

THE PREDICTIVE ABILITY OF THE YIELD SPREAD IN TIMING THE STOCK EXCHANGE: A SOUTH AFRICAN CASE

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DECLARATION OF ORIGINAL WORK

This page declares that the work produced in this thesis is my own and was conducted whilst completing the degree of Master of Commerce in Financial Markets whilst at Rhodes University. Any work that is not my own has been credited accordingly. This thesis has not been submitted to other universities, Technikons or colleges for degree purposes.

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ABSTRACT

The use of the yield curve in forecasting economic recessions is well established in the literature. A new avenue of use for the yield curve has emerged in the form of using it to forecast bull and bear stock markets. This has the potential to change how investors manage portfolios. A dynamic market-timing strategy would allow investors to shift out of or in to stock markets based on the probability of bear stock market in the future. The relationship between the yield curve and the stock market is tested using an adapted probit model. This has proven positive with encouraging results for the US, India and Spain. This is tested for South Africa using the adapted probit model and the SA yield spread. Bear stock markets are identified on the JSE and forms part of the probit modelling process. Bear markets are identified using a six- and four-month criteria. As South Africa is a small, open and developing economy, the probit is also modelled using the US yield spread. The three probit models do not appear to track bear markets well. This is substantiated through the Henriksson-Merton parametric model test which tests for market timing ability. The results for the SA yield spread using both bear market criteria do not show market timing ability, however, the SA and US yield spread model does show potential market timing ability.

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CHAPTER 1: INTRODUCTION

1.1 Research Background

The term structure of interest rates, also known as the yield curve, refers to the relationship between the yields on bonds with different terms to maturity (Bain and Howells, 2008). The yield curve makes use of the return or yield spread on long- and short-term securities differentiated solely by their term to maturity (Estrella and Truben, 2006). Extensive research has been undertaken to better understand the link between the yield curve and real economic activity as this relationship has great forecasting potential for future economic activity. In particular, it is the relationship between the business cycle and the term structure of interest rates that has proven in the literature to be useful.

In South Africa, the yield curve is typically constructed by comparing the yield on 31-day Treasury Bills and 10-year Government Bonds (Clay and Keeton, 2011). The yield curve has three distinct shapes. An upward sloping yield curve which is 'normal' with long-term interest rates above short-term interest rates. A positively sloped curve is also indicative of a risk premium required by investors to hold bonds of longer duration (Clay and Keeton, 2011). When long-term rates fall below short-term rates the yield curve becomes inverted and this is typically indicative of an economic downswing (Clay and Keeton, 2011). If short-term rates are much higher than long-term rates, this may signal that the economy is in recession. Between an upward sloping and inverted curve, the yield curve can be flat. This occurs when short- and long-term rates are equal. This is commonly a transitional phase and could indicate the beginning or ending of a recession (Clay and Keeton, 2011).

Estrella and Mishkin (1996) explain that the steepness of the yield curve contains valuable information in forecasting possible recessions. One of the reasons being that monetary policy has a significant influence on the yield curve spread and also on real economic activity. They use an example of a rise in the short-term rate which tends to both flatten the yield curve as well as to slow real growth in the near term (Estrella and Mishkin, 1996). They explain that expectations of future inflation and future real interest rates contained in the yield curve spread appear to play an important role in predicting economic activity.

The usefulness of the yield curve as a predictor of recessions has been a topic of much debate and empirical investigation over recent years. Some authors (Harvey, 1989, Hu, 1993 and Haubrich and Dombrosky, 1996) have suggested the yield curve has lost its previous predictive powers, while others (Dueker, 1997, Clay and Keeton, 2011 and Keeton and Botha, 2014) argue that its predictive powers remain useful. Estrella and Mishkin (1996) adopt the middle ground, arguing that the yield curve is a useful supplement to other large econometric models due to its simplicity and double-checking function.

While there is still debate on its forecasting usefulness, a new area of possible application has emerged. More recently there has been research into using changes in the term structure of interest rates (the spread in the yield curve) to predict changes in stock markets. Fund managers have always been concerned with designing the optimal investment strategy and empirical evidence has shown the potential benefits of a dynamic investment strategy as opposed to a buy-and-hold strategy (Bhaduri and Saraogi, 2010). The very popular mean-variance optimization approach can prove to be limiting as it is based on a set of expected asset returns, whereby variances and covariances are captured by time invariant sample averages. Bhaduri and Saraogi (2010) argue that portfolios rebalanced using this method are only changed to achieve fixed weights and do not respond to changes in economic conditions. Dynamic strategies, on the other hand, rebalance portfolios based on available information in each period. The benefit in using a dynamic strategy, however, lies in the possibilities that asset returns can be predictable under certain economic conditions (Bhaduri and Saraogi, 2010). Potentially, changes in the yield spread can be used to guide decision making in such dynamic strategies.

Literature on the predictive power of the yield spread in timing the stock market is still scarce. Campbell (1987) was among the first to identify a possible link between the three variables: the yield spread, economic activity and the stock market. As stated in Bhaduri and Saraogi (2010: 262) “the price of a share is the discounted value of expected cash flows. The strength of the economy determines the magnitude of these cash flows. The price of equity thus reflects expectations of real activity, and changes in the value of equity partially reflects revisions in these expectations.” Siegel (1998, cited in Resnick and Shoemith, 2002: 82) also discussed the relationship between stock market performance and the business cycle. He noted that “stock values are based on corporate earnings, and the business cycle is a prime

determinant of these earnings". Siegel's analysis, which forms the basis of Resnick and Shoesmith's 2002 paper, showed that being able to correctly predict turning points in the business cycle and using this in a market timing strategy can yield an annual increase in returns compared with a stock-only buy-and-hold strategy. This strategy involves moving out of stocks and into Treasury Bills before a peak and switching from Treasury Bills into stocks before a trough (Resnick and Shoesmith, 2002). Resnick and Shoesmith (2002) used a probit model to ascertain whether the yield spread could be used to time the stock market in the US. This is the model that will be followed for South Africa in this research. They found that the yield spread between the composite 10-year+ Treasury Bond yield and the three-month Treasury Bill yield holds important information about the probability of a bear stock market. An inverted yield curve spread of (-0.83) percent implied an *ex ante* 50 percent probability of a bear stock market one month later. Their out-of-sample testing also proved to be reliable in forecasting stock market turning points one month ahead.

Bhaduri and Saraogi (2010) followed a similar method for the Indian Stock Exchange. They make use of the probit model; however, they use three filtering techniques in order to determine bear and bull phases of the stock market. Bhaduri and Saraogi (2010) argue that using multiple filtering techniques as opposed to only one technique gives greater credibility to their results. A probit model was again used by Fernandez-Perez *et al.* (2014) to assess the yield spread's ability to predict turning points in the Spanish stock market. An optimal probit model was identified using a genetic algorithm that involved many other variables besides the yield spread and increased the complexity significantly. Like Resnick and Shoesmith (2002) and Bhaduri and Saraogi (2010) their probit model outperformed a buy-and-hold stock-only strategy. Fernandez-Perez *et al.* (2014) found that due to Spain being a relatively small economy, including in their model the yield spread of Spain's close trading partners, Europe, improved their predictions of a bear market.

1.2 Goals of the Research

The main goal of this research is to identify whether or not the yield curve in the South African case contains significant market timing ability for a given time period, and whether investors are able to use this inherent information in a dynamic market timing strategy to outperform a simple stock-only buy-and-hold strategy. The simple buy-and-hold strategy will be represented by the Johannesburg Stock Exchange (JSE) All Share Index.

Achieving this objective requires meeting the following sub-goals. The first sub-goal is to determine whether it is possible to use the yield spread to accurately predict bear markets on the JSE. The second sub-goal is to identify, at different screening levels of probability, whether a dynamic strategy based on the yield-spread has market timing ability. This second sub-goal is tested using the Henriksson-Merton parametric model test.

1.3 Data, Methods and Techniques

The data used will be all be monthly time series from April 1994 to December 2018 based upon monthly averages of the long and short interest rates and month-end data of the JSE All Share Index (ALSI). The South African yield spread used is the difference between the 10-year Government Bond and the 91-day Treasury Bill rate. The JSE ALSI will be used as a proxy for measuring the returns of holding an equity portfolio and the 91-day Treasury Bill as the proxy for holding bonds.

The methodology proceeds in three steps. The first step will be to identify bull and bear phases in the Johannesburg Stock Exchange for the period April 1994 to December 2018. As in Resnick and Shoesmith (2002) a bear market is initially defined as six or more consecutive months of a generally declining stock market and analogously a bull market is defined as six or more consecutive months of a generally rising stock market. Because of the relatively small number of bear markets identified in this manner over the selected time period, the definition is then relaxed to four or more months of a declining stock market.

The next step is to model the relationship between the bear phases in the JSE and the spread of the yield curve using a probit model, initially developed by Estrella and Mishkin (1998) and adapted by Resnick and Shoesmith (2002) for this purpose. An out-of-sample forecasting is

done which gives an *ex ante* probability forecast of a bear market. This is done by successively adding one more month's data to the initial period. Out-of-sample testing is preferable to in-sample testing as out-of-sample performance provides a truer test of an indicator's real-world forecasting ability (Estrella and Mishkin, 1996). There is an expected structural change in the data in the beginning of 1994 due to the lifting of global financial sanctions and the end of Apartheid.

The final step is to test for market timing ability using the Henriksson-Merton parametric test. This test will show whether the probit model is capable of producing statistically significant market timing results for a particular model and time period. If these results prove to be significant this shows that the yield spread contains market timing information which investors can use to develop a dynamic market timing strategy.

1.4 Thesis Plan

The structure of the remainder of this thesis is as follows. Chapter 2 examines the relevant literature surrounding the yield curve and its usefulness in predicting recessions, as well as the more recent literature linking the yield curve to bear markets of the stock exchange. Chapter 3 outlines the data used and the methods and techniques used to conduct the research. Chapter 4 presents and discusses the results of the research. Finally, Chapter 5 concludes and make recommendations about the potential for market timing strategies used in the South African context as well as discusses areas for future research.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter discusses the literature surrounding the term structure of interest rates (the yield curve) and its relationship to the business cycle and the stock market. It is the relationship between these three variables that is of interest to this research and, in particular, the possibility that it may prove useful in guiding a dynamic market timing investment strategy. This relationship is presented by explaining the link between the yield curve and the business cycle, the relationship between the business cycle and the stock market and, finally, the possible relationship between the yield curve and stock market performance.

Section 2.2 begins by introducing the yield curve and its underlying theory. Once the yield curve has been thoroughly discussed, its link with the business cycle is then presented. In particular, evidence of the yield curve's usefulness in predicting recessions is presented. Section 2.3 then investigates the relationship between the business cycle and the stock market. This is an important link leading up to section 2.4 which presents the expected relationship between changes in the yield curve and stock market performance. This is the relationship which is the subject of the empirical investigations in this half-thesis. Evidence of the relationship between the yield curve, or, more accurately, changes in the yield spread and stock market performance for a number of countries is then presented. Section 2.5 summarises the findings of the literature.

2.2 Yield Curve and the Business Cycle

In its simplest form an interest rate is described by Howells and Bain (2005: 183) as “a payment from borrower to lender which compensates the latter for parting with funds for a period of time and at some risk.”. An interest rate can therefore be seen as the price the lender is willing to accept for giving up current consumption in return for future benefit. The returns investors receive when investing in bonds is referred to as the yield on a bond. And the relationship between the yield on bonds with different terms to maturity is referred to as

the term structure of interest rates, or more commonly known as the yield curve (Hu, 1993 and Howells and Bain, 2008).

The yield curve is made up of the return or yields on long- and short-term securities differentiated solely by their term to maturity (Estrella and Truben, 2006). This means that bonds with similar risks, liquidity and tax considerations may have different yields only because their terms to maturity differ (Mishkin, 2007). The term structure, or yield curve, thus investigates the effect that the term to maturity has on yields when all other possible explanations for yield variation have been removed (Howells and Bain, 2008).

Extensive research has been undertaken to better understand the link between changes in the yield curve and real economic activity as this relationship has potential for forecasting future economic activity (Hu, 1993, Estrella and Mishkin, 1996, 1998, Haubrich and Dombrosky, 1996, Deuker, 1997, Siegel, 1998, Clay and Keeton, 2011 and Estrella and Truben, 2006).

There is no clear measure of yield curve steepness as it may not change consistently in line with changing maturity. It may be flat at the short end and steep at the long end, or vice versa. Estrella and Truben (2006) identify this lack of consistency of a yield curve measure as a practical issue. For this reason, a yield spread as opposed to slope is used to standardise the measure (Haubrich and Dombrosky, 1996). This creates a linear approximation of the non-linear yield curve. Multiple yield spreads are possible. However, in South Africa, the yield curve is typically constructed by comparing the yield on 31-day Treasury Bills and 10-year Government Bonds (Nel, 1996, Moolman, 2002, Aziakpono and Khomo, 2007 and Clay and Keeton, 2011). It is common practise internationally to use the spread between the 3-month rate and either the 10+ year or 30-year bond as the long rate (Estrella and Mishkin, 1996, 1998, Fama and French, 1989, Harvey, 1989, Resnick and Shoesmith, 2002 and McCown, 2001).

The yield curve has three distinct shapes: upward sloping, inverted or downward sloping, and flat (Howells and Bain, 2005 and Mishkin, 2007). An upward sloping yield curve is considered 'normal' as it is the most commonly occurring state of the yield curve with long-term interest rates above short-term interest rates. Higher long-term interest rates compensate savers for reduced liquidity. A positively sloped curve could also be indicative of a high risk-premium

required by investors (Deuker, 1997 and Clay and Keeton, 2011). It has become commonly understood that an upward sloping yield curve is usually indicative of strong economic prospects, while a flattening yield curve may be indicating a looming economic downturn or recession (Hu, 1993).

When long-term rates fall below short-term rates the yield curve becomes inverted and this is typically indicative of an economic downswing (Clay and Keeton, 2011). If short-term rates are much higher than long-term rates, this may signal that the economy is in recession. Between upward sloping and inverted curves, the yield curve can be flat. This occurs when short- and long-term rates are equal. This is commonly a transitional phase and could indicate the beginning or ending of a recession (Clay and Keeton, 2011).

2.2.1 Yield Curve Theory

Of the many theories that attempt to explain changes in the slope of the yield curve the Expectations theory or hypothesis is perhaps the most commonly known. The Expectations hypothesis claims that, for any choice of holding period, the expected return is the same for any combination of bonds of different maturities that one might hold in that period (Haubrich and Dombrosky, 1996, Deuker, 1997 and Howells and Bain, 2008). By this logic, the interest rate on long-term bonds should contain information about the future expected short-term interest rates. Thus, a flattening of the yield curve predicts that short-term rates are likely to fall in future.

The Expectations theory relies on the assumption that investors are indifferent between holding long or short bonds and that long and short bonds are completely substitutable, allowing arbitrage in the market to ensure that the long rate is equal to the average of expected future short-term rates (Howells and Bain, 2005). According to the Expectations theory the yield curve takes on the shape determined by the market's expectations of the future level of interest rates and, if the theory holds, implied forward rates can be measured from the curve. However, Howells and Bain (2005), explain that these implied forward rates are not certain and future short rates cannot accurately be determined using the Expectations theory. The best the Expectations theory can do at predicting future short-term rates from

the yield curve is in its shape. The shape of the yield curve can be used as a guide to the expected direction of change in future rates (Howells and Bain, 2005).

The Expectations theory is only the beginning of an explanation of the shape of the yield curve. The Term Premium and Preferred Habitats theory are also used alongside the Expectations theory to explain the yield curve's shape at a point in time.

It has been observed that the yield curve generally tends to slope upwards, indicating that higher yields are available on longer-term bonds. While this contradicts the Expectations theory it supports the Term Premium theory. The Term Premium theory is also referred to as the Liquidity Premium theory. However, Howells and Bain (2005) argue that it is more accurate to refer to a risk- or term-premium instead of a liquidity premium as highly developed, and therefore very liquid, secondary markets exist for government bonds in most developed and also many developing countries. Thus, the risk experienced by investors is not term or liquidity risk but rather capital risk, and capital risk rises with the term to maturity. Furthermore, the interest elasticity of bond prices varies with duration (Howells and Bain, 2005). Bond prices are more sensitive to changes in interest rates at greater duration. Therefore, the generally upward sloping tendency of the yield curve can be explained by investors' capital-risk aversion and the interest elasticity of bond prices to bond duration (Howells and Bain, 2005).

If the homogeneity assumption of the Expectations theory is dropped and bonds with differing terms to maturity are viewed as having their own risk characteristics then the Preferred Habitat or Market Segmentation theory states that investors have preferences for specific parts of the maturity spectrum (Howells and Bain, 2005). There are investors whose liabilities match with the risk characteristics present in a particular maturity. Using either the Preferred Habitat or Market Segment theory, the shape of the yield curve is determined by the demand and supply of bonds within each particular term segment (Howells and Bain, 2005). Under these theories the yield curve would be characterised by 'humps' rather than the linear trend we see under the Expectations theory. However, investors with weak preferences could be induced by the availability of a premium to shift slightly out of their preferred segment, thus smoothing the 'hump' between term segments (Howells and Bain, 2005).

2.2.2 The Yield Spread and Economic Activity (Business Cycle)

The relationship between the yield curve and the business cycle has been extensively documented and, as such, the link between bond market interest rates and real economic activity is well established (Kessel, 1965, Hu, 1993, Estrella and Mishkin, 1996,1998, Haubrich and Dombrosky, 1996, Nel 1996, Dueker, 1997, Ang *et al.*, 2006, Estrella and Truben, 2006 and Clay and Keeton, 2011).

The usefulness of the yield spread in predicting future changes in economic activity comes from the expectation information it contains (Hu, 1993, Estrella and Mishkin, 1996, and Estrella and Truben, 2006). Estrella and Truben (2006) explain that the correlation between the yield curve and future economic activity, recessions in particular, flows through monetary policy and, in particular, investors' expectations channels of changes in monetary policy. The yield curve may be flattened or inverted by an expected tightening of monetary policy, possibly due to rising expected inflation. Tightening monetary policy typically results in a rise of all interest rates, with short-term interest rates rising by more than longer term rates. This is because longer term rates tend to reflect longer term expectations and are not as affected by changing monetary policy in the short-run (Deuker, 1997 and Estrella and Truben, 2006). Haubrich and Dombrosky (1996) use the phrase 'policy anticipations hypothesis' to explain the monetary policy channel.

A rise in short-term interest rates induced by tightening monetary policy can also affect investors' expectations of future real demand for credit and future inflation (Estrella and Truben, 2006). This rise in short-term rates could lead to expectations of a future slowdown in economic activity and resulting decrease in the demand for credit, putting downward pressure on future short-term rates. The expectations of future economic slowdown may result in lower expected inflation, thus increasing the likelihood of future easing of monetary policy. The expected future decline in short-term rates through the various channels tends therefore to reduce current long-term rates even though current short-term rates have risen and so leads to a flattening of the yield curve.

Asgharian *et al.* (2007) explains that the yield spread is also likely to exhibit cyclical behaviour and contain information about the business cycle through the risk premium. In times of

uncertainty investors require a higher risk premium to compensate for their future income uncertainty. Thus, the size of the risk premium may indicate the stages of the business cycle.

It is very difficult to give a simple explanation of how the predictive power of the yield curve will anticipate future economic activity and future recessions or upswings (Hu, 1993, Estrella and Mishkin, 1996 and Estrella and Truben, 2006). A complex intermingling of policy actions may take place, and different channels may be more dominant at times. As explained by Estrella and Truben (2006: 2) “if one channel is not in play at any one time, other channels may take up the slack”.

While the theories explaining the correlation between the yield curve and economic activity are not precisely understood, what is certain is that a robust empirical relationship has been found to exist between the yield curve and economic activity.

This relationship has been used most notably to help predict future recessions. A yield curve inversion has preceded almost all recessions in the US and South Africa. However, its usefulness did come under scrutiny when it falsely predicted a recession in the US in 1998. South Africa also later experienced a false positive yield curve inversion in 2002/03. These false positives lead to robust debate on the future usefulness of the yield curve in predicting future recessions. However, a large number of authors argue that the evidence in favour of the yield curve’s predictive ability outweigh that against it (Haubrich and Dombrosky, 1996, Estrella and Mishkin, 1996, Estrella and Truben, 2006, Clay and Keeton, 2011 and Botha *et al.*, 2017).

It is argued also that the yield curve remains a useful supplement to other large econometric models due to its simplicity, its double-checking function and its dominance as a leading economic indicator (Haubrich and Dombrosky, 1996, Howells and Bain, 2005 and Estrella and Truben, 2006). This is supported by the yield spread’s continued inclusion in the Stock/Watson index of leading and coincident economic indicators, as well as it remaining one of the most closely watched indicators (Forbes, 2019).

2.3 Economic Activity and the Stock Market

The price of a share is regarded as the discounted value of the firm's expected cash flows, and these cash flows are determined in aggregate largely by the strength of the economy (Harvey, 1989, Siegel, 1998 and Asgharian *et al.*, 2007). Stock prices are likewise informed by expected future dividend streams which depend on expected corporate earnings and these earnings are determined by the state of the economy (Estrella and Mishkin, 1996). It is this association which cements the relationship between the stock market and real activity. Expected future earnings growth is seen as a pro-cyclical variable and as consensus of a forthcoming recession grows, investors adjust downward their forecasts of firms' earnings which can be seen in a drop of stock prices.

It is important to note that there are many more factors which may cause stock prices to fluctuate. Harvey (1989) recognised a change of the discount rate as a leading other cause of fluctuating stock prices. However, since then there has been rapid growth in stock markets globally, with many more people and companies becoming involved and many companies' earnings becoming increasingly global, which has made it increasingly difficult to correctly identify the signals given by changing stock prices (Hu, 1993). Stock prices react sensitively to economic news with different unanticipated events having a more pervasive effect than others (Chen *et al.*, 1986).

It was earlier believed that changes in stock market prices were the best predictor of future real activity (Fischer and Merton, 1984 cf. Hu, 1993). However, this claim has since been disqualified. Stock market price changes are no longer the best predictor of future economic activity as its signal is lost within the noise of the exchange. Harvey (1989) found that the bond market contained more information about future economic activity than did the stock market. This was confirmed by Fama and French (1989). Hu (1993) also argues that the yield spread is the better predictor of future economic activity.

For the purpose of this research it is not the predictive power of changes in stock market prices that is particularly important. It is the relationship that exists between the stock market and real activity which is of particular interest. In order to be able to use the yield spread to signal when to enter or exit the stock market, it is vital that there exists a robust and persistent link between real activity and the stock market.

2.4 The Yield Curve and the Stock Market

Section 2.2 has provided the link between the yield curve and real activity and section 2.3 has shown the link between real activity and the stock market. Section 2.4 now discusses the relationship of interest in this research, namely, the relationship between the yield curve and the stock market.

While the yield curve remains an important indicator of future recessions, another possible use for its predictive power has become more apparent. There has been much research into the relationship between the slope of the yield curve, economic growth and stock market returns (Chen, Roll and Ross, 1986, Campbell, 1987, Harvey 1989, Liu, Resnick and Shoesmith, 2004). Following the link through economic activity, the relationship between the yield curve and the stock market shows great potential for use in a dynamic market timing investment strategy.

Financial managers have always been concerned with designing the optimal investment strategy and empirical evidence has shown the potential benefits of a dynamic investment strategy as opposed to a buy-and-hold strategy (Resnick and Shoesmith, 2002, Asgharian *et al.*, 2007, Bhaduri and Saraogi, 2010, and Fernandez-Perez *et al.*, 2014). Bhaduri and Saraogi (2010) argue that the popular mean-variance optimization approach can prove to be limiting as it is based on a set of expected asset returns, whereby variances and covariances are captured by time invariant sample averages. The portfolios rebalanced using this method are only changed to achieve fixed weights and do not respond to changes in economic conditions. Dynamic strategies on the other hand rebalance portfolios based on available information in each period. The benefit in using a dynamic strategy, however, lies in the possibilities that asset returns can be predictable under certain economic conditions (Siegel, 1998 and Bhaduri and Saraogi, 2010).

According to Asgharian *et al.* (2007) several studies have identified the yield spread as one of the most important variables in explaining the variance of stock returns. The remainder of this section will focus on three studies which have sought to use the yield spread to time the stock market for the United States, India and Spain.

Siegel's (1989) analysis, which forms the base of Resnick and Shoesmith's 2002 paper, showed that being able to correctly predict turning points in the business cycle and using this in a market timing strategy can yield an annual increase in returns compared with a stock-only buy-and-hold strategy. This strategy involves moving out of equities and into Treasury bills before a business cycle peak and switching from Treasury bills into stocks before a trough (Resnick and Shoesmith, 2002). Siegel (1989) recommended doing this four-months before any peak or trough.

Resnick and Shoesmith (2002) investigated whether this would yield significantly successful investment returns using a probit model adapted from Estrella and Mishkin (1996, 1998), initially used to predict recessions. Using monthly data for the S&P 500 mutual fund as a proxy for holding a stock-only market portfolio and the yield spread as the difference between the 10-year Treasury note and the 3-month Treasury bill, the period under investigation was January 1960 to December 1999. For the out-of-sample period, January 1971 to December 1999, the strongest estimation results for the probit model are for forecasting bear markets one and two months ahead.

They continue their study focusing on predicting bear markets one month ahead and this became the norm for future researchers. They then found the associated probability of a bear market one month ahead with its specific yield spread. For instance, an inverted yield spread of -0.83 percent implies an *ex ante* 50 percent probability of a bear market in one month's time. Probability screens of 30, 40 and 50 percent were found to be the most useful. These probability screens are used as threshold values which indicate to investors when to switch between equities or Treasury bills. Resnick and Shoesmith (2002) found that a probit market timing strategy for all probability screens was able to outperform the annual compound returns of 14.17 percent of a stock-only buy-and-hold strategy over the 29-year period. The 50 percent probability screen in particular yielded an extra 2.29 percentage points annually over the S&P 500 mutual fund.

Thus, the yield curve spread model used by Resnick and Shoesmith (2002) was able to predict stock market turning points one month ahead and they were successful in using this to create a dynamic portfolio that outperformed a stock-only buy-and-hold strategy. Assuming costless switching between a no-load S&P 500 mutual fund and a money market fund belonging to

the same fund family, the probit market timing strategy is able to produce larger excess returns and lower levels of total and systematic risk than a stock-only buy-and-hold strategy.

Following on from Resnick and Shoesmith's research, Bhaduri and Saraogi (2010) investigate if it is possible to find a probit model to predict stock market turning points one month ahead and develop a market timing strategy to outperform a market portfolio for India. They use monthly data of the Bombay Stock Exchange Sensitive Index as a proxy for a market portfolio and the yield spread between the 10-year Government of India (GOI) yield to maturity (YTM) and the 90-day GOI YTM over the period May 1991 to March 2009. Instead of using the short-end of the yield spread calculation, the 90-day GOI YTM, as a proxy for returns from holding a government bond portfolio, they use two other measures, the i-Sec's Sovereign Bond index as well as a 15-day GOI security. In order to ensure robustness of their results, Bhaduri and Saraogi (2010) used three filtering techniques to identify bear phases with all finding similar supporting results throughout the study.

Their findings supported those of Resnick and Shoesmith (2002), as they found that the yield spread is able to successfully predict turning points in the stock market and using a probit market timing strategy for all probability screens, in this case 30, 40, 50 and 60 percent, were all able to outperform a stock-only, buy-and-hold strategy. A 60 percent probability screen proved to provide the most superior returns. Thus, a dynamic market timing strategy based on yield spreads is a successful predictor of stock market turning points in the Indian stock market and provides superior returns to that of a stock-only buy-and-hold strategy.

Fernandez-Perez *et al.* (2014) also conducted a similar study for the Spanish stock market. However, their method was different in that they used a Genetic Algorithm by means of a Schwarz Information Criteria (GASIC) to identify the most appropriate probit model. This led them to assess around 19 different probit models with a variety of exogenous variables which included the yield spreads of close trading partners, the US and Europe, as well as local macro-variables such as consumer price index, unemployment rate and/or the industrial production index.

Fernandez-Perez *et al.*'s (2014) findings support those of Resnick and Shoesmith (2002) and Bhaduri and Saraogi (2010). They found that the slope of the local yield curve is the best predictor of bear markets in the IBEX 35, the benchmark stock market index of Spain's

principal stock exchange. Perhaps the most interesting result found was that of the multitude of models run, the only two that were able to outperform a stock-only, buy-and-hold strategy were those that included only yield spreads as exogenous variables for all probability screens, 30, 40 and 50 percent. One of the models included the yield curve slopes of Spain, the US and Europe and was able to achieve a highest mean return of 17.02 percent versus the market portfolio of 8.12 percent, at the 40 percent probability screen. The other model included only the yield curve slopes of Spain and Europe and even outperformed the previous model, achieving at its greatest a mean return of 18.16 percent at the 40 percent probability screen.

Liu *et al.* (2004) continue from the work of Resnick and Shoemith (2002) by including foreign developed country's yield spreads into their probit model. Both Liu *et al.* (2004) and Fernandez-Perez *et al.* (2014) find that the yield spreads of a country's major trading partners have a significant influence on its ability to predict turning points in its own stock market. This is of interest for the South African case because, like Spain, South Africa is a small, open and developing economy and as its stock market grows more integrated into the world economy so does its sensitivity to both local and international news.

2.5 Conclusion

As has been shown throughout this chapter the yield curve has a strong connection with real economic activity and in turn with the stock market. The majority of the literature still speaks to the yield curve's ability in predicting recessions, however, there is growing interest in its ability to predict turning points in the stock market and furthermore allowing investors to take advantage and create dynamic portfolios that are able to outperform simple stock-only, buy-and-hold strategies. As this is a relatively new field of interest the literature on the subject is still scarce yet growing. The cases for the US, India and Spain presented above provide promising results and a relatively standard methodology to follow for South Africa in this study.

CHAPTER 3: DATA AND RESEARCH METHODOLOGY

3.1 Introduction

This chapter describes the methods and techniques used to conduct the research. Section 3.2 describes the research paradigm and section 3.3 describes the data used as well as where and how it was collected and the reasoning behind the time period selected. Section 3.4 then explains aspects of the research design, including the techniques used. Section 3.5 concludes the chapter.

3.2 Research Paradigm

As the previous chapters have illustrated, the yield curve has proven useful not only in helping to predict recessions for many countries, but more recently in helping to predict bear stock markets. This predictive power potentially enables investors to create dynamic market timing portfolios that are able to achieve greater mean returns than a stock-only, buy-and-hold strategy. This research seeks to test whether the South African yield curve is able to help predict bear markets on the JSE and, if so, to create a dynamic market timing strategy. The research is best described as explanatory and positivist in nature. The method attempts to reveal market timing information from the yield spread through observation over time. This is done by using quantitative time series data to prove whether, in the South African context, there is sufficient information present in the yield spread to assist an investor in predicting bear markets one month ahead and whether acting on these predictions would enable an investor to earn greater mean returns through a dynamic market portfolio for the given period. The yield spread data is not heavily manipulated in order to identify a causal link between the yield spread and bear markets. This can also be referred to as deterministic and is a part of the positivist paradigm. The method also seeks to prove the relationship through empirical evidence and in so doing hopes to generalise the findings, in particularly for the South African case. Observations are quantified using the Henriksson-Merton parametric model test thus satisfying the ultimate goal of this research.

3.3 Data and Data Sources

Since there are only two variables of interest the data used is simple. The yield spread is represented by the difference between the 10-year Treasury Bond and the 91-day Treasury Bill rate and the stock market is represented by the JSE All Share Index levels. Both the 10-year Treasury Bond and 91-day Treasury Bill rate were obtained from the South African Reserve Bank online database and data on the JSE All Share Index was obtained from the IMF's online International Financial Statistics (2019). The South African 91-day Treasury Bill rate was only available as weekly data and so a monthly series was created by finding the average of the weekly measures for each month. The US 10-year Treasury Bond and 91-day Treasury Bill rate were also collected to create the US yield spread and were obtained from Thomson Reuters Datastream (2019).

All data sets are presented as monthly time series from April 1994 to December 2018. The modelling was first attempted with data from January 1980 to December 2018. However, preliminary results were insignificant and so the time period was shortened in an attempt to exclude the financial instability and international isolation of the Apartheid¹ period.

3.4 Research Design

As in Resnick and Shoesmith (2002) and Bhaduri and Saraogi (2010), the relationship between bear phases of the JSE and the yield spread is modelled using a probit model. This probit model was first used by Estrella and Mishkin (1996) to forecast recessions but has since been adapted for the purpose of forecasting bear stock markets instead.

¹ A legally enforced economic and social racial discrimination system under which South Africa was governed until democracy in 1994. International opposition against Apartheid gained momentum in the 1980s when South Africa's major trading partners imposed economic sanctions.

3.4.1 Model Specification and Theoretical Framework

3.4.1.1 Probit Model

Resnick and Shoesmith (2002) make provision for their estimation to forecast a bear market k months later. From this they found that the most accurate predictions arise one month ahead as has been confirmed by other studies (Asgharian *et al.*, 2007, Bhaduri and Saraogi, 2010 and Fernandez-Perez *et al.*, 2014) and as will be followed below.

Formally the probit model can be stated as,

$$P(y = 1|x) = F(\alpha_0 + x\alpha) \quad (1)$$

But, more commonly it is presented as,

$$P(\text{dummy}_{t+1}) = F(\alpha_0 + \alpha_1 \text{spread}_t) \quad (2)$$

Where, P = the probability of a bearish stock market one-month ahead, $\text{dummy}_{t+1} = 1$ if the stock market in month $t+1$ is bearish, else 0, α_0 = the intercept, α_1 = the coefficient of the yield spread variable and spread_t = yield spread in month t . F is the standard normal cumulative distribution function. This ensures that the probability will lie strictly between 1 and 0 as it should for any event.

The probit model was also run for three-months ahead (dummy_{t+3}), however, the results from the one-month ahead probit models were stronger, confirming the results found in the literature. Those results for one-month ahead are therefore the results that will be presented in the remainder of this research.

The probit model can also be run using multiple variables. Many other additional variables can be included such as the yield spreads of other countries, the inflation rate or unemployment rate (Fernandez-Perez *et al.*, 2014). Fernandez-Perez *et al.* (2010) and Liu *et*

al. (2014) investigate the impact of including the yield spreads of major trading partners or world powers and found successful results. Following from this, the US yield spread is included in the probit model and tested. The results are presented along with the results of SA only yield spread probit models in Chapter 4. This probit can be presented as,

$$P(\text{dummy}_{t+1}) = F(\alpha_0 + \alpha_1 \text{spread}_{SA,t} + \alpha_2 \text{spread}_{US,t}) \quad (3)$$

Where, P = the probability of a bearish stock market one-month ahead, $\text{dummy}_{t+1} = 1$ if the stock market in month $t+1$ is bearish, else 0, α_0 = the intercept, α_1 = the coefficient of the South African yield spread variable, $\text{spread}_{SA,t}$ = South African yield spread in month t , α_2 = the coefficient of the United States yield curve and $\text{spread}_{US,t}$ = United States yield curve. F is the standard normal cumulative distribution function.

3.4.1.2 Market Timing Model

The method to be used has thus far followed that of Resnick and Shoesmith (2002) and Bhaduri and Saraogi (2010) quite closely. However, for the next step of the research the method is changed slightly. While Resnick and Shoesmith (2002) and Bhaduri and Saraogi (2010) first simulated dynamic portfolios and then tested for significant market timing effects, this study will immediately test for significant market timing effects using the Henriksson-Merton (HM) parametric model test. This thesis attempts to identify market timing ability and not the potential excess returns from using a market timing strategy and so the method of the previous authors is amended for this reason.

The HM test is run using the excess returns on the market timing portfolio over and above the risk-free return and these excess returns are regressed on the bull market risk premium and bear market risk premium (Bhaduri and Saraogi, 2010). This Up/Down model is usually used to assess the market timing ability of portfolio managers and is done by casting portfolio betas as a binary variable, constrained to one value during up markets and another value during down markets, as follows:

$$R_{pt} = a_p + b_{pd}R_{mt} + u_{pt} \text{ for all } t \text{ such that } R_{mt} \leq 0 \quad (4)$$

$$R_{pt} = a_p + b_{pu}R_{mt} + u_{pt} \text{ for all } t \text{ such that } R_{mt} > 0 \quad (5)$$

Which can be combined to form the dummy variable regression:

$$R_{pt} = a_p + b_{pd}R_{mt} + b_{po}R_{mt}D_t + u_{pt} \quad (6)$$

Where R_{pt} is the return on market timing portfolio in month t ; R_{mt} is the return on the market portfolio, D_t is a dummy variable and is equal to one if R_{mt} is greater than zero or equal to zero otherwise; u_{pt} represents the zero-mean white noise process (Philippas and Tsionas, 2011). b_{pu} is the systematic risk during bull markets and b_{pd} is the systematic risk during bear markets. The slope coefficient b_{po} is the variable of interest when testing for market timing results as it is equal to the difference between bull and bear market betas for the market timing portfolio ($b_{pu} - b_{pd}$).

For there to be significant market timing results, $b_{po} > 0$ and must be statistically significant (Philippas and Tsionas, 2011). If these conditions are met, the probit model has been successful in forecasting bear markets one month ahead.

The model is run by first finding the bull and bear market betas using equation 4 and 5. And finally market timing is established by running equation 5. These results are presented in Chapter 4 with three different probability screens and for two sub-periods as well as the full period under study.

3.4.2 Description of Variables and *a priori* Expectations

The theoretical link between the yield spread and bear stock markets is explained in chapter 2. The yield spread is the difference between the 10-year Treasury bond and 91-day Treasury bill rate, or alternatively the difference between the long- and short risk-free rates. What has

typically been the case is an inverted yield curve preceding a recession, thus long rates falling below short rates. However, Botha *et al.* (2017) found that the economic downswing starting in December 2013 was not preceded by an inverted yield curve but rather a narrowing yield spread, whereby the long rate fell but did not fall below the short rate. While an inverted yield curve may be a strong indicator of an upcoming economic downswing, a narrowing of the yield spread may provide just as much indication.

Resnick and Shoesmith (2002) were able to identify a particular yield spread and its associated probability of a bear stock market one month ahead. They found that only high levels of probability had associated negative yield spreads, therefore, even a narrowing of the yield spread can increase the probability of a bear stock market. It is expected that the spread coefficient, α_1 , is negative regardless of whether the spread is positive or negative as even a small positive yield spread has an associated probability of a bear market. This holds true for the addition of other countries' yield spreads. In equation 3, the US's yield spread is used. A decrease in the yield spread in the US could indicate an upcoming economic downturn in that country which may impact South Africa through a contagion effect, however, at a lag. It is expected that the addition of the US yield spread should improve the accuracy of the model.

3.4.3 Method and Estimation Techniques

The method is most easily described in three steps. The first step involves identifying bear stock markets on the Johannesburg Stock Exchange. The second step is modelling the relationship between these bear markets on the JSE and the yield spread using a modified probit model which is done using out-of-sample forecasting. The final step tests for a statistically significant market timing ability using the Henriksson-Merton parametric model test. The results clearly illustrate whether there is market timing opportunity on the JSE, revealed by the yield spread, that is able to outperform a stock-only, buy-and-hold strategy.

A bear phase, like a recession, is defined as a generally declining trend of 6 or more consecutive months (Resnick and Shoesmith, 2002). There may be monthly stock market upticks within a bear phase, but this will ultimately still be counted within the bear phase when the following months continue to decline. Any monthly uptick may not exceed the

previous stock market peak or it will be considered as having broken the generally declining trend and will be counted as a new peak. It is important here to note that a bear phase is identified generally, meaning that a change in the monthly market direction from downward to upward does not immediately cancel the downward trend (Resnick and Shoemsmith, 2002). It is important to see whether the turnaround continues in the next month to be able to identify whether there was in fact a change in the trend, or rather a downward trend is re-established after this temporary uptick.

The first step in identifying the market trends is to identify if the All Share Index in the current month increased or decreased from the previous month. Numerically, if $P_t < P_{t-1}$, there was a decrease in the Index. After identifying increases or decreases for each month, these changes were cumulated in order to give an indication of where there were 6 months or more of monthly decreases. The data was then manually checked to identify generally declining trends. For example if it was identified that there were four months of consecutive decreases and then a single monthly increase followed by another decrease this would be manually checked to see if it fits into a generally declining trend qualifying as a bear market. This was conducted for the full period 1994/04 to 2018/12, during which only 5 bear market were identified. Table 1 gives the start and end dates of each bear phase, the number of months of its duration and the percentage change of the lowest point of the bear market compared with the previous peak in the Index. The bear markets are also ranked in terms of their severity, measured in terms of the percentage change from peak to trough.

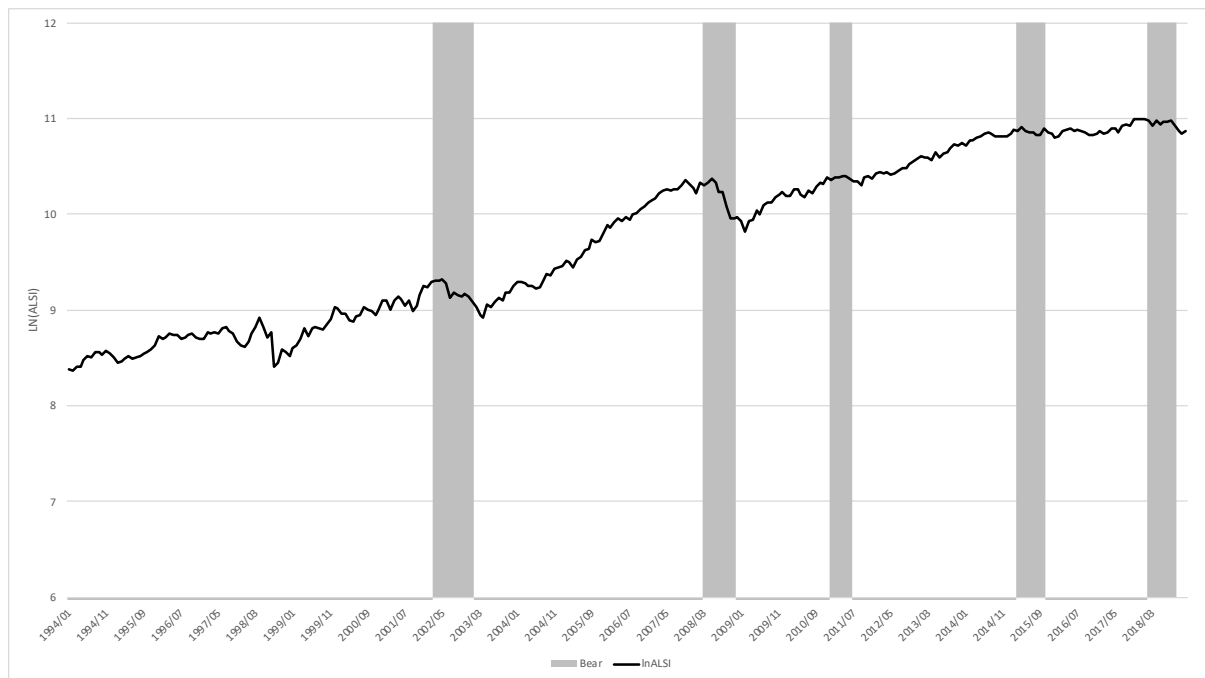
Table 1: Bear Phases of the JSE for the period 1994-2018

Bear Phase #	1	2	3	4	5
Start Date	2002/06	2008/06	2011/04	2015/06	2018/05
End Date	2003/04	2009/02	2011/09	2016/01	2018/12
Length (months)	11	9	6	8	8
Peak	10657,73	30413,43	32836,23	53793,74	58668,48
Trough	7510,4	18465,33	29674,2	49141,94	50663,94

% Change	-41,91	-64,71	-10,66	-9,47	-15,8
Severity Ranking	2	1	4	5	3

Source: Author's calculations

Figure 1: Bear Markets (six-month criteria) and Natural Log of All Share Index for the period 1994-2018



Source: Author's calculations

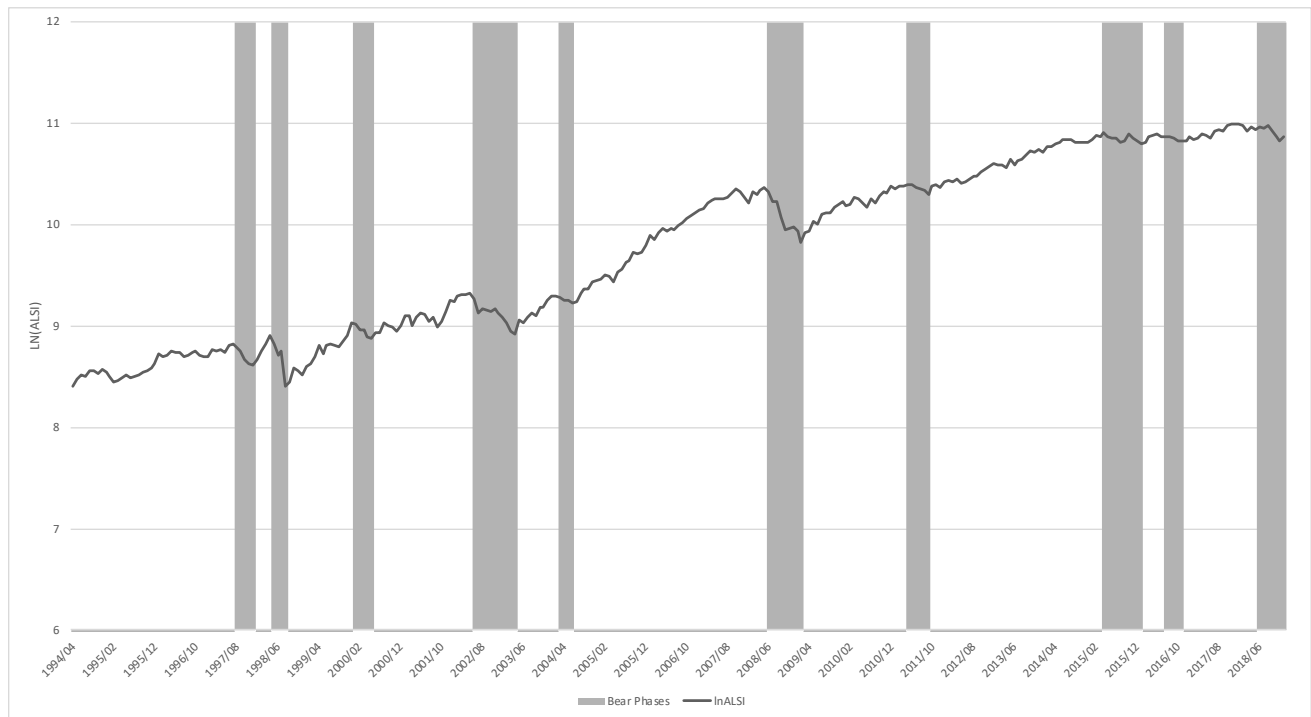
In Figure 1 the identified bear phases are shown graphically against the log of the All Share Index.

While using a 6-month generally declining trend as the criteria for a bear market follows what has been done in majority of the literature, it would appear from Figure 1 that having such a stringent criterion is missing potentially profitable dips in the market that lasted just short of 6-months, but during which the Index fell sharply. For example, the sharp dip in the period May 1998 to September 1998 is only a 5-month dip thus not being counted as a bear phase, however, this was a 31% dip from peak to trough over the 5-month period and would have been counted as the 3rd most severe bear market in *Table 1* under this measure.

Asgharian *et al.* (2007) conducted research using the same method as Resnick and Shoesmith (2002) for Russia and Italy. Due to data availability limitations the Russian analysis in that study was conducted using weekly data and the bear phases identified were as short as 2 weeks of consecutive market decline. The Italian analysis in that study was conducted using monthly data with a bear phase length criterion of only 2 months of market decline. Asgharian *et al.* (2007) found positive market timing results for both Russia and Italy. Thus, following

on from these findings, the bear phase length in this study is shortened to 4-months and market-timing calculations are made using this definition as well as the 6-month criterion.

Figure 2: Bear Markets (four-month criteria) and Natural Log of All Share Index for the period 1994-2018



Source: Author's calculations

The number of bear markets when defined as 4-months of decline doubles to 10 for the period. These are shown against the log of the All Share Index in Figure 2. It appears that no obvious potentially profitable market dips are ignored using this less stringent definition of what constitutes a bear market.

Once bear stock markets have been identified, the dummy variables are ready to be used in the probit model. Multiple probit models are run as stated in section 3.4.1.1. The results from the probit models will then be testing using the Henriksson-Merton parametric model test as stated in section 3.4.1.2 to identify whether the yield spread has market timing ability in South Africa for the given time period.

3.5 Conclusion

This chapter has laid out the data used as well as the methods and techniques to be followed in testing whether or not the South African yield spread is able to forecast bear stock markets on the JSE and, if so, whether there exists significant market timing ability. The data and their sources have been identified as well as the *a priori* expectations of the variable coefficients. The structure of the analysis is laid out and the method of identifying bear stock markets of both 6-month and 4-month duration is clearly identified. The probit model and market timing testing model are stated and explained. In the following chapter the results of the analysis are presented and discussed.

CHAPTER 4: FINDINGS AND INTERPRETATION OF RESULTS

4.1 Introduction

In this section the relationship between the yield spread and its forecasting ability for bear markets on the South African stock market is analysed econometrically. Section 4.2 will present the findings of the multiple preliminary probit models run and identify which were successful and chosen to be further tested. The following sections will present the findings for each model, with section 4.3 presenting the results from the selected probit models with illustrative graphs for SA yield spread and 6-month bear market criteria, the SA yield spread and 4-month bear market criteria and the SA and US yield spread with 6-month bear market criteria. In section 4.4 the market timing ability of the individual models is also tested at three probability screens for each selected model and time period using the Henriksson-Merton parametric model test. The HM test is done for the overall period, January 2006 - December 2018, as well as for two sub-periods, January 2006 - December 2011 and January 2012 - December 2018. The 1994-2006 period is used in the out-of-sample process and therefore does not form part of the forecasts presented. Section 4.5 then concludes the chapter.

4.2 Preliminary Probit Models

Preliminary probit models were run to test which models appeared to be successful in predicting bear markets one month ahead. Multiple models were run, however, only those that presented significant results for all 3 sample periods were considered for further study. The out-of-sample forecasting process is inefficient as it requires much manual computing time, thus the models were first run in increments of five years instead of for each additional month.

The probit model was first run using a time period from January 1981 - December 2018. However, results were all insignificant regardless of whether the bear market criteria length was six- or four-months. The probit model was also run using US yield spreads as an additional variable, however, the results still remained insignificant. It was then decided to shorten the

time period to exclude the effects of the Apartheid period when South African financial markets were largely isolated from international capital flows as a result of financial sanctions. The period was thus shortened to April 1994 - December 2018. Once this change was made the preliminary probit models using the SA yield spread and bear markets criteria of four- and six-months were both successful, as was the probit using SA and US yield spreads and a six-month bear market criterion. The probit using SA and US yield spreads and four-month bear market criteria was unsuccessful and was therefore not carried through to the next stage of testing. Both successful and unsuccessful preliminary probit models can be found in Appendix A.

The probit model was also run using a rolling-window regression in addition to the out-of-sample forecasting method. The rolling-window regression maintains a constant base period of 60 months, whereas the out-of-sample forecasting increases the base period by one month each iteration and will eventually equal the total sample size. The rolling-window regression has the benefit of placing more emphasis on recent events as well as to test the strength of the relationship over time (Chinn and Kucko, 2015). The rolling-window regression was attempted to possibly improve on the out-of-sample methodology, however, none of the rolling-window regressions were successful overall. Examples of these regressions can be found in Appendix B.

The three successful probit models that were carried through are the out-of-sample models using SA yield spreads for both four- and six-month bear market criteria and the model using both SA and US yield spreads and six-month bear market criterion. All three of these models presented plausible preliminary probit models and presented significant results for every iteration of the full probit model. Each model is presented in its own section below.

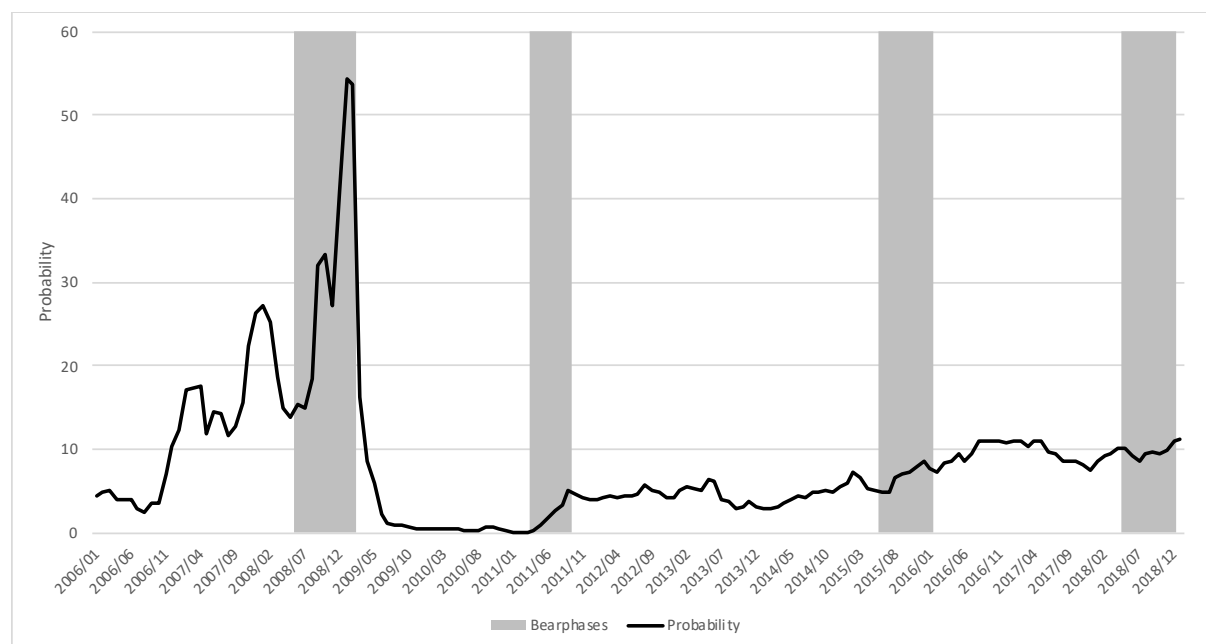
4.3 Probit Model Results

Using out-of-sample forecasting for the base period April 1994 - December 2005, the probability of a bear market one month ahead was calculated. Due to the iterative nature of the out-of-sample process the probabilities are best presented in graphical form. Figure 3 presents the forecast probability of a bear market one month ahead for the period January 2006 - December 2018.

The line graph represents the probability of a bear market, on the y-axis, occurring one month ahead in the associated month on the x-axis. The shaded area represents the calculated bear stock markets of at least 6 months duration within the period.

4.3.1. SA Yield Spread with six-month Bear Market Criteria

Figure 3: Probability of Bear Market one-month ahead – SA Yield Spread, six-month criteria



Source: Author's calculations

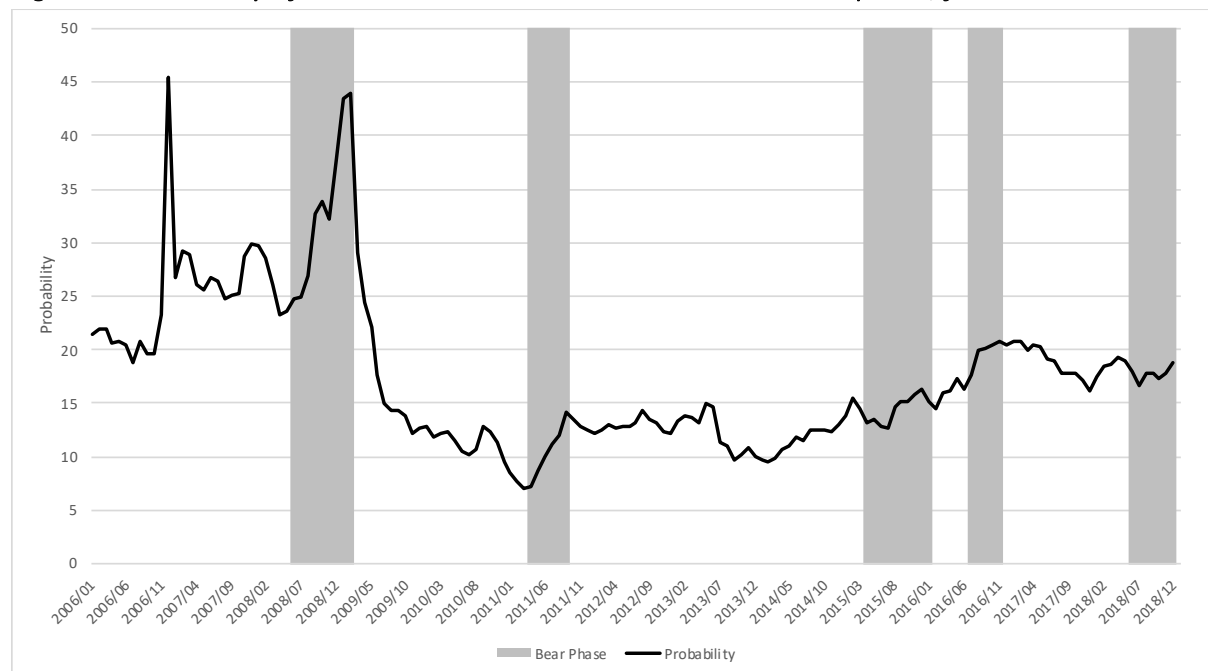
At first glance it does not appear that the model is able to consistently or successfully predict bear stock markets. There is a spike in the probability of a bear market one month ahead at the beginning of 2007, but this dissipates soon after. There is another spike in probability at

the end of 2007 and the beginning of 2008 and another spike towards the end of 2008. There is increasing probability of a bear stock market from the beginning of the actual bear stock market and the probability falls sharply once the bear market ends. After the end of the bear market in February 2009 the probability levels remain between 0 and 10 percent, except for the period, July 2016 to July 2017, when the probability levels rise just above 10 percent but a bear market was not actually recorded.

This pattern does not visually track the 4 recorded bear markets well. Although there are small increases in the probability levels before or at the beginning of the bear markets, these increases remain under 10 percent level of probability for all bear markets except for 2008-2009. The much larger spikes around the period of the 2008 global financial crisis do not appear to conform to the normal pattern seen for the rest of the period. It could be the instability surrounding the global financial crisis that had caused such a large spike compared with the pattern post the global financial crisis, rather than the probit model's ability to forecast a bear market at that time.

4.3.2. SA Yield Spread with four-month Bear Market Criteria

Figure 4: Probability of Bear Market one-month ahead – SA Yield Spread, four-month criteria



Source: Author's calculations

In Figure 4 the impact of decreasing the criteria for a bear market from 6- to 4-months is demonstrated. There appears to be greater movement in the probability levels of a bear market over the full forecast period 2006-2018. As was the case in the 6-month criteria model above, the sustained highest probability spikes occur around the 2008 global financial crisis. The highest spike, at just over 45%, occurs well before the crisis in 2006 when a bear market did not occur. Over the whole period, a similar pattern can be seen as in the 6-month criteria model. The greatest spikes occur before and during the global financial crisis, reaching highs of just under 45% probability. However, after the first quarter of 2009 these effects fade and the movement in the probability levels thereafter does not fluctuate nearly as much.

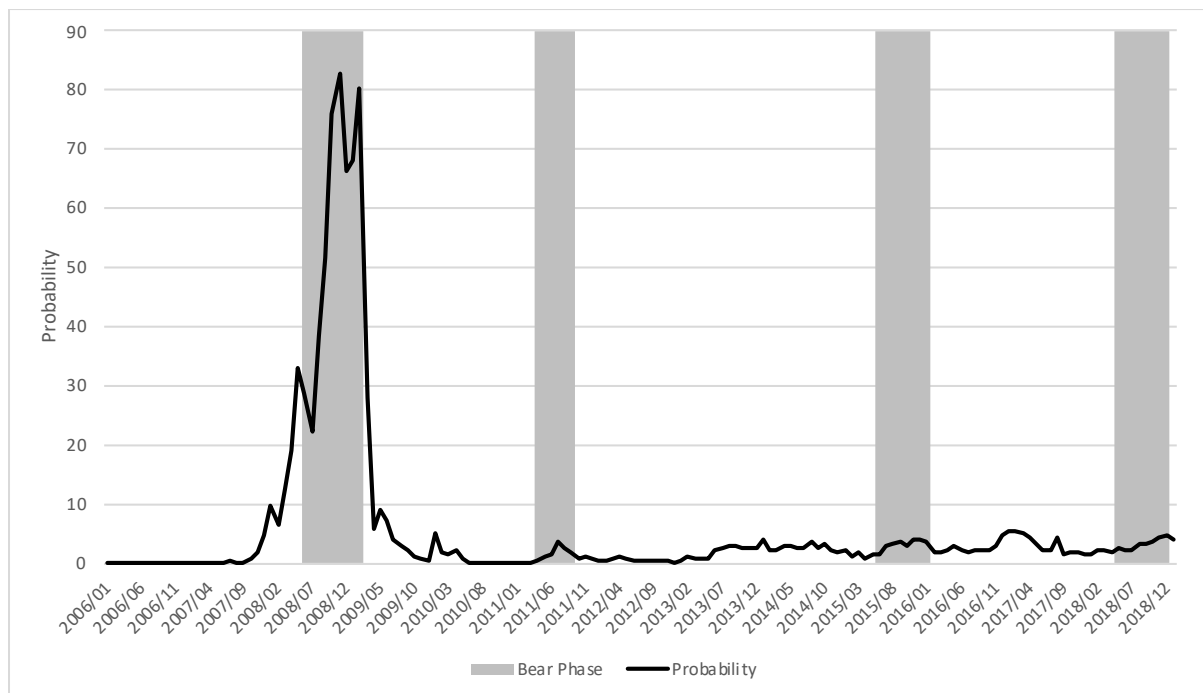
The bear market beginning in March 2011 presents an interesting case. A rise in the probability leading up to the bear market is expected, however, in this case we see a fall in the probability by about 5 percentage points to less than 10% and then a rise in the probability levels throughout the duration of the bear market, with the peak of less than 15% coinciding with the end of the bear market. A similar pattern appears with the other bear markets in the model; namely, initially a fall in the probability level followed by a flattening out or rise in the

probability level during the actual bear market and with maximum probabilities of only 15-20%. This is opposite to the *a priori* expectations.

As in the 6-month bear market model, the fluctuations post the 2008 global financial crisis are not as substantial as before the crisis. In the 4-month model fluctuations post the crisis in the forecast probability of a bear market remain between 7 and 20 percent (compared with 0-10% in the 6-month bear market model).

4.3.3. SA and US Yield Spreads with six-month Bear Market Criteria

Figure 5: Probability of a Bear Market one-month ahead – SA and US Yield Spread, six-month criteria



Source: Author's calculations

Following the findings of Liu *et al.* (2004) and Fernandez-Perez *et al.* (2014) the model was expanded to include the yield spread of the US. It is expected that the addition of the US yield spread would improve the forecasts of bear markets. The pattern seen in figure 5 is very similar to that of the model of only the SA yield spread with a six-month bear market. Again, there is a large spike in the forecast probability level around the global financial crisis (with probability now rising to 80%), with probability levels falling almost immediately afterwards

and not rising to even 10 percent for any of the other identified bear markets. The forecast probability levels do appear to rise just before or at the beginning of the bear markets, however, these rises are very small and do not even reach the 5 percent probability level.

4.4. Market Timing Results

In order to measure whether each model has significant market timing ability the Henriksson-Merton parametric model test is used (see section 3.4.1.2). The results are presented in three tables for each model, with each table showing the results for a particular probability screen level.

A reminder that b_{pu} represents the systematic risk during bull markets, and b_{pd} represents the systematic risk during bear markets. While these two variables may be interesting, it is b_{po} that is of particular interest. The slope coefficient b_{po} is equal to the difference in bull and bear market betas for the market timing portfolio ($b_{pu} - b_{pd}$). Thus, if the coefficient is statistically significant and positive then we can conclude that it is possible for a dynamic market timing portfolio to outperform a stock-only, buy-and-hold strategy.

4.4.1 SA Yield Spread with six-month Bear Market Criteria

Table 2: HM Market Timing Test Results, Probability screen < 0.1

2006 – 2011			
	b_{pu}	b_{pd}	b_{po}
Coefficient	0.621712	1.749750**	-0.707395
Std. error	(0.594119)	(0.254137)	(0.479940)
Adjusted R-squared	0.001337	0.395251	0.438394
F-statistic	1.095045	47.40401**	28.71161**
2012 – 2018			
	b_{pu}	b_{pd}	b_{po}
Coefficient	5.141339**	5.028827**	-0.297281
Std. error	(0.967744)	(1.072877)	(0.628673)
Adjusted R-squared	0.246994	0.201694	0.792229
F-statistic	28.22487**	21.97016**	159.2389**
2006 – 2018			
	b_{pu}	b_{pd}	b_{po}
Coefficient	1.110968**	1.853870**	-0.384003
Std. error	(0.449167)	(0.209595)	(0.382800)
Adjusted R-squared	0.031962	0.332570	0.406236
F-statistic	6.117695**	78.23401**	54.02323**

Source: Author's own estimation using Eviews 11

Note: The significance level is indicated by *** for significance at the 1% level and ** for significance at the 5% level.

Table 3: HM Market Timing Test Results, Probability screen < 0.2

2006 – 2011			
	b_{pu}	b_{pd}	b_{po}
Coefficient	-0.398378**	0.728485**	-0.255401**
Std. error	(0.169578)	(0.102589)	(0.104735)
Adjusted R-squared	0.059838	0.410419	0.647060
F-statistic	5.518912**	50.42442**	66.08355**
2012 – 2018			
	b_{pu}	b_{pd}	b_{po}
Coefficient	-0.100137	0.345094**	-0.129334
Std. error	(0.123319)	(0.111049)	(2.025480)
Adjusted R-squared	-0.004121	0.094451	0.454204
F-statistic	0.659380	9.657151**	35.53575**
2006 – 2018			
	b_{pu}	b_{pd}	b_{po}
Coefficient	-0.234214**	0.623172**	-0.232440**
Std. error	(0.106538)	(0.074624)	(0.069858)
Adjusted R-squared	0.024132	0.307221	0.580425
F-statistic	4.832987**	69.73653**	108.2108**

Source: Author's own estimation using Eviews 11

Note: The significance of individual coefficients is indicated by *** for significance at the 1% level and ** for significance at the 5% level.

Table 4: HM Market Timing Test Results, Probability screen < 0.3

2006 – 2011			
	b_{pu}	b_{pd}	b_{po}
Coefficient	-0.343982**	0.661132**	-0.210854**
Std. error	(0.153720)	(0.092373)	0.090379
Adjusted R-squared	0.053427	0.414314	0.687049
F-statistic	5.007407**	51.22539**	75.74083**
2012 – 2018			
	b_{pu}	b_{pd}	b_{po}
Coefficient	-0.084087	0.313287**	-0.111281
Std. error	(0.110367)	(0.099163)	0.078457
Adjusted R-squared	-0.005080	0.097643	0.492832
F-statistic	0.580475	9.981353**	41.32694**
2006 – 2018			
	b_{pu}	b_{pd}	b_{po}
Coefficient	-0.195658**	0.567786**	-0.193995**
Std. error	(0.096576)	(0.067263)	(0.06274)
Adjusted R-squared	0.019636	0.311895	0.618137
F-statistic	4.104479**	71.25624**	126.4523**

Source: Author's own estimation using Eviews 11

Note: The significance of individual coefficients is indicated by *** for significance at the 1% level and ** for significance at the 5% level.

Looking first at the 10% probability screen, the b_{po} coefficient is negative and not statistically significant for any of the time periods presented. This indicates that investors are not able to derive benefit from following a market timing strategy at the 10% probability level.

When looking at the 20% probability screen, the coefficient value is statistically significant at the 5% level of significance in the 2006-2011 sub-period, is not significant in the 2012-2018 sub-period, but is significant at the 1% level of significance in the overall 2006-2018 period. The coefficient is however, negative in all three cases. Thus, investors are unable to benefit from following a market timing strategy at the 20% probability level.

The same situation occurs at the 30% probability screen. The b_{po} coefficient is statistically significant in the 2006-2011 and 2006-2018 periods at the 5% and 1% levels respectively. However, all coefficient values are negative and thus investors are not able to derive benefit from following a market timing strategy at the 30% probability level either.

4.4.2 SA Yield Spread with four-month Bear Market Criteria

There is greater range than is present in the 6-month model and thus the probability screens selected change. The selected screens are 15%, 20% and 30%. Although the probability screens are adjusted, this makes no difference to the outcome of the test. The results are largely the same as for the SA Yield Spread with six-month Bear Market Criteria case and so the results table is not included in this section. The results table can however be found in Appendix C.

At the 15%, 20% and 30% probability screens all b_{po} coefficients are negative and so regardless of statistical significance indicate that there is no benefit to be gained from a market timing strategy based on the yield spread's forecasting ability.

4.4.3 SA and US Yield Spreads with six-month Bear Market Criteria

Table 5: HM Market Timing Test Results, Probability screen < 0.1

2006 – 2011			
	b_{pu}	b_{pd}	b_{po}
Coefficient	0.040638**	0.019319**	-0.020486
Std. error	(0.015084)	(0.002984)	(0.012043)
Adjusted R-squared	0.081007	0.365552	0.448577
F-statistic	7.258456**	41.90822**	29.87889**
2012 – 2018			
	b_{pu}	b_{pd}	b_{po}
Coefficient	0.284480**	0.246522**	0.036204
Std. error	(0.043781)	(0.044041)	(0.036103)
Adjusted R-squared	0.331840	0.267639	0.726121
F-statistic	42.22168**	31.33211**	111.0268**
2006 – 2018			
	b_{pu}	b_{pd}	b_{po}
Coefficient	0.044989**	0.020098**	0.025362*
Std. error	(0.012013)	(0.002524)	(0.010201)
Adjusted R-squared	0.077518	0.286987	0.368927
F-statistic	14.02502**	63.38748**	46.30675**

Source: Author's own estimation using Eviews 11

Note: The significance of individual coefficients is indicated by *** for significance at the 1% level and ** for significance at the 5% level.

Table 6: HM Market Timing Test Results, Probability screen < 0.2

2006 – 2011			
	b_{pu}	b_{pd}	b_{po}
Coefficient	0.035633**	0.017581**	0.017289
Std. error	(0.013789)	(0.002719)	(0.011041)
Adjusted R-squared	0.074052	0.365019	0.44152
F-statistic	6.678213**	41.81440**	29.02353**
2012 – 2018			
	b_{pu}	b_{pd}	b_{po}
Coefficient	0.253316**	0.221751**	0.030325
Std. error	(0.039853)	(0.039864)	(0.033499)
Adjusted R-squared	0.321901	0.265116	0.711224
F-statistic	40.40103**	30.94306**	103.2101**
2006 – 2018			
	b_{pu}	b_{pd}	b_{po}
Coefficient	0.039235**	0.018390**	0.021278**
Std. error	(0.010989)	(0.002296)	(0.009331)
Adjusted R-squared	0.070450	0.289403	0.364164
F-statistic	12.74736**	64.12632**	45.38685**

Source: Author's own estimation using Eviews 11

Note: The significance of individual coefficients is indicated by *** for significance at the 1% level and ** for significance at the 5% level.

Table 7: HM Market Timing Test Results, Probability screen < 0.3

2006 – 2011			
	b_{pu}	b_{pd}	b_{po}
Coefficient	0.030627**	0.015843**	0.014092
Std. error	(0.012513)	(0.002460)	(0.010065)
Adjusted R-squared	0.065677	0.363124	0.430953
F-statistic	5.990861**	41.48172**	27.88501**
2012 – 2018			
	b_{pu}	b_{pd}	b_{po}
Coefficient	0.222152**	0.196979**	0.024447
Std. error	(0.035991)	(0.035754)	(0.030995)
Adjusted R-squared	0.308907	0.261254	0.691044
F-statistic	38.099590**	30.35259**	93.82328**
2006 – 2018			
	b_{pu}	b_{pd}	b_{po}
Coefficient	0.033480**	0.016682**	0.017195**
Std. error	(0.009984)	(0.002074)	0.008484
Adjusted R-squared	0.062004	0.291174	0.357342
F-statistic	11.24590**	64.67149**	44.09285**

Source: Author's own estimation using Eviews 11

Note: The significance of individual coefficients is indicated by *** for significance at the 1% level and ** for significance at the 5% level.

The model using both SA and US Yield spreads presents a peculiar set of results. For all probability screens, the b_{po} coefficient is positive and statistically significant at the 5% level of significance for the overall period 2006-2018. However, the b_{po} is positive but not significant in either of the sub-periods for any of the probability screens. This could possibly be explained by the singular spike in the data at the time of the 2008 global financial crisis, especially since all other probability levels remain so low compared to that spike. An alternative explanation could be that the addition of a foreign country's yield spread alters the model in an unanticipated manner.

Regardless, according to the test methodology the results indicate that an investor may benefit from following a market timing strategy using both the SA and US Yield Spreads with six-month Bear Market Criteria at all probability screens over the whole time period. But the failure to obtain similar results in the post-crisis 2012-2018 advises caution in accepting such a conclusion.

4.5 Conclusion

This chapter has presented the findings of three probit models using only SA and SA plus US Yield spreads with four- or six-month bear market criteria. Overall, the models did not visually appear to forecast the identified bear markets well. All three models presented exhibit the same pattern of a major spike, or spikes in some cases, around the time of the 2008 global financial crisis, with little to no fluctuation in the forecast probability levels post the global financial crisis period even though bear markets did occur.

This visual assessment was confirmed by the market timing test, the HM parametric model test. For SA Yield Spread with both four- and six-month bear market criteria the HM test found no statistical difference between the systematic risk of bull and bear markets and thus investors would not be able to derive any benefit from employing a market timing strategy using the SA yield spread at any probability screening level.

The results change when looking at the model using both the SA and US yield spreads with six-month bear market criteria. Here the HM test found, at the 5% level of significance, a statistical and positive difference in the bear and bull market betas over the full forecast period and thus investors could potentially benefit from employing a market timing strategy

at all probability screen levels. A word of caution must accompany the findings for this model. The relationship between the SA and US yield spreads is not thoroughly reviewed in this research and it is not recommended for investors to employ this strategy without further research into the complex intermingling of the cross-country effects and potential policy effects of these two variables.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

The overarching aim of this thesis was to identify if there is significant market timing information present in the South African yield spread. If there is significant market timing information present, would an investor be able to, using a dynamic market timing strategy, outperform a stock-only, buy-and-hold strategy? Confirming a robust relationship between the yield spread and future bear markets could drastically change the manner in which portfolios are managed. However, this thesis merely provides a starting point for the South African context.

As mentioned earlier, there are numerous studies detailing the relationship between the yield spread, or yield curve, and economic activity and this relationship has mostly been used to help predict future recessions in the economy. While there has been debate as to the robustness and relevance of this linking relationship, the yield curve remains a useful tool for investors and analysts. More recently, the yield curve's forecasting ability and been used to predict shorter-term changes in the economy, within the stock exchange to be precise. The rationale is that if the yield curve contains significant market information that is able to help investors forecast recessions in the economy, could this not be extended to help forecast more short-term changes in the stock exchange? And if there is in fact enough market information contained in the yield curve, could investors exploit this information by developing a dynamic market timing strategy? This model or strategy would alert investors to a possible bear market in the future, say one or two months ahead. Investors are then able to shift their investment out of the stock exchange and into a 'safer' short-term investment such as Treasury Bills, in which the investment can ride out the bear market without losing significant value. This strategy would also give an indication of when to shift out of the short-term investment and back into the stock exchange.

This thesis does not seek to develop such a model, but only to identify if such a relationship exists between the yield curve and the stock exchange in South Africa for the period April 1994 through December 2018.

5.1 Literature Review and Methods

A literature review was presented in Chapter 2 and begins with an outline of the basic yield curve theory. There is a series of relationships that are used to explain the final relationship between the yield curve and the stock exchange. First the relationship between the yield curve and economic activity is presented, next the relationship between economic activity and the stock exchange and finally the relationship between the yield curve and the stock exchange is discussed.

The yield curve is used to compare the returns on bonds differentiated solely by their term to maturity (Howells and Bain, 2008). The yield spread is used as a standard measure of the yield curve and in South Africa the yield curve is taken as the difference between the 10-year Government Bond rate and the 91-day Treasury Bill rate. The yield curve has three distinct states: an upward sloping curve which is taken to be the normal state, an inverted curve and a flat curve. An upward sloping curve occurs when long-term rates, typically the 10-year Government Bond, is above the short-term rates, the 91-day Treasury Bill rate. An upward sloping curve is commonly understood to indicate strong economic prospects. An inverted or negatively sloped curve occurs when the short-term rates are above the long-term rates. Inverted yield curves are taken as an indication of looming economic downturns and possible recession. A flat yield curve or flattening yield curve usually occurs during a transition and could indicate the beginning or ending of a new economic condition.

Of the many hypotheses that attempt to explain the shape of the yield curve, the Expectations theory is possibly the most widely known. The Expectations theory states that, for any choice of holding period, the expected return will be the same for any combination of bonds of different maturities that one might hold in that period (Haubrich and Dombrosky, 1996, Deuker, 1997 and Howells and Bain, 2008). The Expectations theory relies on investors being indifferent between holding short- or long-term bonds that are completely substitutable. According to the Expectations theory the yield curve takes on the shape determined by the market's expectations of the future level of interest rates and, if the theory holds, implied forward rates can be measured from the curve. The theory is not able to predict future rates; however, the yield curve can be used as a guide to the expected direction of change in future rates (Howells and Bain, 2005).

The term premium theory or liquidity premium theory is used with the Expectations theory in order to try explain the shape of the yield curve. The term premium theory states that investors require greater compensation for holding longer-term bonds because they are taking on an increased risk of capital loss over the longer period as opposed to investing in short-term bonds. This is the argument used to explain why the yield curve is generally upward sloping.

Given that the yield curve is commonly used as a guide to changes in future rates, it comes as no surprise that the yield curve would be used as a predictive tool for future economic conditions. Extensive research has been done regarding the relationship between the yield curve and economic activity particularly concerning the use of the yield curve in helping to predict future recessions (Kessel, 1965, Hu, 1993, Estrella and Mishkin, 1996,1998, Haubrich and Dombrosky, 1996, Nel 1996, Dueker, 1997, Ang *et al.*, 2006, Estrella and Truben, 2006 and Clay and Keeton, 2011). This relationship is not yet precisely understood, however, there is substantial empirical evidence of it at play for both South Africa and internationally (Haubrich and Dombrosky, 1996, Estrella and Mishkin, 1996, Estrella and Truben, 2006, Clay and Keeton, 2011 and Botha *et al.*, 2017).

It will come as no surprise that there is a close association between what happens in the economy and the stock markets, locally as well as globally. Stocks markets have grown rapidly and are now common place in any conversation regarding the state of the economy. Stock prices are informed by expected future earnings growth and these earnings are determined by the state of the economy (Estrella and Mishkin, 1996). And as the stock markets have become more integrated into the economy, stock prices react sensitively to economic news with different unanticipated events having a more pervasive effect than others (Chen *et al.*, 1986). It was previously believed that changes in stock market prices was the best predictor of future real activity, however, it was more recently found that the bond market contained more information about future economic activity than stock prices (Fischer and Merton, 1984 cf. Hu (1993) and Harvey, 1989). This thesis has not investigated the predictive power of changes in the stock market, however, this relationship is important for the overall relationship of the yield curve and the stock market.

Through the relationship between the yield curve and economic activity and economic activity and the stock market, the link between the yield curve and the stock market is

established. And it is this relationship that presents great potential for investors to design dynamic market timing strategies. Resnick and Shoemith (2002), Bhaduri and Saraogi (2010) and Fernandez-Perez *et al.* (2014) are the three studies done and presented in the literature review of Chapter 2 for the US, India and Spain respectively. All three of these studies found that investors were able to successful outperform a stock-only, buy-and-hold strategy by using a dynamic market timing strategy to time the bear markets.

The method used by all three studies are very similar. They make use of a probit model which was adapted for this purpose, but originally developed by Estrella and Mishkin (1996) for forecasting recessions. This model is relatively simple as the only exogenous variable is the yield spread of the country under study. However, depending on the complexity of the study multiple variables can be included in the model. The probit used in this study remained quite simple with only the SA yield spread used for two of the models and the SA and US yield spread used for the third model. The probit model is used to estimate the probability of a bear market occurring one-month ahead. These probabilities are tracked over time and compared to the identified bear markets to see if the probabilities are able to potentially forecast these bear markets. The bear markets are identified manually. Probability screening levels are used as indicators of when to move out of- or shift into- the stock exchange or short-term bond market. The market timing ability of these probit models is then tested using the Henriksson-Merton (HM) parametric model test which gives an indication of whether or not the model has market timing ability. The models are tested for market timing ability at all different probability screen levels.

5.2 Findings

Probit models were run for SA yield spreads with a six-month and four-month bear market criteria and run for SA and US yield spreads with a six-month bear market criterion. The initial probit findings from these three models, presented graphically, did not appear to track the identified bear markets well. It is expected that the probability of a bear market occurring one month ahead would increase before a bear market period, however, this was not the case. All three models experienced the most significant spike in probability levels around the global financial crisis. This noise surrounding this appeared to have impacted the data for the remaining period. Small increases in the probability levels are seen before the bear markers

or the probability falls but then rises during the bear market. These changes are very small and initially do not appear to be significant.

The market timing ability is then tested using the HM model and the results for the SA yield spread case using both bear market criteria show that there is, in fact, no market timing ability present in the models. This finding is surprising due to the positive results found in the literature for both developed and developing countries. The SA and US yield spread case did however return a positive and statistically significant result indicating that the model using both yield spreads shows some market timing ability at the 5% level of significance. These results however should be used with caution as this relationship would need considerably more research before being attempted.

5.3 Recommendations and Further Research

The yield curve as a predictor of stock market fluctuations is an incredible interesting and complex area of research. It is still a relatively new area, but shows potential growth. This thesis attempted to investigate this relationship for South Africa, but was only conducted at a surface level. More research still needs to be conducted regarding the relationship between the yield curve and the stock market in South Africa. An additional area with huge potential is the impact other countries' yield curve fluctuations may have on the South African stock exchange. The contagion effect appears to be significant as the only model to show significant results was the model that included SA and US yield spreads.

As the only major spikes in probability levels occurred around the global financial crisis it would be helpful to investigate the impact crisis had on the relationship between the yield curve and the stock markets.

Dynamic market timing strategies still have a long way to go before they become a viable portfolio management tool in South Africa. Investors should be cautious when attempting to forecast any economic variable and especially stock market fluctuations because of the increasing levels of noise on the exchange.

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APPENDICES

Appendix A: Preliminary Probit Models

Table A. 1: SA Yield Spread with six-month criteria for the period 1981-2018

January 1981 – December 2018				
SA Yield Spread Slope Coefficient				
	Months Ahead			
	1	2	3	4
1981 – 2000	-0.014590	-0,007379	-0,000329	0,006623
1981 – 2005	-0,048471	-0,035346	-0,020973	-0,007736
1981 – 2010	-0,071318	-0,057227**	-0,041613	-0,026007
1981 – 2015	-0,056028**	-0,042840	-0,028483	-0,017412
1981 - 2018	-0,050613	-0,038324	-0,024948	-0,014681

Source: Author's own estimation using Eviews 11

*Note: The significance level is indicated by *** for significance at the 1% level and ** for significance at the 5% level.*

Table A. 2: SA Yield Spread with four-month criteria for the period 1981-2018

January 1981 – December 2018				
SA Yield Spread Slope Coefficient				
	Months Ahead			
	1	2	3	4
1981 – 2000	-0,031948	-0,025936	-0,025936	-0,018416
1981 – 2005	-0,054027	-0,041167	-0,033045	-0,033045
1981 – 2010	-0,069784**	-0,055518**	-0,044612	-0,033382
1981 – 2015	-0,05819**	-0,045796	-0,038613	-0,030962
1981 - 2018	-0,052331**	-0,040421	-0,033020	-0,024669

Source: Author's own estimation using Eviews 11

*Note: The significance level is indicated by *** for significance at the 1% level and ** for significance at the 5% level.*

Table A. 3: SA Yield Spread with six-month criteria for the period 1994-2018

April 1994 – December 2018				
SA Yield Spread Slope Coefficient				
	Months Ahead			
	1	2	3	4
1994 - 2005	-0,437906***	-0,329074***	-0,230735***	-0,161715
1994 - 2010	-0,560150***	-0,431876***	-0,323950***	-0,227956***
1994 - 2015	-0,185424***	-0,156751***	-0,123469**	-0,101787
1994 - 2018	-0,152689***	-0,129698***	-0,102383**	-0,084989

Source: Author's own estimation using Eviews 11

*Note: The significance level is indicated by *** for significance at the 1% level and ** for significance at the 5% level.*

Table A. 4: SA Yield Spread with four-month criteria for the period 1994-2018

April 1994 – December 2018				
SA Yield Spread Slope Coefficient				
	Months Ahead			
	1	2	3	4
1994 - 2005	-0,345841***	-0,255816***	-0,208321***	-0,164778**
1994 - 2010	-0,415958***	-0,318666***	-0,243854***	-0,195363***
1994 - 2015	-0,174283***	-0,142558***	-0,125445**	-0,114073**
1994 - 2018	-0,140736***	-0,113411**	-0,097037**	-0,083971

Source: Author's own estimation using Eviews 11

Note: The significance level is indicated by *** for significance at the 1% level and ** for significance at the 5% level.

Table A. 5: SA and US Yield Spread with six-month criteria for the period 1994-2018

April 1994 – December 2018					
SA Yield Spread Slope Coefficient					
		Months Ahead			
		1	2	3	4
1994 - 2005	SA	-0,642647***	-0,494744***	-0,374724***	-0,270146**
	US	1,027807***	0,984277***	1,026936***	1,010468***
1994 - 2010	SA	-0,818206***	-0,645557***	-0,523541***	-0,366690***
	US	1,197638***	1,110401***	1,106211***	1,106211***
1994 - 2015	SA	-0,218085***	-0,192425***	-0,158981***	-0,158981***
	US	0,528601***	0,579922***	0,623296***	0,618687***
1994 - 2018	SA	-0,154693***	-0,134301***	-0,109244**	-0,094360
	US	0,275338***	0,315162***	0,350572***	0,356241***

Source: Author's own estimation using Eviews 11

*Note: The significance level is indicated by *** for significance at the 1% level and ** for significance at the 5% level.*

Appendix B: Rolling-Window Regressions

Table B. 1: SA Yield Spread Rolling Regression for the period 1994-2018

April 1994 – December 2018				
SA Yield Spread Slope Coefficient				
	Months Ahead			
	1	2	3	4
1994M04 – 2005M12	-0,435456***	-0,325645***	-0,226770	-0,157562
2006M01 – 2010M12	-1,272975***	-0,886829***	-0,886829***	-0,336323**
2011M01 – 2015M12	0,184360	0,190460	0,148085	-0,042630
2016M01 – 2018M12	-1,6843366**	0,831649	0,451636	0,101776

Source: Author's own estimation using Eviews 11

*Note: The significance level is indicated by *** for significance at the 1% level and ** for significance at the 5% level.*

Table B. 2: SA and US Yield Spread Rolling Regression for the period 1994-2018

April 1994 – December 2018				
SA Yield Spread Slope Coefficient				
		Months Ahead		
		1	2	3
1994M04 – 2005M12	SA	-0,642647***	-0,642647***	-0,374724***
	US	1,027807***	0,984277***	1,026936***
2006M01 – 2010M12	SA	-2,353462	-1,137085***	-0,932736***
	US	3,148851**	2,079412**	1,89821**
2011M01 – 2015M12	SA	-0,323628	-1,709706	-1,751618
	US	0,630876	1,106420**	1,393914***
2016M01 – 2018M12	SA	1,858746**	0,333408	0,024080
	US	-2,174967**	-9,68959**	-5,829627**

Source: Author's own estimation using Eviews 11

*Note: The significance level is indicated by *** for significance at the 1% level and ** for significance at the 5% level.*

APPENDIX C: Market Timing Results SA Yield Spread with four-month Bear Market Criteria

Table C. 1: HM Market Timing Test Results, Probability screen < 0.15

2006 – 2011			
	b_{pu}	b_{pd}	b_{po}
Coefficient	-0.273615	0.762583***	-0.134900
Std. error	(0.184284)	(0.107506)	(0.088764)
Adjusted R-squared	0.016681	0.40989	0.774228
F-statistic	2.204473	50.31647***	122.7385***
2012 – 2018			
	b_{pu}	b_{pd}	b_{po}
Coefficient	-0.105752	0.370919***	-0.027937
Std. error	(0.119751)	(0.100695)	(0.070937)
Adjusted R-squared	-0.002659	0.131515	0.650901
F-statistic	0.779853	13.56874***	78.37756***
2006 – 2018			
	b_{pu}	b_{pd}	b_{po}
Coefficient	-0.145643	0.625114***	-0.135765**
Std. error	(0.108841)	(0.075405)	(0.057916)
Adjusted R-squared	0.005075	0.304079	0.718309
F-statistic	1.790597	68.72640***	198.6246***

Source: Author's own estimation using Eviews 11

Note: The significance of individual coefficients is indicated by *** for significance at the 1% level and ** for significance at the 5% level.

Table C. 2: HM Market Timing Test Results, Probability screen < 0.2

2006 – 2011			
	b_{pu}	b_{pd}	b_{po}
Coefficient	-0.254971	0.728890***	-0.121450
Std. error	(0.175819)	(0.102309)	(0.082059)
Adjusted R-squared	0.015298	0.412045	0.787725
F-statistic	2.103041	50.75745***	132.7358***
2012 – 2018			
	b_{pu}	b_{pd}	b_{po}
Coefficient	-0.017926	0.359319***	-0.063186
Std. error	(0.123533)	(0.108701)	(0.070703)
Adjusted R-squared	-0.011935	0.106825	0.669316
F-statistic	0.021057	10.92677***	84.99729***
2006 – 2018			
	b_{pu}	b_{pd}	b_{po}
Coefficient	-0.124412	0.625555***	-0.119686**
Std. error	(0.108942)	(0.073818)	(0.056329)
Adjusted R-squared	0.001959	0.3133001	0.733183
F-statistic	1.304181	71.61885***	213.9611***

Source: Author's own estimation using Eviews 11

*Note: The significance of individual coefficients is indicated by *** for significance at the 1% level and ** for significance at the 5% level.*

Table C. 3: HM Market Timing Test Results, Probability screen < 0.3

2006 – 2011			
	b_{pu}	b_{pd}	b_{po}
Coefficient	-0.217683	0.661504***	-0.094550
Std. error	(0.159092)	(0.092118)	(0.068721)
Adjusted R-squared	0.012136	0.415961	0.817585
F-statistic	1.872208	51.56713***	160.1110***
2012 – 2018			
	b_{pu}	b_{pd}	b_{po}
Coefficient	-0.011641	0.325576***	-0.053170
Std. error	(0.110512)	(0.097069)	(0.059698)
Adjusted R-squared	-0.012058	0.109917	0.705387
F-statistic	0.011095	11.24976***	100.3627***
2006 – 2018			
	b_{pu}	b_{pd}	b_{po}
Coefficient	-0.099758	0.569724***	-0.095374**
Std. error	(0.098617)	(0.066633)	(0.047347)
Adjusted R-squared	0.000150	0.317495	0.769538
F-statistic	1.023262	73.10454***	259.7806***

Source: Author's own estimation using Eviews 11

Note: The significance of individual coefficients is indicated by *** for significance at the 1% level and ** for significance at the 5% level.