MASTERS THESIS

THE YIELD SPREAD AS A PREDICTOR FOR BUY OR SELL SIGNALS FOR SECTORAL INDICES OF THE JSE

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PLAGIARISM DECLARATION

This is to declare that the work on this thesis is of my own in fulfilment of the partial thesis with help provided to me by my supervisors. Any work that is not mine that was adapted from other sources has been properly acknowledged and referenced. This thesis has not been submitted to any other university, colleges or Technikons for any degree purposes.

ABSTRACT

The predictive nature of the yield curve has been of interest to researchers for years. In this thesis, the evidence for the yield curve as a predictor is examine, specifically as a predictor for bear markets in the JSE stock market for 8 sub-sectoral indices. The study explores a dynamic market timing strategy for timing the South African stock market compared to a normal buy-and-hold strategy. First, probit models are estimated for each of the sectoral indices which did not prove to have tracked well all the bear market phases. Then a dynamic market timing portfolio is simulated against a buy-and-hold only strategy, the dynamic market timing portfolio proved to have outperformed a buy-and-hold strategy for almost all the indices. Thus, a Henriksson-Merton parametric model test which tests for market timing ability was done on these sub-indices. The research finds that the yield curve in South Africa is not a useful tool for a buy-sell strategy for most of the sub-sectoral indices of the JSE.

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CHAPTER 1: INTRODUCTION

1.1 Research Content

An investor able to perfectly time buying shares before the stock market rises and selling them before it falls would clearly achieve superior returns to investors adopting a buy-and-hold strategy (Wim, 2018). To achieve such perfect timing in stock markets requires, however, that an investor be able to correctly predict bull and bear phases and invest accordingly (Alramady *et al*, 2014). In practice this is difficult and there is little empirical evidence that a strategy of timing the market in practice outperforms a buy-and-hold strategy (Shen, 2003). Sharpe (1975) argues that time in the market is more important than timing the market. However, Sharpe (1973) and Alramady *et al* (2014) find that a timing strategy could potentially yield incremental long term returns almost 4% per annum better than returns of a buy-and-hold strategy. For this to work in practice superior forecasting abilities are needed.

Campbell (1987) notes that there is a link between the stock market, yield spread and economic activity. According to Campbell (1989:38) "the stock market contains information about the future path of economic growth". Resnick and Shoesmith, (2002: 82) cite Siegel (1999) in discussing the relationship between business cycles and the performance of stock markets and state that "stock values are based on corporate earnings, and the business cycle is a prime determinant of these earnings". Bhaduri and Saraogi (2010) further expand on this point, noting that share prices are discounted values of expected cash flows, and the magnitudes of those cashflows are determined by the strength of an economy. This means that stock prices represent investors' expectations of real economic activity and any change in those expectations will mean that share price are revised. It can be said that earnings and share prices are expected follow the business cycle and if an investor is able to accurately predict turning points in the business cycle that information can be used to time the stock market (Resnick and Shoesmith, 2002).

Campbell (1987) and Khomo and Aziakpono (2007) conclude that the body of empirical evidence provides evidence that the yield curve (the difference between long- and short-term interest rates) can forecast not only recessions but also changes in the growth rate of real output. Estrella and Mishkin (1996) state that the steepness of a yield curve gives off useful information when forecasting what could be considered a possible recession. This is due to the major impact that monetary policies have on both real economic activity and on the spread of a yield curve (Khomo and Aziakpono, 2007). Estrella and Mishkin (1996) explain that a short-term rise in interest rates flattens the yield curve while also slowing down economic activity. Estrella and Mishkin (1996, 1998) believe the yield curve is a good predictor and could be useful when used simultaneously with other econometric models to predicting a recession.,

According to Clay and Keeton (2014:468) the yield curve can predict future economic activity. Nel (1996) quoted in Clay and Keeton (2014) found that in South Africa “the yield curve is positively related to gross domestic product (GDP) growth and is a successful indicator of current and expected monetary policy”. Estrella and Gikas (1991) explain that the positive slope of the yield curve has more predictive powers over the index than any of the other indicators such as real short-term interest rates in predicting recessions in about two to six quarters ahead. The yield curve was able to also predict a recession even though not as strongly as the Stock-Watson index (Clay and Keeton, 2011). Estrella and Gikas (1991) tested and found that the results were consistent with expectations in that, a flatter (steeper) slope of the yield curve implies slower (faster) future growth in real output. Monetary policy gives out the simplest explanation behind the yield spreads, that is relatively high (low) spread reflects loose (tight) monetary policies (Hvozdenska, 2015). The expectations theory gives theoretical justification for the use of spread in this case. Thus, the yield curve is important in predicting economic activities as the spreads contain ‘expectation information’ (Clay and Keeton, 2011). Clay and Keeton (2011) and Hvozdenska (2015) explain that future inflation expectations and real interest rates reflected by the spread on the yield curve help with predicting economic activities. Therefore, the overall correlation between the yield curve and future economic activities flows though monetary policies but mostly looking at investors’ expectations on the movements within the policy (Cook, 2019:10).

When monetary policy tightens, the rise in short-term interest rates affects investor’s future expectations of real demand and their expectations of future inflation (Cook, 2019). Cook (2019) explains that it would be difficult to state for sure how the predictive power of the yield curve will anticipate future economic activity as also explained by Hu (1993) and Estrella and Mishkin (1996). Cook (2019) explains that there will need to be a blend of policies and different channels may have more weight at times. However, what is important to note is the robust empirical relationship that exists between the yield curve and economic activity.

Dueker (1997), Clay and Keeton (2011) and Keeton and Botha (2014) support the finding that that the yield curve has predictive abilities about future economic activity that could be useful for investors. Researchers such as Harvey (1989), Haubrich and Dombrosky (1996) however, suggest that the yield curve has lost its predictive ability and may not prove to be useful for investors.

Lockhart *et al.* (2022) argues that since the US dollar has a central position in the global financial system, the US yield curve acts as a barometer for investors' future expectations Lockhart *et al* (2022) argue that historical data demonstrates that investors who used the yield curve to position their portfolio produced superior performance as compared to those who had not. Cook (2019) notes that while there have not been much studies of the ability of the yield curve to give buy/sell signals the few that have been done found it to be successful in the USA, India and in Spain. Resnick and Shoesmith (2002) examined the predictive ability of the yield curve in the USA, Bhaduri and Saraogi (2010) did so for India and Fernandez-Perez *et al.* (2014) for Spain. All 3 studies found that using a probit model of the yield curve showed superior results that outperformed the normal buy-and-hold stock-only strategy.

Cook (2019) likewise used the yield curve to generate buy/sell signals for the JSE All Share Index (JSE ALSI) but was unsuccessful in her findings. The reason for the unsuccessful results, she suggested, was that the JSE ALSI has a very high weighting of shares of companies that do not rely on earnings from South Africa and therefore their earnings are not affected by the South African business cycle (Cook, 2019). Accordingly, the focus of this research will be to examine whether changes in the yield gap in South Africa can be used to generate buy/sell signals for the different sub-sector indices of the JSE. The expectation is that while the yield curve may not be able to generate buy/sell signals for the JSE ALSI, it may be able to do so for specific sub-sectors, some of which, unlike the ALSI, rely heavily on South African earnings e.g., the retail sectors. This expectation is supported by Mapanda (2019) who found that several of the JSE sub-indices were impacted by changes in South African GDP.

1.2 Goals of the Research

The main goal for this research paper is to assess whether the yield curve can be used to predict changes in the separate sectoral indices of the JSE.

Secondary goals are to:

- Use the yield curve to signal when investors should have moved into or out of the individual sectors of the JSE and out of/into cash earning interest over the period April 1996 to December 2021.
- Compare the results with a buy-and-hold strategy for each sector to test whether a market-timing strategy based upon the yield curve delivers superior investment returns.

1.3 Methods, Procedures, Techniques and Ethical consideration

Time series data was used for the period April 1996 to December 2021, a total period of 25 years. The data are monthly and were extracted from Thompson-Reuters Datastream. The data were analysed using EViews 12 software.

The main variables used were the sub-sector indices of the JSE, namely mining, retail, banking, construction, mobile/wireless telecommunication, and software and computer services. These sectors were also used by Mapanda (2019) to study their correlation to macroeconomic factors. The yield curve is represented by the difference between the 10-year government bond yield and the 91-dayTreasury Bill. This data was obtained from the SA Reserve Bank online database.

The method used follows that of Estrella and Mishkin (1998), Resnick and Shoesmith (2002) and Cook (2019) and involves three steps; the first being to identify bull and bear phases in the periods 1996 to 2021 for each of the JSE sub-indices. Resnick and Shoesmith (2002) define a bear market as six or more consecutive months of a general decline in the stock market while a bull phase is six or more consecutive months of a general rise in the stock markets. However, the six months appears to be too restrictive. Cook (219) found it identifies a relatively small number of bear markets for the JSE so, like Cook (2019), the definition is relaxed to four months of decline/rise.

The second step is to use a probit model initially found by Estrella and Mishkin (1998) and adapted by Resnick and Shoesmith (2002) to model the relationship between bear phases and the spread of the yield curve. In order to get an *ex ante* (prediction of a particular event in the future) probability, out-of-sample forecasting will be done by adding to the initial period, one extra month's data. According to Estrella and Mishkin (1998) this testing provides an accurate test of an indicator's real world forecasting ability.

The final step is to test for the market timing ability using the Hensriksson-Metron parametric test (Bhaduri and Saraogi, 2010 and Cook, 2019). This shows whether the probit model used in step two is capable of producing statistically significant market timing results for specific sectors. When the results are significant a market timing portfolio is simulated for individual sectors. Total monthly returns from the market timing sector-portfolio are compared to total monthly returns from a buy-and-hold strategy for the same sector. The returns from the equity portfolio are changes in the sectoral index. The Money market deposit rate is used as an alternative to the sector index in the market timing portfolio.

1.4 Thesis Plan

This study comprises the following chapters detailed below:

Chapter 1: Introduction. This chapter is the research proposal which gives a clear overall view of the paper, the background, the goal of the research, the data and type of methodology used.

Chapter 2: Literature Review. This chapter discusses the theoretical and empirical literature surrounding the research topic. From an empirical analysis perspective, research findings on previous studies done on the yield curve, its predictive nature, timing abilities and how the sectors relate to the yield based on research already done.

Chapter 3: Outlines the Research Methodology and Data. This chapter will discuss the research technique and methodology applied in the paper to get to the results.

Chapter 4: Empirical Results. This chapter discusses and synthesises the results and findings conducted in chapter.

Chapter 5: Summary, Conclusion and Recommendations. This chapter presents a summary of the study, as well as conclusions and recommendations based on the findings. Furthermore, and possible further areas to look at the in the future for research purposes.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter looks at the relevant literature focused around the topic of the yield curve (also known as the term structure of interest rates) and how it relates to the business cycle, economic activity and changes in the stock market. The relationship between these variables is of importance, as it may prove to be useful in guiding a market timing strategy for stock market investors. Thus, looking at the yield curve, its link to the business cycle, then the relationship between the business cycle and the stock market will allow an understanding of the possible relationship that lies between changes in the yield curve and the timing of investments in the stock market.

The sections to follow present the expected link between these variables. Section 2.2 discusses the literature that outlines timing in the stock market. Section 2.3 examines earnings and share prices and how they relate to the business cycle. Section 2.4 then relates the yield curve to the business cycle, focusing specifically on the yield curve's theoretical ability to predict economic recessions, as well as the expected relationship between changes in the yield curve and stock market performance. Lastly, Section 2.5 presents evidence of the yield curve's record internationally as an indicator of buy or sell signals in relation to the stock market.

2.2 Timing the stock market

Financial participants are always concerned about the best investment strategy that yields the best possible returns. Thus, having a dynamic investment strategy as the optimal investment strategy has proven to be more beneficial for an investor than a normal buy-and-hold strategy (Perold and Sharpe, 1995, Resnick and Shoesmith, 2002, Shiryaev *et al.*, 2008 and Bhaduri and Saraogi, 2010).

To achieve the best possible outcomes from their portfolios, portfolio managers look for the best possible investment strategies then measure how much risk they are willing to take for a level of reward. Bhaduri and Saraogi (2010) argue that the most popular strategy is the mean-variance optimization approach which is based on the expected return on an asset. They however explain that it is said to be limiting, in that the variance and covariance are both captured by time invariant sample averages. When using historic data to measure expected returns, variance and covariance as sample averages, the weights are usually held constant.

That is, this approach does not account for changes in economic conditions, thus managers who choose to apply this approach will have to portfolio rebalance to achieve fixed weights. With dynamic strategies, portfolio rebalancing is based on all available information and is said to offer superior risk and expected return trade-offs on portfolios (Siegel, 1999, Bansal *et al*., 2004 and Bhaduri and Saraogi, 2010).

For stock market researchers, improvement in returns on investment is achieved by successfully choosing the best possible stock and picking the right time to buy, sell or hold their chosen stocks (Ahmadi *et al*., 2018). Researchers have shown that factors affecting performance in the stock market create non-linear market fluctuations. Ahmadi *et al*. (2018) explains that the stock market, as a non-linear dynamic system, makes predicting the future path of prices rather challenging and not everyone can get it right. The non-static, noisy nature of stock prices presents difficulties for investors to accurately predict. This is because with many companies, specific as well as macro-economic factors - such as company policies, interest rates, animal spirits, political issues and general economic conditions - all have significant impact on overall stock price movement (Ahmadi *et al*., 2018 and Ortobelli, 2017). Two types of analysis are widely used to study possible determinants of stock prices. The first is fundamental analysis, which is a study of the industrial, financial and economic issues of a company, including looking into its management and other qualitative and quantitative factors that impact on its share price. The second is technical analysis, which looks at price trends of a stock and uses previous prices to predict what the future price may be.

Investors, such as portfolio managers, use the results of such analyses to take positions in the market and thus adjust their holding according to expected price performance. Investment decisions and market timing are also related to an investor's risk appetite.

2.3 The Yield curve and the business cycle

The yield curve has been a focus study for many researchers across the world because of its historically proven usefulness for predicting where the economy is heading. In particular, a negative yield curve has often predicted an economy moving into recession (Estrella and Mishkin, 1996 and Moolman, 2002). The yield on bonds is described by Adam and Merkel (2019) as the interest or amount earned on a security (bonds or debentures) within a specified period of time. In relation to bonds, it refers to the interest earned on a debt instrument, expressed on an annual basis as a percentage based on the security's current market or face value. An investor buying a bond will receive a certain amount of cash flow based on the yield at the time of purchase. Put differently, Cook (2019) explains the yield from a bond as the 'return' on investment of a security (bond) that an investor receives.

The relationship between the yields on bonds which hold different terms to maturity is defined at the yield curve, sometimes also referred to as the term 'structure of interest rates' (Hu, 1993 and Howells and Bain, 2008). Kumar *et al*., (2021:1) describe the yield curve as "the relationship between the yield rates and the different maturity terms of specific type of assets such as government bonds". The yield curve is crucial in the role it plays when it comes to pricing financial assets, when conducting monetary policies, portfolio allocation for holders and managers and when managing financial risk (Kumar *et al*., 2021). Estrella and Mishkin (1996 and 1998), Clay and Keeton (2011) and Kumar *et al*. (2021) and other researchers have found that the most important leading indicator property of the yield curve is that of changes in its slope, which they deemed most useful when looking to predict changes in the business cycle. Thus, the link between changes in the yield curve and changes in real economic activity is important, as it has potential value in forecasting future economic activity.

The shape of the yield curve indicates market participants' views at a point in time, with regards to future economic developments (Kumar *et al*., 2021). The shape of the yield curve may change over time. It may be steep at the long end, or flat at the short end, or vice versa. Estrella and Truben (2006) describe the lack of consistency of the shape of the yield curve as nothing but a practical issue. That is because as interest rates rise and fall, the yield curve will correspond by shifting up and down to take different slopes (Kumar *et al*., 2021).

The yield spread/term spread is used as a standardised measure to compare changes in the yield curve over time. Prasanna and Sowmya (2017) describe the yield spread as the difference between short-term and long-term rates, while Cook (2019:7) notes that the yield spread creates a "linear approximation of the non-linear yield curve creating room for possibly multiple yield spreads". The yield spread can be used to predict economic activities. Policy makers, financial users/planners and investors are mostly interested in examining and understanding the relationship between the yield spread and economic activities together with the ability of the yield curve to predict economic activities (Kumar *et al*., 2021). The yield spread consists of two main components which are helpful when forecasting; the expected interest rates and the expected inflation levels.

The yield curve in South Africa is constructed by comparing the yield of a 91-day Treasury Bill and 10-year Government Bond (Clay and Keeton, 2011, Khomo and Aziakpono, 2007 and

Mohapi, 2013). The yield curve can form 3 distinct shapes which give an idea of market participants' expectations of future interest rates and their views on economic activities. The curve can either have an upward slope, downward/inverted slope or flat (Khomo and Aziakpono, 2007, Krishna and Nag, 2022). When yields' long-term interest rates are above short-term interest rates, the yield curve shows an upward sloping/ 'steepening' curve and this is most common. Krishna and Nag (2022) explain that the steepening of the curve is an indication of stronger growth moving ahead, which Cook (2019), quoting Clay and Keeton (2011), explains that it is also an indication of high risk-premium required by investors. In a case where short-term interest rates are now higher that long-term rates, the shape of the yield curve is inverted, which is a signal for an economic downswing/downfall (Clay and Keeton, 2021 and Krishna and Nag, 2022). Thus, an upward sloping curve is believed to show strong economic prospects, while a flattening curve is believed to indicate a possible recession (Hu, 1993 and Krishna and Nag, 2022). Further, the period between an inverted curve and an upward sloping curve is the flat curve, often referred to as the transitional phase, where the curve may go in either direction and could be an indication of either the end or beginning of a recession (Clay and Keeton, 2011).

2.3.1 Yield curve Theories

According to Kumar *et al*, (2021) the shape of the curve is best explained by 3 theories: the expectations theory, segmented theory and the liquidity premium theory. Some researchers include a fourth theory which is the preferred habitat theory, but since it is closely linked to the liquidity premium theory, they are considered by researchers to be the same (Mohapi, 2013). These theories seek to explain the relationship between interest rates of bonds with different maturity terms and have been developed by researchers to explain the empirical observations/facts, which Mishkin (2001: 137) lists: "as the interest rate on bond of different maturities move together over time, yield curve will be upward-sloping when the long-term interest rates are above the short-term interest rates; downward-sloping when the long-term interest rates are below the short-term interest rates"; and lastly that "the yield curve is typically upward sloping" (Mishkin, 2001: 137) quoted in (Mohapi, 2013:23).

To link the theories to the empirical observations, the expectations theory explains the first and second observations. The segmented theory is able to explain only the third observation about the slope of the yield and the liquidity premium theory explains all three observations (Mohapi, 2013).

To explain briefly the theories separately:

2.3.1.1 The expectations theory

This is most commonly known out of all the theories, and states that interest rates on long-term bonds represent the expectation of what average short-term interest rates will be for the entire maturity period of the long-term rates (Moolman, 2002, Mohapi, 2013, and Cook, 2019). This means, for example, that if the market expects that the average of short-term rates over the next ten years will be 5%, then the expectations theory proposes that long-term interest rates with a maturity of ten years will also be 5%. So, whatever happens to average short-term rates, the expectation is that the same will happen to long-term rates of the same period. This means that long-term interest rates contain information about what the expected future average short-term rate will be. Therefore, a flat yield curve suggests that the yield spread between interest rates on long and short-term bonds is decreasing and there is little to no benefit in holding long-term bonds over short-term bonds.

The main assumptions of the expectations theory are that investors are indifferent about holding long or short-term securities (bonds), that they maximize profits, and that the two holdings are complete substitutes which "allows arbitrage in the market to ensure that the long rate is equal to the average of expected future short-term rates" (Cook, 2019:8).

In terms of the expectations theory, investors are indifferent towards the risks on interest rates of different maturities (Kamar *et al*., 2021). The expectations theory suggests an investor will be indifferent to investing in three consecutive one-year bonds (short-term bonds) or investing in a three-year bond as the returns at the end of the two options will yield the same return (Shelile, 2006).

The expectations theory is useful in explaining the shape of the yield curve. The shape of the yield curve is an indication of expected future short-term rates (and therefore of the future economic conditions that drive changes in short-term rates). According to O'Donnell (2020) and Howells and Bain (2008), even though investors can measure expected future rates based on the curve, there is however still doubt concerning the certainty of those implied forward rates.

If yields rise as the maturity of securities lengthens, there will be an upward-sloping yield curve, which is also called a positive yield curve. The positive yield curve means market participants expect that average future short-term rates will rise (Shelile, 2006 and Mohapi, 2013). The opposite occurs and the yield curve will be negative (downward sloping) when market participants expect that average future short-term rates will be below current short-term rates. When the yield curve is flat, the expectation theory states that, on average, short-term rates are not expected to change in the future (Howells and Bain, 2008:197)

Mishkin (2001) explains that even though the expectations theory can explain a lot on the behaviour of term-structure of interest rates, there is however a limitation, as the theory does not provide enough evidence as to why the yield curve usually slopes upward. This is where the market segmentation theory comes in.

2.3.1.2 The market segmentation theory

This theory states that the interest rate on bonds of different maturities is determined by the different supply and demand levels for bonds of different maturities (Mishkin, 2001). It maintains that, unlike the expectations theory, market participants have preferences for investments that are based on the nature (maturity) of their liabilities (Howells and Bain, 2005). The main assumption for this theory is that investors are mainly concerned about the terms to maturity of bonds and so the interest rates on securities of different maturities are independently determined in separate markets. Since investors are assumed to be risk-averse, they prefer investments with less risk, and they therefore rather go for short-term bonds. Thus, since long-term bonds are not as attractive to risk-averse investors, demand for such bonds will be lower, resulting in higher yields for longer maturities (Shelile, 2006).

This theory however fails to explain why interest rates of different maturities sometimes move together. Also, it fails to explain why the yield curve slopes upwards when short-term interest rates are low, but slopes downwards when short-term rates are high (Shelile, 2006).

2.3.1.3 The liquidity premium theory

This theory, just like the expectations theory, states that interest rates on long-term bonds are determined by the average rate on expected short-term bonds, and like the segmented theory, it also takes into account the supply and demand associated with bonds of different maturity.

The difference between this theory and the two stated above is that it assumes that bonds of different maturity terms are substitutes, but not perfect/close substitutes (Mishkin, 2001). Even though the theory assumes that the expected rate of return on a bond influences the return of another with a different maturity, it also allows investors to have preferences over different bonds. Because investors are risk-averse, they prefer short-term bonds, as they carry less risk.

Thus, for an investor to consider a longer-term bond, they must be offered a liquidity premium to encourage them to go long and accept additional risk. This then modifies the initial expectations theory, as a positive liquidity premium gets added which then produces an upward sloping yield curve as a representation of investors' preference for short-term bonds (Mohapi, 2013). The theory therefore cannot explain why the yield curve is sometimes negatively sloped.

2.3.1.4 The preferred habitat theory

According to Howells and Bain (1994), the preferred habitat theory is said to be closely linked to the liquidity premium. Preferred habitat theory takes a slightly different approach in modifying the expectations theory but still arrives at the same conclusion as the liquidity premium.

The theory states that both investors and borrowers have a preferred range over the length of time the bonds they acquire mature. They will only break out of this set range if there is a higher yield to maturity to substitute towards. Since an investor can prefer a bond of a certain maturity from that of a different maturity, these bonds will not be classified as perfect substitutes and the expected return might differ (Mishkin, 1990). Where an investor prefers to hold short-term bonds, the term premium would increase as the maturity for long-term bonds increases (Mishkin, 1990). This helps to explain the upward slope of the yield curve.

2.3.2. The yield spread and changes in economic activity – the business cycle

The relationship between the yield curve and the business cycle has been extensively examined in the literature (Bonser-Neal and Morley, 1997, Hamilton and Kim, 2000, Clay and Keeton, 2011, Cook, 2019).

According to Moneta (2003:10), quoted in Mohapi (2013:40), the expected relationship between the yield curve and changes in economic activity is explained in two ways: "The first argument stems from the effects of the monetary policy stance on the yield curve, while the second argument explains the hedging behaviour of consumers". Monetary policy is important in this case as it helps explain the empirical relationship that exists between the yield spread and future economic activity through investors' expectations. An expected tightening of monetary policy caused by an expected rise in inflation may result in either a flattened or inverted yield curve. This is because long-term interest rates are not strongly affected by monetary policy in the short-run, as they tend to reflect future long-term interest rate expectations. So tighter monetary policy will cause long-term interest rates to rise less than the rise in short-term rates (Haubrich and Dombrosky, 1996, Bonser-Neal and Morley, 1997, Hamilton and Kim, 2000, Cook, 2019). The rise in interest rates will result in a narrower yield spread, which might even turn negative. At the same time, a rise in interest rates means that the cost of borrowing is higher, thus spending on interest rate sensitive sectors like commercial banks will be reduced, and economic growth will slow as a result. Hence, a negative yield spread is associated with expectations of slow real economic growth in the future. An expected slowdown in economic activities due to the fall in demand for credit may also result in lower levels of expected future inflation, thus reducing the pressure on future monetary policy decisions. If short-term rates are expected to decline in the future, long-term rates tend to fall. With current short-term rates having risen to combat inflation, this too results in a flat or negative yield curve (Cook, 2019).

In sum, according to the expectation's theory, if the yield curve has flattened, market participants expect a fall in future inflation as a result of current contractionary monetary policy (Moolman, 2002). Market participants expect that the current contraction in monetary policy will result in an economic recession and short-term rates will fall in the future (Moolman, 2002). As market participants' expectations of the future occurrence of a recession grow, an inverted yield curve is induced. However, if monetary policy attempts to increase economic growth through a decrease in short-term interest rates, market participants would expect a rise in future inflation levels and in short-term rates, resulting in an increase of long-term rates above short-term rates and a positive yield curve. Thus, the relationship between the yield curve and economic activity appears to be positive (Mohapi, 2013).

A second explanation of the link between the yield curve and economic activity lies in the hedging behaviour of consumers. According to Khomo and Aziakpono (2007) this explanation has been ignored in many studies which focused mainly on the expectations theory. Khomo and Aziakpono (2007) note that expectations theory does not, however, provide a detailed explanation for why long-term interest rate might exceed short-term rates. This is what the 'hedging behaviour of consumers' seeks to explain. At the same time, it identifies a link between the yield curve and economic activity.

According to Khomo and Aziakpono (2007), this explanation is based on the assumption that consumers will always aim to maximise their objective functions. Moneta (2003) identifies that consumers prefer to smooth their consumption patterns across the business cycle. That is, instead of receiving high levels of income in an expansionary phase, and low levels during a slowdown, consumers prefer to smooth their levels of income across cycles. Applying a simple model where the only financial instrument available for investors is a default free bond, if market participants anticipate an economic recession then, in order to try and smooth their consumption, they will move their investments to financial instruments that have future payoffs big enough to compensate for any loss in their income levels during an economic slowdown (Moneta, 2003 and Mohapi, 2013). As investors acquire long-term bonds to achieve this objective, demand for long-term bonds will rise, prices rise due to the increase in demand, and the corresponding yield decreases. For investors to finance purchases of these long-term bonds, Khomo and Aziakpono (2007) and Moneta (2003) suggest that they would have to sell their short-term bonds, thereby increasing the supply of short-term bonds, making prices fall and the corresponding yield increase. Thus, "the increasing yields on short-term securities and the declining yields on long-term securities drive the short-term interest rates to increase above the long-term interest rates, and thus inducing an inverted yield curve" (Mohapi, 2013:44). The inverted yield curve therefore reflects consumers'/investors' expectations of economic recession.

This, together with the expectations theory and the hedging behaviour of consumers, explains the relationship between changes in the yield spread and economic activity. Researchers have used this relationship to test whether the yield curve does indeed predict future recessions. Cook (2019) states that in the USA and SA, the literature demonstrates that yield curve inversion has preceded the majority of all recessions. However, in 1998 the US yield curve predicted a possible recession which did not occur, which brought about some scrutiny and criticism as researchers began to question the yield curves continued forecasting abilities. Likewise, in 2002, SA yield curve inversion was not followed by recession. Due do these false signals, some researchers questioned the yield curve's ability to predict future recessions. However, since the data in favour of the yield curve's ability to predict recessions historically is well supported and has great weight, many researchers still believe it to be relevant (Estrella and Mishkin, 1996, Haubrich and Dombrosky, 1996, Bonser-Neal and Morley, 1997, Estrella and Truben, 2006, Clay and Keeton, 2011).

The recent 2019 inversion of the US yield curve was followed by a recession that few forecasters had predicted. This inversion helped restore the strong track record of the yield curve to be able to predict recessions (Bruce-Lockhart *et al.*, 2022). However, in SA the economy has been in a downturn phase of the business cycle since December 2013. The yield curve has remained strongly positive throughout, creating some doubt about its ability to forecast future recessions (Cook, 2019).

2.4 Economic activity, the stock market and the yield curve

While sub-section 2.3.2 explains the relationship that exists between real economic activity and the yield curve, this section examines the link between real economic activity and the stock market. The relationship between economic activity and the stock market is crucial for purposes of this paper as it will allow the use of the yield spread to predict changes in the stock market and its sub-indices. The literature supports the existence of a robust and persistent link between these two factors.

2.4.1 Economic activity and stock market

Multiple researchers have examined the relationship between the stock market and economic activity (Carlsson and Holm, 2021 and Tiwari *et al*., 2015). The prices of stocks will always fluctuate over time (Tiwari *et al*., 2015). The movement in stock prices is influenced by a number of factors including, financial performance, interest rates, fiscal/monetary policies, and changes in sales linked to changes in domestic economic activity. Stock prices usually follow the financial performance of a company. That is, if a company's overall performance is good then the stock price usually rises (Prihatni, 2020 and Zhang and Gimeno, 2016). Consequently, there are other macroeconomic variables that are important to consider, such as Gross Domestic Product (GDP), as such variables affect company earnings which in turn affect current stock prices (Carlsson and Holm, 2021).

The price of a share is defined 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" (Cook, 2019:20). Estrella and Mishkin (1996) explain that since share prices are determined by expected future dividends, the dividend expected also depends on the company's expected earnings while those earnings are dependent on the state of the economy.

It is from this relationship (price determined by the present value of future expected cash flows) that the stock market is itself sometimes considered a potential indicator of future economic activity. However, Harvey (1989) and Fink *et al*., (2003) found that the bond market yield curve is a more accurate predictor of future economic activity. This finding is supported by Bernanke (1990), Estrella and Hardouvelis (1991) and Hu (1993) who showed that changes in the slope of the yield curve contain information about the future outcome of real economic performance.

Thus, this paper focuses not on the predictive nature of the stock market, but rather on the relationship between stock market and economic activity. This is important for the purposes of this paper as the robust link between the stock market sector indices and economic activity is necessary to be able to use the yield spread to pick entry and exit points in the stock market. Such a link is supported by research into the relationship between the yield curve and the stock market in a number of countries examined in the next section.

2. 5 The relationship between the yield curve and the stock market.

Section 2.4 explained that the stock market has a robust relationship with real economic activities, while section 2.3 explained the relationship between changes in the yield curve and domestic economic activity. This section will examine evidence of the relationship between the yield curve and the stock market.

Researchers such as Harvey (1989), Resnick and Shoesmith (2002) and Clay and Keeton (2011) have all highlighted the relationship between economic activity, the yield curve and the stock market. Four main studies have looked directly at the relationship between the yield curve and stock market returns in the United States, India, Spain and South Africa.

Resnick and Shoesmith (2002) adapted a probit model based on Siegel's (1999) study and showed that, if correctly applied, a market timing strategy based on changes in the yield curve can yield higher annual returns for the US stock market than a stock only buy-and-hold strategy. That is, an investor can use the yield curve to time when to move out of equities/stocks and into Treasury bills before a peak in a business cycle is reached, and then switch again back to stocks before a trough (Resnick and Shoesmith, 200)2. The use the of value between composite long term 10-year+ U.S. Treasury bond yield and the 3-month Treasury bill yield to measure the yield spread was found to provide more information on the probability of a bear stock market. The period under focus was 1960–1999 and they used total monthly returns for the S&P 500, inclusive of dividends. They used an out-of-sample period of 01/1971 – 12/1999 with the strongest estimation results for forecasting a bear market being for one and two months ahead (Resnick and Shoesmith, 2002).

They found that using probability screens at 30, 40 and 50 percent was most useful and accurate. The probability screens are used as thresholds which help investors decide when to switch between equities to Treasury bills and when to go back to equities. The results found that using the probit model timing strategy, "all probability screens 20, 30, 50 and 60 percent were able to outperform the annual compound returns of 14.17 percent of a stock-only buy-and-hold strategy for the specified period" (Resnick and Shoesmith, 2002 quoted in Cook, 2019). Specifically, using the 50 percent screen over the S&P 500, the strategy yielded an extra 2.29 percentage point's annual return.

Thus, Resnick and Shoesmith (2002), under the assumption that there are no costs involved when switching between funds that belong to the same holding, found that using the yield spread to determine buy/sell decisions was successful in the US. They were able to predict stock market turning points looking one month ahead and using this strategy to create a dynamic portfolio was able to outperform a stock-only buy-and-hold strategy. The probit market timing strategy developed therefore managed to produce higher excess returns while maintaining low levels of total and systematic risk.

Bhaduri and Saraogi (2010) followed Resnick and Shoesmith's (2002) study and focused on the Indian stock market using monthly data for the Bombay Stock Exchange Sensitive Index and a yield spread based on the difference between 10-year Government of India (GOI) yield to maturity (YTM) and the 90-day GOI YTM for the period 1991 to 2009. They used the 15-day GOI security and the i-Sec's Sovereign Bond index as their proxy for returns for holding government bonds in their portfolio.

Bhaduri and Saraogi (2010) found that using three filtering techniques to identify bear phases in the market would ensure that the results are robust. They found that, using a probit market timing strategy with the same probability screens as those in Resnick and Shoesmith (2002), the yield spread was able to predict stock market turning points one month ahead. Consistent with Resnick and Shoesmith (2002), a probit-based market timing strategy outperformed a stock-only buy-and-hold strategy. However, instead of the 50 percent probability screen which Resnick and Shoesmith (2002) found most successful, they found that a 60 percent probability screen yielded the highest returns. Thus, the yield-curve proved to be a successful predictor for stock market turning points for India also, able to provide higher returns than a normal stock-only buy-and-hold strategy (Bhaduri and Saraogi, 2010).

Fernandez-Perez *et al.* (2014) conducted a similar study for the stock market in Spain. However, they used a Generic Algorithm by means of Schwarz Information Criteria (GASIC) to identify the most appropriate probit model. Their research was broader as it also included a number of exogenous variables for assessing 19 different probit models. Some of the 19 variables used included macroeconomic variables such as the consumer price index and unemployment as well as the yield spreads for Spain's trading partners such as Europe, and the USA. Consistent with Resnick and Shoesmith (2002) and Bhaduri and Saraogi (2010), Fernandez-Perez *et al.* (2014) also found that for IBEX 35 which is the official index of the Spanish Continuous Exchange, the local yield curve was the best predictor for bear markets.

Even though they run a number of models, only the two models with yield spreads as exogenous variables were able to outperform a stock-only buy-and-hold strategy for all probability screens. One model that had the slopes of the local (Spain) yield curve and those of the USA and Europe managed to achieve the highest mean return of 17.02 percent at 40 percent probability, which was 8.9 percent higher than the market portfolio. The highest return of all was a model with just the local yield curve slope and that of Europe which achieved an 18.16 percent mean return (9.9% outperformance) at the 40 percent probability screen. These results therefore supported those of Resnick and Shoesmith (2002) and Bhaduri and Saraogi (2010) that the yield curve can be used to guide a buy-and-sell strategy that outperforms a buy-and-hold strategy.

Cook (2019) conducted a similar study for South Africa using the JSE ALSI and SA's yield spread between 91-days Treasury bill and the 10-year government bond for the period 1994 – 2018. Cook's (2019) probit models used bear markets of both six-months and four-months for just the SA yield spread, and six-months for both the SA and the US yield spread, making it three models in total. Cook (2019) was however unsuccessful in her findings as the results did not track the bear markets in SA well. Cook (2019) went on to test for the market timing ability using the HM model, using SA's yield spread, and found that there was no market timing ability present in the models.

Cook (2019) explains the difference between her findings for South Africa and those for the US, India and Spain by suggesting this could be the result of a large proportion of the market capitalisation of the JSE ALSI being made up by very large companies whose earnings are largely from outside of South Africa. Thus, their earnings are not impacted by changes in South African domestic economic activity. As a result, this study will look at the JSE sectoral indices, as it is expected that some of these will comprise largely of companies whose earnings are mainly in South Africa. The expectation is that these sectoral indices will be able better to respond to a predictive model based upon the South African yield curve.

2.6 Conclusion

This chapter has demonstrated the theoretical and empirical relationship between the yield curve and changes in domestic economic activity. The literature provides evidence of the yield curve as the predictor of recessions. This is found to hold in most empirical research including recent studies in the US. Theory and literature also suggests a positive relationship between changes in domestic economic activity with changes in stock market valuations because of the positive impact on sales and revenue. Studies in the US, India and Spain combined these theoretical and empirically-evident relationships and found that the yield curve can also be used to predict turning points in the stock market. Buy/sell signals generated by the yield curve would increase investor returns above those achieved through a buy/hold investment strategy in all three markets. However, Cook (2019) found the yield curve did not generate reliable buy/hold signals for the JSE ALSI. She suggests this might be because a large weighting of the JSE ALSI is made up by stocks whose principal earnings are not in South Africa. But the earnings of stocks that make up some of the sub-sector indices of the JSE are mainly generated in South Africa. Hence, theory and the literature suggest it is worth investigating whether changes in the SA yield gap can generate buy/sell indices for such sub-indices. If the yield curve can similarly predict changes in the sub-indices of the JSE, this will allow portfolio managers to outperform a simple buy-and-hold investment strategy by applying a market timing strategy based on the yield curve to their sectoral portfolios.

CHAPTER 3: RESEARCH METHODOLOGY AND DATA

3.1 Introduction

This chapter presents the methodology and data used in this thesis. It highlights the method and techniques followed to examine whether the yield spread can be used in South Africa as a predictor for a buy-sell strategy for portfolio managers for each of the major JSE sectoral indices. It explains the research paradigm, research design, the description of data and variables used, the estimation of the timing of bear markets for each sector and the technique used to model these against the yield spread to calculate the returns of a buy-sell strategy based upon these results.

3.2 Research Paradigm

A research paradigm is described in Kivunja and Kuyini (2017) as a philosophical way of thinking, a conceptual framework that a research project is based on. It gives an overview of the research project's values, beliefs, assumptions, and understandings on which the project's practices and theories operate. Lincoln and Guba (1985) (quoted in Kivunja and Kuyini (2017) categorise paradigms to be defined by four elements which are, methodology, epistemology, axiology, and ontology. According to Hatch (2002) the epistemology and ontology elements comprise research philosophy, while a combination of research philosophy and methodology comprises a full research paradigm.

Kivunja and Kuyini (2017) explain the three underlying philosophical assumptions, namely, critical theory paradigm, interpretivism/constructivist paradigm and positivism paradigm. It is important to have understanding and knowledge of these elements as they consist of the basic assumptions, pattern, and values that the paradigm hold. The research being undertaken will be understood to be guided and upheld by the assumptions and values that apply for that paradigm (Rubin and Babbie, 2010). Thus, a good research project should have followed and adhered to those specified by the paradigm.

As with the major studies on the yield curve related to this thesis, this research will follow a post-positivist paradigm. The post-positivist paradigm is based on data collection, controlled experiments and statistics and interpretation thereof in an objective manner (Panhwar *et al.*, 2017). The thesis will analyse data and interpret the results.

It is based upon previous research studies that give creditable foundation for the research. The main foundation was laid in chapter 2, where it was shown that previous research by Resnick and Shoesmith (2002), Bhaduri and Saraogi (2010) and Fernandez-Perez *et al.* (2014) found that the yield curve is a powerful and useful predictor of bear markets for the stock exchange in the US, India and Spain and therefore of buy/sell signals that allow an investor to outperform market returns using a dynamic market timing strategy rather than a buy-and-hold investment strategy.

3.3 Research question

The main goal of the research is to assess whether the yield curve for South Africa can be used to predict changes in the separate sectoral indices of the JSE.

Secondary goals are:

- Use the yield curve to signal when investors should have moved into or out of the individual sectors of the JSE and out of/into interest earning assets (Deposit jnterest rate) over the period April 1996 to May 2022.
- Compare the results with a buy-and-hold strategy for each sector to test whether a market-timing strategy based upon the yield curve delivers superior investment returns.

3.4 Research Design

This section looks at the theoretical framework, model specification, the description of variables and *a priori* expectations, and finally the method and estimation techniques.

3.4.1 Model Specification and Theoretical Framework

As in Resnick and Shoesmith (2002), Bhaduri and Saraogi (2010) and Cook (2019), a probit model is used to illustrate and model the relationship between bear phases for each of the JSE sub-sectoral indices and the yield spread.

Monthly time series data is used to test the market timing ability from the yield spread. The observations are for South Africa from April 1996 (the earliest date for which the sub-sector indices are available) to May 2022. As in previous literature, the yield curve is used to predict sectoral bear markets 1 month-before. If, as previous literature suggests, the yield curve provides an investor with information on predicting bear markets, the results are used to measure whether investors can use these predictions to adjust their portfolio holdings through a buy-sell strategy so as to outperform a buy-hold strategy.

3.4.1.1 Data and Data Sources

The time series data consist of the 8 JSE sectoral indices, namely, the FTSE/JSE Basic Materials index, FTSE/JSE Financial index, FTSE/JSE Health Care index, FTSE/JSE

Industrial index, FTSE/JSE Technology index, FTSE/JSE Telecommunication index, FTSE/JSE Consumer Discretionary index, and the FTSE/JSE Consumer Services index. Data for each index was collected from the IRESS Expert (2022) website. Data are the closing price for the month for each sector. As with previous studies Nel (1996), Aziakpono and Khomo (2007), Clay and Keeton (2011) and Cook (2019) the yield spread is represented by the difference between the South African 10-year-and-over Treasury Bond, and the 91-days Treasury Bill rates. Data for these two variables were extracted from the South African Reserve Bank online database and are available on a monthly basis.

The period under research is from August 1996 - as this is earliest date for which the FTSE/JSE sectoral indices were compiled - and ends in May 2022, thus a period of just less than 26 years. All the series are on a monthly basis.

3.4.1.2 Method and Estimation technique

The methodology closely follows that used by Bhaduri and Saraogi (2010) and later by Cook (2019). It involves three steps. These are:

- Identify the bear markets for each of the sectoral indices of the JSE.
- Use a probit model for each index to model the relationship between the found bear markets and the yield spread for out-of-sample, in-sample and full sample periods.
- Test for statistical significance of market timing ability using the Hendrikkson-Merton parametric model test.

The results indicate which sectoral indices present market timing opportunities. The results are then be used to calculate the returns of a buy-sell strategy, which are then compared to returns for each sectoral index of a buy-hold strategy.

3.4.1.3 How bear phases are identified

A bear phase is defined for this research as a general decline in a sectoral index of 4 or more consecutive months. As the stock market is known to be volatile, a bear phase may include a positive month (stock market uptick). Provided the uptick does not cancel out previous declines, then this is still counted as a full bear phase including the uptick within it. Where the positive month exceeds the previous peak, it is accounted for as breaking the bear phase and considered to be a new peak. Bear phases for each sectoral index were manually calculated.

The decision to use 4 consecutive months to define a bear market instead of the 6 months used by Resnick and Shoesmith (2002) and Bhaduri and Saraogi (2010) follows the finding by Cook (2019) that there were very few downturns lasting 6 months for the FTSE/JSE ALSI. The shorter period is also justified given the relatively shorter period for which FTSE/JSE sectoral indices are available.

3.4.1.4 Out-of-sample, In-sample and full-sample analysis

A probit model is used to model the relationship between the bear markets for each sectoral index and the yield spread for out-of-sample, in-sample and full sample periods. The yield spread is used as the independent variable to get the beta values of each sample.

The period from August 1996 to April 2022 is used to model for the full sample. In-sample is for the period 1996 to 2000 and out-of-sample forecasts are for the period 2001-2022.

3.4.1.5 The Probit Model

Probit models make use of cumulative Gaussian normal distribution and are commonly used in predicting recessions as they give the probability of an event that will or will not occur. A probit equation formerly developed by Estrella and Mishkin (1995) is useful in that it restricts variables in the model being predicted to just two possible values. Estrella and Mishkin (1996) first adopted the model to specifically forecast recessions, then other scholars and researchers such as Resnick and Shoesmith (2002) and Bhaduri and Saraogi (2010) adopted it to identify and forecast one month before stock market bear phases.

The initial probit model is:

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

For better understanding, it is presented as:

$$P(dummy_{t+1}) = F\ (\alpha_0 + \alpha_1 spread_t) \qquad (2)$$

where, P = the probability of a bear stock market one month before, (dummy_{t-1}) = 1 is the dummy variable that states a condition for 1 if the stock market in month t-1 is found to be a bear phase, so JSE index numbers 1 for bear phases and 0 for non-bear phases. For $F\ (\alpha_0 + \alpha_1 spread_t)$, F is a standard normal cumulative distribution function of: α_0 is the intercept, α_1 = the coefficient of the yield spread variable; and spread_t = yield spread at month t (month time) (Cook, 2019). This function is used to ensure that the probability of an event (for JSE index numbers 1 for bear phases and 0 for non-bear phases) will lie strictly between 0 and 1.

The probit model will be run for one month ahead as Cook (2019) found that three months ahead resulted in weaker results than those of a one month ahead model.

3.4.1.6 Market Timing Model: Henriksson-Merton (H-M) parametric model test

As with Cook (2019) the Henriksson-Merton (H-M) parametric model test is used to test for significant market timing effects. The H-M test is used to test whether the market timing abilities of the probit models are statistically significant.

The H-M test is run using the excess returns on the market timing portfolio over and above those of risk-free returns. These excess returns are regressed on the bear market and bull market risk premium (Bhaduri and Saraogi, 2010 and Cook, 2019). The model presents bull (up-market) and bear (down-market) models used to evaluate portfolio managers' market timing ability. This is done through having betas of a portfolio cast as the binary variables. A binary variable is one that can take only one of two values; thus, the portfolio betas will only take one value for a bullish market phase and another during a bear market phase. Deb (2007) explains successful fund managers will normally select a high up-market beta and a low down-market beta. The betas are confined to just two values as follows:

$$R_{pt} = a_p + b_{pd}\, R_{mt} + u_{pt} \text{ for all t such that } R_{mt} \leq 0 \qquad (3)$$

$$R_{pt} = a_p + b_{pu}\, R_{mt} + u_{pt} \text{ for all t such that } R_{mt} > 0 \qquad (4)$$

To form a dummy variable regression, equations 3 and 4 are combined to look as follows:

$$R_{pt} = a_p + b_{pd}\, R_{mt} + b_{p+\text{U}}\, R_{mt} D_t + u_{pt} \qquad (5)$$

Where,

R_{pt} = return on market timing portfolio in month t,

R_{mt} = return on the market portfolio,

D_t = dummy variable

Set to equal one if R_{mt} is greater than zero otherwise set equal to zero

U_{pt} = the zero-mean white noise process

b_{pu} = bull market's systematic risk

b_{pd} = bear market systematic risk

The important variable when testing for market timing in this case is the slope coefficient $b_{po.}$ This is because the slope is the difference between a bull market beta and a bear market beta for a market timing portfolio ($b_{pu} - b_{pd}$) (Cook, 2019:21 and Deb, 2007). To quantify the probit model as successful the slope coefficient b_{po} must be (i) > 0; and (ii) be statistically significant. Then the conclusion will be that there are significant timing market results, and the probit model can successfully forecast bear markets one month ahead.

3.5 Description of Explanatory Variables and *a priori* Expectations

The dependent variables consist of 8 sectoral stock market indices of the JSE and are the same as those used in Mapanda (2019). They are extracted as monthly closing prices for each of the stock market indices. The change in the closing prices is used as a measure of monthly index returns. The sectoral indices are as follows:

3.5.1 FTSE/JSE Basic Materials index

According to Industry Classification Benchmark (2022) this sectoral index is made up of the Mining and Industrial Metals, Mining, Basic Materials Index, Chemicals and Forestry and Paper.

3.5.2 FTSE/JSE Financial index

According to the Industry Classification Benchmark (2022) this index consists of Insurance, Banks, Financial and Real Estate.

3.5.3 FTSE/JSE Health Care index

According to the Industry Classification Benchmark (2022) this index consists of sub sectors such as the Pharmaceuticals and Biotechnology and the Health Care Equipment and Services.

3.5.4 FTSE/JSE Industrial index

According to the Industry Classification Benchmark (2022) this index is made up of sub sectors such as Electronic and Electrical Equipment, Aerospace and Defence, Industrial Transportation, Industrial Engineering, Construction & Materials and Support Services indices.

3.5.5 FTSE/JSE Technology index

According to the Industry Classification Benchmark (2022) this index consists of sub sectors such as Software & Computer Services and the Technology Hardware & Equipment indices.

3.5.6 FTSE/JSE Telecommunication index

According to the Industry Classification Benchmark (2022) this index is made up of the Fixed-line Telecom Services and Mobile/wireless Telecommunication sub sectors.

3.5.7 FTSE/JSE Consumer Discretionary

According to the Industry Classification Benchmark (2022) this index is made up of durable goods, high-end apparel, entertainment, leisure activities and automobiles.

3.5.8 FTSE/JSE Consumer Services index

According to the Industry Classification Benchmark (2022) this index is made up of General Retailers, Food and Drug Retailers and Media and Travel and Leisure.

3.5.9 The Yield Spread

The yield spread represents the spread between short-term and long-term yields to maturity (Bhaduri and Saraogi, 2010) and is defined here as the difference between the SARB's 10-year-and-longer government bond index and the 91-days Treasury Bill.

As with Resnick and Shoesmith (2002) the 91-day Treasury Bill yield represent the returns a portfolio manager makes when moving between the stock and bond market in a market-timing portfolio.

3.5.10 *A priori* Expectations

As Resnick and Shoesmith (2002) and later in a similar study Liu and Shoesmith (2004), found that high probability levels were associated with a negative yield spread. It is then expected that when the yield spread is negative or inverted and sometimes narrowing, the probability of a bear market will be high. Thus, the coefficient of yield spread, α_1, is expected to be negative this will hold regardless of whether the spread is negative or positive as Resnick and Shoesmith (2002) explained even a small positive yield spread can be associate with an approaching bear market.

3.6 Identification of sectoral bear markets

The first step was to identify the market trend for each of the sectoral indices, that is calculate monthly market increases and decreases. Microsoft Excel was used to calculate the percentage change/difference between P_t and P_{t-1}, where $Pt < Pt-1$ is a decrease in the index. This allowed the manual identification of periods where there are 4 or more consecutive negative months, fulfilling the first definition of a bear market. To fulfil the second definition, the data was manually checked for negative trends that contain monthly upticks, but where the positive spike does not exceed the previous peak.

This exercise was computed for all 8 indices for the period August 1996 to May 2022. Table 1 shows the bear phases for each index, the dates when each bear phase started and ended, how long it lasted, the percentage change for the bear market's lowest point compared with the previous peak, and which of these bear phases included positive monthly spikes within them.

The results in Table 1, show that whereas Cook (2019) identified only 10 bear markets of 4 months consecutive decline for the JSE ALSI over the period 1994-2018, the number of bear markets for the sectoral indices range from 9 for the Raw Materials index to 14 for the Technology index. The longest bear markets lasted 8 Months – for the Health Care index and Consumer Discretionary index, both for the period November 2007 to June 2008 (during the Global Financial Crisis). The steepest fall was for the Telecommunications index, which fell -58.19% from May to September 1998.

Table 1: Identified Bear phases for each of the JSE sectoral indices

Sectoral index	Bear phase	Period			Peak	Trough	% change
		Start	End	Length - Months			
	1	1997/08/31	1998/01/31	6	5487.74	3132.04	-43.00
Basic Materials	2**	1998/05/31	1998/08/31	4	4141.36	2784.16	-32.77
	3**	1998/11/30	1999/02/28	4	3406.06	2894.9	-16.41
	4	2008/07/31	2008/10/31	4	40596.07	19816.94	-51.00
	5	2011/05/31	2011/09/30	5	31694.01	26405.78	-17.00
	6**	2012/02/29	2012/08/31	7	30350.85	25013.06	-17.59
	7	2014/08/31	2014/12/31	5	31357.78	22879.11	-27.00
	8	2015/05/31	2015/09/30	5	24937.44	19012.94	-24.00
	9**	2021/03/31	2021/09/30	7	48602.74	41697.7	-15.70
Financials	1**	1998/04/30	1998/08/31	5	12748.59	6718.12	-47.30
	2	2002/12/31	2003/03/31	4	8913.91	7086.58	-20.00
	3**	2008/03/31	2008/06/30	4	21116.73	16402.43	-22.32
	4	2015/11/30	2016/02/29	4	45463.35	38980.8	-14.00
	5**	2020/01/31	2020/05/31	5	39353.62	24914.12	-37.00
Health Care	1	1997/08/31	1997/12/31	5	660.84	523.09	-20.85
	2	1998/05/31	1998/09/30	5	684.21	367.18	-46.34
	3**	2000/01/31	2000/05/31	5	576.66	440.29	-23.65
	4	2002/09/30	2003/03/31	7	717.05	535.47	-25.32
	5**	2007/06/30	2007/09/30	4	2250.73	1856.28	-17.53
	6**	2007/11/30	2008/06/30	8	2031.72	1411.2	-30.54
	7	2015/03/31	2015/06/30	4	11187.23	9764.95	-12.71
	8	2015/11/30	2016/02/29	4	9710.47	8692.71	-10.48
	9	2016/08/31	2016/11/30	4	10085.6	7936.38	-21.31
	10	2017/11/30	2018/02/28	4	7640.8	6982.41	-8.62
	11	2018/09/30	2018/12/31	4	7368	4885.37	-33.70
	12**	2019/03/31	2019/08/31	6	4940.48	3620.14	-26.72
	13	2020/06/30	2020/10/31	5	3951.92	3385.98	-14.32
Industrials	1	1997/08/31	1997/12/31	5	6702.77	4923.93	-26.54
	2	1998/05/31	1998/08/31	4	6214.2	3371.13	-45.75
	3	2000/01/31	2000/04/30	4	6169.07	5622.05	-8.87
	4	2002/12/31	2003/03/31	4	7861.27	6604.64	-15.99
	5**	2008/09/30	2009/02/28	6	26053.33	17767.4	-31.80
	6	2011/06/30	2011/09/30	4	28205.33	26541.08	-5.90
	7	2015/05/31	2015/09/30	5	46687.26	42864.28	-8.19
	8	2016/08/31	2016/11/30	4	47990.86	45464.53	-5.26
	9	2019/05/31	2019/08/31	4	44841.29	37907.21	-15.46
	10**	2019/11/30	2020/03/31	5	40710.92	24255.6	-40.42
Technology	1	1997/08/31	1997/11/30	4	26078.34	24470.85	-6.00
	2**	1999/04/30	1999/09/30	6	42542.03	31997.56	-24.79
	3	2000/09/30	2000/12/31	4	51613.5	37008.75	-28.00
	4	2001/06/30	2001/09/30	4	27742.9	9893.84	-64.00
	5	2002/05/31	2002/09/30	5	9950.89	3999.44	-60.00
	6	2002/12/31	2003/03/31	4	4961.93	3355.39	-32.00
	7**	2004/02/29	2004/07/31	6	8164.94	5828.52	-28.62
	8	2010/08/31	2010/11/30	4	21563.45	19707.05	-9.00
	9	2015/08/31	2016/01/31	6	67271	48418.27	-28.00
	10**	2017/05/31	2017/09/30	5	57191.89	45466.83	-20.50
	11	2017/11/30	2018/05/31	7	48436.71	25827.22	-47.00

	12	2019/08/31	2019/11/30	4	31645.7	27787.26	-12.00
	13	2021/03/31	2021/09/30	7	46917.54	32135.01	-32.00
	14	2022/01/31	2022/04/30	4	33195.69	21038.36	-37.00
Telecommunication	1**	1998/05/31	1998/09/30	5	1046.13	437.36	-58.19
	2	2000/05/31	2000/11/30	7	1675.77	1022.12	-39.01
	3**	2001/02/28	2001/07/31	6	1359.56	772.05	-43.21
	4	2002/06/30	2002/09/30	4	819.61	589.84	-28.03
	5	2008/08/31	2008/11/30	4	6154.82	5001.46	-18.74
	6	2013/01/31	2013/04/30	4	8540.95	7685.33	-10.02
	7**	2015/05/31	2015/08/31	4	11741.43	8998.62	-23.36
	8	2016/07/31	2016/11/30	5	7882.42	6476.94	-17.83
	9	2019/11/30	2020/03/31	5	5401.15	3295.73	-38.98
Consumer Discretionary	1	1997/08/31	1997/12/31	5	1283.49	1106.09	-13.82
	2	1998/05/31	1998/09/30	5	1558.51	791.99	-49.18
	3	2000/01/31	2000/05/31	5	1323.74	973.65	-26.45
	4	2001/12/31	2002/03/31	4	767.91	632.06	-17.69
	5	2002/12/31	2003/03/31	4	829.76	727.34	-12.34
	6**	2007/11/30	2008/06/30	8	3604.72	2643.69	-26.66
	7	2016/09/30	2016/12/31	4	19318.57	16888.45	-12.58
	8	2017/12/31	2018/03/31	4	26196.89	22800.59	-12.96
	9**	2019/11/30	2020/05/31	7	22673.73	15463.94	-31.80
	10	2022/01/31	2022/04/30	4	33684.11	28021.16	-16.81
Consumer Services	1	1997/08/31	1997/12/31	5	1116.49	944.16	-15.43
	2	1998/05/31	1998/08/31	4	1285.88	623.69	-51.50
	3	2000/01/31	2000/05/31	5	1438.71	950.67	-33.92
	4	2000/09/30	2000/12/31	4	1084.91	640.2	-40.99
	5	2001/12/31	2002/03/31	4	663.27	517.24	-22.07
	6	2002/12/31	2003/03/31	4	756.31	668.23	-11.65
	7	2007/05/31	2007/09/30	5	3784.98	2960.49	-21.78
	8	2008/03/31	2008/06/30	4	2411.73	1910.8	-20.77
	9	2013/05/31	2013/08/31	4	6259.39	5816.03	-7.08
	10	2015/11/30	2016/02/29	4	8233.4	6895.03	-16.26
	11	2018/04/30	2018/07/31	4	8648.65	6926.66	-19.91
	12	2018/12/31	2019/03/31	4	7205.96	6061.59	-15.88
	13	2019/11/30	2020/03/31	5	5798.07	3088.02	-46.74

Source: Author's calculations

*Note: bear phases with uptick are presented with ** next to the bear phase number e.g., 2** for Basics Material index*

3.6 Conclusion

Chapter 3 laid out the data, methods, and techniques used in Chapter 4 to test whether the yield spread can forecast bear markets for each of the sub sectoral indices of the JSE. Tests for any significant market timing ability that may exist were explained. The data used is identified and identified bear market phases or each index shown in table format. The following chapter will present the results.

CHAPTER 4: PRESENTATION AND DISCUSSION OF RESULTS

4.1 Introduction

This chapter presents the results of the econometric analyses of the ability of the yield spread to forecast bear phases for each of the 8 JSE sectoral indices. First, it is important to analyse the data and understand its characteristics. The characteristics of the data are presented in section 4.2. Section 4.3 then presents and discusses the results of the probit models for each sectoral index. Section 4.4 presents and discusses the findings of the market timing tests based on the Henriksson-Merton parametric model. Section 4.5 concludes the chapter.

4. 2 Descriptive Statistics -stylised facts

The section covers the stylized facts of the data. The presentation starts by analyzing the measures of central tendencies and their distribution. This is followed by graphical depictions of the individual sectoral indices and the yield spread.

The sectoral descriptive statistics for the full sample period, August 1996 to May 2022, are presented in Table 2. The descriptive statistics include mean, median, standard deviation, kurtosis and the Jarque-Bera test for normality and are used to better understand the dataset used for the econometric modelling. Before doing the regressions on the data it is important to first understand the type and characteristics of the data used.

The mean and median explain the central tendency of the data. It is important to note that the mean values are more sensitive to unusual cases such as outliers than is the median. Thus one needs to be careful when using the mean as the representation for the average price over the years. The standard deviation (St. Dev.) represents average distance from the mean and the quantity of each data set e.g., 12159.87 for Basics Materials represents the spread of the data from the mean, that is, the index prices differ from the mean on an average of about 12159.87 index points. With Kurtosis, a distribution with less than 3.0 kurtosis is known as platykurtic. This means index prices with less than 3.0 kurtosis have low probability of having extreme events. A platykurtic distribution would normally suit a risk-averse investor as they will not experience extreme events in the market.

Table 2: Descriptive statistics

Variables	*Mean*	*Median*	*St. Dev.*	*Kurtosis*	*Jarque-Bera (JB)*	*Prob-Value*	*Sum. Sq. Dev*
Basics Materials	21441.49	23431.45	12159.87	2.882868	6.266201	0.043582	4.57e+10
Financials	2993.40	21096.50	12863.57	1.715505	28.62075	0.000001	5.11E+10
Health Care	3404.612	2232.770	3009.691	2.566553	41.62755	0.000000	2.79E+09
Industrials	25204.38	25758.10	15551.35	1.624442	24.72742	0.000004	7.45E+10
Telecommunication	4589.071	5089.680	3044.224	2.039430	14.23821	0.000809	2.85E+09
Technology	27965.27	27437.83	16264.53	2.019553	17.11446	0.000192	8.15E+10
Consumer Discretionary	8351.820	3563.170	8713.909	2.496794	48.21584	0.000000	2.34E+10
Consumer Services	3714.792	3077.990	2600.121	1.628200	30.14655	0.000000	2.08E+09
Yield Curve	1.835	1.965	2.024	3.690	6.434	0.04003	1045.177

Source: Author's computation from Eviews

The Technology, Industrial and Basics Material sub-indices had the highest mean values with means of 27965.27, 25204.38 and 21441.49 respectively. These three indices had the highest average compared to the other indices. The standard deviations are highest for the Financials, Health Care, Consumer Discretionary and Consumer Services sub-indices and so these are the most volatile of all the indices. The yield curve also has a high standard deviation. This means yield curve data is widely dispersed in relation to the mean, which reduces the likelihood of a significant relationship with indices that are more normally distributed.

With all the indices having a kurtosis less than 3 this means there is no leptokurtic behaviour. Basics Materials and the Health care sub-index have a kurtosis closest to 3 at 2.882868 and 2.566553 respectively, which means they are a mesokurtic distribution, resembling a normal distribution behaviour. All the other indices have kurtosis closer to 2 and would thus be the less risky with a platykurtosis behaviour. Lower riskiness reduces the possible benefits of a buy-hold investment strategy. The yield curve, however, has a kurtosis of more than 3 at 3.690 which means it has a leptokurtic behaviour and a peaked distribution. This greater riskiness compared with the indices suggests the predictive power of the yield curve may be reduced.

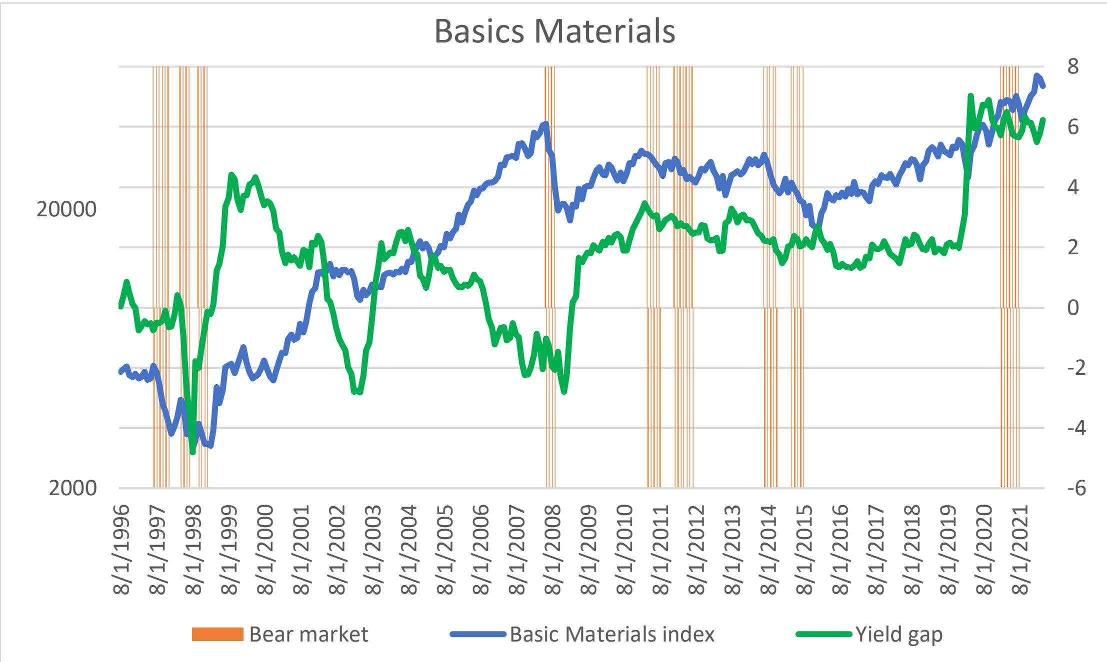
With the exception of Basic Materials (at 0.043583) and the yield curve (0.04003) all the p-values are significant at 1%. However, the high Jarque-Bera values suggest that none of the indices come from a normal distribution. For example, the Consumer Discretionary had a

Jarque-Bera test value of 48.21584 indicated significant departures from normality for the index.

4.3 Illustration of the relationship between the sub-sectoral indices and the yield spread

The relationships between the yield spread and the JSE sub-indices are shown graphically in this section. Theory suggests that the yield spread and sub-indices should move in the same direction i.e. a fall in the yield spread (indicative of a weakening economic outlook) should be accompanied by a weakening of the sub-index and a rise in the yield spread (a strengthening economic outlook) should be accompanied by a rising sub-index. Bear markets for the sub-index should occur at times of a falling and possibly negative yield curve. The sub-index is shown as a log scale to allow downturns and upturns to be more visually apparent.

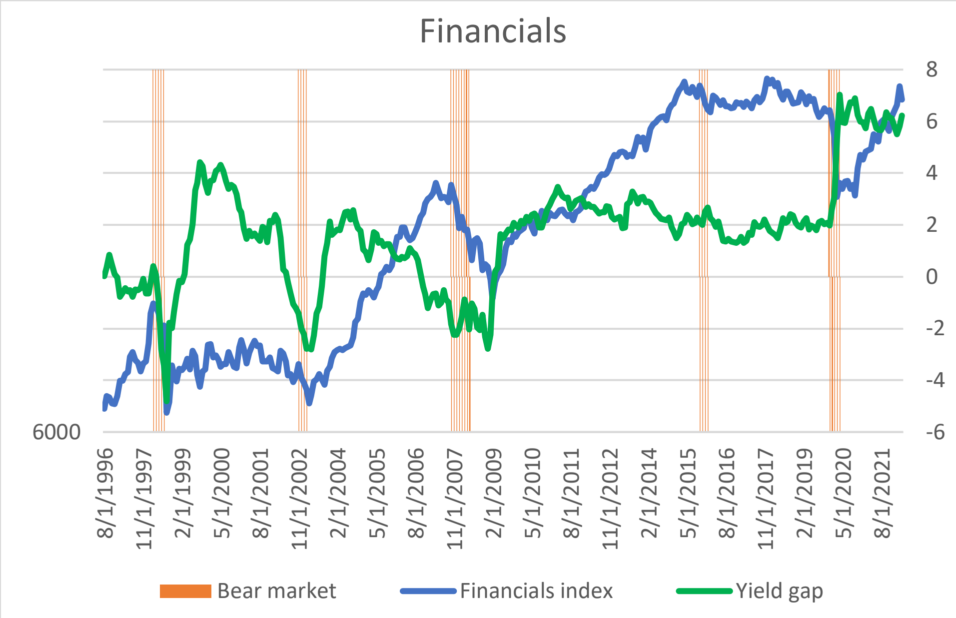
Figure 1: Relationship between Basics Material sub-sectoral index (log scale) and the yield spread.



Source: Author's calculations

In Figure 1 the Basics Material does not seem to move in line with the yield gap. The sudden drop in the yield spread in early 2003 and 2005 did correspond with slight false plunges in the index but for the period 2003 – 2009 the index rises consistently when the yield spread falls, which means contrary to our *a* priori expectation they are negatively correlated at these times. The index dropped significantly in late 2008 as the economy was hit by the Global Financial Crisis and the yield curve was negative. The index rises consistently after 2015 with little change in the yield gap until 2020 when the yield gap jumps sharply with the onset of the COVID-19 and the index continues to rise slowly.

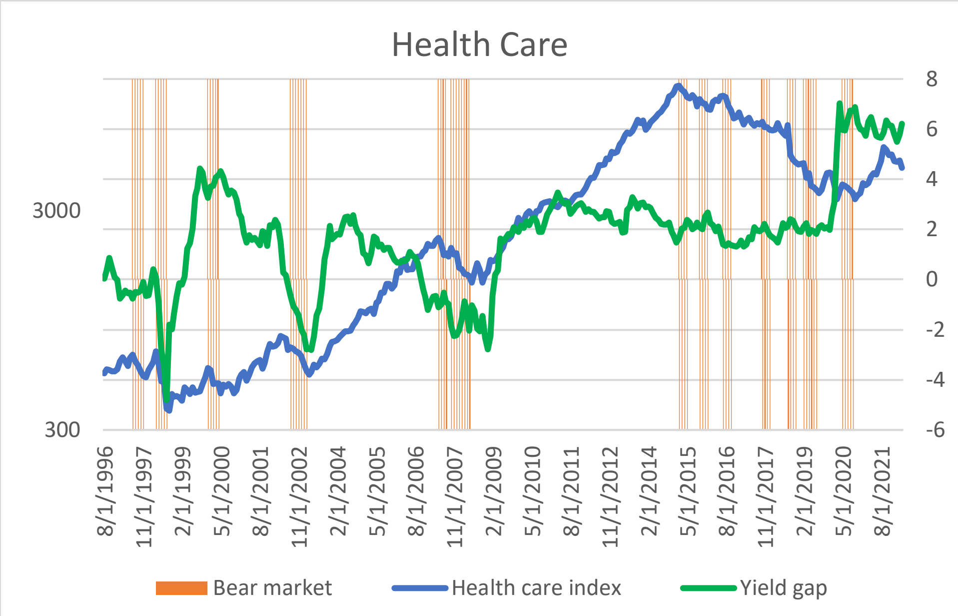
Figure 2: Relationship between Financial sub-sectoral index (log scale) and the yield spread



Source: Author's calculations

Figure 2 shows that the first three bear markets for the Financials index in 1998, 2002 and 2007 were closely tracked by a negative yield gap. But during the bear market in 2015 the yield gap seems to have a small rise and in the last bear market in 2020 the yield gap had a drastic rise while the Financials Index had a significant fall. Contrary to *a priori* expectations the Financials sub-index and the yield spread moved in opposite directions during these last two bear markets. This is the opposite of what theory predicts as periods of economic weakness are expected to be accompanied by a falling or negative yield spread. The trends however could be argued to be positively correlated the majority of the time.

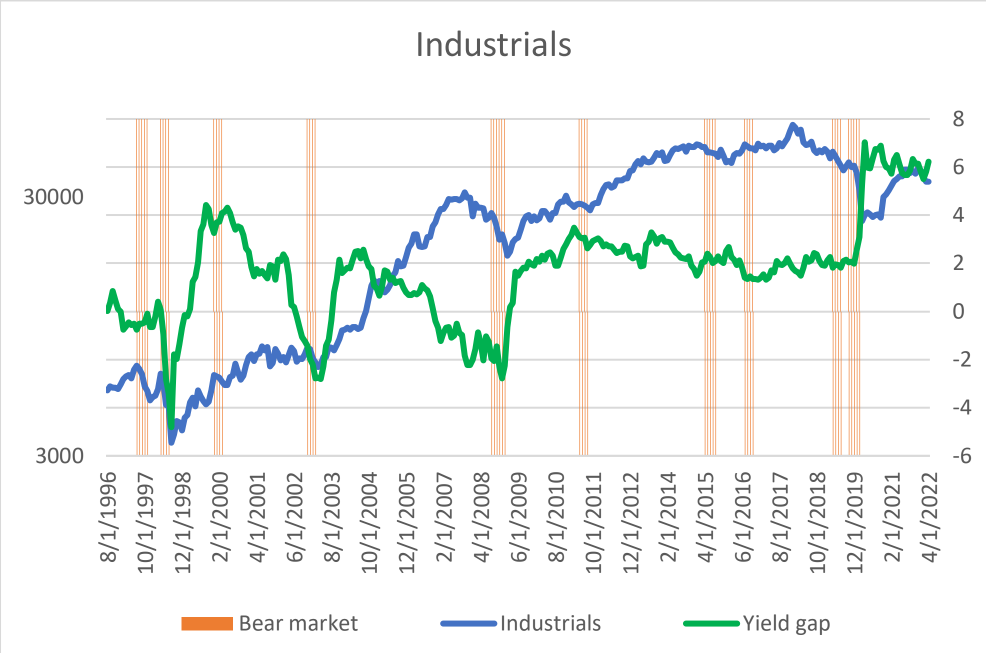
Figure 3: Relationship between Health Care sub-sectoral index (log scale) and the yield spread



Source: Author's calculations

Figure 3 shows that the bear markets phases before 2009 for the Health Care index in 1997, 1998, 2000, 2002, 2007 and 2008 were closely tracked by a negative yield gap. The yield gap remained positive from 2009, while the Health Care index had maintained an uptrend which rises consistently until 2015. The yield gap seems fall slightly then rises during the 2015 bear market while the index rises and falls on the same period. This seems to be consistent with the bear markets that followed from 2015 to 2019 where, when the yield gap slightly rises, the index falls. Contrary to *a priori* expectations the Health Care sub-index and the yield gap moved in opposite directions during these bear markets. In the last bear market in 2020 the yield gap had a drastic rise while the Health Care index had a plunge before rising with the yield gap.

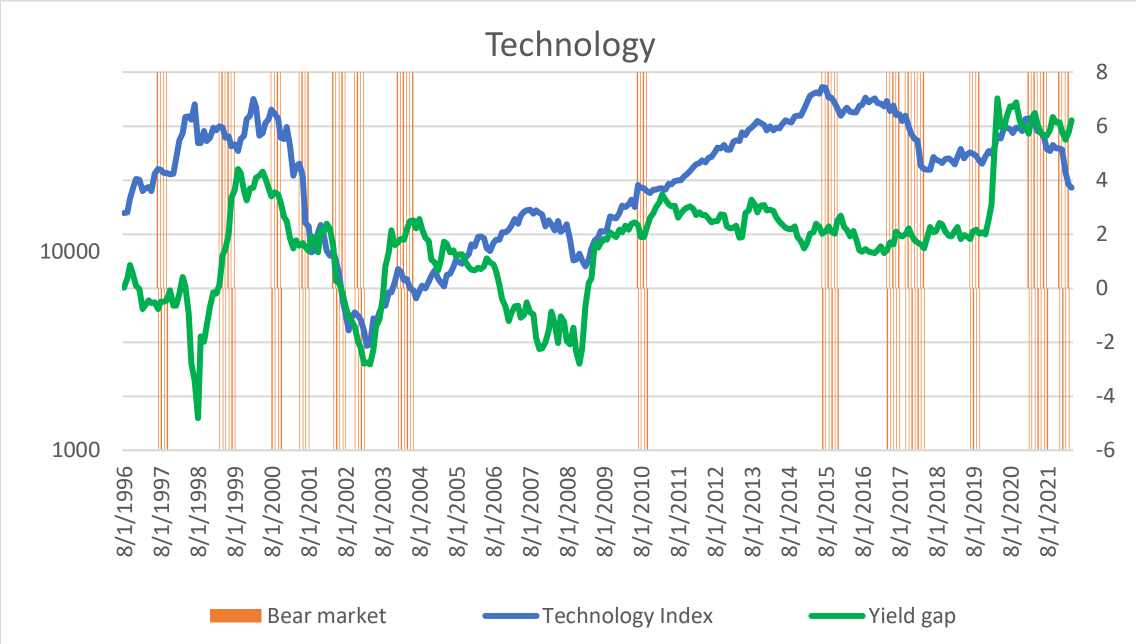
Figure 4: Relationship between Industrial sub-sector index (log scale) and the yield spread



Source: Author's calculations

Figure 4 shows the relationship between Industrial sub-index and the yield gap appears similar to that of the indices above, a negative yield gap before 2009 seems to clearly track the Industrial Index bear markets around 1997, 1998, 2000, 2002 and 2008. The Industrial sub-index and yield spread could be said to be positively correlated the majoring of the time, as the yield gap falls the index seems to fall even though sometimes slightly. In 2009 when the yield gap rises the index also picks up and continues to rise above the yield gap. The yield gap fell slightly as the bear markets in 2011, 2015 and 2016 approached but the index had no noticeable reaction until the drop in 2018. In 2020 the yield spikes sharply as the index falls showing a structural break in the behaviour but the index rises with the yield gap.

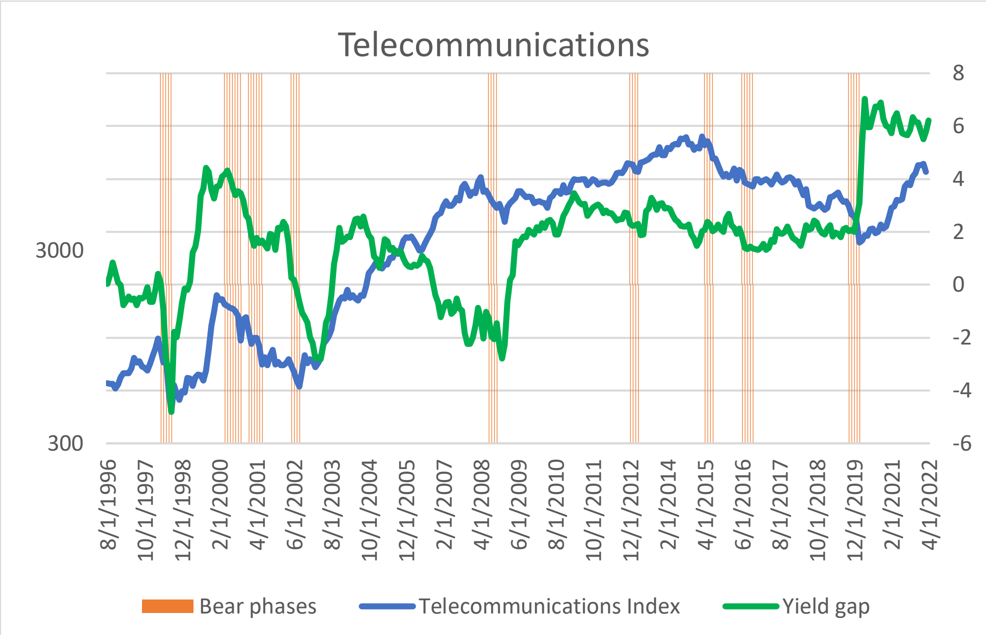
Figure 5: Relationship between Technology sub-sector index (log scale) and the yield spread



Source: Author's calculations

Figure 5 shows that the Technology Index had the most amount of bear markets than all the indices with 14 bear markets. Weakness in the Technology index in 2002 and 2007 is accompanied by a falling and even negative yield spread and the fairly consistent rise in the index from 2009-2015 occurs alongside a positive yield spread. At these times the index and the yield spread seem to be positively correlated thus a rise in the yield spread is met with strong index. The fall in the index from 2015-16 occurs alongside little change in the yield spread, but from 2016-17 the index rises, and the yield spread falls slightly. In 2019 both the index and yield spread rise. Overall, the relationship between the technology sub-index and the yield spread could be said to be positively correlated as a rise in the yield spread seems to be mostly accompanied by a slight rise in the index.

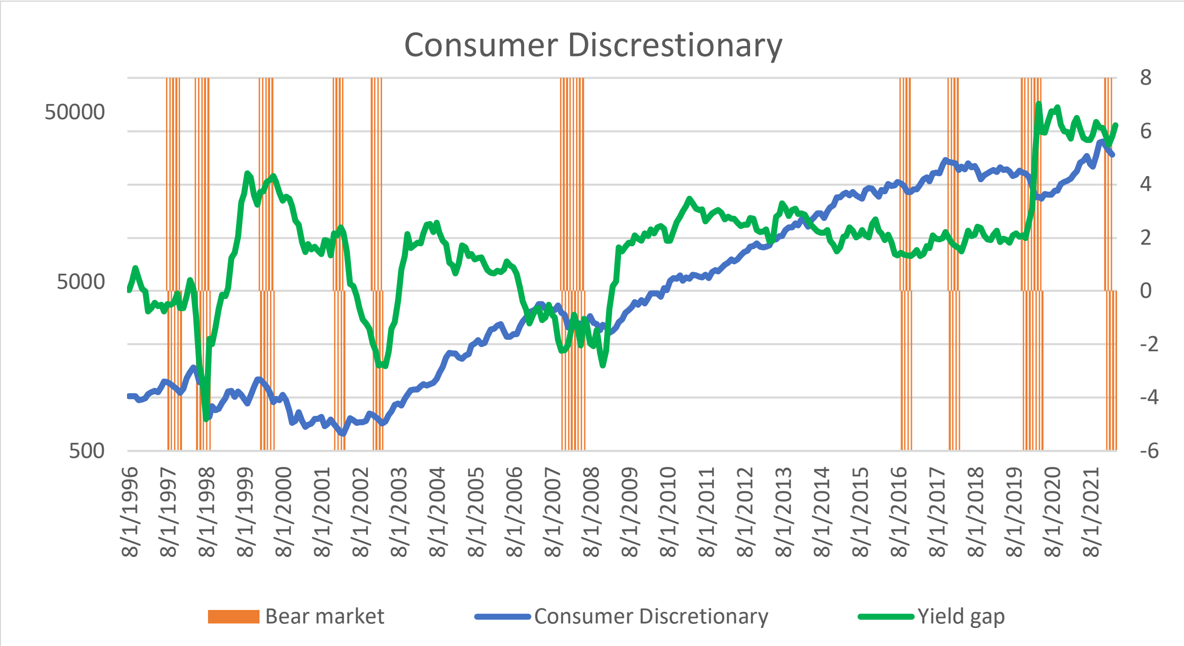
Figure 6: Relationship between Telecommunication sub-sector index (log scale) and the yield spread



Source: Author's calculations

In Figure 6 the yield gap and the Telecommunications index falls at the beginning of the first bear market. The yield gap falls to the negatives and rises when the bear market ends and the index rises with yield and both peak before the second bear phase begins, the two showing positive correlation and conforming prior expectation that negative yield spread is excepted to be accompanied by weak economic periods. In 2002approaching the 4th bear phase, the yield gap dropped significantly to the negatives and this was again met with a slight fall in the index which was already weak at this point. However, after 2005 the Telecommunications sub-index and the yield spread seem to demonstrate negative correlation as the yield spread hits negative levels, the index appears to rise until it plunges slightly in 2008 with a negative yield spread. From 2009, the yield spread started rising with the index also rising slightly and positive yield spread was followed by a rise in the index in 2019 during the last bear phase. This would appear to be positive correlation and though one cannot say if the rise in the yield spread caused the rise in the index because correlation does not mean causation.

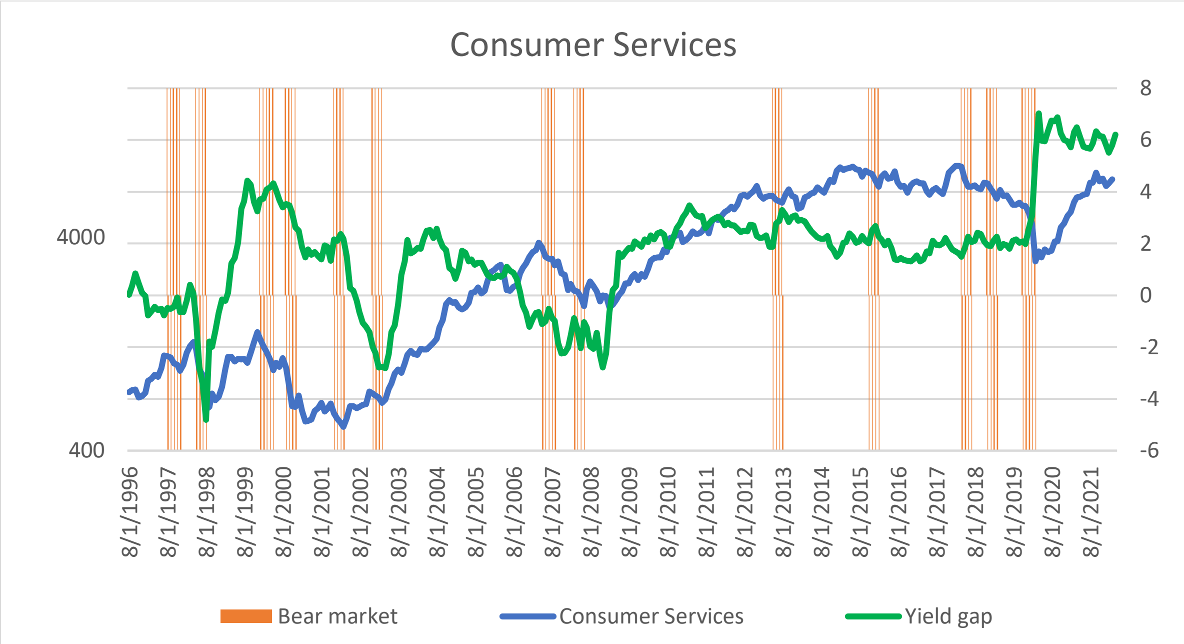
Figure 7: Relationship between Consumer discretionary sub-sector index (log scale) and the yield spread



Source: Author's calculations

In Figure 7 yield gap dropped sharply to the negative approaching the bear market in 1998, the Consumer Discretionary index also showing a drop at the same time. For the two following bear markets not only is the yield gap positive but seems to have a slight rise during the bear markets while the index shows slight fall. The yield gap then falls significantly to a negative in late 2002 before rising again following the spike at the end of the 2002 bear market. In 2007/8 the yield gap fell right before the start of bear phase and fluctuated together with the index slightly during the entire bear market phase period. The yield gap rose sharply above the index from 2008 while the index maintained an upward trend, both rising until 2014 when the yield plunges to below the index. The drop in the index in late 2019-20 was accompanied by a sharp rise in the yield gap, it does not appear that movements in the yield gap coincide with those of the index and appears to inversely correlate.

Figure 8: Relationship between Consumer services sub-sector index (log scale) and the yield spread



Source: Author's calculations

In Figure 8 the Consumer Services sub-index and the yield gap cross each other a number of times, indicating that they may be inversely related in contrast to the expected positive relationship. Thus, a drop in the yield spread in 2006 occurred while the index was still rising, though the index did fall later when the yield spread become negative. The COVID-19 related sharp rise in the yield spread in 2019 was initially met by a sharp fall in the index. However, in the period after 2006 the yield spread remained consistently positive. Bear markets in 2012 and 2015 were both accompanied by rising yield gaps.

4.4 Summary of graphical findings

The findings of the graphical analysis are not very encouraging for the predictive power of the yield curve in determining bull and bear markets in the sub-indices. While there is some evidence of the expected relationship pre-2008, the consistently positive yield curve after this date is not consistent with periods of both weakness and strength (including bear markets) in the sub-indices.

4.5 Presentation and discussion of Probit model results.

To model the relationship between the yield spread, bear and bull market phases for each of the JSE sectoral indices, probit models were run. In line with the findings of Cook (2019) that rolling-window regressions were not successful in improving the out-of-sample methodology in this type of estimation, this methodology was not attempted for purposes of this study. Instead, the study used an out-of-sample forecasting for probit model estimation. This was estimated using a base period of August 1996 to December 2000. An out-of-sample forecasting was done by adding one month's data into the initial sample period. This way obtaining an ex ante probability forecast of a bear market for the entire sample period of this study.

Then a probit model is run for the period 1996 to 2000 for each of the sub-indices. The sample period for each of the probit models run thereafter is extended to the end of the next bear phase. After the first probit model is run, the number of models per sub-index thus depends upon the number of bear markets for that index over the period 2001 to 2022.

4.6 The probit model

Table 3 presents the best fitted probit model results as per the 1996 – 2022 periods with in-sample period 1996-2000. The results estimate the probability of a bear phase being one month ahead. The relationship between the yield spread and the probability of a bear market is expected to be negative. That is, a fall/negative in the yield spread increases the probability of a bear market phase on month ahead. A negative α_1 coefficient confirms *a priori* expectation for this relationship. E.g. the Financials sub-index results shows a negative α_1, which demonstrates that the yield spread has a negative relationship with the probability of a bear phase for this sub-index.

Though most of the indices depict this negative relationship well, with negative α_1, the probability value also needs to be a statistically significant. A P-value less than 5% suggests that the model can predict the probability of a bear market one month ahead for that specific period. Looking at the Financials index for example not only does the negative relationship hold true, but also the P-values are all statistically significant at less than 5% level. Thus, the model may be able to successfully predict a bear phase one month ahead for this index. However, sub-sectoral indices such as Basics Material, Telecommunications, Technology and Consumer Services have a combination of negative and positive α_1, suggesting that the negative relationship between the yield spread and the probability of a bear phase does not hold true for the entire time series on these indices.

Table 3: The probit model estimates

Industries	Period	α_0	Prob value	α_1	Prob value
Basics Material	1996/09 – 2000/11	-0.546565	0.0137	-0.428243***	0.0011
	1996/09 – 2008/09	-1.239422***	0.0000	-0.393128***	0.0001
	1996/09 – 2011/08	-1.069933***	0.0000	-0.171293***	0.0085
	1996/09 – 2012/07	-0.955161***	0.0000	-0.074572	0.1923
	1996/09 – 2014/11	-0.929401***	0.0000	-0.071763	0.1831
	1996/09 – 2015/08	-0.886402***	0.0000	-0.047479	0.3673
	1996/09 – 2021/08	-1.026618***	0.0000	0.010227	0.8065
Financials	1996/09 – 2000/11	-1.336650***	0.0000	-0.325575**	0.0391
	1996/09 – 2003/02	-1.350076***	0.0000	-0.513377***	0.0009
	1996/09 – 2008/05	-1.464726***	0.0000	-0.624073***	0.0000
	1996/09 – 2016/01	-1.211407***	0.0000	-0.345250***	0.0000
	1996/09 – 2020/04	-1.157732***	0.0000	-0.188639***	0.0004
Health Care	1996/09 – 2000/11	-0.467464***	0.0175	-0.092757	0.2522
	1996/09 – 2003/02	-0.431456***	0.0084	-0.225003***	0.0035
	1996/09 – 2007/08	-0.742355***	0.0000	-0.233186***	0.0009
	1996/09 – 2008/05	-0.613872***	0.0000	-0.300013***	0.0000
	1996/09 – 2015/05	-0.761987***	0.0000	-0.287629***	0.0000
	1996/09 – 2016/01	-0.761987***	0.0000	-0.287629***	0.0000
	1996/09 – 2016/10	-0.711151***	0.0000	-0.253375***	0.0000
	1996/09 – 2018/01	-0.666169***	0.0000	-0.245602***	0.0000
	1996/09 – 2018/11	-0.645836***	0.0000	-0.230922***	0.0000
	1996/09 – 2019/07	-0.575617***	0.0000	-0.190182***	0.0001
Industrials	1996/09 – 2000/11	-0.601731***	0.0027	-0.073618	0.3770
	1996/09 – 2003/02	-0.676865***	0.0001	-0.173321**	0.0259
	1996/09 – 2009/01	-0.994375***	0.0000	-0.202160***	0.0027

	1996/09 – 2011/08	-0.962176***	0.0000	-0.149657***	0.0110
	1996/09 – 2015/08	-0.948121***	0.0000	-0.152166***	0.0046
	1996/09 – 2016/10	-0.902869***	0.0000	-0.149000***	0.0047
	1996/09 – 2019/07	-0.902871***	0.0000	-0.147757***	0.0043
	1996/09 – 2020/02	-0.862987***	0.0000	-0.119179***	0.0181
Telecommunication	1996/09 – 2000/11	-0.777722***	0.0002	0.043469	0.5785
	1997/09 – 2001/06	-0.586356***	0.0021	0.071133	0.3491
	1996/09 – 2002/08	-0.538458***	0.0020	0.016737	0.8228
	1996/09 – 2008/10	-0.945918***	0.0000	0.032591	0.5952
	1996/09 – 2013/03	-1.034643***	0.0000	-0.001936	0.9721
	1996/09 – 2015/07	-1.031829***	0.0000	-0.007725	0.8849
	1996/09 – 2016/10	-0.982614***	0.0000	-0.008538	0.8706
	1996/09 – 2020/02	-1.009743***	0.0000	-0.002744	0.9577
Technology	1996/09 – 2000/11	-0.743134***	0.0007	0.127990	0.1424
	1996/09 – 2001/08	-0.670791***	0.0011	0.121087	0.1548
	1996/09 – 2002/08	-0.536096***	0.0030	0.058576	0.4637
	1996/09 – 2003/02	-0.387995***	0.0140	-0.009121	0.8980
	1996/09 – 2004/06	-0.432675***	0.0029	0.059367	0.3696
	1996/09 – 2010/10	-0.876162***	0.0000	0.122440**	0.0439
	1996/09 – 2015/12	-0.937758***	0.0000	0.035744	0.5106
	1996/09 – 2017/08	-0.924966***	0.0000	0.039468	0.4638
	1996/09 – 2018/04	-0.869022***	0.0000	0.05313	0.3129
	1996/09 – 2019/10	-0.868140***	0.0000	0.052570	0.3179
	1996/09 – 2021/08	-0.886225***	0.0000	0.068104***	0.0985
	1996/09 – 2022/03	-0.898660***	0.0000	0.084948**	0.0287
Consumer Discretionary	1996/09 – 2000/11	-0.487339***	0.0125	-0.090289	0.2648
	1996/09 – 2002/02	-0.486814***	0.0073	-0.083109	0.2885
	1996/06 – 2003/02	-0.457141***	0.0041	-0.127032*	0.0807
	1996/09 – 2008/05	-0.706274***	0.0000	-0.185625***	0.0036

	1996/09 – 2016/11	-0.880455***	0.0000	-0.230376***	0.0000
	1996/09 – 2018/02	-0.845107***	0.0000	-0.211905***	0.0001
	1996/09 – 2020/04	-0.839278***	0.0000	-0.132089***	0.0054
	1996/09 – 2022/03	-0.851568***	0.0000	-0.089603**	0.0240
Consumer Services	1996/09 – 2000/11	-0.463663***	0.0176	0.071524	0.3621
	1996/09 – 2002/02	-0.519999***	0.0046	0.065060	0.3988
	1996/09 – 2003/02	-0.447130***	0.0046	0.005611	0.9355
	1996/09 – 2007/08	-0.705805***	0.0000	-0.032066	0.6131
	1996/09 – 2008/05	-0.658980***	0.0000	-0.048948	0.4134
	1996/09 – 2013/07	-0.811439***	0.0000	-0.072847	0.1634
	1996/09 – 2016/01	-0.819664***	0.0000	-0.079117	0.1160
	1996/09 – 2018/06	-0.831625***	0.0000	-0.080472*	0.1072
	1996/09 – 2019/02	-0.804173***	0.0000	-0.070035	0.1562
	1996/09 – 2020/02	-0.784716***	0.0000	-0.053227	0.2743
	1996/09 – 2020/09	-0.632190***	0.0000	-0.095121**	0.0237

Source: Author's calculations

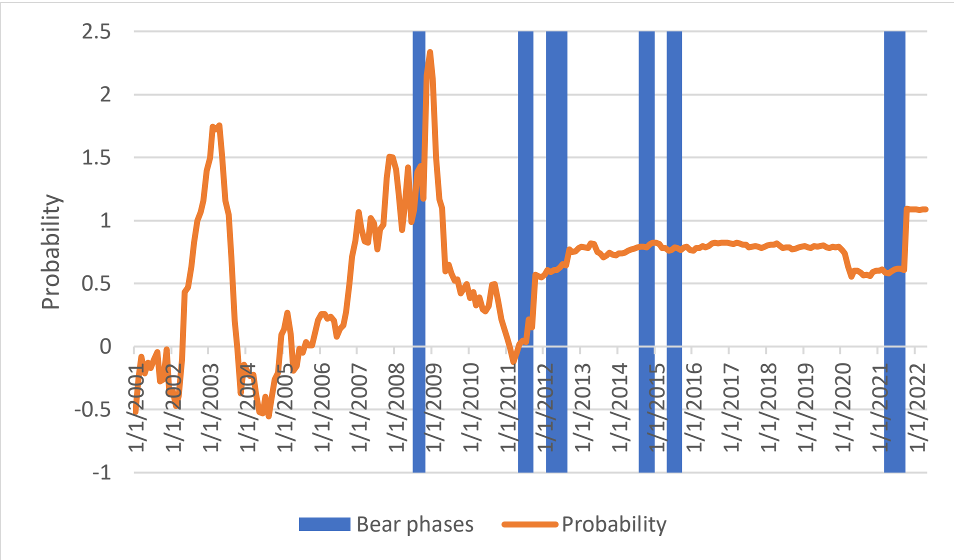
*Notes: *, ** and *** denote significance at 10%, 5% and 1%, respectively*

From the probit results in Table 3, the Financials sub-index and the Health Care sub-index appear to be the two indices that seem to indicate to have the strongest ability to model the relationship between the occurrence of a bear market and the yield spread. This is evident by the significance level, where all the probit results proved to be significant at 1% for Financials sub-index and all except one were significant at 1% for Health Care sub-index. While indices like Telecommunications seemed to have the weakest ability to model the relationship between the occurrence of a bear market and the yield spread. The results of the probit models in this study are important not in their own right, but for their ability to generate statistically significant market timing/buy-sell signals for their respective sub-indices. This is tested in Section 4.8.

4.7 The yield spread with 4 months bear market criteria

The probabilities of a bear market one month ahead are next calculated using the probit results for out-of-sample forecasting with the base period August 1996 – December 2000 and are shown graphically. The Figures below illustrate the forecasted probability of a bear market one month ahead for each of the sub-sectoral indices for the period January 2001 – April 2022 versus bear markets that were actually recorded for each sub-index.

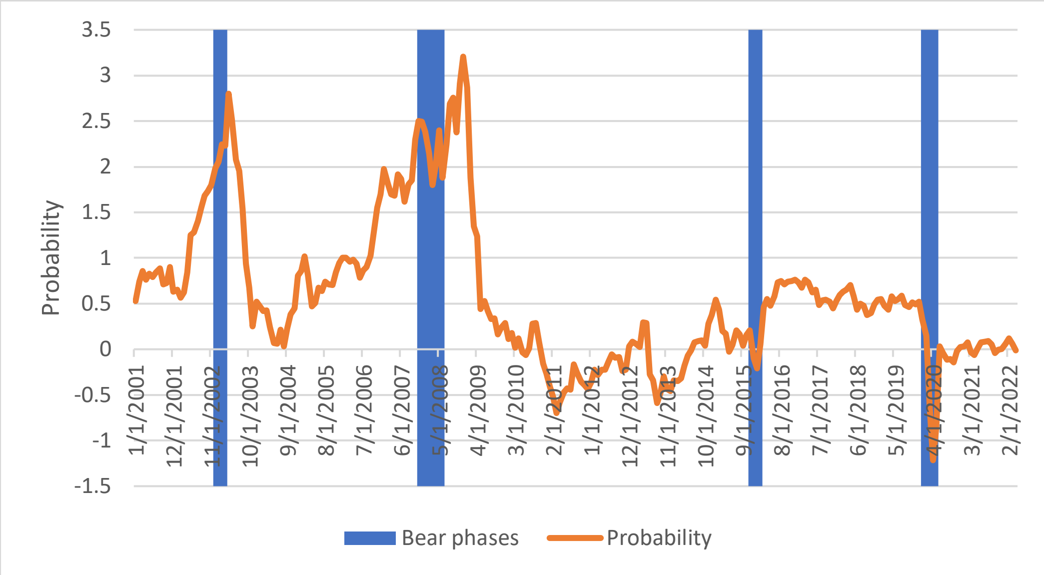
Figure 9: Probability of Bear Market for Basics Materials one-month ahead



Source: Author's calculations

It appears that the model is not able to consistently predict bear market phases for the Basics Material sub-index. The probability of a bear phase first spikes in 2003 (where the probability of a bear phase was more than 100%) but a bear phase was not recorded at this time. In 2008, the model appears to have predicted the first bear phase in 07/2008, but it should be noted that the probability peaked at more than 200% even after the bear phase ended. In early 2011 the probability of a bear phase plunged to below 0%, just before the next bear phase began. It then rose above 50% before the 3rd bear phase in 2012, but remained consistently above 50% from 2012, with no noticeable spikes to indicate incoming bear phases in 2014, 2015 and 2021. A buy-sell strategy at both 50% and 70% probability would have seen an investor in cash for almost all of the period after 2012, even though the index rises strongly after 2015 (Figure 1).

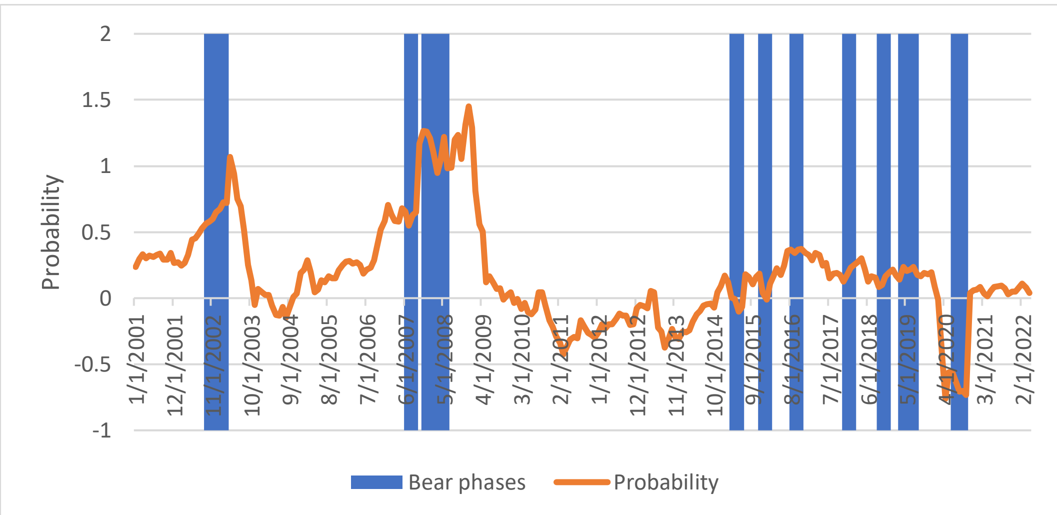
Figure 10: Probability of Bear Market for Financials sub-index one-month ahead



Source: Author's calculations

The financial sub-index only presents 4 bear phases, in 2002, 2008, 2015 and 2020 respectively. The probability of a bear phase rises strongly before the first 2 bear but does not rise for either of the next 2 bear phases. For the first two bear phases probability measures rise to more than 250% and 300% respectively, so a buy-sell strategy based upon 50% or 70% probability would have trigged sell a long time before the bear phase actually occurred. The 3rd and 4th bear phases coincide with probability dropping below 0%. The yield curve therefore does not seem to be a good indicator of buy-sell signals for the Financials sub-index.

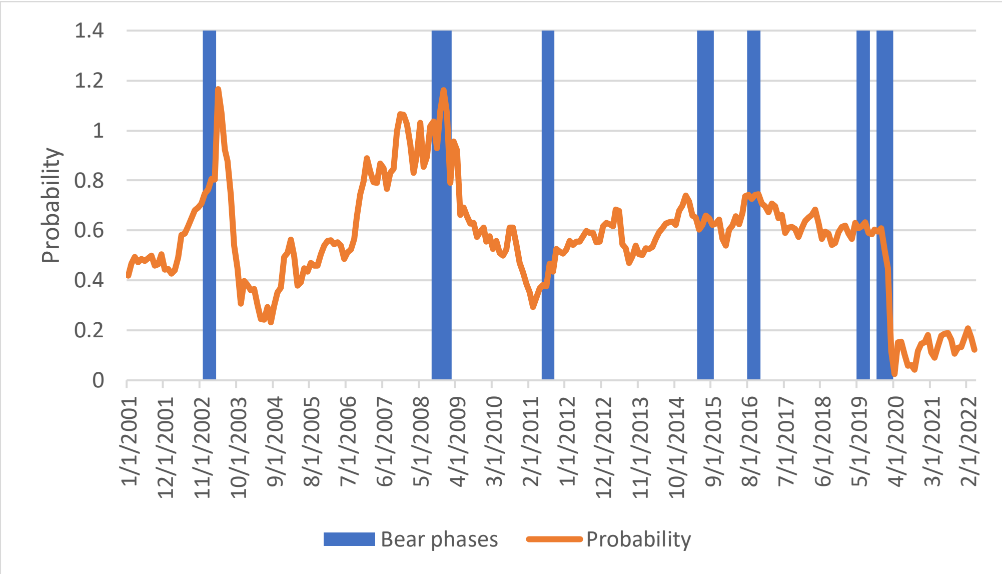
Figure 11: Probability of Bear Market for Health Care sub-index one-month ahead



Source: Author's calculations

The Health Care sub-sectoral index had one of the lowest levels of probability for a bear market despite the large number of bear markets recorded across the period. The model starts off as a reasonably good signal for the first 3 bear phases with probability levels rising to above 50%. But probabilities peaked after the bear phases were over. From 2009 the probability of a downturn drops to very low levels and is even negative for long periods. This is despite 7 bear phases being recorded for this sub-index between 2014 and 2022. This means that the bear phases that occurred after 2014 were not successfully predicted.

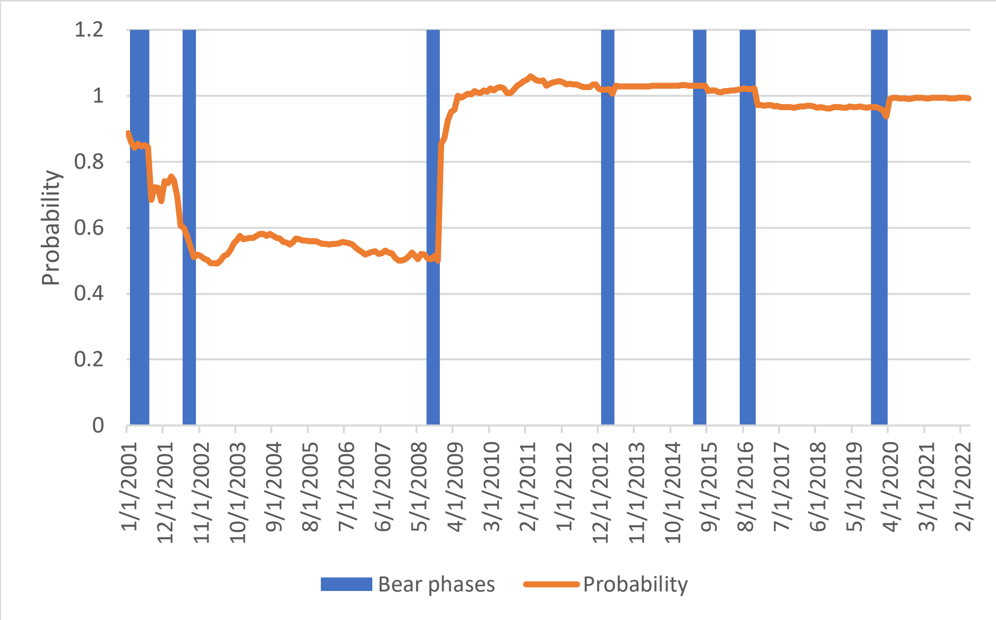
Figure 12: Probability of Bear Market for Industrials sub-index one-month ahead



Source: Author's calculations

The probability of bear phases for the Industrials sub-index is quite volatile. The probability increases to 70% in the third quarter of 2002 which is then followed by the 1st bear phase, and so is in accordance with the *a* priori expectations. The probability hits a peak above 100% again towards end of 2008 during a bear phase but probability had exceeded 50% for almost 2 years before the actual bear phase occurred. The model misses the next bear phase in 2011 when probability is only around 30%. However, the model does show an uptrend thereafter and rises to above 50%. The model is above 50% probability for the bear phases after 2015, but this is because it is consistently above 50% for most of the period. Probability plunges to below 20% during the last bear phase towards the end of 2019, possibly because the yield gap spikes to new highs over this period.

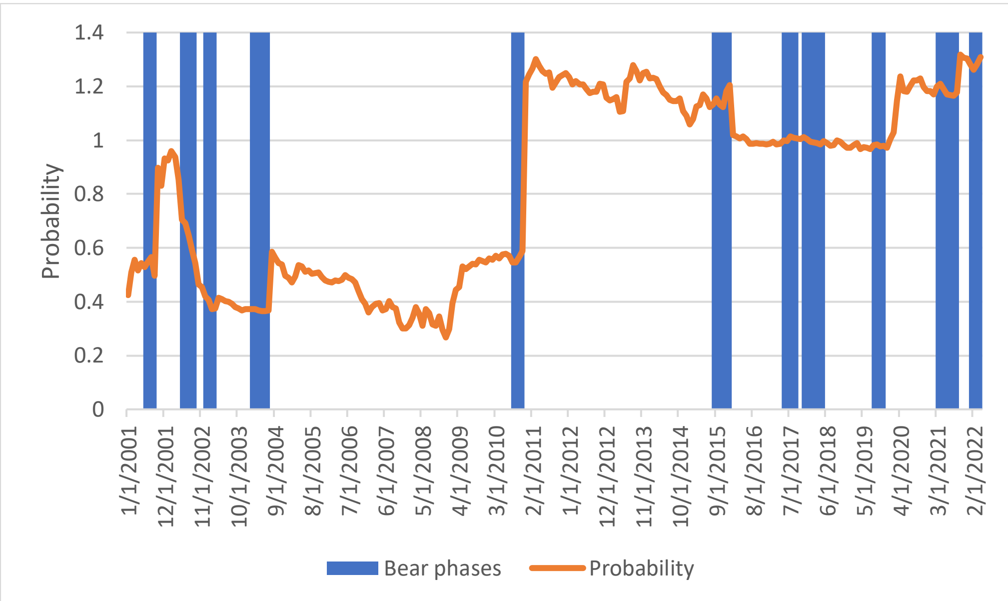
Figure 13: Probability of Bear Market for Telecommunication sub-index one-month ahead



Source: Author's calculations

Probability levels for the Telecommunication sub-index are above 50% for the entire period. Probability soars to consistently above 100% after 2008 and thus offers little warning of the 4 bear markets that occur during this period.

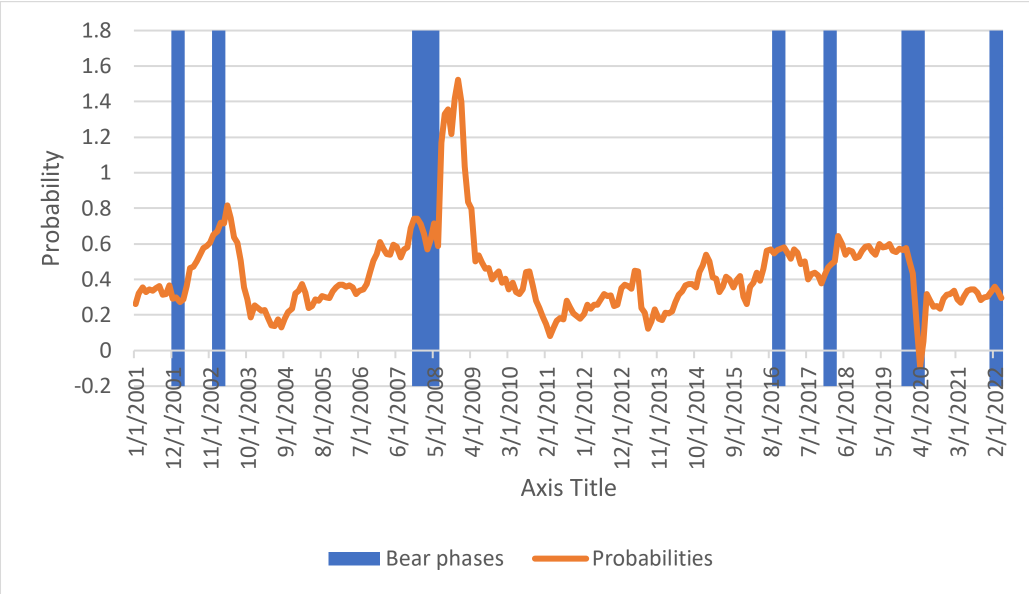
Figure 14: Probability of Bear Market for Technology sub-index one-month ahead



Source: Author's calculations

The Technology sub-index has one of highest number of recorded bear phases. The model does not appear to be able to consistently predict these bear market phases. While the predicted probability of a bear phase fluctuates from above 20% to above 100% these changes do not coincide well with actual recorded bear phases. The rise in the predicted probability seemed to rise only at the end of the bear phases. This is seen from the spike in 09/2001, 07/2004, 10/2010, 12/2009 and 09/2021 where the rise in the probability would occur towards the end of the bear phase.

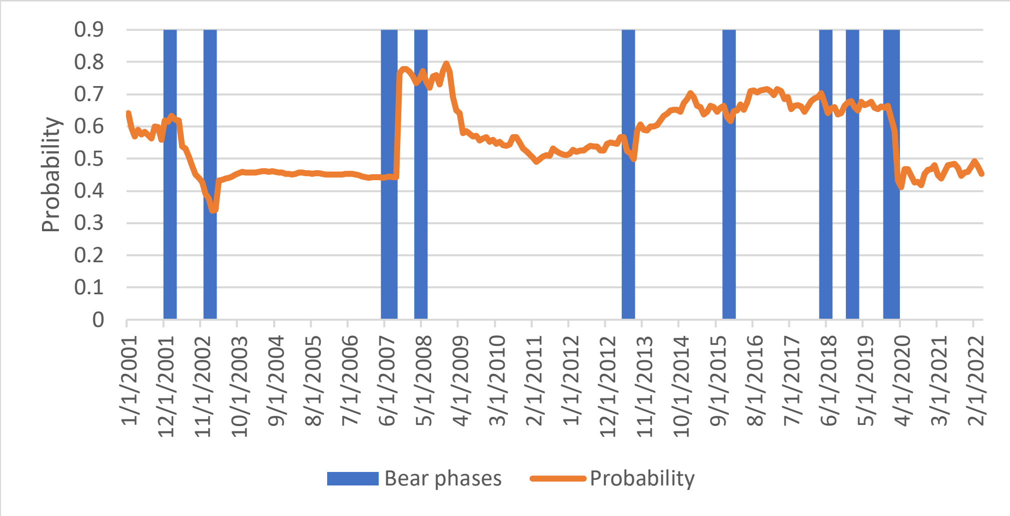
Figure 15: Probability of Bear Market for Consumer Discretionary sub-index one-month ahead



Source: Author's calculations

The model does not seem to be able to consistently predict bear market phases for the Consumer Discretionary sub-index. For the first bear phase in 2002 the probability of a bear phase was below 40%, but started rising after the first bear phase ended. In late 2002 the probability of a second bear phase was correctly predicted. One month before the bear phase in 2007 occurred, the probability rose to 60%, but had been above 50% for more than a year before the bear phase started and rose further to more than 90% after the bear phase was over. The probability of a bear phase fluctuates around 60% from 2015 but plunges to negative levels during the 2019 bear phase.

Figure 16: Probability of Bear Market for Consumer Services sub-index one-month ahead



Source: Author's calculations

The model does not seem to be able to consistently predict bear market phases for the Consumer Services sub-index. The probability for the Consumer services sub-index remained at 50% and above for most of the period. The first bear phase occurred at 60% probability, but the model did not manage to predict the second bear phase that occurred at the end of 2002 when probability was just 40%. The model did not predict the third bear phase in 2007 either, as the probability remained at 40%. But the probability then jumped to 70% when it was correctly followed by the fourth bear phase. The model dropped again to around 50% probability even though there were no bear market phases recorded for 4 years. During the bear phase in 2013, the probability dropped from above 50% to just below 50% during the bear phase and then rose after the bear phase ended. The probability levels increased to 60 – 70% thereafter, before dropping again during the 2019 bear phase to 40%.

The conclusion from Figures 9 – 16 is that the yield gap model does not seem to have consistently predicted bear markets, and thereby provided accurate buy-sell signals for any of the JSE sub-indices. This conclusion is tested in the following sections.

4.8 Market Timing Test

The market timing test is done to calculate the possible returns from a portfolio for each sub-index of a buy-and-hold strategy versus a market timing strategy using two probability thresholds, at 50% and 70%, as the signal to sell the sub-index and hold cash, and then use the cash to buy the index again. In Table 4, each of the sub-indices are presented, showing first the annual returns for a portfolio following a buy-and-hold strategy throughout the period. as well as the annual returns for market timing portfolio using both 50% and 70% probability levels as the signal to sell/buy the sub-index. The annual returns of the market timing strategy are then calculated to also include the interest earned when the portfolio has sold equities at the 50% or 70% bear market probability signal and holds cash in an interest yielding account.

Having identified which of the annual returns for a market timing strategy out-performed a simple buy-and-hold strategy, these will be tested using the Henriksson-Merton parametric model test to determine whether the results are significant, and the market timing strategy is indeed able to out-perform the buy-and-hold-strategy for any of the sub-indices.

Table 4: Annual returns of buy-and-hold versus market-timing portfolios (% per annum)

Indices	Market timing strategy: Threshold level				Buy and Hold strategy
	No interest		With interest		
	50%	70%	50%	70%	
Basics Material	7.9139	10.8385	13.5306	15.7458	10.8627
Financials	7.3672	8.0844	11.1846	11.609	6.6071
Industrials	2.0767	7.4863	7.8273	9.5546	7.3415
Health Care	6.3107	10.5217	12.8067	11.6039	10.3917
Technology	1.9367	-1.9922	7.1780	1.713189	-3.1410
Telecommunication	0.3722	8.7273	4.4969	9.9926	8.2104
Consumer discretionary	14.4800	16.2966	18.2209	18.6799	17.2632
Consumer services	12.2666	15.1637	17.0335	16.3348	11.0894
Cash holding					7.7763

Source: Author's calculations

It is important to first compare the annual returns of a buy-and-hold strategy with buy-and-sell at the 50% and 70% probability signals. Only then should the impact of interest earned during the sell period be examined. This is because for some sub-indices the period of holding cash is very long. The comparison of buy-sell plus interest with buy-hold then becomes almost a calculation of whether it was better to hold the index itself or to hold cash, rather than whether a buy-sell strategy is adding value to investing in the sub-index itself.

The first thing to note is that a buy-sell strategy at 50% probability produces lower returns than buy-hold for 5 of the 8 sub-indices. Only for Financials, Technology and Consumer services are returns without interest improved compared with buy-hold. For a buy-sell strategy based upon the 70% probability threshold, returns are improved compared to the 50% threshold for financials and consumer services but are reduced for technology. It should be noted that returns of the buy-hold strategy for Technology are negative, so it is the longer period in cash of the 50% strategy compared to the 70% strategy that increases returns, rather that superior buy-sell signals. Returns for Industrials, Health care and Telecommunications at a 70% probability now also exceed a buy-hold strategy, but the improvement is very small in all three cases. Consumer discretionary is the only sub-index for which buy-hold exceeds buy-sell at both the 50% and 70% probability.

Returns improve significantly when an investor earns interest and when they do not. This is because the models generate long periods when the investor is in cash for all sub-indices. At the 50% threshold returns on several of the indices almost double when comparing buy-sell without interest with buy-sell with interest. Comparing interest-earning buy-sell returns to the buy-and-hold strategy, the Telecommunication index was the only index with results that did not out-perform those of a buy-and-hold strategy for one of the threshold levels. It had returns for 8.2104% for a buy-and-hold strategy and only 4.4969% with a market timing strategy with interest rate at 50% probability. It did however outperform the buy-and-hold strategy at a 70% threshold with 9.9926% for the market timing strategy with interest, and 8.2104% for a buy-and-hold strategy.

Annual Returns of investing in Cash (Table 4) for the whole period from 2001 to 2022 was calculated to be 7.7763% using the deposit interest rate. Looking at the cash returns compared with the returns with interest for the different sub-indices strategies, it is evident that for the Technology index the investor would have been better off holding cash the entire period, as both probabilities 50% and 70% presented lower returns compared to cash. The buy-and-hold strategy also returned negative returns for the Technology sub-index confirming that cash holding would have been better. Telecommunication sub-index also returned lower returns at 50% probability compared to the returns from holding cash the entire period. The rest of the sub-indices had greater returns at both probability thresholds compared to returns from holding cash.

Since the returns on all other indices except for Telecommunications sub-index at 50% seemed to out-perform the returns of a buy-and-hold strategy, the Henriksson-Merton parametric model test is performed on all the indices excluding the telecommunications sub-index at the 50% probability, but on all sub-indices at the 70% probability.

4.9 Henriksson-Merton parametric model test

Henriksson-Merton (HM) parametric model tests were conducted to determine whether the results in Table 4 are statistically significant and can legitimately be used to simulate a portfolio at each threshold level. That is, the HM test is used to determine whether the market timing results for each of the sectoral indices are statistically significant and can be used in timing the market for the sub-index. The tests were done using the formula previously explained equation (5),

$$R_{pt} = a_p + b_{pd}\, R_{mt} + b_{pu}\, R_{mt}\, D_t + u_{pt}$$

Where, the excess returns on the market timing portfolio over and above the risk free return are regressed on the systematic risk premium for a bull market (b_{pu}) and the systematic risk premium for a bear market (b_{pd}), this was done for each of the sectoral indices and is shown in Tables 5 and 6. Though b_{pu} and b_{pd} are important together with their significance level, for the test to hold the slope (b_{po}) will have to be positive and statistically significant such that $b_{pu} - b_{pd} = b_{po} > 0$. Only then it can be said that a portfolio for a dynamic market timing strategy outperforms that of a stock-only buy-and-hold strategy.

Table 5: HM Market Timing Test Results, Probability screen < 0.5

Index	b_{pu}	b_{pd}	$b_{po} = (b_{pu} - b_{pd})$	Significance
Basics Material	3.2955***	0.7571***	2.5384	Significant
Financials	1.0629	0.5672***	0.4957	Not significant
Industrials	2.0821***	0.4685***	1.6136	Significant
Health Care	-1.9427	0.4660***	-2.4087	Not significant
Technology	1.5822**	0.8328***	0.7494	Significant
Consumer discretionary	1.5923	0.4855***	0.7373	Not significant
Consumer services	1.2254	0.5227***	0.7027	Not significant

Source: Author's calculations

*Notes: *, ** and *** denote significance at 10%, 5% and 1%, respectively*

Table 6: HM Market Timing Test Results, Probability screen < 0.7

Index	b_{pu}	b_{pd}	b_{po}	Significance
Basics Material	5.7575*	0.6662***	5.0913	Not significant
Financials	0.9286	0.5464***	0.3822	Not significant
Industrials	2.0953	0.4765***	1.6188	Not significant
Health Care	-1.8023	0.3928***	-2.1951	Not significant
Technology	1.7906**	0.7092***	1.0814	Significant
Consumer discretionary	2.0609	0.5112***	1.5497	Not significant
Telecommunication	0.9664*	0.8391***	0.1273	Not significant
Consumer services	1.0704	0.5116***	0.5588	Not significant

Source: Author's calculations

*Notes: *, ** and *** denote significance at 10%, 5% and 1%, respectively*

The tests were done on out-of-sample simulations for two threshold levels of 50% and 70% since all these had delivered better results than the buy-and-hold strategy on either one or both threshold levels as shown in Tables 5 and 6. The results for the HM test are significant for only three sub-indices (Basics Material, Industrials and Technology) indices at the 50% threshold value, and just one sub-index (Technology) at the 70% threshold value. . The results show that generating excess returns using the market timing is only possible for basic materials, Industrial and Technology and either the 50% or 70% thresholds. By adjusting for exposure through anticipating market movements an investor can increase returns. Thus, although the 70% threshold had higher returns than buy-hold for all 8 sub-indices, the results are significant at the 5% level for only 1 sub-index.

Looking at Basics Material sub-sectoral index at 50% probability, for example, the coefficients for both the bull and bear market are significant at 1% thus results are significant. Thus, the investor would be able to benefit from holding a portfolio with a market timing strategy at a 50% level. However, even though b_{po} is positive at the 70% threshold, the bull market coefficient is significant only at 10%, which we consider to be too weak, so it is not significant for our analysis. Hence the coefficient of the bull market statistically is no different from zero, the result will not be significant, and the investor will not benefit for following a market timing strategy for their portfolio for this sub-index.

Though the Financials and Consumer discretionary sub-indices have positive b_{po}, the bull market coefficient is not statistically significant and thus the results will not be significant for either 50% or 70% threshold levels. Investors will thus not benefit from a market timing strategy.

The Health Care sub-index has a negative b_{po} which means the bull market coefficient is not statistically significant, and thus the results will not be significant for both threshold levels. Thus, investors will thus not benefit from a market timing strategy.

Results for the Industrial sub-index are significant at the 50% level. The bull market coefficient is significant at a 5% level significance and thus investors will benefit from following the market timing strategy for their portfolios. At 70% probability, however, though b_{po} is positive, the coefficient of the bull market statistically is not different from zero, and the result will not be significant. Thus, investors will thus not benefit from a market timing strategy at the 70% probability level. It should be noted, however, that the 50% probability buy-sell strategy achieved only very modestly improved returns compared with the buy-hold strategy (7.8273% versus 7.3415% per annum).

For the Telecommunication sub-index a negative b_{po} means the bull market coefficient is not statistically significant and thus the results will not be significant. At 70%, it is statistically significant only at 10%, but this is considered too weak significance level for this analysis. Thus, the results are considered not significant, and investors will not benefit from following a market timing strategy.

The Technology sub-sectoral index has statistically significant coefficients at 5% for both the 50% and 70% probabilities. The b_{po} is positive and thus results are statistically significant, and investors will benefit for following a market timing strategy for their portfolio for this sub-index. But it should be remembered that returns for buy-hold for this index are negative. An investor would therefore have been better off holding cash and ignoring this sub-index altogether.

4.10 Conclusion

This chapter presented the results computed to answer the research question. The findings presented are those of the yield spread against each of the sub-sectoral indices to demonstrate whether the movement of the yield spread coincides with that of the index. Probit models are simulated using the yield spread to predict bear markets lasting a minimum of 4 months for each sub-sectoral index. The models produce some very high levels of probability above 100% and some very low levels that are negative.

Graphical examination of the results suggested that for the most part the models only managed to track some of bear phases of the sub-indices, with most of the bear phases being missed. For some of the indices an investor following a buy-sell strategy would have spent most of the time not in the equity market, while for others they would be in the market and still experience the bear phases the model did not manage to predict.

Market timing portfolios were simulated to find out which of a market timing and a buy-and-hold strategy would yield superior results for each sub-index. The results for market timing portfolios generally gave superior returns after interest earned when out of the market is included. HM parametric model tests were then conducted to determine whether these results are statistically significant and so can be used by an investor to follow a market timing strategy. The results for all 8 indices found that the superior results at a 50% probability threshold were significant for only 3 sub-indices and only 1 sub-index was significant at a 70% probability threshold. This means that an investor will achieve statistically significant superior returns for a market timing strategy only for these sub-indices at these particular threshold levels. However, it was cautioned that the Technology sub-index yielded negative returns across the time period as a whole, so ignoring the index completely would have been even better than a buy-sell strategy. Improved returns for the Industrial index were very modest, even when interest earned is included.

The findings are thus not what theory and most previous studies had predicted. The theory of the yield curve suggests that changes in the yield gap can be linked to changes in domestic economic activity and this relationship is supported by most empirical studies, including for South Africa. Theory and empirical evidence also suggest that changes in domestic economic activity are positively related to changes in stock market values. The combination of these findings – that changes in the yield gap can be used to predict changes in the stock market – were borne out in studies of the US, Spain and Indian stock markets, but not for the JSE ALSI. This study tested whether changes in the yield gap could be used instead to predict changes in the sub-indices of the JSE. But the findings were significant for only 3 sub-indices at a 50% probability threshold and only 1 sub-index was significant at a 70% probability threshold.

CHAPTER 5: SUMMARY, CONCLUSION AND RECOMMENDATIONS

This chapter summarises the study, concludes on the findings and provides possible recommendations on the study.

This objective of the research is to determine whether the South African yield spread presents any statistically significant information for timing the South African stock market. Thus, the objective was to find out whether statistically significant information from the yield curve can be used by an investor to simulate a market timing portfolio using a dynamic market timing strategy for each of the JSE sub-sectoral indices that will outperform a simple stock-only buy-and-hold strategy. Such a positive finding would be crucial information for portfolio managers, allowing them to predict bear market phases in the JSE's sub-indices from changes in the yield spread. As most investors believe that it is "time in the market" that matters and not "timing the market", being able to use the yield spread to time the market would be a game changer for investors, allowing them to achieve superior returns to those adopting a buy-and-hold strategy.

5.1 Summary and conclusion

The yield spread as an important predictor of future economic activities has long been of interest to researchers. This also means that the relationship between the yield curve, yield spread, economic activity and the stock market have been the focus of research. Though the relationship between the yield curve and economic activity have been used over the years to predict future recessions, the ability of its predictive nature was questioned by a number of researchers when it falsely predicted recessions first in the US in 1998 and in South Africa in the early 2000. However, Estrella and Mishkin (1996), Estrella and Truben (2006) and Clay and Keeton (2011) all argued that the evidence in favour of the ability of the yield curve to predict economic downturns far outweighs those against. It is also because of its simple nature that the yield curve is still considered a useful supplement to other large econometric models.

The yield curve can be either upward sloping, flat or inverted. The normal state of a yield curve is upward sloping. This occurs when long-term rates are above short-term rates which suggests that investors expect future short term rates to rise. This upward slope is this an indicator for strong economic prospects. A flat curve indicates a change in economic conditions. An inverted yield curve occurs when long-term rates fall below short-term rates, and is an indication for a downturn in economy as investors are concerned about a possible recession and therefore expect future short term rates to fall.

Economists have studied the relationship between financial assets yields of different maturities for years. Four theories have helped explain this relationship, namely, the expectations theory, market segmentation theory, the liquidity premium theory and preferred habitats theory. Though the most commonly used theory is the expectations theory, the liquidity premium and preferred habitats theories are both used alongside it, to better explain the shape of the yield curve at any point. The expectations theory states that long-term rates are equal to an average of current and expected future short-term rates. That is, short-term interest rates are forecasted using current long-term rates, and investors are indifferent to holding either short-term or long-term bonds.

The expectations theory also helps explain the relationship between changes in the yield curve and economic activity. Where short term interest rates are high to combat inflation, the expectations is that current contractionary money policy may result in a recession and thus a fall in future short-term rates, and this will induce an inverted yield curve. As short-term rates decline, the expectation will be that inflation levels and short term interest rates will rise in the future, and so long-term rates will rise above short-term rates, creating a positive yield curve. This demonstrates the positive relationship between the yield curve and economic activity using the expectations theory.

It is important to note the relationship between the stock market and economic activity in South Africa and internationally (Estrella and Mishkin, 1996, and Botha *et al.*, 2017). Since stock prices are determined by the present value of future cash flows, for that reason the stock market is also considered a potential indicator for future economic activity. This is because stock prices are sensitive to news or movements in the economy since cash flow earnings are closely related to the state of the economy. Though authors such as Hu (1993) and Harvey, 1989 found the bond market to reveal more useful information than stock prices about future economic activity, this research examines only the relationship between the stock market and the yield curve, and not the predictive nature of the stock market.

The expected links between the yield curve, economic activity and the stock market are the starting point for a possible dynamic market timing strategy. Four studies - one South African case and three international cases – have investigate such a possibility. Resnick and Shoesmith (2002), Bhaduri and Saraogi (2010) and Fernandez-Perez *et al*. (2014) looked at the USA, India and Spain respectively and found that investors using a dynamic market timing strategy based upon the yield curve can out-perform a normal buy-and-hold stock-only strategy. Cook (2019), however, did not find the same results for South Africa. Cook (2019) suggested that her findings may be because the JSE All-share index is dominated by large global companies whose earnings are not affected by changes in the South Africa's economic activity. Hence, it was thought that examining the sub-indices of the JSE could better focus attention on the relationship between the yield curve and sub-sectors whose earnings are more dependent on local economic activity.

5.2 Findings

The study ran probit models one month ahead for each of the sub-sectoral indices of the JSE using a yield spread criteria to predict bear phases of 4 months of consecutive decline in the sub-indices. The results of the probit models are shown graphical illustrations of the calculated probabilities of a bear phase are presented. The graphical illustrations suggested that the yield spread did not appear to be able to identify many of the historical sub-sector bear markets. For several of the indices the investor spent most of the period outside the stock market holding interest yielding cash.

A market timing test was done on out-of-sample forecasting period starting from 2001/01 to 2022/04 and forecasted probabilities were obtained. Using probability levels of 50% and 70% as the points to sell/buy the sub-indices, investors were able to increase returns for most sub-indices, but only after including interest earned when out of the stock market. The results for the simulated dynamic market timing portfolios therefore appeared to deliver superior results to a simple buy-and-hold stock only portfolio.

However, a market timing ability test was needed to test the significance of these results. A HM model proved that out of the 8 sectoral indices, for the 50% threshold level, only 3 indices provided significant superior results and thus the yield spreads would have market timing abilities only for these indices. At a 70% threshold level, only 1 index presented significant results. However, it was noted that the Technology sub-index yielded negative returns across the time period as a whole, so ignoring the index completely would have been even better than the buy-sell strategies which had proved statistically significant. It was noted that improved returns for the Industrial index were very modest, even when interest earned is included. Thus using the yield curve as the basis for a market-timing strategy at the sub-sectoral index level would not be useful in South Africa.

The findings of this research were thus contrary to what theories of the yield curve's link to domestic economic activity, and changes in domestic economic activity's links to the stock market, suggested. Unlike studies for the US, Spain and India, the yield curve provides very modest market timing signals for the South African stock market, even at the sub-indices level.

5.3 Recommendations

This thesis was solely based on South Africa, and thus cannot be considered a definitive study on the predictive nature of the yield curve for investment decisions in other stock markets. It seeks only to find if there is evidence that the yield curve can be used as a predictor for each of the JSE sub-sectoral indices, and if there is any statistical significance in the results found. It would be useful to conduct similar studies at the sub-sector level for the US, India and Spain -- where earlier studies found the yield curve is useful as the basis of a buy-sell strategy for the overall market. It would also be useful to conduct similar studies for other developing economies at both the overall and sub-index level. This will help determine whether the seeming change in the relationship between the yield curve, domestic economic activity and the stock market in South Africa is unusual, or a more common feature of developing economies.

It will also be useful to examine why the yield curve does not give better market timing signals for South Africa. It is possible that this is because, contrary to what theory and previous studies indicated, changes in the yield gap are no longer a reliable signal of changes in economic activity in South Africa.

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