Gordon Institute of Business Science
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Predictability of equity premium in South Africa using financial and macroeconomic indicators

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ABSTRACT

The equity premium represents the additional rate of return, in excess of the risk-free rate, required by investors for holding equity. The equity premium is one of the most important numbers in modern day finance and economics. Despite its importance, it has been challenging to predict. The purpose of the present study was to assess the predictability of the equity premium in South Africa. The literature review identified numerous factors that impact the equity premium. The relationship between various financial and macroeconomic indicators and the equity premium was assessed. Individually, eight of the fourteen variables tested demonstrated a statistically significant association with the equity premium. Regression models that condition on a large number of independent variables were assessed in terms of their in-sample significance and relative out-of-sample performance. The results found that equity premium is predictable when utilising penalised regressions. The introduction of statistical constraints improved model performance. The significance of the variance explained by the models indicated that they have the potential to be beneficial to stakeholders.

Keywords: equity premium, financial indicators, macroeconomic indicators, predictability, regression.

DECLARATION

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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GLOSSARY

ADF	Augmented Dickey-Fuller
ALSI	Johannesburg stock exchange All Share Index
Alteryx	Alteryx Designer x64
CAPM	Capital asset pricing model
CPI	Consumer price index
EP	Equity premium
FTSE100	Financial Times Stock Exchange 100 index
GDP	Gross domestic product
GIBS	Gordon institute of business science
JSE	Johannesburg stock exchange
JSE Top 40	Johannesburg stock exchange top 40 index
KS	Kitchen sink
Lasso	Least absolute shrinkage and selection operator
MSCI	Morgan Stanley Capital International
MSE	Mean square error
R^2	Coefficient of determination
S&P500	Standard and Poor's 500 index
SPSS	IBM SPSS v.25 Statistics
t-stat	*t*-statistic
US	United States of America
VIF	Variance inflation factor

1. DEFINITION OF PROBLEM AND PURPOSE

This research aims to determine whether the equity premium (EP) is predictable in-sample and out-of-sample based on underlying financial and macroeconomic indicators. The framework used for prediction is a linear regression model that conditions on a large number of financial and macroeconomic indicators subject to the imposition of statistical and economic constraints. This chapter will define the problem and consider the importance of being able to accurately predict the EP. The chapter will also set out the purpose and objectives of the research.

1.1. Research problem definition

The EP represents the added rate of return required by investors to reward them for the additional risk that they incur in comparison to holding a “risk-free” asset (Voss, 2011). This is often thought of as one of the most critical numbers in modern finance and economics (Siegel, 2017). Unfortunately, however, the exact amount that an investor can expect to return is unknown (Cornell, 2016).

The average annual return for shares on the Johannesburg Stock Exchange (JSE) for the period 1900 to 2010 was 14.7% with an average EP of 8.5%, indicating that in South Africa, there has been a significant reward available to investors who are willing to bear the additional risk (Firer, Ross, Westerfield & Jordan, 2012). The EP assumes that there is a trade-off between the reward that can be generated and the risk associated with holding an asset. Mehra and Prescott (1985) demonstrated that, based on historical returns in the United States (US), there was an atypical excess return generated by the share market in contrast to the bond yields over the same period. This EP has been a puzzle amongst financial academics due to the fact that the additional returns cannot be explained by the investors’ risk aversion. In South Africa, the EP returned has been equally puzzling, especially considering the turbulent economic conditions experienced by investors (Hassan & van Biljon, 2010). The historical EP has been too significant in relation to the relative risk taken on by investors and it is therefore expected to be lower in future (Firer et al., 2012). The forward-looking EP is of significance and it is therefore important to determine whether an accurate prediction of EP is possible. However, in practice, the estimation of the EP is surprisingly chaotic (Damodaran, 2018).

1.2. Business rationale for the research

The ability to predict the EP is critically important in determining the optimal allocation of assets (Baltas & Karyampas, 2018). The allocation of assets is fundamentally dependent on the relationship between the risk of holding an asset and the return that can be generated.

The EP is often used as a critical assumption in the determination of hurdle rates in the assessment of capital projects (Graham & Harvey, 2018). It is also utilised as a key component of the widely used Capital Asset Pricing Model (CAPM), which considers the relationship that exists between the expected share returns and systematic risk, and provides the ability to determine expected asset returns (Graham & Harvey, 2018). An adequate determination of the amount is therefore critical to ensure better decision making.

The EP is also utilised by financial economists as a key input to models that test the pricing of assets and in those that measure the state of the macroeconomy (Avdis & Wachter, 2017). An assessment of the future state of the economy would therefore require an accurate prediction of the EP.

Research suggests that in determining the future expectations of share movements, a large number of investors believe that the share prices will continue to move in line with their past performance and that investors' expectations are extrapolative (Greenwood & Shleifer, 2014). The ability to more accurately estimate the EP therefore has important implications for analysts, economists and investors.

1.3. Academic rationale for the research

Lettau and Ludvigson (2001) concluded that share returns in excess of the Treasury Bill rate can be predicted when the impact of a number of financial variables, such as earnings price ratios, dividend price ratios and dividend earnings ratios are taken into consideration. This built upon the previous research that indicated that such financial indicators have predictive power in determining the EP over long-term time horizons (Campbell & Shiller, 1988; Fama & French, 1988; Flood, Hodrick & Kaplan, 1986; Hodrick, 1992; Lamont, 1998; Shiller, Fischer &

Friedman, 1984). A review of the literature from that time would leave one to conclude that the EP is predictable.

Welch and Goyal (2008) performed a comprehensive re-examination of the performance of models aimed at predicting the EP. They systematically investigated the in-sample and out-of-sample performance of linear regressions that conditioned on economic and financial indicators. They concluded that the majority of models were, at best, unstable and suggest that "*the profession has yet to find some variable that has meaningful and robust empirical EP forecasting power*" (Welch & Goyal, 2008, p. 1505).

Indeed, a review of the recent literature, would lead one to conclude that there has been a methodological advance with newer models addressing the instability of the earlier work. The work performed and findings can be summarised as follows:

- Baetje and Menkhoff (2016) – in order to predict EP in the US, economic and technical indicators were used and it was found that the technical indicators are capable of delivering economic value that remains consistent in the out-of-sample period.
- Kolev and Karapandza (2017) – utilising 21 predictors it was demonstrated that there is a benefit that could be obtained by investors if they were to utilise out-of-sample forecasts of EP, based on the so-called traditional predictors.
- Li and Tsiakas (2017) – using predictive regressions with statistical and economic constraints, they found that EP can be predicted out-of-sample and delivered a return of about 2.7% per annum over the benchmark in the US.
- Meligkotsidou, Panopoulou, Vrontos and Vrontos (2019) – using a quantile predictive approach by combining financial and macroeconomic indicators through time-varying weighting schemes, strong evidence was provided to support the fact that EP is predictable out-of-sample based on individual financial and macroeconomic variables.
- Neely, Rapach, Tu and Zhou (2014) – the statistical significance of macroeconomic and technical indicators in estimating the EP in the US was

assessed. The paper found that technical indicators display economically and statistically significant results, both out-of-sample and in-sample. In addition, by combining the information with macroeconomic variables, the results were improved.

- Pettenuzzo, Timmermann and Valkanov (2014) – by integrating a measure of time-varying volatility, they concluded that economic constraints are capable of methodically reducing the inherent uncertainty in the regression models' parameters. This contributed to an increase in the economic and statistical measures when assessing the performance in the out-of-sample period.

- Silva (2018) – the study utilised industry indices to forecast EP and concluded that it is predictable out-of-sample, with previously high performing industries providing better results.

- Stivers (2018) – using disaggregated portfolio returns with a partial least squares regression the author found positive out-of-sample performance and it was concluded that a shareholder would be willing to forego a proportion of their invested capital in order to benefit from the information.

A review demonstrates that the academic literature utilises either financial and macroeconomic data or technical indicators as the variables in predicting the EP. All the articles attempted to forecast the US EP and there is a relative dearth of work in emerging markets. However, the recent literature consistently found evidence to suggest that EP is predictable out-of-sample. Considering the significance of the measure, it is important to assess whether the frameworks developed have value in a context other than the US.

In South Africa, an assessment of the out-of-sample predictability was performed by evaluating various methods of prediction that were based on a large number of variables (Gupta, Modise & Uwilingiye, 2016). In particular, Bayesian regressions represented the most stable and provided relatively good out-of-sample performance (Gupta et al., 2016).

In order for a forecast model to have appropriate practical application, it is critical that it is able to deliver accurate and consistent results in out-of-sample testing. It is therefore important to assess the models that have demonstrated out-of-sample predictive performance.

1.4. Research motivation

Current estimates show that emerging markets are anticipated to return between 4% and 4.5% over Treasury Bill rates, while developed markets are expected to only offer a premium of around 3.5% (Johnson, 2019). In part, this is based on the relative risk that is perceived to exist in holding emerging market assets.

In South Africa, the JSE has underperformed expectations during the last five years, with the JSE Top 40 Index and All Share Index having remained relatively flat, with a capital return of only 2.4% (based on an opening index price of 41,482 and a closing index price of 46,726; data obtained from the Thompson Reuters Eikon database). Investments in local liquid instruments have outperformed equity investments over the same period (Lamprecht, 2019). The relatively low returns have been attributed to the difficult social, economic and governance situation in South Africa as a result of the political turmoil under the former South African President (Sguazzin, 2019). There is an expectation that this will turn around if the country's economic situation can stabilise, however this remains uncertain.

Typically, investors use extrapolative techniques, taking into account their expectations of the future economic environment, to develop outlooks of future EP (Greenwood & Shleifer, 2014). This results in an increased uncertainty regarding an appropriate estimate of the EP for South Africa. Considering the state of the share market over the last five years, equity investors would have been well advised to consider a higher weighting of cash in their portfolios. Incorrect assumptions regarding the EP can result in suboptimal asset allocation (Chen, 2016).

The South African economy experienced technical recessions in the first two quarters of 2018, with the overall economic growth for 2018 returning a real annual growth rate of 0.8% (Statistics South Africa, 2019). Inaccurate assumptions regarding the EP would dissuade persons from investing in capital projects due to an inaccurate calculation of alternative cost of equity (Damodaran, 2018). This, at a time when the South African economy is desperate for investment to stimulate economic growth.

It is against this backdrop that one can understand the importance of being able to accurately assess the EP. If the EP is predictable out-of-sample, it would create greater certainty and enable better decision making. The research is therefore motivated by the question, is the EP predictable in South Africa, as the current prevailing research would seem to suggest.

1.5. Research purpose and objectives

The purpose of the research is to assess the predictability of EP in South Africa. The intention of the study can be considered in two parts. The first is to assess the in-sample performance of EP prediction models. The second is to assess whether the model that develops the best in-sample performance is able to deliver out-of-sample performance. The following are the research objectives in support of this purpose:

1. Assess the relationship between the EP and individual financial and macroeconomic indicators utilising a standard univariate predictive regression (Wang, Pan, Liu & Wu, 2019).

2. Following the approach adopted by Li and Tsiakas (2017), determine whether EP is predictable in-sample by applying a kitchen sink (KS) regression that utilises a large number of variables. In addition, assess whether the introduction of statistical limitations improves the forecast accuracy.

3. Assess the out-of-sample performance of regression models that incorporate economic and statistical constraints to ascertain whether they are able to consistently deliver superior forecasts relative to a benchmark (Li & Tsiakas, 2017; Meligkotsidou et al., 2019; Wang et al., 2019).

The assessment of the significance of the relationship between the financial and macroeconomic predictors will enable an evaluation of the relationship that exists between each indicator and equity returns on the JSE. This will allow managers to gain a greater understanding of the expected response of the equity market in relation to movements in financial and economic fundamentals, which will result in more informed decision making.

By applying statistical and economic constraints, the researcher aims to add to the findings of Gupta et al. (2016) and Li and Tsiakas (2017) who found evidence that penalised regressions that condition on a large set of fundamentals provide good out-of-sample performance. This will contribute to the current body of knowledge in two ways. Firstly, it will consider the credibility of the model adopted by Li and Tsiakas (2017) in financial markets other than the US, which in this case is South Africa. Secondly, it will add to the work of Gupta et al. (2016), by assessing an additional regression models and by introducing constraints that are based on prevailing economic literature.

The ability to accurately forecast the EP out-of-sample has important implications for both asset allocation and decision making in relation to capital projects. Increased certainty will result in more informed decision making. An accurate forward-looking assessment of the EP has important implications for testing the efficiency of the market (Neely et al., 2014).

1.6. Summary of chapter

The objective of the chapter was to define the research problem and outline the purpose of the research. The identified problem is the ability to accurately predict the EP given that, in the past, the EP has been too significant in relation to the risk undertaken by investors. The business rationale for the research highlighted the relevant business importance of the EP and how the ability to more accurately predict the EP can enable greater management decision making. The academic rationale demonstrated that EP is predictable out-of-sample. However, these frameworks need to be assessed in contexts other than the US.

The chapter considered the motivation for the research, which can be summarised as the importance of enabling better asset allocation at a time where EP in South Africa has severely underperformed relative to the past. The chapter ended with the researcher outlining the research purpose and objectives, which is to assess the predictability of EP in South Africa.

2. LITERATURE REVIEW

2.1. Introduction

The purpose of the literature review was to analyse the existing literature relating to equity premium (EP). The chapter begins with an explanation of EP and its importance. The historical EP in South Africa will then be discussed to obtain an understanding of the geographic context of the research. The aspects that influence the EP will then be considered. Thereafter the various methods of estimating EP will be considered, specifically outlining the financial and macroeconomic indicators utilised in predicting EP. The chapter will end with a consideration of forecasting methods and the relevance of statistical and economic constraints in predicting EP.

2.2. Equity premium and its importance

The EP is the expected return on equities less a suitable risk-free rate (Avdis & Wachter, 2017). The EP represents the additional return required by an investor as a reward for accepting the additional risk inherent in an asset or portfolio of assets (Firer et al., 2012). The EP is a measure of the underlying assumptions that an investor has regarding the risk that is apparent in the economy in which the asset is located (Damodaran, 2018). The relative magnitude of the EP required by an investor is dependent upon the systematic risk of the investment (Firer et al., 2012).

The EP is a crucial measure of the interplay between the risk and return of investments (Avdis & Wachter, 2017). Rational investors are risk averse and therefore, if investors anticipate higher risk associated with the future cash flows of an asset, they will be willing to pay less for that asset (Damodaran, 2018). It is noteworthy to mention that the EP provides a market estimate of the amount that an investor would require in addition to the risk-free rate (Ibbotson, 2016). It is therefore useful as an input in various financial and economic models and forecasts. Corporate finance analyses and valuation techniques frequently make use of EP as it represents an important factor in the determination of the cost of equity (Damodaran, 2018).

The EP is a key input into the CAPM (Barberis, Greenwood, Jin & Shleifer, 2015). A survey of listed South African companies found that 71.4% of them utilised the CAPM in order to determine the cost of equity (Correia & Cramer, 2008). The EP however remains the single most debated measure utilised in the CAPM formula (PwC, 2017).

2.3. The security market line

The amount of systematic risk inherent in an asset determines the premium that an investor will receive for bearing that additional risk (Rozeff, 1984). The systematic risk contained in an asset or portfolio of assets is signified by Beta (Acharya, Pedersen, Philippon & Richardson, 2017). A risk-free asset would have no systematic risk, a beta of zero. As the risk of holding an asset increases, the relative return would also have to increase (Acharya et al., 2017). If not, investors would simply be attracted to the higher reward for less risk. This ratio therefore must be the same for all assets in the market (Firer et al., 2012). If all shares in a portfolio were plotted on a graph, with axes of beta and return on asset, the resultant straight line represents the security market line. The gradient of the security market line signifies the EP (Rozeff, 1984).

2.4. The equity premium puzzle

Mehra and Prescott (1985) demonstrated that, based on historical returns in the US, there was an atypical excess return generated by the share market in contrast to the bond yields over the same period. They argued that this return was simply too significant in relation to the risk appetite that investors were expected to possess (Mehra & Prescott, 1985). Similarly, in South Africa, Hassan and van Biljon (2010) confirmed that the so-called EP puzzle that had been documented in developed countries was just as relevant in South Africa.

Myopic loss aversion has been considered as one of the possible explanations for the relatively high equity returns that have been realised in the past (Benartzi & Thaler, 1995). The theory suggests that the combination of investors' inherent aversion to accept losses and frequent portfolio evaluation is an explanation for the EP puzzle (Benartzi & Thaler, 1995). Costa (2018) analysed the EP in 20 developing countries and found that there is partial support for the idea that myopic loss aversion theory explains the EP puzzle. The fundamental underlying assumption of the research centred around the fact that there exists an inverse association between the rate of inflation and the probability of nominal losses and the frequency of the evaluation of a given portfolio (Costa, 2018). Importantly, the research concluded that, in developing countries, inflation has the potential to explain the EP, even if, individually, it is only capable of accounting for a small part of the variation (Costa, 2018). Inflation is an important determinant and should be considered when attempting to forecast EP, however, one would also need to account for the effects of other variables that impact EP. The other variables which impact EP are discussed in greater detail below.

Based on historically documented observations of the EP, it is apparent that the returns that have been generated are in excess of those that can reasonably be explained by utilising traditional utility models for wealth (Damodaran, 2018). This emphasises the problematic use of estimates of the EP based on historically observed data as it can conceivably result in the overestimation of EP.

2.5. The equity premium in South Africa

The South African equity market is the largest in Africa and has a market capitalisation that ranks it within the top 20 globally (JSE, 2019a). The South African economy is highly capitalised and has a highly liquid bond market (Hassan & van Biljon, 2010). Therefore, one of the relative advantages of assessing the EP in the South African market is access to and availability of information.

The estimated average annual EP realised over a long-term time horizon in South Africa was estimated at between 5% and 9%, dependent on the chosen risk-free rate (Hassan & van Biljon, 2010). This is a significant return realised by equity investors when one considers the highly volatile conditions that the country experienced over the same time period (Hassan & van Biljon, 2010).

Global equity markets are increasingly interconnected, demonstrating increased financial turbulence through increased price volatility (Baele & Inghelbrecht, 2010). Heymans and da Camara (2013) found evidence that the JSE All Share Index is impacted by contagion in other countries undergoing crisis, confirming that

European, Asian and American equity markets impact share returns in South Africa. This supported the findings of Samouilhan (2006) who found evidence to suggest that there is a strong association between share returns in South Africa and foreign equity markets. The EP in South Africa would therefore be impacted by movements in foreign equity markets.

2.6. The risk-free rate

The choice of the risk-free rate is a major consideration in assessing historical EP (Damodaran, 2018). The Treasury Bill is widely regarded as an appropriate measure of the risk-free rate. However, in South Africa, the Treasury Bill was not a liquid instrument until relatively recently and as a result, Firer and McLeod (1999) suggested the use of the Money Market Index as a measure of the risk-free rate in South Africa. This is especially important as a lack of supply of a liquid instrument can cause a temporary surge in demand, due to various requirements compelling the holding of such assets (Firer & McLeod, 1999). These economic conditions cause spikes in the interest rates which result in a distortion of the rate (Firer & McLeod, 1999). In examining the historical EP, it may therefore be appropriate to utilise the Money Market Index as a measure of the risk-free rate.

A survey conducted by PwC (2017) found that the R186 South African bond was deemed to be a yardstick for the risk-free rate amongst financial analysts and corporate financiers. The R186 bond had a 10-year maturity as at the date of the survey. The most popular method of determining a risk-free rate was to use 10-year bonds yields derived from the yield curve (PwC, 2017).

2.7. The determinants of equity premium

There are numerous factors which influence the EP. The following offers a discussion of those factors.

Risk aversion

The EP changes in response to investors' perception of risk. As investors grow older, their appetite for risk decreases and this would result in an increase in the EP (Bakshi & Chen, 1994). From a market perspective, as the mean age of the investors increases, the EP would also increase (Liu & Spiegel, 2011). In South Africa, investors' risk aversion is heightened as a result of seasonal depression experienced during winter when temperatures and daylight hours decrease (Apergis & Gupta, 2017). The result is that EP could be higher in years with less adverse weather conditions. Investors' risk perception is heightened in instances where they have previously experienced, either financially or emotionally, the impacts of stock market crashes or similar negative events (Guiso, Sapienza & Zingales, 2018).

Consumption preferences

In regions where investors prefer consumption over savings and are more short-term focused, the EP would be higher (Rieger, Wang & Hens, 2013). The increase in the EP will result in a decrease in the price of equities. EPs are linked to consumer savings rates, with higher savings rates lowering the expected additional return on shares (Damodaran, 2018). A shift to long-term, equities-based savings, will result in increased market participation. This will create an increased demand for equities and as a result thereof, there will be a corresponding decrease in the EP (Favilukis, 2013).

The state of the economy

Research has found that the EP moves in response to the overall volatility in economic measures such as the gross domestic product (GDP) growth, employment and measures of aggregate consumption (Lettau, Ludvigson & Wachter, 2008). This is intuitive as there is an inherent link between risk and volatility, with increased volatility resulting in increased risk. The risk in equity is therefore linked with the ability to forecast the overall state of the economy (Damodaran, 2018). Macroeconomic indicators are gauges of the overall risk that exists in the underlying economy and assuming that the market is efficient, a reasonable expectation would be that this is priced into equities (Lattau et al., 2008). A review of macroeconomic indicators demonstrated that in particular, inflation (the consumer price index (CPI) and producer price index), balance of trade, unemployment, housing starts and monetary aggregate are strong identifiers of underlying risk and impact the EP (Flannery & Protopapadakis, 2002). The announcements of these indicators influence the trading volumes of the stock market. Positive trends over time lead to less volume traded, thereby less volatility in the equity markets and, as a result, a decrease in the EP (Flannery & Protopapadakis, 2002).

In contrast, research conducted by behavioural economists found that there is no apparent link between the magnitude of economic volatility and changes in macroeconomic fundamentals (Bhar & Malliaris, 2011). Bhar and Malliaris (2011) demonstrated that the EP fluctuates in response to financial, macroeconomic and behavioural (an indicator of momentum was utilised for behaviour) measures in inconsistent percentages during different phases of the economy. The movements in EP are dynamic, and it therefore appears as if it cannot simply be explained through individual economic indicators.

Information

The availability of information about the companies that make up a market has an impact on the EP (Damodaran, 2018). When investors perceive that information is not accurate and transparent, they will insist on a higher return due to the additional risk. A study conducted by Lau, Ng and Zhang (2012) found that there is a link between investors' access to information and lower EPs. This is an important consideration in emerging markets which generally have a lower reporting quality compared to established markets (Chen, Hope, Li & Wang, 2011). In addition, income inequality contributes to access to information or the lack thereof. Access to financial information is costly and those with the requisite financial resources are more capable of accessing and interpreting relevant information (Kacperczyk, Nosal & Stevens, 2018). One would therefore expect a higher EP in emerging markets as a result of the relative lack of access to information, due to higher income inequality.

Liquidity

The liquidity of an asset impacts the relative risk of holding that asset and the pricing of that asset (Schwarz, 2018). Even in markets with advanced stock exchanges where volumes of transactions are high, the cost of illiquidity can increase as a result of negative macroeconomic conditions (Damodaran, 2018). When there is a high risk of illiquidity it will result in an increase in the EP. A study of illiquidity in developing economies found that variances in the realised EP could be partially attributed to the different levels of liquidity (Bekaert, Harvey & Lundblad, 2007).

Catastrophic risk

Events that have profound effects on financial markets, both positive and negative, and are difficult to anticipate, impact the EP as the pricing of the asset has to reflect that risk (Damodaran, 2018). A recent example that impacted South Africa was the British referendum to withdraw from the European Union. The result was a loss of approximately $2 trillion of value in the global equities (Corporate Finance Institute, 2019). Guo, Wang and Zhou (2014) found evidence that catastrophic risk, specifically the downside risk, is a significant factor in the determination of the EP. Investors require a higher premium to be included in the return to compensate for the possibility of negative catastrophic risk factors (Guo, Wang & Zhou, 2014). Time-varying disaster risk models demonstrate that investors will require a higher EP when a high likelihood of disasters exists, with a movement of 1% in EP for every change of one standard deviation in measured risk (Berkman, Jacobsen & Lee, 2017).

Government policy

Pastor & Veronesi (2012) found that the EP increases when there is uncertainty regarding government policy. The increased uncertainty results in higher volatility in the markets (Pastor & Veronesi, 2012). This increased risk contributes to an increase in the EP demanded by investors. A country's bureaucratic environment and the stability of its government have an impact on its equity returns, with a study of 49 countries showing that the additional risk of operating in a poor state results in an annual EP of approximately 8% (Lam & Zhang, 2014).

Monetary policy

The EP is calculated as the surplus of the equity returns above the risk-free rate. The risk-free rate is impacted by a country's monetary policy, with the central bank determining key variables such as inflation rates and lending rates (Kung, 2015). Bekaert, Hoerova and Duca (2013) found that the implementation of a slack monetary policy results in a decrease in investors' risk aversion. Simply, investors will be more willing to take risks in environments where interest rates are lower, thereby increasing the EP (Bekaert et al., 2013). In addition, aggressive inflation targeting policies create greater volatility and result in an increase in EP (Kung, 2015, Peng & Zervou, 2014). Rising inflation would lead to a corresponding decline in the EP (Peng & Zervou, 2014).

Behavioural impacts

The irrational behaviour of investors impacts the EP (Damodaran, 2018). The Modigliani-Cohn theory showed evidence that the Standard and Poor's 500 Index (S&P 500) was undervalued as a result of investors not adequately accounting for inflation in their expectations of future equity performance (Modigliani & Cohn, 1979). Campbell and Vuolteenaho (2004) found evidence to support the fact that investors tend to forecast market returns based on past realised nominal returns, and underestimate the impact of inflation. In addition, narrow framing, an investor's propensity to overestimate the inherent risks in the equity market, can result in the overvaluation of the expected EP (Benartzi & Thaler, 1995).

It is evident that there are a large number of variables that impact the EP. It is also clear that not all impacts, such as the irrational behaviour of investors, can be measured with observed indicators. This increases the complexity with regards to determining an appropriate number that can be utilised in various financial and economic models and the calculation of the cost of equity. Due to its relative importance, it is clear that an appropriate methodology for determining the expected EP is required.

2.8. Estimating equity premium

According to Damodaran (2018), the techniques utilised in order to estimate EP can be categorised into three broad approaches, namely, surveys of investors, extrapolation of historical EP and prediction of implied premiums. It is important to consider the various techniques utilised in order to gain a further insight into the items that impact the EP. The focus of the current research is on the prediction of implied premiums using econometric models. The approach followed is due to the research performed in the past five years that has shown that there is robust evidence to support the out-of-sample predictability of the EP (Baetje & Menkhoff, 2016; Kolev & Karapandza, 2017; Li & Tsiakas, 2017; Meligkotsidou, et al., 2019; Neely et al., 2014; Pettenuzzo, et al., 2014; Silva 2018; Stivers 2018).

2.8.1. Estimation using surveys

The survey of investors, analysts and financial officers is a method that has been utilised in order to assess an appropriate measure of EP (Graham & Harvey, 2018). Data is collected from respondents and the average response is deemed to be an appropriate measure of the EP. The wide range of potential participants in a survey can impact the outcome of the study, with, for example, accounting officers showing higher levels of optimism with regards to the economy (Graham & Harvey, 2018). The use of surveys is a relatively simple method of obtaining a measure of the EP. It is however constrained by the fact that estimates are not checked for reasonableness and they tend to be volatile and short term, i.e. less than one year (Damodaran, n.d.).

An assessment of the EP in 71 countries in 2016 demonstrated that there are wide ranging opinions regarding the EP with South African results showing a standard deviation of 1.5% with a median of 6.3% (Fernandez, Ortiz & Acín, 2016). Surveys undertaken by PwC (2017) in Southern Africa showed that the EP applied by companies range between 2% and 20%, with an average of between 5.6% and 7.9% utilised in South Africa. This represents a significant variance in EP and highlights the potential pitfalls of using EP derived on the basis of surveys.

2.8.2. Extrapolation of historical premiums

The EP can be estimated through a process of extrapolating the realised historical share returns (Siegel, 2017). The historical EP is calculated as the excess of the returns on an equity portfolio and the return that could be generated on a risk-free security (Fernandez, Aguirreamalloa & Acín, 2015). The historical EP in South Africa for the period 1900 to 2005 is summarised in Table 1 (Dimson, Marsh & Staunton, 2011).

Table 1. Historical equity premium in South Africa: 1900 to 2005

% per annum	Historical EP relative to Tbills			Historical EP relative to bond		
	Geometric mean	Arithmetic mean	Standard deviation	Geometric mean	Arithmetic mean	Standard deviation
South Africa	6.20	8.25	22.09	5.35	7.03	19.32

Source: Dimson et al., 2011

The first issue apparent with the historical EP is whether one should use geometric means or arithmetic means. The arithmetic mean is a measure of the simple average of the annual returns (Marshall, 2017). The geometric mean is calculated on the basis of compounded annual returns (Marshall, 2017). The arithmetic mean is arguably a superior metric due to the fact that, in estimating future returns, the objective is to calculate an unbiased EP which should therefore exclude the returns of previous periods (Damodaran, 2018). There is, however, an argument that suggests that geometric means are more appropriate due to the negative correlation that exists within stock returns over time (Rapach & Zhou, 2016). Evidence from developing markets found that, in the short-term, equities demonstrated sustained periods of negative return correlations (Dimic, Kiviaho, Piljak & Äijö, 2016). Hassan and van Biljon (2010) reassessed the EP in South Africa using both arithmetic and geometric means, and found a two-percentage point difference per year. Table 1 reflects a similar variance between the geometric and arithmetic means.

The use of extrapolation techniques is inherently problematic in estimating future EP as they are backward looking. Even after considering modifications, it is fundamentally based upon on underlying historical data that may or may not be repeated in the future (Ilmanen, 2003). In addition, the high levels of volatility exhibited in equity in the short term, can result in a wide range of estimates that would limit their usefulness (Ilmanen, 2003).

2.8.3. Prediction of premiums

Discounted cash flow model-based premiums

Asset pricing reflects investors' perception of risk, as the return generated includes the risk premium that they require in order to hold a riskier asset. By applying the dividend discount model, it may be possible to infer an estimate of the EP (Claus & Thomas, 2001; Ilmanen, 2003). Equation 1 represents the Gordon growth model which assumes dividends will increase at a constant rate in perpetuity (Copeland, Copeland & Copeland, 2017):

$$Value\ of\ equity = \frac{Expected\ dividends}{(Required\ return\ on\ equity - Expected\ growth\ rate)}$$

Equation 1. Gordon growth model

In order to estimate the EP, one would solve for the return on equity (ROE). The value of equity would equal the current prevailing market price. An estimate of the expected dividends and expected growth rate would return the required return on equity (Copeland et al., 2017). This return less the current risk-free rate would equal the EP. It is important to note that the model assumes that a constant rate of growth for dividends is the base for calculating the value of equities (Copeland et al., 2017). The dividend yield is therefore a measure of the EP (Rozeff, 1984).

The model can be extended by assuming that the expected growth rate can be specified as a function of ROE and the dividend payout ratio $\left(\frac{Dividends}{Earnings}\right)$. The growth rate would therefore be calculated as follows (Damodaran, 2018):

$$Growth\ rate = (1 - \ Dividend\ payout\ ratio)\ \times\ (ROE)$$

Equation 2. Extended Gordon growth model

And therefore, the Gordon growth model can be restated as (Damodaran, 2018):

$$Value\ of\ equity = \frac{Expected\ dividends}{(Required\ ROE - (1 - \ Payout\ ratio)\ \ \times\ (ROE))}$$

Equation 3. Restated Gordon growth model

Furthermore, if it is assumed that the return on equity matches the required ROE (i.e. the organisation does not generate excess returns), the equation can be simplified to (Damodaran, 2018):

$$Value\ of\ equity = \frac{Expected\ earnings}{Required\ ROE}$$

Equation 4. Simplified Gordon growth model

When solved for required return (Damodaran, 2018):

$$Required\ ROE = \frac{Expected\ earnings}{Value\ of\ equity}$$

Equation 5. Required return on equity

It is important to consider that this equation is the inverse of the price earnings ratio $\left(\frac{Share\ price}{Earnings}\right)$(Firer et al., 2012). Assuming that companies earn the required rate of return, at a consistent growth rate, then the inverse of the price earnings ratio, less the risk-free rate, would provide a method for the calculation of the EP (Carlson, Pelz & Wohar, 2002). There exists a link between the risk contained in a share portfolio, the dividend yield and the average rate of capital gains (Bhar & Malliaris, 2011). The dividend yield plus the average share return can therefore be considered as a predictor of the EP (Bhar & Malliaris, 2011). In the US, the use of earnings as a predictor of the EP, was deemed significant for the period 1872 to 1950, however thereafter it only contained partial predictive ability (Fama & French, 2002).

The discounted cash flow-based models are relatively simple to implement as a method for determining the EP (Damodaran, 2018). The calculated EP is however sensitive to the assumptions that are made regarding the anticipated earnings (typically dividends) and the expected consistent growth rate (Copeland et al., 2017). The results of these models have often show signs of significant optimism bias and in most cases need to be adjusted downwards (Claus & Thomas, 2001).

Default spread-based equity premiums

The EP represents the additional return that investors require to hold the additional risk inherent in equities. However, in owning any asset, an investor requires an additional return over and above the risk-free rate; a risk premium (Damodaran, 2018). This risk premium is associated with the underlying risk-free rate and they are all therefore related. It is therefore conceivable that the movements in bond premiums will have an impact on EP (Siegel, 2017). Bond premiums are generally calculated as the difference between corporate bond rates and government bond rates (i.e. the risk-free rate) (Welch & Goyal, 2008). The difference between these two bond rates can be defined as the default spread. The EP can therefore be calculated based on the observed relationship between the EP and the default spread (Chen, Collin-Dufresne & Goldstein, 2008).

Option pricing model-based equity premiums

As discussed above, it is not apparent whether there is a clear link between volatility in the market and the EP. However, if one was to assume that the EP is representative of the underlying market volatility, then it is possible to derive the EP from the current option prices as a relationship should exist between the two (Damodaran, 2018). It has been shown that there is high degree of correlation between the EP reported by company officers and the volatility index (Graham & Harvey, 2018), an index calculated using implied volatilities in traded options. The connection between options and the EP was confirmed by Ross (2015) who utilised forward rates to estimate future equity prices and risk premiums. Carr and Wu (2016) found that options data can be utilised to predict future share returns, and by implication, a forward looking estimate of the EP. Santa-Clara and Yan (2010) measured ex-ante risk, the future projected risks in a share portfolio, as assessed by investors, by considering share options as a basis for determining the EP. They looked at EP as a function of diffusive volatility and intensity of the risk associated with portfolio switching (jump risk). The findings indicated that a relationship exists between volatility and the EP, but that this relationship is based on implied risk as opposed to actual share market volatility (Carr & Wu, 2016; Santa-Clara & Yan, 2010). Realised volatility underestimates risk, whereas option prices provide a more appropriate assessment of the implied risk in the futures markets (Santa-Clara & Yan, 2010). This method of determining EP appears to represent an appropriate estimation technique (Carr & Wu, 2016). However, it is more suitable to short-term forecasts of EP and starts to lose accuracy as the time frame increases (Santa-Clara & Yan, 2010). This is most likely due to the increased difficulty of accurately pricing long-term options.

Regression-based forecasting

The research performed in the past five years has shown that there is robust evidence to support the out-of-sample predictability of the EP using regressions as a base of forecasting (Baetje & Menkhoff, 2016; Kolev & Karapandza, 2017; Li & Tsiakas, 2017; Meligkotsidou et al., 2019; Neely et al. 2014; Pettenuzzo et al., 2014; Silva 2018; Stivers 2018). The current literature demonstrates that the use of either financial and macroeconomic data or technical indicators has provided evidence that they contain predictive powers in estimating EP (Baetje & Menkhoff, 2016; Kolev & Karapandza, 2017; Li & Tsiakas, 2017; Meligkotsidou et al., 2019; Neely et al., 2014; Pettenuzzo et al., 2014). It is therefore necessary to understand the use of technical indicators.

Technical analysis consists of the estimation of share prices based on patterns identified in past market data (Lo & Hasanhodzic, 2010). The use of technical indicators is common in modern portfolio management, with quantitative trading strategies employing such techniques. Goh, Jiang, Tu and Zhou (2013) found evidence in Singapore of the ability of technical indicators to predict bond yields. Neely et al. (2014) demonstrated that technical indicators can be utilised in forecasting the stock market. The technical indicators used included moving averages, momentum and volume.

The model adopted by Li and Tsiakas (2017), showed evidence that financial and macroeconomic indicators provided better out-of-sample performance than the technical indicators. Therefore, the current research will utilise this model, which uses a large number of financial and macroeconomic indicators, in the context of South Africa. Further support for this approach, is the findings of Gupta et al. (2016), who demonstrated that a large number of variables, which included financial and macroeconomic indicators, had the ability to predict the EP in South Africa.

2.8.4. Financial and macroeconomic indicators

The concept of being able to predict share returns based on dividends was first considered by Shiller et al. (1984) who demonstrated that, contradictory to the efficient market hypothesis, there was a market overreaction to dividends that influenced share prices. However, this was followed by research which illustrated that, in the context of stock market bubbles, the use of regressions based on lagged dividend price ratios was not adequately capable of describing the EP (Flood et al., 1986). The inability of lagged dividend price ratios to predict share returns, at any time horizon, was confirmed by Campbell and Shiller (1988), but they were able to confirm that log earnings price ratios and the log dividend price ratio had predictive abiltiy. Fama and French (1988) illustrated, using regression, the ability of dividend yields to forecast share returns, with the significance increasing in line with the time horizon, i.e. that the predictive ability was greater over longer time horizons. Using alternative statistical methods, the predictive power of dividend yields was once again confirmed by Hodrick (1992). The dividend payout ratio as a predictor was later considered and results demonstrated that there exists a dynamic relationship between expected returns and dividend and earnings ratios (Lamont, 1998).

Lettau and Ludvigson (2001) attempted to summarise the prevailing literature at the time which accepted financial indicators, such as the earnings price ratio and dividend earnings ratio, as predictors of EP. It was apparent that financial indicators had become widely accepted as predictors of share performance in the US. The comprehensive re-examination undertaken by Welch and Goyal (2008) called into question the predictive ability of economic and financial indicators.

In order to assess whether share returns are predictable, the literature has predominantly focused on utilising an ordinary least squares regression. The findings showed that the *t*-statistic (*t*-stat) is significant, and therefore based on the critical values, one would conclude that there is evidence to suggest that returns, and thereby the EP, are predictable (Campbell & Yogo, 2006).

There remains a number of financial and macroeconomic variables that have been identified as producing statistically significant results in terms of their ability to predict the EP. The intention of the research is to assess whether such variables have any predictive ability in the South African context.

2.9. The kitchen sink regression

The KS regression is a form of linear regression in which all known independent variables are encompassed in the analysis so that one is able to predict the dependent variable (Li & Tsiakas, 2017). The EP is impacted by a multitude of financial and macroeconomic indicators, as discussed above. The KS regression represents an appropriate framework from which to attempt to forecast the EP.

As demonstrated by Welch and Goyal (2008), the use of regression models that conditioned on financial and macroeconomic indicators showed "*high in-sample significance, but exceptionally poor out-of-sample performance*" (p. 1478). In order to address the poor out-of-sample performance, Li and Tsiakas (2017) introduced economic and statistical constraints into the regression framework. This yielded positive out-of-sample performance that exceeded numerous other models which are based on technical indicators and economic fundamentals (Li & Tsiakas, 2017).

The KS regression has however been criticised as being used in circumstances where the researcher is searching for a relationship without analysing whether the variable is relevant (Kellogg School of Management, n.d.). This can lead to a loss of precision in measurement and care should be taken to ensure that there is an adequate reason for including the variable in the analysis (Kellogg School of Management, n.d.). The following discusses the rationale for utilising each of the identified financial or macroeconomic indicators in the framework. Please note, the name denoted in the brackets represents the name utilised in the statistical analyses.

Share-based indicators

Dividend price ratio ("DividendPrice") – the net of the log of dividends and the log of lagged prices (Li & Tsiakas, 2017). Dividends are an indicator of the underlying asset's fundamental price as they represent the future cash flow that can be realised from the investment (Campbell & Shiller, 1988). If the fundamental price is lower than the current prevailing market price, the subsequent asset returns tend to be higher (Campbell & Shiller, 1988).

Earnings price ratio (“EarningsPrice”) – the net of the log of earnings and the log of prices (Li & Tsiakas, 2017). The earnings price ratio has demonstrated predictive power in estimating share returns (Campbell & Shiller, 1988; Fama & French, 1988; Flood et al., 1986; Hodrick, 1992; Shiller et al., 1984).

Volatility (“Volatility”) – the volatility in the JSE Top 40 Index. The underlying market volatility is utilised as a measure of risk that exists in the market at any given time. There exists a link between volatility and the EP (Carr & Wu, 2016; Santa-Clara & Yan, 2010). Periods of increased risk will increase the volatility, thereby impacting the EP (Guiso et al., 2018).

S&P 500 Index (“SP500”) – an index of the top 500 companies listed on US stock exchanges. The South African equity market is impacted by foreign equity movements (Baele & Inghelbrecht, 2010; Heymans & da Camara, 2013; Samouilhan, 2006). This could be a predictor of the EP in South Africa (Gupta et al., 2016).

Financial Times Stock Exchange 100 Index (“FTSE100”) – an index of the top 100 companies listed on the London Stock Exchange. The South African equity market is impacted by foreign equity movements (Baele & Inghelbrecht, 2010; Heymans & da Camara, 2013; Samouilhan, 2006). This could be a predictor of the EP is South Africa (Gupta et al., 2016).

Morgan Stanley Capital International World Index (“MSCI”) – a broad global equity index that incorporates equity across 23 developed markets, with no exposure to emerging markets. The South African equity market is impacted by foreign equity movements (Baele & Inghelbrecht, 2010; Heymans & da Camara, 2013; Samouilhan, 2006).

Interest-based indicators

Treasury Bill rate ("Tbill") – the 91-day Treasury Bill rate. The rate has demonstrated in-sample predictive ability (Wang et al., 2019).

Term spread ("Spread") – the net of the long-term yield on government bonds and the risk-free rate (i.e. the money market index) (Li & Tsiakas, 2017). The term spread is a measure of risk in share market returns (Park et al., 2017).

Long-term rate of return on government bonds ("BondYield") – the long-term rate of return on government bonds is a key measure of the risk-free credit maturity over time and is central to the pricing of long-term assets (Turner, 2014).

Relative money market rate ("MoneyMarket") – the net of the RT130 money market rate and the 12-month backward looking average (Gupta et al., 2016).

Economic indicators

Inflation ("CPI") – the consumer price index in South Africa. Investors' risk aversion changes in response to the current inflation, with an increase in inflation resulting in investors reducing their appetite for risk (Brandt & Wang, 2003). With an increase in inflation one would therefore expect a corresponding decrease in the EP (Peng & Zervou, 2014). In developing countries, inflation has been identified as a key measure that can impact the EP (Costa, 2018).

Real effective exchange rate ("ExchangeRate") – the weighted average of the South African Rand in relation to a basket of international currencies. The basket of international currencies is determined by the South African Reserve Bank. Cointegration exists between a country's asset prices and that country's real effective exchange rate (Gelman, Jochem, Reitz & Taylor, 2015). In addition, exchange rates are a measure of risk in stock market returns (Park, Ryu & Song, 2017). The real effective exchange rate has the potential to explain variances in the EP.

Manufacturing production (*"IndustrialProd"*) – the EP is impacted by a variety of economic variables, with the relative risk in equity being inextricably linked with the aggregate economy (Lettau et al., 2008). The output of the manufacturing sector can be viewed as a measure of the aggregate economy (Carriero, Clark & Marcellino, 2018). The level of production in the manufacturing sector may therefore have predictive ability.

World oil production ("*OilProd*") – Wang et al. (2019) found that incorporating oil price shocks, through the incorporation of asymmetric oil returns into the predictors, increased the accuracy of univariate and multivariate regression models in the US. The link between oil and the EP is due to the fact that oil is considered an important gauge for the global economy with supply an important determinant of the oil price (Byrne, Lorusso & Xu, 2019). In line with Gupta et al. (2016), the current research will consider oil production as a possible influencing variable of the EP.

2.10. Statistical and economic constraints

Statistical constraints

Predictive regressions offer a framework for evaluating the relationship that exists between predictor variables and the independent variable. Linear regressions obtain estimates by determining a linear relationship between the known data points by minimising the sum of squared residuals (Tuffery, 2011). The standard linear regression model is given by (Tuffery, 2011):

$$\hat{y} = \hat{\beta}_0 + x_1\hat{\beta}_1 + \ldots + x_p\hat{\beta}_p + \epsilon_{t+1}$$

Equation 6. Linear regression

where,

y = the dependent variable;

$\hat{\beta}_0$ = intercept;

x = the vector, the independent variable;

$\hat{\beta}$ = the estimator;

ϵ_{t+1} = the model's error terms.

The framework utilises a least squares approach to minimise the residual sum of squares (Fox, 2018). The objective is to utilise collected data points to find a 'best fit' that will enable prediction of undetermined y values given the predictor x values (Fox, 2018). In general, two characteristics are important when utilising a regression model:

1. The model needs to be capable of adequately predicting the unknown values, i.e. it must be accurate (Zou & Hastie, 2005).

2. It is beneficial if the model is capable of explaining the relationship that exists between the dependent and independent variables, i.e. it must be interpretable (Zou & Hastie, 2005). When the model utilises a large number of predictor variables, parsimony is an especially important characteristic (Zou & Hastie, 2005).

The method of using ordinary least squares has been criticised for lacking these two important aspects (Zou & Hastie, 2005). In response to this, statisticians have considered two alternative methods of minimising the residual sum of the square errors, namely ridge regression and the least absolute shrinkage and selection operator (lasso) regression. Ridge regression adds a penalty by shrinking the slope coefficients asymptotically towards zero (Hoerl & Kennard, 2000). Lasso regression includes a penalty by shrinking certain parameters to zero (Tibshirani, 1996). Zou and Hastie (2005) combined the two methods to develop a penalised regression that includes an element of both ridge and lasso, the elastic net regression. This is particularly useful when a model contains many variables, where their qualities are undefined (Zou & Hastie, 2005).

The objective of applying statistical constraints in attempting to predict EP is to introduce bias in order to minimise variance (Li & Tsiakas, 2017). This is achieved by shrinking the predictor coefficients in order to obtain a model that more closely represents the actual model, which is unknown, assuming that the KS regression utilised has predictive power (Li & Tsiakas, 2017). In contrast, the in-sample predictive regression represents a model that is based on sample data and it will therefore be a biased estimate as it merely represents a fit to the sample data (Fox, 2018). The objective is therefore to introduce initial bias which will result in a worse initial fit to the data, but that will be more stable for long-term prediction due to the fact that it contains less variance (Friedman, 2012; Starmer, 2018b).

Economic constraints

The introduction of restrictions, based on economic theory, to the sign coefficients in traditional predictive regression frameworks that condition on financial indicators show positive performance out-of-sample (Campbell & Thompson, 2008). A rational investor would not maintain an investment in an underlying asset if a negative EP was expected to be generated, as there is no reward for bearing the additional risk (Pettenuzzo et al., 2014).

In using the in-sample predictive regressions, the objective is to determine the slope coefficient of the independent variable in order to determine its predictive ability with regards to the dependent variable (Fox, 2018). A negative coefficient may result from short-term estimates; however, according to theory, this coefficient ought to be greater than zero as an investor would not make use of negative estimates that would result in perverse outcomes (Campbell & Thompson, 2008). From a practical perspective, this negative coefficient would be disregarded. There would be no apparent reason for investors to hold an investment in shares when they could simply switch their position to risk-free bonds which command a higher yield (Ilmanen, 2003).

2.11. Summary of chapter

The chapter defined the EP and briefly outlined its importance in modern finance and economics. A brief overview of the EP in South Africa was given in order to provide a context for the current research. The factors that influence the EP were discussed in order to outline the large number of variables that need to be taken into consideration in order for an appropriate assessment of the forward-looking EP to be made. The different methods that can be utilised to forecast the EP were outlined. The historical use of financial and macroeconomic indicators as key determinants of the EP was reviewed. The literature indicated that there are mixed opinions regarding the predictive ability of the independent variables. The problems could however be overcome by using individual variables and combining all of them into a forecast model. Due to the importance of out-of-sample predictability, the chapter considered the techniques utilised in order to optimise the models. This includes the use of statistical and economic constraints.

3. RESEARCH HYPOTHESES

The objective of the research is to assess whether various financial and macroeconomic variables have the power to estimate equity premium (EP) in South Africa. Therefore, the following hypotheses have been formulated in order to test this objective.

3.1. Evaluate the relationship between individual predictors and the equity premium

The first objective is to assess the relationship between the EP and individual financial and macroeconomic indicators utilising a standard univariate predictive regression. The researcher considered whether the EP is predictable using individual indicators by utilising an ordinary least squares regression. An important question is whether there is a statistically significant association between the EP and the predictor variable given by the regression equation. The null and alternative hypotheses can therefore be stated as follows:

Hypothesis 1:

Null hypothesis ($H1_0$): the relevant financial or macroeconomic indicator is not related to the EP, at a 95% confidence level.

Alternative hypothesis ($H1_A$): the relevant financial or macroeconomic indicator is related to the EP, at a 95% confidence level.

$$H1_0 : \beta_1 = 0$$
$$H1_A : \beta_1 \neq 0$$

β represents the relevant coefficient and the resultant slope of the model (Stephens, 2004). In order to evaluate the relative in-sample performance of the predictive regressions, the research will assess whether the sample test statistic, *t*-stat, is within the critical region for acceptance (Campbell & Yogo, 2006). When the *t*-stat is in the range, it is indicative of the fact that there is no statistically significant relationship between the EP and the independent variable (Stephens, 2004).

3.2. Utilise a large number of predictors to assess predictability

The second objective is to consider whether EP is predictable in-sample by applying a KS regression that utilises a large number of variables. In addition, whether the introduction of statistical limitations improves the predictive ability of the model. In short, whether the penalised KS regressions are capable of predicting the EP in-sample. A measure of effectiveness of a regression model is the coefficient of determination (R^2). The R^2 can be seen as a measure of the explanatory ability of the independent variables (in this instance, the financial and macroeconomic indicators) in determining the dependent variable, the EP (Wegner, 2016b). The R^2 is a measure of the proportion of the variance that can be explained by the independent variables (Dunteman & Ho, 2006). The R^2 provides a measure of the predictability of the dependent variable, the EP, based on the set of predictor variables used in the regression analysis (Zhang, 2017). The R^2 ranges from 0 to 1, with a higher value indicating a greater predictive ability (see Figure 1) (Wegner, 2016d). A moderate relationship is apparent when the model's coefficient of determination ranges between .50 and .80 (Fox, 2018). Figure 1 is a useful graphic in order to assess the relative strength of association indicated by the R^2 (adapted from Wegner, 2016d).

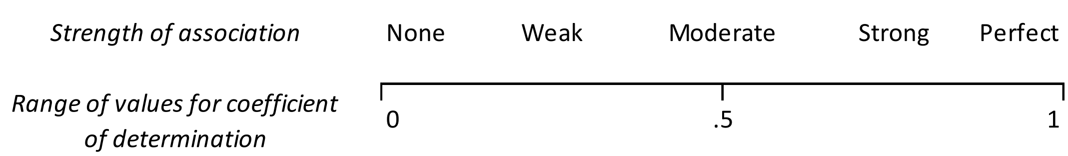

Figure 1. Strength of association given by coefficient of determination
Source: Adapted from Wagner, 2016d.

The purpose of the current research is to assess the predictability of the EP. In order to conclude that a model has predictive performance, it should be capable of offering economic benefits to investors. Campbell and Thompson (2008) demonstrated that predictive regressions that have modest explanatory ability can result in sizeable benefits for investors. The research will therefore consider whether a moderately strong model exists and will use .60 as the threshold. Statistically, .60 represents a moderate to strong association between the variables (Fox, 2018; Wegner, 2016d). This therefore represents a model that can be of use to investors (Campbell & Thompson, 2008). If a model has use to stakeholders, it can be deemed to contain adequate predictive performance to be considered a model capable of predicting the EP. This is further supported by Rapach and Zhou (2016) who note that, when attempting to predict the EP, a minor degree of predictability can result in considerable utility gains. The null and alternative hypotheses can therefore be stated as follows:

Hypothesis 2:

Null hypothesis (H_0): the proposed model does not have any predictive power in determining the EP, with the adjusted coefficient of determination not exceeding .60, at a 95% confidence level.

Alternative hypothesis (H_A): the proposed model has predictive power in determining the EP, with the adjusted coefficient of determination exceeding .60, at a 95% confidence level.

$$H2_0 : R^2 \leq .60$$
$$H2_A : R^2 > .60$$

The adjusted coefficient of determination is the R^2 that includes an adjustment to account for the number of coefficients in the analysis (MathWorks, 2019a). The adjusted coefficient of determination is utilised because, as additional variables are incorporated into the model, the coefficient of determination will increase, potentially leading to incorrect conclusions. The adjusted R^2 is also useful in comparing models that utilise a different number of independent variables (Zhang, 2017).

3.3. Assess the out-of-sample performance of the kitchen sink predictive regression compared to a benchmark

The third objective is to assess the out-of-sample performance of the KS regression after introducing statistical and economic constraints to evaluate whether the proposed model is able to consistently deliver superior forecasts relative to a benchmark. In order to assess the out-of-sample performance, the research will evaluate the out-of-sample R^2 statistic (R^2_{OOS}), which compares the alternative forecast with a historical mean benchmark of an alternative model (Campbell &

Thompson, 2008). The MSE of the forecasts will be compared, with a positive value indicating that the alternative e model has the ability to perform better than the benchmark (Li & Tsiakas, 2017; Meligkotsidou et al., 2019; Wang et al., 2019). The benchmark forecast will be the best performing model as assessed in the previous objectives. The null and alternative hypotheses can therefore be stated as follows:

Hypothesis 3:

Null hypothesis (H_0): the proposed model's out-of-sample performance does not exceed the benchmark model's out-of-sample performance.

Alternative hypothesis (H_A): the proposed model's out-of-sample performance exceeds the benchmark model's out-of-sample performance.

$$H3_0 : R^2_{OOS} \leq 0$$
$$H3_A : R^2_{OOS} > 0$$

4. RESEARCH METHODOLOGY

4.1. Research design

The objective of the research paper is to assess the predictability of the equity premium (EP), based on financial and macroeconomic indicators. The assessment was split between an analysis of the in-sample performance of the model's specified in the literature as well as an assessment of the out-of-sample performance of the KS regression, with statistical and economic constraints. The ultimate aim was to determine whether an accurate prediction of the EP could be achieved.

The study was quantitative in nature as it aimed to establish statistical relationships between variables in order to test statistical models (Saunders, Lewis & Thornhill, 2012). The study relied purely on the use of quantitative secondary data, being the returns on the JSE and associated financial and economic indicators. The study applied a positivist philosophy as it was highly structured, and used methods designed to produce unambiguous observations directly from the collected data (Saunders & Lewis, 2018). A deductive approach was utilised that involved the testing of a number of hypotheses in order to evaluate the models developed by the literature, as opposed to generating a new theory (Shank, 2008).

Descriptive research encompasses the exploration of the relationship that exists between two or more variables, and seeks to describe the association between the variables, such as the relationship between financial and macroeconomic indicators and the EP (Williams, 2007). In order to test the hypotheses, the researcher applied a mono-method quantitative methodological approach (Saunders & Lewis, 2018). Causal comparative research is concerned with the testing of the relationship that exists between a dependent variable and the independent variables (Williams, 2007). The research was causal comparative in that it compared the EP, the dependent variable, with the financial and macroeconomic indicators, the independent variables.

4.2. Universe, population, sampling method and size

In research, the universe consists of all the elements of interest that are relevant in order to answer the research question (Butler, 2011). In the proposed study, the universe was the EP realised on all equity markets, globally.

A population is the entire set of entities from which one wishes to draw inferences and a sample is a subgroup of the population (Litt, 2012). The population applicable to the study was all returns generated on the JSE. The returns that were assessed in the enquiry were the monthly returns of the JSE Top 40 Index. The US studies (Li & Tsiakas, 2017; Welch & Goyal, 2008) utilise the returns on the S&P 500 to assess EP. The S&P 500 is an index representing the top 500 companies listed on exchanges in the US. The JSE Top 40 Index is comparable as it represents the top 40 companies, by market capitalisation, listed on the JSE. These returns were assessed using purposive sampling. Purposive sampling is a form of non-probability sampling, which is a technique that utilises the judgment of the researcher in making the selection (Saunders & Lewis, 2018). While Purposive sampling is normally utilised in qualitative research, it is appropriate to use it in certain quantitative research problems (Leedy & Ormrod, 2015). It was appropriate as the current study was a form of replication of the studies undertaken in the US. The current research assessed models that had demonstrated predictive ability in the US in a South African context. The use of purposive sampling was justified.

In statistical testing, the standard error will decrease in line with the increase in the sample size resulting in more accurate estimates (Wegner, 2016a). This was taken into account to ensure that an appropriate sample size was selected. The proposed timeframe for the study was the period December 1996 to December 2018 (N = 265). The in-sample analysis was informed by the period December 1996 to December 2013 (n = 205). The out-of-sample performance was assessed as the period January 2014 to December 2018 (n = 60). The dates were informed by the researcher access to and the availability of the data.

4.3. Unit of analysis

The unit of analysis represents the subject matter of the study (SAGE Dictionary, 2011) The unit of analysis was the historical EP realised in relation to the JSE Top

40 Index. This was calculated as the monthly percentage return on the shares less the risk-free rate for the same period.

For the purposes of this paper, the researcher considered the EP as representative of the average additional return that an investor in the JSE would have earned above the risk-free rate over the same period. This was deemed to be the share return that represents the compounded amount that an investor would have earned on the JSE Top 40 Index, including dividends received, less the risk-free rate. The US studies utilised the returns on the S&P 500 Index (Welch & Goyal, 2008) and therefore the JSE Top 40 Index was used as the South African equivalent of that index. In addition, the JSE Top 40 index is recognised as an overall benchmark of the local stock market (JSE, 2019b). It therefore represents an appropriate portfolio of shares in which to consider the EP.

4.4. Measurement instrument

A measurement instrument is the research tool utilised in collecting and measuring data (Hsu & Sandford, 2012). The study was quantitative in nature and relied on secondary data, being share returns on the JSE and associated financial and macroeconomic indicators drawn at the same intervals. The research therefore did not utilise a primary measurement instrument such as interviews or surveys.

4.5. Data gathering process

The study aimed to use the historical financial and macroeconomic data that was publicly available. The researcher obtained the information through the Gordon Institute of Business Science (GIBS) electronic databases. The sources that were utilised to obtain the secondary data included the IRESS Research Domain, for information regarding share returns, volumes traded and market capitalisation and the Thompson Reuters Eikon database, for historical data on financial and macroeconomic variables. The South African Reserve Bank was utilised for data on the past interest rates and Statistics South Africa for the relevant inflation rates.

4.6. Research ethics

Historical financial and macroeconomic data (secondary data) which is publicly available was used in the present study. The data was obtained from sources that did not require any specific approvals, other than those provided by the GIBS. GIBS databases are available for use by all students. Information obtained from Statistics South Africa and the South African Reserve Bank was available on their websites. There were no ethical concerns apparent in undertaking the research. The researcher obtained ethical approval for the study. The sources utilised by the researcher have been cited and acknowledged.

4.7. Analysis approach

4.7.1. Analysing the relationship between individual indicators and the equity premium

A standard predictive regression framework was utilised in order to assess the significance of each predictor individually on the EP. The formula used was in line with that utilised by Wang et al. (2019) and was as follows:

$$r_{t+1} = \alpha + \beta_i x_t + \varepsilon_{t+1}$$

Equation 7. Linear predictive regression

The regression uses an independent lagged predictor, x_t, to predict the EP, r_{t+1}, where β_i represents the significance of the variable in estimating the amount and was the variable of interest in the present study. ε_{t+1} represents the model's error terms (the residuals) and α represents the y-intercept.

In order to assess whether the sample *t*-stat was within the critical region for acceptance, the following formula was utilised:

$$t - stat = r\sqrt{\frac{(df)}{1 - r^2}}$$

Equation 8. t-statistic

where:

$r =$ sample correlation coefficient;

$df =$ degrees of freedom, calculated as $n - 2$ (Wegner, 2016d).

Where the *t*-stat was within the critical range of acceptance, it indicated a failure to reject the null hypothesis (Stephens, 2004).

4.7.2. The kitchen sink regression

The objective of Hypothesis 2 was to assess whether EP is predictable in-sample based on a KS regression. The KS regression is a linear predictive regression that conditions on a large set of predictor variables (Li and Tsiakas, 2017). The equation that was used is consistent with Li and Tsiakas (2017) and was as follows:

$$r_{t+1}^{e} = \alpha + \sum_{j=1}^{N} \beta_j x_{j,t} + \varepsilon_{t+1}$$

Equation 9. Kitchen sink regression

where, for $j = n$ observations:

$r_{t+1}^{e} =$ the EP at time $t + 1$, calculated as the twelve-month rolling return on the JSE Top 40 Index less the equivalent risk-free rate;

$x_j =$ explanatory variables at time t;

$\alpha = y$-intercept;

$\beta_j =$ slope coefficients for explanatory variables;

$\epsilon_{t+1} =$ the model's error term (the residuals).

The KS regression incorporated all of the independent variables in the model regardless of the results of Hypothesis 1. The pre-screening of variables based on results of univariate regressions can result in incorrectly excluding them in the multivariate model (Heinze & Dunkler, 2017). The variables may include important qualities that balance the multivariate regression (Heinze & Dunkler, 2017). Similarly, omitting a variable based on its insignificance can be dangerous as it can result in a suboptimal final model as the variable may contain vital information (Heinze & Dunkler, 2017). The researcher therefore did not exclude any variable from the analyses as a result of that variable being identified as insignificant, in either the univariate or multivariate analyses.

Introduction of statistical constraints

In addition to assessing the KS regression individually, the objective of Hypothesis 2 was to assess the performance of the model by including the elastic net shrinkage coefficient. The regression coefficients were regularised by solving the following system (Li & Tsiakas, 2017; Zou & Hastie, 2005):

$$\hat{\beta}^{en} = \min_{\beta} \frac{1}{2} \sum_{t=1}^{t-1} \left(r_{t+1}^{e} - \alpha - \sum_{j=1}^{N} \beta_j x_{j,t} \right)^2 \quad \text{s.t.} \sum_{j=1}^{N} |\beta| < S_1 \quad \text{and} \quad \sum_{j=1}^{N} \beta_j^2 < S_2$$

Equation 10. Elastic net system

Where,

β = coefficients;

s.t. = subject to;

α = intercept;

en = elastic net;

S_1 and S_2 are positive constants.

The objective of the system (as denoted in Equation 10) was to estimate S_1 and S_2 in a manner that minimised the mean squared errors (MSE) of the forecast, i.e. the prediction error (Hastie, Tibshirani & Friedman, 2017). S_1 was estimated on the basis of the absolute value of the slope coefficients and therefore represented the lasso regression penalty (Hastie et al., 2017). S_2 was estimated on the basis of the square of the slope coefficients and therefore represented the ridge regression penalty (Hastie et al., 2017). The research assessed the impact of all three regularised KS regressions; lasso, ridge and elastic net. In determining the best model fit, the model was specified to utilise cross validation, at folds of 10 (Stanford University, 2006). For the ridge and lasso regressions, the researcher assessed the best model fit as the most parsimonious model (Zou & Hastie, 2005).

Cross validation was utilised in order to split the in-sample data into training and testing sets with the intention of finding the optimal algorithm (Stanford University, 2006). This was achieved by iterative analyses at *k* folds defined by the researcher. The data was split into *k* sets of data of equal size, where *k* was set to 10 (Stanford University, 2006). The method is utilised to determine the values of the parameters, S_1 and S_2, based on the training data (Hastie et al., 2017). The errors are then calculated on the basis of the remaining one tenth of the data for each iteration (Hastie et al., 2017). The result is an estimated prediction error curve. Cross validation identifies the best value for the tuning parameters for each of the regression models at the point in which the estimated prediction error is minimised (Starmer, 2018a). The optimal model was deemed to be the model at the point in which the prediction error was minimised.

4.7.3. Assessing the out-of-sample performance of the kitchen sink regression

The research utilised a time series model, rolling-window analysis, in order to assess the accuracy of the forecast model in the out-of-sample period. The assessment was performed by calculating the MSE of the forecasts in order to compare them against one another (MathWorks, 2019b). The researcher followed the approach of comparing the out-of-sample R^2 statistic, with the in-sample R^2 statistic of a benchmark forecast (Campbell & Thompson, 2008; Li & Tsiakas, 2017; Meligkotsidou et al., 2019; Wang et al., 2019; Welch & Goyal, 2008):

$$R_{OOS}^2 = 1 - \frac{\sum_{t=1}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=1}^{T}(r_t - \bar{r}_t)^2}$$

Equation 11. Out of sample R^2

Where, r_t is the observed EP, $\hat{r}_t$ is the value determined by the predictive regression and $\bar{r}_t$is the value determined by the benchmark.

In order to calculate the predicted values for each of the forecasts, the researcher utilised the ‘score’ tool in Alteryx Designer x64. The tool utilises the set of supplied independent variables to create a predicted value by using the designated regression model (Alteryx Inc., 2019). The researcher utilised the tool to determine a predicted value of the EP for each regression assessed in terms of Hypothesis 3.

Introduction of economic constraints

Another feature of the method adopted by Li and Tsiakas (2017) was the inclusion of constraints based on economic theory in order to improve the out-of-sample predictably of the regression. In line with that approach, the researcher included the following constraint; where the out-of-sample forecasts of the EP were negative, the amounts were replaced by zero (Campbell & Thompson, 2008; Pettenuzzo et al., 2014).

4.8. Quality controls

The use of regressions in statistics to define the relationship between variables requires fundamental underlying prerequisites in order to ensure that the results are valid. Where possible, the data was tested to ensure that the criteria were satisfied, otherwise certain assumptions were made by the researcher. The researcher tested the data for normality of distribution (section 4.8.1), multicollinearity between the variables (section 4.8.3), heteroscedasticity of error terms (section 4.8.4), stationarity of time series (section 4.8.5) and the existence of outliers (section 4.8.6). The researcher assumed that there would be no adverse consequences arising as a result of survivorship bias (section 4.8.2).

4.8.1. Normality

The research utilised regression analyses which assumed that the data was normally distributed. In general, when sample sizes are large enough (greater than 40), a breach of the assumption of normality should not result in any significant statistical problems (Ghasemi & Zahediasl, 2012). The sample size was large enough for the researcher to be able to confidently assume normality and that it did not have any material impact on the analyses. However, descriptive statistics were performed in order to assess the reasonableness of the assumption.

4.8.2. Survivorship bias

The study aimed to assess the EP in relation to the JSE Top 40 Index over a 22-year period of time. There was therefore a risk that survivorship bias could impact analyses of the historical performance. However, Ritter (2005) argued that survivorship bias is unlikely to have any meaningful impact on EP. In addition, it is an important consideration when assessing historic past returns but not in predicting future returns (Ritter, 2005). The researcher therefore assumed that survivorship did not impact on the analyses.

4.8.3. Multicollinearity

A significant issue with multiple regressions is multicollinearity which exists when there is high correlation between the independent variables (Kumar, n.d.). The consequence of the presence of multicollinearity can is large standard errors, which can lead to a failure to accept the alternate hypothesis (Williams, 2015b). A method for detection of multicollinearity is to assess the variance inflation factors (VIFs) that exist between the variables (Mansfield & Helms, 1982). The VIF gives the researcher an indication of the quantum of variance that is affected by multicollinearity (Mansfield & Helms, 1982). In order to test for multicollinearity, the VIF statistic was calculated for each of the independent variables. All values greater than 10 indicated the presence of multicollinearity, with a value of between five and 10 indicating a correlation between the variables and the potential for damage to be caused to the proposed regression model (Stine, 1995). The researcher analysed the VIF using IBM SPSS Statistics v.25 (SPSS). All variables that contained VIF in excess of 10 were removed from the analyses (in testing Hypotheses 2 and Hypothesis 3). Specific consideration was given where values exceeded five by assessing additional warning signals when performing the analyses. However, when prediction is the main consideration for performing a regression analysis, multicollinearity is not considered to be a significant hindrance as the response variables should not be harmfully affected (Williams, Grajales & Kurkiewicz, 2013).

In order to assess whether multicollinearity between the remaining variables existed, in the analyses, the researcher considered the following warning signals:

- Whether the *F*-stat was statistically significant but none of the *t* ratios were (Williams, 2015b);
- Whether high correlations existed between the independent variables (Williams, 2015b). The Pearson correlation coefficient was utilised as the data series were assumed to follow a normal distribution (Tuffrey, 2011). In regression analysis, correlations are deemed to be unacceptable when the coefficient is greater than .90 (Tuffrey, 2011). Where the value is greater than .80 it is deemed risky and a value greater than .70 should be treated with caution (Tuffrey, 2011).

4.8.4. Heteroscedasticity

In regression analysis, one of the assumptions is that the model's error terms have a finite variance that remains constant across all levels of the independent variables (Williams et al., 2013), i.e. that there exists homoscedasticity of errors. In order to identify heteroscedasticity, a visual inspection of the scatter plots of the standardised residuals and the standardised predicted values of the independent variables is appropriate (Williams et al., 2013). The researcher plotted the standardised residuals and standardised predicted values on a scatter plot and visually inspected them for an indication of the existence of heteroscedasticity of error terms. When the scatter plots present a cone like appearance, this was an indication of the existence of heteroscedasticity and an indication that further analysis was required (Williams, 2015a).

4.8.5. Stationarity

Stationarity relates to the manner in which the statistical properties of a variable are related when assessing that variable over a period of time. When a data series has the property of even distribution around the mean, the data series is known to be stationary (Gordon, 1995). Stationarity is an important consideration when attempting to predict an item using a regression framework (Balakrishnan, 2010). When non stationary data is utilised in a regression analysis, the results can be spurious, specifically, the coefficient of determination and *t*-stat can exhibit unrealistic and unreliable results (Giles, 2007). This would lead one to make incorrect conclusions. The researcher therefore tested the stationarity of the variables in the present study. The test performed was the Augmented Dickey-Fuller (ADF) test. The ADF test was carried out using gretl 2019c which is an open source software package for econometric analysis. The ADF model specified was that of constant with no trend. When executing the test, the researcher confirmed the assumption by inspecting the time series plot.

The ADF tests for the existence of a unit root in a data series. The existence of a unit root in time series data is an indicator that the series is non stationary (Balakrishnan, 2010). The test utilises a regression to determine whether the coefficient of the lagged regressor equals zero (Haider, 2016). The hypothesis for the test is stated as follows (Bleikh & Young, 2014; Haider, 2016).

Null hypothesis (H_0): the time series variable contains a unit root, at a 95% confidence level. This would occur when the p-value exceeds .05. The conclusion would therefore be that the time series is non stationary.

Alternative hypothesis (H_A): the time series does not contain a unit root, at a 95% confidence level. This would occur when the *p*-value is less than .05. The conclusion would therefore be that the time series is stationary.

$H_0 : \theta = 0$, the time series contains a unit root;
$H_A : \theta = 1$, the time series does not contain a unit root.

The number of lags as an input into the ADF test is a consideration. The effects of the different number of lags should not be ignored because the test can be sensitive to the lag order in bounded samples (Cheung & Lai, 1995). If too few lags are specified in the test, the results may be unpredictable, whereas if several lags are included the test can become ineffective (Gordon, 1995).

4.8.6. Outliers

An outlier is an individual observation of a series of data that has a highly unusual value (Williams et al., 2013). The existence of outliers in the variables can have severe negative consequences on the results and the predictive ability of regression models (Stevens, 1984). This is even more critical when the sample sizes are relatively small (Wegner, 2016c). The researcher tested the data for normality, and it was therefore assumed that the sample had a Gaussian distribution. It was therefore appropriate to utilise the z-score, a popular method for detecting outliers (Ratner, 2011). This is simply a measure of how far the value is from the mean of the data. The formula utilised was as follows (Wegner, 2016c):

$$z = \frac{x - u}{\sigma}$$

Equation 12. z test

where,

$z =$ z score

$x =$ data point of interest;

$u =$ mean of the sample;

$\sigma =$ sample standard deviation.

The researcher tested for the existence of outliers that lie more than three standard deviations from the mean of the data series. Any outliers identified were analysed in further detail to consider whether the amount should be removed from the analyses. The variable was however only removed if there existed a valid and substantiated reason to do so (Williams et al., 2013).

4.9. Limitations

The study was undertaken in manner that aimed to ensure the integrity of the data at all times in order to ensure that the results could be scrutinised and replicated. However, the following limitations were noted with regards to the current study:

- There is difficulty in accurately measuring the average realised EP. The actual EP observed in the past may be different to what was actually reported.
- In order to estimate the future EP, the relevant model was developed and executed on data points observed in the past. The past may not be representative of the future and could lead to the misrepresentation of the forecast numbers.

- The time horizon adopted was limited to data points for the periods 1996 to 2018. This period was limited and will not be a reflection of all possible events and circumstances that impact the EP. Using a different time horizon could produce different results.
- Reasonability checks were performed on the data collected. The researcher relied on the integrity of the sources publishing the data.
- The research utilised the closing monthly data points for the share returns and financial and macroeconomic indicators. This ignored volatility and fluctuations that may have occurred during the period.

5. RESULTS

5.1. Introduction

The purpose of this chapter is to outline the results of the research project undertaken. The process utilised to address the research questions outlined in Chapter 3 is discussed. The data has been analysed in a manner that has enabled the researcher to assess whether there was evidence to either reject, or alternatively, fail to reject, the null hypotheses. The detailed analyses of the results are presented in Chapter 6.

The chapter begins with an overview of the process of sample generation. Thereafter, the calculation of the realised historical equity premium (EP) is discussed. This is followed by a discussion of the preparation of the data for use in the analysis. The data was tested for suitability by calculating and analysing the descriptive statistics relevant to each of the variables utilised in the study.

The results are subsequently presented on a per hypothesis basis, as stated in Chapter 3. The method utilised the results are presented. The full results of the statistical tests performed are presented in the appendices as referenced.

5.2. Sample generation

The main unit of interest in the present study is the EP. The EP represents the return generated on all equities in excess of that which an investor could have realised in bond yields over the same period. The population was therefore all equity returns realised. The current study limited the equity returns to the JSE Top 40 Index. Due to the nature of the research, access to a large number of financial and macroeconomic indicators was required over the same period. As a result, the study assessed the period 1997 to 2018. The sample utilised was the monthly returns realised in the JSE Top 40 Index less the risk-free rate of return that an investor could have realised over the same period. The risk-free rate was assumed to be equal to the yield on long-term government bonds, in line with the generally accepted methodology for obtaining the risk-free rate (Damodaran, 2018). The dataset consisted of 265 months of returns on the JSE Top 40 Index and the yield on long-term government bonds. The return on the 10-year bond was utilised. This was due to the fact that it was identified as the most utilised measure of the risk-free rate in private practice (PwC, 2017). The calculation of the EP is discussed in further detail in the next subsection.

The data collected was from the period December 1995. However, the analysis only started from January 1997. The apparent discrepancy in starting dates is due to the need for (i) the EP to be calculated as the 12-month rolling EP, and (ii) certain independent variables to be calculated with reference to their 12-month moving averages (refer to section 5.4 below for further details). In addition, due to the fact that the EP is a lagged variable, data relating to EP was obtained for January 2019. This enabled an assessment of the predictors of data captured in period the December 2018. The net result is that the sample utilised in the analyses consists of 265 data points relating to EP.

5.3. Historical equity premium

The first step was to calculate the historical EP from the collected data. The EP was calculated as the 12-month rolling return on the JSE Top 40 Index less the equivalent risk-free rate. The starting point of the data collected was December 1995. This was done in order to ensure that it was possible to calculate the 12-month rolling return over the sample period. The EP for the 22-year period January 1997 to December 2018 was calculated and represents the sample period for the analyses. This represents 265 data points for the EP. The EP utilised in this study was calculated as the arithmetic mean returns. The arithmetic mean was chosen as it is arguably better than the geometric mean, as in estimating future returns, the intention is to calculate an unbiased estimate of the EP (Damodaran, 2018). Figure 2 shows the movement in the 12-month rolling nominal EP utilising the returns on JSE Top 40 Index for the period under review. The graph also plots the EP utilising the rate on the 91-day Treasury Bill for comparative purposes. This was done as a reasonability check to confirm that there were no apparent adverse movements in the bond rate. This Treasury Bill rate was chosen as it represents an appropriate measure of the risk-free rate in South Africa (Firer & McLeod, 1999). There were no inconsistencies noted.

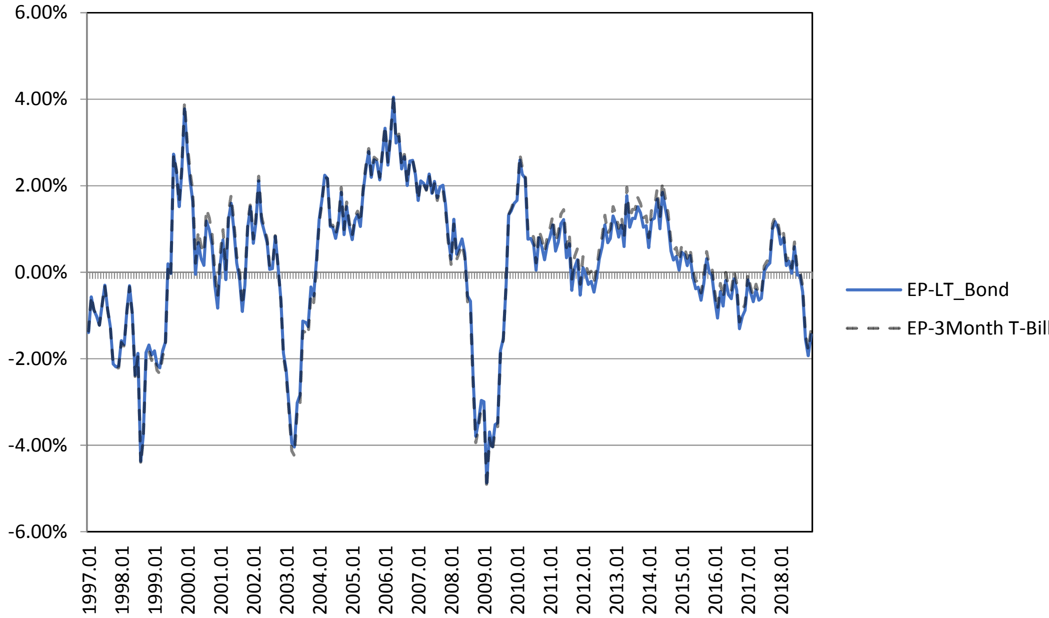

Figure 2. 12-month rolling equity premium

The first statistical test performed on the historical EP was descriptive statistics in order to obtain a greater understanding of the realised EP in South Africa over the sample period. The analysis considered the EP calculated utilising both the JSE Top 40 Index and the JSE All Share Index. The inclusion of the All Share Index was utilised as a comparative to ensure the reasonability of the data obtained for the Top 40 index. It represents a suitable comparative due to the fact that ratio of risk to reward must be the same of all assets in the market (Firer et al., 2012). As discussed above, both the Treasury Bill rate (91 days) and the return realised on bonds were utilised as the risk-free rate. Table 2 represents the results of the analysis. There were no indicators that raised any concerns. The analysis therefore determined both the JSE Top 40 Index and the long-term bond yield as appropriate measures for the calculation of the EP.

Table 2. Equity premium descriptive statistics

	Bond Yield		91-day T-Bill	
12-month nominal EP	Top 40	ALSI	Top 40	ALSI
Number of observations	265	265	265	265
Mean	0.31%	0.35%	0.24%	0.27%
Median	0.55%	0.56%	0.39%	0.34%
Standard deviation	1.67%	1.58%	1.61%	1.52%
Range	9.12%	8.86%	8.91%	8.65%
Cumulative EP	2.35%	2.75%	3.30%	3.71%

The cumulative realised historical EP was calculated to give a long-term view of the EP for the sample period (starting January 1996). The cumulative realised EP on the JSE Top 40 Index, utilising the bond yield as the risk-free rate, was 2.35% (Table 2). The low cumulative EP could partially be attributed to the starting date. At the time, the South African 10-year bond was offered a yield of approximately 15%. If one had to invest ZAR 100 in the JSE Top 40 Index at the beginning of January 1996, the amount would be worth ZAR 1,660 as at the end of January 2018, ignoring the effects of inflation. Alternatively, had one invested ZAR 100 in long-term government bonds, the amount would have returned the equivalent of ZAR 972 as at the end of January 2018, ignoring the effects of inflation. The additional return represents the additional risk held by investors to reward them for investing in shares, a riskier asset.

5.4. Data preparation

The purpose of this section is to provide an overview of the preparation of the data that was obtained in order for it to be utilised in each of the tests that were performed. The data was obtained at monthly intervals. Where the last day of any of the months under review was on a weekend, the closing rate was deemed to be equal to the closing price on the last available day reported. Table 3 presents an overview of the independent variables utilised in the analysis.

Table 3. Description of independent variables

Variable	Description of variable
DividendPrice	The dividend price ratio at a log level. Please refer below for details regarding the calculation of the variable.
EarningsPrice	The earnings price ratio at a log level. Please refer below for details regarding the calculation of the variable.
Volatility	The volatility in the JSE Top 40 Index as reported.
SP500	The 12-month rolling change in the price index of the S&P 500 index at a log level (the log transformation is discussed below).
FTSE100	The 12-month rolling change in the price index of the Financial Times Stock Exchange 100 Index at a log level (the log transformation is discussed below).
MSCI	The 12-month rolling change in the price index of the Morgan Stanley Capital International World Index at a log level (the log transformation is discussed below).
Tbill	The difference between the yields on the 91-day Treasury Bill at month *t* less the twelve-month moving average yield on the same instrument.
Spread	The difference between the yield on the South African 10-year government bond and the yield on the 91-day Treasury Bill.
BondYield	The difference between the yields on the South African 10-year government bond at month *t* less the 12-month moving average yield on the same instrument.
MoneyMarket	The difference between the rates on the money market (RT130) at month *t* less the 12-month moving average yield on the same instrument.
CPI	The first difference in log levels of the CPI in South Africa (the log transformation is discussed below).
ExchangeRate	The real effective exchange rate index for the South African Rand at a log level (the log transformation is discussed below).
IndustrialProd	The growth rate in industrial production in South Africa at a log level (the log transformation is discussed below).
OilProd	The growth rate in world oil production at a log level (the log transformation is discussed below).

The tests for hypotheses one and two were in the form of linear regressions. Where variables are multiplicatively related or grow exponentially over time, it is possible to explain their behaviour with linear models by utilising the logarithms of the variables (Haider, 2016). As per the Table 3, certain data points for the variables were transformed into their natural logarithms (i.e. $\log_e x$ / $\ln e$, where e is equal to 2.71828). The log transformations were done in accordance with the following methodology.

The dividend price ratio at a log level was calculated by utilising the following formula. It should be noted that the dividend is at period *t* – 1 to ensure that it was known as at the start of the period (Campbell & Shiller, 1988).

$$Dividend\ Price\ Ratio_t = \ln(dividend_{t-1}) - \ln(price_t)$$

Equation 13. Log dividend price ratio

The earnings price ratio at a log level was calculated by utilising the formula that follows. It should be noted that the earnings are at period *t* – 1 to ensure that it was known as at the start of the period (Campbell & Shiller, 1988).

$$Earnings\ Price\ Ratio_t = \ln(earnings_{t-1}) - \ln(price_t)$$

Equation 14. Log earnings price ratio

The log level of the other variables (SP500, FTSE100, MSCI, ExchangeRate, CPI, IndustrialProd & OilProd) were obtained by calculating the first difference of the logarithm, given by the following formula (Bleikh & Young, 2014; Haider, 2016):

$$\Delta \ln(Y_t) = \ln(Y_t) - \ln(Y_{t-1})$$

Equation 15. First difference log level

The data preparation and calculations were performed using Microsoft Excel. A data table was created whereby the data was ordered in such a manner that EP was stated at period, *t* + 1, and all other variables were stated at time period *t.* The data was uploaded into SPSS for further analysis.

5.5. Descriptive statistics

The data was analysed through descriptive statistics techniques. The purpose of the analyses was to confirm that the data series were appropriate for the execution of the tests of the hypotheses. The following section details the results for each of the tests performed.

5.5.1. Test for normal distribution

The research utilised regression analyses. In order for the results to be valid, the regression framework assumes that the data is normally distributed. It should be noted that by transforming data into their log equivalents it ensures that the data follows a normalised distribution. However, histograms were created for each of the variables in order to confirm that the data followed a normal distribution. Figure 3 is an example of the distribution of DividendPrice. The histograms for each of the other variables is shown in Appendix A. The results of the testing of normality are presented in Table 4.

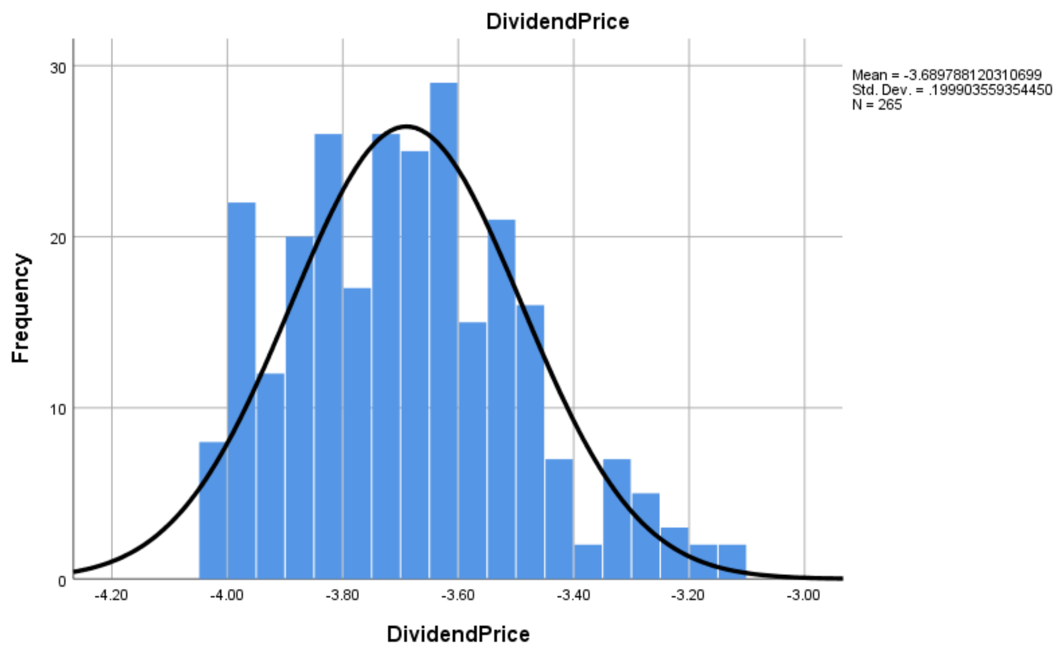

Figure 3. Histogram: DividendPrice

Table 4. Summary of test for normal distribution

	Histogram follows a normal distribution	Assumption violated
DividendPrice	Yes	No
EarningsPrice	Yes	No
Volatility	Yes	No
SP500	Yes	No
FTSE100	Yes	No
MSCI	Yes	No
Tbill	Yes	No
Spread	Yes	No
BondYield	Yes	No
MoneyMarket	Yes	No
CPI	Yes	No
ExchangeRate	Yes	No
IndustrialProd	Yes	No
OilProd	Yes	No

5.5.2. Test for stationarity

Stationarity is a concern when analysing time series data. In essence, by testing for stationarity the researcher attempted to ensure that the statistical properties of the variables were stationary. The tests for stationarity were conducted by using the ADF test. Table 5 presents a summary of the results and conclusion of the test for stationarity. The *p* values for all of the variables was less than .05. The data series therefore did not contain a unit root. The researcher concluded that all the data series were stationary.

Table 5. Summary of test for stationarity

Variable	Inspection showed trend in time series*	*p***	< .05	Hypothesis – ADF test	Conclusion
EP	No	.00217	True	Reject H_0	Stationary
DividendPrice	No	.01033	True	Reject H_0	Stationary
EarningsPrice	No	.04769	True	Reject H_0	Stationary
Volatility	No	.00442	True	Reject H_0	Stationary
SP500	No	.00001	True	Reject H_0	Stationary
FTSE100	No	.00001	True	Reject H_0	Stationary
MSCI	No	.00001	True	Reject H_0	Stationary
Tbill	No	.00005	True	Reject H_0	Stationary
Spread	No	.04489	True	Reject H_0	Stationary
BondYield	No	.00001	True	Reject H_0	Stationary
MoneyMarket	No	.00002	True	Reject H_0	Stationary
CPI	No	.00000	True	Reject H_0	Stationary
ExchangeRate	No	.00000	True	Reject H_0	Stationary
IndustrialProd	No	.00000	True	Reject H_0	Stationary
OilProd	No	.00000	True	Reject H_0	Stationary

* The inspection was to confirm that the use of the model was appropriate (see **)

** model: constant with no trend; $k = 7$;

5.5.3. Test for multicollinearity

The use of multiple independent variables in a regression framework can be negatively impacted if there is multicollinearity within the data. In order to test for multicollinearity, the VIF statistic was determined for each of the independent variables. All values greater than 10 indicate the presence of multicollinearity. The results are presented in Appendix B. The test indicated that multicollinearity was specifically a problem with the independent variables SP500 and MSCI as the VIF values exceeded 10. These two variables were therefore removed from the analyses, as performed in terms of hypotheses 2 and 3, as they could negatively impact on the results.

Where the VIF is greater than 5, it could be indicative of a potential problematic existence of multicollinearity. The variable Tbill was therefore a concern as the VIF was greater than 5. In order to protect against any potential negative conclusions resulting from the existence of multicollinearity, the researcher looked for any additional warning signals as outlined in chapter 4.8.3, namely:

- whether the *F*-stat was statistically significant but none of the *t* ratios were (Williams, 2015b).
- whether high correlations existed between the independent variables (Williams, 2015b).

This is discussed in further detail with the results of the KS regression below. The results are presented in Table 11.

5.5.4. Test for heteroscedasticity

The analysis made use of parametric analysis. In order to be comfortable that the regression had the ability to predict the dependent variable consistently across a full range of independent variables, it was important to test the model's error terms to ensure that they are homoscedastic. This was done by visually inspecting the scatter plots or the model's error terms. When data is heteroscedastic, it will have a cone like appearance as this is a representation of the fact that the error terms are not the same across the range of the independent variable. Figure 4 provides an example of a heteroscedastic data distribution (Williams, 2015a).

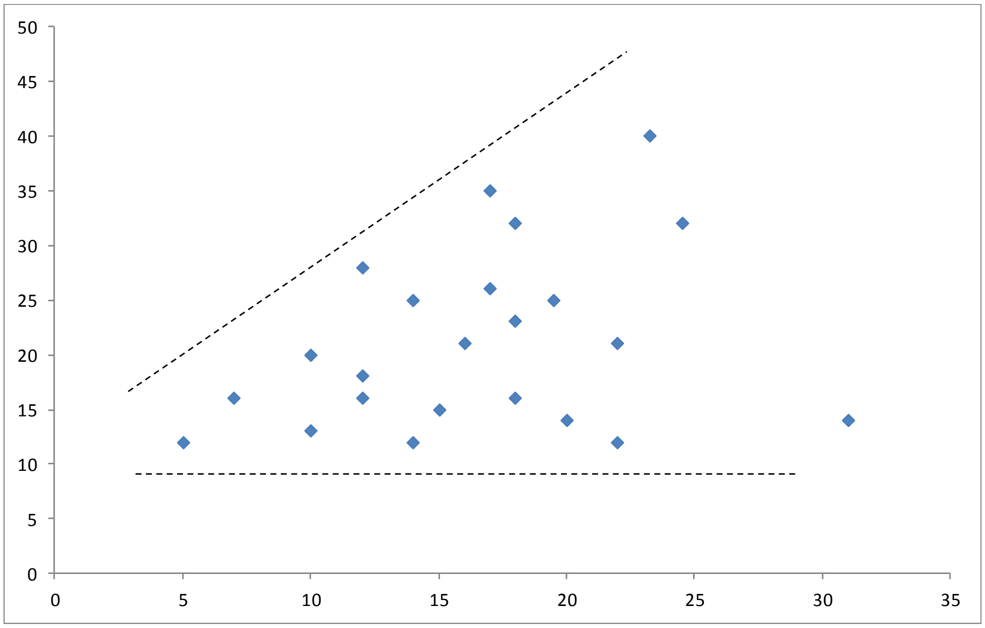

Figure 4. Example of heteroscedasticity

Source: Adapted from Williams (2015a)

Figure 5 shows the scatter plot between the residuals and the DividendPrice. Please refer to Appendix C for the scatter plots of the other independent variables. If the scatter plots demonstrated an appearance that could be considered to be cone like, in line with the example provided in Figure 4, it was an indication that further analysis was required. In addition, it was an indication that the variable may not be suitable for use in a predictive model.

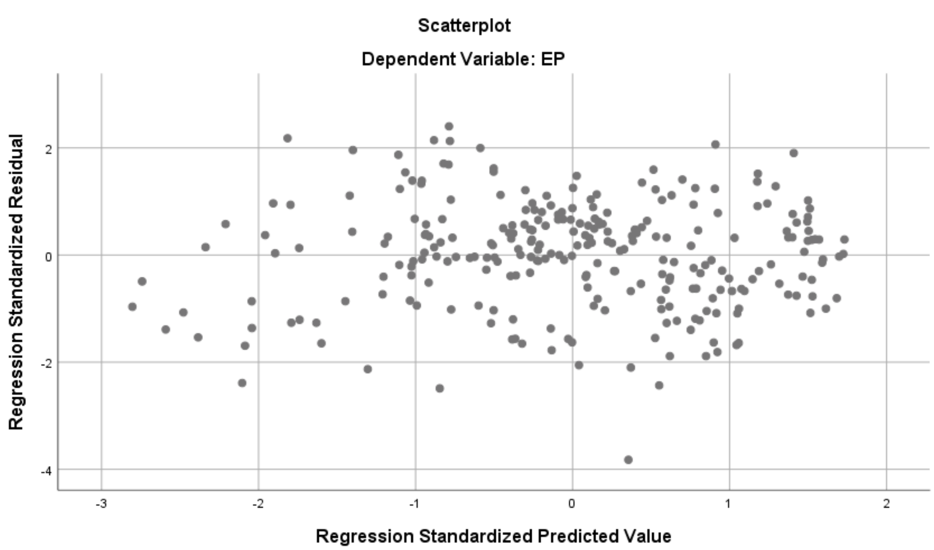

Figure 5. Residuals scatterplot: DividendPrice

The analysis of the scatterplot for the DividendPrice, as shown in Figure 5, indicated that the residuals formed a rectangular shape. This is indicative of homoscedasticity. This does therefore not violate the assumption for the regression. The results for all of the variables are summarised in Table 6. The results found that none of the variables displayed a cone like appearance and therefore none of the variables appeared to violate the assumption of homoskedasticity.

Table 6. Summary of test for heteroscedasticity

	Scatter show cone like appearance	Assumption violated
DividendPrice	No	No
EarningsPrice	No	No
Volatility	No	No
SP500	No	No
FTSE100	No	No
MSCI	No	No
Tbill	No	No
Spread	No	No
BondYield	No	No
MoneyMarket	No	No
CPI	No	No
ExchangeRate	No	No
IndustrialProd	No	No
OilProd	No	No

5.5.5. Test for outliers

The existence of outliers in the variables can have negative consequences on the results and predictive ability of regression models. This is even more critical when the sample sizes are relatively small. The researcher tested the data for normality, and it was therefore assumed that the sample had a Gaussian distribution. It was therefore appropriate to utilise a *z*-test. This is simply a measure of how far the value is from the mean of the data. For each of data series, the *z* score was calculated. The existence of outliers was deemed to occur where the values were greater than three standard deviations from the mean. Table 7 summarises the results of the test to identify outliers in the data series.

Table 7. Summary of test for outliers

	Number of data points more than three standard deviations from the mean
DividendPrice	0
EarningsPrice	0
Volatility	6
SP500	2
FTSE100	3
MSCI	2
Tbill	4
Spread	0
BondYield	3
MoneyMarket	4
CPI	8
ExchangeRate	3
IndustrialProd	3
OilProd	3

The data series contained a number of outliers (a total of 41 as illustrated in Table 7). Consideration was required of whether these outliers needed to be removed for the purposes of the analyses. This required inspection of each of the outliers to assess whether there was any viable reason that they should be removed. The nature of the outlier is an important consideration. It is not acceptable to remove an outlier simply because it is an outlier. It may be a valid observation and removing it will reduce the robustness of the model (Williams et al., 2013). However, an outlier could be an indication of an error in data measurement or collection and each of the outliers identified above was investigated in more detail.

The researcher assessed each of the outliers noted in the above test. There was however no evidence to suggest that the values did not represent valid observations of the underlying indicator. None of the values were therefore removed for the purpose of performing the statistical testing.

5.6. Evaluate the relationship between individual predictors and the equity premium: Test of Hypothesis 1

The first objective was to assess the relationship between the EP and individual financial and macroeconomic indicators utilising a standard univariate predictive regression. The aim of the test was to assess the predictive ability, in relation to the EP, of certain key financial and economic variables, as identified in the literature. The test was performed by utilising a standard regression framework as outlined in Chapter 4. The dependent variable was the EP, with the independent variable being the identified predictor. The results of the predictive regressions for each of the variables is presented in Table 8.

The values of interest are the adjusted R^2 and the *t*-stat. The adjusted R^2 represents the measure of how much of the movement in the EP can be explained by the independent variable, which in this case is the dividend price ratio. The intention was to assess whether the *t*-stat was in the critical range for acceptance.

In order to test the hypothesis, the calculation of the critical region of the *t*-stat was required, at a 95% confidence level. Given that the degrees of freedom of the residual was equal to 263 (*n* – 2), the critical region of acceptance was calculated as follows (calculated using the T.INV.2T formula in Excel):

$$-1.97 \leq t \leq 1.97$$

The t-stat for each of the variables was calculated based on the results of the regression, using the formula stated in section 4.7.1. Where the *t*-stat was outside this given range, the result was failure to reject the null hypothesis. The results of the hypothesis test for each of the variables is presented in the following table, Table 8. Six of the variables (BondYield, CPI, ExchangeRate, FTSE100, OilProd, SP500) were within the critical region for acceptance, at a 95% confidence level, as their *t*-stat values were within the range -1.97 to 1.97. The outcome was therefore a failure to reject the null hypothesis. The other eight variables (DividendPrice, EarningsPrice, IndustrialProd, MoneyMarket, MSCI, Spread, Tbill & Volatility) were outside the critical region of acceptance at a 95% confidence level. The result was a rejection of the null hypothesis.

Table 8. Results of Hypothesis 1

*	N	Adjusted R Square	*t*-stat**	*p*	In critical region	Outcome
DividendPrice	265	.352	-12.01	.000	No	Reject $H1_0$
EarningsPrice	265	.263	-9.76	.000	No	Reject $H1_0$
Volatility	265	.183	-7.75	.000	No	Reject $H1_0$
SP500	265	.010	1.88	.061	Yes	Fail to reject $H1_0$
FTSE100	265	.008	1.80	.074	Yes	Fail to reject $H1_0$
MSCI	265	.020	2.54	.012	No	Reject $H1_0$
Tbill	265	.012	-2.04	.043	Yes	Reject $H1_0$
Spread	265	.135	6.50	.000	No	Reject $H1_0$
BondYield	265	-.004	0.12	.905	Yes	Fail to reject $H1_0$
MoneyMarket	265	.026	-2.82	.005	No	Reject $H1_0$
CPI	265	-.003	-0.39	.698	Yes	Fail to reject $H1_0$
ExchangeRate	265	-.003	-0.40	.692	Yes	Fail to reject $H1_0$
IndustrialProd	265	.031	-2.92	.004	No	Reject $H1_0$
OilProd	265	-.003	-0.47	.637	Yes	Fail to reject $H1_0$

* Dependent variable: EP
** 5% level of significance

5.7. Utilise a large number of predictors to assess predictability: Test of Hypothesis 2

5.7.1. Kitchen sink regression

The second objective was to consider whether EP is predictable in-sample by applying a KS regression that utilised a large number of variables. In addition, whether the introduction of statistical limitations improved the predictive ability of the model. In order to assess the predictability of the EP, a large of number financial and macroeconomic indicators were assessed to determine whether a relationship existed. The KS regression was performed using SPSS. The dependent variable was the EP with the independent variables being the values, calculated in accordance with Table 3. The EP was at the stated period, $t + 1$. The full sample was utilised, i.e. $N = 265$. Table 9 and Table 10 show the results of the analysis. The adjusted R^2, .510, was lower than the threshold for rejection of the null hypothesis, .6, as defined in Chapter 3. The results of the hypothesis test are presented in Table 14.

Table 9. Results of kitchen sink regression

*	Adjusted R Square	*p***
KS	.510	.000

* Dependent variable: EP
** Predictors: DividendPrice, EarningsPrice, Volatility, FTSE100, Tbill, Spread, BondYield, MoneyMarket, CPI, ExchangeRate, IndustrialProd, OldProd

Table 10. Results of kitchen sink regression: Table of coefficients

*	Unstandardised coefficients	Standardised coefficients	*t*	*p*
DividendPrice**	-0.04	-0.52	-9.12	.000
EarningsPrice	0.00	0.03	0.49	.626
Volatility**	-0.06	-0.24	-4.10	.000
FTSE100	0.01	0.03	0.73	.469
Tbill	0.02	0.02	0.17	.865
Spread**	0.15	0.16	2.75	.006
BondYield**	0.26	0.12	2.19	.029
MoneyMarket**	-0.41	-0.33	-3.45	.001
CPI	-0.01	-0.02	-0.37	.712
ExchangeRate	0.02	0.05	1.05	.294
IndustrialProd***	-0.06	-0.08	-1.74	.083
OilProd	-0.02	-0.01	-0.26	.797

* Dependent variable: EP
** significant at a 5% level of significance
*** significant at a 10% level of significance

In order to confirm that multicollinearity did not negatively affect the results of the regression, the warning signals (as discussed in 4.8.3) were considered. The warning signal, assessment and results of the assessment are presented in Table 11.

Table 11. Assessment of warning signals for multicollinearity

Warning signal	Assessment	Conclusion
Whether the *F*-stat was statistically significant but none of the t ratios were (Williams, 2015b).	The *F*-stat (Table 9) and five of the t ratios (Table 10) are statistically significant at a 95% confidence level, with six being statistically significant at a 10% level of significance.	Multicollinearity deemed to not to be adversely impacting the model.
Whether high correlations existed between the independent variables (Williams, 2015b).	The correlations between the variables are presented in Appendix D, Table 18. The correlation between MoneyMarket and Tbill is the only value that exceeds .7. The value of 89 signifies significant risk (Tuffrey, 2011).	Potential issue caused by correlation between MoneyMarket and Tbill.

The correlation between the variables MoneyMarket and Tbill is the only warning sign that indicates the problematic existence of multicollinearity is executing the KS regression. However, considering the primary purpose in executing the test is the predictability of the EP, the potential risk is minimised as the response variables should not be harmfully affected (Williams et al., 2013). The researcher was therefore comfortable with the results for the testing of hypothesis 2.

5.7.2. The use of statistical constraints

The introduction of statistical constraints was in the form of utilising ridge regression, lasso regression and elastic net regression. The same variables used in the KS regression were used for the in-sample period, namely, December 1996 to

December 2013 (December 1996 is utilised in order to be able to predict the EP for January 1997, as the predictors are lagged). This represents a sample size of 205 data points for each variable. The regularisation was performed using SPSS. For each of the regressions performed, namely ridge, lasso and elastic net, the optimisation was performed by the use of a process of cross validation. Resampling was performed using cross validation, with the number of folds set at ten. The objective was to optimise the coefficients, through either adjustment or variable selection, for each independent variable.

The first step was to understand how the coefficients responded to the optimisation. The regularisation plots demonstrate how the regression coefficients plotted against the regularisation penalty. This is useful as it provides a view of how the coefficients changed over the range of penalties tested. The regularisation paths are shown in the Figure 6. The plots for the lasso and elastic net are presented in Appendix E.

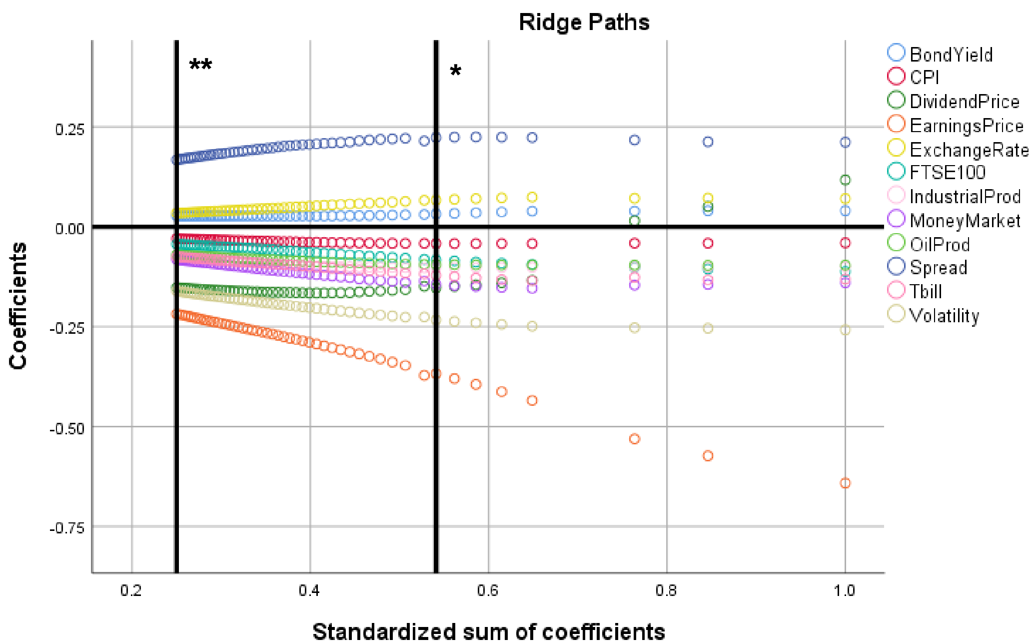

Figure 6. Regularisation paths: Ridge regression

* Ridge penalty = .140. Optimal model at the point where the expected prediction error is minimised. Standardised sum of coefficients = .541.

** Ridge penalty = 1.000. Most parsimonious model within 1 standard error. Standardised sum of coefficients = .250.

Table 12, shows the optimised coefficient after the regularisation of each of the independent variables (see the column β). The β value shown is at the point of the most parsimonious model, as denoted on the ridge paths shown in Figure 6. Please refer to Appendix F for the tables of the optimised coefficients for the lasso and elastic net regressions.

Table 12. Ridge regression coefficients

*	β	df	*F***	*p*
DividendPrice	-0.15	3	56.63	.000
EarningsPrice	-0.22	3	83.75	.000
Volatility	-0.16	2	32.32	.000
FTSE100	-0.04	1	0.54	.464
Tbill	-0.08	3	4.17	.007
Spread	0.17	2	13.87	.000
BondYield	0.08	1	0.61	.436
MoneyMarket	-0.08	3	17.62	.000
CPI	-0.03	1	0.79	.375
ExchangeRate	0.03	1	0.73	.396
IndustrialProd	-0.08	2	16.34	.000
OilProd	-0.07	1	1.97	.163

* Dependent variable: EP
** 5% level of significance

In order to test the hypothesis, the output of interest was the coefficient of determination. The R^2 and adjusted R^2 are shown after the optimisation of each of the independent variables has been taken into account. The summary of the R^2 values for each of the regression models is shown in Table 13. The results of the test for hypothesis 2 are shown in Table 14.

Table 13. Results of penalised regressions

Model*	Adjusted R^2**	Regularisation R^2***	*p*
Ridge	.74	.71	.000
Lasso	.71	.70	.000
Elastic net****	.69	.72	.000

* Dependent variable: EP; Predictors: DividendPrice, EarningsPrice, Volatility, FTSE100, Tbill, Spread, BondYield, MoneyMarket, CPI, ExchangeRate, IndustrialProd, OldProd
** Adjusted coeffecient of determination where model minimises the sum of the square errors
*** Adjusted coeffecient of determination at most parsimonious model within 1 stadard error
**** Ridge penalty .800; Lasso penalty .280
Note: All models significant at a 95% confidence level

Table 14. Summary of results of Hypothesis 2

Model	Full sample			In sample		
	N	Adjusted R^2	Outcome	*n*	Adjusted R^2*	Outcome
KS	265	.51	Fail to reject $H2_0$	205	.56	Fail to reject $H2_0$
Ridge				205	.71	Reject $H2_0$
Lasso				205	.70	Reject $H2_0$
Elastic net				205	.72	Reject $H2_0$

* Assessed as the R^2at the most parsimonious model, as denoted by the regularisation R^2in Table 13.

In order to test the relative in-sample predictive ability, the model determined by the regression analysis was used to predict the EP based on the sample data utilised in determining the model. This allowed the researcher to calculate the MSE of the in-sample values. Please refer to section 5.8 for further details.

5.8. Assess the out-of-sample performance of penalised regressions compared to a benchmark: Test of Hypothesis 3

The third objective is to assess the out-of-sample performance of the KS regression after introducing statistical and economic constraints to evaluate whether the proposed model is able to consistently deliver superior forecasts relative to a benchmark. The methodology was to calculate the out-of-sample R^2 statistic in line with the formula noted in section 4.7.3 above. This required the calculation of predicted values for the out-of-sample period. The period was defined as January 2014 to December 2018 (*n*=60). Therefore, using the different regression models determined with reference to the in-sample data, the EP was calculated by utilising the independent variables from the out-of-sample period. The prediction was performed using Alteryx Designer x64 (Alteryx). Figure 7 shows the workflow that was created for the purposes of predicting the values of interest using the ridge regression framework. All of the workflows used in the analysis are presented in Appendix G. The input is the data as captured in SPSS. The results of the calculations were output to Excel for further analysis.

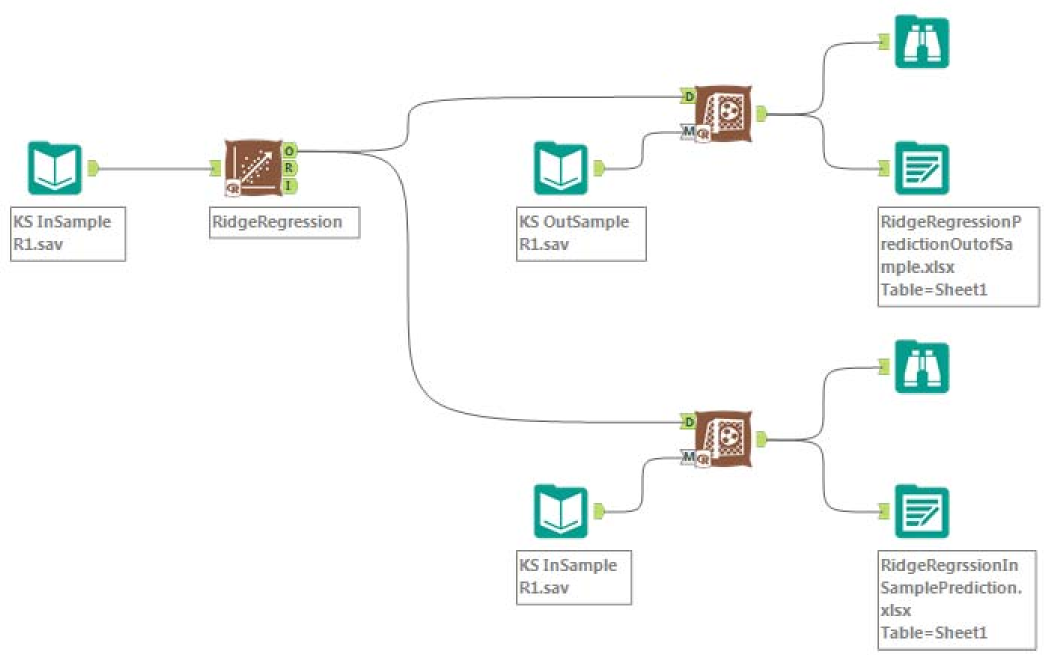

Figure 7. Alteryx process flow: Ridge regression

For completeness purposes, the results of executing the workflow are shown for each of the processes. Figure 8 represents the execution of the ridge regression (please refer to Appendix H for the screenshots for all processes). The warnings for each process execution were due to the process amending certain names. This had no impact on the results.

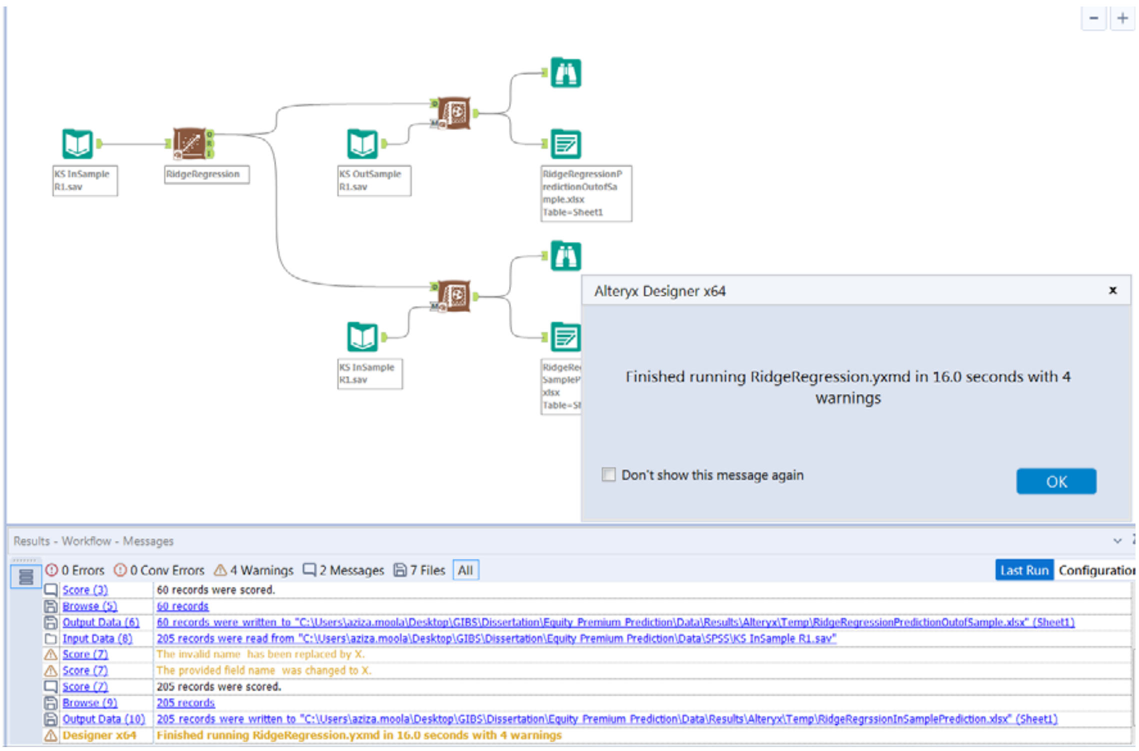

Figure 8. Alteryx execution of process: Ridge regression

The predicted values for the ridge regression are shown in Figure 9. The predicted values for the KS, lasso and elastic net regressions are shown in Appendix I.

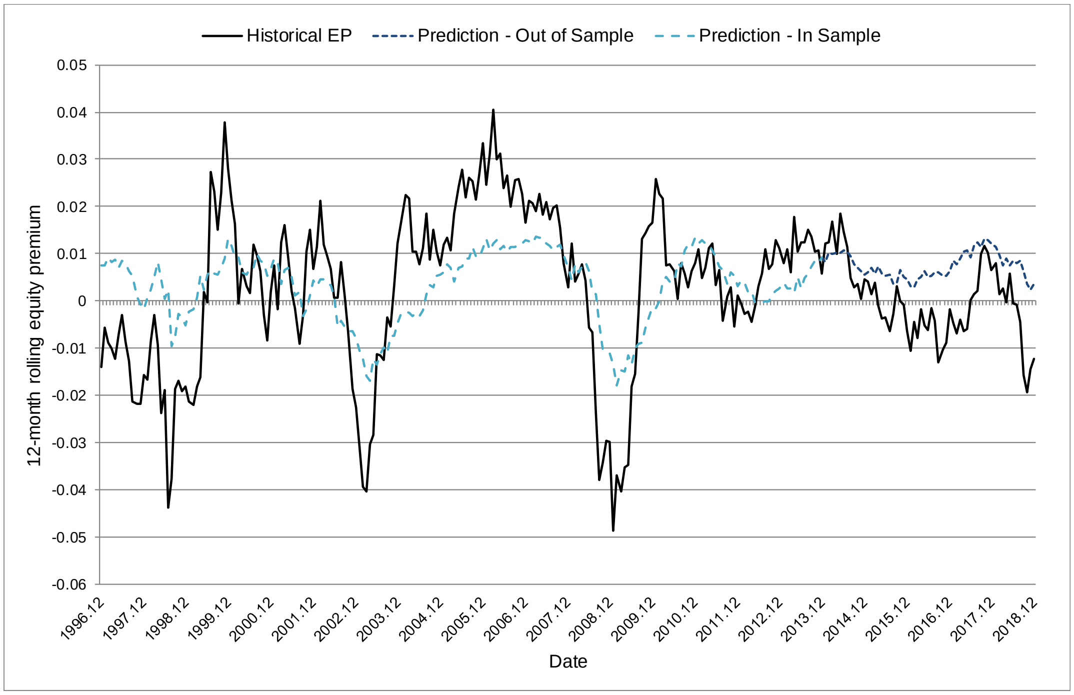

Figure 9. Ridge regression time series

In order to test the hypothesis that the use of constraints increases the forecast accuracy of the model, the research required the R^2 statistic for both in-sample and out-of-sample predictions. The benchmark for the analysis was the KS regression as this was the model that demonstrated the best in-sample predictive performance. This was determined by selecting the model with the highest adjusted R^2 of the each of the regressions that were not subject to optimisation. The out-of-sample forecast for the ridge, lasso and elastic net regressions were the models assessed against the KS regression. The first step was to calculate the MSE for each of the regressions. For each period the squared difference between the historical EP (r_t) and the forecast EP (r) was calculated as $(r_t - r)^2$. The sum of the squared differences was divided by the sample size (n = 60) to obtain the MSE of the forecasts. In order to calculate the R^2_{OOS}, the formula, as stated in section 4.7.3, was utilised. The results for each of the comparisons are presented in Table 15 along with the results of the test of Hypothesis 3. In comparing the MSE of the forecasts, the high performing model will display the value closest to zero. In testing the hypothesis, a failure to reject the null will occur when the R^2_{OOS} is less than 0.

Table 15. MSE of forecasts: Results of Hypothesis 3

	Out-of-sample		
	MSE	R^2 compared to benchmark	Result of hypothesis test
KS	0.00086		
Ridge	0.00010	.8801	Reject $H3_0$
Lasso	0.00089	-.0381	Fail to reject $H3_0$
Elastic net	0.00058	.3246	Reject $H3_0$

5.8.1. The use of economic constraints

The researcher reviewed the out-of-sample forecasts for negative predictions of the EP in line with the analysis approach suggested in section 4.7.3. However, none of the forecasts (KS, ridge, lasso, elastic net), showed out-of-sample predictions of EP <0 (refer to Figure 9, Figure 42, Figure 43 and Figure 44) There were therefore no adjustments made to the forecasts.

5.9. Summary of chapter

The chapter set out the results of the analyses performed by the researcher in order to test the hypotheses stated in Chapter 3. The starting point was to explain the process of sample generation. Thereafter, a calculation of the historical EP, the focus of the current research, was performed. This was the dependent variable throughout the analyses. An overview of the process of the preparation of the other data, the independent variables, followed.

Various descriptive statistical tests were performed in order to obtain comfort that the assumptions that are required when performing the parametric analyses were appropriate. The results were presented in accordance with the tests performed. A summary of the results was then presented, per hypothesis.

The first test evaluated the relationship between various financial and macroeconomic indicators and the EP. In order to evaluate the relationship, regression analyses were performed. In addition, the critical range for the *t*-stat was calculated, to assess whether the variables were within this range. A summary of the results was presented in the chapter.

In order to test the second hypothesis, the KS regression was performed by including all variables in a predictive regression framework. The results were presented in the chapter. Thereafter, the regressions were performed by including optimisation techniques, namely ridge, lasso and elastic net. The results of the ridge regression were presented in the chapter with the detailed results shown in the appendices.

The results of the test of the third hypothesis were presented in the chapter for the ridge regression framework. The lasso and elastic net are presented in the appendices. The test was performed by predicting the in-sample and out-of-sample values for EP using each of the regression models. The ridge, lasso and elastic net results were then compared against the benchmark forecast, the KS regression. In order to compare the models, the MSE of each of the forecasts was calculated. This enabled a calculation of the R^2_{OOS}.

6. DISCUSSION OF RESULTS

6.1. Introduction

The objective of the current chapter is to assess the results of the research presented in Chapter 5 in the context of the objectives of the research as set out in the definition of problem and purpose of the research section in Chapter 1. Consideration is given to the current body of knowledge and how the results can be interpreted in relation thereto.

The chapter starts with a discussion of the historical equity premium (EP) in South Africa, the variable of interest in the current study. Thereafter, a discussion of the results in terms of each objective is outlined. Each section will consider whether the research objective has been met.

6.2. The equity premium in South Africa

The EP represents the additional reward that investors receive for holding a portfolio of shares, such as the JSE Top 40 Index, in excess of the prevailing risk-free rate (Firer et al., 2012). It is a measure of the risk that investors perceive to exist in the equity market in which they have invested (Damodaran, 2018). It has been suggested that a reasonable EP that one could expect in South Africa ranges from approximately 5% to 7% (Fernandez et al., 2016; Hassan & van Biljon, 2010; PwC, 2017). These estimates are fundamentally based on historically observed EP returns. The historical EP, calculated using the arithmetic mean, in relation to bonds, was 7.03% (Dimson et al., 2011). The research considered the EP in South Africa for the period January 1996 to December 2018. The historical EP realised over this period was calculated as the arithmetic mean return, as this is arguably the superior metric for assessing the EP (Damodaran, 2018). The results of the current study demonstrated that the cumulative realised EP in South Africa for the period under review was 2.35%.

The realised EP over the period (2.35%) is lower than the anticipated return (between 5% and 7%) and the long-term historical return in South Africa (7.03%) by a fair margin. This indicates a potential overestimation of the quantum of returns that an investor would generate in the equity market using traditional methods of

EP estimation, such surveys or extrapolation of past returns. This appears to be in line with findings that there exists an atypical excess return in historical share portfolios in contrast to the bond yields (Hassan & van Biljon, 2010; Mehra & Prescott, 1985).

The EP is a key input into various financial and economic models and forecasts. In South Africa, the CAPM is utilised by more than 70% of listed companies (Correia & Cramer, 2008). An overestimation could conceivably result in incorrect decision making, with wide ranging impacts. This highlights the need for a more robust method of being able to estimate a forward-looking EP with greater accuracy.

6.3. Evaluate the relationship between individual predictors and the equity premium: Objective 1

The first objective is to assess the relationship between the EP and individual financial and macroeconomic indicators utilising a standard univariate predictive regression. The performance of the EP prediction models that conditioned on single predictors were evaluated. The testing methodology utilised a least squares regression framework (Wang et al., 2019) to assess the relationship between the EP, the lagged dependent variable, and the relevant financial or macroeconomic indicator, the independent predictor variable. The results of each of the predictor variables are discussed. Thereafter a brief summary of the results is presented.

DividendPrice

Discounted cash flow models suggest that one is able to infer an estimate of the EP on the basis of future dividends (Claus & Thomas, 2001). The concept of being able to predict share returns on the basis of dividends has a long history, with evidence first being presented by Shiller et al. in 1984. The results presented support the notion that there exists a statistically significant relationship, at a 95% confidence level, between the log of dividend price ratio and the EP.

EarningsPrice

Earnings are considered to be a predictor of the EP as there is a link between the risk that exists in a share portfolio and the earnings of that portfolio (Bhar & Malliaris, 2011). Earnings have shown statistically significant results in predicting the EP in the US (Fama & French, 2002). The results demonstrate that a statistically significant relationship exists between the log of the earnings price and the EP, at a 95% confidence level. The results support the link between the variables, however, the relationship that exists is relatively weak.

Volatility

There is evidence to support a link between stock market volatility and movements in EP (Graham & Harvey, 2018). Santa-Clara and Yan (2010) demonstrated that EP is a function of diffusive volatility and jump risk. In line with this, the volatility demonstrated that there exists a statistically significant association, at a 95% confidence level, between the EP in South Africa and the underlying volatility in the JSE Top 40 Index.

SP500, FTSE100 and MSCI

Research has shown that there exists a strong association between share returns in South Africa and the US, Asia and the London Stock Exchange (Baele & Inghelbrecht, 2010; Heymans & da Camara, 2013; Samouilhan, 2006). There was however no apparent statistically significant association between either the monthly lagged SP500 or the FTSE100 and the EP in South Africa. The current research indicates that the SP500 and FTSE100 are not suitable predictors of the EP in South Africa. In contrast, the MSCI showed a statistically significant relationship with the EP. This indicates that there is a link between global equity movements of developed nations and the EP in South Africa.

Tbill

The results indicate that there exists an extremely weak association between the Treasury Bill rate and the EP in South Africa. The association is statistically significant at a 95% confidence level. This is in line with the findings of Wang et al. (2019).

Spread

The results indicate that there exists a weak association between the term spread and the EP in South Africa. The association is statistically significant at a 95% confidence level. The EP is an indicator of the relationship of risk and reward inherent in equity (Rozeff, 1984). The term spread is a measure of risk (Li &

Tsiakas, 2017). The results support the fact that the spread contains useful information regarding risk and reward.

BondYield

The results indicate that there is no statistically significant relationship, at a 95% confidence level, that exists between the bond yield and the EP. The long-term rate of return on government bonds is a key variable in the consideration of the pricing of assets over the long term (Turner, 2014). The analysis in this research, relative the EP, was short term in nature.

MoneyMarket

There is a statistically significant relationship between the money market rate and the EP at a 95% confidence level. The relationship is however relatively weak. The EP is impacted by a country's monetary policy, with the prevailing interest rates impacting the EP (Bakaert at al., 2013). The results are in line with this understanding.

CPI

The literature review indicated that inflation has the potential to partially explain a small amount of the variance in the EP, especially in developing countries (Costa, 2018). It was anticipated that an increase in inflation would result in a decrease in the EP (Peng & Zervou, 2014). The results indicated that the South African consumer price index was not able to account for the variance in the EP calculated on the basis of the JSE Top 40 Index. There was no statistically significant relationship apparent, at a 95% confidence level. As noted by Costa (2018), the inflation is not able to individually predict the EP, in line with the findings in the current research.

ExchangeRate

Considering the cointegration that exists between a country's asset prices and the that country's real effective exchange rate (Gelman et al., 2015), it is conceivable that there would be a link between the EP and the South African real effective exchange rate. However, the results indicate that there is no significant relationship between the variables, at a 95% confidence level.

IndustrialProd

The results indicated a statistically significant association between the output of the manufacturing sector and the EP. This appears to be in line with the research that indicates that there exists an inextricable link between the aggregate economy and the EP (Lettau et al., 2008).

OilProd

The researcher hypothesised the possibility of a link between oil production and the EP in South Africa. It is well documented that oil price shocks are linked to the share returns in the US (Wang et al., 2019). Due to supply levels being an important determinant of the oil price (Bryne et al., 2019), oil production could signal future movements in equities. However, there was no association found between global oil production and the EP in South Africa.

Summary of results for individual predictors

Lettau and Ludvigson (2001) concluded that, based on the underlying body of knowledge at the time, financial indicators were predictors of the EP. There is no evidence, based on the results presented, to conclude that the EP is predictable on the basis of individual financial or macroeconomic indicators. The results support the findings of Welch and Goyal (2008) who found that only a few predictors showed in-sample significance. They concluded by suggesting that the academic theory is yet to find a financial or macroeconomic variable with the ability to predict the EP. The results presented support this notion. The best performing indicator was the DividendPrice as it showed the highest R^2 (.352 as per Table 8 in section 5.7.1). The EarnignsPrice also showed a relatively high adjusted coefficient of determination (.263 as per Table 8 in section 5.7.1). This supports the body of knowledge that considers that the future earnings on shares as a key determinant of the EP (Carlson et al., 2002).

In line with Wang et al. (2019), the findings do indicate that there are financial and macroeconomic variables that, individually, have a statistically significant relationship with the EP. The results found that eight of the 14 variables considered have a statistically significant association with the EP. The literature review found that the EP is impacted by a multitude of factors. The results indicated that there is important information regarding the EP contained in the variables. It was therefore necessary to consider the predictability of the EP considering a model that accounts for more than a single indicator.

6.4. Utilise a large number of predictors to assess predictability of the equity premium: Objective 2

The second objective was to consider whether EP is predictable in-sample by applying a KS regression that utilised a large number of variables. In addition, whether the introduction of statistical limitations improved the predictive ability of the model. The constraints were in the form of penalised regressions, namely ridge, lasso and elastic net. The performance of the regression was assessed in terms of the adjusted coefficient of determination.

The KS regression indicated a moderate predictive ability based on the results presented for both in-sample data and for the full sample of the data. This conclusion was reached on the basis of the adjusted R^2, which were .51 and .56 respectively (as per Table 14 in section 5.7.2). The research considered .6 as a benchmark due to the reasons discussed in section 3.2. The adjusted R^2 was therefore not sufficient for the researcher to conclude that a KS regression that incorporates various financial and macroeconomic variables is capable of predicting the EP in South Africa. The KS regression did however offer a benchmark framework against which to consider whether the implementation of statistical constraints was capable of increasing both the in-sample and out-of-sample predictability of the EP (Li & Tsiakas, 2017).

The three penalised regression models all demonstrated predictive ability. This was due to the fact that the ridge, lasso and elastic net regressions contained an adjusted R^2 of .71, .70, .72 respectively (at the most parsimonious model as per Table 13). The adjusted R^2 is a measure of the variation in the dependent variable described by the independent variables (Dunteman & Ho, 2006). The elastic net appeared to offer the best results, being capable of explaining approximately 72% of the variance in the EP. The confirmed the finding of Li and Tsiakas (2017) that, through optimisation of the KS regression by utilising statistical constraints on the coefficients, it is possible to increase the performance of a predictive regression model in predicting EP. The inclusion of penalties either shrinks or selects variables by determining the optimal point at which the sum of the squared residuals is minimised (Hastie, et al., 2017). The resulting coefficients therefore offer insight into the relationship between the individual indicator and the EP. It however, should be noted that each of the variables were included in the regression framework on the basis of the literature review. There was a strong theoretical foundation for considering use of the indicator in predicting the EP (see section 2.9).

The ridge regression shrinks the coefficients of the proposed model asymptotically towards zero (Hoerl & Kennard, 2000) whereas the lasso model shrinks certain coefficients and sets others equal to zero (Tibshirani, 1996). The elastic net represents a compromise between the two models by incorporating elements of both (Zou & Hastie, 2005). It is therefore interesting to consider the coefficients determined by each of the models, particularly in the context of the findings presented in section 6.3. Table 16 presents the coefficients determined by the most parsimonious model under each framework:

Table 16. Summary of coefficients for regularised models

*	Ridge		Lasso		Elastic net	
	β	*p*	*β*	*p*	*β*	*p*
DividendPrice	-0.15	.000	0.00	n/a	-0.20	.000
EarningsPrice	-0.22	.000	-0.54	.000	-0.39	.000
Volatility	-0.16	.000	-0.18	.018	-0.24	.000
FTSE100	-0.04	.464	0.00	n/a	0.02	.628
Tbill	-0.08	.007	0.00	n/a	-0.04	.514
Spread	0.17	.000	0.08	.384	0.24	.000
BondYield	0.08	.436	0.00	n/a	0.00	n/a
MoneyMarket	-0.08	.000	-0.07	.059	-0.05	.225
CPI	-0.03	.375	0.00	n/a	0.00	n/a
ExchangeRate	0.03	.396	0.00	n/a	0.00	n/a
IndustrialProd	-0.08	.000	-0.01	.941	-0.04	.230
OilProd	-0.07	.163	0.00	n/a	-0.02	.700

* Values represent the coefficients at the most parsimonious model.

Ridge

By its nature, the ridge regression utilises all predictors (Hastie et al., 2017). It penalises the model by shrinking the coefficients. It can shrink the coefficients arbitrarily close to zero. The ridge path (Figure 6) shown in the results (section 5.7.2) offers insight into the manner in which each of the coefficients has been scaled in order to obtain the optimal model. It is apparent that, at the optimal model, none of the variables have been impacted in a relatively significant manner, i.e. arbitrarily close to zero. The model utilised aspects of all variables. This supports the understanding identified in the literature review that the EP is impacted by a multitude of factors. The model indicates that there exists a moderately strong statistically significant relationship between the EP and a regression model that conditions on a wide range of tested financial and macroeconomic indicators.

Lasso

By applying the penalised regressions, the intention is to find the most parsimonious model, which should result in the model having greater predictive stability in the long term (Friedman, 2012; Starmer, 2018b). As noted by Zou and Hastie (2005), parsimony is an especially important characteristic when attempting to utilise a model that conditions on a large number of predictor variables. The lasso model set the coefficients of seven of the variables to zero, as shown in Table 16. The lasso model removed BondYield, CPI, DividendPrice, FTSE100, ExchangeRate, OilProd and Tbill, from the predictive regression model. The majority of these variables, except for DividendPrice and Tbill, were found to not have a statistically significant association with the EP when assessed individually. However, of specific interest is that the model removed DividendPrice as this appeared to explain the highest variance in EP when assessed individually (adjusted R^2 of .352, refer to Table 8 in section 5.6). It should however be highlighted that the best fit model, i.e. the one that minimised the sum of the squared residuals was achieved at a lasso tuning parameter of .060 (see Figure 36 in Appendix E), with 10 predictors in the model, which included the DividendPrice. The incremental gain from including the 10 predictors, as opposed to including the final five, was determined to not offer sufficient benefit in terms of predicted error. The resulting conclusion is that, based on the results of the research, the EP is moderately strongly associated to EarningsPrice, IndustrialProd, MoneyMarket, Spread and Volatility. The association indicated that the variables are able to predict the EP.

Elastic net

The elastic net balances aspects of both the ridge and lasso and is particularly useful in circumstances when models contain many variables (Zou & Hastie, 2005). The chosen model was given at ridge penalty of .800 and lasso penalty of .280. In this instance, the method removed the BondYield, CPI and ExchangeRate. The most parsimonious model was given at a point that utilised nine predictors. Based on the fact that the elastic net had the highest adjusted R^2 value (Table 14), the elastic net was deemed to be the best performing in-sample model.

Concluding comments

Campbell and Thompson (2008) suggest that a model which contains moderate predictive ability has the potential to offer benefits to investors. Similarly, Rapach and Zhou (2016) note that, when attempting to predict the EP, a small degree of predictability can result in substantial utility gains. The results indicate that the ridge, lasso and elastic net models have the potential to be useful to investors by offering an improved method of forecasting the EP. The results indicate that each of the regressions is capable of providing prediction of the EP that may be useful to users. The next section will consider the relative effectiveness of the models for out-of-sample predictability.

6.5. Assess the relative out-of-sample performance of the models: Objective 3

The third objective of the research was to assess the out-of-sample performance and to evaluate whether the introduction of statistical and economic constraints to a KS regression are able to consistently deliver superior forecasts relative to a benchmark.

The following graph, Figure 10, shows the out-of-sample predictive results of the regressions against the historical EP. It is interesting to note that the predicted values follow the same trend as the realised EP. The intention of utilising statistical constraints in predicting EP was to include initial bias to minimise variance (Li & Tsiakas, 2017). All of the predicted time series are less volatile, showing a smoother trend. None of the graphs predicted negative values for the EP. The graph (Figure 10) appears to indicate that the ridge regression is the best performing model in the out-of-sample analysis. This was confirmed by calculating the MSE and R^2_{OOS} (Table 15). This was assessed relative to the benchmark KS forecast.

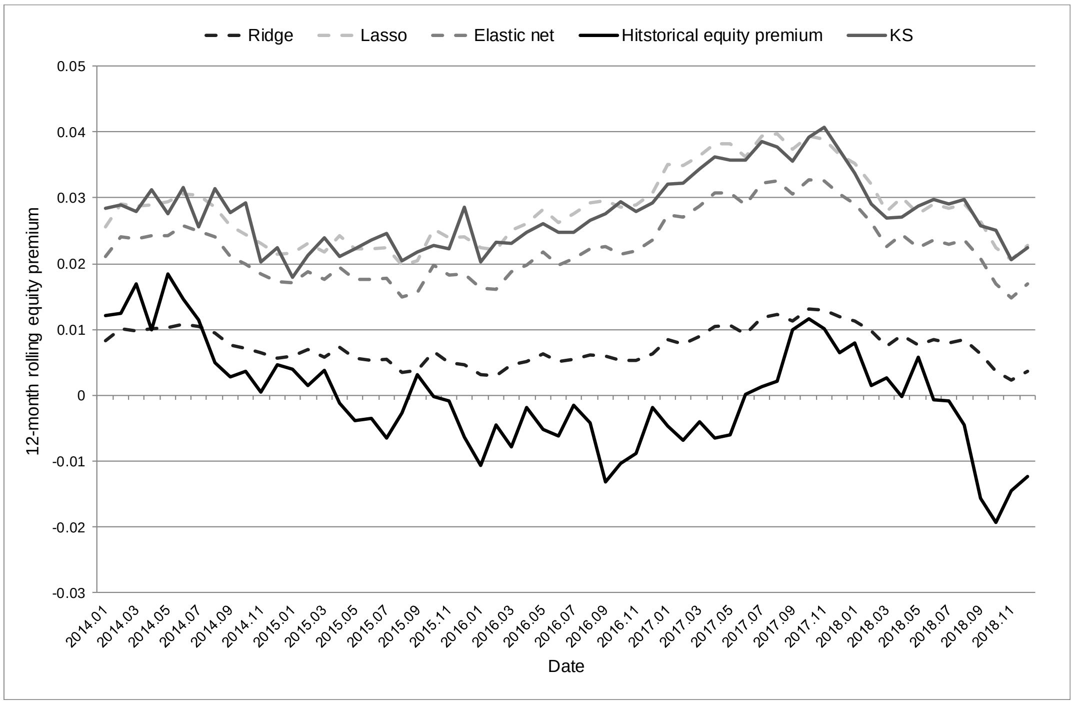

Figure 10. Out-of-sample predicted equity premium

The objective of introducing initial bias was to create a more stable model for out-of-sample prediction of the EP (Li & Tsiakas, 2017; Starmer, 2018a). The results of the current research demonstrate that the use of the ridge and elastic net regression improved out-of-sample performance as the R^2_{OOS} was positive. The lasso regression did not improve forecast accuracy against the benchmark KS regression, as can be seen by the negative R^2_{OOS}. This could be as a result of the fact that the lasso regression removed variables that did not reduce the in-sample predictive error but added value in the out-of-sample period. This is in line with the literature review that found that the EP is impacted by a large number of variables. In line with the current body of knowledge (Gupta et al., 2016; Li & Tsiakas, 2017), the introduction of statistical constraints has the ability to improve the out-of-sample forecast accuracy of regressions that condition on a large number of financial and macroeconomic indicators. However, care should be taken to select the most appropriate model. The elastic net offered the best out-of-sample performance, as denoted by the lowest MSE.

6.6. Summary of chapter

The historical EP in South Africa over the sample period of the research 1996 to 2018, has been less than the various estimates had anticipated. This highlights the need to find a more suitable process of estimating the EP, in the context of the importance of the number in modern finance and economics.

The first object was to assess the relationship between the individual predictors and the EP. The research indicated that eight of the fourteen variables tested demonstrated a statistically significant relationship with the EP. It however appears that the variance explained by each variable, as denoted by the adjusted R^2, is not strong enough to indicate that the EP could reasonably be predictable. The research objective was therefore met.

The second objective was to assess whether the EP is predictable in-sample by applying a KS regression and to assess regressions that incorporated statistical constraints. The results showed that a moderate relationship existed between the EP and the KS regression model. The results also showed that a moderately strong relationship existed between the EP and the regressions that implemented optimisations to the slope coefficients. The moderately strong relationship is sufficient to offer benefits to potential users of the EP, indicating that it is predictable. The research objective was therefore met.

The third objective was to assess the relative out-of-sample performance of the ridge, lasso and elastic net regressions in order to determine whether the inclusion of statistical and economic constraints improved the out-of-sample predictability of the EP. The results showed that the ridge and elastic net models improved relative to the benchmark. The optimisation using these two methods increased the out-of-sample performance of regression models that condition on a large number of financial and macroeconomic indicators in predicting the EP in South Africa. The research objective was therefore met.

7. CONCLUSION

7.1. Principal findings

The equity premium (EP) represents the additional return that an investor can generate by investing in the equity market as opposed to investing in a risk-free asset. The EP is a measure of risk that exists in the underlying market for which an investor demands an additional return. The EP is a crucial variable in modern day finance and economics. However, an accurate forecast of the EP is problematic, with large variances in professionals' expectations.

The literature review highlighted the wide range of factors that influence the EP. This increases the relative complexity in determining an accurate prediction of the EP. However, considering its relative importance, the topic has received significant interest over the past 30 years. There are many studies that have found that individual financial and economic indicators are predictors of the EP. However, even in cases where in-sample results were significant, the out-of-sample performance of the variables has been spurious. In order to be of practical use, a model needs to demonstrate that it is capable of delivering consistent and stable out-of-sample performance.

In order to test the research question, three main objectives were derived based on the current literature. An appropriate hypothesis was developed in order to test each of the objectives. The three objectives were as follows:

1. To Assess the relationship between the EP and individual financial and macroeconomic indicators utilising a standard univariate predictive regression. The individual predictors were determined based on a review of the prevailing literature.

2. Determine whether the EP is predictable in-sample by assessing a KS regression, that utilises a large number of variables. In addition, evaluate whether the introduction of statistical limitations improved the forecast accuracy of the model.

3. Assess the out-of-sample performance of regression models that incorporated economic and statistical constraints to ascertain whether they were able to consistently deliver superior forecasts relative to a benchmark.

The first objective was tested using a standard univariate linear regression framework. The results found that eight of the fourteen variables tested demonstrated statistically significant associations with the EP, at a 95% confidence level. It was however evident that the variance explained by each significant predictor was not sufficient for one to conclude that the EP in South Africa is predictable on the basis of individual indicators. This is line with the current literature that shows that financial and macroeconomic indicators contain important information regarding the EP.

The second objective assessed regression models that conditioned on a large number of variables. The researcher found that the KS regression had moderate predictive ability. This was deemed not sufficient as it may not result in benefits to stakeholders. The forecast accuracy was however improved by the introduction of statistical constraints. The results found that by optimising the coefficients of the variables in the KS regression framework, a model can be developed that is capable of offering a benefit to stakeholders.

The third objective was to assess the out-of-sample performance of the models relative to a benchmark. The findings showed that the imposition of the constrains increased the out-of-sample performance of the frameworks, when utilising the ridge and elastic net estimators. A review of the time-series plots shows that the optimised models appear to track the trend of the historical EP. This indicates that they could offer signalling benefits to stakeholders. These two optimisations introduced bias into the model which improved that stability of the out-of-sample forecasts.

The research was driven by the question, is the EP premium predictable in South Africa? The purpose of the research was to assess the predictability of the EP in South Africa. The literature review demonstrated that EP was predictable, both in-sample and out-of-sample, using econometric models that conditioned on financial and macroeconomic indicators. The results indicated that by utilising regressions that condition on financial and macroeconomic indicators, the EP in South Africa is predictable. The results confirmed that the predictive ability was sufficient to be useful to stakeholders.

7.2. Implications

The research set out to consider the predictability of the EP in South Africa based on financial and macroeconomic indicators. The results confirmed that there are valid statistically significant associations between the EP and predictor variables. In addition, the research found models that are capable of delivering results that will benefit stakeholders. The results of the research demonstrate that the EP in South Africa is predictable at a level that would be useful to users who require accurate forward-looking estimates of the EP. The research confirmed that there exists important information regarding the EP in financial and macroeconomic indicators. These variables are capable of providing useful forecasts of the EP when optimised using various statistical techniques.

The EP is one of the most important numbers in modern finance and economics. Greater accuracy in forecasts of EP has fundamentally important implications for assessing asset pricing. Having access to more accurate forward-looking estimates of the EP will inform decision making of individuals and companies who traditionally rely on surveys or other extrapolative techniques. At a minimum, the research has shown that the frameworks offer an alternative estimation method to consider. This can stimulate discussions concerning estimations of the EP. Hopefully this will encourage stakeholders to question previous norms and challenge their assumptions regarding the EP. This will contribute to more effective decision making, whether that be for capital budgeting, portfolio evaluation or otherwise.

7.3. Limitations of the research

The relatively short-term nature of the assessment is perhaps the most significant limitation of the current study. The research was focused on assessing the monthly EP on the basis of monthly indicators. This is more valuable for optimal asset allocation but less so for long-term capital budgeting decisions. The current body of knowledge indicates that the relative long-term bond yield is a significant predictor of the EP. The current research found no such evidence. This supports the short-term focus of the research. However, the results are positive in the sense that the current body of knowledge demonstrates that EP predictions over longer time horizons are more stable than short-term predictions.

Considering that the population of equity returns in South Africa stretches over more than 100 years, the sample of 22 years is relatively small. Due to the dynamic nature of the EP, the more data utilised in creating a framework for prediction, arguably, the more reliable the results would be. In addition, there are wide variations in stock market returns from year to year which highlights the preference for examining the EP over long sample periods (Hassan & van Biljon, 2010).

The current body of knowledge has identified a multitude of financial and economic variables that have been found to have a statistically significant relationship with the EP. The literature confirmed that there are numerous factors impacting the EP. The current research focused on 14 financial and economic variables. The current study is therefore limited by only considering these indicators. The inclusion of additional variables could yield alternative results. In addition, the EP is affected by factors that are not readily measurable at set periods. For example, there is complexity in measuring behavioural changes and the levels of risk aversion in investors at a given point in time. The models are therefore not capable of accurately accounting for these variables. This could negatively impact the performance of the models.

An accurate calculation of the historic EP remains problematic. The choice of an appropriate risk-free rate is an important consideration. The current research utilised the return on long-term government bonds as a measure of the risk-free rate. Using an alternative measure as the risk-free rate could lead to different results. The use of arithmetic or geometric means in calculating the share returns can have an impact. The current research utilised the arithmetic mean. The results could have been different if the geometric mean was utilised.

7.4. Suggestions for future research

Technical indicators

In would be interesting to assess whether technical indicators are able to deliver in-sample and out-of-sample predictions of the EP in South Africa. Technical indicators have shown promise in their ability to predict bond returns (Goh et al., 2013). In addition, technical indicators have shown promising results in forecasting stock market returns (Neely et al., 2014). The inclusion of technical indicators could assist in providing additional information to explain the variance in EP by providing the model with information not contained in the financial and economic indicators. The development of a more robust model before optimisation has promise in terms of yielding greater predictive accuracy. Baetje and Menkhoff (2016) show evidence supporting the use of technical indicators in forecasting EP out-of-sample.

Alternative statistical frameworks

The current research demonstrated how the incorporation of statistical constraints increased the predictive performance of the regression models. It would be interesting to consider the use of alternative statistical frameworks in estimating the EP. The use of subset quintile regression frameworks have demonstrated consistent and robust out-of-sample performance in the US (Meligkotsidou et al., 2019). The incorporation of time-varying weighting schemes has also been shown to increase the performance of predictive frameworks that condition on a large number of financial and macroeconomic indicators (Meligkotsidou et al., 2019; Pettenuzzo et al., 2014). The advantages of including time-varying weighting schemes is to allow the model to account for underlying changes in the precision of the variables at a given time in order to allow for the model to determine the correct parameters to utilise (Spiegel, 2008). This could increase the practical use of the model.

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APPENDIX A – DISTRIBUTION PLOTS OF INDEPENDENT VARIABLES

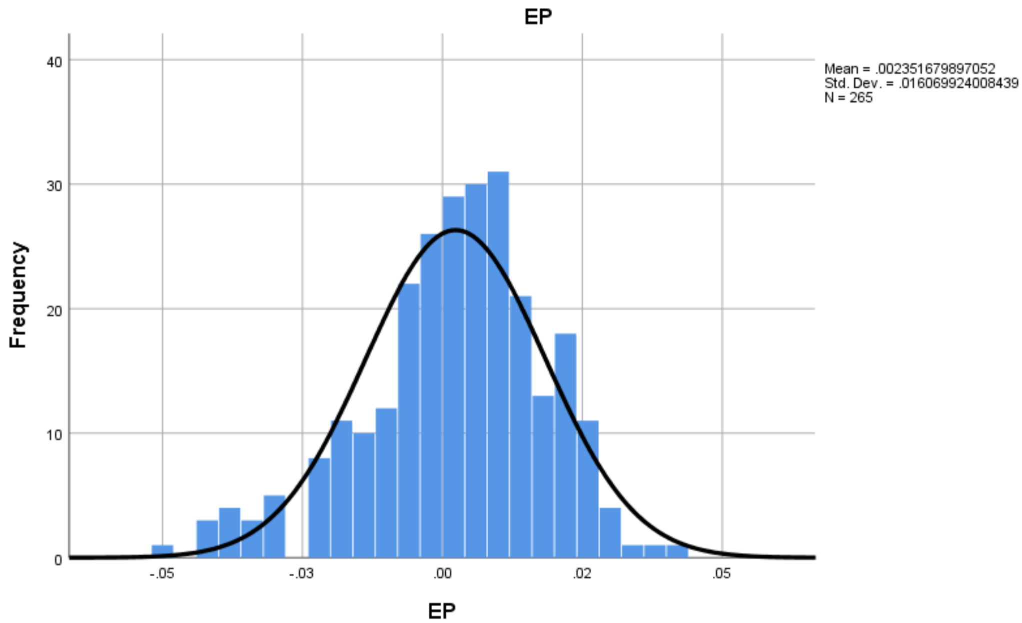

Figure 11. Histogram: Equity premium

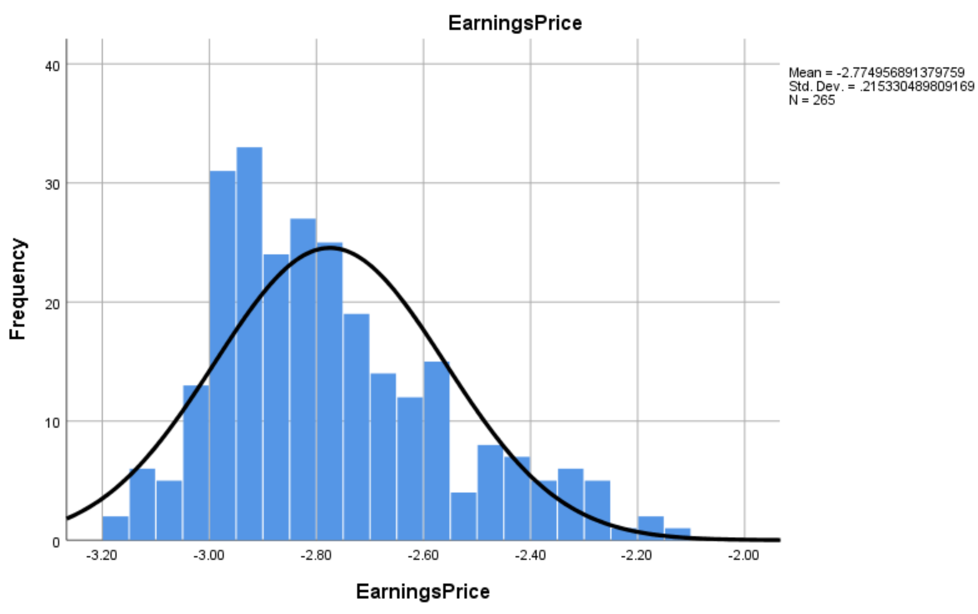

Figure 12. Histogram: EarningsPrice

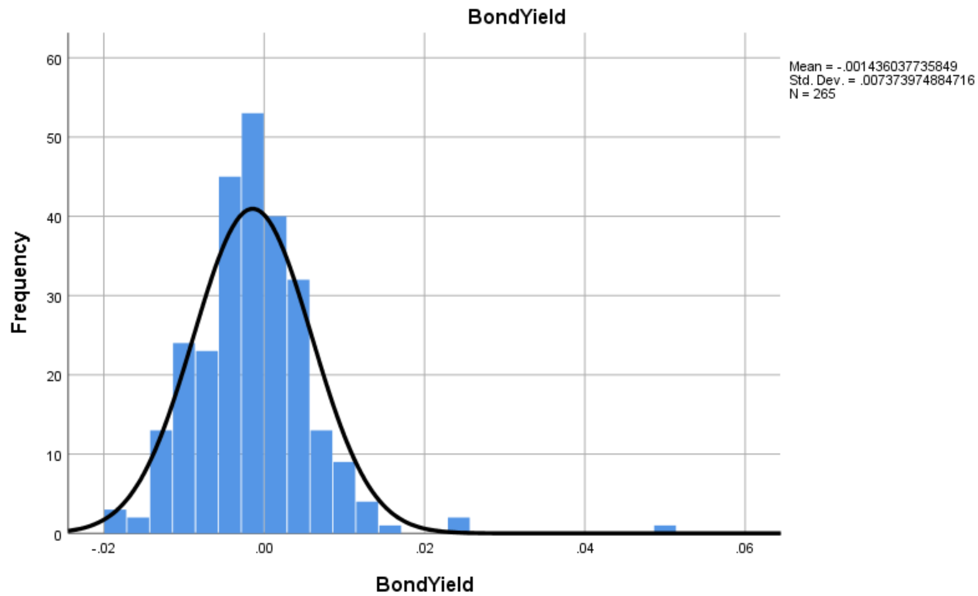

Figure 13. Histogram: BondYield

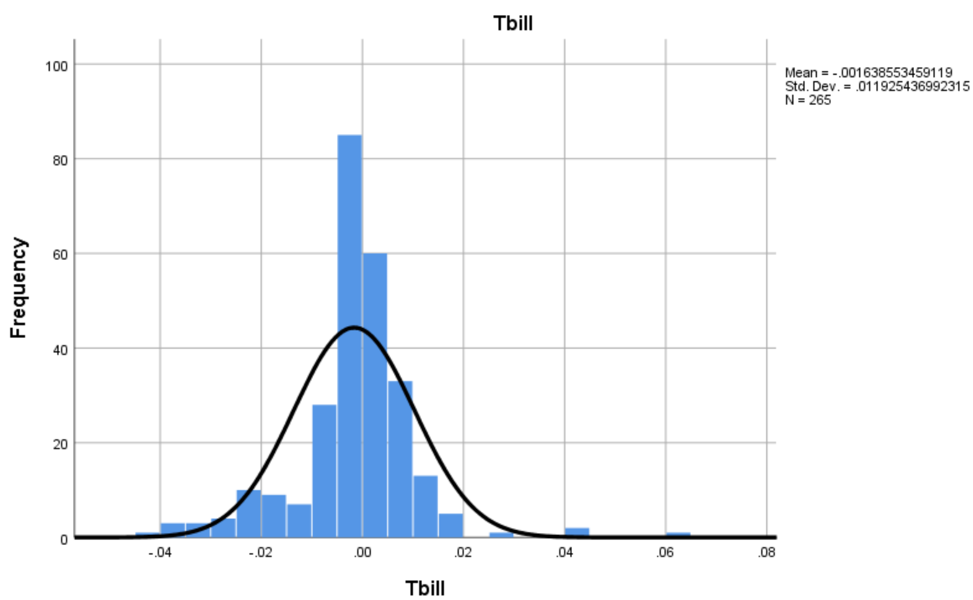

Figure 14. Histogram: Tbill

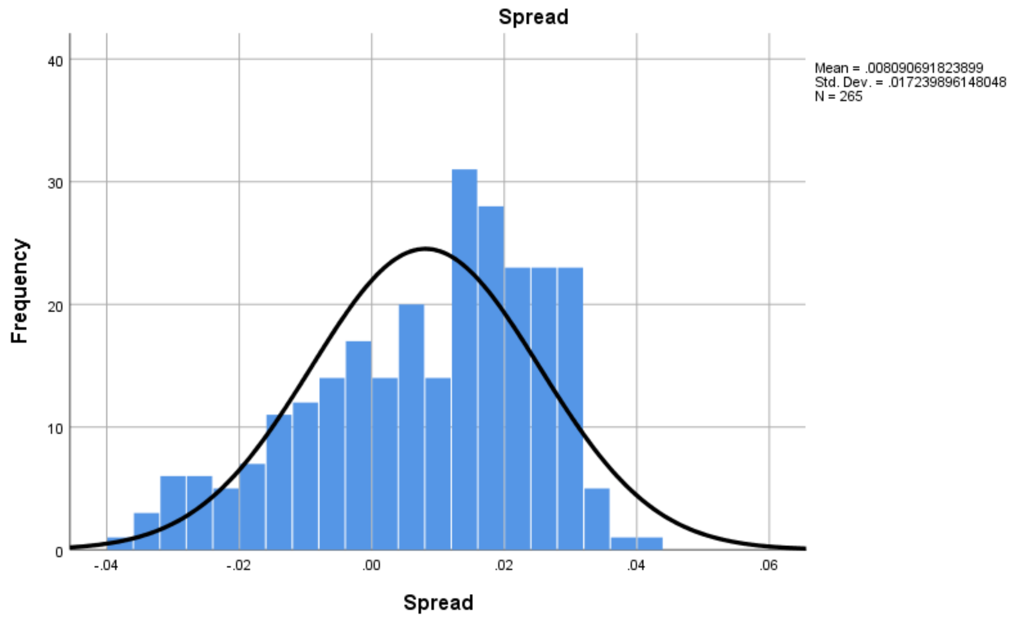

Figure 15. Histogram: Spread

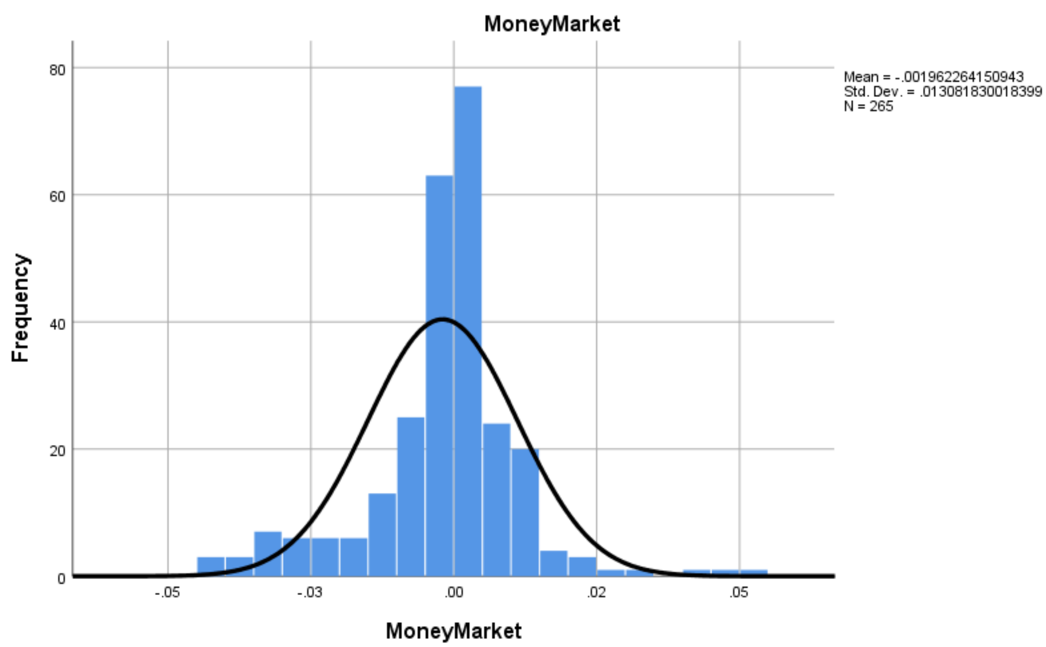

Figure 16. Histogram: MoneyMarket

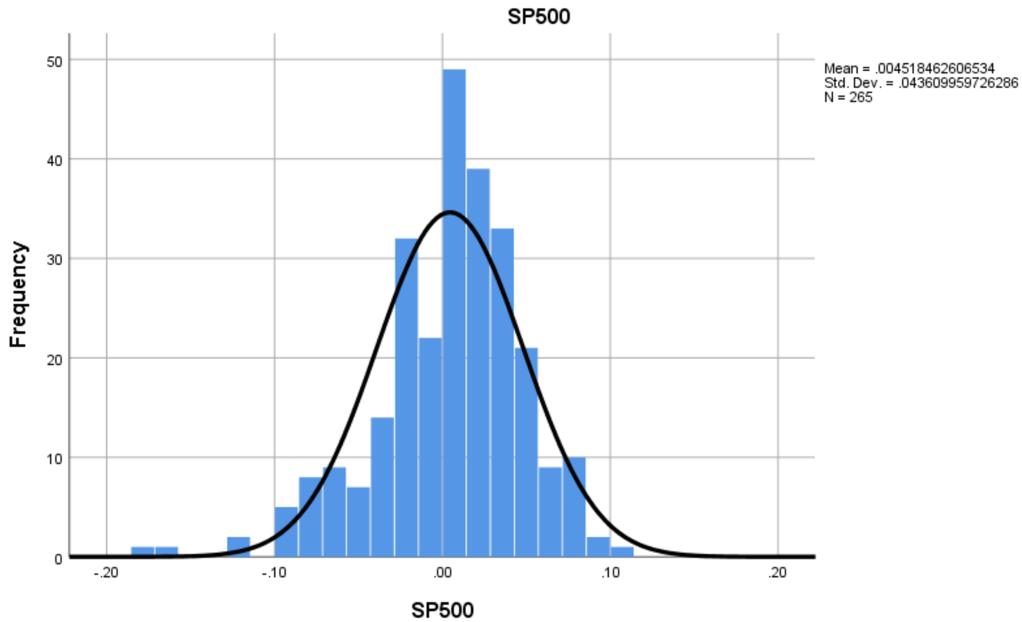

Figure 17. Histogram: SP500

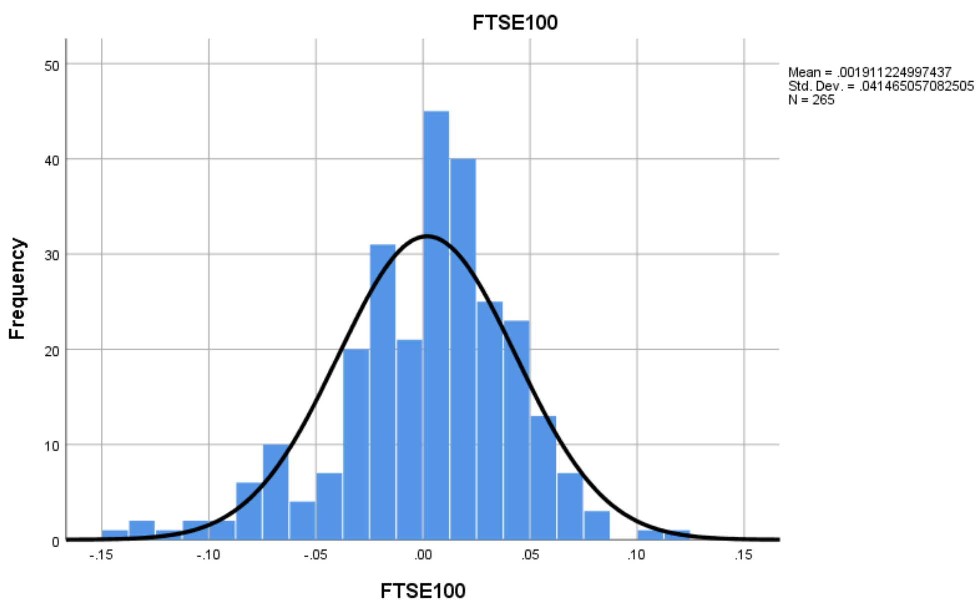

Figure 18. Histogram: FTSE100

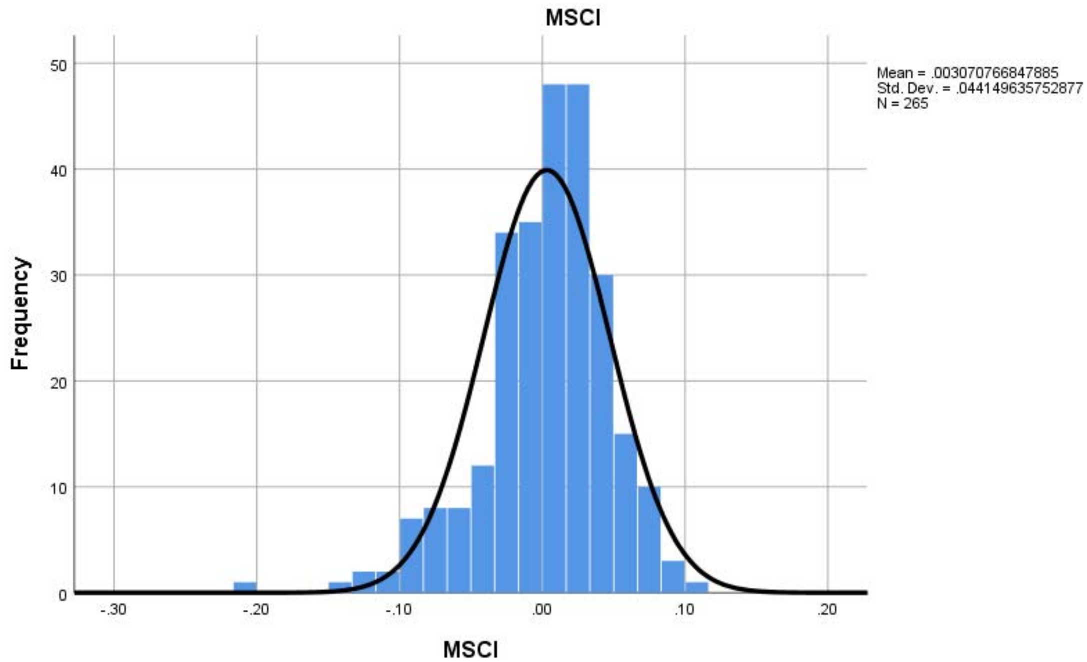

Figure 19. Histogram: MSCI

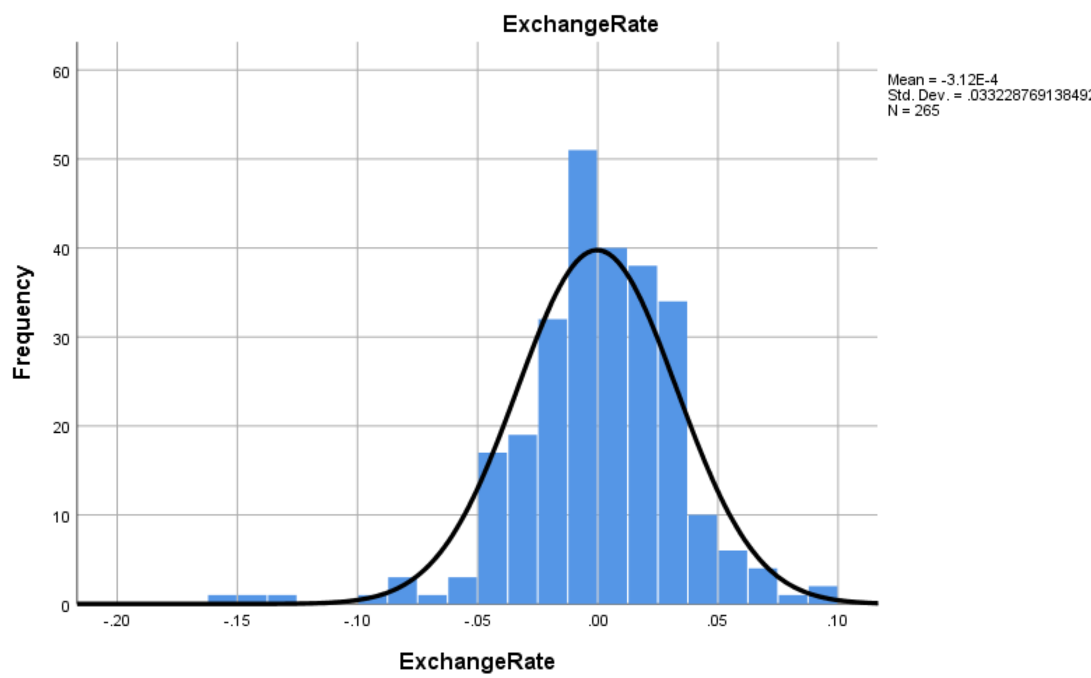

Figure 20. Histogram: ExchangeRate

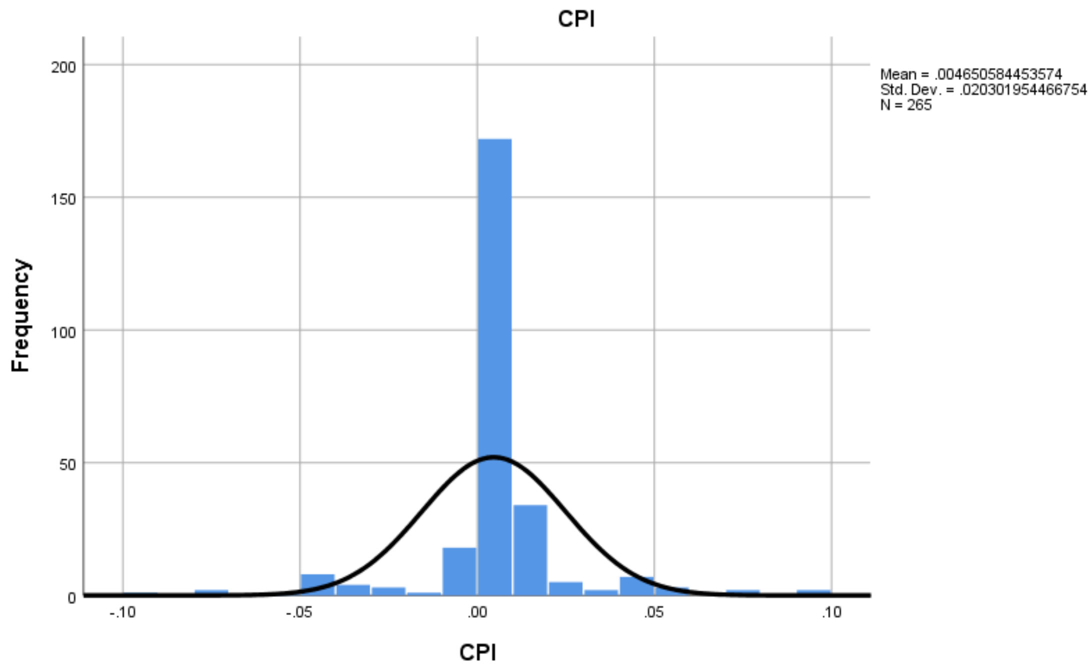

Figure 21. Histogram: CPI

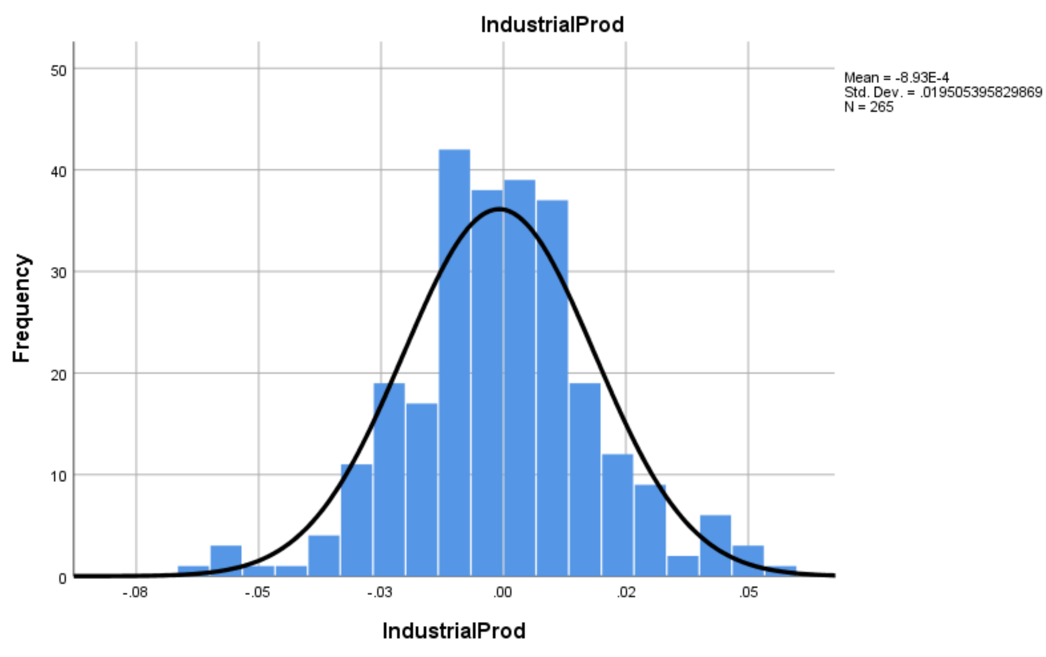

Figure 22. Histogram: IndustrialProd

APPENDIX B – COLLINEARITY STATISTICS

Table 17. Summary of variance inflation factors

VIF	Dividend Price	Earnings Price	Volatility	SP500	FTSE100	MSCI	Tbill	Spread	Bond Yield	Money Market	CPI	Exchange Rate	Industrial Prod	OilProd
DividendPrice		1.23	1.76	1.78	1.78	1.78	1.78	1.77	1.75	1.77	1.77	1.75	1.77	1.77
EarningsPrice	2.04		2.34	2.96	2.97	2.95	2.96	2.58	2.93	2.96	2.96	2.96	2.96	2.96
Volatility	1.86	1.51		1.88	1.88	1.88	1.87	1.79	1.66	1.88	1.87	1.87	1.87	1.85
SP500*	13.76	13.74	13.75		13.71	2.74	13.77	13.69	13.77	13.72	13.75	13.58	13.72	13.72
FTSE100	3.37	3.37	3.37	3.36		2.78	3.37	3.37	3.35	3.37	3.36	3.37	3.37	3.37
MSCI*	17.38	13.31	17.39	3.46	14.32		17.39	17.24	17.39	17.35	17.39	16.97	17.37	17.31
Tbill**	5.53	5.53	5.49	5.53	5.53	5.53		5.51	5.22	1.44	5.39	5.53	5.50	5.53
Spread	1.89	1.65	1.81	1.89	1.90	1.88	1.89		1.68	1.89	1.90	1.90	1.90	1.90
BondYield	1.62	1.63	1.46	1.65	1.64	1.65	1.55	1.46		1.65	1.65	1.64	1.65	1.64
MoneyMarket	4.91	4.94	4.94	4.93	4.94	4.93	1.28	4.93	4.94		4.87	4.94	4.88	4.94
CPI	1.07	1.07	1.07	1.07	1.07	1.07	1.04	1.07	1.07	1.05		1.05	1.07	1.06
ExchangeRate	1.15	1.17	1.17	1.15	1.17	1.14	1.17	1.17	1.16	1.17	1.14		1.16	1.16
IndustrialProd	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.04	1.05	1.05		1.05
OilProd	1.05	1.05	1.04	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.04	1.04	1.04	

* VIF > 10
** < 10 VIF > 5

APPENDIX C – TEST FOR HETEROSCEDASTICITY

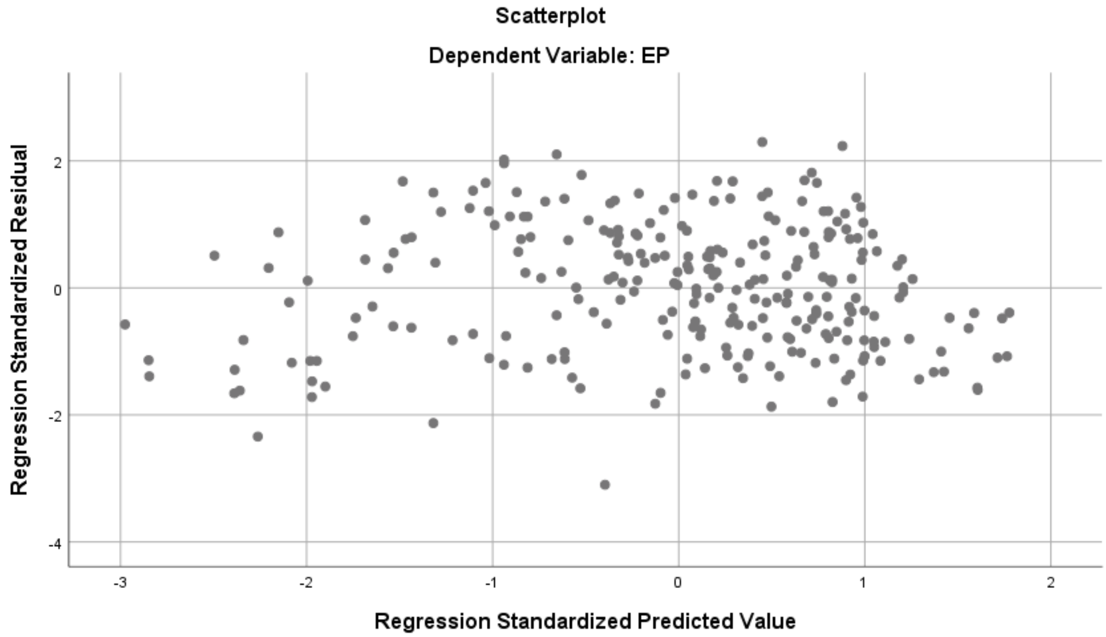

Figure 23. Residuals scatterplot: EarningsPrice

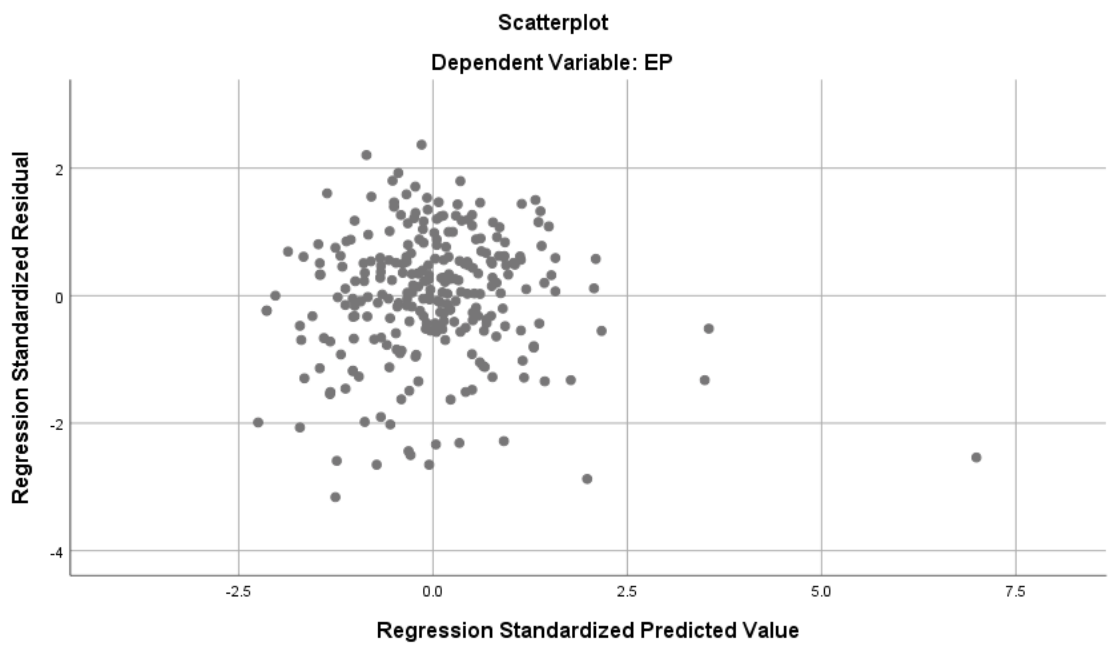

Figure 24. Residuals scatterplot: BondYield

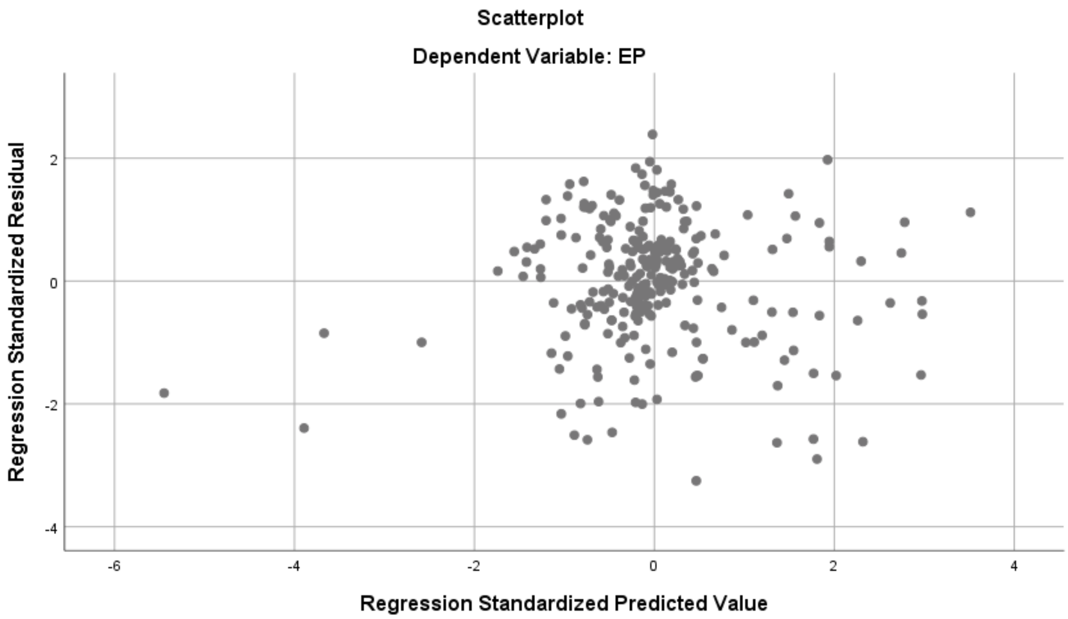

Figure 25. Residuals scatterplot: Tbill

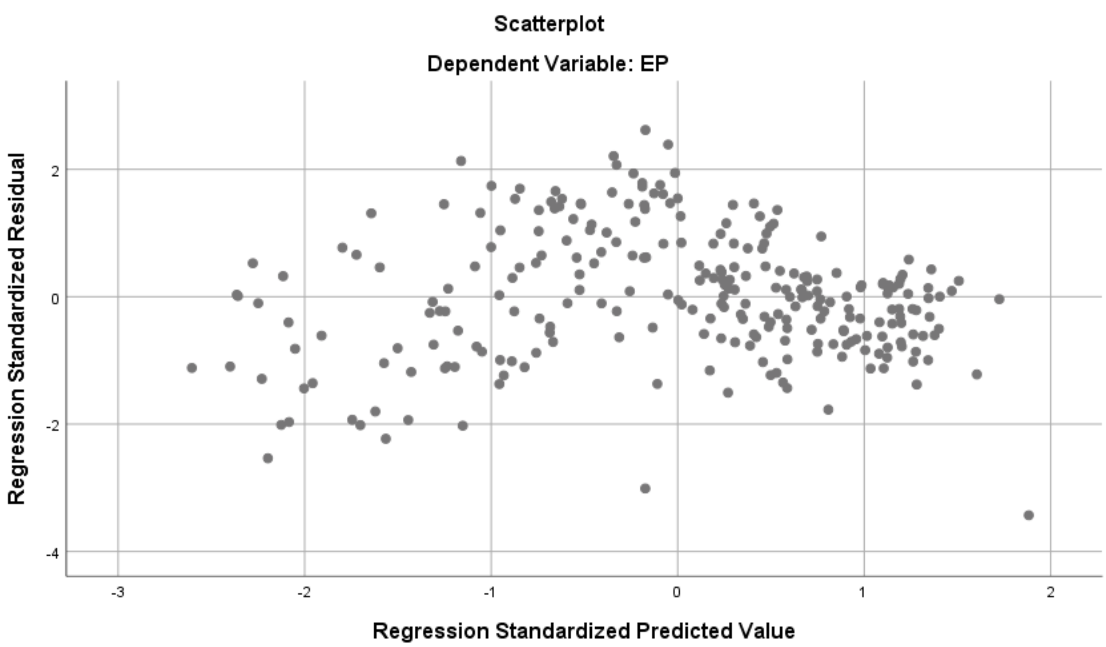

Figure 26. Residuals scatterplot: Spread

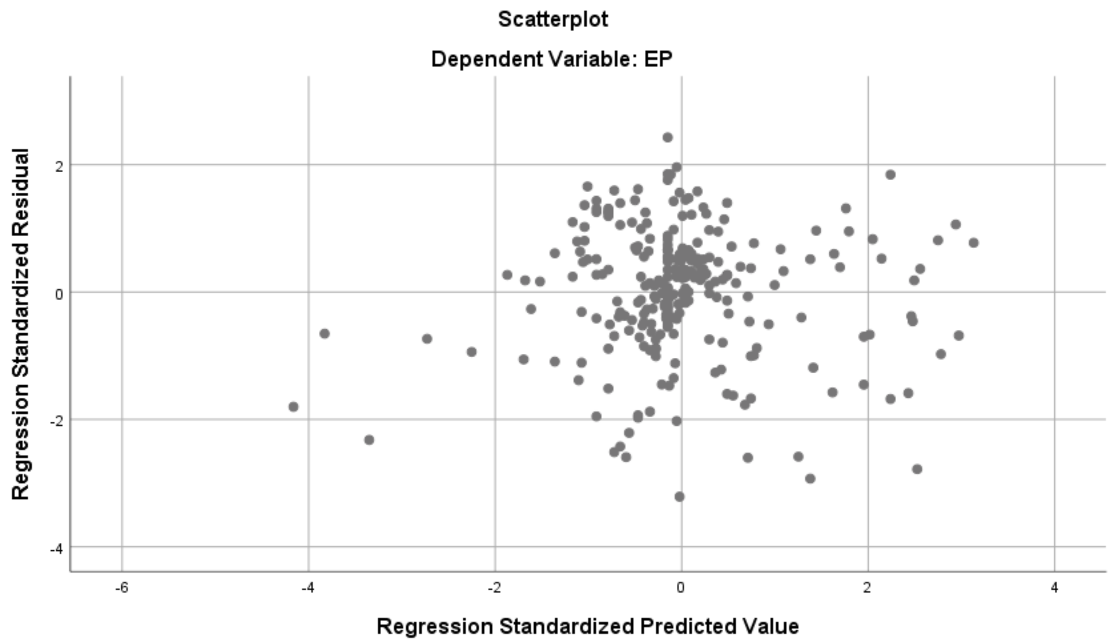

Figure 27. Residuals scatterplot: MoneyMarket

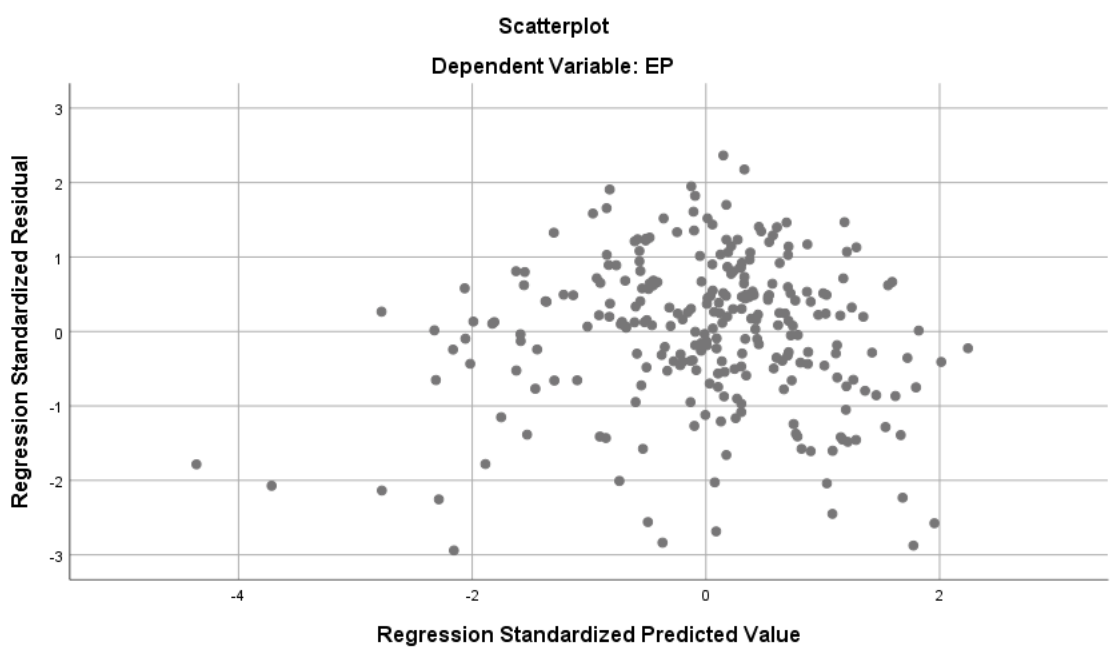

Figure 28. Residuals scatterplot: SP500

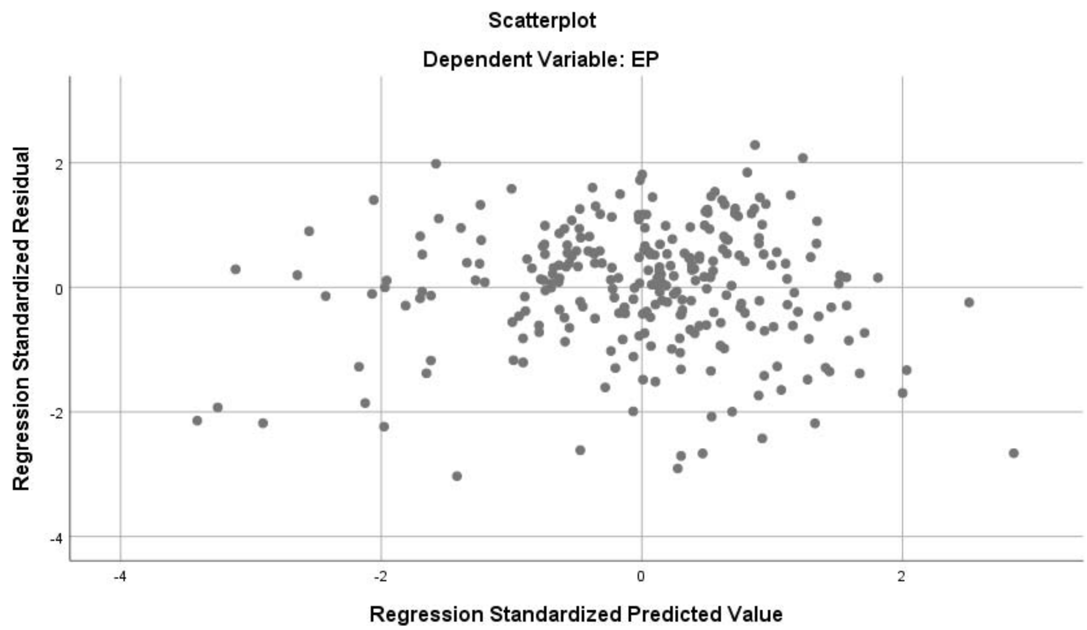

Figure 29. Residuals scatterplot: FTSE100

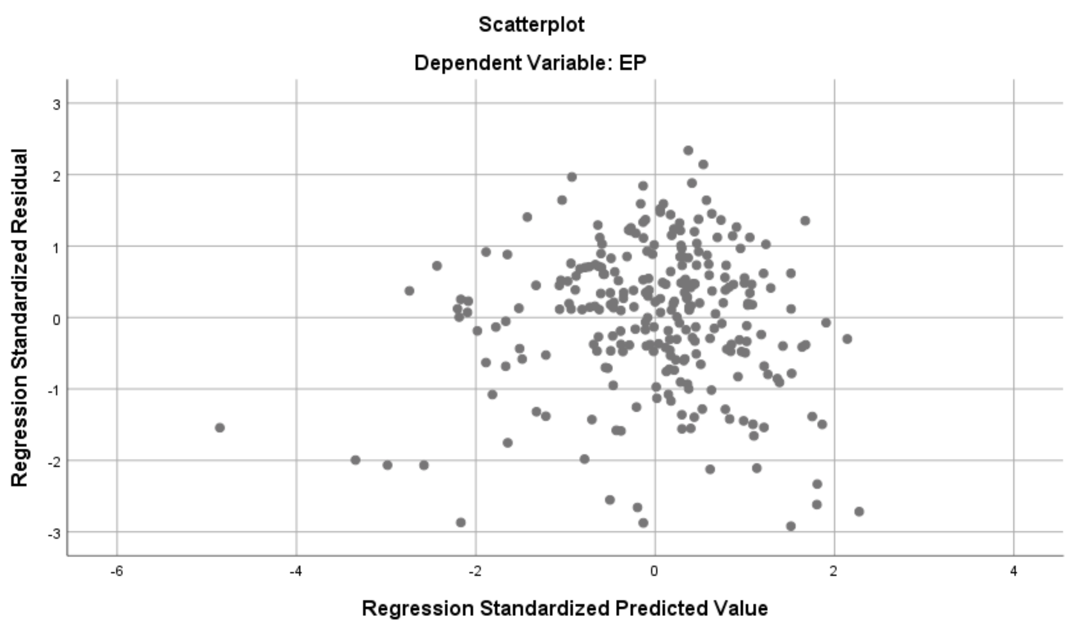

Figure 30. Residuals scatterplot: MSCI

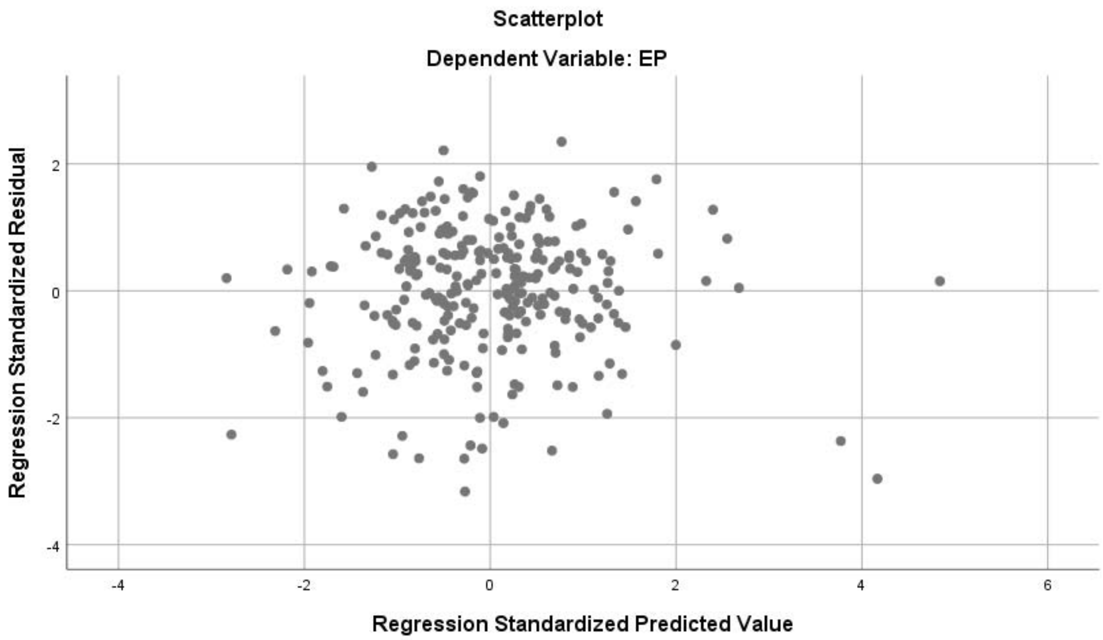

Figure 31. Residuals scatterplot: ExchangeRate

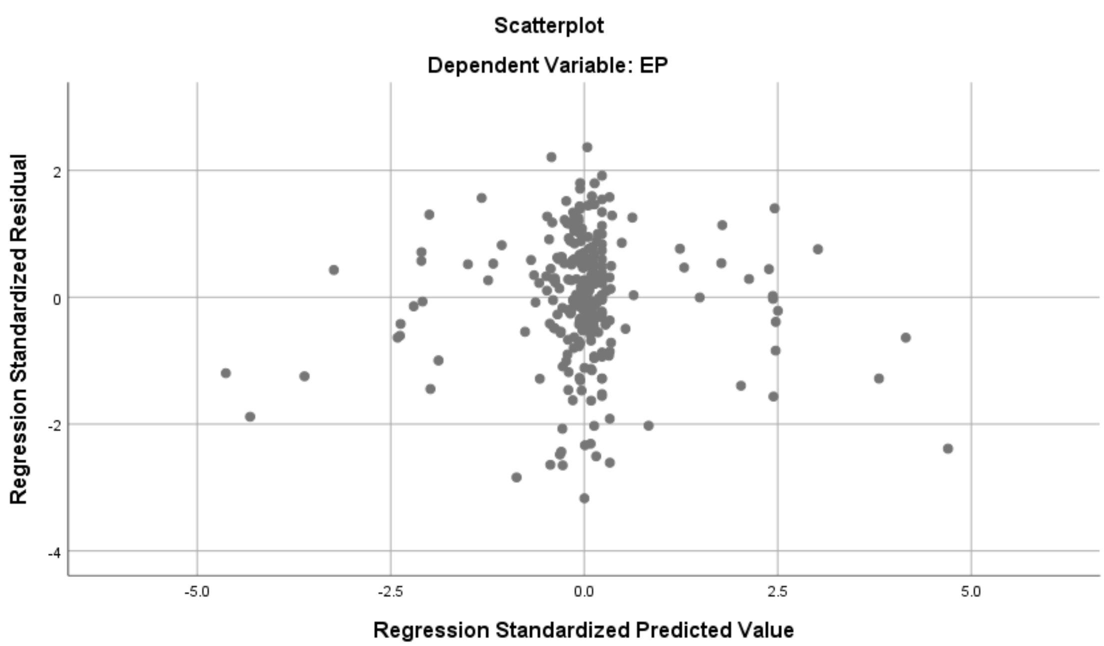

Figure 32. Residuals scatterplot: CPI

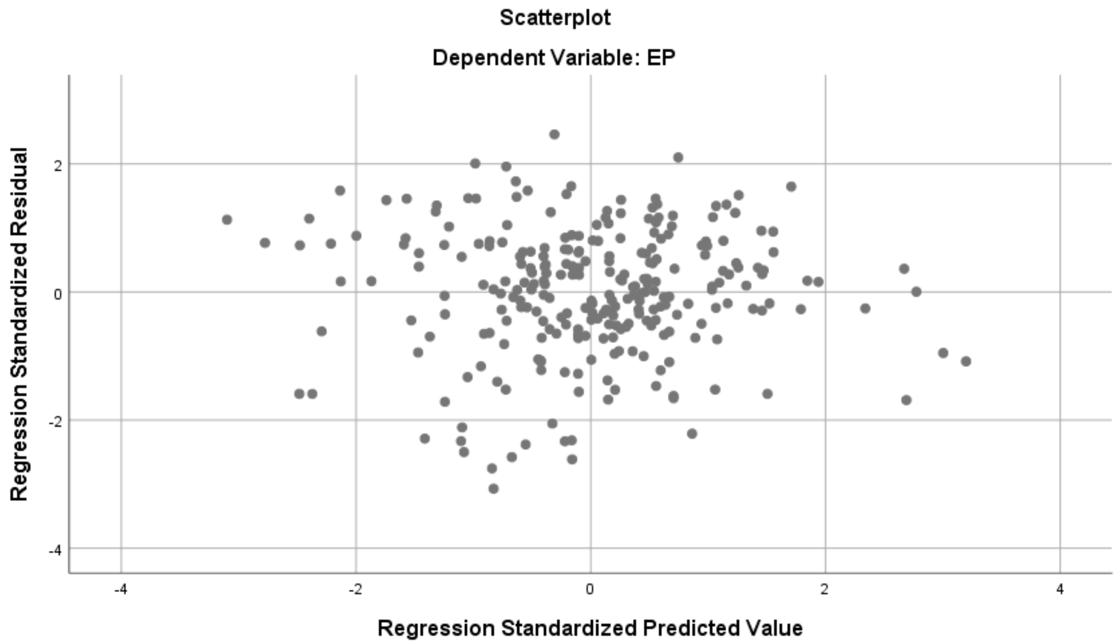

Figure 33. Residuals scatterplot: IndustrialProd

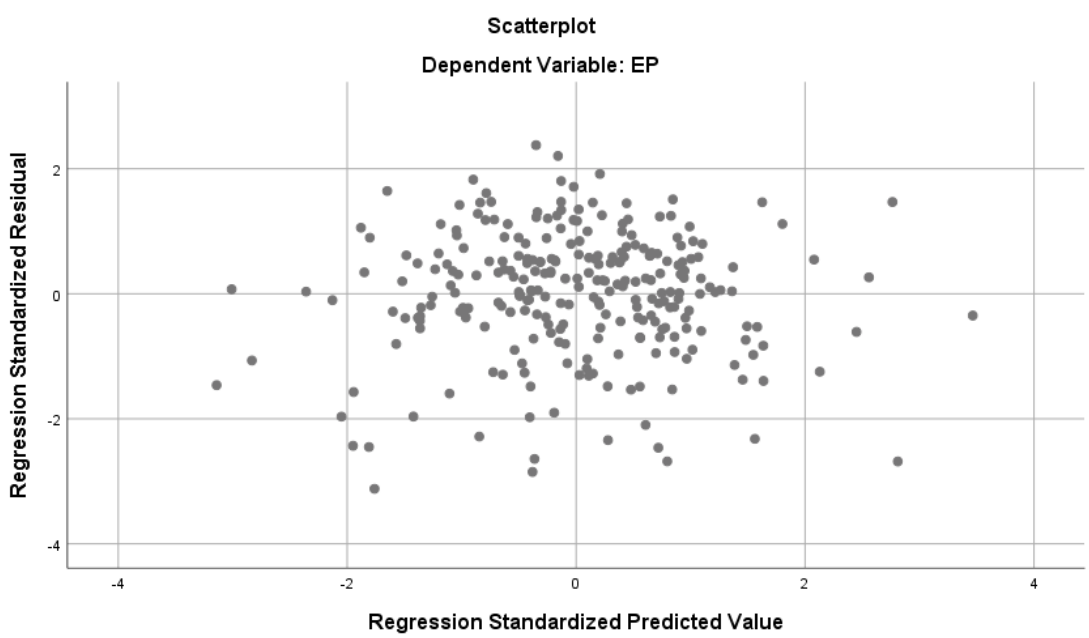

Figure 34. Residuals scatterplot: OilProd

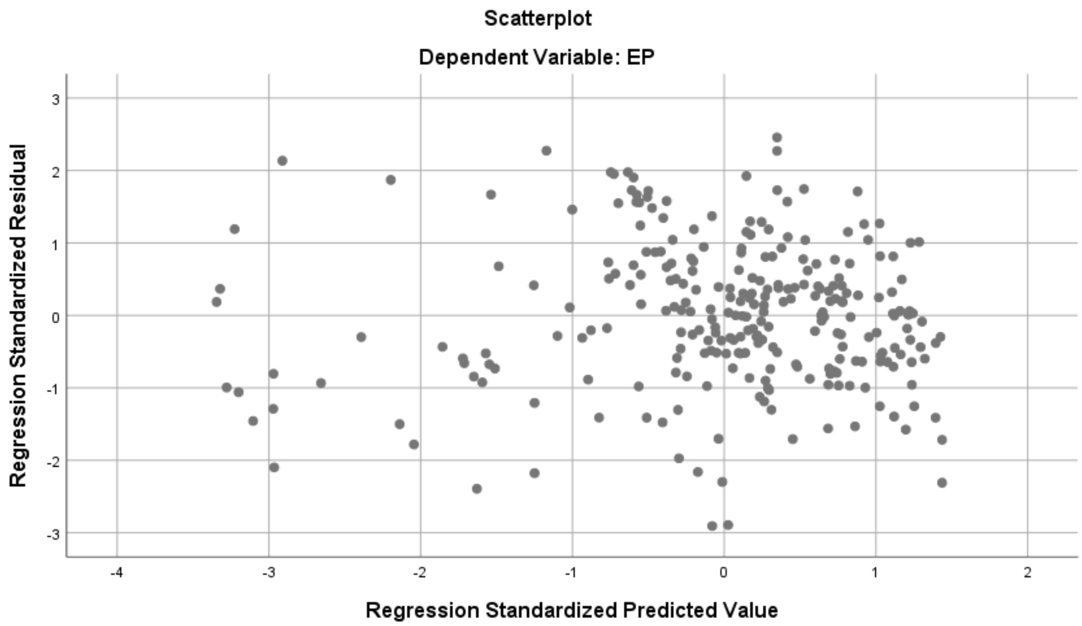

Figure 35. Residuals scatterplot: Volatility

APPENDIX D – PEARSON CORRELATION COEFFICIENTS

Table 18. Pearson correlation coefficients

	Equity premium	Dividend Price	Earnings Price	Volatility	FTSE100	Tbill	Spread	Bond Yield	Money Market	CPI	Exchange Rate	Industrial Prod	OilProd
Equity premium		-.60	-.52	-.43	.11	-.13	.37	.01	-.17	-.02	-.02	-.18	-.03
DividendPrice	.60		.63	.34	-.07	-.08	-.28	.03	-.11	-.02	.11	.09	-.07
EarningsPrice	-.52	.63		.61	-.09	-.14	-.57	-.11	-.13	-.00	.05	.08	-.03
Volatility	-.43	.34	.61		-.04	-.12	-.44	.11	-.10	.03	-.00	.07	.08
FTSE100	.11	-.07	-.09	-.04		-.21	-.07	-.15	-.16	-.04	.24	-.04	-.00
Tbill	-.13	-.08	-.14	-.12	-.21		.27	.46	**.89***	.13	-.08	.02	.06
Spread	.37	-.28	-.57	-.44	-.07	.27		.37	.21	.02	-.12	-.09	-.01
BondYield	.01	.03	-.11	.11	-.15	.46	.37		.38	.04	-.14	-.04	.01
MoneyMarket	-.17	-.11	-.13	-.10	-.16	**.89***	.21	.38		.07	-.05	.06	.07
CPI	-.02	-.02	-.00	.03	-.04	.13	.02	.04	.07		.12	.06	.10
ExchangeRate	-.02	.11	.05	-.00	.24	-.08	-.12	-.14	-.05	.12		.09	-.06
IndustrialProd	-.18	.09	.08	.07	-.04	.02	-.09	-.04	.06	.06	.09		.08
OilProd	-.03	-.07	-.03	.08	-.00	.06	.01	.01	.07	.10	-.06	.08	

* Pearson correlation coefficient <.90 and > .80

APPENDIX E – REGULARISATION PATHS

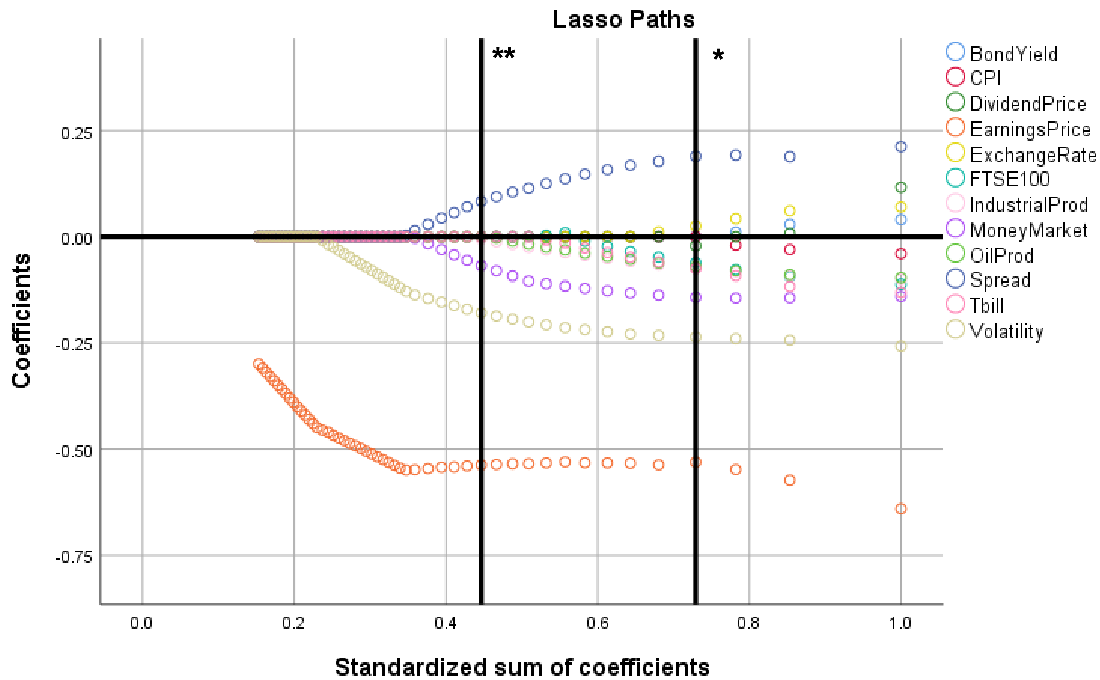

Figure 36. Regularisation paths: Lasso regression

* Lasso penalty = .060. Optimal model at the point where the expected prediction error is minimised. Standardised sum of coefficients = .729 Number of Predictors: 10 (DividendPrice, EarningsPrice, Tbill, Spread, MoneyMarket, FTSE100, ExchangeRate, IndustrialProd, OilProd, Volatility).

** Lasso penalty = .260. Most parsimonious model within 1 standard error. Standardised sum of coefficients = .446. Number of predictors: 5 (EarningsPrice, Spread, MoneyMarket, IndustrialProd, Volatility).

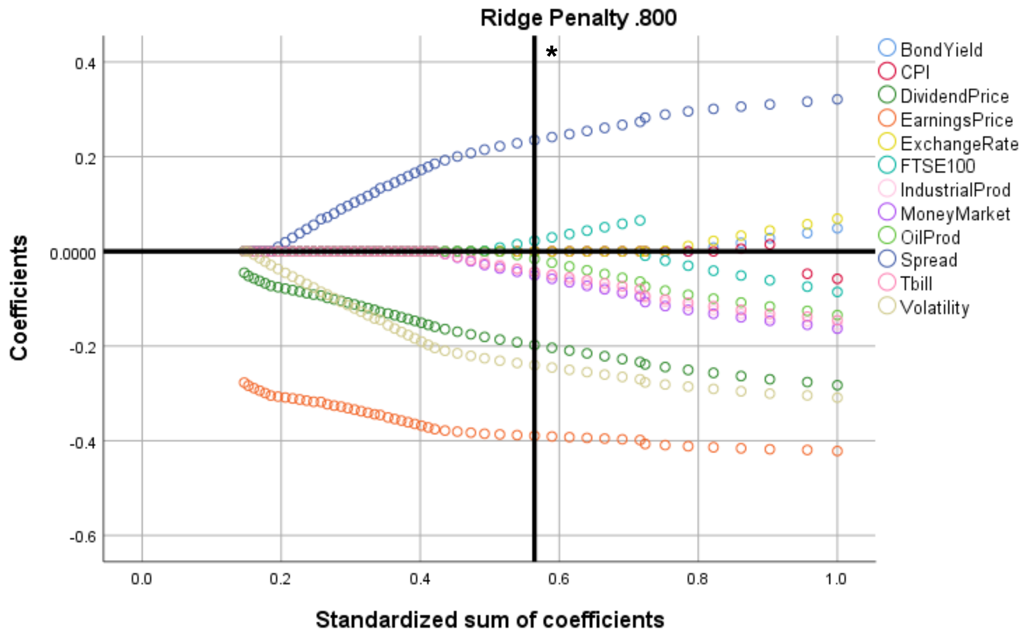

Figure 37. Regularisation paths: Elastic net regression

* Ridge penalty = .800 Lasso penalty = .280. Optimal model at the point where the expected prediction error is minimised. Standardised sum of coefficients = .564 Number of Predictors: 9 (DividendPrice, EarningsPrice, FTSE100, IndustrialProd, MoneyMarket,Spread, OilProd, Tbill & Volatility).

APPENDIX F – REGULARISED TABLE OF COEFFICIENTS

Table 19. Lasso regression coefficients

*	*β*	df	*F***	*p*
DividendPrice	0.00	0	0.00	n/a
EarningsPrice	-0.54	4	18.86	.000
Volatility	-0.18	2	4.09	.018
FTSE100	0.00	0	0.00	n/a
Tbill	0.00	0	0.00	n/a
Spread	0.08	2	0.96	.384
BondYield	0.00	0	0.00	n/a
MoneyMarket	-0.07	3	2.52	.059
CPI	0.00	0	0.00	n/a
ExchangeRate	0.00	0	0.00	n/a
IndustrialProd	-0.01	2	0.06	.941
OilProd	-0.00	0	0.00	n/a

* Dependent variable: EP
** 5% level of significance

Table 20. Elastic net regression coefficients

*	β	df	F**	Sig.
DividendPrice	-0.20	4	16.01	.000
EarningsPrice	-0.39	3	45.89	.000
Volatility	-0.24	2	12.50	.000
FTSE100	0.02	1	0.24	.628
Tbill	-0.04	3	0.77	.514
Spread	0.24	2	19.25	.000
BondYield	0.00	0	0.00	n/a
MoneyMarket	-0.05	4	1.43	.225
CPI	0.00	0	0.00	n/a
ExchangeRate	0.00	0	0.00	n/a
IndustrialProd	-0.04	2	1.48	.230
OilProd	-0.02	1	0.15	.700

* Dependent variable: EP
** 5% level of significance

APPENDIX G – OVERVIEW OF ALTERYX PREDICTION PROCESSES

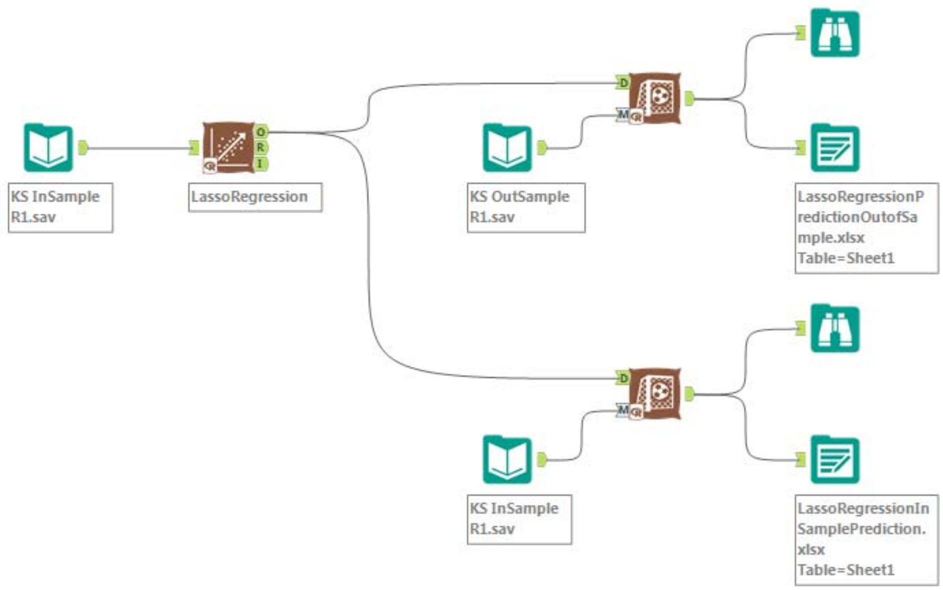

Figure 38. Alteryx process flow: Lasso regression

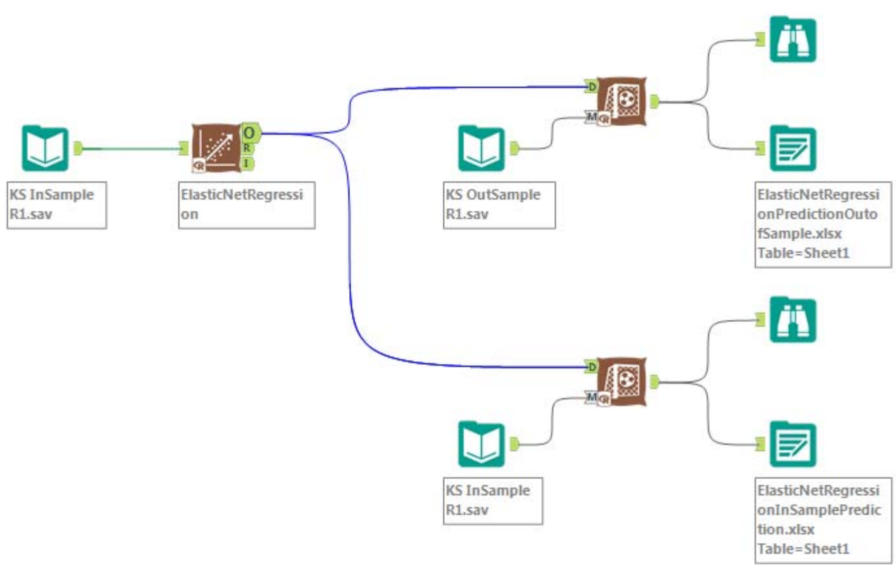

Figure 39. Alteryx process flow: Elastic net regression

APPENDIX H – EXECUTION OF ALTERYX PROCESSES

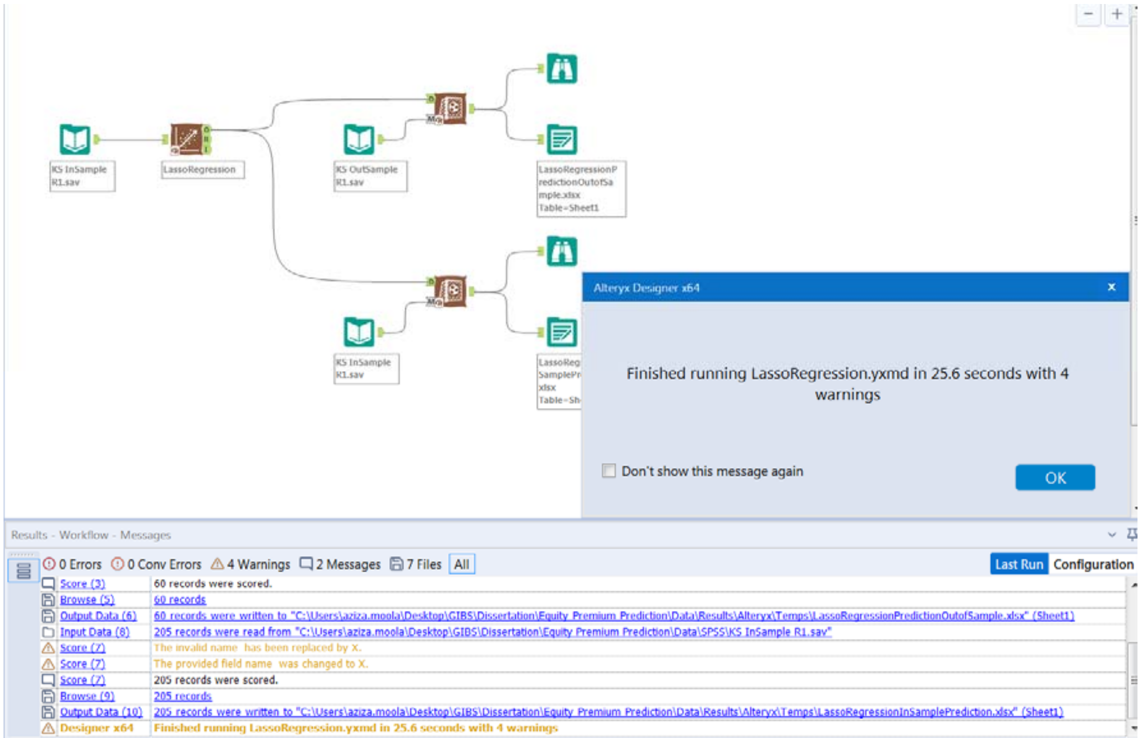

Figure 40. Alteryx execution of process: Lasso regression

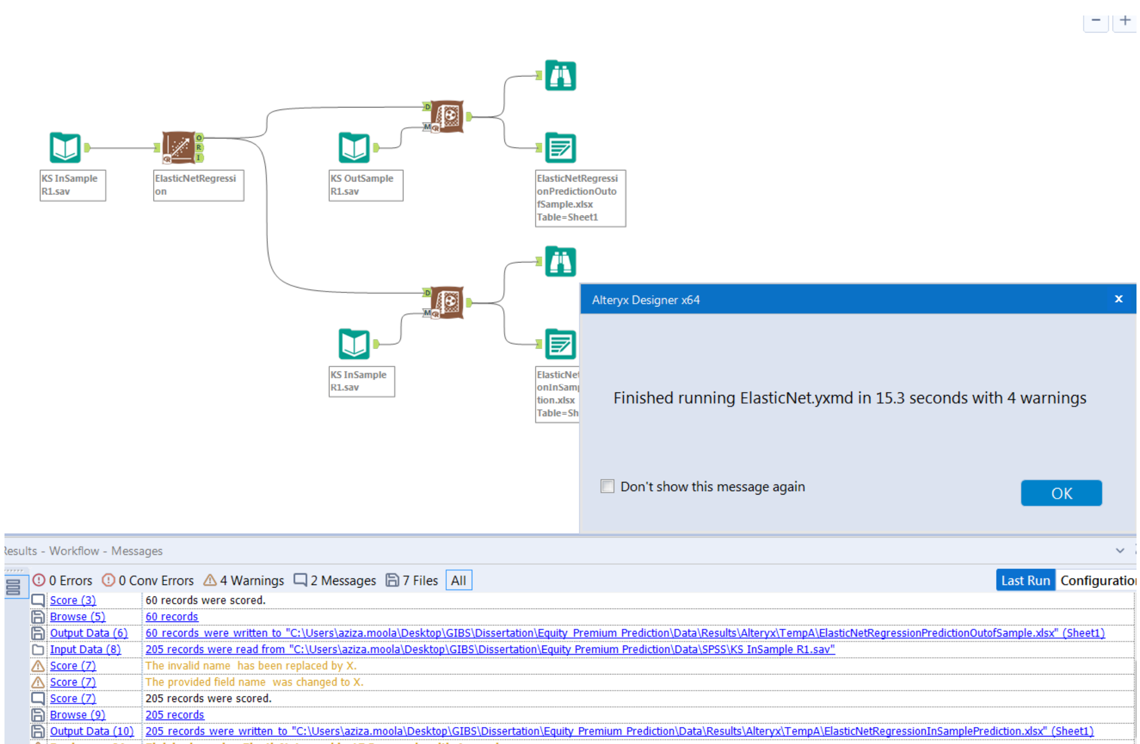

Figure 41. Alteryx execution of process: Elastic net regression

APPENDIX I – REGRESSION TIME SERIES GRAPHS

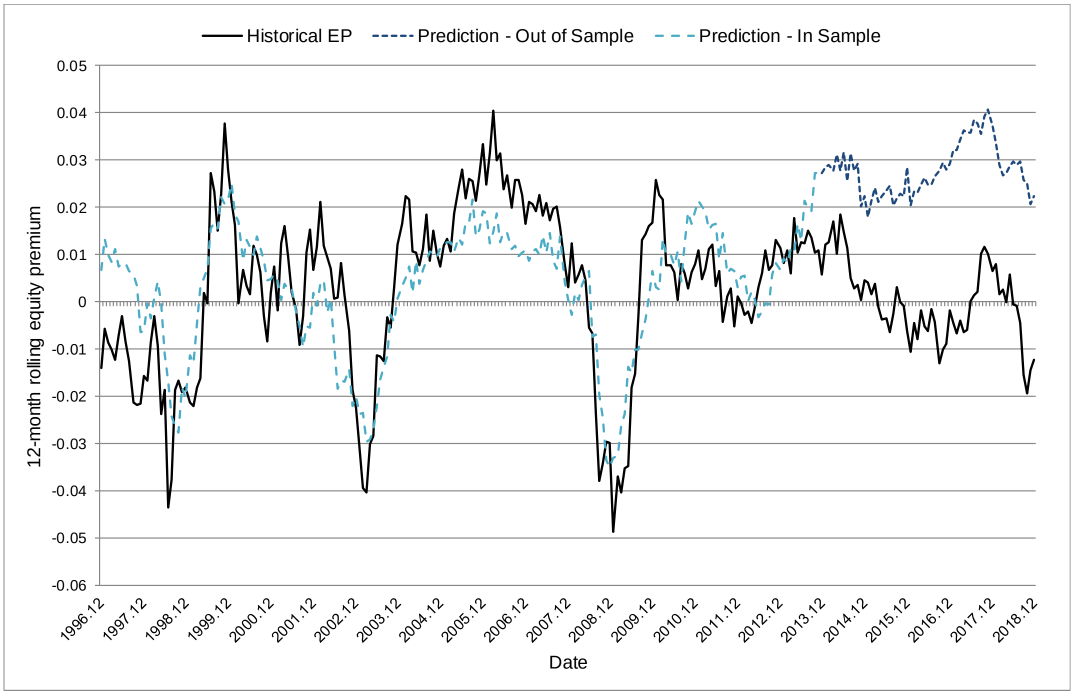

Figure 42. Kitchen sink time series graph

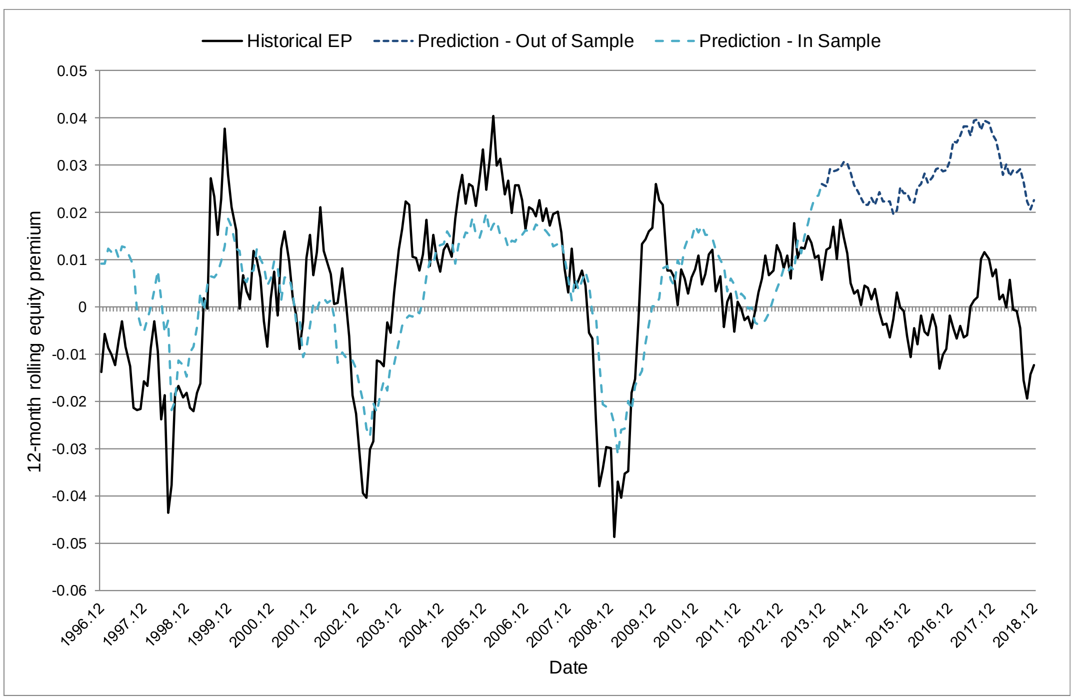

Figure 43. Lasso time series graph

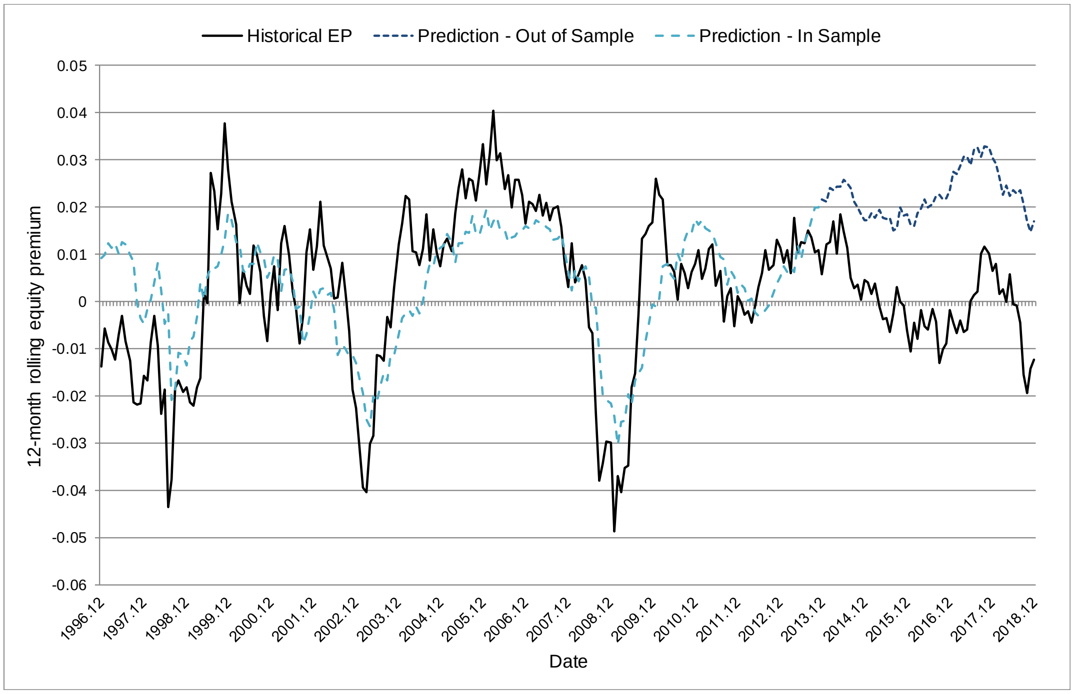

Figure 44. Elastic net time series graph