments. Panel A presents correlation coefficients using equal-weighted value premiums. Panel B presents correlation coefficients using value-weighted value premiums.

PANEL A: EQUAL-WEIGHTED RETURNS					
	Market	**Micro**	**Small**	**Big**	**MLM**
RD	0.16 [0.03]	0.11 [0.14]	0.07 [0.36]	0.18 [0.01]	0.19 [0.01]
PANEL B: VALUE-WEIGHTED RETURNS					
	Market	**Micro**	**Small**	**Big**	**MLM**
RD	0.16 [0.03]	0.15 [0.05]	0.02 [0.76]	0.19 [0.01]	0.17 [0.02]

Source: Researcher's own data

Based on the correlation coefficients in Table 4.9, there appears to be compelling evidence in favour of rejecting the null-hypothesis. There are statistically significant positive links between return dispersion and the value premium for seven of the twelve value premium measurements. For the equal-weighted returns in Panel A, the Market, Large and Market Less Micro segments show positive and significant association with return dispersion. For the value-weighted returns in Panel B, all size segments except the Small segment show positive and statistically significant association with return dispersion.

4.6.3 FURTHER EXPLORATORY ANALYSIS

The correlation coefficients presented in Section 4.6.2 present strong evidence in favour of the proposition that there is a link between return dispersion and the value premium. These coefficients range from around 0.15 to 0.19. Although the coefficients are consistent, their magnitude indicates only a moderate to weak level of positive correlation. Given evidence by Jiang (2010) that return dispersion dominates other asset pricing anomalies in asset pricing tests, it would be interesting to see if a similar phenomenon exists in this share sample.

In order to see if this is the case, this section briefly considers whether return dispersion adds incremental explanatory power to a Fama-French three-factor model. The procedure for estimating the three factor model follows Fama and French (1993). Table 4.10 presents estimated output for a three-factor model. The returns to be explained include 15 portfolios, covering the Micro, Small and Large size segments, with tertile portfolios recalculated as quintile portfolios. The Market Risk Premium (MRP) represents the value-weighted average of returns across all quintile and size portfolios. The size premium (SMB) is equal to the spread between simple averages of all Micro shares and all Large shares. The value premium is equal to the spread between the simple average returns of all low P/B and all high P/B shares. Finally, the analysis uses the value-weighted quintile and tertile portfolios. The table itself reports the coefficient, standard error and p-value for each coefficient, as well as an adjusted R-Squared value. Since the dependent variable is no longer return dispersion, the regressions use Newey and West (1987) robust standard errors to control for serial correlation and heteroscedasticity.

Table 4.10 shows that the three-factor model explains between 50 and 78% of variation in portfolio returns. The MRP coefficient is stable and significant across all 15 portfolios. The LMH coefficient demonstrates the expected negative trend from low to high P/B portfolios in each size segment, with significant observations for 10 of the 15 portfolios. The SMB also reflects the expected negative trend from Micro to Large segments, while coefficients are generally stable within each segment. The SMB coefficients are significant for 14 out of the 15 portfolios. Overall, therefore, the model seems well specified.

If return dispersion is able to add incremental explanatory power, there should be a link between return dispersion and the residual terms from the Fama-French model. Table 4.11 presents Spearman's Rank-order correlation coefficients between return dispersion and the residual terms from the Fama-French three-factor model. The table presents pairwise correlation coefficients, along with their associated p-values. A brief examination of Table 4.11 shows no significant link between return dispersion and the value premium for any of the residuals. An alternative analysis augmenting the three-factor model with return dispersion (not shown) similarly shows that return dispersion does not add incremental value to the three-factor model.

Based on this, there seems limited evidence in the South African equity market for using return dispersion in more advanced asset pricing applications. Nevertheless, the simple positive correlation between return dispersion and the value premium presented in Section 4.6.2 is sufficient to reject the null-hypothesis in favour of the proposition that there is a link

TABLE 4.10

THE FAMA-FRENCH THREE-FACTOR MODEL

This table presents output for a Fama-French three-factor model fitted to quintile portfolios in the Micro, Small and Large segments. The output includes coefficients (coeff.), standard errors (S.E.) and p-values (p-Value) for the market risk premium (MRP), Low minus High (LMH) and Small Minus Big (SMB) terms, as well as the adjusted R-Squared (Adj. RSQ). Regressions use Newey-West (1978) robust standard errors.

Portfolio	**MRP**			**LMH**			**SMB**			**Adj. – RSQ**
	Coeff.	**S.E.**	**p-value**	**Coeff.**	**S.E.**	**p-value**	**Coeff.**	**S.E.**	**p-value**	
Micro										
Low	0.21	(0.02)	[0.00]	0.36	(0.07)	[0.00]	0.61	(0.09)	[0.00]	0.51
2	0.15	(0.01)	[0.00]	0.05	(0.06)	[0.44]	0.42	(0.04)	[0.00]	0.55
3	0.16	(0.01)	[0.00]	-0.09	(0.04)	[0.00]	0.37	(0.04)	[0.00]	0.63
4	0.17	(0.01)	[0.00]	-0.17	(0.04)	[0.00]	0.39	(0.05)	[0.00]	0.69
High	0.2	(0.01)	[0.00]	-0.54	(0.07)	[0.00]	0.45	(0.07)	[0.00]	0.73
Small										
Low	0.18	(0.02)	[0.00]	0.08	(0.06)	[0.15]	0.21	(0.06)	[0.00]	0.52
2	0.17	(0.01)	[0.00]	-0.06	(0.05)	[0.27]	0.21	(0.06)	[0.00]	0.59
3	0.17	(0.01)	[0.00]	-0.04	(0.05)	[0.44]	0.21	(0.05)	[0.00]	0.56
4	0.15	(0.01)	[0.00]	-0.28	(0.07)	[0.00]	0.20	(0.05)	[0.00]	0.59
High	0.18	(0.01)	[0.00]	-0.52	(0.06)	[0.00]	0.23	(0.06)	[0.00]	0.70
Large										
Low	0.21	(0.01)	[0.00]	0.32	(0.08)	[0.00]	-0.27	(0.08)	[0.00]	0.78
2	0.17	(0.01)	[0.00]	0.18	(0.01)	[0.00]	-0.08	(0.06)	[0.17]	0.66
3	0.18	(0.01)	[0.00]	-0.26	(0.05)	[0.00]	-0.13	(0.04)	[0.00]	0.73
4	0.17	(0.01)	[0.00]	-0.15	(0.06)	[0.03]	-0.10	(0.04)	[0.05]	0.66
High	0.19	(0.01)	[0.00]	-0.47	(0.07)	[0.00]	-0.14	(0.06)	[0.01]	0.77

Source: Researcher's own data

TABLE 4.11

CORRELATION OF RETURN DISPERSION WITH

FAMA-FRENCH THREE-FACTOR RESIDUALS

This table shows Spearman's rank order correlation coefficients between return dispersion and error terms from the Fama-French three-factor model fitted to each of the quintile portfolios in each size segment. For each portfolio, the table reports its correlation with return dispersion, as well as a p-value in brackets indicating the statistical significance.

Micro				
Low	**2**	**3**	**4**	**High**
-0.06	0.00	0.05	-0.02	-0.24
(0.43)	(0.98)	(0.54)	(0.77)	(0.00)
Small				
Low	**2**	**3**	**4**	**High**
-0.05	0.02	-0.03	0.09	0.01
(0.54)	(0.81)	(0.69)	(0.24)	(0.93)
Large				
Low	**2**	**3**	**4**	**High**
0.08	-0.17	-0.08	-0.10	-0.09
(0.26)	(0.02)	(0.28)	(0.18)	(0.25)

Source: Researcher's own data

between return dispersion and the value premium. This confirms the theoretical framework in Chapter 3 and empirical evidence by Jiang (2010) and Stivers and Sun (2010).

4.7 ROBUSTNESS ANALYSIS OF FINDINGS

Based on the analysis in Sections 4.2 to 4.6, there seems sufficient evidence to reject all five null-hypotheses. Naturally, there is a possibility that these results are a product of the sample or variable specifications. In order to test the robustness of results to some degree, this section conducts an analysis using an alternate return dispersion measure that includes the top 160 shares ranked by market capitalisation. The estimated outputs for the analyses are reported in Tables B.1 to B.8 in Appendix B.

The evidence appears reasonably robust to an alternate return dispersion specification. As far as the univariate properties are concerned, the results are almost identical. Table B.1 and B.2 show that the alternate return dispersion measure is also stationary, with similarly significant Ljung-Box Q-Statistics. As with the primary specification, an evaluation of the AC and PAC functions reveals a possible ARMA (1, 1) process, which least squares estimation in Table B.3 confirms and updates to include a GARCH (1, 1) process. The AR, MA and GARCH coefficients are approximately equal to the estimated output for the primary return dispersion measure and remain statistically significant at a 5% level. The only noticeable difference for the alternate model is that the adjusted R-Squared jumps from 40 to 60%. Based on this result, there is sufficient evidence to indicate with some degree of confidence that return dispersion in the South African market contains univariate ARMA (1, 1) and GARCH (1, 1) processes over the period June 1996 to December 2011.

The robustness analysis of return dispersion's economic properties yields mixed evidence. Table B.4 shows that the link between return dispersion and industrial production growth disappears for the alternate return dispersion measure. Further analysis (not shown) using correlation coefficients reveals that there is a link between return dispersion and industrial production growth at four lags, but that the association disappears in regression analysis. Turning to the association between return dispersion and economic uncertainty, Table B.5 confirms a negative link between return dispersion and industrial production, a positive link between return dispersion and the risk-premium, as well as additional positive links between return dispersion and both inflation and the term-yield spread.

Table B.6 reports the robustness analysis for return dispersion and foreign exchange rate uncertainty. Although the primary measure of return dispersion contains moderate evidence of an association between return dispersion and foreign exchange rate uncertainty, the association does not hold for the alternative return dispersion measure. As with the primary measure, all of the slope coefficients are positive. Although the slope coefficients retain their sign, none of the coefficients are statistically significant, which indicates that the link between return dispersion and exchange rate uncertainty disappears for the alternate return dispersion measure.

One possible explanation for the disparity between the two measures is that the result for the top 40 measure is statistical artefact. This seems unlikely, however, given the theoretical motivation for a link between return dispersion and exchange rate uncertainty. Perhaps more plausible is the possibility that the disparity is due to the presence of smaller companies in the alternative measure. Smaller companies are less likely to export their goods or services, but most likely still incur import costs[25]. As a result, net importers might dominate the alternate return dispersion measure, which suggests that it probably does not reflect currency-hedging activity. In addition, most foreign investors are probably institutional investors, which suggests that shares outside the top 40 may be too small for foreign investors to invest in, irrespective of their suitability as exchange rate hedges.

Although the link between return dispersion and exchange rate uncertainty disappears, there are interesting results from the robustness analysis of return dispersion and foreign economic uncertainty. Table B.7 shows that, from the original significant results, only the link between return dispersion and the real U.S. T-Bill rate remains. While most of the original links disappear, Table B.7 indicates that there is a significant positive link between the alternate measure of return dispersion and both U.S. inflation and the U.S. risk premium. As such, the alternate measure provides additional evidence against the null-hypothesis of no link between return dispersion and foreign economic uncertainty.

Finally, a robustness analysis of the link between return dispersion and the value premium confirms earlier analysis. Table B.8 shows that there are significantly positive links between return dispersion and 5 of the 12 value premium measurements. Panel A of the Table shows that there are significant positive links between return dispersion and value measurements in the Market, Large and Market less micro segments using equally weighted returns. Panel B shows that there are significant positive links between return dispersion and value measurements in the Micro, Large and Market less micro segments using value-weighted returns. Overall, these results confirm original evidence of a significant positive link between return dispersion and the value premium.

As a whole, the robustness results indicate that there is sufficient evidence to support initial results. The evidence indicates that there are strong grounds for rejecting the first null-hypothesis, moderate grounds for rejecting the second to fourth null-hypotheses and strong evidence for rejecting the fifth null-hypothesis. Based on this evidence, the study continues with its original conclusions regarding the null-hypotheses.

[25] For example; transport costs, which are a feature of most businesses, ties in to the price of petrol (gasoline), which in turn depends on the price of imported crude oil.

4.8 CONCLUSION

This chapter was concerned with the actual empirical analyses. The chapter consisted of five main sections, each of which considered one of the five hypotheses. Based on the analysis conducted in these sections, as well as robustness analysis, the results support the following conclusions:

(i) there is strong evidence that return dispersion is non-random and may be modelled using univariate time-series processes,

(ii) there is moderate evidence that return dispersion leads economic activity in a countercyclical fashion,

(iii) there is strong evidence of a link between return dispersion and both domestic and foreign economic uncertainty and

(iv) there is strong evidence of a link between return dispersion and the value premium.

CHAPTER FIVE
CONCLUSION

5.1 SUMMARY OF FINDINGS

This study set out to identify why return dispersion changes over time and how it relates to the conditional distribution of asset returns. Based on the empirical analysis conducted, it appears that return dispersion is a non-random series, and a function of both economic activity and economic uncertainty. The relationship between return dispersion and economic uncertainty spans both local and foreign economic factors. In addition, it appears that time-variation in return dispersion correlates positively with variation in the value premium.

Each of these empirical findings is a result of careful analysis. First, the claim that return dispersion in the South African equity market is non-random is based on univariate time-series analysis. An evaluation of Box-Ljung Q-statistics reveals that return dispersion is not independently distributed over time, instead exhibiting significant serial correlation. This result confirms evidence by Hwang and Satchell (2004) and Stivers and Sun (2010). Further analysis shows that the serial correlation in return dispersion may be modelled using ARMA (1, 1) and GARCH (1, 1) processes.

Second, the claim that return dispersion is countercyclical to real economic activity is based on results from a regression of return dispersion on the growth rate of industrial production. The regression estimates reveal a negative and statistically significant link between return dispersion and industrial production growth using a one-month lag of return dispersion. A leading countercyclical relationship between return dispersion and economic activity confirms the theoretical model of Gomes et al. (2003) and the empirical evidence of Stivers and Sun (2010) for the United States equity market.

Third, the claim that return dispersion varies with both local and foreign economic uncertainty arises from results obtained from regressions of return dispersion on the conditional variances of selected economic variables. The analysis of local variables reveals significant links between return dispersion and real economic uncertainty, inflation uncertainty and uncertainty over the term structure of interest rates. The analysis of foreign variables reveals significant links between return dispersion and the Rand/U.S. Dollar exchange rate uncertainty, U.S. real interest rate uncertainty and uncertainty over the U.S. term structure of interest rates. These findings support the theoretical framework developed in Chapter 3.

Fourth, the claim that return dispersion correlates positively with the value premium is justified from correlation analysis using return dispersion and the return spread between low and high price-to-book ratio portfolios in a variety of market capitalisation segments. An evaluation of Spearman's ranked correlation coefficients reveals a significantly positive link in seven of the twelve value premium measurements. This result confirms empirical evidence by Jiang (2010) and Stivers and Sun (2010) for the United States equity market.

Based on these empirical results, there is sufficient support to argue that investors can understand why return dispersion changes over time, as well as how to take advantage of changes in return dispersion. First, since return dispersion is non-random, past observations indicate something about likely future observations. Beyond this purely statistical result, there is evidence that return dispersion changes along with the level of economic activity and with economic uncertainty. As a result, investors can form expectations about the level of return dispersion based on its recent levels, the economic outlook and market sentiment. Second, since return dispersion correlates positively with the value premium, the level of return dispersion indicates something about the expected profitability of value shares. As a result, investors can pursue potential active returns by purchasing (selling) value shares or selling (purchasing) growth shares when return dispersion is likely to increase (decrease).

5.2 IMPLICATIONS FOR INVESTORS

Based on these empirical results, there appears to be sufficient evidence to argue that investors can understand why return dispersion changes over time and how to take advantage of changes in return dispersion. To begin with, evidence of serial correlation indicates that there are stochastic trends in return dispersion. As a result, investors can understand why return dispersion is at a certain level based on its recent movements. In addition, evidence of univariate time-series processes can help investors to quantify the influence of stochastic trends.

Beyond this purely statistical result, empirical evidence indicates that return dispersion changes with both the future level of economic activity and the current level of economic uncertainty. As a result, investors can relate changes in return dispersion to the economic outlook as well as uncertainty over the economic state. Taken together with the time-series properties of return dispersion, investors should be able to form accurate expectations of return dispersion in a forward-looking investment context.

Finally, evidence of a link between return dispersion and the value premium offers some clue as to how to take advantage of changes in return dispersion. If return dispersion increases via stochastic trends, decreasing economic activity or increasing economic uncertainty, investors might benefit from investing in value shares and selling off growth shares. As a result, there is definite scope for taking advantage of changes in return dispersion. Overall, these findings suggest that it is possible for investors to manage changes in return dispersion pro-actively.

5.3 CONTRIBUTION TO LITERATURE

Beyond their practical implications, the findings presented in this study also contribute to literature. As mentioned, evidence of serial correlation, countercyclical behaviour and a positive link to the value premium supports empirical evidence in other papers. There are also, to the knowledge of the author, several novel contributions to literature. First, the study provides a unique contribution by identifying ARMA (1, 1) and GARCH (1, 1) processes in return dispersion. Second, no other work in the existing literature uses the stock market modelling approach of Chen et al. (1990) and Schwert (1989) to characterise changes in return dispersion over time. In this, the study has made an original contribution to literature.

5.4 LIMITATIONS AND AREAS FOR FUTURE RESEARCH

Naturally, the findings in this study are predicated on certain assumptions. The most important of these assumptions is that investors are rational economic agents. Although this study took care to justify its use of a rational economic framework, there is still a chance that changes in return dispersion may be accounted for in a behavioural finance framework. Even though a different economic framework will not alter the empirical results documented in this study, it opens an avenue for alternate interpretations of why return dispersion varies over time. This represents an interesting avenue of possible future research.

An additional assumption within the rational economic framework is that economic uncertainty is captured by the conditional variance of economic state variables. While this view is supported by Schwert (1989), there are alternative approaches to quantifying uncertainty. It would be interesting to see if alternative methods using indices or event studies using news releases document a similar link between economic uncertainty and return dispersion.

Staying within the rational economic framework, the study limits itself to an investigation of the relationship between return dispersion and the value premium. Although this is justified within the scope of the study, since the value premium is arguably the easiest to place in an economic framework, there are numerous other asset pricing anomalies. It would be interesting to see if the conditional returns of other anomalies, such as the size or momentum premiums, are also related to return dispersion.

Furthermore, while the study identifies factors associated with changes in return dispersion and a positive link between return dispersion and the value premium, the study stops short of quantifying the economic advantage of timing changes in return dispersion. It would be very interesting to see a study along the lines of Fleming, Kirby and Ostdiek (2001), who test economic value of volatility timing by calculating the spread between an active approach using a time-series volatility timing strategy and a passive approach.

Finally, the investment adage *past returns are no guarantee of future performance* presents an interesting challenge to the results. Naturally, as investors become aware of a link between return dispersion and the value premium, the same rational behaviour that predicts the link will lead investors to eliminate the potential advantage. Based on this, there is no guarantee that the findings documented in this study will hold in the future. It would be interesting, therefore, to see if the same relationships exist some years into the future. As to how long exactly they will hold, only time will tell.

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APPENDIX A
SUPPLEMENT TO RESEARCH METHOD

A.1 MATHEMATICAL PROOF: RISK PREMIUMS AND THE REAL ECONOMY

A key assumption in Chapter 3 is that there is a link between asset prices and real economic activity. This assumption comes from a mathematical proof by Cochrane (2008: 239). This section presents this mathematical proof.

First, it is possible to prove that the price of any asset is equal to a risk-neutral present value plus a discount for risk, where the discount for risk is a function of the covariance between the discount rate and expected payoffs. Consider an asset i at time t in a single-period setting:

$$p_{i,t} = E_t \ \frac{x_{i,t+1}}{m_{t+1}} \qquad \text{(A.1)}$$

Where $p_{i,t}$ is the price of asset i at time t, E_t is the conditional expectation at time t, $x_{i,t+1}$ is the payoff for asset i at time t and m_{t+1} is the discount rate at time $t+1$.

The definition of covariance between two variables X and Y is $Cov\ \ X,Y\ \ = E\ \ XY\ \ - E\ \ X\ \ E(Y)$. Applying this equation to the covariance between the discount factor and the payoff for asset i at time t yields:

$$Cov_t\ \ m_{t+1}, x_{i,t+1}\ \ = E_t\ \ m_{t+1}x_{t+1}\ \ - E_t\ \ m_{t+1}\ \ E\ \ x_{i,t+1} \qquad \text{(A.2)}$$

Using equation (A.1), the first term on the right-hand side of equation (A.2) is equal to $p_{i,t}$. Cochrane (2005:239) defines the risk-free rate as $r_f = 1/E(m)$. Applying this to equation (A.2) yields:

$$Cov_t\ \ m_{t+1}x_{i,t+1}\ \ = p_{i,t} - \frac{E\ \ x_{i,t+1}}{r_{f,t+1}} \qquad \text{(A.3)}$$

Rearranging equation (C.3) yields:

$$p_{i,t} = \frac{E_t\ \ x_{i,t+1}}{r_{f,t+1}} + Cov_t(m_{t+1}, x_{i,t+1}) \tag{A.4}$$

Where the first term on the right-hand side represents a risk-neutral present value and the second term is the covariance between the discount rate and the asset price – in other words a discount for risk.

After proving that the discount rate is a function of the covariance between the discount rate and asset payoff, it is possible to show that the expected excess return of any asset is higher for shares that have a high negative covariance with the discount factor. To begin with, the gross return for asset i is equal to the discount rate, so, using equation (A.1), the return for asset i, or $r_{i,t}$, is:

$$1 = E(\frac{m_{t+1}}{r_{t+1}}) \tag{A.5}$$

Now, the excess return $r_{e,t+1}$ of a zero-cost portfolio that is long asset i and short asset j is:

$$r_{e,t+1} = r_{i,t+1} - r_{j,t+1} \tag{A.6}$$

While the expected excess return is:

$$E(m_{t+1} r_{e,t+1}) \tag{A.7}$$

By substituting (A.6) into (A.7) and using the statistical property $E\ \ aX + aY\ \ = E\ \ aX\ \ + E(aY)$, the expected excess return is:

$$E\ \ m_{t+1} r_{i,t+1}\ \ - E\ \ m_{t+1} r_{j,t+1} \tag{A.8}$$

Equation (A.5) implies that (A.8) is equal to zero, so that:

$$E\ \ m_{t+1} r_{e,t+1}\ \ = 0 \tag{A.9}$$

By using the covariance method in equation (A.2) and a real risk-free rate $1 = E(m)r_f$, equation (A.9) becomes:

$$E\ r_{e,t+1}\ = -r_f Cov(m, r_{e,t+1}) \tag{A.10}$$

Cochrane argues that, for small time periods, $r_f \approx 1$, which means that (A.10) becomes:

$$E\ r_{e,t+1}\ = -Cov(m, r_{e,t+1}) \tag{A.11}$$

Equation (A.11) states that the excess return, or risk premium, for the zero-cost portfolio from (A.6) is a function of the covariance between the discount rate and excess returns.

A first-order condition for rational investors is that the expected discount rate is equal to the growth in the marginal utility of wealth. As a result, the marginal utility may be thought of as a measure of an investor's 'hunger' for one additional unit of wealth. Applying this logic to (A.11) implies that the risk premium is a function of the covariance of returns with the marginal value of wealth. Put differently, investors will prefer assets that do well when marginal value growth is high, or equivalently when money is more valuable. Using simple supply and demand arguments, assets that do well when money is valuable will be in demand, which will drive up prices, or drive down the discount rate. As a result, investors may prefer to hold assets that have a lower expected return, provided these assets do well when money is scarce. Cochrane (2001, 2008) argues that, in intuitive terms, the marginal value of wealth should be greater during 'bad times' such as recessions.

A.2 SHARES USED IN THE RETURN DISPERSION CALCULATION

The return dispersion calculation uses the top 40 shares ranked by market capitalisation from the original sample of 951 shares for each year from 1995 to 2010. The 1995 start date reflects the fact that the first return dispersion observation in June 1996 uses shares ranked on December 1995. Collecting the top 40 shares in each year yields 148 unique share observations. Table A.1 shows the identity of these shares, including their JSE code (alpha) and company name, as well as the listing and termination dates of each share in the sample period.

TABLE A.1

RETURN DISPERSION: SHARES TRADED IN ALL LISTED MONTHS

Alpha	Company name	Start	End[26]
ABL	AFRICAN BANK INVESTMENTS LTD	12/95	12/11
ACL	ARCELORMITTAL SA LTD	12/95	12/11
AEG	AVENG LTD	08/99	12/11
AFB	ALEXANDER FORBES LIMITED	12/96	07/07
AFI	AFRICAN LIFE ASSURANCE COMPANY LD	12/95	02/06
AGL	ANGLO AMERICAN PLC	12/95	12/11
AIT	ANGLO AMERICAN INVESTMENT TRUST LTD	12/95	05/99
AMC	ANGLO AMERICAN COAL CORP LTD	12/95	12/98
AMG	ANGLO AMERICAN GOLD INVESTMENT CO LTD	12/95	05/99
AMI	ANGLO AMERICAN INDUSTRIAL CORP LTD	12/95	02/99
AMS	ANGLO AMERICAN PLAT LTD	12/95	12/11
ANG	ANGLOGOLD ASHANTI LIMITED	12/95	12/11
APN	ASPEN PHARMACARE HOLDINGS LIMITED	12/95	12/11
AQP	AQUARIUS PLATINUM LIMITED	12/04	12/11
ARI	AFRICAN RAINBOW MINERALS LIMITED	12/95	12/11
ASA	ABSA GROUP LIMITED	12/95	12/11
ASR	ASSORE LIMITED	12/95	12/11
AVG	AVGOLD LTD	12/95	05/04
AVI	AVI LIMITED	12/95	12/11
AVM	AVMIN LIMITED	12/95	12/98
BAW	BARLOWORLD LIMITED	12/95	12/11
BIL	BHP BILLITON PLC	08/97	12/11
BOC	BOE CORPORATION LTD	12/95	12/00
BTI	BRITISH AMERICAN TOBACCO PLC	11/08	12/11
BVC	BEV & CONSUMER IND HOLDINGS LTD	12/95	06/01
BVT	THE BIDVEST GROUP LIMITED	12/95	12/11
CFR	COMPAGNIE FIN RICHEMONT	12/95	12/11
CGS	CG SMITH LTD	12/95	02/00
CSF	CG SMITH FOODS LTD	12/95	08/99
CSO	CAPITAL SHOPPING CENTRES GROUP PLC	12/95	07/99
DBR	DE BEERS CONSOLIDATED MINES LTD	12/95	06/01
DDT	DIMENSION DATA HOLDINGS PLC	12/95	12/10
DRD	DRDGOLD LIMITED	12/95	12/11

[26] Start and end dates are displayed in a “Month/Year” format; December 1994, for example, is shown as 12/94.

DSY	DISCOVERY HOLDINGS LIMITED	11/99	12/11
DTC	DATATEC LIMITED	12/95	12/11
ECO	EDGARS CONSOLIDATED STORES LIMITED	12/95	05/07
ELE	ELEMENTONE LTD	12/95	01/10
EXX	EXXARO RESOURCES LIMITED	12/01	12/11
FDS	FEDSURE HOLDINGS LTD	12/95	04/02
FRG	FREE STATE CONS GOLD MINES	12/95	06/98
FSB	FIRST NATIONAL BANK HLD LTD	12/95	05/98
FSR	FIRSTRAND LIMITED	12/95	12/11
GFI	GOLD FIELDS LIMITED	12/95	12/11
GFL	GOLD FIELDS LTD	03/98	05/99
GFS	GOLD FIELDS OF SOUTH AFRICA LTD	12/95	02/01
GMF	GENCOR LIMITED	12/95	05/06
GRT	GROWTHPOINT PROPERTIES LIMITED	12/95	12/11
GSC	GENBEL SECURITIES LTD	06/96	12/00
HAR	HARMONY GOLD MINING COMPANY LIMITED	12/95	12/11
IGE	INGWE COAL CORPORATION LTD	12/95	09/98
IMP	IMPALA PLATINUM HOLDINGS LIMITED	12/95	12/11
INL	INVESTEC LIMITED	12/95	12/11
INP	INVESTEC PLC	08/07	12/11
IPL	IMPERIAL HOLDINGS LIMITED	12/95	12/11
IVG	INVEGO INVESTMENTS LTD	12/95	09/98
JDG	JD GROUP LIMITED	12/95	12/11
JNC	JOHNNIC HOLDINGS LIMITED	12/95	09/08
KIO	KUMBA IRON ORE LIMITED	12/06	12/11
KLO	KLOOF GOLD MINING COMPANY LTD	12/95	01/08
LBH	LIBERTY HOLDINGS LIMITED	12/95	12/11
LBS	LIBLIFE STRATEGIC INVESTMENTS LTD	12/95	06/01
LGL	LIBERTY GROUP LIMITED	04/96	11/08
LON	LONMIN PLC	12/95	12/11
MMI	MMI HOLDINGS LTD	12/95	12/11
MNR	MINORCO SOCIETE ANONYME	12/95	05/99
MSM	MASSMART HOLDINGS LIMITED	08/00	12/11
MTN	MTN GROUP LIMITED	12/95	12/11
MUR	MURRAY AND ROBERTS HOLDINGS LIMITED	12/95	12/11
NBB	NBS BOLAND GROUP LTD	10/97	06/98
NED	NEDBANK GROUP LIMITED	12/95	12/11
NPK	NAMPAK LIMITED	12/95	12/11

NPN	NASPERS LIMITED	12/95	12/11
NTC	NETCARE LIMITED	01/97	12/11
OML	OLD MUTUAL PLC	08/99	12/11
ORH	ORION SELECTIONS HOLDINGS LTD	12/95	07/98
ORS	ORION SELECTIONS LTD	12/95	07/98
PIK	PICK N PAY STORES LIMITED	12/95	12/11
PPC	PRETORIA PORTLAND CEMENT COMPANY LD	12/95	12/11
RAH	REAL AFRICA HOLDINGS LIMITED	12/95	12/11
REI	REINET INVESTMENTS S.C.A	12/95	12/11
REM	REMGRO LIMITED	10/00	12/11
RMB	REMBRANDT BEHERENDE BELEG BPK	12/95	09/00
RMH	RMB HOLDINGS LIMITED	12/95	12/11
RMT	REMBRANDT GROUP LIMITED	12/95	09/00
SAB	SABMILLER PLC	12/95	12/11
SAP	SAPPI LIMITED	12/95	12/11
SBK	STANDARD BANK GROUP LTD	12/95	12/11
SFR	SAFMARINE & RENNIES HOLDINGS LTD	12/95	07/00
SHF	STEINHOFF INTERNATIONAL HOLDINGS LTD	10/98	12/11
SHP	SHOPRITE HOLDINGS LIMITED	12/95	12/11
SLM	SANLAM LIMITED	12/98	12/11
SOL	SASOL LIMITED	12/95	12/11
SON	SOUTHERN LIFE ASSOCIATION LTD, THE	12/95	05/98
TBS	TIGER BRANDS LIMITED	12/95	12/11
TGN	TIGON LIMITED	12/95	04/07
TKG	TELKOM SA LIMITED	04/03	12/11
TON	TONGAAT HULETT LIMITED	12/95	12/11
TRU	TRUWORTHS INTERNATIONAL LIMITED	06/98	12/11
UUU	URANIUM ONE INC	01/06	12/11
VNF	VENFIN LIMITED	10/00	04/06
VOD	VODACOM GROUP LTD	06/09	12/11
WHL	WOOLWORTHS HOLDINGS LIMITED	11/97	12/11

A.3 SHARES USED IN THE VALUE PREMIUM CALCULATION

The data gathering procedure used in Section 3.4.4.2 yields 241 eligible shares over the period June 1996 to December 2011. Table A.2 shows the identity of these shares, including their JSE code, company name, as well as listing and termination dates for each share.

TABLE A.2

VALUE PREMIUM: SHARES TRADED IN ALL LISTED MONTHS

Alpha	Company name	Start	End[27]
1TM	1TIME HOLDINGS LTD	08/07	12/11
AAL	ALPHA	12/95	10/98
ABC	ABACUS TECHNOLOGY HOLDINGS LTD	11/96	04/02
ABU	ABE CONSTRUCTION CHEMICALS LTD	08/07	08/10
ACE	ACCENTUATE LTD	11/06	12/11
ACL	ARCELORMITTAL SA LTD	12/95	12/11
ACT	AFROCENTRIC INVESTMENT CORP LIMITED	05/06	12/11
ADC	ADCOCK INGRAM LTD	12/95	11/99
ADH	ADVTECH LIMITED	11/97	12/11
ADR	ADCORP HOLDINGS LIMITED	12/95	12/11
AEG	AVENG LTD	07/99	12/11
AET	ALERT STEEL HOLDINGS LIMITED	03/07	12/11
AFE	A E C I LIMITED	12/95	12/11
AFR	AFGRI LIMITED	11/96	12/11
AFT	AFRIMAT LIMITED	11/06	12/11
AFX	AFRICAN OXYGEN LIMITED	12/95	12/11
AIP	ADCOCK INGRAM HOLDINGS LTD	08/08	12/11
AKJ	ARTHUR KAPLAN JEWELLERY HOLDINGS LTD	12/95	10/97
ALT	ALLIED TECHNOLOGIES LIMITED	12/95	12/11
AMA	AMALGAMATED APPLIANCE HOLDINGS LD	05/97	12/11
AME	AFRICAN MEDIA ENTERTAINMENT LIMITED	12/97	12/11
AMI	ANGLO AMERICAN INDUSTRIAL CORP LTD	12/95	01/99
ANS	ANSYS LIMITED	06/07	12/11
APG	AUTOPAGE HOLDINGS LTD	12/95	07/00
APN	ASPEN PHARMACARE HOLDINGS LIMITED	12/95	12/11
ARL	ASTRAL FOODS LIMITED	04/01	12/11

[27] Start and end dates are displayed in a "Month/Year" format; December 1994, for example, is shown as 12/94.

ART	ARGENT INDUSTRIAL LIMITED	12/95	12/11
ATN	ALLIED ELECTRONICS CORPORATION LTD	12/95	12/11
ATR	AFRICA CELLULAR TOWERS LIMITED	11/06	12/11
AUK	AUKLAND HEALTH LTD	12/95	08/98
AVI	AVI LIMITED	12/95	12/11
AVU	AVUSA LTD	03/08	12/11
BAW	BARLOWORLD LIMITED	12/95	12/11
BCF	BOWLER METCALF LIMITED	12/95	12/11
BCR	BID CORPORATION LIMITED	12/95	05/97
BCX	BUSINESS CONNEXION GROUP LIMITED	05/04	12/11
BEL	BELL EQUIPMENT LIMITED	12/95	12/11
BLU	BLUE LABEL TELECOMS LIMITED	11/07	12/11
BOU	BOUMAT LTD	12/95	03/00
BSB	THE HOUSE OF BUSBY LIMITED	11/97	03/08
BSR	BASIL READ HOLDINGS LIMITED	12/95	12/11
BSS	BSI STEEL LTD	10/07	12/11
BTG	BYTES TECHNOLOGY LIMITED	12/95	12/07
BTI	BRITISH AMERICAN TOBACCO PLC	10/08	12/11
BTR	BATEMAN INDUSTRIAL CORPORATION LTD	12/95	10/99
BTS	BRITISH AMERICAN TOBACCO SA	12/95	06/99
BVT	THE BIDVEST GROUP LIMITED	12/95	12/11
BWI	B & W INSTRUMENTATION AND ELECTRICAL LTD	07/07	12/11
BZK	BERZACK BROTHERS (HOLDINGS)	12/95	06/98
CAS	CADBURY SCHWEPPES (SOUTH AFRICA) LTD	12/95	11/00
CBH	COUNTRY BIRD HOLDINGS LTD	05/07	12/11
CCI	CIC HOLDINGS LTD	11/07	10/10
CCT	CONNECTION GROUP HOLDINGS LIMITED	10/97	11/05
CEL	CELCOM GROUP LIMITED	11/06	04/09
CET	CHET INDUSTRIES LTD	12/97	11/01
CFR	COMPAGNIE FIN RICHEMONT	12/95	12/11
CGS	CG SMITH LTD	12/95	01/00
CGW	CONSOL LIMITED	12/95	12/97
CHR	CHARTER PLC	12/95	06/98
CHU	CHUBB HOLDINGS	12/95	12/97
CIL	CONSOLIDATED INFRASTRUCTURE GROUP	11/07	12/11
CLC	CLINIC HOLDINGS LTD	12/95	09/01
CLH	CITY LODGE HOTELS LIMITED	12/95	12/11

CLS	CLICKS GROUP LIMITED	03/96	12/11
CLT	CULLINAN HOTEL AND LEISURE GROUP LTD	12/95	09/99
CMI	CONSOLIDATED METALLURGICAL INDUSTRIES LTD	12/95	07/98
CMP	CIPLA MEDPRO SA LTD	06/05	12/11
COM	COMAIR LIMITED	07/98	12/11
COM. DEL	CHROMECORP HOLDINGS	03/96	03/98
CPB	CORPCAPITAL BANK CONTROLLING COMPANY LTD	06/98	09/01
CPM	CORPCOM LTD	07/98	10/01
CRM	CERAMIC INDUSTRIES LIMITED	12/95	12/11
CRS	CARSON HOLDINGS LTD	07/96	09/00
CSF	CG SMITH FOODS LTD	12/95	07/99
CSP	CHEMICAL SPECIALITIES LIMITED	11/07	12/11
CST	CAPESTAR GROWTH INVESTMENTS LTD	08/97	12/01
CVI	CAPEVIN INVESTMENTS LTD	12/95	12/11
DAW	DISTRIBUTION AND WAREHOUSING NETWORK LTD	12/95	12/11
DCT	DATACENTRIX HOLDINGS LIMITED	09/98	12/11
DGC	DIGICORE HOLDINGS LIMITED	12/98	12/11
DNL	DUNLOP AFRICA LTD	12/95	02/02
DON	THE DON GROUP LIMITED	12/95	12/11
DST	DISTELL GROUP LIMITED	12/95	12/11
DTA	DELTA EMD LTD	12/95	12/11
DTC	DATATEC LIMITED	12/95	12/11
ECO	EDGARS CONSOLIDATED STORES LIMITED	12/95	04/07
EHS	EVRAZ HIGHVELD STEEL AND VANADIUM LIMITED	12/95	12/11
ELH	ELLERINE HOLDINGS LIMITED	12/95	12/07
ELI	ELLIES HOLDINGS LIMITED	09/07	12/11
ELR	ELB GROUP LIMITED	12/95	12/11
EOH	EOH HOLDINGS LTD	08/98	12/11
EQS	EQSTRA HOLDINGS LIMITED	05/08	12/11
ESR	ESORFRANKI LTD	03/06	12/11
EVT	EVERITE GROUP LIMITED	12/95	10/96
FAM	FRAME GROUP LTD	12/95	11/00
FBR	FAMOUS BRANDS LIMITED	12/95	12/11
FCS	FEDICS GROUP LTD, THE	09/97	02/00

FDC	FOODCORP LIMITED	12/95	03/98
FIN	FINTECH LTD	12/95	11/01
FSC	FASIC LTD	12/95	12/00
FWD	FREEWORLD COATINGS LIMITED	12/07	12/11
GFN	GRIFFEN SHIPPING HOLDINGS LTD	12/95	06/98
GIJ	GIJIMA GROUP LTD	09/98	12/11
GLH	GLOHOLD LTD	12/95	11/00
GND	GRINDROD LIMITED	12/95	12/11
GPI	GYPSUM INDUSTRIES	12/95	08/96
GRC	GRINAKER CONSTRUCTION LTD	12/96	10/99
GRF	GROUP FIVE LIMITED	12/95	12/11
GTA	GENTYRE INDUSTRIES	12/95	07/97
HAG	HAGGIE LTD	12/95	12/98
HCT	HOECHST SOUTH AFRICA LIMITED	12/95	10/98
HDC	HUDACO INDUSTRIES LIMITED	12/95	12/11
HLM	HULAMIN LIMITED	06/07	12/11
HNC	HUNTCOR	12/95	11/97
HWN	HOWDEN AFRICA HOLDINGS LIMITED	05/96	12/11
IBM	IBM SOUTH AFRICA GROUP LTD	12/95	07/98
IDI	IDION TECHNOLOGY HOLDINGS LIMITED	08/98	10/06
IEH	INTEGRATED TECH HLDG LTD	01/98	05/01
IFS	I-FUSION HOLDINGS LTD	12/95	10/01
ILA	ILIAD AFRICA LIMITED	06/98	12/11
ILE	IMBALIE BEAUTY LIMITED	08/07	12/11
ILV	ILLOVO SUGAR LIMITED	12/95	12/11
IPL	IMPERIAL HOLDINGS LIMITED	12/95	12/11
IPS	IPSA GROUP PLC	10/06	12/11
IRV	IRVIN AND JOHNSON LTD	12/95	12/99
ISB	INSIMBI REFRACTORY & ALLOY SUPPLIES LTD	03/08	12/11
ITE	ITALTILE LIMITED	12/95	12/11
IVT	INVICTA HOLDINGS LIMITED	12/95	12/11
JDG	JD GROUP LIMITED	12/95	12/11
KAP	KAP INTERNATIONAL HOLDINGS LIMITED	12/95	12/11
KEL	KELLY GROUP LIMITED	04/07	12/11
KGM	KAGISO MEDIA LIMITED	12/95	12/11
KIO	KUMBA IRON ORE LIMITED	11/06	12/11
KOH	KOHLER LTD	12/95	07/98
KOP	KOPP ELECTRONICS LIMITED	12/95	01/96

LEW	LEWIS GROUP LIMITED	10/04	12/11
LFS	FIRST LIFESTYLE HOLDINGS LTD	06/97	10/00
LHG	LITHA HEALTHCARE GROUP LTD	10/06	12/11
LNC	LENCO HOLDINGS LTD	12/95	05/01
LTA	LTA LTD	12/95	09/00
MAC. DEL	MACPHAIL HOLDINGS LTD	12/95	07/97
MCR	MCCARTHY GROUP LTD	12/95	06/98
MDC	MEDICLINIC INTERNATIONAL	12/95	12/11
MDM	MACADAMS BAKERY SUPPLIES HOLDINGS LTD	12/95	10/00
MEG	MILLENIUM ENTERTAINMNT GRP LTD	12/95	10/98
MIX	MIX TELEMATICS LTD	11/07	12/11
MKX	MILKWORX LIMITED	09/04	10/09
MML	METMAR LIMITED	05/06	12/11
MND	MONDI Limited	07/07	12/11
MNP	MONDI PLC	07/07	12/11
MOR	MORVEST BUS GROUP LTD	08/04	12/11
MPC	MR PRICE GROUP LIMITED	12/95	12/11
MSM	MASSMART HOLDINGS LIMITED	07/00	12/11
MST	MUSTEK LIMITED	04/97	12/11
MTK	METKOR GROUP LTD	12/95	02/00
MTN	MTN GROUP LIMITED	12/95	12/11
MTR	METROPOLIS TRANSACTIVE HOLDINGS LTD	12/98	09/01
MTX	METOREX LIMITED	12/95	12/11
MUR	MURRAY AND ROBERTS HOLDINGS LIMITED	12/95	12/11
MZR	MAZOR GROUP LIMITED	11/07	12/11
NPK	NAMPAK LIMITED	12/95	12/11
NPN	NASPERS LIMITED	12/95	12/11
NTC	NETCARE LIMITED	12/96	12/11
NUT	NUTRITIONAL HOLDINGS LTD	12/06	12/11
OAO	OANDO PLC	11/05	12/11
OCE	OCEANA GROUP LIMITED	12/95	12/11
OLI	O-LINE HOLDINGS LIMITED	11/07	12/11
OMN	OMNIA HOLDINGS LIMITED	12/95	12/11
OTS	OTIS ELEVATOR COMPANY	12/95	12/97
PAG	PARAGON BUSINESS COMMUNICATIONS LTD	10/97	02/02
PAM	PALABORA MINING COMPANY LIMITED	12/95	12/11
PEG	PEPGRO LTD	12/95	10/00

PEI	PEP LTD	12/95	12/98
PFG	PIONEER FOOD GROUP LIMITED	04/08	12/11
PGS	PLATE GLASS & SHATTERPRUFE INDUSTRIES LTD	12/95	11/99
PHM	PHUMELELA GAMING AND LEISURE LTD	06/02	12/11
PIK	PICK N PAY STORES LIMITED	12/95	12/11
PKH	PROTECH KHUTHELE HOLDINGS LTD	08/07	12/11
PMA	PRIMEDIA LIMITED	12/95	08/07
PNC	PINNACLE TECHNOLOGY HOLDINGS LTD	08/99	12/11
PPC	PRETORIA PORTLAND CEMENT COMPANY LD	12/95	12/11
PRT	PRIMA TOY AND LEISURE GROUP LTD	12/97	10/00
PSV	PSV HOLDINGS LIMITED	04/06	12/11
PSY	PLESSEY CORPORATION LTD	12/95	09/98
PTG	PEERMONT GLOBAL LIMITED	09/04	03/07
PWK	PICK N PAY HOLDINGS LIMITED	12/95	12/11
RAC	RACEC GROUP LTD	10/07	12/11
RAR	RARE HOLDINGS LIMITED	02/07	12/11
RBA	RBA HOLDINGS LTD	09/07	12/11
RBW	RAINBOW CHICKEN LIMITED	12/95	12/11
RBX	RAUBEX GROUP LIMITED	03/07	12/11
REM	REMGRO LIMITED	09/00	12/11
RLF	ROLFES HOLDINGS LTD	05/07	12/11
RLO	REUNERT LIMITED	12/95	12/11
RMB	REMBRANDT BEHERENDE BELEG BPK	12/95	08/00
RNS	RENAISSANCE RETAIL GROUP LTD	03/98	08/01
RTC	RETAIL CORPORATION LTD	12/95	12/99
SAB	SABMILLER PLC	12/95	12/11
SAF	SAFICON INVESTMENTS LTD	12/95	05/96
SAN	SANYATI HOLDINGS LIMITED	06/06	12/11
SAP	SAPPI LIMITED	12/95	12/11
SBH	SABHOLD GROUP LTD	12/95	11/96
SCL	SACOIL HOLDINGS LTD	12/95	12/11
SFH	S A FRENCH LIMITED	11/07	12/11
SFR	SAFMARINE & RENNIES HOLDINGS LTD	12/95	06/00
SHF	STEINHOFF INTERNATIONAL HOLDINGS LTD	09/98	12/11
SHP	SHOPRITE HOLDINGS LIMITED	12/95	12/11
SKY	SEA KAY HOLDINGS LTD	08/07	12/11
SLC	SOLCHEM INVESTMENT HLDS LTD	12/95	08/97

SNS	SUN INTERNATIONAL (CISKEI) LTD	12/95	11/95
SOH	SOUTH OCEAN HOLDINGS LIMITED	02/07	12/11
SOL	SASOL LIMITED	12/95	12/11
SPG	SUPER GROUP LIMITED	12/95	12/11
SPH	SPUR HOLDINGS LTD	12/95	10/99
SPO	SET POINT GROUP LIMITED	11/97	04/10
SPP	THE SPAR GROUP LIMITED	10/04	12/11
SPS	SPESCOM LIMITED	12/95	12/10
SPU	SPUR STEAK RANCHES LTD	12/95	10/99
SRT	SMART GROUP HOLDINGS LIMITED	12/95	10/97
SRY	SENTRY GROUP LTD	10/97	06/01
SSK	STEFANUTTI STOCKS HOLDINGS LTD	08/07	12/11
STC	STORECO LTD	12/95	09/00
STR	STRAND GROUP HOLDINGS LTD	12/95	03/01
SUI	SUN INTERNATIONAL LIMITED	12/95	12/11
SUN	SUNCRUSH LTD	12/95	10/98
SUR	SPUR CORPORATION LTD	11/99	12/11
TAS	TASTE HOLDINGS LIMITED	06/06	12/11
TBS	TIGER BRANDS LIMITED	12/95	12/11
TCH	TECHNIHIRE LTD	12/95	06/98
TCS	TOTAL CLIENT SERVICES LIMITED	04/08	12/11
TEG	TEGNIESE BELEGGINGSKORP BPK	12/95	08/00
TFG	THE FOSCHINI GROUP LTD	12/95	12/11
TIB	TEGNIESE & IND BELEGGINGS BPK	12/95	08/00
TKG	TELKOM SA LIMITED	03/03	12/11
TLJ	TELJOY HOLDINGS LTD	12/95	12/99
TLM	TELEMASTERS HOLDINGS LIMITED	03/07	12/11
TMX	TELEMETRIX PLC	12/95	03/99
TON	TONGAAT HULETT LIMITED	12/95	12/11
TOY	TOYOTA SOUTH AFRICA LTD	12/95	06/01
TRE	TRENCOR LIMITED	12/95	12/11
TRH	TRADEHOLD LTD	12/95	12/96
TRU	TRUWORTHS INTERNATIONAL LIMITED	05/98	12/11
TSH	TSOGO SUN HOLDINGS LTD	12/95	12/11
TUN	T & N HOLDINGS LTD	12/95	11/98
TWP	TWP HOLDINGS LIMITED	11/07	11/09
UBU	UBUBELE HOLDINGS LIMITED	11/09	12/11
UCN	U-CONTROL LIMITED	12/95	11/95

UCS	UCS GROUP LIMITED	09/98	09/11
UHS	UNIHOLD LTD	12/95	05/02
UNI	UNIVERSAL INDUSTRIES CORPORATION LTD	11/07	09/11
UTR	UNITRANS LIMITED	12/95	04/07
VLE	VALUE GROUP LIMITED	10/98	12/11
VLX	VOLTEX HOLDINGS LTD	12/95	02/02
VMK	VERIMARK HOLDINGS LTD	07/05	12/11
VNT	VENTRON CORPORATION LTD	12/95	08/00
VOD	VODACOM GROUP LTD	05/09	12/11
VOX	VOX TELECOM LTD	10/04	10/11
WAL	WALTON STATIONERY CO LTD	12/95	08/97
WBO	WILSON BAYLY HOLMES-OVCON LIMITED	12/95	12/11
WHL	WOOLWORTHS HOLDINGS LIMITED	10/97	12/11
WNB	WINBEL LTD	12/95	09/01
WNH	WINHOLD LIMITED	12/95	12/11

Source: M-BFA

A.4 UNIVARIATE TIME-SERIES MODELS OF ECONOMIC VARIABLES

TABLE A.3

UNIVARIATE TIME-SERIES MODELS OF LOCAL ECONOMIC STATE VARIABLES

Variable	**C**	**I(d)**	**AR(p)**	**MA(q)**	**GARCH(a,b)**
Industrial production	No	(1)	(0)	(1), (3)	(0, 1)
Real T-Bill	Yes	(0)	(1)	(1)	(0, 0)
Real T-Bond	Yes	(0)	(1)	(1)	(0, 0)
Term yield spread	No	(1)	(1)	(0)	(1, 1)
Inflation	Yes	(0)	(1)	(1)	(0, 0)
Risk premium	--	--	--	--	--

Source: Researcher's own data

Statistical analysis reveals that the risk-premium is a white noise-series, based on which the first-difference of the risk premium serves as its conditional variance. The study uses the first-difference since the risk premium is already in the same unit as return dispersion.

TABLE A.4

UNIVARIATE TIME-SERIES MODELS OF FOREIGN ECONOMIC STATE VARIABLES

Variable	**C**	**I(d)**	**AR(p)**	**MA(q)**	**GARCH(a,b)**
PANEL A: EXCHANGE RATE VARIABLES					
Real effective ER	No	(1)	(2)	(1)	(0, 0)
Rand/Euro ER	No	(1)	(0)	(1)	(0, 0)
Rand/British Pound ER	No	(1)	(0)	(1)	(0, 0)
Rand/U.S. Dollar ER	No	(1)	(0)	(1)	(0, 0)
Rand/Japanese Yen ER	No	(1)	(0)	(1)	(0, 0)
PANEL B: U.S. ECONOMIC VARIABLES					
Industrial production	No	(1)	(1)	(1)	(0, 1)
Real T-Bill	No	(0)	(0)	(1)	(0, 0)
Real T-Bond	Yes	(0)	(0)	(1)	(1, 1)
Term yield spread	No	(1)	(0)	(1)	(0, 0)
Inflation	Yes	(0)	(0)	(1)	(1, 1)
Risk premium	No	(0)	(1), (2)	(0)	(0, 0)

Source: Researcher's own data

APPENDIX B

SUPPLEMENT TO RESULTS

B.1 ROBUSTNESS ANALYSIS

TABLE B.1

AUGMENTED DICKEY-FULLER TEST STATISTICS: RETURN DISPERSION

Specification	Lag length	t-statistic	p-value
Intercept	1	-4.52	0.00
Trend and intercept	1	-4.38	0.00

Source: Researcher's own data

TABLE B.2

SUMMARY STATISTICS: TOP 160 RETURN DISPERSION

Lag	AC	PAC	Q-Stat	p-value
1	0.7	0.7	102.1	0.0
2	0.7	0.3	186.3	0.0
3	0.6	0.2	261.3	0.0
6	0.5	0.0	450.5	0.0
12	0.4	0.1	722.3	0.0

Source: Researcher's own data

TABLE B.3

A UNIVARIATE MODEL OF TOP 160 RETURN DISPERSION

Estimated output			
Variable	**Value**	**Standard error**	**p-value**
Constant	0.09	0.01	0.00
AR(1)	0.96	0.03	0.00
MA(1)	-0.62	0.10	0.00
Variance equation			
Constant	0.00†	0.00†	0.20
Residual	0.22	0.08	0.00
GARCH	0.61	0.19	0.00
Model diagnostics			
Statistic	**Adj. R-Squared**	**Durbin-Watson**	**Engle-ARCH p-value**
Value	0.60	1.71	0.89

†Non-zero value appears as zero due to rounding.

Source: Researcher's own data

TABLE B.4

RETURN DISPERSION AND INDUSTRIAL PRODUCTION GROWTH

Estimated output			
Variable	**Value**	**Standard error**	**P-value**
Constant	0.09	0.01	0.00
G(IP)	-0.04	0.05	0.34
AR(1)	0.96	0.03	0.00
MA(1)	-0.63	0.09	0.00
Variance equation			
Constant	0.00	0.00	0.24
Residual	0.22	0.07	0.00
GARCH	0.63	0.09	0.00
Model diagnostics			
Statistic	**Adj. R-Squared**	**Durbin-Watson**	**Engle-ARCH p-value**
Value	0.61	1.73	0.92

Source: Researcher's own data

TABLE B.5

RETURN DISPERSION AND DOMESTIC ECONOMIC UNCERTAINTY

Estimated output				**Model diagnostics**		
Variable	**Lag**	**Intercept**	**Slope**	**Adj. RSQ**	**Durbin-Watson**	**Engle-ARCH p-value**
IP	2	0.09 (0.02) [0.00]	-4.49 (0.69) [0.00]	0.61	1.78	0.73
*T-Bill**	0	0.09 (0.01) [0.00]	6.83 (49.41) [0.89]	0.60	1.73	0.89
*T-Bond**	0	0.09 (0.01) [0.00]	52.14 (32.76) [0.11]	0.61	1.75	0.89
TYS	0	0.09 (0.01) [0.00]	6918.87 (1579.34) [0.00]	0.59	1.73	0.97
Inflation	1	0.09 (0.02) [0.00]	74.17 (22.88) [0.00]	0.62	1.79	0.93
RP	0	0.09 (0.01) [0.00]	3410.31 (852.57) [0.00]	0.37	2.20	0.88

Source: Researcher's own data

TABLE B.6

RETURN DISPERSION AND FOREIGN EXCHANGE RATE UNCERTAINTY

Estimated output				Model diagnostics		
Variable	**Lag**	**Intercept**	**Slope**	**Adj. RSQ**	**Durbin-Watson**	**Engle-ARCH p-value**
*EER**	0	0.09 (0.01) [0.00]	0.29 (0.27) [0.28]	0.61	1.73	0.96
R/EUR	0	0.09 (0.01) [0.00]	0.24 (0.26) [0.34]	0.61	1.73	0.94
R/USD	0	0.09 (0.01) [0.00]	0.35 (0.26) [0.18]	0.61	1.74	0.96
R/GBP	0	0.09 (0.01) [0.00]	0.37 (0.29) [0.20]	0.61	1.73	0.95
R/JPY	0	0.09 (0.01) [0.00]	0.18 (0.24) [0.46]	0.61	1.73	0.94

Source: Researcher's own data

TABLE B.7

RETURN DISPERSION AND FOREIGN ECONOMIC UNCERTAINTY

Estimated output				Model diagnostics		
Variable	**Lag**	**Intercept**	**Slope**	**Adj. RSQ**	**Durbin-Watson**	**Engle-ARCH p-value**
U.S. IP	2	0.09 (0.02) [0.00]	13.31 (14.67) [0.36]	0.61	1.75	0.89
*U.S. T-Bill**	0	0.09 (0.01) [0.00]	159.50 (101.83) [0.11]	0.61	1.76	0.85
*U.S T-Bond**	0	0.09 (0.01) [0.00]	229.20 (82.73) [0.01]	0.62	1.79	0.88
U.S. TYS	0	0.09 (0.01) [0.00]	13661.16 (20137.75) [0.50]	0.61	1.74	0.86
U.S. Inf.	1	0.09 (0.01) [0.00]	212.13 (61.90) [0.00]	0.62	1.80	0.92
U.S. RP	0	0.09 (0.01) [0.00]	0.01 (0.02) [0.00]	0.61	1.73	0.72

Source: Researcher's own data

TABLE B.8

RETURN DISPERSION AND THE VALUE PREMIUM

PANEL A: EQUAL-WEIGHTED RETURNS					
	Market	**Micro**	**Small**	**Big**	**MLM**
RD	0.16 [0.03]	0.14 [0.06]	0.12 [0.11]	0.17 [0.02]	0.22 [0.00]
PANEL B: VALUE-WEIGHTED RETURNS					
	Market	**Micro**	**Small**	**Big**	**MLM**
RD	0.11 [0.14]	0.15 [0.05]	0.02 [0.71]	0.20 [0.01]	0.15 [0.04]

Source: Researcher's own data