UNIVERSITY OF CAPE TOWN
FACULTY OF COMMERCE

Predicting the Bull Run: Scientific evidence for turning points of markets

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Submitted by: Jerome Davies (DVSJER007)
Jeromeeddavies@yahoo.com

Supervisor: Dr Thomas Gstraunthaler and Dr Ryan Kruger
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Abstract

This study investigates predictability in financial markets, specifically the South African financial market, proxied by the Johannesburg Stock Exchange ("JSE") All Share Index ("ALSI"). It provides scientific evidence of past research of turning points in markets, focusing on bull markets as evidence suggests that predictability of bull markets leads to superior returns for an asset manager. In addition, this study provides an analysis of macroeconomic variables that can be used for predictability in the South Africa financial market.

We found that certain macroeconomic variables do contain an element of predictability with the yield spread and short term interest rates being the best indicators. In addition we found that predicting the Bull Run in its earliest phase provides superior returns to an asset manager.

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1 Introduction

Since the inception of financial markets, investors have attempted to forecast and predict financial market performance. A global sentiment across financial markets is that markets are driven by the emotions of fear and greed and that these emotions play a significant role in market movements, which led to the development of behavioural finance. Whilst theory often describes markets as rational and efficient, practitioners often believe otherwise and profit on the irrationality and inefficiency of markets.

To practitioners it has never been a question of whether, but rather the practice of how one should predict market performance and thereby time the market. Practitioners, in their attempt to predict financial markets, use various metrics, styles, strategies, and trading techniques to make such predictions, in addition to analysing the past to find future solutions. Academics on the other hand have focused most of their energy on the behaviour and characteristics of financial markets and using their findings to assess predictability.

Significant evidence exists for and against the ability to predict financial markets. Eugene Fama developed the theory of the Efficient Market Hypothesis ("EMH") in the 1960s as his published PHD Thesis. The basic premise of the EMH is that investors cannot outperform the market on a risk adjusted basis using data that is made available publicly. There is evidence for (Paul Samuelson; Paul Cootner, 1964; Fama, 1970) and against (Khan, 1986; Firth, 1976, 1979, and 1980; Dreman and Berry, 1995; etc) the EMH, however this objective of this paper is not to refute or confirm the EMH. What is clear is that attempts to "beat" the market will continue to attract talent and skills as the reward for doing so is significant, regardless of theory and studies supporting or refuting the EMH.

Asset management talent and skills have come under close scrutiny given the global financial crisis of 2008 and 2009, which is on-going, and caused significant changes in financial markets. Firstly risk management has become the order of the day and money managers have become more risk averse given the unease in these markets. Secondly, many a money manager had to close down shop, thus only leaving those that are able to ride the storm abreast, resulting in the winning money managers being those that are not only skilled at stock selection but also those that are best at timing the market.

Investors often believe that asset managers have a crystal ball; they expect analysts, economists and asset managers to have an opinion of the future of the stock market ("market") and therefore asset allocation and stock selection. Many of the "smartest guys in the room" purport to have such knowledge and are therefore constantly engaged in an effort to forecast the market. The trouble with market forecasting is that it is done by "experts" resulting in their efforts being constantly neutralized. Therefore, the market already absorbed the information which these experts use as a basis for their forecast. The reward for being able to forecast the market is substantial and is the reason for the attempts by academics, practitioners, scholars and alike to attempt to predict the market.

Given the malaise in current financial markets money managers will follow more robust and scientific approaches in their decision making. Timing the market requires the ability to not only predict a bull market but also a bear market. In addition stock selection entails an element of market timing as managers need to buy and sell at the right price and at the right time in order to be successful.

What exactly is the Bull Market or Bull Run and why is this focus of this paper? A Bull Market can be simply defined as a period in financial markets characterized by increasing prices (in the stock market), and increasing investor confidence as a result of an expectation of increasing market prices. This definition, while simple, lacks the identification characteristics required to identify a Bull Run. It is for this reason that there are methods based on rules as well as econometric models utilized to identify the Bull Run (Cakmakli and Dijk, 2010). The rules based methods can be time based, i.e.

there is a minimum “duration” for a bull or bear run, or it can be based on percentage changes/fluctuations in the market. The econometric approach is to distinguish between bull and bear markets using mean returns, variances, and volatility. The main difference between the rules based versus the econometric approaches is that the rules based approach is simple and more transparent than the econometric approach, however the rules bases approach require biased settings that can affect the outcome (Cakmakli and Dijk, 2010).

This paper provides an extensive literature review of scientific evidence of previous attempts to predict financial markets, specifically attempts to predict the Bull Run. This question is of particular importance as empirical evidence suggests that the most profitable investor is the one that identifies the bull market earliest. Research, such as that conducted by Maheu and McCurdy (2000) found that the greatest returns are at the beginning of a bull run and that market gains shows diminishing returns at the latter stages of a bull run. The basic premise is that to outperform the market an Investor must enter a bull market as early as possible (Chen, 2008); (Maheu and McCurdy, 2000), in the gains from doing so will be substantial (Sharpe, 1975); (Droms, 1989); (Resnick and Shoesmith, 2002).

Very few studies have been done on bull and bear markets in South Africa, let alone attempts to predict bull and/or bear markets. This paper provides a detailed literature review of past research on the predictability of bull and bear markets (I.e. Turning points in financial markets). Further I will: investigate the extent to which the yield curve and other variables in South Africa predicts bull and bear markets; attempt to provide a consistent definition of a bull market; identify variables, factors and information that can be used to predict the commencement of such a market and returns; establish why it is important to identify a bull market as early as possible; and in brief discuss possible trading strategies than can be implemented if it is possible to predict such a market.

2 Literature review

Grinold and Kahn (2000) emphasize how the art of investing is evolving into the science of investing. The science of investing basically reflects the on-going attempts by asset managers to predict and thereby time the market in order to provide superior returns to their clients. They explain that the evolution has been happening slowly and will continue for some time as new investment managers, equipment with tools such analysis, structure and intuition, enter the market.

Newer asset managers tend to rely on trading strategies that incorporate an element of predictability. They use metrics such as price earnings multiples, dividend yields, price to book multiples and other such measures to gauge the attractiveness of assets in comparison to their peers. In addition they use these metrics as screening tools for portfolio allocation purposes and for further investment research and is therefore evidence of a more scientific approach highlighted by (Grinold and Kahn, 2000).

Grinold and Kahn (2000) explain that financial economics is conducted with much vigour at leading universities, safe from any need to deliver investment returns, and it is therefore that active portfolio management is a mundane consideration for the financial economist. In keeping with the notion that active portfolio management is a mundane consideration, it is this modern theory that has inspired the move away from active management (trying to beat the market) to passive management (trying to match the market). There is significant evidence to suggest trying to beat the market is a dubious task. In accordance with the March 2011 SA ABSA Monitor for Retirements funds, the top 20 Asset manager failed to provide a return significantly in excess of it benchmark and that the really talent investment managers will take most of the excess returns in the form of performance fees. Passive management is increasingly becoming popular; however as long as there is potential for superior returns in excess of the benchmark, there will always be investors willing to participate in active management.

In order to succeed in active management one has to understand what the challenge entails. So what is active management and what does it entail, and how can active portfolio management incorporate predictability into their trading strategies?

Active portfolio management is forecasting and the manager with the best forecasting ability is the one that will be the most successful provided it is able to utilize that information sufficiently (Grinold and Kahn, 2000). The manager that buys low and sells high will be the most profitable and therefore early identification of a change in market cycles will yield significant profits for the active manager.

Asset managers use various trading strategies or rules for making trading decisions. These trading decisions can be executed based on various styles and techniques such as technical analysis and fundamental analysis. Fundamental analysis is the attempt to forecast the future and determine the value of a share in order to identify under or overpricing using economic and company specific information available to the public. Technical analysis, on the other hand, entails the use historical price movements or information in an attempt to forecast or project future price movements.

2.1 Defining the Bull Run

In order to predict a Bull Run, I will first need to understand and define what is indeed meant by a bull run.

Finance literature does not provide a comprehensively accepted definition of bull and bear markets. However, market participants consider a bull market as an extended period in which asset prices rise, accompanied by extreme optimism. This optimism results in greed with investors racing to invest in assets they believe will continue to provide superior returns.

Traustason (2009) defines the commencement of a bull market as “a period when stock returns go from being negative to positive for two consecutive periods”. Whilst these definitions are simple in definition it does not provide us with a robust means to determine the onset of a bull market. Traustason (2009) provides no definition or guidance on what a period entails. In addition by the time two periods have past most of the returns to be made in a bull run would have eluded an investor as most of the return is made at the beginning of a bull run as explained further in the literature review).

These definitions define markets in the 21st century that came to an abrupt halt in 2008 with the well documented banking crisis. The definition is intuitive as it outlines a characteristic of the “herd” mentality so often highlighted in publications. In other words Investors follow a trend with no regard to the fundamentals of underlying assets.

Such simple definitions do not enable us to fully analyse equity markets, it is for this reason that prior research utilized models such as algorithm based: (Pagan and Sossounov, 2003); (Bry and Boschan, 1971); (Maheu and McCurdy, 2000), and duration dependence based: (Pesaran and Timmermann, 1995); (Lunde and Timmermann, 2004) to understand the characteristics of bull and bear markets.
Chauvet and Potter (2000) define a bull and bear market as “periods when prices are either increasing or decreasing for a period of time”. This sounds simple but is based on a statistical approach and can therefore be highly complex.

Lunde and Timmermann (2004) studied the relationship between market variables, such as interest rates, and its impact on stock market variability by using a probability model to determine the termination or commencement of a bull or bear market. They found that the increasing interest rates results in a “higher likelihood of continued declines in stock prices”. The challenge with duration dependence is that there is no scientific evidence to support the duration derived and used in these studies. In addition duration dependence is not functional in the context of emerging markets where growth is more erratic and its cycles more pronounced.

Pagan and Sossounov (2003) used and algorithm to sort data into bull and bear markets. The data used for the purpose of their exercise was monthly data for the US over the period 1835 to 1997. Pagan and Sossounov (2003) basically define bull and bear markets based on aggregate price changes and determines cycles based on a volatility of stock process within a given period. They found, based on these measures, "that bull markets tend to be longer than bear markets and the durations lasted on average 25 months for bull markets and 17 months for bear markets".

The most basic definition of Bull Run is thus a period of increasing asset prices, further characterised by positive and confident investor sentiment, and low market volatility and oscillations in market cycles. The basic premise is that positive investor sentiment will lead to increasing prices as an increased demand with a constant supply results in the same investors chasing limited assets which pushes up the price and ultimately the market. Identifying this phenomenon early can yield significant profits, provided an investor exits the investment timorously and there are various metrics that can be utilised to identify the Bull Run. Bull runs are caused by investor greed and it would be useful if one could have a "greed index". Perhaps this is an area of study for behavioural science which is becoming more and more part of investment analysis.

For the purposes of our analysis I define a bull market as a period of increasing prices by 20% or more over a period of 6 months. In order to perform the study I used the moving average (Per excel data analysis) for 6 months. I then ran a forecast using IBM SPSS for periods reflected as bull markets. Interestingly our analysis did not identify increases or decreases 20% or more over the sample period. I then amended our test to an increase or decrease of 15% and only two points were identified. This is a function of the fact that emerging markets performance can't be categorized as their fundamentals are different. This is evident by the fact that emerging markets still harbour growth opportunities while developed markets are shrinking.

2.2 Predicting the Bull Run

2.2.1 Evidence of stock returns based on identifying bull or bear markets

Significant evidence exists for predictability of stock returns however once those predictive measures become common knowledge it loses its predictive ability (Maheu and McCurdy, 2000). Maheu and McCurdy (2000) use a model that incorporates duration and volatility, and use these measures to label market states as either "high return stable" or "low return volatile states". Intuitively it makes sense that a bear market will be characterized by low returns and high volatility, however this is not always the case in emerging markets. The approach followed by Maheu and McCurdy (2000) sorts' data into bull or bear market states based on whether the market is in a state of "high return stable state or low return volatile state".

Maheu and McCurdy (2000) found that bull markets display high returns coupled with low volatility, but the bear market has a low return and high volatility. In addition they found that "the best market gains come at the start of a bull market" (Maheu and McCurdy, 2000). This is an important observation as it provides evidence of the importance of identifying bull markets as early as possible.

Similarly Chen (2008) used macroeconomic variables such as interest rate spreads, inflation, money market rates and other, to assess whether it provides evidence or signals for predictability of a recession and found the most useful predictors to be macroeconomic variables such as yield spreads. This is an important observation and motivates our use of the yield spread as a predictor. Similar to Maheu and McCurdy (2000), Chen (2008) found that predicting bear markets is easier than predicting stock returns when using macro-economic variables.

Whether or not stock return predictability can be exploited is a topic of contention.

Many studies for and against stock return predictability have been conducted. Pesaran and Timmermann (1995) interrogated evidence on predictability of US stock returns and found that evidence does exist for predictability however the predictive variables changes over time and varies with return volatility.

Furthermore, Pesaran and Timmermann (1995) assumed that investors used public information to select a forecasting model and used this model in to determine a market timing strategy in terms of weighting their portfolios towards shares or bonds. This is in effect what portfolio managers do in practice when doing their stock screening analysis.

When attempting to forecast stock returns investors must determine the key variables they are likely to use. Pesaran and Timmermann (1995) lists variables such as: short term yields, inflation rates and other production measures that show good potential for predictability. The predictability of stock returns is model dependent and that forecasting models should be flexible enough to allow for changes in the underlying process.

For the purpose of our test I define the bull market as increase in market sentiment and asset prices with price increases of 20% over a moving average of 6 months.

2.2.2 Evidence of stock return predictability

Chauvet and Potter (2000) constructed an index to represent stock market fluctuations. They then used this index to build a "leading financial indicator" similar to the one as published by national reserve banks. They incorporated investors' perception (In South Africa we have a business confidence index for this Purpose) in the index and used this index to forecast financial markets. They found that by doing this they were able to determine factors that identified bull and bear market characteristics. In addition, Chauvet and Potter (2000) found that bull markets endured longer that bear markets. This confirms the conclusions of previous studies highlighted in this paper.

Rapacha, Wohar, and Rangvid (2005) conducted their study using macroeconomic variables in 12 industrialized countries. Similarly to other studies the macroeconomic variables used by them were: “interest rates, the term spread, inflation rate, industrial production, money stocks, and unemployment rate”. They found that for each country the macro variables that provided the most robust evidence of predictability were interest rates and the inflation rate, however these were only for short time horizons.

Chen (2008) investigated the predictability of recessions using macroeconomic variables including interest rate spreads, inflation rates, etc and found, in line with (Rapacha, Wohar, and Rangvid, 2005), that the yield curve spreads and inflation rates to be most useful predictors of recessions in the US stock market. In addition, Chen (2008) found that it is easier to predict bear markets using macroeconomic variables.

Candelon, Piplack, and Straetmans (2008) found, in investigated the usefulness of predicting bear markets for market timing strategies, that “term spreads and inflation rates” to provide the best evidence for predictability. In addition they found predictability of bear markets is more pronounced when compared to predictability of stock returns when using macroeconomic variables and do a better job in predicting bear markets when compared to the ability to predict stock returns.

Hjalmarsson (2008) studied the effects of predictability in stocks returns using a global financial database. Their data spanned 40 international markets and spanned 24 developed markets and 16 emerging markets. Hjalmarsson (2008) found, in developed markets, evidence of predictability when using short term interest rates and term spreads. This corroborates evidence from studies such as those from studies conducted by (Rapacha, Wohar, and Rangvid, 2005), (Chen, 2008), (Candelon, Piplack, and Straetmans, 2008), etc.

Maleev and Nikolenko (2010) wrote an article on predicting stock returns on the basis of financial and market variables. The objective of their research was to develop a statistical model that predicts stock returns and generates abnormal returns to investors. The variables selected for their study was: industry relative earnings yield; industry relative cash flow yield; industry relative sales yield; unexpected quarterly earnings; and six month price changes. The selection of the variables was based previous research that have been conducted and modifications of their own. Their results were not unexpected and they found that portfolios with above average industry-relative earnings, cash flows and sales yields, with positive earnings surprises and strong price performance tend to outperform the market. An area for further research would be to consider the reasons for the outperformance, i.e. is it strong management, dominant market share, are there barriers to entry, etc.

Cakmakli and Dijk (2010) found that macroeconomic variables bear useful information for predicting monthly US excess stock returns and volatility over the period 1980 to 2005. They highlight the fact that stock return predictability remains an issue of hot debate, that there is significant research for and against sock return predictability.

Furthermore they highlight the complicated issue that plague research, I.e. That numerous macro-economic variables are available but typically only a small number of variables are considered as possible predictors in a return regression. In addition they highlight the fact that relations between stock returns and individual predictors appear to be highly unstable and that the predictive ability of individual variables strongly fluctuates over time. In order to eliminate or at least minimize the shortfalls mentioned Cakmakli and Dijk (2010) apply a dynamic factor model to jointly handle the issues of model uncertainty, parameter estimation uncertainty and structural instability.

Cakmakli and Dijk (2010) concluded that whether stock returns are predictable remain a grey area, they do find that individual macroeconomic variables do not have predictive ability for returns for prolonged periods of time. The relation between stock returns and individual macroeconomic predictors appears to be subject to relatively frequent structural breaks and therefore when a given macroeconomic variable may appear to be useful for forecasting stock returns over a certain period it might not be that way over a prolonged period. Furthermore they conclude that studying return predictability with a limited number of individual macroeconomic variables over a long time span is unlikely to find positive results. However they do find that there is a level of predictability in volatility.

Various other studies have been conducted on the predictability of stock returns and the results have yield arguments for and against predictability, that if used correctly the predictive information can yield superior returns. Studies such as Avramov and Chordia (2006) conclude that that returns are predictable by the "dividend yield, the term spread, the default spread, and the treasury bill yield". In addition they found that active management outperforms passive management and that momentum and market timing switching strategies do yield superior returns.

The research summarised above all provide evidence of predictability, proving that predictors related to interest rates and inflation being the most dominant. The problem with these predictors are that market participants now attempt to predict these variables so as to predict the movement in share prices, making these variables of little use when actually published depending of course on the closeness of the predictions made by market participants who will re-examine their forecasts if there are significant deviations from their predictions.

What has been highlighted by the literature above is that macro variables do contain an element of predictability and this is mainly captured by variables like the yield spread and short term interest rates. In addition these variables are subject to structural breaks in economic fundamentals and thus only work for a short period of time. Asset managers would therefore have to continuously update their and processes and models in order to remain relevant. This is however considered business as usual for the active asset manager.

2.2.3 Market timing and stock selection

2.2.3.1 Market timing

Sharpe (1975) concludes that active management outperformance can be done by security selection within a given portfolio or asset allocation (Stocks or bonds). This is corroborated by Lam and Li (2004) who defines market timing as "attempts to outperform the market by holding common stocks during bull markets and cash equivalents during bear markets". In addition a further strategy for market timing is the holding of high beta stock, in bull markets, where stock returns with higher betas are assumed to quicken with the momentum of the stock market, and where losses of low beta stocks are expected to be slower than the momentum of the market. This is usually the strategy executed by hedge fund managers who also leverage their portfolios in an attempt to further enhance their returns.

Practitioners swear by the success of such strategies, which is often refuted by academics. The debate continues and significant evidence for and against market timing are presented below. Potentially, one of the most productive forms of the latter strategy is to hold common stocks during bull markets and cash equivalents during bear markets ("market timing").

Sharpe (1975) assessed the potential for superior returns when implementing a market timing strategy and concluded that gains are minimal given the risk of being able to time the market. In addition Sharpe (1975) concluded that unless a manager can consistently time the market, such attempts should be abandoned as in the long run superior returns will be unlikely. Furthermore, even though Sharpe concludes that "attempts to time the market are not likely to produce incremental returns of more than four per cent per year over the long run for a manager whose forecasts are truly prophetic, he does agree that market timing has the advantage of producing returns that are both higher and less volatile. The biggest criticism to Sharpe's study is the fact that by measuring performance only on an annual (year-end to year-end) basis, the model misses appreciable potential for gains from timing (Ulie, Jack, Ambachtsheer, and Sharpe, 1975). In practice "rebalancing takes place on a quarterly basis so money managers are not restricted to the limits in Sharpe's study.

Droms (1989) conducted a study using the methodology of (Sharpe, 1975). Droms (1989) provided evidence that shows that investment managers have been unable to outperform the market using a market timing strategy. Furthermore, Droms (1989) find that in order for market timing to outperform buy and hold strategies predictive accuracy needs to be as follows:

- "70 per cent bull and 80 per cent bear;
- 80 per cent bull and 50 per cent bear;
- 90 per cent bull and 30 per cent bear;
- 100 per cent bull and any bear".

Droms (1989) study provides evidence "that accuracy in forecasting bull markets is relatively more important than accuracy in forecasting bear markets".

Droms (1989) therefore comes to the same conclusion as Sharpe (1975). i.e. That in order to time the market forecasts requires almost impossible but not improbable accuracy. A skill that eludes most managers over the long term horizon. Furthermore, Droms (1989) also concludes that outperformance requires more frequent forecasting but this should be compared to the transaction costs of more frequent forecasting and that the ability to predict a bull market "earliest" is more important than the ability to forecast a bear market.

In summary predicting the Bull Run is more important than predicting a bear market and the asset manager that is able to identify the Bull Run earliest is able to time the market most successfully. As unlikely as market timing ability is, it still exists in practice, this was evident by the market crash of 2008 where certain asset managers were able to transfer their funds out of equities and into money market investments and thereby beating their benchmarks, some call it luck, other call it skill.

2.2.3.2 Stock Selection

Strategies employed by asset managers for stock selection can follow various themes, all which can be considered to be a market timing strategy. Strategies such as momentum and mean reversion can be considered market timing strategies.

Momentum entails the tendency for asset prices to continue as it has in a preceding period. In other words a tendency for asset prices to continue rising (falling) if it is has a history of strong outperformance (underperformance).

There is strong evidence for the momentum effect (Jegadeesh and Titman, 1993, 1999, 2001). According to Jegadeesh and Titman (2001) "the profits from momentum strategies have generated consistently positive returns for at least the last 60 years in the United States including the 1990s". In addition they found momentum profits in most developed markets and argue that the momentum effect "represents perhaps the strongest evidence against the efficient markets hypothesis".

Mean reversion involves the notion that stock prices will revert to its true value, and that market gyrations between high and low are based on market sentiment and that true value is based on the average between highs and lows. Chaudhuri (2003) documents strong evidence of mean reversion of equity prices in seventeen emerging markets. This is important finding as it provides evidence of mean reversion outside of developed markets

2.2.3.3 Where do active portfolios managers make money

Asset management (active portfolio management), can simply be defined as the professional management of various assets, such as: shares; bonds; real estate; and derivatives, on behalf of investors (third parties) whose investment, via a mandate, they are required to meet. This mandate can be restrictive in the type of investments an asset manager is able to invest and requires a given minimum (benchmark) return. In other words taking third party money and investing it in such a way as to yield profits, be it from income or capital gains (Grinold and Kahn, 2000); (Zhao, 2005); (Engström, 2004). But how do active portfolios managers make money?

Active portfolio management refers to the fact that an investor has delegated the management of its portfolio to an asset manager who will have a specific mandate. The mandate might be to outperform a certain benchmark (An index, or some other measure determined by the parties). In order to beat the benchmark an asset manager needs to actively determine how it is going to invest the assets under its management. In this regard an asset manager will follow a certain strategy or style of investing. This strategy can be one of momentum, mean reversion, a value or growth style, and all depends on the asset manager selected. The ultimate goal of the asset manager is to outperform the benchmark (Grinold and Kahn, 2000); (Zhao, 2005); (Engström, 2004).

As all these strategies entail an element of market timing and I can conclude that regardless of the strategy, technique or style of investing the active portfolio manager that is most profitable is the one that times the market best. Whether an asset manager performs fundamental or technical analysis the ultimate goal is to buy low and sell high and in order to do so an asset manager has to select the correct asset at the correct time and taking a view on whether the asset is over or under priced and a specific point in time.

Asset managers make their money by beating the benchmark and receiving performance related fees. The benchmark can reflect a certain portfolio of assets (Indices) or an inflationary related minimum. When the benchmark is an Index a simple buy and hold strategy by an asset manager will not suffice. The assets within an Index will have certain weightings and the asset manager needs to ensure that their portfolio reflects assets that will outperform its peers in the benchmark. The asset manager can outperform the Index in two ways:

1. By increasing or decreasing the weighting of certain shares in its portfolio so as to be different to that of index; and
2. By selecting assets that is expected to outperform its peers, thus investing in assets that are expected to outperform.

Based on the two strategies above it is clear that market timing and predictability is paramount if the asset manager is to outperform its benchmark (Grinold and Kahn, 2000); (Zhao, 2005); (Engström, 2004).

2.3 Why is it important to detect the Bull Run as early as possible

Market participants may benefit from being able to predict the market as this will enable them to determine market timing or stock selection strategies. As discussed earlier in the literature review, predicting the bull run is more important than predicting a bear market (Droms, 1989), further evidence is provided below.

Empirical evidence suggests that the most profitable investor is the one that identifies the bull markets earliest. Maheu and McCurdy (2000) found that the "best market gains come at the start of a bull market". It is therefore best to enter the bull market earliest as well as to exit in a bear market earliest.

The basic premise is that to outperform the market an investor must enter a bull market as early as possible (Chen, 2008); (Maheu and McCurdy, 2000), and the returns from being able to predict turning points in the market are superior to passive investment (Sharpe, 1975); (Droms, 1989); (Resnick and Shoesmith, 2002).

2.4 What indicators appear to work

Various metrics and indicators have been utilized over time, however these metrics change as investors and active portfolio managers become more scientific in their approaches. Metrics such as interest rate has stood the test of time; however as can be seen by the economic crisis of 2008 to 2011, low interest rates do not necessarily fuel economic activity.

Resnick and Shoesmith (2002) found the yield spread between the 10 year T-note and the 3 month T-bill could forecast an economic recession four quarters in advance. This was corroborated by Resnick and Shoesmith (2002) who found that “the yield curve spread holds important information about the probability of a bear stock market”. Khomo and Aziakpono (2006) performed a similar study for the South African market and found that the yield curve can be used to estimate the likelihood of recessions in South Africa. In addition they find that other macro variables do provide some form of predictability, however it is not a better indicator than the yield spread.

The short term interest rate and the term spread are found to be good predictors of stock returns in developed markets (Hjalmarsson, 2008); (Chen, 2008). Cakmakli and Dijk (2010) find that stock returns contain an element of predictability; however they also recognise that individual macroeconomic variables do not have predictive ability for returns for prolonged periods of time. In addition they find that the relation between stock returns and individual macroeconomic predictors are subject to “frequent structural breaks” and therefore when variable appears to possess and element of predictability it will not be so over a prolonged period of time. Furthermore they conclude that studying return predictability with a limited number of individual macroeconomic variables over a long time span is unlikely to find positive results. However they do find that there is a level of predictability in volatility.

Avramov and Chordia (2006) finds evidence of predictability by the dividend yield, the term spread, the default spread and the Treasury bill yield and Traustason (2009) finds that macro variables can in fact be used to predict turning points and his evidence suggests that strategies based on these predictors will beat a buy and hold strategy.

Perhaps an area for further research would be to use the most popular predictors with a metric for behavioural aspects of stock markets. The reason being, that stock markets possess and element of predictability that is subject to structural breaks due to the behavioural aspect of fear and greed of investors. Perhaps the price of gold or a similar safe haven asset can be used for this research.

The yield spread can be defined as the difference between the 10 year government bond and the 3 month Treasury bill. Traditional term structure theories indicate that there are "three empirical observations about yield curves (Khomo and Aziakpono, 2006):

1. Interest rates on bonds of different maturities tend to move together over time;
2. Yield curves usually slope upwards; and
3. When short term interest rates are low, yield curves are more likely to have a steep upward slope, whereas when interest rates are high, yield curves are more likely to be inverted".

Economic theory suggests that investors expect short term interest rates to rise during a bull market (characterised by increased consumption; credit extension; and inflation) and short term interest rates to fall during a recession. This is definitely the case given the mandate of central banks to control inflation and using short term interest rates for inflation targeting.

The results of Zuliu (1993) suggest that the slope of the yield curve serves as a good predictor of future economic growth. In addition the findings indicate that "the spread between long-term and short-term government bonds serves as a good predictor of future economic growth".

Khomo and Aziakpono (2006), Mehl (2006) found some evidence that suggests that the yield curve may still be useful for forecasting purposes. Mehl (2006) conducted a study using a sample of 14 emerging economies and found that the yield curve has information content in almost all countries. Further Mehl (2006), Chen (2008), Resnick and Shoesmith (2002) all provide evidence of macroeconomic variable predictability.

Based on the above evidence I will assess predictable of the ALSI using the yield spread and other macro variable as detailed in 2.6.2.

I will assess the predictability of the ALSI using variables such as the South African Volatility Index ("SAVI"); Money Supply, GDP growth, and the South African Leading Indicator ("LI").

The SAVI can be defined as a measure of volatility in stock markets used to determine market sentiment, colloquially a fear gauge, and was introduced in South Africa in 2007

I use the SAVI based on research done by (Busschau, Cunningham, Gerstner, Gill, and Sims, 2010) ("BCGGS 2010"). BCGGS 2010 found that the SAVI can be used as a significant market timing leading indicator 3 months forth. Based on the fact that the SAVI was only introduced in 2007, I will use the VIX (Chicago Board of Exchange Volatility index) as its proxy as the SAVI is based on the VIX

3 Data

The analysis was conducted on the Johannesburg Stock Exchange ("JSE"), proxied by the JSE All Share Index ("ALSI") on a weekly basis. The data series starts on 1/5/1997 as this is the first date for which yield spread data is available and ends on 22/1/2012. All data is obtained from Thomson Reuters Eikon, Inet and Sanlam Investment Management Decision Support Systems (DSS).

Weekly observations are used because there is a good trade off between precision and data availability. In addition yield curve data is only determined on a weekly basis. The yield spread can be defined as the difference between the 10 year government bond and the 3 month treasury bill. For the purpose of our analysis and given the liquidity constraints of the SA Market we used the spread between the 10 year government bonds 5 year and 2 years yields spreads using the 3 month yield so as to ensure sufficient data availability.

Our model uses graphs, to visually identify possible relationships and correlations between the ALSI and macro-economic variables as discussed. Once the variables with the best fit are visually identified we run a regression model on these variables to assess the relationships.

4 Methodology and empirical results

4.1 Bull and bear markets

In this section we provide results for tests.

Figure 1 plots the 6mthly price index of the ALSI over the period 1/5/97 to 22/1/2012.

Figure1: ALSI price index 1/5/97 to 22/1/2012

In order to assess and identify bull and bear markets I could use a duration dependence model such as that if (Lunde and Timmermann, 2004) or algorithmic method of (Pagan and Sossounov, 2003). I will not use either of these because determining the starting point of a peak or trough in the duration dependence method will be to complex and will skew the results depending on what is chosen as a starting point. In addition, the duration of a phase is determined by the assumptions of the researcher. To follow an algorithmic method will potentially be more applicable however our results will be skewed by the significant economic growth achieved on the ALSI after South Africa's first democratic election in 1994 which fuelled growth from 1996 and came to an abrupt halt in 2008. I will however still test the applicability of identify bull and bear markets using the moving average analysis tool in excel.

I determined the bull and bear markets to be used for our analysis by calculating a 36 week moving average. I considered a 20% increase or decrease over the moving average for the 36 week period as the commencement of a bull or bear market. I used the Microsoft excel data analysis moving average function to do our calculations. Our calculations did not identify any movements of 20% or more. Similarly calculating a price change of 15% over the moving average period did not yield many results. Detailed calculations can be found in the appendices.

Given the lack of results obtained using the moving average as discussed above I decided that in order to conduct the analysis I will utilize business cycle data as published by the reserve back as a proxy for bull and bear markets. Figure 2 shows Business cycles as published by South African Reserve Bank ("SARB") are as follows since 1945.

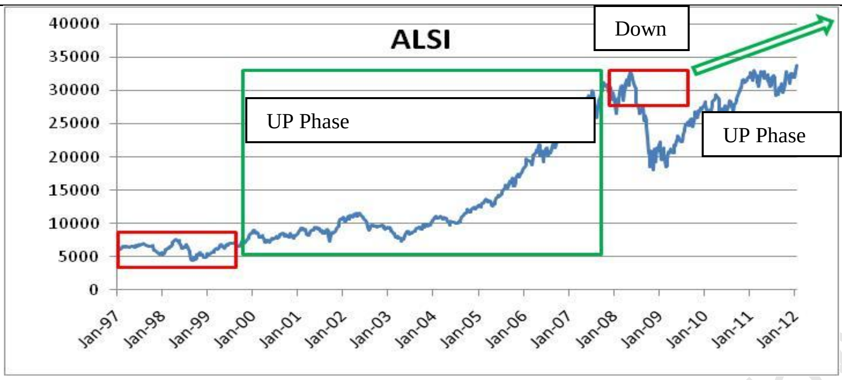
Figure 2: Business cycle phases of South Africa since 1945

Upward Phase		Duration in Months	Downward Phase		Duration in Months
Post war	July 1946	7	August 1946	April 1947	9
May 1947	November 1948	19	December 1948	February 1950	15
March 1950	December 1951	22	January 1952	March 1953	15
April 1953	April 1955	25	May 1955	September 1956	17
October 1956	January 1958	16	February 1958	March 1959	14
April 1959	April 1960	13	May 1960	August 1961	16
September 1961	April 1965	44	May 1965	December 1965	8
January 1966	May 1967	17	June 1967	December 1967	7
January 1968	December 1970	36	January 1971	August 1972	20
September 1972	August 1974	24	September 1974	December 1977	40
January 1978	August 1981	44	September 1981	March 1983	19
April 1983	June 1984	15	July 1984	March 1986	21
April 1986	February 1989	35	March 1989	May 1993	51
June 1993	**November 1996**	**42**	**December 1996**	**August 1999**	**33**
September 1999	**November 2007**	**99**	**December 2007**	**August 2009**	**21**
September 2009					

Source: Reserve bank quarterly bulletin

Below we highlight the various periods and cycles as per the business cycle data.

Figure 3: ALSI reflecting upward and downward trends

<table>
<tr>
<td>


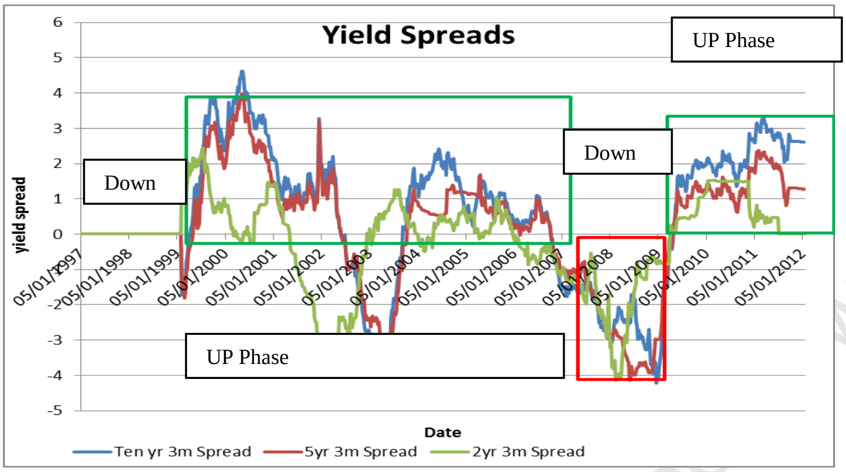
Official records by the SARB[1] indicate the following business cycle phases in SA given our data period.

Downward phases ( ): December 1996 to August 1999 (33mths) and Dec 2007 to Aug 2009 (21mths) whereas the upward phases ( ) are Sept 1999 to Nov 2007 (99mths) and Sept 2009 to current.
</td>
<td>The All Share Index (ALSI) shows a period of significant growth from Jan 1997 to Jan 2008. Where after it is followed by a significant decline from Dec 2007 to Aug 2009 and once again continues upwards, thereafter.</td>
</tr>
</table>

I will perform our analysis using the periods as highlighted above, specifically the periods reflected as upward phases as this papers primary focus is on the Bull Run. Below are the yield spreads 10 year, 5 year and 2 year yield spreads. The yield spread is defined as the difference between government bond (10, 5, and year) and the 3 month Treasury bill.

[1] Quaterly Bulletin March 2012 – S153

Figure 4: Yield spreads reflecting upward and downward business cycles



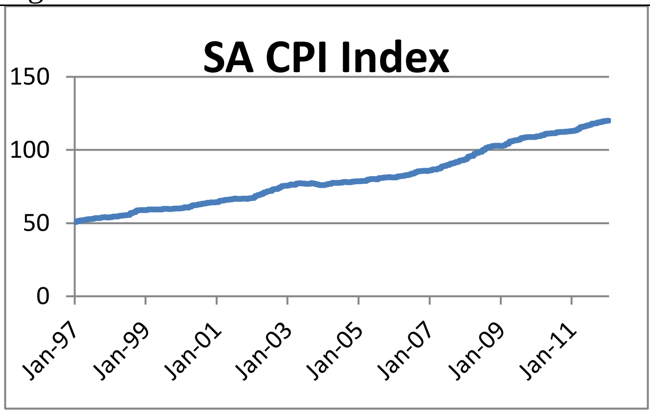
Downward phases ( ): December 1996 to August 1999 (33mths) but no data available before 1999 and Dec 2007 to Aug 2009 (21mths) whereas the upward phases ( ) are Sept 1999 to Nov 2007 (99mths) and Sept 2009 to current.

Yield spreads for the period 1997 to 2012 appears highly volatile. They do appear to be correlated except that the 2 year spread appears to lead the 5 and 10 year spreads.

Visually there appears to be a negative correlation between the ALSI and the yield spread. Data was not available prior to 2000.

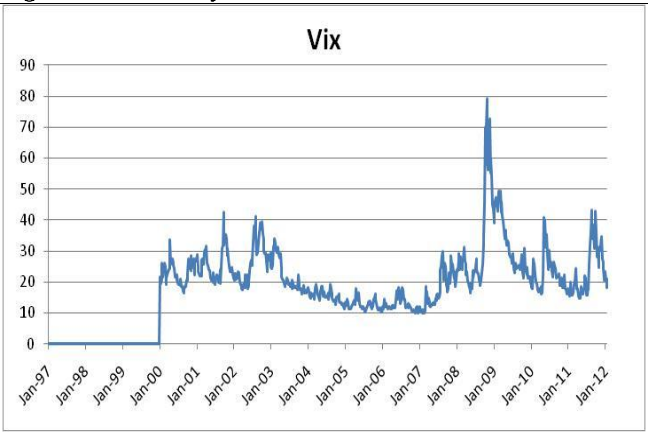
Below is Graph of the CPI Index. We expect there to be a significant correlation between the ALSI and the CPI Index and will therefore not focus our analysis on this relationship.

Figure 5: SA CPI



SA CPI is a function of SARB policy and as such we do not expect this to have a significant impact on financial markets. We do however expect it to have an impact on yield. We will however not test this given the causality in the relationship between the ALSI and CPI.

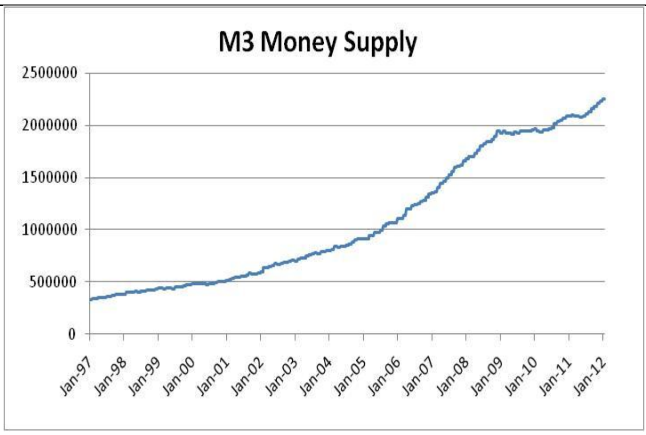
Figure 6: Volatility Index



Various studies have been conducted on whether the VIX (The Chicago Board of Exchange Volatility Index can be used as a significant leading indicator (Busschau, Cunningham, Gerstner, Gill, & Sims, 2010).

We use the VIX as the SAVI ("South African Volatility Index") was only introduced in South Africa in 2007 and given contagion and relationships between economies we consider the VIX to be appropriate. An age old adage is "if the US sneezes, the world catches a cold", which is what has been seen in current economies.

Figure 7: Money Supply



Economic theory suggests that a change in money supply will directly impact consumption and thereby financial markets. Our study will however not focus on this relationship given the causal relationship between financial markets and the money supply.

I used the SPSS expert modeller to determine significant predictors. The variables used in our analysis were the money supply; leading indicator; VIX; 10, 5 and 2 year yield spreads, CPI, and PPI. Our results are discussed below.

SPSS expert modeller was used to determine significant predictors, the results are summarized in the table below with the detailed results in the appendix. The summary below details the significant results and is considered appropriate to draw conclusions on the results and I therefore do not consider an analysis of the detailed results per the appendix necessary.

Table: summary of SPSS expert modeller results

summary of results using SPSS

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
ALSI vs all variables	5	0.522	17.823	18	0.467	0
ALSI vs yield spreads	2	0.302	13.661	18	0.751	0
ALSI vs VIX	1	0.255	15.142	18	0.652	0
ALSI vs Money Supply	1	0.095	10.183	18	0.926	0
ALSI vs CPI	1	0.272	16.714	18	0.543	0

Source: Student calculations using SPSS

Based on the results obtained using SPSS, details of which can be found in appendix I, we determined the following:

- The best results can be obtained when using all variables (excluding PPI and the Five year yield spread) as reflected in the stationary R-squared in the table above. In addition there appears to be a high predictive ability when using all those variables. However the Ljung Box statistic is .467 which means that the model does a reasonable job of explaining the observed observations.

- Surprisingly the yield spreads (Model 2: Appendix I) appear to be a better predictor than the money supply (Model 3: Appendix I) and the CPI (Model 6: Appendix I). Perhaps the reason is that analyst's price in their predictions of CPI and the money supply into financial markets. The result being that small adjustments occur if there are differences between their predictions and actual. In addition CPI and money supply data are released quarterly whereas that of the yield spread occurs weekly.
- The yield spread does however contain a significant element of predictability as reflected in its stationary R-squared of 0.302 (Model 2: Appendix I). In addition, the Ljung-Box statistic is best for the yield spread and indicates a good fit.
- Furthermore, I observed that the money supply has the biggest lag. This is to be expected and in line with economic principles.

5 Conclusion

Based on evidence obtained and provided in the preceding sections it is clear that financial markets do contain a modest amount of predictability in stock returns. That various tools and metrics can be used to predict market cycles and that it is in fact possible to predict the bull run. These metrics however change as markets adapt and become more efficient given permanent shocks to economic fundamentals. It is therefore the asset manager with the most foresight, information, and pioneering research that will be able to predict markets and the bull run in this ever changing world.

We define a bull run as a period of increasing asset prices, further characterised by positive and confident investor sentiment, and low market volatility. While the definition is simple in nature it does provide for adaptability by a user. In addition we provided evidence that the asset manager who is able to predict the onset of a bull run earliest will be the one who is most successful and that asset manager's skills will be in demand as it will be able to provide superior returns to its investors. This will require robust research and investment processes that prevent irrational decisions based on fear and greed.

Our results indicate that the macro variables that were considered do contain an element of predictability, with the yield spread being the most useful predictor. This is in line with practice and the beliefs of South African asset managers. The money supply has a lagged effect which is to be expected given economic fundamentals. We can therefore conclude that scientific evidence exists for predictability of financial markets and that the yield spread is a modest indicator. However no specific evidence exists specifically for the predictability of a bull run and given the importance of being able to predict the Bull Run further research is required. The yield spread should however be used with caution as any shift in market fundamentals can obscure the value of its predictability.

The macro economic variables tested do provide some predictability, however the predictability is weak and not conclusive.

6 Areas for further research

An area for further research would be to consider the reasons for the outperformance, i.e. is it strong management, dominant market share, are there barriers to entry, etc.

In addition research on predictability using the yield curve or other interest rate variables in the South African market should be conducted. Other variables such as foreign currency reserves, foreign exchange rates, should be assessed for predictability of stock market in South Africa. In addition an out of sample analysis should be performed on the returns obtainable when predicting a bull run.

A useful exercise would be to determine a probability model based on the yield spread as a predictor and then use this probability model to forecast the market.

One other area for research is to assess the extent of fundamental and technical analysis within the asset management industry and what metrics are used for screening investments, for making investments decisions and general rules of thumb.

It appears that this volatility is being caused by computer algorithms and further investigation of the impact of algorithm traders should be investigated.

The performance of asset managers net of performance fees versus the ALSI would be a useful area for research as it will give investors insight into whether the decision to outsource its assets to a fund manager is more rewarding than passive investments linked to the ALSI.

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8 APPENDIX I

8.1 Regression Analysis - ALSI vs all variables

Model Description

			Model Type
Model ID	ALSI	Model_1	ARIMA(0,1,0)(0,0,0)

Model Summary

Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile	
					5	10
Stationary R-squared	.522	.	.522	.522	.522	.522
R-squared	.995	.	.995	.995	.995	.995
RMSE	656.391	.	656.391	656.391	656.391	656.391
MAPE	3.435	.	3.435	3.435	3.435	3.435
MaxAPE	14.624	.	14.624	14.624	14.624	14.624
MAE	486.826	.	486.826	486.826	486.826	486.826
MaxAE	2558.499	.	2558.499	2558.499	2558.499	2558.499
Normalized BIC	13.165	.	13.165	13.165	13.165	13.165

Model Fit

Fit Statistic	Percentile				
	25	50	75	90	95
Stationary R-squared	.522	.522	.522	.522	.522
R-squared	.995	.995	.995	.995	.995
RMSE	656.391	656.391	656.391	656.391	656.391
MAPE	3.435	3.435	3.435	3.435	3.435
MaxAPE	14.624	14.624	14.624	14.624	14.624
MAE	486.826	486.826	486.826	486.826	486.826
MaxAE	2558.499	2558.499	2558.499	2558.499	2558.499
Normalized BIC	13.165	13.165	13.165	13.165	13.165

Model Statistics

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
ALSI vs All Variables	5	.522	17.823	18	.467	0

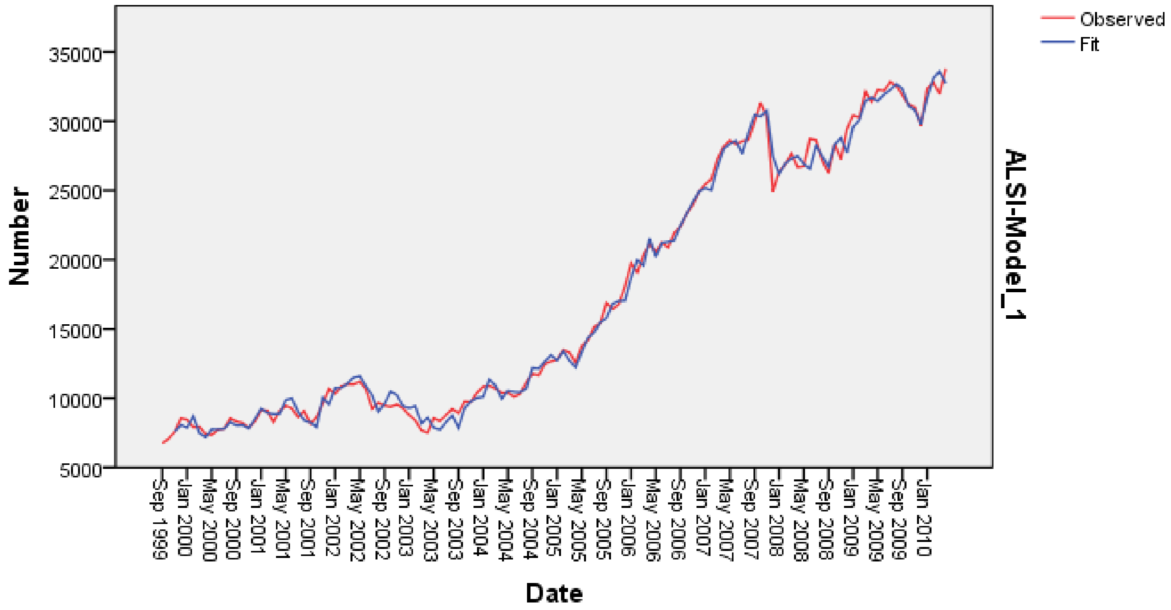
ARIMA Model Parameters

					Estimate	SE
ALSI-Model_1	ALSI	No Transformation	Difference		1	
			Delay		1	
	MoneySupply	No Transformation	Numerator	Lag 0	.021	.004
			Difference		1	
	VIX	No Transformation	Numerator	Lag 0	-112.931	15.197
			Difference		1	
	Ten_3mYield	No Transformation	Numerator	Lag 0	-1317.566	278.867
			Difference		1	
	Five_3mYield	No Transformation	Numerator	Lag 0	729.317	309.749
			Difference		1	
			Delay		1	
	SA_CPI	No Transformation	Numerator	Lag 0	-261.053	82.242
			Difference		1	

ARIMA Model Parameters

					t	Sig.
ALSI-Model_1	ALSI	No Transformation	Difference			
			Delay			
	MoneySupply	No Transformation	Numerator	Lag 0	5.282	.000
			Difference			
	VIX	No Transformation	Numerator	Lag 0	-7.431	.000
			Difference			
	Ten_3mYield	No Transformation	Numerator	Lag 0	-4.725	.000
			Difference			
	Five_3mYield	No Transformation	Numerator	Lag 0	2.355	.020
			Difference			
			Delay			
	SA_CPI	No Transformation	Numerator	Lag 0	-3.174	.002
			Difference			

8.1.1 Regression Analysis Graph - ALSI vs all variables



8.2 Regression Analysis Results: ALSI vs yield spreads

Model Description

			Model Type
Model ID	ALSI	Model_1	ARIMA(0,1,0)(0,0,0)

Model Summary

Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile	
					5	10
Stationary R-squared	.302	.	.302	.302	.302	.302
R-squared	.992	.	.992	.992	.992	.992
RMSE	818.922	.	818.922	818.922	818.922	818.922
MAPE	4.153	.	4.153	4.153	4.153	4.153
MaxAPE	25.351	.	25.351	25.351	25.351	25.351
MAE	653.958	.	653.958	653.958	653.958	653.958
MaxAE	2395.036	.	2395.036	2395.036	2395.036	2395.036
Normalized BIC	13.581	.	13.581	13.581	13.581	13.581

Model Fit

Fit Statistic	Percentile				
	25	50	75	90	95
Stationary R-squared	.302	.302	.302	.302	.302
R-squared	.992	.992	.992	.992	.992
RMSE	818.922	818.922	818.922	818.922	818.922
MAPE	4.153	4.153	4.153	4.153	4.153
MaxAPE	25.351	25.351	25.351	25.351	25.351
MAE	653.958	653.958	653.958	653.958	653.958
MaxAE	2395.036	2395.036	2395.036	2395.036	2395.036
Normalized BIC	13.581	13.581	13.581	13.581	13.581

Model Statistics

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
ALSI-yield spreads	2	.302	13.661	18	.751	0

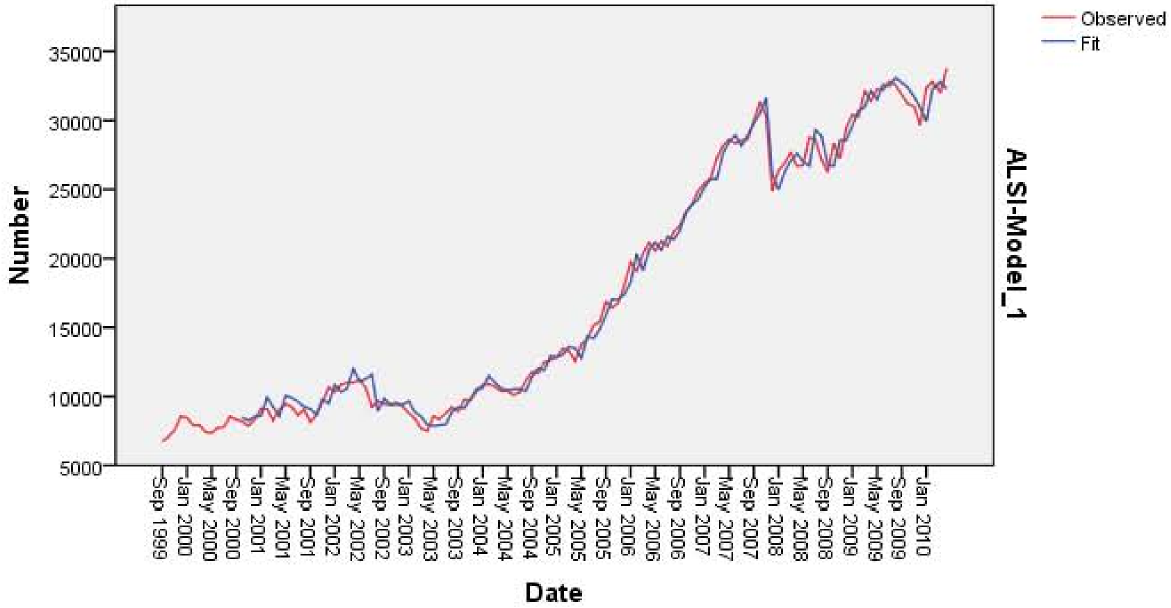
ARIMA Model Parameters

					Estimate	SE
ALSI-Model_1	ALSI	No Transformation	Constant		216.177	76.380
			Difference		1	
	Ten_3mYield	No Transformation	Numerator	Lag 0	-563.632	146.149
			Difference		1	
	Two_3mYield	No Transformation	Numerator	Lag 0	-562.865	191.387
				Lag 12	-404.522	169.761
			Difference		1	

ARIMA Model Parameters

					t	Sig.
ALSI-Model_1	ALSI	No Transformation	Constant		2.830	.006
			Difference			
	Ten_3mYield	No Transformation	Numerator	Lag 0	-3.857	.000
			Difference			
	Two_3mYield	No Transformation	Numerator	Lag 0	-2.941	.004
				Lag 12	-2.383	.019
			Difference			

8.2.1 Regression analysis results graph: ALSI vs yield spreads



8.3 Regression analysis results: ALSI vs Money Supply

Model Description

			Model Type
Model ID	ALSI	Model_1	ARIMA(0,1,0)(0,0,0)

Model Summary

Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile	
					5	10
Stationary R-squared	.095	.	.095	.095	.095	.095
R-squared	.991	.	.991	.991	.991	.991
RMSE	892.402	.	892.402	892.402	892.402	892.402
MAPE	4.198	.	4.198	4.198	4.198	4.198
MaxAPE	12.916	.	12.916	12.916	12.916	12.916
MAE	667.398	.	667.398	667.398	667.398	667.398
MaxAE	2931.350	.	2931.350	2931.350	2931.350	2931.350
Normalized BIC	13.665	.	13.665	13.665	13.665	13.665

Model Fit

Fit Statistic	Percentile				
	25	50	75	90	95
Stationary R-squared	.095	.095	.095	.095	.095
R-squared	.991	.991	.991	.991	.991
RMSE	892.402	892.402	892.402	892.402	892.402
MAPE	4.198	4.198	4.198	4.198	4.198
MaxAPE	12.916	12.916	12.916	12.916	12.916
MAE	667.398	667.398	667.398	667.398	667.398
MaxAE	2931.350	2931.350	2931.350	2931.350	2931.350
Normalized BIC	13.665	13.665	13.665	13.665	13.665

Model Statistics

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
ALSI-Money supply	1	.095	10.183	18	.926	0

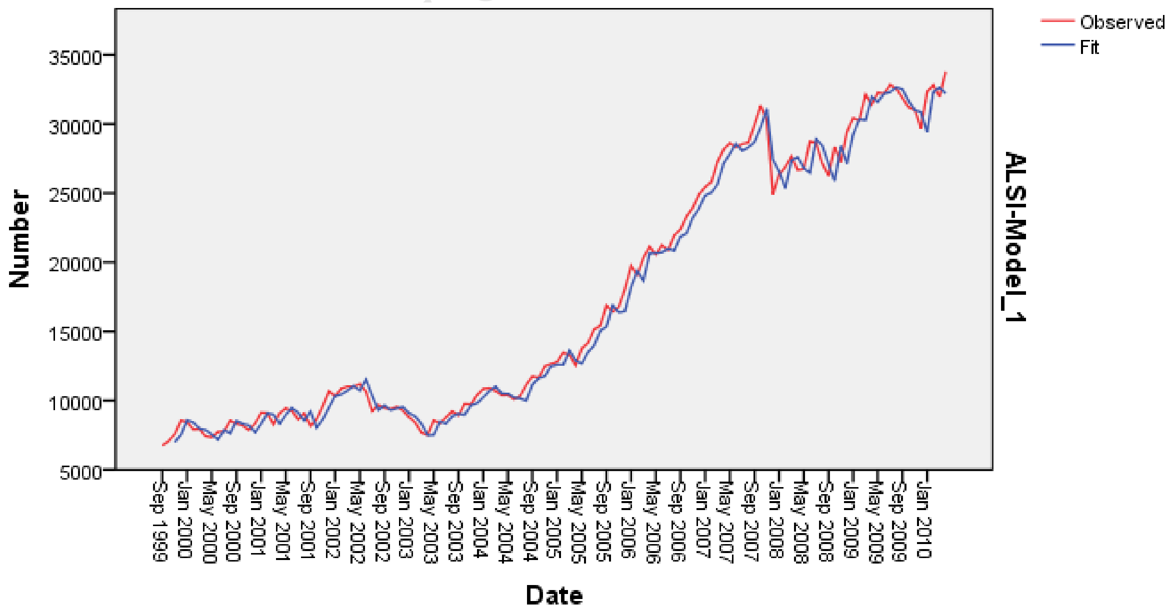
ARIMA Model Parameters

					Estimate	SE
ALSI-Model_1	ALSI	No Transformation	Difference		1	
			Numerator	Lag 0	-.010	.003
	MoneySupply	No Transformation	Difference		1	
			Denominator	Lag 1	-.588	.147

ARIMA Model Parameters

					t	Sig.
ALSI-Model_1	ALSI	No Transformation	Difference			
			Numerator	Lag 0	-4.077	.000
	MoneySupply	No Transformation	Difference			
			Denominator	Lag 1	-3.995	.000

8.3.1 Regression analysis graph: ALSI vs Money Supply



8.4 Regression analysis results: ALSI vs Leading Indicator

Model Description

			Model Type
Model ID	ALSI	Model_1	ARIMA(0,1,0)(0,0,0)

Model Summary

Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile	
					5	10
Stationary R-squared	.227	.	.227	.227	.227	.227
R-squared	.992	.	.992	.992	.992	.992
RMSE	818.542	.	818.542	818.542	818.542	818.542
MAPE	3.893	.	3.893	3.893	3.893	3.893
MaxAPE	15.558	.	15.558	15.558	15.558	15.558
MAE	620.563	.	620.563	620.563	620.563	620.563
MaxAE	2550.552	.	2550.552	2550.552	2550.552	2550.552
Normalized BIC	13.453	.	13.453	13.453	13.453	13.453

Model Fit

Fit Statistic	Percentile				
	25	50	75	90	95
Stationary R-squared	.227	.227	.227	.227	.227
R-squared	.992	.992	.992	.992	.992
RMSE	818.542	818.542	818.542	818.542	818.542
MAPE	3.893	3.893	3.893	3.893	3.893
MaxAPE	15.558	15.558	15.558	15.558	15.558
MAE	620.563	620.563	620.563	620.563	620.563
MaxAE	2550.552	2550.552	2550.552	2550.552	2550.552
Normalized BIC	13.453	13.453	13.453	13.453	13.453

Model Statistics

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
ALSI-Leading indicator	1	.227	14.119	18	.721	0

ARIMA Model Parameters

					Estimate
ALSI-Model_1	ALSI	No Transformation	Difference		1
	SA_LeadingIndicator	No Transformation	Numerator	Lag 0	309.470
			Difference		1

ARIMA Model Parameters

					SE
ALSI-Model_1	ALSI	No Transformation	Difference		
	SA_LeadingIndicator	No Transformation	Numerator	Lag 0	45.854
			Difference		

ARIMA Model Parameters

					t
ALSI-Model_1	ALSI	No Transformation	Difference		
	SA_LeadingIndicator	No Transformation	Numerator	Lag 0	6.749
			Difference		

ARIMA Model Parameters

					Sig.
ALSI-Model_1	ALSI	No Transformation	Difference		
	SA_LeadingIndicator	No Transformation	Numerator	Lag 0	.000
			Difference		

8.4.1 Regression analysis graph: ALSI vs Leading Indicator

8.5 Regression analysis results: ALSI vs VIX

Model Description

			Model Type
Model ID	ALSI	Model_1	ARIMA(0,1,0)(0,0,0)

Model Summary

Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile	
					5	10
Stationary R-squared	.255	.	.255	.255	.255	.255
R-squared	.992	.	.992	.992	.992	.992
RMSE	806.434	.	806.434	806.434	806.434	806.434
MAPE	3.677	.	3.677	3.677	3.677	3.677
MaxAPE	21.176	.	21.176	21.176	21.176	21.176
MAE	548.428	.	548.428	548.428	548.428	548.428
MaxAE	5275.161	.	5275.161	5275.161	5275.161	5275.161
Normalized BIC	13.462	.	13.462	13.462	13.462	13.462

Model Fit

Fit Statistic	Percentile				
	25	50	75	90	95
Stationary R-squared	.255	.255	.255	.255	.255
R-squared	.992	.992	.992	.992	.992
RMSE	806.434	806.434	806.434	806.434	806.434
MAPE	3.677	3.677	3.677	3.677	3.677
MaxAPE	21.176	21.176	21.176	21.176	21.176
MAE	548.428	548.428	548.428	548.428	548.428
MaxAE	5275.161	5275.161	5275.161	5275.161	5275.161
Normalized BIC	13.462	13.462	13.462	13.462	13.462

Model Statistics

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
ALSI-VIX	1	.255	15.142	18	.652	0

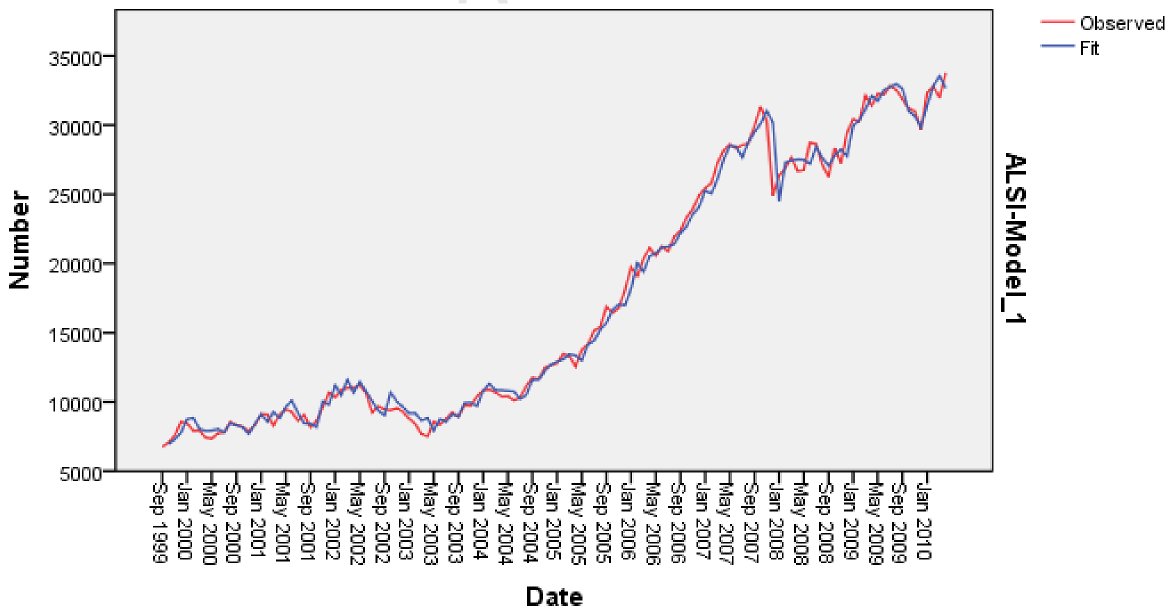
ARIMA Model Parameters

					Estimate	SE	t
ALSI-Model_1	ALSI	No Transformation	Constant		207.640	71.564	2.901
			Difference		1		
	VIX	No Transformation	Numerator	Lag 0	-120.230	18.358	-6.549
			Difference		1		

ARIMA Model Parameters

					Sig.
ALSI-Model_1	ALSI	No Transformation	Constant		.004
			Difference		
	VIX	No Transformation	Numerator	Lag 0	.000
			Difference		

8.5.1 Regression analysis results: ALSI vs VIX



8.6 Regression analysis results: ALSI vs CPI

Model Description

			Model Type
Model ID	ALSI	Model_1	ARIMA(0,1,0)(0,0,0)

Model Summary

Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile	
					5	10
Stationary R-squared	.272	.	.272	.272	.272	.272
R-squared	.992	.	.992	.992	.992	.992
RMSE	797.583	.	797.583	797.583	797.583	797.583
MAPE	4.022	.	4.022	4.022	4.022	4.022
MaxAPE	15.372	.	15.372	15.372	15.372	15.372
MAE	616.714	.	616.714	616.714	616.714	616.714
MaxAE	2502.521	.	2502.521	2502.521	2502.521	2502.521
Normalized BIC	13.439	.	13.439	13.439	13.439	13.439

Model Fit

Fit Statistic	Percentile				
	25	50	75	90	95
Stationary R-squared	.272	.272	.272	.272	.272
R-squared	.992	.992	.992	.992	.992
RMSE	797.583	797.583	797.583	797.583	797.583
MAPE	4.022	4.022	4.022	4.022	4.022
MaxAPE	15.372	15.372	15.372	15.372	15.372
MAE	616.714	616.714	616.714	616.714	616.714
MaxAE	2502.521	2502.521	2502.521	2502.521	2502.521
Normalized BIC	13.439	13.439	13.439	13.439	13.439

Model Statistics

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
ALSI-CPI	1	.272	16.714	18	.543	0

ARIMA Model Parameters

					Estimate	SE
ALSI-Model_1	ALSI	No Transformation	Constant		376.202	74.707
			Difference		1	
	SA_CPI	No Transformation	Numerator	Lag 0	-340.639	49.879
			Difference		1	

ARIMA Model Parameters

					t	Sig.
ALSI-Model_1	ALSI	No Transformation	Constant		5.036	.000
			Difference			
	SA_CPI	No Transformation	Numerator	Lag 0	-6.829	.000
			Difference			

8.6.1 Regression analysis graph: ALSI vs CPI