Essays on Determinants, Spillovers and Predictability of the South African Stock Returns

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Abstract

Following the recent recession, major global economies are still experiencing weak recoveries. The likelihood that the global economy may experience a double-dip recession driven by poor performance by advanced economies stresses the need for predicting the behaviour of leading indicators such as stock returns and equity premium. An understanding of market behaviour helps in guiding both policy and trading decisions. The main objective of this thesis is to assess the predictability, spillovers and determinants of stock returns in South Africa.

Stock returns are determined by a number of financial and macroeconomic variables including valuation ratios (price-earnings ratio and price-dividend ratio), payout ratio, interest rates, the term spread, stock returns of South Africa's major trading partners, the inflation rate, money stock, industrial production and the employment rate, world oil production, the refiner acquisition cost of imported crude oil, global activity index, industrial stock returns and financial stock returns. A number of econometric models are used in investigating the determinants, predictability and spillovers of the stock returns – including; predictive regressions using in-sample and out-of-sample test statistics (t-statistics, MSE-F and the ENC-NEW, R_{os}^2, utility gains, forecasting encompassing test); exponential smooth-transition autoregressive; Monte Carlo simulations; data-mining-robust bootstrap procedure; in-sample general-to-specific model selection, bootstrap aggregating, combining method (simple averages, discounting, clusters, principal components, Bayesian regression methods under the Gaussian and double-exponential prior); sign restriction VAR and a TVP-VAR model specification with stochastic volatility.

The results show that firstly, the stock returns are determined by certain financial and macroeconomic variables (assessing both the statistical and economic significance). Secondly, South African stock returns react differently to different types of oil shocks – suggesting that the cause of the oil price shock is crucial in determining policy. The combination model forecasts, especially the Bayesian regression methods, outperform the benchmark model (AR(1)/random walk model). Further, the analysis does not only show evidence of significant spillovers to consumption and interest rate from the stock market, but, more importantly, it also highlights the fact that these effects have significantly varied over time.

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Without God my personal Saviour, I would not be where I am today. Thanks be to the Almighty for every blessing he has given me. Trust in the LORD with all your heart and lean not on your own understanding; in all your ways acknowledge him, and he will make your paths straight (Proverbs 3:5).

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CHAPTER 1: INTRODUCTION

Forecasting stock market behaviour has received great attention in recent years from both academics and policy-makers. The current uncertainties regarding the economic performance of the major global economies (especially the United States and the Euro zone and major emerging markets such as China and India) and the likelihood that the global economy may experience a double-dip recession has continued to emphasise the importance of predicting the behaviour of leading indicators (including stock returns) accurately. Stock prices are shown to act as leading indicators and help predict the behaviour of output and inflation in the economy both globally and domestically (see for example, Lettau and Ludvigson, 2001, 2004; Ludvigson et al., 2002; Apergis and Miller, 2004, 2005a, b, 2006; Rapach and Strauss, 2006, 2007; Sousa, 2008a, 2008b, 2010a, 2010b, 2010c, 2010d; Bostic et al., 2009; Fratzscher and Straub; 2009, 2010; Fratzscher et al., 2010; Singh and Pattanaik, 2010; Zhou, 2010; Afonso and Sousa, 2011a; Carroll et al., 2011; Koivu, 2012; Peltonen et al., 2012; Singh, 2012, and references cited in these studies). Against this background, this thesis, over seven independent chapters with a common theme, examines the determinants and predictability of stock returns in South Africa. The spillover effects from the stock market to the real economy are also evaluated in this thesis.

In Chapters 2 to 5, the determinants and the predictability of South Africa's stock returns are evaluated. Chapter 2 starts by assessing the predictive power of valuation ratios using a liner and a non-linear framework. Following the results showing lack of predictive power when assessing only valuation ratios, Chapters 3 and 4 not only assess the predictive power of a wider selection of both financial and macroeconomic variables using a bivariate predictive regression, but the analysis also tests the in-sample and the out-of-sample predictability in context of data mining. Chapter 5 examines the impact of different global oil market shocks on South African stock returns using a structural VAR model specification. South African stock returns react differently to different types of global oil market shocks – suggesting that the source of the oil price increase is crucial in determining policy.

In Chapter 6 the existence of spillovers from stock prices onto consumption and the interest rate for South Africa is investigated using a time-varying vector autoregressive (TVP-VAR) model with stochastic volatility. The analysis in Chapter 6 focused on whether real stock price movements have significant spillover effects on consumption decisions and monetary policy in South Africa. The analysis does not only show evidence of significant spillovers on consumption and interest rate from the stock market, but, more importantly, it also highlights the fact that these effects have significantly varied over time.

The popularity of predictive regression models, and the fact that these models are usually estimated using relatively long span of data, necessitates the need to test for the structural stability of the parameters in these models. Numerous macroeconomic and financial variables are unstable over time (Stock and Watson; 1996; Rapach and Wohar, 2006) and as a result, Chapter 7 examines the predictive role of financial and macroeconomic variables for South Africa's equity premium while recognizing potential structural breaks – assessing bivariate and multivariate predictive regression models. There is strong evidence of at least two structural breaks for most bivariate predictive regression models and for both the multivariate predictive regression models of equity premium. Given the structural breaks in the South African data, the results further show that the predictive ability of the financial and macroeconomic variables can vary widely across different regimes.

Although most studies focus on in-sample tests and conclude that there is significant evidence of return predictability, Goyal and Welch (2008) show that these potential predictors are unable to deliver consistently superior out-of-sample forecasts of equity premium relative to a random walk model. To improve out-of-sample equity premium forecasts based on a combination financial and macroeconomic variables, Chapter 8 propose four approaches – bagging forecasts, combination of model forecasts, principal component and Bayesian regressions. The results show that South African equity premium is determined by certain financial and macroeconomic variables (assessing both the statistical and economic significance as well as the in-sample and out-of-sample forecasts). The combination model forecasts, however, tend to outperform the benchmark model (AR(1)/random walk model) and the bivariate predictive regressions. When comparing combination model forecast, the Bayesian regression methods are found to be the standout performers with the models outperforming the individual regressions, forecast combination methods, bagging and principal component regressions.

This thesis contributes to literature in the following manner (not limited to); firstly, looking at South African data, this is a first attempt that assesses the impact on stock returns while disaggregate global oil market shocks – include oil inventories in the analysis to further identify the forward-looking element of oil price shock. Secondly, this is a first attempt to examine the predictability of real stock prices for South Africa based on valuation ratios and using both linear (predictive regression) and nonlinear model (exponential smooth-transition autoregressive) specifications. Thirdly, this is the first study using South African data that looks at not only in-sample, but also out-of-sample forecasting predictability using macroeconomic and financial variables. Fourthly, this is a first attempt to investigate the structural stability of predictive regression models of South Africa's equity premium. Lastly, this is a first attempt, in the literature, to analyse the spillover effects of real stock prices on consumption and interest rate using a TVP-VAR model for the South African economy.

CHAPTER 2: VALUATION RATIOS AND STOCK RETURN PREDICTABILITY IN SOUTH AFRICA: IS IT THERE?[1]

1. Abstract

Using monthly South African data for 1990:01-2009:10, this Chapter examines the predictability of real stock return based on valuation ratios, namely, price-dividend and price-earnings ratios. We cannot detect either short-horizon or long-horizon predictability; that is, the hypothesis that the current value of a valuation ratio is uncorrelated with future stock price changes cannot be rejected at both short- and long-horizons based on bootstrapped critical values constructed from linear representations of the data. We find, via Monte Carlo simulations, that the power to detect predictability in finite samples tends to decrease at long horizons in a linear framework. Though Monte Carlo simulations applied to exponential smooth-transition autoregressive (ESTAR) models of the price-dividend and price-earnings ratios, show increased power, the ability of the non-linear framework in explaining the pattern of stock return predictability in the data does not show any promise both at short- and long-horizons, just as in the linear predictive regressions.

[1] Published in Emerging Markets Finance and Trade, 48(1): 70-82.

2. Introduction

Forecasting stock returns is amongst one of the most important research questions in financial economics. In addition, there exists international evidence that asset prices, including stock prices, not only help in predicting output and inflation by acting as leading indicators (Stock and Watson, 2003), but also that there are major (asymmetric) spillovers from the stock markets to the real sector of the economy (for some recent evidence, refer to, Lettau and Ludvigson, 2001, 2004; Lettau et al. 2002; Apergis and Miller, 2004, 2005a, b and 2006; Rapach and Strauss, 2006, 2007; Pavlidis et al. 2009 and Das et al. forthcoming amongst others). Hence, obtaining accurate predictions of stock prices cannot be understated. In general, stock price predictions are based on a predictive regression model, which essentially amounts to regressing the growth rate of real stock price, i.e., stock returns, (over various horizons) on a variable thought to be capable of explaining the future path of stock prices. Even though the predictive regression model suffers from a variety of econometric problems (Mankiw and Shapiro, 1986; Stambaugh, 1986, 1999; Nelson and Kim, 1993; Kirby, 1997), the general consensus is that valuation ratios (price-dividend and price-earnings ratios) based on measures of fundamental values, can, in fact, forecast stock prices (Fama and French, 1988; Campbell and Shiller, 1988, 1998; Campbell, 1999, 2000 and Rapach and Wohar, 2005). Other studies that appear to provide empirical support for the use of the valuation ratios as a measure of expected stock returns include Rozeff (1984), Hodrick (1992) and Nelson and Kim (1993). An issue with these studies is that stock return regressions used face statistical issues including strong dependency structures and biases in the estimation of regression coefficient. Such model issues tend to make findings against the no predictability hypothesis appear more significant than they really are. Nonetheless, these studies suggest that valuation ratios contain important information that can be useful in predicting future stock returns. Fama and French (1988) and Campbell and Shiller (1988) find that valuation ratios predict future real equity returns, and, more recently, Campbell and Shiller (1998) find that these valuation ratios are useful in predicting future growth in real stock prices using data spanning the late nineteenth to the late twentieth centuries. However, an interesting pattern seem to emerge from these studies, in the sense that evidence for significant stock return predictability is only observed at long, and not short, horizons. In other words, the hypothesis that the current value of price-dividend and price-earnings ratios are uncorrelated with changes in future stock price changes can only be rejected at longer horizons. Two possible explanations for such a pattern are non-linearity in the data and possible increase in statistical power at longer-horizons when considering a linear framework (Rapach and Wohar, 2005).

Against this backdrop in this chapter, using monthly data for 1990:01-2009:10, we for the first time, to the best of our knowledge, examine the predictability of real stock returns for South Africa ranging from one month to sixty months, based on price-dividend and price-earnings ratios. At this stage, it is important to emphasize, that there is still quite a lot of debate not only regarding the predictability of stock returns itself but also the predictors themselves, especially when it involves out of-sample forecasting.[2] See for example Campbell and Thompson (2008), Cochrane (2008), Goyal and Welch (2008) and Rapach *et al.,* (2009) amongst others. Given the wide variety of possible predictors, studies by Ludvigson and Ng (2007, 2009, forthcoming) and Cakmakli and van Dijk (2010) have suggested the use of large-scale factor models to extract common factors, and using them in the predictive regressions to evaluate stock returns predictability. Having said this, valuation ratios do remain important predictors of stock returns, especially given their theoretical importance, and this chapter aims to shed further light on the empirical importance of the price-dividend and price-earnings ratios in predicting stock returns by using a different data set from an emerging economy.

Our empirical analysis starts by estimating predictive regression models for the real stock returns with the log-value of either price-dividend or price-earnings ratio acting as the explanatory variable. The size and power properties of the long-horizon regression tests are then analysed using Monte Carlo simulations outlined in Kilian (1999) and Rapach and Wohar (2005). In addition to the linear predictive regression model, we utilize a parsimonious version of the exponential smooth-transition autoregressive (ESTAR) model proposed by Kilian and Taylor (2003) to reevaluate the predictability of the real stock returns in a non-linear framework. Just as with the linear model, Monte Carlo simulations are also used to measure the size and power properties of the non-linear framework. Note the parsimonious ESTAR framework allows for non-linear mean reversion in the relevant valuation ratio and is quite straightforward in terms of economic interpretation. The remainder of the

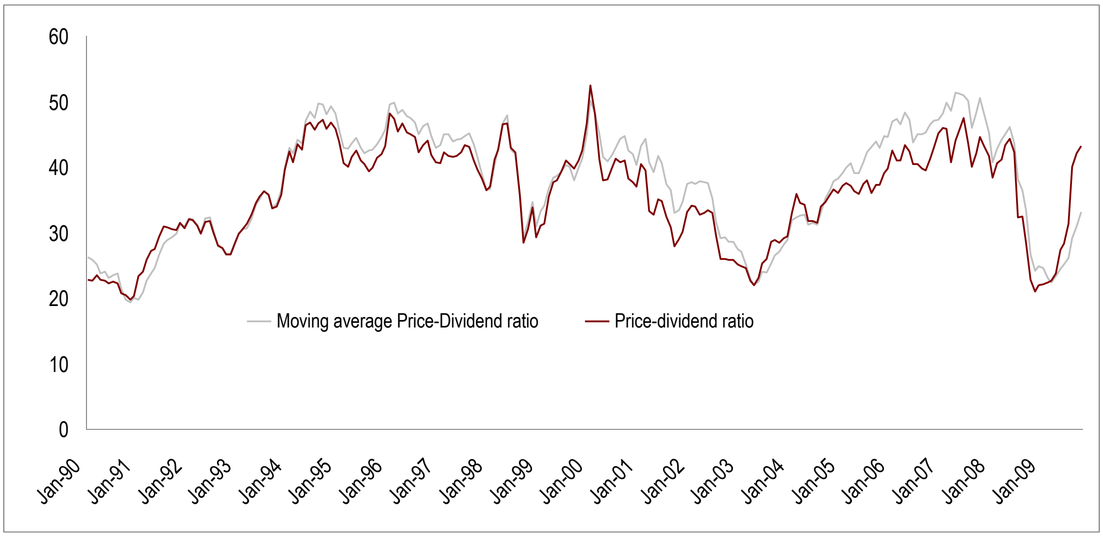
[2] Based on the suggestions of three independent anonymous referees, robustness checks of our results were carried out with seasonally adjusted data using the X-12 approach, as well as, nominal data. However, our basic results remained unchanged. The details of these results have been suppressed to save space, but are available upon request from the authors.

chapter is organized as follows: Section 2 discusses that data and presents the results of real stock returns predictability based on the linear predictive regression. In this section, we also examine the size and power properties of these regressions based on Monte Carlo simulations. In Section 3, we revisit the linear analysis in a non-linear parsimonious ETSAR model. Finally, Section 4 concludes.

3. Predictive regression in a linear framework

In this section, we estimate linear predictive regressions at both short and long horizons, ranging between one to sixty months. We use monthly data on the nominal values of the All Share Stock Index (ALSI), dividends and earnings, which were, in turn, converted to their real values by deflating with the Consumer Price Index (CPI). Following Ang and Bekaert (2007) and Rapach et al. (2009, 2010a, b, c), we take one-year moving sum of the real dividends and real earnings to remove seasonality.[3] We then consider the ability of the valuation ratios (real stock price in January divided by moving sum of real dividends or real earnings over the previous calendar year) to predict future real stock returns over the period of 1990:01-2009:08. Figures 1 and 2 show the plots of the two valuation ratios, both the actual data and the corresponding 12-month moving average, besides the real stock returns[4]. Note all the required data were obtained from the South African Reserve Bank and Statistics South Africa.[5]

Figure 1: Price dividend ratio and the moving average



[3] Based on the suggestions of the referees, we conducted the Andrews (1993) *SupF* structural break test on the real stock returns. However, we could not detect any evidence of a possible structural break. These results are available upon request from the authors. The means for the real stock returns, the price-dividend ratio and price earnings ratio were 0.0859, 35.7262 and 13.7335, while the corresponding standard deviations were 2.2097, 7.3919 and 2.5805 respectively.

[4] Note that the data on the valuation ratios are originally in ratio form. We divide them by the nominal ALSI and then take the reciprocal of the series to obtain the nominal dividend and nominal earnings series.

[5] Based on the Ng and Perron (2001) unit root tests, which have been shown to have good size and power properties relative to the standard unit root tests, we found p_t ~I(1) (Δp_t ~I(0)) and z_t ~I(0) for $z_t = p_t - d_t$ and $z_t = p_t - e_t$. In addition, based on the suggestions of the referees, we conducted the Andrews (1993) *SupF* structural break test on the two predictive regressions. However, we could not detect any evidence of a possible structural break. These results are available upon request from the authors.

Figure 2: Price-earnings ratio and the moving average

We examine whether the valuation ratios are useful for forecasting changes in real stock returns at short and long horizons based on formal statistical tests of the null of no-predictability, using predictive regressions, which can be formally described as follows[6]:

$$\Delta p_{t+k}^{k} = \alpha_k + \beta_k z_t + \varepsilon_{t+k}^{k} \qquad (1)$$

where p_t represents real stock prices in log-levels; z_t is the relevant log-value of the valuation ratio; $\Delta p_{t+k}^{k} = p_{t+k} - p_t$; and, ε_{t+k}^{k} is the error term. More specifically, $z_t = p_t - f_t$; while, f_t represents log of real dividends (d_t) or log of real earnings (e_t). Following Ang and Bekaert (2007), we consider $k = 1,\ldots,60$ months in equation (1). The predictive ability of z_t in a predictive regression, such as equation (1), is assessed through the *t*-statistic corresponding to the OLS estimate of β_k, denoted by $\hat{\beta}_k$. When $k > 1$, the observations for the real stock returns are overlapping, which introduces serial correlation in the error term. Following the extant literature, we use the heteroscedasticity and autocorrelation (HAC) corrected standard errors proposed by Newey and West (1987), based on the Bartlett kernel and a lag truncation parameter of [1.5 • k], where [•] is the nearest integer function (Rapach et al., 2005 and Rapach and Wohar, 2006). Another potential problem with estimating equation (1) is small-sample bias (Stambuagh, 1986, 1999). Nelson and Kim (1993) point out that these biases and the overlapping nature of the observations beyond the first step can severely shift the distribution of the *t*-statistic for $\hat{\beta}_k$, even when one uses HAC corrected standard errors. Hence, drawing inferences on standard asymptotic results, when testing the null hypothesis of no predictability, i.e., β_k =0, can lead to considerable size distortions. Given this, we rely on a bootstrap procedure outlined in Rapach and Wohar (2005), to make valid inferences for our predictive regression tests. For each k (= 1……60), the bootstrap procedure was repeated 500 times in order to generate an empirical distribution of *t*-statistics under the null hypothesis of no predictability. To test the null hypothesis of β_k =0 against the one-sided alternative hypothesis of β_k *<0*, the *p*-value is computed as the proportion of the bootstrapped *t*-statistics which are less than the *t*-statistics obtained from the original data.

[6] Following Teräsvirta (1994), we found that LSTAR and ESTAR models with delays of 3 and 2 and lags of 4 and 6 respectively, for the price-dividend and price-earnings ratio, to be more appropriate empirical representation of the DGP for these two valuation ratios. However, when we used these more general DGPs instead of our parsimonious framework, we still failed to obtain any predictability, even though the *p*-values came down quite significantly at longer horizons. These results are available upon request from the authors.

Table 1: Estimation results for the predictive regression model under the assumption of a linear data-generating process

	$z_t = p_t - d_t$		$z_t = p_t - e_t$	
Horizon (k)	β_k	*t-statistic*	β_k	*t-statistic*
1 months	-0.0034	-0.2833 [0.3800]	0.0016	0.1199 [0.6060]
3 months	-0.0380	-0.9488 [0.2220]	-0.0259	-0.6198 [0.3180]
6 months	-0.0861	-1.1240 [0.1940]	-0.0549	-0.6938 [0.3460]
9 months	-0.1135	-1.0923 [0.2560]	-0.0536	-0.5389 [0.3760]
12 months	-0.1638	-1.1924 [0.1840]	-0.0721	-0.5743 [0.3380]
18 months	-0.2685	-1.3259 [0.2100]	-0.1417	-0.7907 [0.3100]
24 months	-0.3585	-1.3194 [0.2180]	-0.2260	-0.9940 [0.3400]
36 months	-0.6704	-1.7131 [0.1960]	-0.5461	-1.8134 [0.2420]
48 months	-0.8289	-2.1756 [0.1860]	-0.8360	-2.4438 [0.1920]
60 months	-0.6300	-2.3362 [0.2360]	-0.8507	-2.3624 [0.2120]

Note: Numbers in the brackets corresponds to bootstrapped p-values.

The results obtained from the predictive regressions for the price-dividend and price-earnings ratios at horizons 1, 3, 6, 9, 12, 18, 24, 36, 48, and 60 month(s) are reported in Table 1. Unlike the extant literature, we cannot detect predictability of real stock returns at either short- or long-horizons, based on conventional significance levels. Berkowitz and Giorgianni (2001) indicate that in a linear framework, if there is no predictability at the one-step-ahead horizon, one would expect that there is no predictability at any horizon, since multi-step-ahead forecasts of a specific variable are simple extrapolations of the one-step-ahead forecast.

In Table 2, we present the size and power properties of the predictive regression tests at the nominal 10 perc ent level, reported in Table 1, based on Monte Carlo simulations, as discussed in Rapach and Wohar (2005). As can be seen from columns 2 and 4 of Table 2, size distortions are not an issue for our method of inference, since the predictive regression tests are very close to being correctly sized. From columns 3 and 5, we see that the power to detect predictability is quite small and consistently decreases at long-horizons, with the power of the predictive regression tests based on the price-dividend ratio being lower than the predictive regression tests based on the price-earnings ratio. Understandably, with the power of the predictive regression tests decreasing to the nominal size of the tests at long horizons, it is not surprising to observe no-predictability in the real stock returns, based on valuation ratios.

Table 2: Monte Carlo simulation results for the predictive regression tests under the assumption of a linear data-process

	$z_t = p_t - d_t$		$z_t = p_t - e_t$	
Horizon (k)	*Size*	*Power (β_1= -0.003)*	*Size*	*Power (β_1= 0.002)*
1 month	0.10	0.35	0.10	0.53
3 months	0.11	0.36	0.10	0.51
6 months	0.11	0.34	0.10	0.51
9 months	0.10	0.34	0.10	0.48
12 months	0.08	0.35	0.10	0.46
18 months	0.11	0.32	0.09	0.42
24 months	0.11	0.30	0.10	0.38
36 months	0.12	0.24	0.11	0.27
48 months	0.10	0.19	0.13	0.22
60 months	0.11	0.10	0.13	0.18

Note: The size and power are based on 500 Monte Carlo simulations with 500 bootstrapped replications per Monte Carlo simulation.

4. Predictive regression in a nonlinear framework

Since we found no predictability based on linear predictive regressions, we decided to analyse if our results change, when we consider a parsimonious ESTAR model specification, as in Rapach and Wohar (2005). Note, even though our result of no predictability at the one-step-ahead translates to no predictability at any horizon implied that the valuation ratios are linearly related to the real stock returns, we decided to test for non-linearity formally to confirm our findings. Given this, we consider a parsimonious ESTAR specification for the price-dividend and price-earnings ratio, originally outlined in Kilian and Taylor (2003) for analysing nominal exchange rate deviations from purchasing power parity fundamentals that incorporates the idea of risky arbitrage. At this stage, it must be pointed out that ESTAR models are only one of the many possible non-linear models that can be used. For instance Markov-switching models are very popular in analysing stock returns at monthly frequencies (see Franses and van Dijk (2000) for details on various non-linear frameworks used in the literature to model stock returns). However, it was not our intent to undertake an extensive analysis of how well different classes of nonlinear models fit the data. Instead, we wanted to investigate a parsimonious nonlinear model with a straightforward economic interpretation as follows: When both noise traders and arbitrageurs exist in a model, the demand for assets by noise traders is based on beliefs not justified completely by news on fundamentals. While, arbitrageurs form fully rational expectations about the returns to holding an asset and can, in turn, potentially profit from the mistaken beliefs of noise traders. However, arbitrage is risky in these models, since mistaken beliefs of noise traders may cause asset prices to deviate from their underlying fundamentals for considerable periods of time. In this situation, even though the asset prices they will ultimately return to a level in line with the fundamentals, an arbitrageur may have to borrow to trade or be compared to other financial advisors. And then, if the mispricing persists, the arbitrageur can suffer serious losses or fare poorly relative to other advisors. Kilian and Taylor (2003) hypothesize that the risk to arbitrage decreases as the asset becomes increasingly overvalued or undervalued, leading to disproportionately quicker adjustment toward the equilibrium, while, smaller deviations are likely to persist longer.

In light of this, we use the following ESTAR framework:

$$z_t - \mu_z = \left\{\exp\left[\gamma(z_{t-1} - \mu_z)^2\right]\right\}(z_{t-1} - \mu_z) + u_t \qquad (2)$$

where μ_z is the mean of z_t and u_t is an independently and identically distributed error term with mean zero and variance σ^2. The transition function for the above ESTAR model is defined by $\exp\left[\gamma(z_{t-1} - \mu_z)^2\right]$ meaning that if $\gamma < 0$ the mean reversion will be stronger the larger the deviation (in absolute terms) of p_t from f_t. For each valuation ratio, equation (2) is estimated using nonlinear least squares (NLLS). As z_t is stationary under the null hypothesis that $\gamma = 0$, one must be careful when assessing the significance of $\hat{\gamma}$, the NLLS estimate of γ. Hence, following Rapach and Wohar (2005), we use a bootstrap procedure to calculate a *p*-value for the NLLS *t*-statistic corresponding to $\hat{\gamma}$. Based on the estimation $\hat{\gamma}$ =-0.12 and -1.78 respectively for the price-dividend and price- earnings ratios, with the corresponding *t*-statistics and *p*-values in parentheses being -1.54 (0.49) and -1.68 (0.40). The estimates of $\hat{\gamma}$ <0 are insignificant based on the boot-strapped *p*-values for the NLLS *t*-statistics, suggesting no evidence of non-linearity. However, as indicated by van Dijk et al. (2002), precise estimate of $\hat{\gamma}$ is often unlikely. Given this, and to directly compare a linear to a non-linear specification for z_t, we also tested the null hypothesis of a linear AR model specification against the alternative hypothesis of an ESTAR specification based on the Lagrange multiplier test of Granger and Tersävitra (1994). Given the parsimonious ESTAR specification in equation (2), this boils down to estimating the following regression:

$$z_t = \alpha_1 + \alpha_2 z_{t-1} + \alpha_3 z_{t-1}^2 + \alpha_4 z_{t-1}^3 \qquad (3)$$

And testing the joint significance of α_3 and α_4. For both the price-dividend and price earnings ratio, we could not reject the null hypothesis of linearity at the 10 per cent level of significance using either the *F*-statistic or the χ^2–statistic form of the test, with the *p*-values for each statistic being 0.88 and 0.51 respectively. The Lagrange multiplier test, thus, provides further evidence of the lack of a non-linear relationship between the real stock returns and the valuation ratios. Note, Rapach and Wohar (2005) too could not detect non-linearity for the price-earnings ratio based on the Lagrange multiplier test, but went ahead with the estimation of equation (1) accounting for a non-linear adjustment to the fundamentals using a modified bootstrap methodology outlined in Kilian and Taylor (2003). Given this, we too decided to estimate the predictive regression models for both the price-dividend and price-earnings ratios under the assumption of non-linear data-generating process, the results of which have been reported in Table 3. As with the predictive regressions under the assumption that the valuation ratios follow a linear data-generating process, we find no-evidence of predictability at horizons 1 through 60, when we assume that z_t follows an ESTAR process. In addition, the *p*-values obtained now are higher than the corresponding *p*-values reported in Table 1, which assumes linear data-generating process for z_t. This should not come as surprise since we do not find any evidence of non-linearity of z_t.

Table 3: Estimation results for the predictive regression model under the assumption of a non-linear data-generating process

	$z_t = p_t - d_t$		$z_t = p_t - e_t$	
Horizon (k)	β_k	*t-statistic*	β_k	*t-statistic*
1 month	-0.0034	-0.2833 [0.7240]	0.0016	0.1199 [0.8060]
3 months	-0.0380	-0.9488 [0.4900]	-0.0259	-0.6198 [0.5940]
6 months	-0.0861	-1.1240 [0.4720]	-0.0549	-0.6938 [0.6080]
9 months	-0.1135	-1.0923 [0.5100]	-0.0536	-0.5389 [0.6640]
12 months	-0.1638	-1.1924 [0.4960]	-0.0721	-0.5743 [0.6740]
18 months	-0.2685	-1.3259 [0.5160]	-0.1417	-0.7907 [0.6480]
24 months	-0.3585	-1.3194 [0.5560]	-0.2260	-0.9940 [0.6500]
36 months	-0.6704	-1.7131 [0.5900]	-0.5461	-1.8134 [0.5780]
48 months	-0.8289	-2.1756 [0.6040]	-0.8360	-2.4438 [0.5560]
60 months	-0.6300	-2.3362 [0.6260]	-0.8507	-2.3624 [0.6100]

Note: See note to Table 1.

Table 4: Monte Carlo simulation results for the predictive regression tests under the assumption of a nonlinear data-process

	$z_t = p_t - d_t$		$z_t = p_t - e_t$	
Horizon (k)	*Size*	*Power*	*Size*	*Power*
1 month	0.10	0.02	0.08	0.20
3 months	0.09	0.05	0.10	0.29
6 months	0.09	0.11	0.11	0.26
9 months	0.11	0.17	0.10	0.24
12 months	0.10	0.25	0.10	0.24
18 months	0.08	0.33	0.11	0.24
24 months	0.07	0.40	0.11	0.22
36 months	0.07	0.43	0.10	0.22
48 months	0.09	0.38	0.13	0.24
60 months	0.07	0.35	0.11	0.22

Note: See note to Table 2.

Finally, Table 4 presents the size and power properties of the predictive regressions in a non-linear framework. Clearly, as with the linear framework, there is no evidence of size distortions, based on 500 Monte Carlo replications with 500 bootstrapped replications per Monte Carlo replication. To investigate the power in a non-linear framework, we follow the method outlined in Kilian and Taylor (2003) and assume a non-linear process for the fundamental. It is important to highlight that the power of the test will depend on the specific form of the alternative model (Kilian and Taylor, 2003). We use a general-to-specific approach to obtain a relatively parsimonious model for the dividends and earnings process, with the general specification including twelve lags each of Δd_t and Δe_t. Once we obtained the following specific forms for Δd_t and Δe_t:

$$\Delta d_t = \gamma_0 + \gamma_1 \Delta d_{t-1} + \gamma_2 \Delta d_{t-2} + \gamma_3 \Delta d_{t-5} + \gamma_4 \Delta d_{t-7} + \gamma_5 \Delta p_{t-2} + \gamma_6 \Delta p_{t-8} + \gamma_7 \Delta p_{t-10} + \gamma_8 \Delta p_{t-12} + u_{1,t} \quad (6)$$

$$\Delta e_t = \gamma_0 + \gamma_1 \Delta e_{t-1} + \gamma_2 \Delta e_{t-2} + \gamma_3 \Delta e_{t-5} + \gamma_4 \Delta e_{t-6} + \gamma_5 \Delta p_{t-10} + u_{1,t} \quad (7)$$

we follow the bootstrapping procedure in Rapach and Wohar (2005) to obtain the power of the tests. In general, we find that power reaches its maximum value around the medium horizons and dips at the 60th month horizon, but tends to stay higher than those obtained under the assumption of linear data-generating process. But more importantly, just like under the case of linear data-generating process, assuming a non-linear data-generating process based on an ESTAR framework for the price-dividends and price-earnings ratios fail to reject the null of no-predictability at both short- and long-horizons, suggesting that valuation ratios, unlike in the extant literature, do not seem to carry worthwhile information in predicting the future path of real stock returns in South Africa.

5. Conclusion

Using monthly data for 1990:01-2009:10, we for the first time, to the best of our knowledge, examine the predictability of real stock returns for South Africa ranging over one month to sixty months, based on price-dividend and price-earnings ratios. Our empirical analysis starts by estimating predictive regression models for real stock returns with the log-value of either price-dividend or price-earnings ratio acting as the explanatory variable. The size and power properties of the long-horizon regression tests are then analysed using Monte Carlo simulations. In addition to the linear predictive regression model, we utilize a parsimonious version of the ESTAR model to reevaluate the predictability of the real stock returns in a non-linear framework. As with the linear model, Monte Carlo simulations are used to measure the size and power properties of the non-linear framework. We find no evidence of either short-horizon or long-horizon predictability; that is, the hypothesis that the current value of a valuation ratio is uncorrelated with real stock returns cannot be rejected at both short- and long- horizons based on bootstrapped critical values constructed from linear representations of the data. Further, we observe that the power to detect predictability in finite samples tends to decrease at long horizons in a linear framework. Though the ESTAR models of the price-dividend and price-earnings ratios show increased power, the ability of the non-linear framework in explaining the pattern of stock price predictability in the data again fails to show any promise both at short- and long-horizons.

Contrary to the extant literature, where one tends to obtain predictability of the real stock price growth rate at least at the long-horizon, we fail to reject the null hypothesis of no-predictability at both short- and long-horizons. The pertinent question now is: Why is that valuation ratios for South Africa are found to have no predictability for stock returns? To explain our results, we rely on the findings of Ang and Bekaert (2007). These authors too provided international evidence of the lack of predictability of stock returns based on valuation ratios, when considered purely on their own. However, when the predictive regressions were supplemented with the short-term interest rate, valuation ratios were found to predict the path of future stock returns. Ang and Bekaert (2007) then went ahead to build a present value model which showed that short-term interest rate movements, along with the discount rate, play a major role in explaining the variation in the valuation ratios, which, in turn, helped them to explain the above set of observations in the data. Such an explanation seems to hold true even for South Africa, in light of the recent evidence provided by Gupta and Modise (2012a). In their paper they forecast both in- and out-of-sample stock returns based on a wide set of financial variables, including valuation ratios, as well as international stock returns of South Africa’s major trading partners. The authors, just like Ang and Bekaert (2007), observe that though the price-dividend and price-earnings ratios have no predictability both in- and out-of-sample in univariate predictive regression models similar to those considered here. However, when a general-to-specific modeling approach is followed to take account of all the variables used in the forecasting exercise, the valuation ratios show up consistently in the specific model, along with the short-term interest rate, term spread and international stock returns. More importantly, the specific model is now found to contain significant predictive ability both in and out-of-sample.[7]

Given that stock prices serve as a leading indicator and, hence, carries useful information for policy makers as to where the economy might be heading, future research would aim to investigate not only in-sample, but also out-of-sample predictability of real stock returns based on a wider set of financial and macroeconomic variables (Choudhry, 2004; Chancharoenchai et al., 2005; Rapach et al., 2005, 2010a, b, c; Rapach and Wohar, 2006; Ludvigson and Ng, 2007, 2009, forthcoming; Carvalhal and de Melo Mendes, 2008; Goyal and Welch, 2008, Cakmakli and van Dijk, 2010) by extracting factors to serve as explanatory variables in predictive regression

[7] Note, it is important to evaluate the importance of financial and macroeconomic variables in an out-of-sample context as well, since as indicated by Rapach et al. (2005) and Rapach and Wohar (2006), it is possible for a variable to carry significant out-of-sample information, even when it is not the case in-sample.

models or even based on Bayesian vector autoregressive models, with both these approaches capable of handling huge data sets involving hundreds of variables. In addition, one might also want to delve into multifractal (Balcilar, 2003), long memory models (Franses and van Dijk, 2000; Balcilar, 2004) and even non-linear models (Qi, 1999; McMillan, 2001) to capture stock return movements.

CHAPTER 3: SOUTH AFRICAN STOCK RETURN PREDICTABILITY IN THE CONTEXT OF DATA MINING: THE ROLE OF FINANCIAL VARIABLES AND INTERNATIONAL STOCK RETURNS[8]

1. Abstract

Following the poor results regarding the predictive power of valuation ratios in Chapter 2, we extend our analysis by examine the predictive ability, both in-sample and the out-of-sample, for South African stock returns using a number of financial variables. Our analysis is based on monthly data with an in-sample period covering 1990:01 to 1996:12 and the out-of-sample period of 1997:01 to 2010:04 in this Chapter. We use the *t*-statistic corresponding to the slope coefficient in a predictive regression model for in-sample predictions, while for the out-of-sample, the MSE-F and the ENC-NEW tests statistics with good power properties were utilised. To guard against data mining, a bootstrap procedure was employed for calculating the critical values of both the in-sample and out-of-sample test statistics. Furthermore, we use a procedure that combines in-sample general-to-specific model selection with out-of-sample tests of predictive ability to further analyse the predictive power of each financial variable. Our results show that, for the in-sample test statistic, only the stock returns for our major trading partners have predictive power at certain short and long run horizons. For the out-of-sample tests, the Treasury bill rate and the term spread together with the stock returns for our major trading partners show predictive power both at short and long run horizons. When accounting for data mining, the maximal out-of-sample test statistics become insignificant from 6-months onward suggesting that the evidence of the out-of-sample predictability at longer horizons is due to data mining. The general-to-specific model shows that valuation ratios contain very useful information that explain the behaviour of stock returns, despite their inability to predict stock return at any horizon. The model also highlights the role of multiple variables in predicting stock returns at medium- to long-run horizons.

[8] Published in Economic Modelling, 29(3): 908-916.

2. Introduction

The recent financial turmoil has once again highlighted the importance of accurate forecasting, especially when it involves predicting the path of leading indicators of the economy. There exists international evidence that asset prices, including stock prices, not only help in predicting output and inflation by acting as leading indicators (Stock and Watson, 2003), but also that there are major (asymmetric) spillovers from the stock markets to the real sector of the economy (for some recent evidence, refer to, Lettau and Ludvigson, 2001, 2004; Lettau *et al.* 2002; Apergis and Miller, 2004, 2005a, b, 2006; Rapach and Strauss, 2006, 2007; Pavlidis *et al.* 2009 and Das *et al.*, forthcoming, amongst others). Hence, obtaining accurate predictions of stock prices cannot be understated, since if predicted accurately, the forecasts not only paves a path for relevant policy decision in advance, but can also provide important information for policy makers to appropriately design policies to avoid the impending crisis.

In a recent study, Gupta and Modise (2012b), using monthly South African data for 1990:01-2009:10, examined the in-sample predictability of real stock prices based on valuation ratios, namely, price-dividend and price-earnings ratios. The authors could not detect either short-horizon or long-horizon predictability; that is, the hypothesis that the current value of a valuation ratio is uncorrelated with future stock price changes cannot be rejected at both short- and long-horizons based on bootstrapped critical values constructed from both linear and non-linear representations of the data. Gupta and Modise (2012b), however, note that, future research should aim to investigate not only in-sample, but also out-of-sample predictability of real stock returns based on a wider set of financial variables, since it is possible for a variable to carry significant out-of-sample information even when it is not the case in-sample (Rapach *et al.*, 2005; Rapach and Wohar, 2006a). In addition, Gupta and Modise (2012b), following the recent work by Rapach *et al.,* (2010), suggested the need to analyse the role played by stock returns of major trading partners of South Africa in explaining the future path of stock returns.

Against this backdrop, using a predictive regression framework, we aim to implement the above set of extensions suggested by Gupta and Modise (2012b), and here in lies our contribution to the literature. To the best of our knowledge, this is the first study using South African data that looks at not only in-sample, but also out-of-sample forecasting ability of stock returns of South Africa's major trading partners, besides valuation ratios (Campbell and Shiller, 1998), term spread (Campbell, 1987), short-term interest rate (Ang and Bekaert, 2007), and payout ratio (Lamont, 1998). Since we are using quite a number of predictors, we avoid data mining problems by computing appropriate critical values using a bootstrap procedure. Further, given that predictive regressions are essentially a bivariate approach, where the predictability of each of the potential predictors are tested individually, we use general-to-specific model selection in order to choose the best in-sample forecasting model, where we start with a model that includes all the financial variables. This approach allows us to incorporate information simultaneously from (possibly) multiple predictors, without suffering from the degrees of freedom problem. Thus, in essence, the predictive regression framework based on the general-to-specific approach could encompass the bivariate predictive regression model, if in case multiple predictors are chosen in the best forecasting model.

Following the extant literature, our stock price predictions are based on a predictive regression model, which essentially amounts to regressing the growth rate of real stock price (over various horizons) on a variable thought to be capable of explaining the future path of stock prices. Note that the predictive regression framework, despite its limitations discussed below in Section 2, continues to be the most widely used econometric model in examining stock return predictability. Recent innovations involving non-linearity, time-varying parameters, latent factors and Bayesian priors, amongst others, have recently been incorporated into the framework as well.[9] Based on data availability, our in-sample period covers the period from 1990:01 to 1996:12, while our out-of-sample period begins from 1997:01 to 2010:04. Note, the choice of the out-of-sample period is aimed to cover the effects of the East Asian crisis, the move to an inflation-targeting regime, the currency crisis in late 2001 and the recent financial turmoil. We assess in-sample predictability via the *t*-statistic corresponding to the slope coefficient in a predictive regression model. In order to test for out-of-sample predictability, we compare out-of-sample forecasts generated by a model of constant returns to forecasts generated by a model that utilizes a given financial variable using two recently developed powerful test statistics by Clark and McCracken (2001) and McCracken (2004). In addition, following the argument by Inoue and Kilian (2002) that both in-sample and out-of-sample tests are subject to potential data mining problems, we address issues of possible data mining by

[9] The reader is referred to Rapach and Zhou (forthcoming) for an extensive survey in this regard.

computing appropriate critical values for all the test statistics using data-mining-robust bootstrap procedure. Finally, following Clark (2002) and Rapach *et al.* (2005), we first use general-to-specific model selection approach in order to choose the best forecasting model based on in-sample data, where we start with a model that includes all the variables. Using a recursive approach, all the variables that have insignificant *t*-statistics (less than 1.654) are excluded from the final model, as a result, the general-to-specific model that we use will only contain those variables that have significant *t*-statistics. The selected model, in turn, is used to compute forecasts over the out-of-sample period, again based on the Clark and McCracken (2001) and McCracken (2004) test statistics. As before, to guard against overfitting, we base our inferences on a data-mining-robust bootstrap procedure.

Our results show that most of the financial variables in the vast literature show no in-sample predictive power on South Africa's stock returns. Only the stock returns for our major trading partners have relatively strong predictive power on stock returns at longer horizons. For the out-of-sample period only two extra financial variables show some predictive ability. The Treasury bill rate shows predictive ability from three-months-ahead horizon, while the term-spread has relatively weak predictive ability and it's only at a one-month-ahead horizon. Accounting for data mining, only the in-sample test remains significant at all horizons, while for the out-of-sample (from six-months-ahead horizon) both the MSE-F and the ENC-NEW test statistics lack predictive power. On the other hand, the model that combines general-to-specific model selection with out-of-sample test statistics shows interesting results. In all the horizons, at least one valuation ratio is included in the model specification. This may suggest that valuation ratios contain important information about stock return behaviour in South Africa, despite our earlier results showing no predictive ability in both in-sample and out-of-sample periods. Further, the model also tends to indicate predictability at medium to long-term horizons, even after accounting for datamining. The rest of the Chapter is organised as follows: Section 2 discusses the econometric; Sections 3 outlines the data and the results obtained from the models; and Section 4 summarises our main findings and concludes.

3. Econometric methodology

3.1 In-sample predictability

Following extant literature, including Rapach and Wohar (2006a) and Campbell and Shiller (1998), amongst others, we used a predictive regression model to analyse the behaviour of the stock return over the long horizon. The predictive regression takes the form,

$$y_{t+k} = \alpha + \beta \cdot x_t + \gamma \cdot y_t + \mu_{t+k} \qquad (1)$$

where y_t is the real stock return to holding stock from period $t-1$, y_{t+k} is the log real return to holding stock from period t to $t+k$, x_t represents the fundamentals used in predicting future real stock returns and μ_{t+k} is the error term. When $\beta = 0$ then the variable x_t has no predictive power for future stock return (null hypothesis), while under the alternative hypothesis, x_t does have predictive power for future returns ($\beta \neq 0$). Suppose we have observations for y_t and x_t for $t = 1,...,T$. This leaves us with $T-k$ usable observations with which to estimate the in-sample predictive regression model. The predictive ability of x_t is typically assessed by examining the *t*-statistic corresponding to $\hat{\beta}$, the OLS estimate of β in equation (1), together with the goodness of fit measure, R^2. We also normalise each of the predictors x_t by its standard deviation to make it easier to compare the estimated β in the predictive regression, equation (1). This normalisation, however, has no effect on the in-sample and out-of-sample statistical inferences. Note that, the efficient markets hypothesis argues that the best predictor of the next period's stock price is the current stock price, since it contains all the information in the market. Thus, the rate of return on stocks should correspond to a white noise error term. So tests for in-sample and out-of-sample predictability based on other predictors using the predictive regression framework, allows us to search for violations of the efficient markets hypothesis.

Although equation (1) is widely used, it poses potential problems when estimating future stock returns. The first problem is small-sample bias, as x_t is not an exogenous regressor in equation (1). Rapach and Wohar (2006a,b) show a case when $k = 1$ to illustrate the biasness in β. Another potential problem emerges when $k > 1$ in the predictive regression model, equation (1). The observations for the regression in equation (1) are overlapping when $k > 1$ and thus induce serial correlation in the error term, μ_{t+k}. To account for this, we use Newey and West (1987) standard errors, as these account for serial correlation and heteroscedasticity in the error term, μ_{t+k}. Further, we used the Bartlett Kerner and the truncation parameter of $[1.5 \bullet k]$, where $[\bullet]$ is the nearest integer function, when calculating Newey and West (1987) standard errors to compute *t*-statistic. Despite using robust standard errors to compute *t*-statistic, there still exist the potential for serious size distortions when basing inferences on standard asymptotic distribution theory (Nelson and Kim, 1993; Kirby, 1997 and Rapach and Wohar, 2006a). Recent literature, including Rapach and Wohar (2006a), Kilian (1999), Kothari and Shanken (1997), amongst others, suggests using a bootstrap procedure to base inference concerning β in equation (1) in an attempt to guard against potential size distortions. Rapach and Wohar (2006a) lay out the full discussion of the bootstrap procedure that we use in our analysis. Basically we calculate the *t*-statistics corresponding to β using the bootstrap procedure. We then repeat the process 1000 times to obtain an empirical distribution for the *t*-statistic. The *p*-value obtained is the proportion of the bootstrap statistics that are greater than the statistic computed using the original sample.

3.2 Out-of-sample predictability

There is large literature that suggests that in-sample inference tends to be unreliable. One concern is that in-sample tests of predictability will tend to be unreliable in the presents of unmodelled structural change. Goyal and Welch (2003) employ both in-sample and out-of-sample tests to test for the predictive power of the dividend-price ratio for excess returns. Although they find evidence of in-sample predictability, a model that includes the dividend-price ratio exhibits little out-of-sample predictive ability compared to a model of constant returns according to the Diebold and Mariano (1995) and West (1996) statistic. The negative results typically generated by out-of-sample tests suggest that the in-sample evidence of return predictability is spurious. Other studies however (Rapach et al., 2005 and Rapach and Wohar, 2006a) suggest that it is possible for a variable to carry significant out-of-sample information even when it is not the case for in-sample. Similar to Rapach and Wohar (2006a) and Rapach *et al.* (2005), amongst others, we also perform out-of-sample tests of stock returns based on the following recursive scheme. First, we divide the total sample T into in-sample (1990:01 to 1996:12) and out-of-sample (1997:01 to 2010:04) portions. The in-sample observations span the first *R* observations for y_t and x_t and the out-of-sample portion spans the last *P* observation for y_t and x_t. The first unrestricted predictive regression model, equation (1), for the out-of-sample forecast is generated as in Rapach *et al.* (2005). Firstly we estimate the unrestricted predictive regression model via OLS with the data available through period R. The OLS parameters in the predictive regression, equation (1), therefore become $\hat{\alpha}_{1,R}$, $\hat{\beta}_{1,R}$ and $\hat{\gamma}_{1,R}$. Using the OLS parameter estimates from the predictive regression in equation (1) and y_R and x_R, we construct a forecast for y_{R+k} based on the unrestricted predictive regression model using $\hat{y}_{1,R+k} = \hat{\alpha}_{1,R} + \hat{\beta}_{1,R} \cdot x_R + \hat{\gamma}_{1,R} \cdot y_R$. The forecast errors are therefore denoted by $\hat{\mu}_{1,R+k} = y_{1,R+k} - \hat{y}_{1,R+k}$. The initial forecast for the restricted predictive model is generated in a similar manner except that $\beta = 0$ in equation (1). This means that we estimate the restricted model with $\beta = 0$,via OLS using available data through period R to form the forecast $\hat{y}_{0,R+k} = \hat{\alpha}_{0,R} + \hat{\gamma}_{0,R} \cdot y_R$ where $\hat{\alpha}_{0,R}$ and $\hat{\gamma}_{0,R}$ .are the OLS estimates of α and γ in the predictive regression, equation (1), and β is restricted to zero. The forecast error corresponding to the restricted predictive model are denoted by $\hat{\mu}_{0,R+k} = y_{R+k} - \hat{y}_{0,R+k}$. The period is then updated by using data available through $R+1$ to generate a second set of forecasts. We estimate both the unrestricted and the restricted predictive regression models using data available through period $R+1$ and use these parameter estimates and the observations for y_{R+1} and x_{R+1} in order to form unrestricted and restricted model forecasts for $y_{(R+1)+k}$ and their forecast errors, $\hat{\mu}_{1,(R+1)+k}$ and $\hat{\mu}_{0,(R+1)+k}$. We repeat this process for the entire available sample, resulting in two sets of $T-R-K+1$ recursive forecast errors – with $\{\hat{\mu}_{1,t+k}\}_{t=R}^{t=T-k}$ for the unrestricted predictive regression model and $\{\hat{\mu}_{0,t+k}\}_{t=R}^{T-k}$ for the restricted model. We then compare the out-of-sample forecasts from the restricted and the unrestricted predictive forecast models. If the unrestricted model forecasts are superior to the restricted model forecasts, then the variable x_t improves the out-of-sample forecast of y_{t+k} relative to the first-order autocorrelation (AR) benchmark model which excludes x_t. Following Rapach and Wohar (2006a), we use the Theil's U statistic, the ratio of the unrestricted model forecast root-mean-squared error (RMSE), to the restricted model forecast RMSE. The Theil's U compares the prediction from a given model to a random walk model. Even though we include a lagged stock return term in the benchmark model, we still use the term Theil's U. If the RMSE for the unrestricted model forecast is less than the RMSE for the restricted model forecast, then $U<1$.[10] To formally test for the superiority of the unrestricted model forecast to the restricted model forecast, we followed the MSE-F statistics in McCracken (2004) and in Rapach and Wohar (2006a) together with the ENC-NEW in Clark and McCracken (2001).

The MSE-F is the variant of the Diebold and Mariano (1995) and West (1996) statistic designed to test for equal predictive ability. We use the MSE-F to test the null hypothesis that the unrestricted model forecast MSE is equal to the MSE for the restricted model against the one-sided (upper-tail) alternative that the unrestricted model forecast MSE is less than the MSE forecast for the restricted model. The MSE-F statistic is based on the loss differential:

$$\hat{d}_{t+k} = (\hat{\mu}_{0,t+k})^2 - (\hat{\mu}_{1,t+k})^2$$

Let: $\bar{d} = (T-R-k+1)^{-1}\sum_{t=R}^{T-k}\hat{d}_{t+k} = MSE_0 - MSE_1$

Where: $MSE_i = \sum_{t=R}^{T-k}\hat{d}_{t+k}(\hat{\mu}_{i,t+k})^2$, i =0, 1

The McCracken (2004) MSE-F statistic is then given by:

$$MSE-F = (T-R-k+1)\cdot \bar{d}/MSE_1 \qquad (2)$$

A significant MSE-F indicates that the unrestricted model forecasts are statistically superior to those of the restricted model. When comparing forecasts from nested models and for $k=1$, McCracken (2004) shows that the MSE-F statistic has a non-standard limiting distribution that is pivotal and a function of stochastic integrals of Brownian motion. Evidence, shows that the MSE-F statistic has a non-standard and non-pivotal limiting distribution in the case of nested models and $k>1$. Given this last result Clark and McCracken (2001) recommend using a bootstrap procedure to base inference. The bootstrap procedure is repeated 1000 times to obtain an empirical distribution for the *t*-statistic. The *p*-value obtained is the proportion of the bootstrap statistics that are greater than the statistic computed using the original sample.

The second out-of-sample test statistic that we use, the ENC-NEW, relates to forecast encompassing.[11] The forecast encompassing is based on optimally constructed composite forecasts – that is, if the forecasts from the restricted regression model encompass the unrestricted model forecasts, the financial variable included in the unrestricted model provides no useful additional information for predicting returns relative to the restrictive model which exclude the financial variable; but if the restricted model forecasts do not encompass the unrestricted model forecasts, then the financial variable does contain information useful for predicting returns

[10] A GARCH-in-mean model, specifically, AR(1)-GARCH(1,1)-M model was also estimated. However, barring the one-month- and two-months-ahead horizons, the AR(1) model consistently outperformed the AR(1)-GARCH(1,1)-M model. Thus, we decided to use the AR(1) model as the benchmark. These results are available upon request from the authors.

[11] Clements and Hendry (1998) discuss forecast encompassing in detail.

beyond the information already contained in the model that excludes the financial variable. Tests for forecasting encompassing are equivalent to testing whether the weight attached to the unrestricted model forecasts is zero in an optimal composite forecast composed of the restricted and unrestricted model forecasts. The composite forecast takes the form of a convex combination of the restricted and unrestricted model forecast. The Clack and McCracken (2001) ENC-NEW is given by:

$$ENC - NEW = (T - R - k + 1).\bar{c} / MSE_1 \tag{3}$$

where:

$$\hat{c}_{t+k} = \hat{\mu}_{0,t+k}(\hat{\mu}_{0,t+k} - \hat{\mu}_{1,t+k}) \text{ and } \bar{c} = (T - R - k + 1)^{-1} \sum_{t=R}^{T-k} \hat{c}_{t+k}$$

Under the null hypothesis, the weight attached to the unrestricted model forecasts in the optimal composite forecast is zero, and the restricted model forecasts encompass the unrestricted model forecast. Under the one-sided (upper-trail) alternative hypothesis, the weight attached to the unrestricted model forecast in the optimal composite forecast is greater than zero. This means that the restricted model forecasts do not encompass the unrestricted model forecast. Similar to the MSE-F test, the ENC-NEW test accounts for parameter uncertainty inherent in estimating the unrestricted and the restricted model that are used to form the competing forecast. Further, the ENC-NEW test statistic has good size properties and is as powerful as the MSE-F test statistic. As in the case of the MSE-F, this test has limiting distribution which is non-standard and pivotal for $k = 1$ and it is non-standard and non-pivotal for $k > 1$ when comparing forecasts from nested models. As a result, we follow a bootstrap procedure in Rapach and Wohar (2006) as well as in Clark and McCracken (2001) to calculate the *t*-statistics corresponding to the ENC-NEW statistics. The bootstrap procedure is repeated 1000 times to obtain an empirical distribution for the *t*-statistic. The *p*-value obtained is the proportion of the bootstrap statistics that are greater than the statistic computed using the original sample.[12]

As specified earlier, data mining becomes a concern when using a number of variables to predict real stock returns with respect to the in-sample and out-of-sample test statistics. To control for data mining we use appropriate critical values for both test statistics. We follow the data mining procedure in Rapach and Wohar (2006a) and Rapach *et al.* (2005) for our analysis.[13] Basically, we use the maximal *t*-statistic for the in-sample test statistic and the maximal MSE-F and the ENC-NEW for the out-of-sample test statistics. We derived the asymptotic distributions for the maximal in-sample and out-of-sample test statistics under the null hypothesis of no predictability and the alternative hypothesis in the data mining environment. Due to the limiting distributions which are generally data-dependent (making inferences based on asymptotic distributions difficult), we use a bootstrap procedure in Rapach *et al.* (2005) and Rapach and Wohar (2006a). The bootstrap procedure that we follow is similar to the one discussed above, except that it is modified to explicitly account for data mining.

3.3 General-to-specific model

In addition to analysing each financial variable to determine the predictive power, we further identify the "best" forecasting model for South African stock returns. We do this by using a procedure identified and used in Clark (2002) and Rapach *et al.* (2005) that combines the in-sample general-to-specific model with out-of-sample forecasts. We start with the following general form of the predictive regression model:

$$y_{t+k} = \alpha + \beta_1 \cdot x_{1,t} + ... + \beta_M \cdot x_{M,t} + \gamma \cdot y_t + \mu_{t+k} \tag{4}$$

This model is estimated using data only from the in-sample (1990:01 to 1996:12) portion of the overall sample. We then examine each of the *t*-statistics corresponding to the $x_{j,t}$ variables in equation (4) to determine the significant level. Since the benchmark model include the intercept and lagged stock return terms, we always include these two terms. The model that includes all *M* of the $x_{j,t}$ variables will only be selected if the absolute value of the smallest *t*-statistic is greater than or equal to 1.645. However, if the smallest *t*-statistic is less than 1.645, we exclude that $x_{j,t}$ variable which corresponds to the smallest *t*-statistic in the next model that we

[12] For a full discussion on the bootstrap procedure used to base our out-of-sample tests inference see Rapach and Wohar (2006) and Rapach *et al.* (2005).

[13] For a full discussion on the bootstrap procedure used to calculate critical values that account for data mining for both in-sample and out-of-sample test statistics see Rapach *et al.* (2005), as well as, Rapach and Wohar (2006).

consider. We follow this approach until all of the $x_{j,t}$ variables included in the model have significant *t*-statistics – above or equal to 1.645. If not, we select the model that excludes all of the $x_{j,t}$ variables. If at least one of the $x_{j,t}$ variables is selected in the best forecasting model over the in-sample period, we then compare the out-of-sample forecast generated by the "best" selected model to the out-of-sample forecasts for stock returns generated by the benchmark model. Similar to section 2.2, we form out-of-sample forecasts by recursively updating the data, and then compare out-of-sample forecasts from the competing models using the MSE-F and ENC-NEW statistics.

The main aspect of the general-to-specific approach is to select the forecasting model using data only from the in-sample before carrying out the out-of-sample forecasts (Clark, 2002). Therefore, selecting the forecasting model using data from the full sample would result in considerable size distortions. In order to guard against model overfitting, we generate *p*-values for the out-of-sample statistics by modifying the data-mining bootstrap procedure discussed earlier.[14]. The *p*-value obtained for each out-of-sample statistic is the proportion of the bootstrapped statistics that are greater than the statistic computed using the original sample.

4. Empirical results

4.1 Data analysis

We use monthly data from 1990:01 to 1996:12 for the in-sample period and 1997:07 to 2010:04 as the out-of-sample period for the stock returns and the other financial variables[15]. The variables are discussed below:

Allshare index: Real stock returns for South Africa, computed as the first difference in the log-levels of real All Share Stock Index (ALSI);
Price-dividend ratio (log-level): One-year moving sum of the ratio of nominal dividend to nominal stock prices;
Price-earnings ratio (log-level): One-year moving sum of the ratio the ratio of nominal earnings to nominal stock prices;
Payout ratio (log-level): The ratio of price-earnings to the price dividend ratio;
Treasury bill rate: First difference of the 90 days Treasury bill rate;
Term spread: The difference between long-term (10 years) government bond yield and the 90 days Treasury bill rate;
DAX (log-level): The real stock returns for Germany, computed as the first difference of the real DAX (Deutscher Aktien-Index) - a blue chip stock market index consisting of the 30 major German companies trading on the Frankfurt Stock Exchange;
CAC (log-level): The real stock returns for France, computed as the first difference of the real CAC 40 (the benchmark French stock market index);
S&P 500 (log-level): The real stock returns for the United States, computed as the first difference of the real S&P 500, which is the free-float capitalisation-weighted index of the prices of 500 large-cap common stocks;
FTSE 100 (log-level): The real stock returns for the UK, computed as the first difference of the real FTSE 100 all-share index, which is a capitalisation-weighted index of around 100 companies traded on the London Stock Exchange;
NIKKEI (log-level): The real stock returns for Japan, computed as the first difference of the real Nikkei 225 stock index for the Tokyo Stock Exchange;
Hang-Seng (log-level): The real stock returns for Hong Kong, computed as the first difference of the real Hang Seng Index, which is a free float-adjusted market capitalisation-weighted stock market index.

Note, real stock price for each country was computed by deflating the respective nominal stock price index with the consumer price inflation for that country. Further, barring the Treasury bill rate, for which we use its first difference, all the other variables were found to be stationary based on standard unit roots tests.[16]

[14] See Rapach *et al.*, (2005) for further details.

[15] Using the *supF* statistics developed by Andrews (1993), the variables used in our analysis exhibit only out-of-sample structural break, barring the price-dividend ratio, in which case the predictive regression model showed a break in 1993:04. The structural breaks that appear in the model, however, do not affect the out-of-sample forecasts, as these are generated recursively, whereby the parameter estimate is continuously updated. Further, when we used the CUSUM test for the predictive regression model, no structural break could be detected for any of the variables over the entire sample period. These results are available upon request from the authors.

Table 5: Descriptive statistics, monthly data (1990:01-2010:04)

Variable	Mean	Standard deviation
Allshare index	0.099	2.188
Price/Dividend ratio	1.560	0.106
Price/Earnings ratio	1.149	0.096
Payout ratio	1.587	0.043
Treasury Bills	-0.047	0.506
Term spread	0.804	1.947
DAX	0.147	2.829
CAC 40	0.051	2.496
S&P 500	0.118	1.907
FTSE 100	0.036	1.864
NIKKIE	-0.238	2.850
Hang Seng	0.246	3.342

Note: Germany = DAX (Deutscher Aktien-Index); France = CAC 40; USA = S&P 500; UK = FTSE 100 Index; Japan = Nikkei 225
Hong Kong = Hang Seng Index

4.2 *Analysing the individual predictive ability of the financial variables*

We used monthly data from 1990:01 to 2010:04 for the stock return and the financial variables. All the financial variables used (price-dividend ratio, price-earnings ratio, Treasury bill rate, term spread and the payout ratio) appear widely in the financial economics literature and have been shown to be possible predictors of stock returns in a number of countries (Rapach *et al.,* 2005). The domestic stock prices are further affected by movements in the stock prices of the major trading partners and should exhibit a positive relationship. We include only countries with data available from 1989:10 or earlier, and these include Germany, France, USA, UK, Japan and Hong-Kong. These countries account over 60 per cent of the South Africa's trading partners. These stock returns also represent the major stock exchanges in the United States (S&P 500), Europe (FTSE 100, DAX and CAC 40) and Asia (NIKKEI 225 and Hang Seng Index).[17] In Table 5 we report the descriptive statistic (the mean and the standard deviations) for the stock return and each of the possible predictors.

Table 6 reports the in-sample and the out-of-sample predictive ability of the financial variables for horizons 1, 3, 6, 9, 12, 15, 18, and 24. For the in-sample forecast we used the period 1990:01 to 1996:12 (84 time series data points), while for the out-of-sample forecast the period was between 1997:01 and 2010:04. The table reports the *t*-statistics for the in-sample tests together with the Theil's U, the MSE-F and the ENC-NEW statistics for the out-of-sample tests. The *p*-values (given in brackets) for the in-sample and the out-of-sample results reported in Table 6 are generated using the bootstrap procedure described earlier. The *p*-values in bold indicate significance at the 10 per cent level, while entries in bold, underlined and italics are entries that remain significant when accounting for data mining.

[16] These results are available upon request from the authors. Given that the predictive regression framework uses stationary variables, and barring the treasury bill rate all variables were found to be I(0), issues of cointegration, does not arise.

[17] We also analyzed whether the deviations (shocks) of the stock returns of our major trading partners from their long-run values could serve as better predictors than the stock returns per se. In this regard, we used HP-filtered stock returns as measure of shocks. However, our results indicated that in fact the stock returns, rather than the so-called shocks of stock returns performs better. Further, we also separated out the positive and negative shocks of stock returns, to investigate the role of asymmetry, but the results fail to highlight any such asymmetric effect in the sense that both positive and negative stock return shocks tended to carry negligible predictive content.

Table 6: In-sample and out-of-sample predictability test results, 1997:01-2010:04 out-of-sample period

	Horizon							
	1	3	6	9	12	15	18	24
	Price/Dividend ratio							
Estimated β	-0.166	-0.583	-1.125	-1.568	-2.130	-2.660	-3.052	-4.224
t-statistics	-1.219	-1.385	-1.432	-1.429	-1.458	-1.407	-1.313	-1.413
	[0.224]	[0.226]	[0.257]	[0.258]	[0.300]	[0.318]	[0.361]	[0.396]
R 2	0.101	0.049	0.033	0.040	0.055	0.066	0.073	0.113
Theil's U	0.998	0.997	0.993	0.991	0.990	0.990	0.992	0.964
MSE-F	0.600	1.091	2.219	2.720	2.999	3.083	2.427	10.352
	[0.111]	[0.133]	[0.116]	[0.111]	[0.131]	[0.140]	[0.144]	[0.111]
ENC-NEW	0.547	1.082	1.702	1.908	2.195	2.294	1.815	6.340
	[0.240]	[0.268]	[0.285]	[0.290]	[0.308]	[0.307]	[0.333]	[0.270]
	Price/earnings ratio							
Estimated β	-0.142	-0.466	-0.772	-0.950	-1.191	-1.389	-1.511	-2.513
t-statistics	-1.037	-1.168	-1.041	-0.959	-0.932	-0.852	-0.771	-1.060
	[0.268]	[0.312]	[0.353]	[0.398]	[0.470]	[0.496]	[0.532]	[0.491]
R 2	0.099	0.043	0.018	0.016	0.018	0.018	0.017	0.039
Theil's U	0.999	0.998	1.002	1.006	1.010	1.014	1.017	0.997
MSE-F	0.304	0.515	-0.545	-1.884	-2.826	-3.963	-4.593	0.909
	[0.124]	[0.147]	[0.167]	[0.191]	[0.242]	[0.232]	[0.259]	[0.169]
ENC-NEW	0.353	0.629	-0.018	-0.797	-1.265	-1.841	-2.208	0.713
	[0.255]	[0.308]	[0.377]	[0.417]	[0.484]	[0.484]	[0.500]	[0.377]
	Payout ratio							
Estimated β	-0.009	0.023	0.160	1.117	1.972	2.776	3.485	4.590
t-statistics	-0.064	0.064	0.300	1.359	1.753	1.887	2.062	2.467
	[0.430]	[0.493]	[0.418]	[0.161]	[0.122]	[0.112]	[0.097]	[0.077]
R 2	0.095	0.032	0.010	0.022	0.050	0.079	0.109	0.154
Theil's U	1.008	1.024	1.030	1.046	1.057	1.073	1.064	1.112
MSE-F	-2.365	-7.243	-8.771	-13.107	-15.579	-18.983	-16.673	-25.933
	[0.727]	[0.767]	[0.676]	[0.625]	[0.613]	[0.620]	[0.576]	[0.654]
ENC-NEW	-1.052	-2.482	-2.055	1.789	5.535	9.145	14.585	10.988
	[0.896]	[0.859]	[0.651]	[0.287]	[0.216]	[0.168]	[0.143]	[0.182]
	Treasury bills							
Estimated β	-0.274	-1.386	-1.819	-1.607	-1.871	-1.929	-1.514	-2.538
t-statistics	**-1.972**	**-3.320**	**-4.110**	**-2.899**	**-2.486**	**-2.349**	-1.491	**-2.635**
	[0.018]	**[0.004]**	**[0.001]**	**[0.014]**	**[0.018]**	**[0.037]**	[0.117]	**[0.022]**
R 2	0.109	0.119	0.075	0.040	0.042	0.034	0.018	0.040
Theil's U	1.001	0.984	0.980	0.989	0.986	0.994	0.999	0.990
MSE-F	-0.381	***5.309***	**6.478**	**3.524**	**4.126**	**1.820**	0.353	**2.814**
	[0.233]	***[0.009]***	**[0.020]**	**[0.055]**	**[0.039]**	**[0.091]**	[0.209]	**[0.067]**
ENC-NEW	0.753	***8.054***	**6.015**	**3.125**	**3.237**	1.397	0.636	**3.585**
	[0.150]	***[0.007]***	**[0.024]**	**[0.092]**	**[0.068]**	[0.183]	[0.279]	**[0.066]**

	Term spread							
Estimated β	0.251	0.546	0.925	1.417	1.843	2.394	3.154	2.721
t-statistics	1.847	1.357	1.122	1.192	1.305	1.444	1.579	1.167
	[0.108]	[0.122]	[0.174]	[0.175]	[0.165]	[0.160]	[0.144]	[0.231]
R 2	0.035	0.047	0.024	0.033	0.043	0.057	0.083	0.049
Theil's U	0.997	1.001	1.010	1.017	1.018	1.016	1.007	1.025
MSE-F	***0.854***	-0.191	-3.092	-5.103	-5.158	-4.475	-1.978	-6.588
	[0.067]	[0.148]	[0.259]	[0.320]	[0.334]	[0.339]	[0.254]	[0.387]
ENC-NEW	0.906	0.525	-0.463	-0.477	0.136	1.105	3.062	-0.169
	[0.138]	[0.273]	[0.382]	[0.412]	[0.365]	[0.354]	[0.304]	[0.425]
	DAX							
Estimated β	0.669	0.548	0.735	0.790	0.778	0.728	0.390	0.453
t-statistics	***4.887***	***1.705***	***1.872***	1.295	***1.466***	1.266	0.632	0.590
	[0.000]	***[0.056]***	***[0.039]***	[0.119]	***[0.099]***	[0.135]	[0.304]	[0.338]
R 2	0.177	0.045	0.016	0.011	0.009	0.005	0.001	0.001
Theil's U	0.959	1.003	1.004	1.008	1.002	1.005	1.005	1.005
MSE-F	***13.859***	-0.887	-1.365	-2.344	-0.650	-1.416	-1.301	-1.389
	[0.000]	[0.412]	[0.640]	[0.790]	[0.436]	[0.674]	[0.660]	[0.714]
ENC-NEW	***13.454***	0.572	-0.125	-0.786	-0.131	-0.521	-0.506	-0.558
	[0.000]	[0.188]	[0.444]	[0.830]	[0.479]	[0.733]	[0.748]	[0.810]
	CAC 40							
Estimated β	0.730	0.724	0.788	0.949	0.998	1.279	1.048	0.984
t-statistics	***5.413***	***2.397***	***1.899***	1.500	***1.646***	***1.924***	***1.714***	1.236
	[0.000]	***[0.014]***	***[0.029]***	[0.101]	***[0.082]***	***[0.045]***	***[0.066]***	[0.165]
R 2	0.194	0.055	0.017	0.015	0.013	0.015	0.008	0.006
Theil's U	0.949	0.994	1.000	1.002	0.998	0.998	0.999	1.002
MSE-F	***17.394***	***2.007***	-0.144	-0.739	0.590	0.495	0.184	-0.433
	[0.000]	***[0.038]***	[0.206]	[0.406]	[0.140]	[0.141]	[0.188]	[0.418]
ENC-NEW	***14.636***	**2.406**	0.295	-0.142	0.438	0.516	0.158	-0.130
	[0.000]	**[0.045]**	[0.253]	[0.465]	[0.248]	[0.219]	[0.310]	[0.529]
	S&P 500							
Estimated β	0.876	0.868	1.184	1.378	1.362	1.077	1.067	1.079
t-statistics	***6.870***	***3.500***	***3.129***	***2.623***	***2.518***	***1.600***	***1.963***	1.440
	[0.000]	***[0.000]***	***[0.000]***	***[0.011]***	***[0.021]***	***[0.089]***	***[0.049]***	[0.123]
R 2	0.244	0.067	0.034	0.030	0.023	0.011	0.009	0.007
Theil's U	0.903	0.986	0.992	0.992	0.993	1.001	0.999	1.000
MSE-F	***36.137***	***4.443***	**2.592**	**2.480**	**1.945**	-0.327	0.226	-0.091
	[0.000]	***[0.010]***	**[0.019]**	**[0.028]**	**[0.047]**	[0.331]	[0.190]	[0.290]
ENC-NEW	***32.185***	**5.653**	**2.731**	**2.427**	**2.063**	0.172	0.351	0.154
	[0.000]	**[0.004]**	**[0.034]**	**[0.040]**	**[0.068]**	[0.314]	[0.252]	[0.362]
	FTSE 100							
Estimated β	0.900	1.106	1.562	1.811	1.710	1.868	1.622	1.726
t-statistics	***6.932***	***4.176***	***4.843***	***3.736***	***3.498***	***3.677***	***3.628***	**3.250**

	[0.000]	***[0.000]***	***[0.000]***	***[0.000]***	***[0.000]***	***[0.000]***	***[0.002]***	**[0.011]**
R 2	0.246	0.086	0.054	0.048	0.033	0.031	0.020	0.017
Theil's U	0.907	0.976	0.979	0.988	0.991	0.991	0.993	0.994
MSE-F	***34.331***	***7.710***	**6.605**	**3.743**	**2.707**	**2.676**	**1.897**	**1.684**
	[0.000]	***[0.000]***	**[0.001]**	**[0.014]**	**[0.030]**	**[0.022]**	**[0.049]**	**[0.071]**
ENC-NEW	***26.976***	**7.860**	**5.743**	**3.849**	**2.545**	**2.414**	**1.490**	1.277
	[0.000]	**[0.000]**	**[0.001]**	**[0.011]**	**[0.038]**	**[0.035]**	**[0.084]**	[0.100]
					NIKKEI			
Estimated β	0.521	0.581	1.142	1.453	1.431	1.525	1.541	1.862
t-statistics	***3.705***	***2.058***	***2.862***	***3.395***	***3.165***	***3.186***	***2.793***	**2.597**
	[0.000]	***[0.031]***	***[0.006]***	***[0.001]***	***[0.007]***	***[0.005]***	***[0.013]***	**[0.026]**
R 2	0.144	0.047	0.030	0.031	0.023	0.020	0.018	0.020
Theil's U	0.974	0.997	0.990	0.988	0.989	0.991	0.991	0.991
MSE-F	***8.600***	***0.875***	**3.060**	**3.654**	**3.179**	**2.662**	**2.539**	**2.448**
	[0.000]	***[0.082]***	**[0.021]**	**[0.011]**	**[0.018]**	**[0.030]**	**[0.029]**	**[0.036]**
ENC-NEW	***5.724***	1.073	**2.344**	**2.583**	**2.130**	**1.744**	**1.527**	**1.437**
	[0.001]	[0.117]	**[0.048]**	**[0.024]**	**[0.060]**	**[0.057]**	**[0.084]**	**[0.096]**
					Hang Seng			
Estimated β	0.743	0.894	1.061	1.496	1.449	1.076	0.930	0.811
t-statistics	***5.519***	***2.940***	***1.880***	***2.711***	***3.358***	***1.783***	***1.752***	1.248
	[0.000]	***[0.001]***	***[0.051]***	***[0.017]***	***[0.008]***	***[0.070]***	***[0.070]***	[0.175]
R 2	0.197	0.067	0.028	0.034	0.025	0.011	0.007	0.004
Theil's U	0.937	0.986	0.995	0.986	0.989	0.998	0.997	0.999
MSE-F	***21.965***	***4.593***	**1.630**	**4.392**	**3.210**	0.459	0.955	0.357
	[0.000]	***[0.006]***	**[0.061]**	**[0.009]**	**[0.027]**	[0.184]	[0.105]	[0.194]
ENC-NEW	***16.449***	**4.825**	**1.408**	**3.296**	**2.755**	0.757	0.789	0.371
	[0.000]	**[0.005]**	**[0.109]**	**[0.021]**	**[0.046]**	[0.181]	[0.163]	[0.260]

Note: Estimated β and t-statistic are the OLS estimate of β in equation (1) and its corresponding t-statistic; R2 is the goodness-of-fit in equation (1); U is the ratio of the RMSE for the out-of-sample forecasts for the unrestricted model to the RMSE for the out-of-sample forecasts for the restricted model; MSE-F and ENC-NEW are the out-of-sample statistics; p-value are given in brackets; bold entries indicate significance at the 10 per cent level. Entries in bold, underlined and italics are significant when accounting for data mining.

Table 6 shows some interesting results, firstly only the stock returns for our major trading partners have in-sample predictive power at some horizons, where the *p*-values are less than the 10 per cent level, thus rejecting the null hypothesis of no predictability. The FTSE 100 and the NIKKEI are the only stock returns that have predictive power for all the horizons (up to 24 months), while the S&P 500, the Hang Seng index and the CAC 40 can only predict stock returns for up to 18 months. Amongst the financial variables, only the treasury bill rate has in-sample predictability (one-month-ahead horizon to 15-months-ahead horizon, and the 24th-month-ahead horizon), while the term spread has predictive power at the one-month-ahead horizon. Similar to the in-sample test, only the FTSE 100 and the NIKKEI have long-horizon out-of-sample predictive power.

Overall, the results confirm proposals from McCracken (2004), as well as Clark and McCracken (2001), in the sense that financial variables that have in-sample predictive power also have out-of-sample predictive capabilities. Including a large number of financial variables in an attempt to predict stock price return renders the predictability tests susceptible to data mining, despite some of these variables exhibiting significant in-sample and out-of-sample predictive ability. Inoue and Kilian (2002) further show that both in-sample and out-of-sample forecasts are susceptible to data mining. Rapach and Wohar (2006a) propose a bootstrap procedure in a data mining environment to control for data mining. Basically, we test for stock return predictability using $\beta = 0$ for the null hypothesis for all financial variables in Table 6 and test it against the alternative hypothesis that $\beta > 0$ for at least one of the financial variables using the maximal in-sample *t*-statistic and the maximal out-of-sample MSE-F and ENC-NEW statistics. The critical values for the maximal *t*-statistic and the maximal statistics of the MSE-F and ENC-NEW are reported in Appendix 3.1. We use these critical values to check whether the significance of the best statistic in Table 6 is mainly due to data mining. In Table 6, the entries that remain significant after accounting for data mining are in bold, underlined and italic.

From Table 6, the significant results for the one-month-ahead forecast are not due to data mining since the maximal *t*-statistic, maximal MSE-F statistic and the maximal ENC-NEW remain significant when using the critical values that account for data mining. For three-months-ahead forecast horizon, the maximal *t*-statistic and the maximal MSE-F statistic remain statistically significant when accounting for data mining, while the ENC-NEW becomes insignificant. The results, therefore, become somewhat robust for the three-months-ahead horizon since we account for data mining. For the six-months-ahead horizon to the 18-months-ahead horizon, only the in-sample maximal *t*-statistics remain significant in a data mining environment, while there was no significant out-of-sample maximal statistics (neither the MSE-F statistic nor the ENC-NEW statistics) when accounting for data mining. For the 24-months-ahead horizon, all the maximal test statistics are insignificant in a data mining environment. The results in Table 6, therefore, show that only the in-sample tests have robust predictive ability at longer horizons. The out-of-sample tests, however, show no evidence of predictability for stock returns at any horizon longer than three-months-ahead.

4.3 General to specific model selection and out-of-sample forecasting ability

The results obtained using the general-to-specific model specification are reported in Table 7. We combine the in-sample general-to-specific model selection with tests of out-of-sample forecasting ability. The in-sample period ends in 1996:12 and the out-of-sample period begins in 1997:01 for all the variables. Despite these variables' inability to predict stock price returns both in-sample and out-of-sample, the valuation ratios are almost always included among the explanatory variables in the model selected over the in-sample period. The model also includes some stock returns of our major trading partners – with the S&P 500 and the FTSE 100 being the main stock returns that explain developments in South Africa's stock returns. Since only one external stock returns appear at each horizon, South Africa's stock returns, according to this model specification, is explained by only one country's stock returns in each horizon. Contrary to the findings in Rapach *et al.* (2005) where interest rate variables play a crucial role in determining the behaviour of stock return in a number of countries, our results emphasise the importance of valuation ratios and stock returns of our major trading partners. Interest rate variables become important only at a longer horizon (from 12-months-ahead horizon).

Table 7: General-to-specific model selection results

	Horizon							
	1	3	6	9	12	15	18	24
Variables included	CAC 40	P/D ratio, P/E ratio and S&P 500	P/E ratio, term spread and FTSE 100	Payout ratio and FTSE 100	P/D ratio, term spread and FTSE 100	P/D ratio, P/E ratio, payout ratio, term spread and FTSE 100	P/D ratio, P/E ratio, payout ratio, treasury bills, term spread and DAX	P/D ratio, P/E ratio, treasury bills, term spread and S&P 500
U	0.949	1.015	0.975	1.034	0.994	1.015	0.984	1.026
MSE-F	**17.394**	-4.589	**8.161**	-9.648	**1.806**	**-4.249**	**4.661**	-6.784
	[0.000]	[0.130]	**[0.023]**	[0.129]	**[0.053]**	**[0.099]**	**[0.072]**	[0.147]
ENC-NEW	**14.636**	3.529	10.169	5.029	12.647	20.958	**32.856**	20.783
	[0.004]	[0.226]	[0.156]	[0.294]	[0.186]	[0.136]	**[0.098]**	[0.170]

Note: U is the ratio of the RMSE for the out-of-sample forecasts for the selected model to the RMSE for the out-of-sample forecasts for the restricted model; MSE-F and ENC-New are the out-of-sample statistics; *p*-values are given in brackets; bold entries indicate significance at 10 per cent level.

The model further shows that the explanatory variables increases, with the horizon, since at a one-month ahead there only are three explanatory variables while at 24 months-ahead horizon, the explanatory increases to five. Since the U is greater than 0.9 for all horizons (with *U* greater than 1 at horizons 3, 9, 15 and 24) the forecasting gains are typically small according to relative RMSE criterion. This basically means that the predictable component in South African stock returns is fairly small. The forecast encompassing tests indicate that the selected model contains information that is useful for forecasting beyond that contained into benchmark model for horizons 1 and 18- months ahead.

5. Conclusion

In this Chapter, we examine the predictive ability of 5 financial variables and 6 global stock returns on South Africa's stock returns. We look at the two valuation ratios, term spread, Treasury bill rate, payout ratio, and stock returns of our major trading partners and use these variables for both the in-sample and the out-of-sample forecasts. The in-sample period starts from 1990:01 to 1996:12 and out-of-sample period is from 1997:01 to 2010:04. To account for data mining, we employ a data-mining-robust bootstrap procedure used by Rapach and Wohar (2006a). Using this procedure we obtain critical values that account for data mining. Further, we combine the in-sample general-to-specific model selection with tests of out-of-sample forecasting ability.

Our results show that adding more financial variables does not improve the predictive ability of the valuation ratios. Further, only the stock returns for our major trading partners have in-sample predictive ability at any horizon. For the out-of-sample forecast, the stock returns of our trading partners together with the Treasury bill rate and the term-spread have some predictive ability at certain horizons. Using critical values that account for data mining, we find that only the in-sample test statistics for most horizons remain significant (except the 24-months-ahead horizon), while, for the out-of-sample forecasts, the MSE-F and the ENC-NEW test statistics become insignificant from six-months-ahead horizon. The results we obtain from the general-to-specific model show that the valuation ratios play a crucial role in explaining movements in stock returns, despite their inability to predict stock return when using in-sample and out-of-sample test statistics. The results from the model further show that the S&P 500 and the FTSE 100 are the main stock returns which explain movements in South Africa's stock returns.

Based on the current analysis, especially when accounting for data mining, one could conclude that financial variables and stock returns of trading partners have limited information content over and above the first lag of the South African stock return in forecasting the latter both in- and out-of-sample. Given this, future research should be aimed at analysing whether adding macroeconomic variables could help in improving the predictability of South African stock returns.

Appendix 3.1

Data-mining bootstrap critical values

	10 per cent	5 per cent	1 per cent
1-month-ahead Horizon			
maximal *t*-statistic (lower)	-2.650	-2.928	-3.592
maximal *t*-statistic (upper)	2.542	2.757	3.309
MSE-F	3.499	4.555	7.486
ENC-NEW	4.125	5.306	7.069
3-months-ahead Horizon			
maximal *t*-statistic (lower)	-3.069	-3.499	-4.239
maximal *t*-statistic (upper)	2.877	3.156	3.827
MSE-F	6.572	9.177	15.498
ENC-NEW	8.625	11.179	19.578
6-months-ahead Horizon			
maximal *t*-statistic (lower)	-3.266	-3.674	-4.720
maximal *t*-statistic (upper)	3.082	3.576	4.313
MSE-F	11.941	17.549	34.268
ENC-NEW	16.688	21.051	35.584
9-months-ahead Horizon			
maximal *t*-statistic (lower)	-3.737	-4.146	-5.277
maximal *t*-statistic (upper)	3.269	3.711	4.722
MSE-F	17.198	27.234	46.764
ENC-NEW	22.319	31.999	55.045
12-months-ahead Horizon			
maximal *t*-statistic (lower)	-4.033	-4.517	-6.904
maximal *t*-statistic (upper)	3.521	3.961	5.310
MSE-F	24.820	37.899	68.642
ENC-NEW	30.276	42.608	74.314
15-months-ahead Horizon			
maximal *t*-statistic (lower)	-4.417	-5.029	-6.942
maximal *t*-statistic (upper)	3.453	3.956	5.416
MSE-F	29.242	40.788	84.874
ENC-NEW	36.032	50.759	79.613
18-months-ahead Horizon			
maximal *t*-statistic (lower)	-4.518	-5.198	-9.819
maximal *t*-statistic (upper)	3.584	4.097	5.874
MSE-F	30.216	46.587	94.588
ENC-NEW	35.993	50.115	89.815
24-months-ahead Horizon			
maximal *t*-statistic (lower)	-5.430	-6.141	-8.115
maximal *t*-statistic (upper)	4.103	4.893	6.889
MSE-F	39.463	57.394	108.905
ENC-NEW	46.778	62.285	110.865

Notes: Critical values were computed using the data-mining bootstrap procedure described in section (2.3). The critical values correspond to the maximum values of the statistics reported in Table 6.

CHAPTER 4: MACROECONOMIC VARIABLES AND SOUTH AFRICAN STOCK RETURN PREDICTABILITY[18]

1. Abstract

Chapter 3 focuses only on financial variables to examine the predictability of stock returns in South. In this Chapter we extend from Chapters 2 and 3 by examine both in-sample and out-of-sample predictability of South African stock return using macroeconomic variables. Our analysis is still based on a predictive regression framework, using monthly data covering the in-sample period between 1990:01 and 1996:12, and the out-of sample period commencing from 1997:01 to 2010:06. The in-sample and the out-of-sample tests statistics are similar to those used in Chapter 3. We also guard against data mining by employing a bootstrap procedure to construct critical values that account for data mining. An in-sample general-to-specific model selection with tests of out-of-sample forecasting ability is also used to examine the significance of each macro variable in explaining the stock returns behaviour. Unlike in Chapter 3, we further use a diffusion index approach by extracting a principal component from the macro variables, and test the predictive power thereof. For the in-sample tests, our results show that different interest rate variables, world oil production growth, as well as, money supply have some predictive power at certain short-horizons. For the out-of-sample forecasts, only interest rates and money supply show short-horizon predictability. Further, the inflation rate shows very strong out-of-sample predictive power from 6-months-ahead horizons. A real time analysis based on a subset of variables that underwent revisions, resulted in deterioration of the predictive power of these variables compared to the fully revised data available for 2010:6. The diffusion index yields statistically significant results for only four specific months over the out-of-sample horizon. When accounting for data mining, both the in-sample and the out-of-sample test statistics for both the individual regressions and the diffusion index become insignificant at all horizons. The general-to-specific model confirms the importance of different interest rate variables in explaining the behaviour of stock returns, despite their inability to predict stock returns, when accounting for data mining.

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2. Introduction

The current uncertainties regarding the fragile global economic recovery continue to highlight the importance of accurately forecasting the path of the leading indicators of the economy. There exists wide international evidence (Gupta and Hartley, forthcoming) that asset prices, including stock prices, help in predicting output and inflation by acting as leading indicators (see Stock and Watson, 2003, and Forni *et al.,* 2003 for excellent summaries in this regard). More recently, Gupta and Hartley (forthcoming) highlight the importance of asset prices, especially stock prices, in forecasting inflation and output for South Africa. In addition, the fact that there are major (asymmetric) spillovers from the stock market to the real sector of the economy has also been depicted by a wide number of recent international studies, for example, Lettau and Ludvigson (2001, 2004), Lettau *et al.* (2002), Apergis and Miller, (2004, 2005a, b, 2006), Rapach and Strauss (2006, 2007), Pavlidis *et al.* (2009) to name a few, and for South Africa by Das *et al.* (forthcoming). Hence, obtaining accurate predictions of stock prices cannot be understated, since if predicted accurately, the forecasts not only paves a path for relevant policy decision in advance, but can also provide important information for policy makers to appropriately design policies to avoid the impending crisis.

In a recent study, Gupta and Modise (2012a), using monthly South African data for 1990:01-2009:10, examined the in-sample predictability of real stock prices based on valuation ratios, namely, price-dividend and price-earnings ratios. The authors could not reject the hypothesis that the current value of a valuation ratio is uncorrelated with future stock price changes at both short- and long-run horizons. Literature (Rapach *et al.*, 2005; Rapach and Wohar, 2006) shows that it is possible for a variable to carry significant out-of-sample information even when it is not the case in-sample. Given this and also the need to incorporate the role played by stock returns of major trading partners of South Africa in explaining the future path of real stock returns, Gupta and Modise (2012b) use a wide set of financial variables, as well as international stock returns, for analysing both in- and out-of-sample stock return predictability. ,They show that, with in-sample forecasts only the stock returns of the major trading partners have predictive power at certain short- and long-run horizons. For the out-of-sample, the Treasury bill rate and the term spread together with the stock returns of the major trading partners show predictive power both at short- and long-run horizons. However, when the authors accounted for data mining, the maximal out-of-sample test statistics became insignificant from 6-months onwards, suggesting that the evidence of out-of-sample predictability at longer horizons is due to data mining.

Against this backdrop of limited predictability of stock returns in South Africa based on financial variables, we follow the vast international literature (see Rapach *et al.*, 2005 for a detailed literature review in this regard) in investigating the predictability of stock returns using macro variables in this Chapter. The choice of using macro variables for stock return predictability is quite natural, since these macroeconomic variables tend to influence not only the firm's expected cash flows, but also, the rate of discount for the same cash flows (Rapach *et al.*, 2005). In addition, as indicated by Breeden (1979), Campbell and Cochrane (1999) and Merton (1973), macro variables are key state variables in intertemporal asset-pricing models and represent priced factors in Arbitrage Pricing Theory (Ross, 1976), besides playing a role in affecting future investment opportunities and consumption. There has been vast literature investigating the relationship between stock returns, interest rates, inflation and real activity (Fama (1981, 1990), James et al. (1985), Mandelker and Tandon (1985), Asprem (1989), Schwert (1990), Lee (1992) and Canova and De Nicolo (2000)) while others consider the relationship between stock returns and a wider spectrum of financial and macroeconomic variables (Chen et al. (1986), Fama and French (1989) Ferson and Harvey (1991) and Cheung and Ng (1998)). Further to assessing the predictive power of individual macro variables, we combine the information from these macro variables and extract a principal component (diffusion index) to allow for a simultaneous role of the macro variables. The diffusion index effectively summarizes the information from the twelve macro variables used in our analysis, which is then used to test for predictability of South African stock returns, in an attempt to verify if combining information from all the macro variable help in improving the prediction of stock returns.

To the best of our knowledge, this is the first study to employ a wide array of macroeconomic variables, drawn from the extant literature, to examine both in-sample and out-of-sample stock return predictability in South Africa in the context of a predictive regression framework – the empirical workhorse used in forecasting stock returns. Besides, standard macroeconomic variables like the inflation rate, money stocks, aggregate output, (un)employment rate, interest rates, term spreads on bonds, we also consider world oil production and the refiner acquisition cost of imported crude oil to capture the impact developments on both the demand- and supply-sides of the global oil market, following the suggestions of Peersman and Van Robays (2009). The authors indicate that the underlying source of the crude oil price shift is crucial in determining the exact repercussions on the real and financial sectors of the economy. Although focusing on the US, Kilian and Park (2007) also show that the response of stock returns may differ greatly depending on whether the increase in the price of crude oil is driven by demand or supply shocks in the oil market.

Our time series data covers the in-sample period of 1990:01 to 1996:12 and the out-of-sample period of 1997:01 to 2010:06, with the latter covering the Asian financial crisis, South Africa's decision to move to an inflation targeting regime in 2000, the currency crisis in 2002, and finally the US sub-prime crisis. For in-sample predictability, we use the *t*-statistic corresponding to the slope coefficients in a predictive regression model. For the out-of-sample period, we use the MSE-F and the ENC-NEW test statistics developed by Clark and McCracken (2001) and McCracken (2004). To account for data mining – since both the in-sample and the out-of-sample test statistics are subjected to data mining when one uses a large number of predictors (Inoue and Kilian, 2002) – we compute appropriate critical values for all the test statistics using a data-mining-robust bootstrap procedure. We also use a methodology that combines in-sample general-to-specific model selection with tests of out-of-sample forecasting ability to assess the importance of macro variables in explaining the behaviour of stock returns.

Our in-sample results show that most of the interest rate variables, included in our analysis, have short-run predictive ability, while, the world oil production and money supply have some predictive power at certain horizons. For the out-of-sample period, the change in the inflation rate exhibits very strong predictive power over the medium- to long-run horizons. Other variables that show some predictive ability – although very weak – are the relative Treasury bill rate, term spread, narrow money supply growth, relative money market rate and the world oil production. As we are using monthly data to predict stock prices, it is crucial that the data used is of the same vintage, since data revisions may be detrimental in discerning causal relationships between different time series. In light of this, we decided to put together a real-time version of our data set. Amongst the 12 predictors that we used, only four (industrial production, narrow money, broad money and real effective exchange rate) of them underwent constant revisions. We found that the forecast performance of these four predictors deteriorated both in- and out-of-sample compared to the fully revised data available for 2010:6. For the diffusion index predictive regression model, the in-sample predictive power is only obtained for 1-month-ahead, 3-months-ahead, 6-months-ahead and 24-months-ahead horizons. In case of the out-of-sample forecasting exercise, predictability is only noticeable for the 3-months-ahead and the 6-months-ahead horizons. When investigating the predictive ability of a number of macro variables, concerns about data mining arises naturally. To guard against data mining, we use appropriate critical values, for both our in-sample and out-of-sample tests. It is interesting to note that when accounting for data mining, both the in-sample and the out-of-sample test statistics for the individual macro variables and the diffusion index lack the predictive ability at all horizons; suggesting that data mining is strongly evident in our results. The findings for the model that combines the in-sample general-to-specific model selection with tests of out-of-sample forecasting ability show that interest rates contain important information about the stock return behaviour in South Africa, despite their inability to predict stock returns for the in-sample and out-of-sample periods. The remainder of the Chapter is organized as follows: Section 2 describes the econometric methodology; Section 3 discusses the data and the results obtained from the models, while, Section 4 summarises our core findings and concludes.

3. Econometric methodology

3.1 In-sample predictability

Following Rapach and Wohar (2006) and Campbell and Shiller (1998), amongst others, we used a predictive regression framework to analyse stock return predictability. The predictability framework takes the form,

$$y_{t+1}^{k} = \alpha + \beta \cdot z_t + \gamma \cdot y_t + \mu_{t+1}^{k} \qquad (1)$$

where y_t is the log real return to holding stock from period $t-1$ to period t, $y_{t+1}^{k} = y_{t+1} + ... + y_{t+k}$ is the real stock returns from period t to $t+k$, z_t represents the fundamentals used in predicting future real stock returns and μ_{t+k}^{k} is the error term. When $\beta = 0$ (our null hypothesis) then the variable z_t has no predictive power for future stock returns, while under the alternative hypothesis ($\beta \neq 0$), z_t is assumed to have predictive power for future returns. Inoue and Kilian (2002) recommend using a one-sided alternative hypothesis if theory makes strong predictions about the sign of β in equation (1), as this increases the power of in-sample tests. Similar to Rapach *et al.* (2005), for the macro variables that we consider, theory does not always make strong predictions as to the sign of *β*, so we use a two-sided alternative hypothesis. Following Lettau and Ludvigson (2001) as well as Rapach *et al.* (2005), we include a lagged stock return term in equation (1) as a control variable when testing the predictive ability of z_t. The partial autocorrelation function for real stock returns indicates that a single real stock return lag is sufficient in equation (1). Our results are in line with findings in Rapach *et al.* (2005) and are expected as stock returns are known to display only limited persistence. Suppose we have observations for y_t and z_t for $t = 1,...,T$. This means that there are only $T - K$ usable observations with which to estimate the in-sample predictive regression model. The predictive ability of z_t is typically assessed by examining the *t*-statistic corresponding to $\hat{\beta}$, the OLS estimate of β in equation (1), together with the goodness of fit measure, R^2.

Although the predictive regression, equation (1), described above is widely used in financial economic literature, it poses potential problems when estimating future stock returns. The first problem is small-sample bias, as z_t is not exogenous regression in equation (1). Rapach and Wohar (2006) show a case when $k = 1$ to illustrate the biasness in β. Another potential problem emerges when $k > 1$ in the predictive regression model. The observations for the regression in equation (1) are overlapping when $k > 1$ and thus induces serial correlation in the error term, μ_{t+1}^{k}.[19] To deal with the latter problem, we use Newey and West (1987) standard errors, as these are robust to serial correlation and heteroscedasticity in the error term. Further, we used the Bartlett Kerner and the truncation parameter of $[1.5 \bullet k]$ - where $[\bullet]$ is the nearest integer function – when calculating Newey and West (1987) standard errors to compute *t*-statistic. However, even when robust standard errors are used to compute *t*-statistics, there is the potential for serious size distortions when basing inferences on standard asymptotic distribution theory (Nelson and Kim, 1993, Kirby, 1997 and Rapach and Wohar, 2006). To guard against potential size distortions, we follow a procedure in much of the recent predictability literature and base inferences concerning β in equation (1) on a bootstrap procedure similar to the procedure in Rapach *et al.* (2005), Rapach and Wohar (2006), Kilian (1999), Kothari and Shanken (1997), amongst others. Rapach and Wohar (2006) lay out the full discussion of the bootstrap procedure that we use in our analysis. Basically we calculate the *t*-statistics corresponding to β using their bootstrap procedure. We further repeat the process 1000 times to obtain an empirical distribution for the *t*-statistic. The *p*-value obtained is the proportion of the bootstrap statistics that are greater than the statistic computed using the original sample.

3.2 Out-of-sample predictability

As discussed in the introduction, we also perform out-of-sample tests of stock return predictability. For the out-of-sample tests for stock return predictability, we employ the recursive scheme similar to Rapach and Wohar (2006) and Rapach *et al.* (2005). The total sample of T observations is divided into in-sample (1990:01 to 1996:12) and out-of-sample (1997:01 to 2010:06) portions. The in-sample observations span the first *R* observations for y_t and z_t and the out-of-sample portion spans the last *P* observations for y_t and z_t. The first unrestricted predictive regression model, equation (1), for the out-of-sample forecast is generated as in Rapach *et al.* (2005). Firstly we estimate the unrestricted predictive regression model via OLS with the data available through period R. The OLS estimates in equation (1) therefore become $\hat{\alpha}_{1,R}$, $\hat{\beta}_{1,R}$ and $\hat{\gamma}_{1,R}$. Using the OLS

[19] To illustrate the problem of overlapping observations in equation 1, consider a case where $k = 3$. Equation 1 can then be written as: $y_{t+1}^{3} = \alpha + \beta \cdot z_t + \gamma \cdot y_t + \mu_{t+1}^{3}$.
where $y_{t+1}^{3} = y_{t+1} + y_{t+2} + y_{t+3}$ represents the continuously compounded 3-period real stock returns. The error term μ_{t+1}^{3} is an element of the time $t+3$ information set and is serially correlated with μ_{t+1}^{2} and μ_{t+1} error terms.

parameter estimates from the predictive regression in equation (1) and y_R and z_R, we construct a forecast for y_{R+1}^k based on the unrestricted predictive regression model using $\hat{y}_{1,R+1}^k = \hat{\alpha}_{1,R} + \hat{\beta}_{1,R} \cdot z_R + \hat{\gamma}_{1,R} \cdot y_R$. The forecast error is therefore denoted by $\hat{\mu}_{1,R+1}^k = y_{R+1}^k - \hat{y}_{1,R+1}^k$. We next generate the forecast error for the restricted model in a similar manner, except we set $\beta = 0$, using the data available to period R in order to obtain the OLS estimates in equation (1), $\hat{\alpha}_{0,R}$ and $\hat{\gamma}_{0,R}$. We construct a forecast for y_{R+1}^k based on the restricted predictive regression model using $\hat{y}_{0,R+1}^k = \hat{\alpha}_{0,R} + \hat{\gamma}_{0,R} \cdot y_R$. The forecast error corresponding to the restricted predictive model are denoted by $\hat{\mu}_{0,R+1}^k = y_{R+1}^k - \hat{y}_{0,R+1}^k$

In order to generate a second set of forecasts, we update the above procedure one period using data available through period $R+1$. That is, we estimate both the unrestricted and the restricted predictive regression models using data available through period $R+1$ and we use these parameter estimates and the observations for y_{R+1} and z_{R+1} in order to form unrestricted and restricted model forecasts for y_{R+2}^k and their forecast errors, $\hat{\mu}_{1,R+2}^k$ and $\hat{\mu}_{0,R+2}^k$. We repeat this process for the entire available sample, resulting in two sets of $T-R-K+1$ recursive forecast errors – with $\{\hat{\mu}_{1,t+1}^k\}_{t=R}^{T-k}$ for the unrestricted predictive regression model and $\{\hat{\mu}_{0,t+1}^k\}_{t=R}^{T-k}$ for the restricted model. We then compare the out-of-sample forecasts from the restricted and the unrestricted predictive forecast models. If the unrestricted model forecasts are superior to the restricted model forecasts, then the variable z_t improves the out-of-sample forecast of y_{t+1}^k relative to the first-order autocorrelation (AR) benchmark model which excludes z_t. Rapach and Wohar (2006) show that Theil's U statistic is a simple metric for comparing forecasts, which is the ratio of the unrestricted model forecast root-mean-squared error (RMSE) to the restricted model forecast RMSE. By definition, the Theil's U compares the prediction from a given model to a random walk model. Even though we include a lagged stock return term in the benchmark model, we still use the term Theil's U. If the RMSE for the unrestricted model forecast is less than the RMSE for the restricted model forecast, then $U < 1$. To formally test for the superiority of the unrestricted model forecast to the restricted model forecast, we followed the MSE-F statistics in McCracken (2004) and in Rapach and Wohar (2006) together with the ENC-NEW in Clark and McCracken (2001). The MSE-F is the variant of the Diebold and Mariano (1995) and West (1996) statistic designed to test for equal predictive ability. We use the MSE-F to test the null hypothesis that the unrestricted model forecast MSE is equal to the MSE for the restricted model against the one-sided (upper-tail) alternative that the unrestricted model forecast MSE is less than the MSE forecast for the restricted model. The MSE-F statistic is based on the loss differential,

$$\hat{d}_{t+k}^k = (\hat{\mu}_{0,t+1}^k)^2 - (\hat{\mu}_{1,t+1}^k)^2$$

Let: $\bar{d} = (T-R-k+1)^{-1} \sum_{t=R}^{T-k} \hat{d}_{t+1}^k = \hat{MSE}_0 - \hat{MSE}_1$

where: $\hat{MSE}_i = (T-R-k+1)^{-1} \sum_{t=R}^{T-k} (\mu_{i,t+1}^k)^2$, i =0, 1

The McCracken (2004) MSE-F statistic is therefore given by:

$$MSE-F = (T-R-k+1) \cdot \bar{d} / MSE_1 \qquad (2)$$

A significant MSE-F indicates that the unrestricted model forecasts are statistically superior to those of the restricted model. When comparing forecasts from nested models and for $k=1$, McCracken (2004) shows that the MSE-F statistic has a non-standard limiting distribution that is pivotal and a function of stochastic integrals of Brownian motion. Literature shows that the MSE-F statistic has a non-standard and non-pivotal limiting distribution in the case of nested models and $k > 1$. Given this last result Clark and McCracken (2001) recommend using a bootstrap procedure to base inference. The bootstrap procedure is repeated 1000 times to obtain an empirical distribution for the *t*-statistic. The *p*-value obtained is the proportion of the bootstrap statistics that are greater than the statistic computed using the original sample.

The second out-of-sample test statistic that we use, the ENC-NEW, relates to forecast encompassing.[20] The forecast encompassing is based on optimally constructed composite forecasts – that is, if the forecasts from the restricted regression model encompass the unrestricted model forecasts, the macro variable included in the unrestricted model provides no useful additional information for predicting returns relative to the restrictive model which exclude the macro variable; but if the restricted model forecasts do not encompass the unrestricted model forecasts, then the macro variable does contain information useful for predicting returns beyond the information already contained in the model that excludes the macro variable. Tests for forecasting encompassing are equivalent to testing whether the weight attached to the unrestricted model forecasts is zero in an optimal composite forecast composed of the restricted and unrestricted model forecasts. The composite forecast takes the form of a convex combination of the restricted and unrestricted model forecast. The Clack and McCracken (2001) ENC-NEW is given by:

$$ENC - NEW = (T - R - k + 1) \cdot \bar{c} / MSE_1 \qquad (3)$$

where:

$$\hat{c}^{k}_{t+1} = \hat{\mu}^{k}_{0,t+1}(\hat{\mu}^{k}_{0,t+1} - \hat{\mu}^{k}_{1,t+1}) \text{ and } \bar{c} = (T - R - k + 1)^{-1} \sum_{t=R}^{T-k} \hat{c}^{k}_{t+1}$$

Under the null hypothesis, the weight attached to the unrestricted model forecasts in the optimal composite forecast is zero, and the restricted model forecasts encompass the unrestricted model forecast. Under the one-sided (upper-trail) alternative hypothesis, the weight attached to the unrestricted model forecast in the optimal composite forecast is greater than zero. This means that the restricted model forecasts do not encompass the unrestricted model forecast.

Using the MSE-F and the ENC-NEW test statistics for testing out-of-sample predictability has a number of advantages including accounting for parameter uncertainty inherent in estimating the unrestricted and the restricted model that are used to form the competing forecast. Further, the MSE-F and the ENC-NEW statistics have good size properties and are more powerful than other standard tests. Similar to the MSE-F, the limiting distribution of the ENC-NEW statistic is non-standard and pivotal for $k = 1$ and is non-standard and non-pivotal for $k > 1$ when comparing forecasts from nested models. As a result, we follow a bootstrap procedure in Rapach and Wohar (2006) as well as in Clark and McCracken (2001) to calculate the *t*-statistics corresponding to the ENC-NEW statistics. The bootstrap procedure is repeated 1000 times to obtain an empirical distribution for the *t*-statistic. The *p*-value obtained is the proportion of the bootstrap statistics that are greater than the statistic computed using the original sample.[21]

Rapach and Wohar (2006) point out that data mining becomes a concern when using a number of variables to predict real stock returns with respect to the in-sample and out-of-sample test statistics. To control for data mining we use appropriate critical values for both our in-sample and out-of-sample predictability tests. We follow the data mining procedure in Rapach and Wohar (2006) and Rapach *et al.* (2005) for our analysis.[22] Basically, we use the maximal MSE-F and the ENC-NEW for the out-of-sample test statistics and the maximal *t*-statistic for the in-sample test statistic. We derived the asymptotic distributions for the maximal in-sample and the out-of-sample test statistics under the null hypothesis of no predictability and the alternative hypothesis in the data mining environment. Due to the limiting distributions which are generally data-dependent (making inferences based on asymptotic distributions difficult), we use a bootstrap procedure in Rapach *et al.* (2005) and

[20] Clements and Hendry (1998) discuss forecast encompassing in detail.
[21] For a full discussion on the bootstrap procedure used to base our in-sample and out-of-sample tests inference see Rapach *et al.* (2005).
[22] For a full discussion on the bootstrap procedure used to calculate critical values that account for data mining for both in-sample and out-of-sample test statistics see Rapach *et al.* (2005), as well as, Rapach and Wohar (2006).

Rapach and Wohar (2006). The bootstrap procedure that we follow is similar to the one discussed above, except that it is modified to explicitly account for data mining.

3.3 Diffusion index regression

Given the relationship between business-cycle fluctuations and stock return predictability, it is not surprising that model uncertainty and parameter instability are highly relevant for stock return forecasting, as these factors are also important to macroeconomic forecasting. The substantial model uncertainty and parameter instability surrounding the data-generating process for stock returns render out-of-sample return predictability challenging to uncover. Raphach and Zhou (forthcoming) suggest that using a diffusion index will provide statistically and economically significant out-of-sample gains. Against this background and also proposed by Ludvigson and Ng (2007), Kelly and Pruitt (2012), and Neely et al. (2011), we employ a diffusion index which enabled us to summarise the information contained in the 12 macro variables into one[23] factor (the diffusing index) (F_t) and use it in equation 1 instead of the individual predictors z_t. This helps with the problem of in-sample over-fitting when using a large number of variables (Ludvigson and Ng, 2007, 2009; Rapach and Zhou, forthcoming). Note that, we check for the possibility of data-mining in this case as well, by checking the significance of the out-of-sample statistics obtained from the diffusion index model, using the data-mining critical values generated for the twelve macroeconomic variables considered together.

3.4 General-to-specific model specification

Besides analysing each of the macro variables individually, we use a procedure used by Clark (2004) in an effort to identify the "best" forecasting model for South Africa. We start with the following general form of the predictive regression model:

$$y_{t+1}^{k} = \alpha + \beta_1 \cdot z_{1,t} + \ldots + \beta_M \cdot z_{M,t} + \gamma \cdot y_t + \mu_{t+1}^{k} \qquad (4)$$

This model is estimated using data only from the in-sample portion of the overall sample. We then analyse each of the *t*-statistics corresponding to the $z_{j,t}$ variables in equation (4). If the absolute value of the smallest *t*-statistic is greater than or equal to 1.645, we select the model that includes all *M* of the $z_{j,t}$ variables. However, if the smallest *t*-statistic is less than 1.645, we exclude that $z_{j,t}$ variable which corresponds to the smallest *t*-statistic in the next model that we consider. We follow this approach until all of the $z_{j,t}$ variables included in the model have significant *t*-statistics. If not, we select the model that excludes all of the $z_{j,t}$ variables. Since the benchmark model includes the intercept and lagged stock return terms, we always include these two terms. If at least one of the $z_{j,t}$ variables is selected in the best forecasting model, we then compare the out-of-sample forecast generated by the "best" selected model to the out-of-sample forecasts for stock returns generated by the benchmark model. As before, we form out-of-sample forecasts by recursively updating the data, and then compare out-of-sample forecasts from the competing models using the MSE-F and ENC-NEW statistics.

Note the main aspect of the general-to-specific approach is to select the forecasting model using data only from the in-sample before carrying out the out-of-sample forecasts (Clark, 2004). We generate *p*-values for the out-of-sample statistics to avoid model overfitting by employing a data-mining robust bootstrap, details of which are provided in Rapach et al., (2005).

4. Empirical results

4..1 Data analysis

[23] The choice of one factor was confirmed when we formally tested for the optimal number of factor(s) based on the test proposed by Alessi *et al.,* (2010) for data sets with relatively small number of variables (*N*) compared to the length of the time series (*T*). The details of this test are available upon request from the authors.

We use monthly data from 1990:01 to 1996:12 for the in-sample period and 1997:07 to 2010:06 as the out-of-sample period for the stock returns and the other financial variables. The variables are discussed below:

Relative long-term bond yield: Difference between the long-term government bond yield and a 12-month backward-looking moving average;
Relative 90 days Treasury bill rate: Difference between the 90 days Treasury bill rate and a 12-month backward-looking moving average;
Term spread: Difference between long-term government bond yield and the 90 days Treasury bill rate;
Employment growth rate: First difference in the log-levels of employment;
The inflation rate: First difference in the log-levels of the consumer price index;
Real effective exchange rate: First difference in log-levels of real effective exchange rate index;
Broad money supply growth rate: First difference in the log-levels of real broadly defined money stock;
Narrow money supply growth rate: First difference in the log-levels of real narrowly defined money stock;
Industrial production growth rate: First difference in the log-levels of industrial production;
Relative money market rate: Difference between the prime rate and the 12-month backward-looking moving average;
World oil production growth rate: First difference in the log-levels of the world production;
Crude oil price growth rate: Refiner acquisition cost of imported crude oil growth rate in real terms. To obtain the rand denominated price, we use the rand/dollar exchange rate, and then deflate the nominal value using the consumer price index to obtain the real crude oil price.

Note, the data was obtained from the South African Reserve Bank, Statistics South Africa, Bloomberg and the US Energy Information Administration websites. Further, barring the Treasury bill rate and the inflation rate, for which we use the first difference, all the other variables were found to be stationary based on standard unit roots tests.[24] Following Rapach *et al.* (2005), we measure interest rates as deviations from a backward moving average. This is because, if real interest rates play a crucial role in determining stock returns, then measuring the interest rate as deviations from a backward-looking moving average may go some way towards making the nominal interest rate effectively a real interest rate. That is, as the behaviour of expected inflation is such that most of the fluctuations in the relative nominal interest rate reflect movements in the relative real component. We also use growth rates for the other variables, all in an effort to have macro variables that are stationary. We measure real stock return as the first difference in the log-levels of real stock price. The nominal stock price is measured by the All Share Stock Index (ALSI), and is converted to its real value by deflating it with the consumer price index. Table 8 reports the descriptive statistics (mean and standard deviation) for each of the macro variables.

Table 8: Descriptive statistics, monthly data (1990:01-2010:06)

Variable		Mean	Standard deviation
Allshare index (Real stick returns)	ALI	0.084	2.190
Relative long-term bond yield	LTB	0.175	0.917
Relative 90-days Treasury bill rate	TRB	0.236	1.380
Term-spread	TS	0.826	1.943
Employment growth rate	ER	-0.013	0.446
Inflation rate	CCPI	-0.046	0.574
Real effective exchange rate	REER	0.000	0.014
Broader money supply growth rate	M3	0.005	0.006
Narrow money supply growth rate	M1	0.005	0.018
Industrial production growth rate	IP	0.000	0.012
Relative money market rate	PR	0.227	1.434
World oil production growth rate	WOP	0.000	0.004
Crude oil price growth rate	OIL	10.379	38.903

4.2 Analysing the individual predictive ability of each of the macro variables

[24] The unit root tests are available upon request from the authors.

We use monthly data from 1990:01 to 1996:12 for the in-sample predictive regression and from 1997:01 to 2010:06 for the out-of-sample tests. The macro variables we use (long-term bond, Treasury bill rate, term spread, employment, inflation, real effective exchange rate, broad and narrow money supply, industrial production, and money market rate) appear in vast financial economics literature. We further include two different oil measures to capture the supply and demand shocks to the economy. We use refiner acquisition cost of imported crude oil to capture the supply shock, while the world oil production variable is used as a demand shock variable (Pearsman and Van Robays, 2009). Our in-sample and out-of-sample predictive test statistic results for horizons 1, 3, 6, 9, 12, 15, 18 and 24 are reported in Table 9. Specifically, Table 9 reports the in-sample test statistics and the out-of-sample test statistics, the MSE-F and the ENC-New test statistics. We are more interested in the out-of-sample predictive ability of the macro variables as this period is affected by a number of global shocks as well as a change in the South Africa monetary policy regime. The *p*-values for the in-sample and the out-of-sample test statistics reported in Table 9 are generated using the bootstrap procedure described above and the bracketed bold entries indicate significance at the 10% confidence level.

Table 9: In-sample and out-of-sample predictability test results, 1997:01-2010:06 out-of-sample period

	Horizon							
	1	3	6	9	12	15	18	24
	Relative long-term bond yield							
Estimated β	0.186	0.657	1.442	1.673	1.694	1.346	0.907	1.762
t-statistics	1.349	1.887	1.838	1.402	1.150	0.834	0.615	1.138
	[0.074]	**[0.044]**	**[0.057]**	[0.117]	[0.151]	[0.227]	[0.277]	[0.157]
R^2	0.099	0.051	0.050	0.044	0.036	0.018	0.007	0.021
Theil's U	1.004	1.004	1.003	1.007	1.007	1.013	1.014	1.007
MSE-F	-1.235	-1.198	-0.948	-2.001	-2.123	-3.680	-3.867	-1.977
	[0.545]	[0.261]	[0.220]	[0.303]	[0.328]	[0.503]	[0.542]	[0.399]
ENC-NEW	-0.170	0.523	1.016	-0.198	-0.771	-1.648	-1.774	-0.581
	[0.420]	[0.261]	[0.278]	[0.402]	[0.481]	[0.674]	[0.706]	[0.526]
	Relative 90-days Treasury bill rate							
Estimated β	0.315	0.982	1.263	1.356	1.472	1.562	2.216	4.103
t-statistics	2.274	2.823	1.732	1.194	1.031	0.919	1.174	1.686
	[0.006]	**[0.010]**	**[0.090]**	[0.162]	[0.189]	[0.218]	[0.175]	**[0.097]**
R^2	0.111	0.075	0.039	0.029	0.027	0.023	0.039	0.106
Theil's U	1.004	0.981	0.991	1.015	1.015	1.020	1.029	1.020
MSE-F	-1.157	6.301	2.811	-4.484	-4.311	-5.829	-7.931	-5.280
	[0.508]	**[0.021]**	[0.109]	[0.403]	[0.423]	[0.513]	[0.633]	[0.532]
ENC-NEW	0.727	5.248	2.443	-1.067	-1.337	-1.610	-0.066	6.692
	[0.159]	**[0.058]**	[0.199]	[0.489]	[0.557]	[0.601]	[0.418]	[0.140]
	Term spread							
Estimated β	0.246	0.781	1.086	1.515	1.923	2.359	3.078	3.188
t-statistics	1.818	1.805	1.350	1.322	1.386	1.509	1.670	1.358
	[0.037]	**[0.059]**	[0.151]	[0.147]	[0.167]	[0.122]	[0.139]	[0.200]
R^2	0.105	0.060	0.031	0.038	0.047	0.056	0.082	0.067
Theil's U	0.998	0.993	1.001	1.008	1.009	1.008	1.003	1.015
MSE-F	0.695	2.372	-0.259	-2.283	-2.709	-2.463	-0.897	-4.024
	[0.081]	**[0.074]**	[0.196]	[0.219]	[0.256]	[0.234]	[0.220]	[0.305]
ENC-NEW	0.805	2.326	0.943	0.781	1.154	1.946	3.749	1.334
	[0.162]	[0.152]	[0.322]	[0.307]	[0.330]	[0.295]	[0.266]	[0.359]
	Employment growth rate							
Estimated β	0.003	-0.122	-0.528	-0.408	-0.221	0.493	0.979	1.198
t-statistics	0.024	-0.382	-0.832	-0.439	-0.235	0.542	1.011	1.219

	[0.485]	[0.641]	[0.755]	[0.657]	[0.603]	[0.324]	[0.193]	[0.123]
R^2	0.092	0.032	0.011	0.005	0.003	0.003	0.007	0.008
Theil's U	1.005	1.007	1.007	1.014	1.011	1.001	1.001	1.003
MSE-F	-1.725	-2.348	-2.133	-4.289	-3.107	-0.300	-0.149	-0.957
	[0.723]	[0.494]	[0.364]	[0.530]	[0.462]	[0.246]	[0.257]	[0.446]
ENC-NEW	-0.725	-1.027	-0.623	-1.886	-1.400	0.177	0.304	-0.306
	[0.849]	[0.686]	[0.470]	[0.716]	[0.654]	[0.378]	[0.361]	[0.581]
	Inflation rate							
Estimated β	0.059	-0.474	-1.535	-1.895	-2.140	-2.349	-2.533	-3.231
t-statistics	0.435	-1.448	-2.947	-2.208	-2.026	-2.247	-2.251	-3.000
	[0.323]	[0.885]	[0.997]	[0.974]	[0.954]	[0.969]	[0.978]	[0.996]
R^2	0.093	0.042	0.059	0.059	0.059	0.056	0.054	0.064
Theil's U	1.002	0.998	0.975	0.976	0.981	0.982	0.982	0.978
MSE-F	-0.484	0.616	7.946	7.742	5.715	5.305	5.201	6.287
	[0.266]	[0.143]	**[0.008]**	**[0.014]**	**[0.026]**	**[0.019]**	**[0.019]**	**[0.005]**
ENC-NEW	-0.176	0.751	5.964	4.901	3.551	3.270	3.048	3.874
	[0.444]	[0.227]	**[0.019]**	**[0.031]**	**[0.069]**	**[0.051]**	**[0.060]**	**[0.012]**
	Real effective exchange rate							
Estimated β	0.025	-0.301	0.013	0.324	0.167	0.665	0.225	0.449
t-statistics	0.182	-0.642	0.021	0.703	0.366	1.526	0.519	0.746
	[0.420]	[0.726]	[0.488]	[0.251]	[0.362]	[0.104]	[0.354]	[0.294]
R^2	0.092	0.036	0.005	0.004	0.003	0.005	0.001	0.001
Theil's U	1.013	1.020	1.021	1.006	0.999	1.000	1.001	1.000
MSE-F	-4.105	-6.163	-6.467	-1.967	0.398	-0.127	-0.255	0.051
	[0.953]	[0.978]	[0.982]	[0.813]	[0.144]	[0.289]	[0.339]	[0.266]
ENC-NEW	-1.247	-1.675	-1.562	-0.568	0.330	0.689	-0.032	0.234
	[0.955]	[0.968]	[0.961]	[0.786]	[0.236]	[0.177]	[0.461]	[0.294]
	Broad money supply growth rate							
Estimated β	0.242	0.056	-0.074	0.013	-0.616	-0.730	-0.851	-1.254
t-statistics	1.817	0.227	-0.204	0.028	-1.049	-1.071	-1.300	-1.947
	[0.035]	[0.415]	[0.562]	[0.482]	[0.809]	[0.832]	[0.848]	[0.939]
R^2	0.105	0.032	0.005	0.003	0.007	0.006	0.006	0.011
Theil's U	1.003	1.004	1.003	1.003	1.000	1.000	1.001	0.997
MSE-F	-0.810	-1.303	-0.897	-1.056	-0.098	-0.024	-0.225	0.739
	[0.380]	[0.680]	[0.493]	[0.525]	[0.251]	[0.223]	[0.328]	[0.142]
ENC-NEW	0.823	-0.573	-0.357	-0.448	0.293	0.180	0.253	0.697
	[0.129]	[0.828]	[0.620]	[0.661]	[0.289]	[0.297]	[0.320]	[0.186]
	Narrow money supply growth rate							
Estimated β	0.104	0.370	0.439	0.537	0.005	-0.060	0.196	-0.111
t-statistics	0.774	1.476	1.858	1.994	0.019	-0.187	0.728	-0.416
	[0.233]	**[0.051]**	**[0.028]**	**[0.027]**	[0.509]	[0.550]	[0.242]	[0.654]
R^2	0.095	0.038	0.009	0.007	0.002	0.000	0.000	0.000
Theil's U	1.002	0.999	1.000	0.998	1.000	1.000	1.000	1.000
MSE-F	-0.566	0.342	-0.040	0.504	-0.113	-0.116	-0.061	-0.015
	[0.308]	**[0.096]**	[0.249]	**[0.051]**	[0.391]	[0.367]	[0.367]	[0.333]
ENC-NEW	-0.169	0.371	0.149	0.457	-0.042	-0.016	-0.028	0.002
	[0.463]	[0.142]	[0.225]	**[0.087]**	[0.505]	[0.449]	[0.519]	[0.472]
	Industrial production growth rate							

Estimated β	0.142	0.190	0.157	-0.085	-0.279	0.022	0.098	0.005
t-statistics	1.060	0.937	0.762	-0.380	-0.836	0.065	0.340	0.020
	[0.164]	[0.138]	[0.221]	[0.656]	[0.757]	[0.467]	[0.397]	[0.488]
R^2	0.096	0.033	0.006	0.003	0.003	0.000	0.000	0.000
Theil's U	1.003	1.000	1.000	1.000	1.001	1.001	1.000	0.999
MSE-F	-0.805	-0.069	0.011	-0.091	-0.163	-0.378	0.087	0.163
	[0.394]	[0.225]	[0.198]	[0.258]	[0.352]	[0.554]	[0.223]	[0.173]
ENC-NEW	-0.165	0.045	0.043	-0.041	-0.077	-0.096	0.080	0.091
	[0.460]	[0.333]	[0.342]	[0.430]	[0.559]	[0.592]	[0.339]	[0.284]
	Relative money market rate							
Estimated β	0.365	1.103	1.648	1.735	1.993	2.182	2.800	4.459
t-statistics	2.627	3.176	2.209	1.488	1.304	1.188	1.350	1.685
	[0.004]	**[0.004]**	**[0.043]**	[0.111]	[0.158]	[0.168]	[0.156]	**[0.096]**
R^2	0.117	0.086	0.062	0.046	0.046	0.042	0.059	0.120
Theil's U	0.999	0.977	0.981	1.015	1.023	1.025	1.042	1.022
MSE-F	0.410	7.629	6.140	-4.392	-6.553	-6.982	-11.496	-5.815
	[0.100]	**[0.020]**	**[0.067]**	[0.376]	[0.528]	[0.480]	[0.684]	[0.486]
ENC-NEW	3.133	8.132	6.298	0.299	-0.399	0.028	1.965	8.934
	[0.027]	**[0.034]**	[0.102]	[0.363]	[0.454]	[0.369]	[0.295]	[0.097]
	World oil production growth rate							
Estimated β	0.057	0.445	0.849	0.276	0.010	0.324	0.597	0.716
t-statistics	0.421	1.435	2.647	0.838	0.027	0.958	1.798	1.517
	[0.336]	**[0.090]**	**[0.007]**	[0.199]	[0.458]	[0.203]	**[0.065]**	**[0.087]**
R^2	0.093	0.041	0.022	0.004	0.002	0.001	0.003	0.004
Theil's U	1.003	0.998	0.999	1.003	1.002	1.000	0.999	0.999
MSE-F	-0.919	0.604	0.342	-0.817	-0.451	0.045	0.204	0.256
	[0.448]	[0.104]	[0.104]	[0.597]	[0.451]	[0.207]	[0.206]	[0.161]
ENC-NEW	-0.366	0.602	1.226	-0.278	-0.215	0.042	0.164	0.148
	[0.604]	[0.163]	**[0.055]**	[0.694]	[0.637]	[0.365]	[0.303]	[0.291]
	Crude oil price growth rate							
Estimated β	-0.229	-0.834	-1.449	-1.499	-1.487	-0.913	-0.455	-1.506
t-statistics	-1.720	-1.866	-1.512	-1.060	-0.960	-0.621	-0.331	-1.081
	[0.962]	[0.937]	[0.895]	[0.801]	[0.779]	[0.703]	[0.596]	[0.785]
R^2	0.103	0.066	0.053	0.038	0.029	0.008	0.002	0.014
Theil's U	1.004	1.005	0.995	1.015	1.016	1.012	1.013	1.063
MSE-F	-1.260	-1.571	1.505	-4.494	-4.747	-3.566	-3.728	-15.771
	[0.531]	[0.305]	[0.126]	[0.368]	[0.38]	[0.342]	[0.387]	[0.819]
ENC-NEW	-0.156	0.183	1.585	-0.500	-1.338	-1.074	-1.495	-0.823
	[0.429]	[0.336]	[0.246]	[0.402]	[0.494]	[0.477]	[0.553]	[0.522]

Note: Estimated β and t-statistic are the OLS estimate of β in equation (1) and its corresponding t-statistic; R^2 is the goodness-of-fit in equation (1); U is the ratio of the RMSE for the out-of-sample forecasts for the unrestricted model to the RMSE for the out-of-sample forecasts for the restricted model; MSE-F and ENC-NEW are the out-of-sample statistics given in equation (1); *p*-values are given in brackets; bold entries indicate significance at the 10 per cent level.

The results reported in Table 9 show that interest rate variables (relative Treasury bill rate, term spread and the relative money market rate) appear to be the most consistent and reliable in-sample and out-of-sample predictions of stock returns at shorter horizons (1, 3 and 6-month-ahead horizons). The short-run predictive ability of interest rates for the entire sample period is also evident in Ang and Bekaert (2001). The relative long-term bond on the other hand exhibit only in-sample predictive ability at shorter horizons. From the real variables, only the narrow money supply has both in-sample and out-of-sample predictive power at shorter horizon. Interestingly, the inflation rate shows strong out-of-sample predictive power at medium- to long-run horizons, despite its ability to predict stock returns in-sample. The strong evidence of predictive ability for the inflation rate may suggest that South African inflation rate does capture global shocks that also influence stock returns behaviour, as our out-of-sample period is more influenced by global developments than our in-sample period. Overall, our results obtained for the interest rate variables are in line with findings in Rapach *et al.* (2005) and Ang and Bekaert (2001) which point to the reliability of interest rates as predictors of stock returns. Despite Bossaerts and Hillion (1999), and Goyal and Welch (2003) showing that in-sample and out-of-sample tests have different conclusions for the same economic variables, vast literature suggests that in-sample and out-of-sample tests results are often in agreement. Apart from the inflation rate, our results are in line with findings in Rapach *et al.* (2005) as they show some agreement between in-sample and out-of-sample tests for the same variables. The agreement in our results may be due to the increased power (Rapach *et al.*, 2005) of the recently developed test statistics that we employ in our study for the out-of-sample period.

Including a number of macro variables to predict stock returns renders the predictability tests susceptible to data mining, despite some of these variables exhibiting significant in-sample and out-of-sample predictive ability. Table 10 reports critical values for the maximal *t*-statistics, maximal MSE-F and the maximal ENC-NEW test statistics. The critical values are generated using the data-mining-robust bootstrap procedure described in section 2. We use these critical values in Table 10 to check if the significance of the best statistics reported in Table 9 is due primarily to data mining.

Table 10: Data-mining bootstrap critical values

	1-month Horizon		
	10 per cent	5 per cent	1 per cent
maximal t-statistic (upper)	2.584	2.735	3.420
maximal t-statistic (lower)	-2.695	-2.883	-3.620
MSE-F	3.961	4.923	7.640
ENC-NEW	4.266	5.318	7.849
	3-month Horizon		
	10 per cent	5 per cent	1 per cent
maximal t-statistic (upper)	2.997	3.259	4.010
maximal t-statistic (lower)	-3.040	-3.475	-4.763
MSE-F	8.063	10.915	18.044
ENC-NEW	9.718	12.359	19.171
	6-month Horizon		
	10 per cent	5 per cent	1 per cent
maximal t-statistic (upper)	3.205	3.673	4.391
maximal t-statistic (lower)	-3.364	-3.653	-4.377
MSE-F	15.125	20.489	34.379
ENC-NEW	17.597	21.651	37.536
	9-month Horizon		
	10 per cent	5 per cent	1 per cent
maximal t-statistic (upper)	3.275	3.652	4.670
maximal t-statistic (lower)	-3.503	-3.776	-4.712
MSE-F	17.712	24.748	41.909
ENC-NEW	20.948	27.028	44.621
	12-month Horizon		
	10 per cent	5 per cent	1 per cent
maximal t-statistic (upper)	3.534	3.973	5.025
maximal t-statistic (lower)	-3.688	-4.022	-5.531
MSE-F	22.612	30.202	49.654
ENC-NEW	24.911	34.146	57.204
	15-month Horizon		
	10 per cent	5 per cent	1 per cent
maximal t-statistic (upper)	3.535	4.061	5.500

maximal t-statistic (lower)	-3.535	-4.074	-5.811
MSE-F	23.482	31.483	54.750
ENC-NEW	26.263	35.443	57.508
	18-month Horizon		
	10 per cent	5 per cent	1 per cent
maximal t-statistic (upper)	3.478	3.956	5.649
maximal t-statistic (lower)	-3.915	-4.779	-6.170
MSE-F	24.046	35.367	64.844
ENC-NEW	28.816	39.698	72.022
	24-month Horizon		
	10 per cent	5 per cent	1 per cent
maximal t-statistic (upper)	3.737	4.344	5.742
maximal t-statistic (lower)	-3.850	-4.452	-5.825
MSE-F	23.967	38.190	72.773
ENC-NEW	28.300	39.901	69.727

Notes: Critical values were computed using the data-mining bootstrap procedure described in section (2). The critical values correspond to the maximum values of the statistics reported in Table 9

From Table 9, the maximal in-sample *t*-statistic of 2.627 at a 1-month-ahead horizon corresponds to the prime rate. Using the critical values accounting for data mining in Table 10, the *t*-statistic remains significant at 10% level. The out-of-sample maximal MSE–F of 0,695 corresponding to the term spread at 1-month-ahead horizon becomes insignificant when accounting for data mining. Further, the maximal ENC-NEW of 3,133 corresponding to the prime rate at a 1-month-ahead horizon also becomes insignificant when accounting for data mining. At a 1-month-ahead horizon our results show that the conventional wisdom that the out-of-sample tests are not subjected to data mining biases does not hold – suggesting that Inoue and Kilian (2002) were correct in arguing that out-of-sample tests are just as susceptible to data mining biases as in-sample. The rest of the significant results for the entire sample period and for all horizons become insignificant when accounting for data mining. Rapach *et al.* (2005) also show that the significant evidence of in-sample and out-of-sample tests for some of the macro variables they employ in their analysis was due to data mining.

Our result suggest that the forecasting gains appear to be limited according to a relative RMSE criterion as embodied in the U values reported in Table 9. In situations where $U < 1$, so that the out-of-sample forecasts corresponding to a model that includes a given macro variable have a lower RMSE than the benchmark model, the reduction in RMSE is never greater than 5%. Together with the relatively low in-sample R^2 values in Table 9, the small reductions in RMSE underscore the notion from the extant empirical literature that the predictive component in stock returns is small. Nevertheless, the significant MSE-F statistics in Table 9 indicate that the reduction in MSE is significant in a number of cases.

Table 11: General-to-specific model selection results

	Horizon							
	1	3	6	9	12	15	18	24
Variables included	TS, ER, REER, OIL	LTB, TS	LTB, TRB, TS, ER, M3, WOP	LTB, TRB, TS, ER, CCPI, PR, WOP	LTB, TRB, TS, ER, PR, OIL	LTB, TS, WOP, OIL	LTB, TS, CCPI, REER, OIL	LTB, TRB, TS, ER, CCPI, M1, PR, OIL
Theil's U	1.004	1.015	1.044	1.102	1.109	1.097	1.086	1.028
MSE-F	-1.466	-1.805	-13.961	-29.599	-30.690	-27.139	-23.911	-8.238
	[0.068]	**[0.059]**	[0.203]	[0.384]	[0.378]	[0.355]	[0.318]	[0.143]
ENC-NEW	3.267	5.215	9.672	-2.452	0.653	-2.920	1.737	12.031
	[0.115]	[0.172]	[0.153]	[0.553]	[0.401]	[0.529]	[0.393]	[0.217]

Note: U is the ratio of the RMSE for the out-of-sample forecasts for the selected model to the RMSE for the out-of-sample forecasts for the restricted model; MSE-F and ENC-NEW are the out-of-sample statistics given in equation (1); *p*-values are given in bracketed bold entries indicate significance at 10 per cent level

In Table 11 we report the result obtained for the procedure that combines in-sample general-to-specific model selection with tests of out-of-sample forecasting ability. Again interest rate variables seem to be important in predicting stock returns, as at least one of the interest rate variables is always included among the explanatory variables in the model selected over the in-sample period for each horizon. With an exception of the 3-month-ahead horizons, the variables that capture the external shocks to the economy (the world oil production and the crude oil price) appear in all other horizons, showing that different shocks contain important information in explaining the behaviour of stock returns. The model further shows that, on average, explanatory variables increase with the horizons, since at one-month ahead there are only four explanatory variables, while at 24-months-ahead horizon, the explanatory variables increases to eight. Since the Theil's U is greater than one for all horizons, the forecasting gains are insignificant according to RMSE criterion. This means that the predictable component in South African stock returns (using macro variables) is relatively small.

4.3 Analysing the individual predictive ability of each of the macro variables based on a real-time data set:

As we are using monthly data to predict stock prices, it is crucial that the data used is of the same vintage, since data revisions may be detrimental in discerning causal relationships between different time series (Koenig *et al.,* 2003). In light of this, we decided to put together a real-time version of our data set. Amongst the 12 predictors that we used, only four (industrial production, narrow money, broad money and real effective exchange rate) of them underwent constant revisions. So, a real time database was compiled for these four variables at each point of the out-of-sample horizon, accounting for possible revisions that might have taken place for these variables in the earlier period(s). The last vintage for the out-of-sample forecasting exercise corresponded to 2010:06 (such that the observations on these variables for this specific month was still unavailable), while the forecast statistics, as well as the data-mining critical values, were computed based on the same actual revised data for the period 2010:6, which we used for our regular forecasting exercise discussed in the main text. Note that, for the in-sample analysis, we use vintage data for these four variables available at 1997:01, so that it includes the data for 1996:12 – to correspond with the in-sample period used with the revised data.

Table 12. In-sample and out-of-sample predictability test results, using real time data 1997:01-2010:06 out-of-sample period

	Horizon							
	1	3	6	9	12	15	18	24
	Real effective exchange rate							
Estimated β	0.007	-0.261	0.056	0.416	0.296	0.828	0.477	0.692
t-statistics	0.049	-0.623	0.099	0.866	0.627	0.950	0.982	1.005
	[0.492]	[0.743]	[0.468]	[0.214]	[0.273]	[0.141]	[0.216]	[0.199]
R^2	0.092	0.034	0.005	0.005	0.003	0.007	0.002	0.003
Theil's U	1.013	1.022	1.024	1.008	0.999	0.998	1.000	1.001
MSE-F	-4.096	-6.921	-7.412	-2.552	0.218	0.466	0.040	-0.274
	[0.958]	[0.982]	[0.981]	[0.806]	[0.182]	[0.153]	[0.251]	[0.345]
ENC-NEW	-1.152	-1.542	-2.248	-0.802	0.262	1.287	0.213	0.120
	[0.946]	[0.948]	[0.980]	[0.828]	[0.275]	[0.120]	[0.326]	[0.358]
	Broad money supply growth							
Estimated β	0.239	0.062	-0.053	0.024	-0.615	-0.750	-0.886	-1.219
t-statistics	0.812	0.255	-0.147	0.051	-1.047	-1.093	-1.331	-1.967
	[0.141]	[0.417]	[0.543]	[0.497]	[0.826]	[0.795]	[0.877]	[0.945]
R^2	0.104	0.031	0.005	0.002	0.007	0.006	0.007	0.011
Theil's U	1.003	1.004	1.003	1.003	1.000	1.000	1.001	0.997
MSE-F	-0.866	-1.305	-0.918	-1.055	-0.094	0.027	-0.165	0.717
	[0.415]	[0.674]	[0.479]	[0.525]	[0.219]	[0.239]	[0.281]	[0.151]
ENC-NEW	0.818	-0.574	-0.366	-0.447	0.303	0.210	0.295	0.692
	[0.161]	[0.814]	[0.625]	[0.691]	[0.264]	[0.329]	[0.267]	[0.191]
	Narrow money supply growth							

Estimated β	0.103	0.372	0.449	0.533	0.008	-0.077	0.180	-0.036
t-statistics	0.773	1.493	1.922	1.978	0.027	-0.242	0.699	-0.132
	[0.219]	**[0.053]**	**[0.030]**	**[0.020]**	[0.500]	[0.598]	[0.254]	[0.542]
R^2	0.095	0.038	0.010	0.007	0.002	0.001	0.000	0.000
Theil's U	1.002	0.999	1.000	0.998	1.000	1.000	1.000	1.000
MSE-F	-0.578	0.393	0.008	0.202	-0.116	-0.112	-0.066	-0.029
	[0.289]	[0.177]	[0.202]	[0.105]	[0.385]	[0.404]	[0.370]	[0.348]
ENC-NEW	-0.174	0.384	0.178	0.259	-0.043	-0.014	-0.030	-0.005
	[0.437]	[0.123]	[0.201]	[0.283]	[0.532]	[0.464]	[0.556]	[0.468]
	Industrial production growth							
Estimated β	-0.215	-0.891	-1.360	-1.058	-1.277	-0.790	-0.449	-0.326
t-statistics	-1.019	-1.785	-2.441	-1.808	-2.389	-1.187	-0.264	-0.152
	[0.851]	[0.921]	[0.970]	[0.899]	[0.962]	[0.832]	[0.610]	[0.563]
R^2	0.096	0.047	0.022	0.010	0.011	0.003	0.001	0.000
Theil's U	1.004	1.003	0.997	1.002	1.003	1.007	1.009	1.009
MSE-F	-1.220	-0.983	0.939	-0.624	-0.925	-2.098	-2.733	-2.570
	[0.563]	[0.411]	[0.209]	[0.366]	[0.449]	[0.646]	[0.739]	[0.721]
ENC-NEW	0.790	4.093	3.258	0.084	0.402	-0.119	-0.717	-0.627
	[0.152]	[0.102]	[0.105]	[0.379]	[0.278]	[0.469]	[0.741]	[0.722]

Note: Estimated β and t-statistic are the OLS estimate of β in equation (1) and its corresponding t-statistic; R2 is the goodness-of-fit in equation (1); U is the ratio of the RMSE for the out-of-sample forecasts for the unrestricted model to the RMSE for the out-of-sample forecasts for the restricted model; MSE-F and ENC-NEW are the out-of-sample statistics given in equation (1); p-values are given in brackets; bold entries indicate significance at the 10 per cent level.

Not surprisingly, and as also pointed out by Koenig *et al.,* (2003), the forecast performance of these four predictors deteriorated both in- and out-of-sample as observed from Table 12. Specifically, we observe that, for the variables that have no predictive power (both using the actual data and the real time data), i.e. the real effective exchange rate and the industrial production, the test statistics tend to become more insignificant, also at certain horizons the R^2 values are smaller, and the Theil's U increases and remains above 1. This is especially for the industrial production growth rate. Secondly, all the test statistics for the broad money supply become insignificant, while for the actual data, the in-sample test statistic for the one-month-ahead horizon is statistically significant. Thirdly, the narrow money supply shows some predictive power both in-sample and out-of-sample in the short to medium-term when using actual data. When real time data is used, however, the variable only exhibits in-sample predictive power for the same period. When using critical values that account for data mining, the few positive results become statistically insignificant.

4.4 Analysing the predictive ability of the diffusion index

Ludvigson and Ng (2007, 2009), and Rapach and Zhou (forthcoming) tends to suggest that the individual predictors fail to deliver consistent forecast gains relative to the random walk model, and suggests combining information of individual predictors. Given this, we extract one common factor from the twelve macroeconomic variables, with the estimate of the factor being continuously updated recursively over the out-of-sample horizon. We then use this index to assess its predictive ability for both the in-sample and the out-of-sample periods. Table 13 reports the in-sample test statistics and the out-of-sample test statistics, the MSE-F and the ENC-New test statistics obtained when using the index. Similar to the individual macro variables, we are more interested in the out-of-sample predictive ability of the diffusion index due to a number of global shocks experienced during this time period. The *p*-values for the in-sample and the out-of-sample test statistics reported in Table 13 are generated using the bootstrap procedure described above and the brackets-bold entries indicate significance at the 10% confidence level.

Table 13: In-sample and out-of-sample predictability test results for the diffusion index, 1997:01-2010:06 out-of-sample period

	Horizon							
	1	3	6	9	12	15	18	24
Estimated β	0.332	1.184	1.930	2.184	2.490	2.701	3.221	4.862
t-statistics	2.368	2.996	2.140	1.507	1.342	1.238	1.377	1.701
	[0.011]	**[0.008]**	**[0.037]**	[0.105]	[0.130]	[0.167]	[0.138]	**[0.077]**
R^2	0.113	0.093	0.082	0.070	0.070	0.065	0.081	0.146
Theil's U	1.003	0.979	0.991	1.021	1.026	1.036	1.048	1.044
MSE-F	-0.855	6.948	2.926	-6.156	-7.497	-9.936	-12.890	-11.417
	[0.388]	**[0.019]**	**[0.088]**	[0.479]	[0.556]	[0.668]	[0.755]	[0.712]
ENC-NEW	1.235	8.052	6.331	0.973	0.010	-0.302	1.538	8.213
	[0.110]	**[0.020]**	**[0.084]**	[0.308]	[0.387]	[0.435]	[0.306]	[0.114]

Note: Estimated β and t-statistic are the OLS estimate of β in equation (1) with *F* replacing *z* and its corresponding t-statistic; R^2 is the goodness-of-fit in equation (1); U is the ratio of the RMSE for the out-of-sample forecasts for the unrestricted model to the RMSE for the out-of-sample forecasts for the restricted model; MSE-F and ENC-NEW are the out-of-sample statistics given in equation (1); *p*-values are given in brackets; bold entries indicate significance at the 10 per cent level.

The results reported in Table 13 show combining the macro variables does not necessarily yield better results relative to individual variables themselves. For the 1-month-ahead and the 24-months-ahead horizons, the index can only predict stock returns over the in-sample period, while for the 3-months-ahead and the 6–months–ahead horizons the index is able to predict stock returns over both the in-sample and the out-of-sample periods. The results suggest that there is minimal value added when combining information from the macro variables. Our results are, however, contrary to literature[25] in general, which tends to suggest that combining information tends to improve the forecasting gains.

Because of concerns of data mining, we also use the critical values presented in Table 10 to make inferences on the test statistics obtained when using the diffusion index. From Table 13, the in-sample *t*-statistic at the 1-month-ahead horizon becomes insignificant when using the critical values that account for data mining. This is also the case for the in-sample test statistic for the 24-months-ahead horizon. The significant in-sample and out-of-sample test statistics for the 3-months-ahead and 6-months-ahead horizons also become insignificant when accounting for data mining. This suggests that the few positive results that we obtained under the diffusion index model were due to data mining, thus reiterating the minimal forecasting gains when combining information on macro variables to predict stock returns in South Africa.[26]

5. Conclusion

In this Chapter, we examine the predictability of South African stock returns using 12 macro variables. The macro variables we consider include different interest rates, employment, inflation, money supply, industrial production, global oil production and crude oil price. We consider both in-sample (from 1990:01 to 1996:12) and out-of-sample (from 1997:01 to 2010:06) test statistics. For the in-sample tests we use the *t*-statistic corresponding to the slope coefficient and for our out-of-sample, we use the recently developed Clark and McCracken (2001) and McCracken (2004) tests, as these appear to be more powerful than other tests in the

[25] See Rapach and Zhou (forthcoming), Ludvigson and Ng (2007), Kelly and Pritt (2010), as well as Neely *et al.* (2012).

[26] Based on the suggestions of an anonymous referee, we also analyzed the out-of-sample forecastability of the stock returns using different forecast combination methods. Following the recent work of Gupta and Hartley (forthcoming), we looked at simple combination methods (mean, median and trimmed mean), discount MSFE combinations, cluster combinations, and principal component combinations. We found that, in general, barring the principal component forecast combination method, all the other combination methods produced Theil U values of less than one consistently over all the forecast horizons. However, the encompassing tests revealed that except at the one-month-ahead and three-months-ahead horizons, there are no statistically significant gains from using the combination methods over the restricted model based on only the lagged stock returns. The details of these results are available upon request from the authors.

financial literature. We also summarise the information contained in the macro variables into one diffusion index. We also compare our results against data mining by using a data-mining-robust bootstrap procedure. We further combine the in-sample general-to-specific model selection with tests of out-of-sample forecasting ability to further examine the importance of these macro variables in explaining the behaviour of stock returns.

Our results show that most interest rate variables included in the analysis exhibit in-sample and out-of-sample predictive ability, although at shorter horizons. For the real sector, only the world oil production and the narrowly defined money supply have some predictive power at certain horizons for the entire sample period. The inflation rate exhibits very strong predictive power over the medium- to long-run horizons for the out-of-sample period – suggesting that inflation is also directly influenced by external shocks. A real time analysis based on a subset of variables that underwent revisions, resulted in deterioration of the predictive power of these variables when compared to the fully revised data available for 2010:6. The diffusion index exhibits some predictive power at only four specific months (1, 3, 6 and 24) over the out-of-sample horizon. When accounting for data mining, both the in-sample and the out-of-sample test statistics for the individual macro variables regressions and the diffusion index become insignificant at all horizons, suggesting that our strong evidence is due to data mining. The results confirm the findings by Inoue and Kilian (2002) that both in-sample and out-of-sample test statistics are susceptible to data mining biases. The results for the model that combines the in-sample general-to-specific model selection with tests of out-of-sample forecasting ability show that interest rate variables contain important information about the stock return behaviour in South Africa, despite their inability to predict stock returns for both in-sample and out-of-sample periods when accounting for data mining. Both the demand and the supply shock variables also contain crucial information for stock return behaviour, as at least one of these variables appear in every horizon (with an exception of the 3-month-ahead horizon).

The results in the present Chapter, and those in Chapters 3 tend to suggest that macroeconomic and financial variables do not seem to contain much information in predicting South African stock return in a linear predictive regression framework, especially when one accounts for data mining. The implication of this result is that, in a linear predictive regression framework, that South African stock market is efficient in that the lagged stock return is all one needs to forecast the future stock return. However, LeRoy (1973), using a dynamic portfolio model indicated that under general conditions, particularly relating to risk-aversion, the martingale property will be satisfied only as an approximation and that no rigorous theoretical justification for it can be obtained. In light of this, as part of future research, it would be interesting to analyse stock return predictability in a nonlinear framework, as in Qi (1999), Gallagher and Taylor (2001) and McMillan (2001).

CHAPTER 5: DO DIFFERENT OIL PRICE SHOCKS MATTER FOR SOUTH AFRICAN STOCK RETURNS? A STRUCTURAL VAR APPROACH

1. Abstract

In this Chapter, we investigate the dynamic relationship between different oil price shocks and the South African stock market using a sign restriction structural VAR approach for the period 1973:01 to 2011:07. The results show that for an oil-importing country like South Africa, stock returns only increase with oil prices when global economic activity improves. In response to oil supply shocks and speculative demand shocks, stock returns and the real price of oil move in opposite directions. The analysis of the variance decomposition shows that the oil supply shock contributes more to the variability in real stock prices. The main conclusion is that different oil price shocks affect stock returns differently and policy makers and investors should always consider the source of the shock before implementing policy and making investment decisions.

2. Introduction

As an oil-importing emerging economy, South Africa is exposed to developments in the global market for crude oil. The recent increases in the global oil price affected the South African economy through a number of channels including the transfer of wealth to oil-exporting countries, increased costs of domestic production, inflationary pressures and financial markets – through volatility in the equity market. An extensive macroeconomic literature suggests a strong negative link between oil prices and real variables, especially for oil-importing countries (see e.g,. Hamilton, 1983; Hamilton 2003; Hooker, 1996; Eltony and Al-Awadi, 2001 and Keane and Prasad, 1996, amongst others). Hamilton (1983) points out that 10 of the 11 postwar economic downturns have been immediately preceded by a significant rise in oil prices. The literature on the impact of oil prices on macroeconomic activity has been widening in recent years, with the focus shifting to variables such as inflation, interest rates, labour markets, exchange rates and stock prices. Chisadza *et al.* (2013) assesses the impact of different shocks that influence the global oil market on the South African economy. They focus on the exchange rate, output, inflation and interest rates channels. In this Chapter, we focus on the relationship between the global oil market shocks and the South African stock returns. It is crucial to investigate the determinants of stock price behavior not only because stock prices act as leading indicators for domestic economic activity (Gupta and Hartely, forthcoming, Stock and Watson, 2003 and Forni *et al.*, 2003) but also because they reflect the expected earnings of companies. For South Africa, Aye *et al.* (2012) investigate the existence of spillovers from stock prices onto consumption and the interest rate. Their findings suggests that there are important spillover effects emanating from stock returns to the real economy, emphasing the importance of financial markets.

The existing literature has so far mainly concentrated on assessing the impact of global oil market shocks on the stock returns of developed economies (see Aktham, 2004; Ono, 2011; Kilian and Park, 2009; Park and Ratti, 2007; Guntner, 2011; Apergis and Miller, 2008; Al-Fayoumi, 2009). In general, there has been no consensus about the relationship between oil price shocks and stock returns. Chen *et al.* (1986) and Jones and Kaul (1996) conclude that oil price changes have no effect on asset prices. On the other hand, Kaul and Seyhun (1990), Sadorsky (1999), Papapetrou (2001), Hong *et al.* (2002), O'Neil *et al.* (2008) and Park and Ratti (2008) generally found a negative relationship between oil price shocks and stock returns for advanced economies. In contrast, Gogineni (2007) and Yurtsever and Zahor (2007) showed that oil prices are positively associated with stock prices if oil prices reflect changes in aggregate demand. There have been some studies that focused on this relationship for emerging markets, and in these studies, there has also been no consensus on the impact of oil price shocks on stock returns of these economies. Ono (2011) assessed the impact of the oil price shock on the BRIC[27] economies, and found that this shock has a positive impact on the Indian and Russian real stock returns, while no impact was observed for the Brazilian and Chinese stock returns. Cong *et al.* (2008) concluded that the supply shock has no impact on stock markets for India, Russia and China; and Fang (2010) found that such an impact exists for these countries.

Kilian (2009) has criticized most of the earlier conventional studies because the research tends to treat all oil price shock as exogenous. There have been studies arguing that oil prices respond to factors also affecting stock prices and as a result, the aggregate oil price shock should be decomposed (Barsky and Kilian, 2004; Hamilton, 2003; Kilian, 2009). Following Kilian and Park (2009) and Kilian and Murphy (2013), we distinguish between three types of shocks to the global oil market. First, an oil supply shock which reflects an unexpected changes in the physical volume of oil. Second, an aggregate demand shock which corresponds to changes in the demand for industrial commodities that are driven by fluctuations in the global business cycle. Third, a speculative demand shock which captures changes in oil prices driven by speculative motives and forward-looking behavior. Kilian and Park (2009) found that US stock prices react negatively only to oil prices increases driven by speculative demand, while oil production disruptions have no significant impact on the US stock market. Oil price shocks due to an overall improvement in global real economic activity have a persistent positive effect on stock prices. Apergis and Miller (2008) concluded that although global stock returns do not respond in a large way to oil market shocks, different oil-market structural shocks play a significant role in explaining the adjustments in stock returns. For emerging markets, Fang (2010) investigates how explicit structural shocks that characterize the endogenous character of oil price changes affect stock returns for Brazil, China, India and Russia. Fang (2010) shows that the different oil shocks have no significant impact on India's stock market, while for Russia, both global and oil-specific demand shocks have significantly positive effects on the stock price.

[27] Brazil, Russia, India and China.

We assess the impact of different oil price shocks on South African stock returns by using an improved methodology proposed in Kilian and Park (2009). Unlike in previous studies that only look at the demand and supply shocks to the global oil market; we also add oil inventories to our analysis. Following Kilian and Murphy (2013), oil inventories are used as a tool to identify the forward-looking element of the real price of oil. The idea is to separate the speculative component of the real price of oil from the components driven by demand and supply flows and to characterize the relative importance of each type of oil demand and supply shock and for changes in oil inventories. Further, we consider both dynamic and static restrictions. We select our model using short run oil demand elasticity in use. The choice to investigate the South African case is based on the familiarity with the structure of the economy and the considerable lack of such literature.

According to our knowledge, this is the first study to assess the relationship between different global oil market shocks and the South African stock returns using a sign restriction VAR model specification (which combines static and dynamic sign restrictions) that explicitly allows for shocks to the speculative demand for oil and the flow demand and supply shocks. Our results show that stock returns are positively influenced by developments in the aggregate demand. An unexpected increase in aggregate demand will result in a positive and persistent reaction of stock returns. The flow supply shock and the speculative demand shock affect stock returns negatively. The variance decomposition analysis shows that an oil supply shock tends to drive the behavior of stock returns much more than the other two shocks. The explanation power of different global oil shocks for the stock returns also increases with the horizons.

The Chapter proceeds as follows. Section 2 deals with the data and the methodological issues. Section 3 presents the empirical results, while the conclusion of the research is provided in Section 4.

3. The VAR model

Following the recent literature (Kilian and Park, 2009; Kilian and Murphy, 2012; Kilian and Murphy, 2013; Baumeister and Peersman, forthcoming (a,b); amongst others), we base our analysis on a dynamic simultaneous equation model in a form of a structural VAR (including five variables). The model specified in our analysis improves the model presented in Kilian and Park (2009) in that it includes oil inventories used to capture possible shocks to expectations in the global oil market. Let z_t be a vector of endogenous variables included in the analysis – the per cent change in global crude oil production, a measure of global real activity expressed in per cent changes, the real price of crude oil, the change in crude oil inventories and per cent changes in real stock prices.

3.1 Data description

We estimate a 5 variable structural VAR model using monthly data for the period 1973:01 to 2011:07. For the global oil market variables, we include the price of crude oil based on the US refiners' acquisition cost for imported crude oil obtained from the US Department of Energy starting from 1974:01. Following Barsky and Kilian (2002) the data for the price of crude oil has been extrapolated back to 1973:01 and was deflated using the US consumer price index (CPI) inflation. We also obtained the data for the global oil production measured in millions of barrels of oil – expressed in per cent changes. As described in Kilian and Murphy (2013), we use the data for US crude oil inventories provided by the Energy Information Administration (EIA). These data are scaled by the ratio of Organisation for Economic Co-operation and Development (OECD) petroleum stocks over US petroleum stocks for each time period. The data provided by the EIA includes crude oil (including strategic reserves) as well as unfinished oils, natural gas plant liquids, and refined products. The data, however, does not provide petroleum inventory data for non-OECD countries. The data for the OECD countries is therefore used as a proxy for global petroleum inventories. Since the EIA data for petroleum stocks is not available prior to 1987:12, the per cent change in the OECD inventories is extrapolated backwards at the growth rate of U.S. petroleum inventories. We define the resulting proxy for global crude oil inventories in changes rather than per cent changes. Expressing oil inventories as changes is required to compute the correct oil demand elasticity as this computation is not feasible when using percentage changes. To measure global real economic activity we rely on an index constructed by Kilian (2009). The global activity index is constructed by cumulating average rates of increase in dry cargo ocean shipping freight rates. The series is deflated using the US

CPI inflation[28]. The index is stationary by construction – since the fluctuations in real activity are measured in per cent deviation from the trend. Finally, we measure the variable of interest as the Johannesburg Securities Exchange Allshare Index – which is the main index of the South African share market. The index is made out of the top 40 shares by market capitalization and another 22 shares across all industries and sectors. The variable of interest is deflated using South African CPI inflation. The first difference of the natural logarithm is obtained to allow for stationarity in the series.

3.2 The structural VAR model

In line with Kilian and Murphy (2013), and Kilian (2009), our reduced-form structural VAR model allows for 24 months lags to adequately capture the transmission of oil price shocks. The structural VAR model is specified as:

$$A_0 z_t = \alpha + \sum_{i=1}^{24} A_i z_{t-i} + \varepsilon_t \quad (1)$$

where ε_t denotes the vector of serially and mutually uncorrelated structural innovations, α denotes a constant and $A_i, i = 0, \ldots, 24$, denotes the coefficient matrices. The ε_t are grouped into two blocks where the first block consist of a global crude oil market model, while the second block comprises of the variable of interest – South African stock returns. Following the intuition in Kilian and Murphy (2012), ε_t in the first block consists of a shock to the flow of the production of oil (flow supply shock). A shock to the flow demand for oil and other industrial commodities (flow demand shock) captures unexpected movements in the global business cycle. A shock to the demand for oil inventories arising from forward-looking behavior (speculative demand shock) is designed to capture innovations to the oil demand, reflecting revisions to expectations about future demand and supply rather than current demand and/or supply flows. We also include a residual shock in the first block that captures all structural shocks not otherwise accounted for and has no direct economic interpretation. The second block contains only one structural innovation - an innovation to real stock returns not necessary driven by shocks in the first block.

3.3 Restrictions imposed on the VAR model

Following Baumeister and Peersman (Forthcoming, a) and Kilian and Murphy (2013) we identify our model by imposing a combination of static and dynamic sign restrictions, contemporaneous zero restrictions and boundary restrictions on the impact price elasticities of oil supply and oil demand. Each set of restrictions is discussed below.

Impact sign restrictions

The first sets of restrictions that we impose are the static sign restrictions which are derived from simple theoretical supply-demand model of the global oil market. The identification that we use combines sign restrictions in the oil market block with contemporaneous zero restrictions on the domestic variable. Using both sign restrictions and contemporaneous zero restrictions on selected impact responses allows us to improve identification of the structural shocks and thus to enhance the interpretation of the respective impulse response functions by exploiting additional information (Kilian and Murphy, 2012). The impact sign restrictions on the responses of the five endogenous variables are reported in Table 14 below.

[28] For a detailed discussion of the data sources and construction of the variables refers to Kilian (2009).

Table 14: Sign restrictions on impact responses in the VAR model

	Oil supply shock	Aggregate demand shock	Speculative demand shock
Oil price	-	+	+
World oil production	+	+	+
World activity	+	+	-
Inventories	?	?	+
Stock returns	?	?	?

Our model assumes that the real price of oil is determined by the current demand and supply flows for oil as well as expectations about future demand and supply conditions. Global oil production measures the flow supply of oil such that an unexpected disruption in oil production will increase the real price of oil. This will in turn cause global real activity to weaken. For inventories we do not restrict the impact effect of an oil supply shock a priori because the response can go either way. Unexpected fluctuations in global real activity (flow demand) lead to shifts in the demand for oil associated with the global business cycle. This means that an unanticipated improvement in the global real activity will result in higher oil prices, stimulating global production. As in the case of the oil supply shock, the impact on inventories is left unrestricted.

Since oil is storable, the real price may also be determined by demand for inventories. Any information regarding future oil supply or oil demand will influence the current quantity of inventories and as a result, affect the current price of oil. This means that an upward revision to expected future demand for oil will increase the demand for oil inventories in the current period, resulting in an increase in the real price of oil. This shock is expected to negatively affect global real activity and increase global oil production – these effects are indirect and most likely to be small in nature. Given that the effect of the different types of oil price shocks on real stock returns is the key object of interest, the response is not constrained.

For the stock price shock, we impose contemporaneous zero restrictions and assume that domestic stock price changes do not immediately affect variables in the first block. These zero restrictions are imposed on impact only. The results for this shock are not reported in this study because the focus is on the oil price impact on domestic stock returns rather than how the global market change given fluctuations in the domestic stock market.

Dynamic sign restrictions

In line with Kilian and Murphy (2013) we impose dynamic sign restrictions after an oil supply shock. We assume that the response of the real price of oil to a negative oil supply shock must be positive for at least twelve months after the impact period. As shown in the literature, a positive response of the real price of oil tends to be accompanied by a persistently negative response of oil production. This means that after we impose the first dynamic restrictions, we must also ensure that global real activity responds negatively to oil supply shocks. Basically, the set of dynamic restrictions are such that the responses of oil production and global real activity to an unanticipated oil supply disruption are negative for the first twelve months, while the response of the real price of oil is positive during the same period.

Bounds on the impact price elasticity of oil supply and the short run oil demand elasticity in use

Following Kilian and Murphy (2012, 2013), we impose an upper bound on the impact oil supply elasticity. There is a consensus in the literature that this short-run price elasticity of oil supply is close to zero (Hamiltom, 2009; Kilian, 2009) and ignoring this restriction will imply an impact oil supply elasticity that is far too large to be economically plausible. Using historical episodes of well-defined and exogenous oil price shocks, Kilian and Murphy (2013) show that this elasticity is around 0.025. We impose this upper bound on impact price elasticity of oil supply in selecting a set of admissible models in our analysis.

Given that the impact elasticity of oil supply is based on a shift of the oil demand curve along the supply curve, we can compute the oil supply elasticity after a speculative demand shock and after a flow demand shock.

Following Kilian and Murphy (2013) we select our surviving model using the short-run oil demand elasticity in use. This elasticity is based on the change in the quantity of production and the depletion of oil inventories. The model is specified as:

$$U_t = Q_t - \Delta S_t$$

where U_t represents the amount of oil used in period t, Q is the quantity of oil produced in the same period and ΔS_t is the oil that is added to the stock of inventories. This means that the change in oil used over time equals the change in oil production minus the change in the addition to inventories stocks:

$$\Delta U_t = \Delta Q_t - \Delta^2 S_t$$

The price elasticity of demand in use is therefore given by:

$$\eta_t^{use} = \frac{\%\Delta U_t}{\%\Delta P_t} = \frac{\dfrac{\Delta Q_t - \Delta^2 S_t}{Q_{t-1} - \Delta S_{t-1}}}{\%\Delta P_t}$$

where Δ denotes changes and $\%\Delta$ indicates percentage changes in response to an oil supply shock in period t, while P_t represents the real price of oil. We also define the following terms:
$\tilde{B}_{11}$ = impact response of the per cent change in oil production to an oil supply shock.
$\Delta Q_t = Q_{t-1} \times \tilde{B}_{11}/100 - Q_{t-1} = Q_{t-1} \times \tilde{B}_{11}/100$, the implied change in oil production.
$\Delta^2 S_t = \Delta S_t - \Delta S_{t-1} = \overline{\Delta S} + \tilde{B}_{41} - \overline{\Delta S} = \tilde{B}_{41}$, where the change in oil inventories in response to the oil supply shock equals the impact response $\tilde{B}_{41}$ and before the shock, the change in oil inventories is equal to its mean $\overline{\Delta S}$ and is observable.
$\tilde{B}_{31}$ = impact per cent change in the real price of oil in response to an oil supply shock.
Given the above terms, the demand elasticity in use can be formulated as:

$$\eta_t^{use} = \frac{\dfrac{(Q_{t-1} \times \tilde{B}_{11}/100) - \tilde{B}_{41}}{Q_{t-1} - \overline{\Delta S}}}{\tilde{B}_{31}/100}$$

Since the elasticity in use is time varying as it depends on Q_{t-1}, we report the average oil demand elasticity in use over the sample period.

Implementation of the identification procedure

Given the set of identifying restrictions and consistent estimates of the reduced-form VAR model, the construction of the set of admissible structural models follows the standard approach on VAR models identified based on sign restrictions. Imposing these restrictions to our VAR model we follow Uhlig (2005). Consider equation (1) as a reduced form:

$$A(L)z_t = e_t \qquad (2)$$

Where $A(L)$ is a finite-order autoregressive lag polynomial. The construction of structural response functions require an estimate of the $N \times N$ matrix $\tilde{B}$ in $e_t = \tilde{B}\varepsilon_t$.[29] Because in our case we impose zero restrictions on the stock price shock, we only rotate the 4×4 submatrix instead of the entire N$\times N$ matrix. Let $\sum_{e_t} = P\Lambda P'$ and $B = P\Lambda^{0.5}$ such that B satisfies $\sum_{e_t} = BB'$. This means that $\tilde{B} = BD$ also satisfies $\tilde{B}\tilde{B} = \sum_{e_t}$ for any orthonormal 4×4 submatrix D. We examine a wide range of possibilities for $\tilde{B}$ by repeatedly drawing at random from the set D of orthonormal rotation matrices and discarding candidate solutions for $\tilde{B}$ that do not satisfy a set of priori restrictions on the implied impulse response functions.

[29] For a detailed review of the construction of these structural impulse responses, please refer to Fry and Pagan (2005, 2011).

The basic idea is to firstly draw a 4×4 submatrix K of $NID(0,1)$ random variables and then derive the QR decomposition of K such that $K = Q \cdot K$ and $QQ' = I_4$. We let $D = Q'$ and compute impulse responses using the orthogonalisation $\tilde{B} = BD$ and only retain D if all the implied impulse response functions satisfy the identifying restrictions, otherwise discard D. We repeat this 1 million times and stored impulse response functions corresponding to each D that satisfied the restrictions. The resulting $\tilde{B}$ comprises the set of admissible structural VAR models. In our analysis, only 25 candidate models satisfy all identifying restrictions. To select one model that yields an impact price elasticity of oil demand in use closest to the posterior median of this elasticity, we rely on a procedure described in Kilian and Murphy (2013)[30]. This can be done without loss of generality since the other admissible models yield virtually similar response estimates.

4. Empirical results

4.1 Impulse response functions

The results obtained from using the structural VAR model specified in section 3 are presented in Figure 3. The responses of the real price of crude oil, world oil production, global real economic activity, crude oil inventories and South African stock returns after the three structural shocks are shown in Figure 3 (together with the corresponding pointwise 16 per cent and 84 per cent posterior quantiles). The oil supply shock has been normalized to present a negative shock, whereas the aggregate demand shock and oil-market specific demand shock have been normalized to represent positive shocks such that all three shocks would tend to increase the real price of oil.

Figure 3 shows that one model lies outside the confidence bands (the response of the real priced of oil to an oil supply shock and for only the first four months). This can be explained by the fact that the pointwise 16 per cent and 84 per cent posterior quantiles are constructed slightly different from the final model presented in Figure 3. The first difference is the selection of the models. The surviving model is selected based on the point estimates of the reduced form VAR model. The one standard deviation error bands are, however, selected by drawing from the posterior. All the models used for both cases satisfy all the restrictions (dynamic and static) that we impose and the boundary restrictions on the impact price elasticities of oil demand and oil supply. As discussed earlier, to select the surviving model, we rely on the procedure proposed Kilian and Murphy (2013) and we use the short-run oil demand elasticity in use, while for the 68 per cent posterior confidence bands, we use pointwise error bands. There has been a number of criticism again using pointwise error bands (see Fry and Pagan, 2011; Inoue and Kilian, 2011). Firstly, pointwise 68 per cent posterior error bands provide little protection against mischaracterising the impulse response dynamics. This is the case in Figure 3 as two models lie outside the constructed confidence bands (although not for the entire horizon). Secondly, pointwise intervals tend to understate the estimation uncertainty compared with credible sets that capture the joint uncertainty over all impulse response functions. Nonetheless, this methodology is still used widely and we also construct our error bands using pointwise error bands.

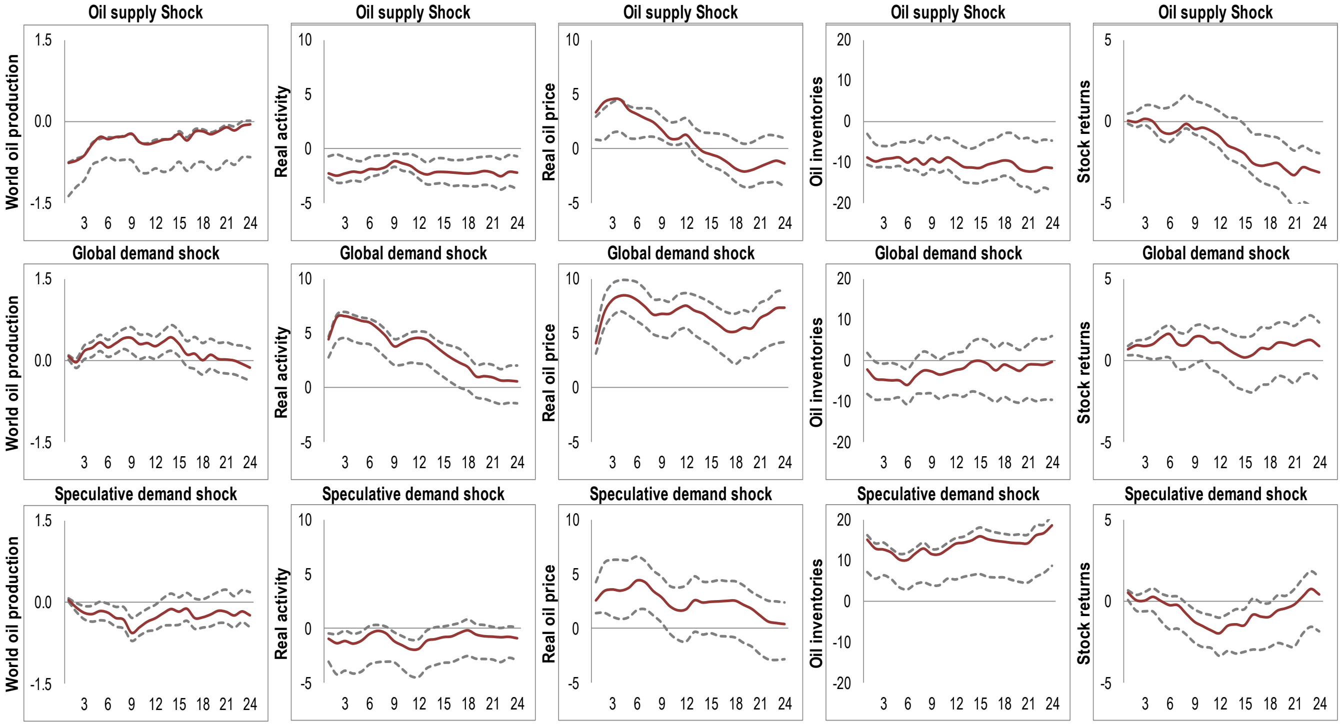
An oil supply shock

The first row of Figure 3 shows the response to a negative oil supply shock which results in a decline in oil production of 0.8 per cent, decreases global real activity by 2.3 per cent and drives real oil prices higher by 3.4 per cent. Oil inventories decline following the shock which implies that consumers start drawing down oil inventories to make up for the loss in production. An increase in the oil price emanating from an unfavourable oil supply shock results in a general decline in the South African stock returns over the medium- to longer-term horizon. This outcome is in line with findings from a number of studies. Kilian and Park (2009) found a similar reaction for the US stock returns. Ghorbel and Younes (2010) assess the impact of an oil supply shock on 27 countries and find that for some countries the impact is negative, especially for oil importing countries. Park and Ratti (2007) conclude that an unfavourable oil supply shock has a negative impact of stock returns for oil importing countries. An increase in the real price of oil due to oil supply disruptions has a negative effect on consumer income and wealth, resulting in a fall in stock returns. The findings in these studies are in contrast with some of the literature on emerging markets and what we find in the short-run. Aktham (2004) similar to our

[30] For a detail description of this procedure, the reader is referred to Kilian and Murphy (2013).

results in the short term finds that oil shock have no significant impact on stock returns in emerging markets suggesting that stock market returns do not rationally signal shocks in the crude oil market.

Figure 3: Impulse Response Functions



Note: the solid line represents the results of the admissible structural model with an impact price elasticity of oil demand in use closest to the posterior median of that elasticity. The gray lines show pointwise 16 per cent and 84 per cent posterior quantiles based on 204 admissible draws from the posterior. Oil production and oil inventories refer to the cumulative per cent change in oil production and oil inventories.

An aggregate demand shock

The second row of Figure 3 shows that an unexpected increase in demand for crude oil driven by an improved global activity will result in higher oil prices, increased global real activity and rising world oil production. The real oil price increases significantly in response to a global demand shock, especially within the first 5 months of the shock and is relatively persistent over the response horizon– although moderating. As envisaged, an unexpected increase in global demand for all industrial commodities will lead to higher and sustained global real activity. This shock presents a significant improvement in the world economic activity and remains positive for the entire horizon, although gradually approaching zero. The increased demand for commodities, followed by higher oil prices is likely to influence producers to increase their oil production to take advantage of the higher returns emanating from higher oil prices. As presented in Figure 3, an aggregate demand shock will result in an increase in global oil production. The positive impact, however, only lasts for up to 20 months and becomes negative thereafter. The unexpected increase in aggregate demand will result in lower inventories for the first 15 months before gradually recovering. Not surprisingly, oil inventories will be utilized to sustain the rapid demand in the global market, thereafter, inventories buildups will take place. The global demand shock has a positive and lasting effect on stock returns over the horizon although the impact is only significant in the shorter horizon. The South African stock returns reaction is in line with the results obtained by Kilian and Park (2009) for the US economy. South Africa is a commodity exporting economy and an improvement in global demand means rising exports demand and commodity prices. This will result in higher income into the country – increasing household incomes and company profits – thereby increase the wealth which will translate into higher stock returns. Fang (2010) finds a similar reaction for the Russian stock returns. Although Russia is an oil exporting country, while South Africa exports platinum, gold and other mining products, the general increase in global commodity prices following a positive global demand shock results in the same effects for these two countries.

A speculative demand shock

An unfavourable speculative demand shock will result in a general decline in world oil production, a fall of 0.9 per cent in real global activity and an overall decline in the stock returns although positive for the first five months. Only the price of oil (2.6 per cent) and inventories (15.1 per cent) will increase following such a shock. The rationale for the reaction of these variables to a speculative shock is as follows. If there is a belief that oil prices will change in the future, then the current flow demand and supply will be affected by the speculation. Assuming that investors believe that the demand for oil will increase in period $t + 1$ then the current price of oil will increase, while both the global real activity and the world oil production will decrease. As expected, current oil inventories will increase on speculation about future developments in the market for crude oil. Similar findings are reported in Kilian and Murphy (2013) where they show that inventories react positively to a speculative demand shock and the impact is persistently positive over 15 months. Although the impact is positive for the first five months, the overall impact of a speculative demand shock is negative on stock returns in South Africa. This is because a speculative demand shock will results in higher oil prices, with no increase in the prices of other global commodities. This effect will be inflationary in South Africa, thereby reducing household wealth. Not surprising, the results are in line with recent literature for oil importing countries. Guntner (2011) finds that stock returns of oil importing countries are negatively affected by a speculative demand shock. Kilian and Park (2009) present the same results for the US as a net oil importing economy.

4.2 Variance decomposition

Table 15 presents the variance decomposition of real oil prices and the real stock prices due to oil supply shock, aggregate demand shock and speculative demand shock. The figures quantify the importance of the global oil market shocks that we have identified on the real oil price and real stock prices. The data is presented for 1 month, 12 months and 24 months horizons. On impact, 46 per cent of the variability in the real price of oil can be explained by an aggregate demand shock, 31 per cent of the variability is explained by an oil supply shock, while only 18.3 per cent of variability on impact is explained by a speculative demand shock. At the medium horizon (12 months), an aggregate demand shock explains above 50 per cent of the variability in the real oil price, while the contribution of both the oil supply shock and the speculative demand shock moderates (27.7 per cent and 17.7 per cent, respectively). At a long horizon (24 months) the ratio of contributions remains unchanged, although the percentage contribution of the oil supply shock rises marginally and for the other two shocks, the contributions moderate. These results suggest that, on average, fluctuations in the real oil price mainly reflect developments in the global activity, but there are also elements of production smoothing and speculation. Our results are also in line with findings in Baumeister and Peersman (Forthcoming, a) as well as Kilian (2008 and 2009), showing that demand increases rather than supply reductions drive global oil prices.

Table 15: Percentage contribution of global oil market shocks to the variability of real price of oil and the South African real stock returns

	Horizon		
	1 Month	12 Months	24 Months
	Impact on the real price of oil		
Oil supply shock	31.0	27.7	28.8
Aggregate demand shock	46.0	50.2	48.6
Speculative demand shock	18.3	17.7	17.0
Other shocks[1]	4.7	4.4	5.6
	Impact on the real stock returns		
Oil supply shock	0.0	24.9	36.9
Aggregate demand shock	2.1	17.2	21.9
Speculative demand shock	1.2	12.0	12.0
Other shocks[1]	96.7	45.9	29.2

[1] Shocks that are not captured by global oil market developments

Table 15 also shows that on impact, the effect of the identified global oil market shocks is negligible on South African real stock returns, with only 3.3 per cent of the variability in real stock returns associated with shocks that drive the global oil market. The explanation power increases significantly in the medium horizon (12 months), with global oil market shocks accounting for 54.1 per cent of the variability in the domestic real stock returns – with the oil supply shock exhibiting the largest contribution of close to 25 per cent. For the long horizon, the contribution increases further to 70.8 per cent, with the oil supply shock maintaining the largest contribution. In contrast to the findings in Kilian and Park (2009), the variability in South African real stock returns in the medium to long horizons is driven by oil supply shocks, followed by aggregated demand shocks, while speculation only accounts for 12 per cent.

5. Conclusion

We added to the limited literature that assesses the relationship between stock returns and different oil market shocks by improving on Kilian and Park (2009) methodology of disaggregating the effects of oil market shocks on South African (as an oil-importing emerging economy) stock returns by distinguishing between flow demand, flow supply and speculative demand shocks. For the speculative demand shock, we rely on the help of oil inventories. To do this, we rely on a structural VAR model specification with both static and dynamic sign restrictions using monthly data from 1973:01 to 2011:07. We further construct a variance decomposition to assess the impact of oil shocks on stock returns over time.

The results show that South Africa's stock returns react differently to oil shocks, depending on the underlying causes of the increase in the oil price. An unexpected positive aggregate demand shock has a positive impact on stock returns. Our results are in line with some of the findings in the literature that suggests a positive relationship between oil price shocks due to aggregate demand and stock returns and a negative relationship for the other shocks. The negative relationship emanated from the fact that South Africa is an oil-importing emerging market. The variance decomposition analysis shows that South African stock returns are mostly driven by an oil supply shock since this shock contributes more than the other shocks to the variability of stock returns. Our results propose that policy makers and investors should consider the source of the oil price shock before implementing policies or make investment decisions. Future research may be aimed at assessing how this relationship has changed over time, using a TVP-VAR model combined with sign restrictions along the lines proposed in Baumeister and Peersman (Forthcoming, a,b).

CHAPTER 6: DO STOCK PRICES IMPACT CONSUMPTION AND INTEREST RATE IN SOUTH AFRICA? EVIDENCE FROM A TIME-VARYING VECTOR AUTOREGRESSIVE MODEL

1. Abstract

This Chapter investigates the existence of spillovers from stock prices onto consumption and the interest rate for South Africa using a time-varying vector autoregressive (TVP-VAR) model with stochastic volatility. In this regard, we estimate a three-variable TVP-VAR model comprising of real consumption growth rate, the nominal three-months Treasury bill rate and the growth rate of real stock prices. We find that the impact of a real stock price shocks on consumption is in general positive, with large and significant effects observed at the one-quarter ahead horizon. However, there is also evidence of significant negative spillovers from the stock market to consumption during the financial crisis, at both short and long-horizons. Monetary policy response to stock price shocks has been persistent, and strong especially post-the financial liberalization in 1985, but became weaker during the financial crisis. Overall, we provide evidence of significant time-varying spillovers on consumption and interest rate from the stock market.

2. Introduction

The permanent income hypothesis postulated by Friedman (1957), asserts that real stock (asset) price inflation increases the expected lifetime wealth of households and hence, their desired consumption. This is known as the wealth effect. In light of this, there exists wide international evidence suggesting that there are major spillovers from the stock market to consumption, in both advanced and emerging economies (see for example, Lettau and Ludvigson, 2001, 2004; Ludvigson *et al.*, 2002; Apergis and Miller, 2004, 2005a, b, 2006; Rapach and Strauss, 2006, 2007; Sousa, 2008a, 2008b, 2010a, 2010b, 2010c, 2010d; Bostic *et al.*, 2009; Fratzscher and Straub; 2009, 2010; Fratzscher *et al.*, 2010; Singh and Pattanaik, 2010; Zhou, 2010; Afonso and Sousa, 2011a; Carroll *et al.*, 2011; Koivu, 2012; Peltonen et al., 2012; Singh, 2012, and references cited in these studies). As far as South Africa is concerned, to the best of our knowledge, there exists only one study by Das *et al.*, (2011), who, based on a single-equation error-correction model, indicate that real stock prices affect consumption significantly both in the short- and long-runs.[31] The literature relating to stock prices in South Africa has mainly dealt with the effect of monetary policy on stock prices, largely based on (structural) vector autoregressive (VAR) and at times panel data approaches with South Africa as a country in the panel; with all the studies indicating a negative impact on stock prices (returns) following a contractionary monetary policy.[32] The lack of studies analysing the impact of stock prices on consumption is quite baffling in South Africa, especially when one accounts for the fact that financial wealth accounts for 49.95 per cent of household's total assets and 61.59 per cent of household's net worth (South African Reserve Bank, Quarterly Bulletin, 2012).

Besides the fact that stock market spillover could be inflationary if it significantly affects aggregate demand through consumption, the recent financial crisis has once again rekindled the debate on whether central banks should conduct monetary policy in a more active manner to prevent the development of bubbles that can be costly in terms of future output and financial stability (André *et al.,* 2011; Peretti, forthcoming). Further, given the fact that the South African Reserve Bank (SARB) has moved to an official inflation-targeting framework since the first quarter of 2000,[33] there is clearly added value in analysing this question for the country specifically. Recently, Naraidoo and Ndahiriwe (forthcoming) and Naraidoo and Raputsoane (2010) have developed financial conditions indices (FCI), which include stock prices amongst other financial variables, and have analysed the importance of the FCI using linear and non-linear Taylor (1993)-type rules in South Africa. These studies tend to show that the SARB has systematically reacted to the FCI; more so during the recent financial crisis. Darracq Pariès and Notarpietro (2008) and Finocchiaro and von Heideken (2009) suggests that trying to address the endogeneity problem in stand-alone monetary policy reaction functions using General Method of Moments (GMM) methods produces biased and dispersed estimates. Thus, there are concerns using single-equation Taylor (1993)-type models. Furthermore, the studies using a FCI, which is a composite of four or five asset-related variables, does not specifically indicate the role of stock prices in the monetary policy reaction functions. To the best of our knowledge, there are only two papers that specifically looks at the behavior of the interest rate in response to stock price movements in South Africa is by Bonga-Bonga (2011) and Muroyiwa (2011).[34] Bonga-Bonga (2011) assessed the dynamic responses of stock prices on inflation, economic activity and monetary policy using a structural vector error-correction model, and concluded that there is a positive relationship between equity prices and interest rates in South Africa. Similar conclusions were also reached by Muroyiwa (2011) based on a SVAR where shocks were identified using a combination of both short-run and long-run restrictions.

Against this background, the objective of this Chapter is to analyse whether real stock price movements have significant spillover effects on consumption decisions and monetary policy in South Africa. In addition, unlike the sparse literature in South Africa on these two issues, which essentially relies on constant parameter models, we use a time-varying parameter vector autoregressive (TVP-VAR) model with stochastic volatility. TVP-VARs

[31] Using a structural vector error-correction model, Bonga-Bonga (2011) showed that equity prices have a significant impact on economic activity in South Africa. Caporale and Sousa (2011), however, could not find significant wealth effects on consumption for South Africa, with the wealth variable being a composite of real house price, real stock price and real per capita M2.

[32] See for example, Small and de Jager (2001), Coetzee (2002), Prinsloo (2002), Durham (2003) , Hewson and Bonga-Bonga (2005), Alam and Uddin (2009) , Chinzara (2010), Mallick and Sousa (2011), Mangani (2011) and Muroyiwa (2011).

[33] In the February of 2000, the Minister of Finance announced that inflation targeting would be the sole objective of the SARB. Currently, the Reserve Bank's main monetary policy objective is to maintain CPI inflation between the target-band of three to six percent, using discretionary changes in the repo rate as its main policy instrument.

[34] For a detailed international literature review in this regard, the reader is referred to Mishkin and White (2002), Crowder (2006), Neri (2004), Sousa (2008a, 2010d), Bjørnland and Leitemo (2009), Napolitano (2009), Agnello and Sousa (2011a), Iglesias and Haughton (2011) and Bjørnland and Jacobsen (forthcoming).

are quite common in the analysis of macroeconomic issues and allow us to capture the time-varying nature of the underlying structure in the economy in a flexible and robust manner (Nakajima, 2011). Therefore, this Chapter makes the first attempt in the context of South Africa, to analyse the time-varying spillover effect of stock price shocks on consumption and interest setting behavior, with the time-varying framework allowing us to not only identify the general relationship between the variables of interest, but more importantly, enables us to view how these relationships change depending on the underlying macroeconomic structure of the economy.

To the best of our knowledge, this is the first attempt, in the literature, to analyse the spillover effect of real stock prices on consumption and interest rate using a TVP-VAR model. The decision to use South Africa as our country of investigation simply emanates from our familiarity with major structural changes and shifts in monetary policy regimes in the economy over the period of the analysis, and their possible effects on the variables under consideration in the TVP-VAR model. The only other paper that is somewhat related to our study is the work by Baumeister et al., (2008). However, this Chapter is more interested in analysing how the dynamic effects of excess liquidity shocks on economic activity, asset prices and inflation differ over time. They show that the impact varies considerably over time and depends on the source of increased liquidity and the underlying state of the economy. The remainder of the Chapter is organized as follows: Section 2 discusses the methodology of the TVP-VAR technique. Section 3 lays out the data used. Section 4 presents the results of a stock price shock on consumption and the monetary policy interest setting behavior. Finally, section 5 concludes.

3. Methodology

A vector autoregression (VAR), proposed by Sims (1980), has become a popular technique used in econometric analysis and is adaptable to a vast array of economic settings (Baltagi, 2011). In this study, a TVP-VAR model with stochastic volatility is used. The TVP-VAR is common in the analysis of macroeconomic issues and allows us to capture the time-varying nature of the underlying structure in the economy in a flexible and robust manner (Nakajima, 2011). The parameters in the VAR specification are assumed to follow a first order random walk process, thereby incorporating both temporary and permanent changes to the parameters. The inclusion of stochastic volatility is an important aspect in this TVP-VAR model. In many situations, a data-generating process of economic variables seems to have drifting coefficients and shocks of stochastic volatility. In that case, the application of a time-varying parameter model but with constant volatility may result in biased estimations of the time-varying coefficients, since a possible variation of the volatility in disturbances is ignored. The TVP-VAR model with stochastic volatility avoids this misspecification. Although stochastic volatility makes the estimation difficult due to the intractability of the likelihood function, the model can be estimated using Markov Chain Monte Carlo (MCMC) methods in the context of a Bayesian inference.

Following Nakajima (2011), this Chapter estimates a time-varying parameter VAR model with stochastic volatility of the form:

$$y_t = c_t + B_{1t} y_{t-1} + \ldots + B_{st} y_{t-s} + e_t, \quad e_t \sim N\left(0, \Omega_t\right), \tag{1}$$

for $t = s+1, \ldots, n,$ where y_t is a $(k \times 1)$ vector of observed variables, $B_{1t}, \ldots, B_{st}$ are $(k \times k)$ matrices of time-varying coefficients, and Ω_t is a $(k \times k)$ time-varying covariance matrix. A recursive identification scheme is assumed by the decomposition of $\Omega_t = A_t^{-1}\Sigma_t\Sigma_t A_t^{'-1}$, where A_t is a lower-triangle matrix with diagonal elements equal to one, and $\Sigma_t = \text{diag}(\sigma_{1t}, \ldots, \sigma_{\kappa t})$. Let us define β_t as the stacked row vector of $B_{1t}, \ldots, B_{st}$; a_t is the stacked row vector of the free lower-triangular elements of A_t; and $h_t = (h_{1t}, \ldots, h_{kt})$ where $h_{jt} = \log \sigma_{jt}^2$. The time-varying parameters are assumed to follow a random walk process:

$$\begin{aligned} \beta_{t+1} &= \beta_t + \upsilon_{\beta t}, \\ a_{t+1} &= a_t + \upsilon_{at}, \\ h_{t+1} &= h_t + \upsilon_{ht}, \end{aligned} \qquad \begin{pmatrix} \varepsilon_t \\ \upsilon_{\beta t} \\ \upsilon_{at} \\ \upsilon_{ht} \end{pmatrix} \sim N \left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix} \right),$$

for $t = s+1, \ldots, n,$ with $e_t = A_t^{-1}\Sigma_t \varepsilon_t$ where Σ_a and Σ_h are diagonal, $\beta_{s+1} \sim N(\mu_{\beta o}, \Sigma_{\beta o})$, $a_{s+1} \sim N(\mu_{ao}, \Sigma_{ao})$, and $h_{s+1} \sim N(\mu_{ho}, \Sigma_{ho})$.[35]

A Bayesian inference is used to estimate the TVP-VAR models via MCMC methods. The goal of MCMC methods is to assess the joint posterior distributions of the parameters of interest under certain prior probability densities that are set in advance. We assume the following priors, as in Nakajima (2011): $\Sigma_\beta \sim IW(25,\ 0.01I)$, $(\Sigma_\alpha)_i^{-2} \sim G(4,\ 0.02)$, $(\Sigma_h)_i^{-2} \sim G(4,\ 0.02)$, where $(\Sigma_\alpha)_i^{-2}$ and $(\Sigma_h)_i^{-2}$ are the *i*-th diagonal elements in Σ_α and Σ_h respectively. IW and G denotes the inverse Wishart and the gamma distributions respectively. For the initial set of the time-varying parameter, flat priors are set such that: $\mu_{\beta o} = \mu_{ao} = \mu_{ho} = 0$ and $\Sigma_{\beta o} = \Sigma_{ao} = \Sigma_{ho} = 10 \times I$.

4. Data

The data sample covers the quarterly period of 1960:1 until 2011:04. A three-variable TVP-VAR model is estimated, capturing the time-varying nature of the macroeconomic dynamics in the South African economy between real consumption, nominal interest rate and real stock prices. Seasonally adjusted real personal consumption expenditure data is obtained from the official website (www.resbank.co.za) of the SARB, while the three-month Treasury bill rate, the All Share Stock Index and Consumer Price Index (CPI) data, used to convert nominal stock prices into its real counterpart, is derived from the International Financial Statistics of the International Monetary Fund. Based on all the standard unit root tests, namely, Augmented Dickey-Fuller (1981) (ADF), Phillips-Perron (1988) (PP), Dickey-Fuller test with generalized least squares detrending (DF-GLS), the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) (1992) test; the Elliot, Rothenberg, and Stock (ERS) (1996) point optimal test, the Ng-Perron (2001) modified versions of the PP (NP-MZt) test and the ERS point optimal (NP-MPT) test, real consumption expenditure and real stock prices were found to be non-stationary, so the variables were converted to their corresponding growth rates, and denoted as *DC* and *DRSP*. The nominal interest rate was found to be stationary at the 10 per cent level of significance using ADF, DF-GLS, ERS, NP-MZ_t and NP-MP_T tests, and hence, was used in levels, and denoted as *TBILL*.[36] The stable[37] TVP-VAR is estimated based on two lags, as was unanimously suggested by all the popular lag-length tests, namely, the sequential modified LR test statistic, the Akaike information criterion, the Schwarz information criterion, applied to a constant parameter VAR. Accounting for stationarity and lags, our effective sample period start from 1960:04.

5. Results

To compute the posterior estimates, we draw *M* = 50,000 samples after the initial 10,000 samples are discarded. Table 16 presents the estimates for the posterior means, standard deviations, 95 per cent credible intervals[38], the convergence diagnostics (CD) of Geweke (1992) and the inefficiency factors of selected parameters of the TVP-VAR, computed using the MCMC sample.[39] Based on the CD statistics, the null hypothesis of the convergence to the posterior distribution in the estimated result is not rejected for the parameters at the 5 per cent level of

[35] For a comprehensive analysis of the TVP-VAR methodology and the estimation algorithm, refer to Nakajima (2011).

[36] These results are available upon request from the authors.

[37] The constant parameter VAR is found to be stable as all roots were found to lie within the unit circle.

[38] Bayesian inference uses "credible intervals" as opposed to "confidence intervals" used in the frequentist approach to highlight parameter uncertainty.

[39] Geweke (1992) suggests the comparison between the first n_0 draws and the last n_1 draws, dropping out the middle draws, to check for convergence in the Markov chain. The CD statistics are computed as follows: $CD = (\bar{x}_0 - \bar{x}_1) / \sqrt{\hat{\sigma}_0^2 / n_0 + \hat{\sigma}_1^2 / n_1}$, where $\bar{x}_j = (1/n_j)\sum_{i=m_j}^{m_j+n_j-1} x^{(i)}$, with $x^{(i)}$ being the *i*-th draw, and $\hat{\sigma}_j^2 / n_j$ is the standard error of $\bar{x}_j$ respectively for *j* = 0, 1. If the sequence of the MCMC sampling is stationary, it converges to a standard normal distribution. We set m_0=1, n_0=10000, m_1=25001, and n_1=25000. $\hat{\sigma}_j^2$ is computed using a Prazen window with bandwidth (B_m) = 500. The inefficiency factor is defined as $1+2\sum_{s=1}^{B_m} \rho_s$, where ρ_s is the sample autocorrelation at lag *s*, which is computed to measure how well the MCMC chain mixes.

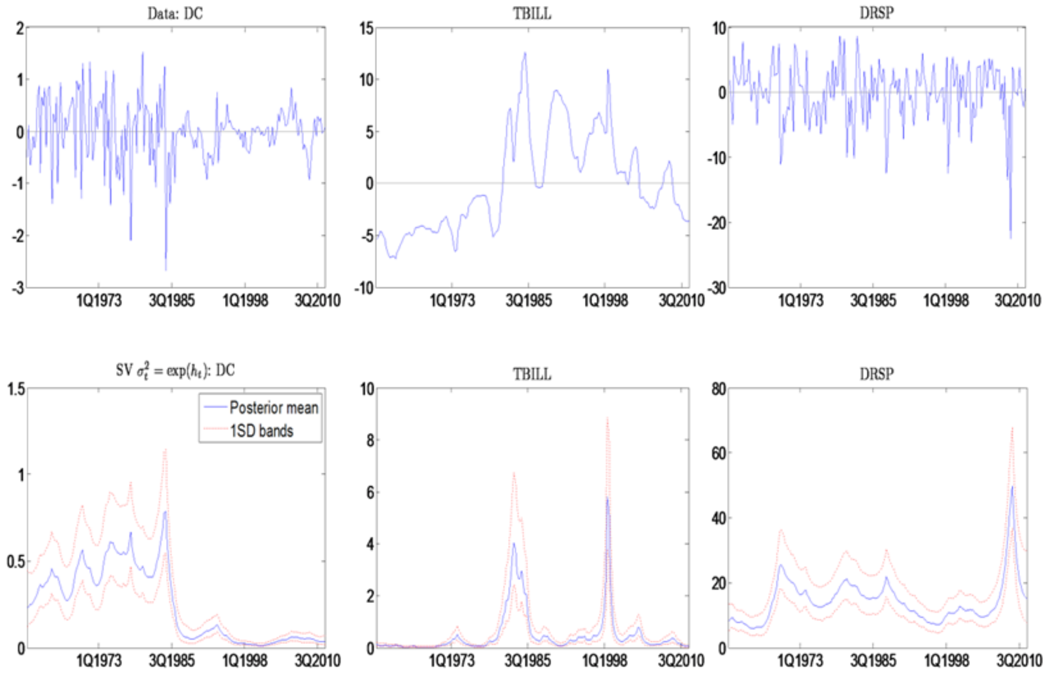
significance. In addition, the efficiency factors are quite low in general. Finally, the 95 per cent confidence intervals include the estimated posterior mean for each of the parameters estimated. Therefore, the results show that the MCMC algorithm produces posterior draws efficiently. Figure A, in Appendix 6.1, presents the estimation results of the TVP-VAR model with stochastic volatility.

Table 16: Estimation results of select parameters in the TVP-VAR model

Parameter	Mean	Std Dev.	95% Intervals	CD	Inefficiency
$(\Sigma_{\beta})_1$	0.0040	0.0013	[0.0024, 0.0072]	0.645	69.72
$(\Sigma_{\beta})_2$	0.0044	0.0017	[0.0024, 0.0091]	0.419	53.99
$(\Sigma_{a})_1$	0.0056	0.0017	[0.0034, 0.0097]	0.925	67.45
$(\Sigma_{a})_2$	0.0056	0.0016	[0.0034, 0.0097]	0.204	57.45
$(\Sigma_{h})_1$	0.2515	0.0753	[0.1255, 0.4187]	0.565	90.1
$(\Sigma_{h})_2$	0.5182	0.0967	[0.3510, 0.7288]	0.768	28.36

Figure 4 reports the data of the three variables in our analysis (*DC*, *TBILL*, and *DRSP*) in the top panel. The corresponding posterior estimates of stochastic volatility are plotted in the bottom panel. The time-series plots consist of the posterior draws on each date. The results show that stochastic volatility of consumption growth is highly volatile during the early period of our sample and peaks around 1985, followed by a general downward trend thereafter. This is intuitive as the financial liberalisation in 1985 following the recommendations of the De Kock Commission led to easy availability of credit which led to a consumption boom. The stochastic volatility of consumption remains low and stable from 1990s. The low stochastic volatility towards the end of the sample period may reflect more certainty in consumption behavior derived from a more stable economic and political environment in South Africa. The Treasury bill rate exhibits two major spikes in stochastic volatility during the financial liberalization of 1985 and around 1999, just before the SARB formally introduced inflation targeting. A minor rise in volatility of the Treasury bill rate is also observed around the first oil price shock in 1973. Not surprisingly, the real stock returns are found to exhibit the most stochastic volatility, with a major peak around 2008, due to the decline in stock returns following the recent financial crisis. Smaller peaks are observe around the 1973 oil price crisis and the financial liberalization. The significant posterior estimates of the stochastic volatility present in the variables of interest, justifies the use of a TVP-VAR model with stochastic volatility to avoid biased estimation.

Figure 4: Posterior Estimates for Stochastic Volatility



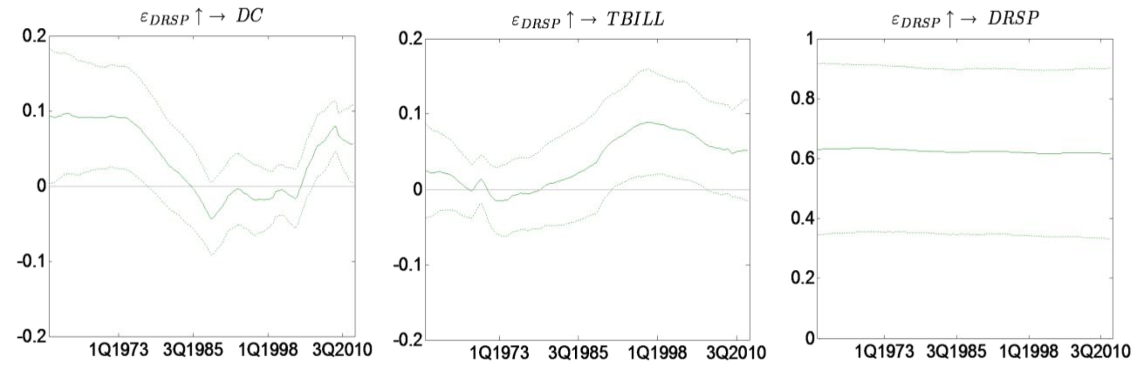
Note: Top panel presents the data values. Bottom panel depicts the posterior mean estimates (solid line) and 95 per cent credible intervals (dotted lines) for stochastic volatility of a structural shock.

Impulse responses are used as a tool to capture the macroeconomic dynamics in the estimated VAR system. For a standard constant parameter VAR model, the impulse responses are drawn for each set of two variables, whereas for a TVP-VAR model, the impulse responses can be drawn in an additional dimension, as the responses are computed at all points in time using the time-varying parameters. There are several ways to simulate the impulse responses based on the parameter estimates of the TVP-VAR model. Following Nakajima (2011), we compute the impulse responses by fixing an initial shock size equal to the time-series average of stochastic volatility over the sample period, and using the simultaneous relations at each point in time, for considering the comparability over time. The time-series average of the stochastic volatility of stock returns is 14.47. In the VAR, the variables are ordered in an attempt to identify the stock price shock using a recursive or Choleski identification scheme, as obtained based on the lower-triangular matrix A_t. We order the variables as follows: *DC, TBILL* and *DRSP* following the literature analysing asset price shocks on measures of real economic activity and monetary policy behavior. The ordering implies that consumption is not contemporaneously affected by interest rates and real stock prices. The interest rate is assumed to respond contemporaneously to consumption, but with a delay to real stock prices. Finally, stock prices react contemporaneously to an aggregate demand (consumption) shock and a monetary policy shock, while consumption and interest rates are assumed to react to changes in stock returns with a lag. Bjørnland and Leitemo (2009)and Bjørnland and Jacobsen (forthcoming) indicate that recursive ordering fail to take into account the possibility of contemporaneous response of monetary policy to stock price movements, and in turn, recommends the usage of short and long-run restrictions in structural VARs to identify shocks. However, Muroyiwa (2011) indicated a delayed response of interest rates to stock price movements even when allowing for contemporaneous relationship between interest rates and stock prices in his constant parameter SVAR, imposing short- and long-run restrictions as suggested by Bjørnland and Leitemo (2009) and Bjørnland and Jacobsen (forthcoming). Hence our ordering of stock prices after interest rate is well-warranted. Having said this, it would be interesting to analyse the possibility of a contemporaneous monetary policy response to stock prices in a TVP-VAR model based on the sign-restriction approach, as popularized recently by Baumeister and Benati (2012) and Baumeister and Peersman (2012, forthcoming). To compute the recursive innovation of the variable, the estimated time-varying coefficients are used from the current date to future periods. Around the end of the sample period, the coefficients are set constant in future periods for convenience. Although a time series of impulse responses for selected horizons or impulse responses for selected periods are often exhibited in the literature, one could draw a three-dimensional plot for the time-varying impulse responses.

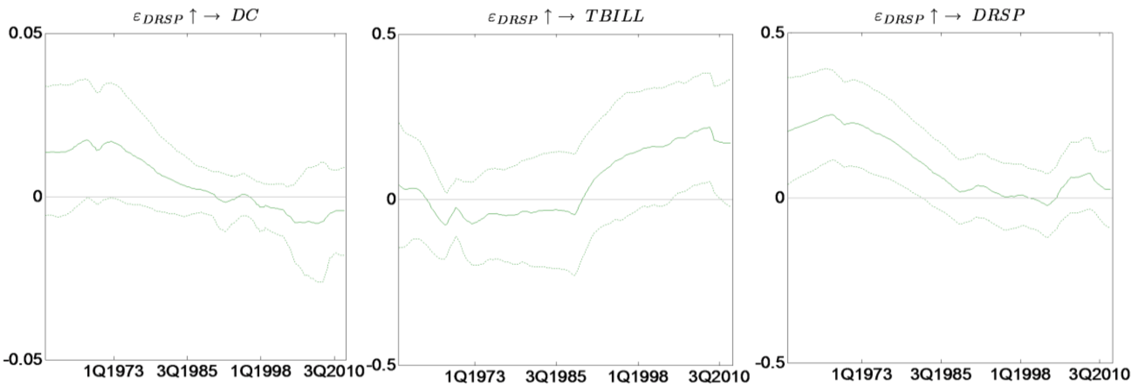
Figure 5 illustrates the time varying response trajectories at different horizons of one-quarter, four-quarters, eight-quarters and twelve-quarters ahead at each point of the sample, for the three variables of our concern following a shock to real stock price. In the figure, we report the mean of the posterior together with 16th and 84th percentiles.

Figure 5: Impulse responses of the TVP-VAR model following a real stock price shock

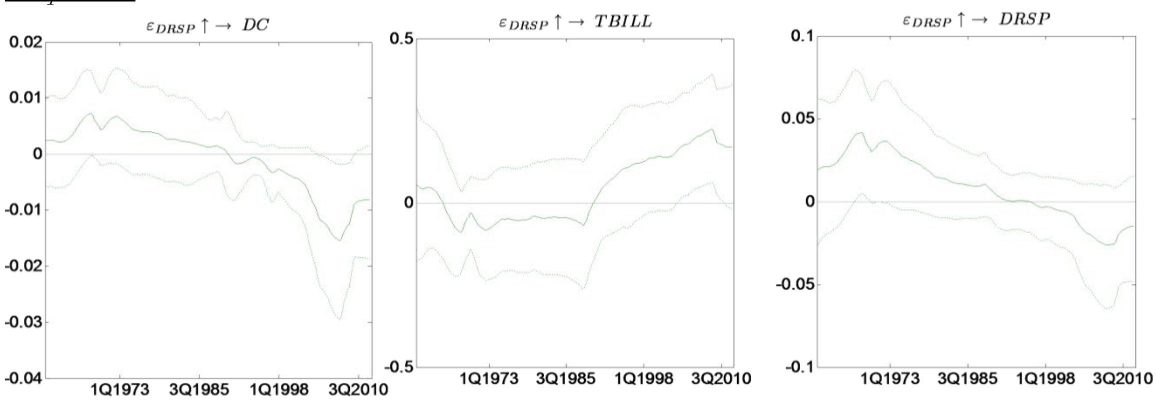
1-step ahead



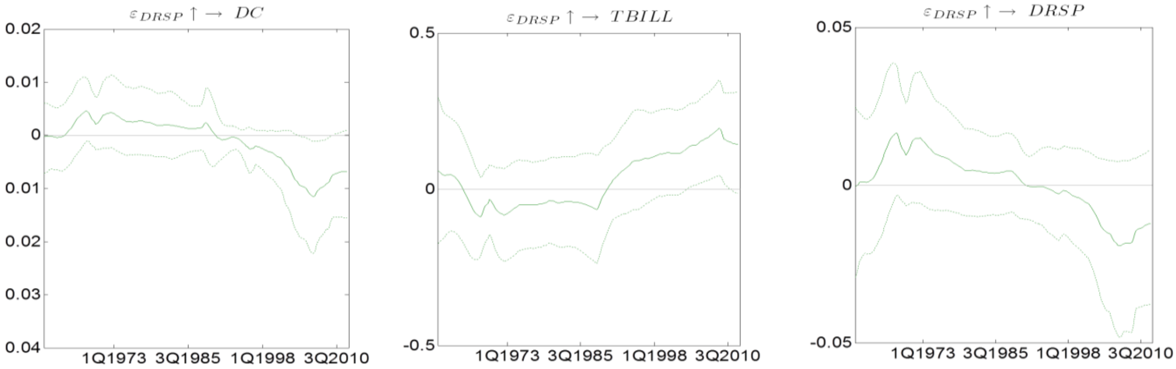
4-steps ahead



8-steps ahead



12-steps ahead



Note: *Posterior mean (solid line) and 16 per cent and 84 per cent quantiles (dotted line)*

Following a shock to real stock price, the effect on stock price itself is mostly positive, especially for one-quarter and four-quarters ahead horizons. The effect is significant over the entire sample period for the one-quarter-ahead horizon, while the significance for the 4-steps ahead impulse responses lasts till the mid-1980s. Though the effect on stock price is positive for majority of the sample at longer horizons, the effect is not significant at any point of time. Following a positive shock to real stock price, consumption in general responds positively, with the effect becoming negative when stock prices become negative. The results show that for a one-step-ahead horizon, a 14.47 percentage points increase in stock prices resulted in consumption increasing by around 0.1 percentage points during the 1960s and early 1970s. The impact decreased and became negative, reaching a low of -0.04 in 1990, remaining negative during the 1990s. The effect increased during the 2000s, with a peak of 0.09 just before the 2008 financial crisis. The effect on consumption is primarily significant at the one-quarter ahead horizon, barring the period of mid-1980 till the late 1990, when the effect was insignificantly negative even when real stock prices were significantly positive. Interestingly, at the one-year ahead horizon following the stock price shock, the effect on consumption is hardly significant for the entire period. Negative significant effects on consumption are seen in the latter part of the sample, mainly during the financial crisis, for eight-quarters ahead and twelve-quarters ahead impulse responses, when the stock price in itself was negative, though not significantly. Note that based on the scales of the graphs, the size of the effect on consumption following an increase in real stock prices diminished at longer horizons since the effect for the 12-step-ahead horizon is only between 0.01 and -0.01 percentage points during the sample period.

The behaviour of the interest rate following a real stock price increase is quite interesting. For the one-quarter ahead impulse responses, the effect is positive in general, barring a short-period in mid to late 1970s, but the effect is only significant post financial liberalization, until the financial crisis. This means that an increase in stock prices by 14.47 percentage points resulted in interest rates increasing by 0.02 percentage points in 1960, before increasing to 0.1 percentage points in 1998. The effect moderated thereafter (although remaining positive), averaging by around 0.07 percentage points in the 2000s. For the one-year ahead horizon, the impulse responses are initially positive, and then become negative, though insignificant, until shortly after financial liberalization. A positive and significant response is observed from there on until the end of the sample, though the effect weakened during the financial crisis. A similar pattern, to the four-quarters ahead horizon, is observed for the eight-quarters ahead and twelve quarters ahead horizons. Contrary to the reaction of consumption to a stock price shock, the effect on interest rates increases with the horizon – with the effect between 0.2 and -0.2 percentage points for the 4, 8, and 12-steps-ahead horizons. It seems that the monetary authority started to respond positively to stock price movements more seriously after financial liberalization, with its response reaching a peak just before the financial crisis. The results tend to suggest that for a prolonged period after the first oil price shock till financial liberalization, the SARB was quite happy to allow the stock markets to grow, by lowering interest rate following a positive shock to stock prices. Further, there seems to be quite a bit of persistence in the effect of interest rate movement to stock price behaviour, since the interest rates were positive and significant at longer horizons (eight and twelve) even when the effect on stock price following a shock on itself had become negative. This could possibly indicating the SARB's attempt to keep inflation in check that could have originated from the wealth effect of real stock price increases on consumption as the SARB targets inflation – an indirect effect. The indirect channel that an increase in stock returns could affect the interest rates is through rising inflation as a result of increasing consumer demand. Higher stock returns are usually translated into improved household wealth, resulting in increased consumption – which tends to be inflationary. Since the SARB targets inflation, and demand driven inflation can be controlled by increasing interest rates, it is likely to increase the Repo rate when consumption increases. It is important to note that the impact of an increase in the Repo rate on inflation has a lag, as a result, it is not surprising that interest rates remain persistently positive and significant after a stock price shock, even when the effect of a stock price shock on itself becomes negative.. In addition, based on the scales of impulse responses, the effects are bigger at longer horizons, than immediately following the shock on stock prices.[40]

The results suggest that there is high degree of variability in the behaviour of both consumption and interest rates to a stock price shock during different periods and trajectories. The behaviour of stock price following a shock to itself also exhibits different responses depending on the trajectory analysed. All this variability in the behaviour of the variables of our concern, justifies the use of a TVP-VAR with stochastic volatility.

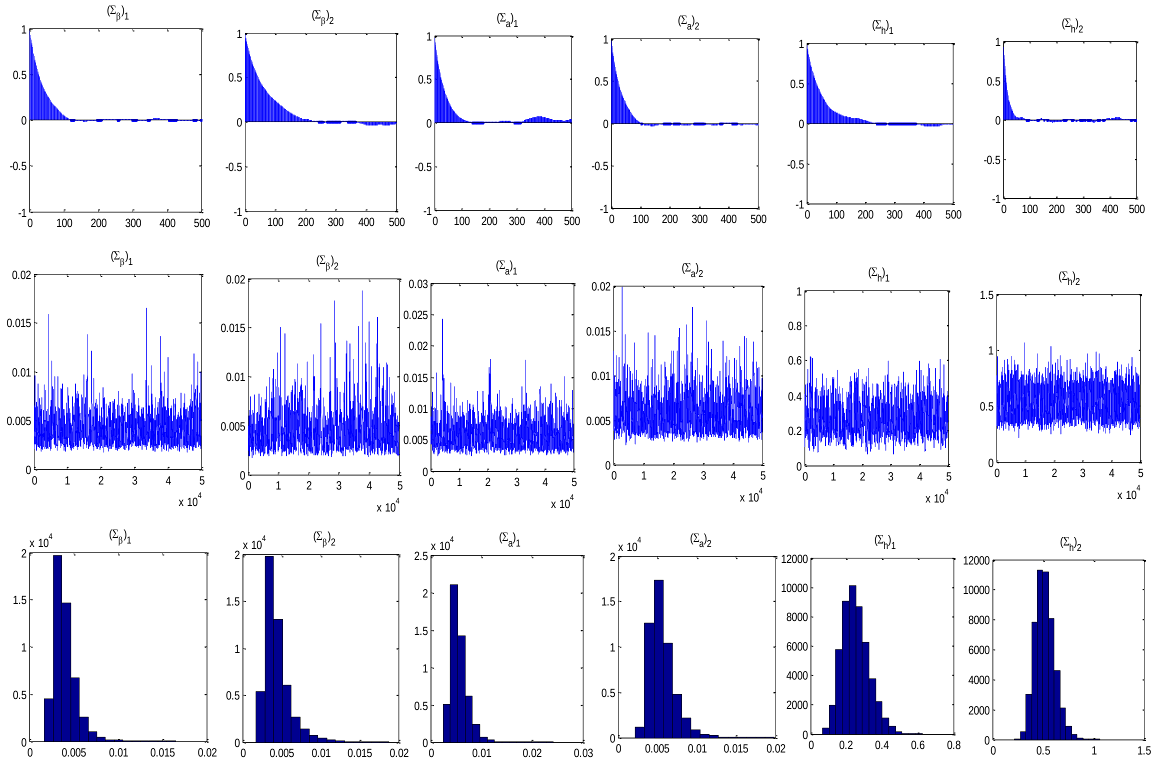
6. Conclusion

This Chapter uses a three variable (growth rate of real consumption, nominal three-months Treasury bill rate and real stock price growth rate) TVP-VAR model with stochastic volatility to analyse the impact of a stock price shock on consumption levels and monetary policy for South Africa over the quarterly period of 1960:1-2011:4. We find that the impact of a real stock price shock on consumption is in general positive, with large and significant effects observed at the one-quarter ahead horizon. However, there is also evidence of significant negative spillovers from the stock market to consumption during the financial crisis, at both short and long-horizons. Monetary policy response to stock price shocks has been persistent and strong, especially post-financial liberalization, but became weaker during the financial crisis. Overall, we provide not only evidence of significant spillovers on consumption and interest rate from the stock market, but, more importantly, we also highlight the fact that these effects have significantly varied over time, which we would not have been able to capture without the usage of a time-varying model. Given that recent papers by Afonso and Sousa (2011b), Agnello and Sousa (2011b), Castro and Sousa (2012) and Agnello et al., (forthcoming) have analysed the impact of fiscal policy on asset prices and also the possible feedback of asset prices on setting of fiscal policy, it would be interesting to carry out such analyses for South Africa using a TVP-VAR approach in the future. Since, this would not only allow us to account for possible nonlinearity amongst the variables of interest, but also how the relationship has evolved over time.

[40] The impulse response functions for a shock to *DC* and *TBILL* were found to be in line with standard economic theory; overall, a positive consumption shock (aggregate demand shock) led to a rise in the interest rate and the real stock price, while, a contractionary monetary policy shock reduced consumption and real stock price. These results are available upon request from the authors.

Appendix 6.1

Figure A: Estimation results of selected parameters in the TVP-VAR model



Note: Sample autocorrelations (top panel), sample paths (middle panel), and posterior densities (bottom panel). The estimates of Σ_β and Σ_a are multiplied by 100.

CHAPTER 7: STRUCTURAL BREAKS AND PREDICTIVE REGRESSIONS MODELS OF SOUTH AFRICAN EQUITY PREMIUM[41]

1. Abstract

In Chapters 2 to Chapter 4 the focus was mainly to evaluate the determinants of stock returns using – amongst other models – predictive regressions. The use of predictive regression and the fact that these models are usually estimated using relatively long span of data, necessitates the need to test for the structural stability of the parameters in these models. In this chapter we therefore test for the structural stability of both bivariate and multivariate predictive regression models for equity premium in South Africa over the period of 1990:01 to 2010:12, based on 23 financial and macroeconomic variables. We employ a wide range of methodologies, namely, the popular Andrews (1993) $SupF$ statistic and the Bai (1997) subsample procedure in conjunction with the Hansen (2000) heteroskedastic fixed-regressor bootstrap. We also used the Elliott and Müller (2003) $\hat{J}$ statistic and Bai and Perron (1998, 2003a, 2004) methodologies. We find strong evidence of at least two structural breaks in 22 of 23 bivariate predictive regression models. We also obtain evidence of structural instability in the multivariate predictive regression models of equity premium. The results also show that the predictive ability of the 23 variables can vary widely across different regimes.

[41] Forthcoming in Frontiers in Finance and Economics

2. Introduction

Recently, major global economies experience economic slowdown. The likelihood that the global economy may experience a double-dip recession stresses the need for predicting the behaviour of leading indicators such as stock returns and equity premium. An understanding of market behaviour helps in guiding both policy and trading decisions. The main objective of this study is to examine the predictive role of financial and other economic variables for South Africa's equity premium while recognizing potential structural breaks. The equity premium is the expected excess return on a stock market portfolio over the risk-free interest rate. Equity prices capture expected firms' profitability, which is linked to the future rate of growth of the economy [Pástor and Stambaugh (2001), Kim et al. (2005)]. The popularity of predictive regression models, and the fact that these models are usually estimated using relatively long span of data, necessitates the need to test for the structural stability of the parameters in these models. Numerous macroeconomic and financial variables are unstable over time (Stock and Watson; 1996; Rapach and Wohar, 2006). Ignoring structural changes have statistical inference as well as investment allocation implications. From statistical inference perspective, it is shown that ignoring structural breaks in financial or economic time series can have persistence or long memory effects [Mikosch and Stărică (2004), Hillebrand (2005)] and can have implications about the existence of higher order unconditional moments such as kurtosis or tail index in financial time series [Mikosch and Stărică (2004), Andreou and Ghysels (2005)] as well as forecasting [Pesaran and Timmermann (2004)]. Therefore, ignoring structural breaks in econometric modelling can lead to model misspecification and spurious estimation results of model parameters. From an economic perspective, structural breaks can affect fundamental financial indicators such as, financial returns and volatility, the tail of the distribution and risk management measures, the shape of the option implied volatility smile, the equity premium, credit risk models and default measures. [Pástor and Stambaugh (2001), Andreou and Ghysels (2005, 2006, 2009), Horváth et al. (2006).

More importantly, structural breaks affects optimal asset allocation decisions since these rely on forecasts of future returns, often at long horizons. For instance, Pettenuzzo and Timmermann (2005) find empirically that model instability can have a larger effect on the asset allocation than sources of risk such as parameter estimation uncertainty and can lead to a steep negative slope in the relationship between the investment horizon and the proportion of wealth that a buy-and-hold investor allocates to stocks. Various economic events can lead to structural changes detected in a large number of financial series, such as major changes in market sentiment, speculative bubbles, regime changes in monetary policy, changes in debt management policies, and learning by investors, financial liberalization of emerging markets, integration of world equity markets, collapse of exchange rate systems among others [Pesaran and Timmermann (2002), Andreou and Ghysels (2009)]. The precise estimation of a change point helps to uncover the source of a structural change by spotting special events around the break dates and can also be used to evaluate the impact of an event or a new policy by estimating the response time of the economy to the shocks [Liao (2008)]. Similar events as listed above may have occurred in South Africa especially within the last two decades. As we do not have strong prior beliefs concerning the exact timing of possible breakpoints in predictive regression models of equity premium, the role of statistical tests in contrast to simple assumption in detecting the exact change point cannot be overstressed as this gives a better and more scientific judgement.

A number of studies have predicted the behaviour of equity premium using financial and other macroeconomic variables. Nelson (1976) and Fama and Schwert (1977) found predictive ability for the inflation rate. Rozeff (1984), Fama and French (1988), Campbell and Shiller (1988a, 1988b) and Bekaert and Hodrick, (1992) presented evidence that valuation ratios, such as the dividend yield, predict the equity premium. Similarly, Keim and Stambaugh (1986), Campbell (1987), Breen, *et al.* (1989), and Fama and French (1989) found that nominal interest rates and interest rate spreads, such as the default and term spreads, predict the equity premium. More recent studies continue to support equity premium predictability using valuation ratios [Cochrane (2008), Pástor and Stambaugh (2009)], interest rates [Ang and Bekaert (2007)], and inflation [Campbell and Vuolteenaho (2004)]. Other studies identified additional financial and macroeconomic variables with predictive power, including financial share prices; money supply, corporate bond yields, industrial production, world oil production, oil price and employment rates [Baker and Wurgler (2000), Lettau and Ludvigson (2001), Guo (2006), Boudoukh, *et al.* (2007), Campbell and Thompson (2008), Goyal and Welch (2003, 2008), Allen and Bujang (2009), Jiang *et al.* (2009), Kellard *et al.* (2010), Nelly *et al.* (2010, 2011), Rapach *et al.* (2010), Rapach *et al.* (2011), Gupta *et al.* (2011)]. Majority of these studies are conducted for US and other advanced countries. Findings may often differ depending on the specific country or methodology. Moreover, none of these studies formally examined structural breaks in predictive (bivariate or multivariate) models of equity premium.[42] Therefore, the current study formally tests for structural breaks in the predictive regression model of South Africa's equity premium based on the 23 financial and macroeconomic variables that appear popularly in the literature of in-sample equity premium prediction. To the best of our knowledge, the structural stability of predictive regression models of South Africa's equity premium has not been previously investigated.

To test for structural break, we use the methodology described in Rapach and Wohar (2006). However, instead of testing structural stability of predictive stock returns as in Rapach and Wohar (2006), we test for structural stability of equity premium. Specifically, the Andrews (1993) $SupF$ statistic in concert with the Hansen (2000) heteroskedastic fixed-regressor bootstrap, as well as the recently developed $\hat{J}$ statistic of Elliott and Müller (2003) were used to test for a structural break at an unknown date in the parameters of 23 bivariate predictive regression models of South Africa's equity premium for 1990:01–2010:12 periods. The sample period covers events including a move to democratic rule in 1994 in South Africa, the Asian financial crisis, South Africa's decision to move to an inflation targeting regime in 2000, the currency crisis in late 2001, and the global financial crisis since late 2007. We use the 23 financial variables listed in the data section below as explanatory variables in the bivariate predictive regression models of South Africa's equity premium. We also use the subsample procedure of Bai (1997) and the Bai and Perron (1998, 2003a, 2004) methodologies to explicitly test for multiple structural breaks at unknown dates in the bivariate predictive regression models. In addition to the bivariate models, we also test for structural breaks in multivariate predictive regression models of equity premium.

The rest of the Chapter is organized as follows. Section 2 describes the econometric procedures. Section 3 describes the data and reports the results of the tests for structural breaks in bivariate and multivariate predictive regression models of equity premium. Section 4 concludes.

3. Econometric methodology

The standard bivariate predictive regression model is specified as

$$r_t = \beta_0 + \beta_1 z_{t-1} + \varepsilon_t \qquad (1)$$

where r_t is the equity premium from period $t-1$ to period t, z_{t-1} is a candidate predictor lagged one time, ε_t is the disturbance term and $t = 1,...,T$. Using array notation, the predictive regression model can be expressed as

$$r_t = x'_{t-1}\beta + \varepsilon_t \qquad (2)$$

where $x_{t-1} = (1, z_{t-1})'$, $\beta = (\beta_0, \beta_1)'$. The structural stability of the regression parameters β_0 and β_1 are tested. Breaks in both the intercept and slope coefficients of the predictive regression model are considered as both these affect the conditional expected equity premium, $E(r_t / z_{t-1})$. Suppose there is a structural break in the predictive regression model at period k, so that

$$r_t = x'_{t-1}\beta^0 + \varepsilon_t,\ t = 1,...,k \qquad (3)$$

$$r_t = x'_{t-1}(\beta^0 + \delta) + \varepsilon_t,\ t = k+1,...,T \qquad (4)$$

where $\beta^0 = (\beta_0^0, \beta_1^0)'$ and $\delta = (\delta_0, \delta_1)'$. The model with a structural break could be written in matrix notation as

$$r = X\beta^0 + X_{0k}\delta + \varepsilon \qquad (5)$$

where $r = (r_1,..., r_T)'$, $X = (x_0,..., x_{T-1})'$, $X_{0k} = (0,...,0.x_k,..., x_{T-1})'$ and $\varepsilon = (\varepsilon_1,..., \varepsilon_T)'$.

If the breakpoint k is known a priori, the familiar Chow (1960) procedure can be used to test the null hypothesis of no structural change $(H_0 : \delta = 0)$ against the alternative hypothesis of a structural break at period k $(H_1 : \delta \neq 0)$. The Chow (1960) test is based on the Wald statistic,

$$F_k = [(T-2)\hat{\sigma}_R^2 - (T-4)\hat{\sigma}_k^2] / \hat{\sigma}_k^2 \qquad (6)$$

[42] Pástor and Stambaugh, 2001; Fama and French, 2002; Chang-Jin et al. 2005; Kim et al., 2005 examined structural breaks in equity premium in a univariate framework.

where $\hat{\sigma}_k^2 = (\hat{\varepsilon}_k{}' \hat{\varepsilon}_k)/(T-4)$, $\hat{\sigma}_R^2 = (\hat{\varepsilon}_R{}' \hat{\varepsilon}_R)/(T-2)$, $\hat{\varepsilon}_k$ is the vector of least-squares residuals from Equation (5), and $\hat{\varepsilon}_R$ is the vector of least-squares residuals from Equation (5) with the restriction $\delta = 0$ imposed. The null hypothesis of no structural break is rejected if the calculated F-statistics is greater than the critical value (the rejection-acceptance limit) at a pre-specified significance level.

The key weakness of the Chow (1960) test is that it is not operational if the breakpoint k is unknown, as is likely to be the case in many instances (Rapach and Wohar, 2006). In our case, we are not certain of the exact timing of possible breakpoints in predictive regression models of South Africa's equity premium. Building on Quandt (1960), Andrews (1993) makes the Chow (1960) test operational for the case of an unknown breakpoint. Chow (1960) derives the limiting distribution of the supremum of the F_k statistics over the interval $[\pi T, (1-\pi)T]$, or the test statistic,

$$SupF = \sup_{k \in [\pi T, (1-\pi)T]} F_k \tag{7}$$

where π is a trimming parameter (required for the asymptotic distribution theory) that is typically set equal to 0.05, 0.10, or 0.15. Andrews (1993) shows that the limiting distribution of the $SupF$ statistic is non-standard and depends on the trimming parameter π. For a given value of the trimming parameter, the null hypothesis of no structural break can be tested using the asymptotic critical values in Andrews (1993). If the null hypothesis is rejected, the breakpoint can be consistently estimated as

$$\hat{k} = \arg\min_{k \in [\pi T, (1-\pi)T]} (\hat{\varepsilon}_k{}' \hat{\varepsilon}_k) \tag{8}$$

Bai (1997) notes that given the formula for F_k in Equation (6), $\hat{k}$ will coincide with the value of k corresponding to the $SupF$ statistic in Equation (7). In Section 3, the $SupF$ statistic is used to test the structural stability of 23 bivariate predictive regression models of equity premium. Following the recommendation of Andrews (1993), the trimming parameter π is set equal to 0.15.

To guard against possible nonstationarities in the marginal distribution of the regressors, we follow Rapach and Wohar (2006) and rely on the Hensen (2000) heteroskedasticity fixed regressor bootstrap procedure to make inferences for the SupF statistic in Section 3 below.

Multiple structural breaks are likely to exist in the predictive regressions for South Africa's equity premium because of changes in the regimes and external shocks that may have changed the structure of the data during the period under review. As a result, we follow Rapach and Wohar (2006) and test for multiple structural breaks using the Bai (1997) procedure – augmented with the Hansen (2000) heteroskedastic fixed-regressor bootstrap.43

In addition to Bai (1997), we used the recently developed methodology of Bai and Perron (1998, 2003a, 2004) to test for multiple structural breaks in the predictive regression models. Their methodology is explicitly designed for estimating and testing regression models with multiple structural breaks. Consider the predictive regression model with m breaks ($m+1$ regimes),

$$r_t = z'_{t-1}\beta^j + \varepsilon_t, \; m \tag{9}$$

for $j = 1, \ldots, m+1$, where β^j is the vector of regression coefficients in the jth regime. The m-partition $(T_1, \ldots, T_m)$ represents the breakpoints for the different regimes (by convention, $T_0 = 0$ and $T_{m+1} = T$). Bai and Perron explicitly treat the breakpoints as unknown. Equation (9) is estimated using least squares. For each m-partition $(T_1, \ldots, T_m)$, the least-squares estimates of β^j are generated by minimizing the sum of squared residuals,

$$S_T(T_1, \ldots, T_m) = \sum_{i=1}^{m+1} \sum_{t=T_{i-1}+1}^{T_i} (r_t - z'_{t-1}\beta^j)^2 \tag{10}$$

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43 For further details on how the Bai (1997) procedure is constructed, the reader is referred to Rapach and Wohar (2006).

Let the regression coefficient estimates based on a given m-partition $(T_1,...,T_m)$ be denoted by $\hat{\beta}(\{T_1,...,T_m\})$, where $\beta = (\beta^{1'},...,\beta^{m+1'})'$. Substituting these into Equation (10), the estimated breakpoints are given by

$$(\hat{T}_1,...,\hat{T}_m) = \arg\min_{T_1,...,T_m} S_T(T_1,...,T_m) \tag{11}$$

where the set of admissible m-partitions is subject to a set of restrictions given below. From Equation (11), it is clear that the breakpoint estimators correspond to the global minimum of the sum of squared residuals objective function. With the breakpoint estimates in hand, it is straightforward to calculate the corresponding least-squares regression parameter estimates as $\hat{\beta} = \hat{\beta}(\{\hat{T}_1,...,\hat{T}_m\})$. Bai and Perron (2003a) described an efficient algorithm for the minimization problem in Equation (11) based on the principle of dynamic programming.

A special testing procedure aimed at identifying the number of structural breaks (m) in Equation (9) was developed by Bai and Perron (1998). They begin by testing the null hypothesis of no structural breaks against the alternative of $m = b$ breaks. Let $(T_1,...,T_b)$ be a partition such that $T_i = [T\lambda_i](i = 1,...,b)$. Also define R such that $(R\beta)' = (\beta^{1'} - \beta^{2'},...,\beta^{b'} - \beta^{b+1''})$. Bai and Perron (1998) specify the following statistic:

$$F_T(\lambda_1,...,\lambda_b) = \frac{1}{T}\left(\frac{T-(b+1)2}{2b}\right)\hat{\beta}'R'\left[R\hat{V}(\hat{\beta}R')\right]^{-1}R\hat{\beta} \tag{12}$$

where $\beta = (\beta^{1'},...,\beta^{b+1''})'$ is the vector of regression coefficient estimates and $\hat{V}(\hat{B})$ is an estimate of the variance-covariance matrix for $\hat{\beta}$ that is robust to heteroskedasticity and serial correlation. Bai and Perron (1998) then consider a type of maximum F-statistic corresponding to Equation (12),

$$SupF_T(b) = F_T(\hat{\lambda}_1,...,\hat{\lambda}_b) \tag{13}$$

where $\hat{\lambda}_1,...,\hat{\lambda}_b$ minimize the global sum of squared residuals, $S_T(T\lambda_1,...,T\lambda_b)$, under the restriction that $(\hat{\lambda}_1,...,\hat{\lambda}_b) \in \Lambda_\pi$, where $\Lambda_\pi = \{(\lambda_1,...,\lambda_b);|\lambda_{i+1} - \lambda_i| \geq \pi, \lambda_1 \geq \pi, \lambda_b \leq 1-\pi\}$ for some arbitrary positive number π (the trimming parameter). Bai and Perron (1998) develop two statistics, called the "double maximum" statistics, for testing the null hypothesis of no structural breaks against the alternative hypothesis of an unknown number of breaks given an upper bound M. The first double maximum statistic is given by

$$UD\max = \max_{1 \leq m \leq M} SupF_T(m) \tag{14}$$

The second double maximum statistic, $WD\max,$ applies different weights to the individual $UD\max$ statistics so that the marginal p-values are equal across values of m; see Bai and Perron (1998:59) for details.

Bai and Perron (1998) also developed the $SupF_T(l+1|l)$ statistic which is used to test the null hypothesis of l breaks against the alternative hypothesis of $l+1$ breaks. This test is further useful in that it is used to test whether the additional break leads to a significant decrease in the sum of squared residuals. Bai and Perron (1998, 2003b) derive asymptotic distributions for the double maximum and $SupF_T(l+1|l)$ statistics and provide critical values for various values of π and M.

One of the advantages of the Bai and Perron methodology is that it allows for general specifications when computing test statistics and confidence intervals for the break dates and regression coefficients. These specifications include autocorrelation in the regression model residuals, heteroskedasticity in the residuals, and different moment matrices for the regressors in the different regimes. The latter two specifications are potentially important for our applications, and we allow for heteroskedasticity in the residuals and different moment matrices for the regressors in our applications. Using the notation of Bai and Perron (2004), we set $cor\_u = 0$, $het\_u = 1$, and $het\_z = 1$ in our applications of the Bai and Perron methodology in Section 3.

We consider the sequential application of the $SupF_T(l+1|l)$ statistics – a specific to general modelling strategy – discussed by Bai and Perron (1998) as a way of determining the number of structural breaks as this procedure was found to perform well in a number of circumstances (Bai and Perron, 2004).

While Bai and Perron (2004) find that the Bai and Perron sequential procedure performs well in a number of settings, its performance can be improved upon when multiple breaks are present, as the $SupF_T(1|0)$statistic, which is essentially the Andrews (1993) test, can have low power in the presence of multiple breaks (as discussed above). With multiple breaks, Bai and Perron (2004) find that the double maximum statistics are much more powerful. Based on their Monte Carlo simulations, Bai and Perron (2004) recommended the following strategy. First, examine the double maximum statistics to determine if any structural breaks are present. If the double maximum statistics are significant, then examine the $SupF_T(l+1|l)$ statistics to decide on the number of breaks, choosing the $SupF_T(l+1|l)$ statistic that rejects for the largest value of l. We also use this strategy – referred to as the Bai and Perron double maximum procedure – in our applications in Section 3 below. Finally, Bai and Perron (2004) recommend using a trimming parameter π of at least 0.15 (corresponding to $M = 5$) when allowing for heteroskedasticity, and we follow this recommendation.

Monte Carlo simulations in Paye and Timmermann (2005) have potential implications for the testing procedures we employ. Paye and Timmermann (2005) consider processes where returns are generated by Equation (1), and the predictor z_t in Equation (1) is governed by a first-order autoregressive process,

$$z_t = \alpha_0 + \alpha_1 z_{t-1} + u_t \tag{15}$$

They find that the $UD\max$ statistic, as well as the $SupF$ statistic based on the fixed-regressor bootstrap, can exhibit considerable size distortions in situations where z_t is highly persistent (α near unity) and the disturbance terms in Equations (1) and (15) (ε_t and u_t) are strongly correlated. This is likely to be the case when z_t is a valuation ratio such as the dividend-price or price-earnings ratio. Paye and Timmermann (2005) find that a recently developed statistic by Elliott and Müller (2003) has relatively good size properties when z_t is highly persistent and the disturbance terms in Equations (1) and (15) are strongly correlated. Elliott and Müller (2003) use the $\hat{J}$ statistic to test the null hypothesis that $\beta_t = 0 \ \ \forall t$, where $\beta = (\bar{\beta} + \beta_t)$ in Equation (2), against the alternative hypothesis that $\beta_t \neq 0$ for some $t > 1$. Details on the computation of the $\hat{J}$ statistic are given in steps 1–6 of Elliott and Müller (2003:12), and they provide asymptotic critical values in their Table 17. Following Rapach and Wohar (2006), we include the Elliott and Müller (2003) $\hat{J}$ statistic in our analysis as a robustness check that guards against potential size distortions in our other tests.

4. Results

The results obtained from the various tests for structural break in the predictive regression models of South Africa's equity premium are discussed in this section and reported in Tables 17 to 20. We begin by discussing the data used in the analysis.

4.1 Data

We use monthly data from 1990:01 to 2010:12 for the equity premium and the 23 predictors. The variables are discussed below:

Equity premium: Nominal return on a stock market index (All-share index) in excess of the risk-free interest rate (the Treasury bill rate);

Financials share prices: Real stock returns for the financial sector in South Africa, computed as the first difference in the log-levels of real Financial Stock Index;

Industrial share prices: Real stock returns for the industries in South Africa, computed as the first difference in the log-levels of real Industrial Stock Index;

Price-dividend ratio (log-level): One-year moving sum of the ratio of nominal dividend to nominal stock prices;

Price-earnings ratio (log-level): One-year moving sum of the ratio of nominal earnings to nominal stock prices;

Payout ratio (log-level): The ratio of price-earnings to price-dividend;
Relative long-term bond yield: Difference between the long-term government bond yield and a 12-month backward-looking moving average;
Relative 90 days Treasury bill rate: Difference between the 90-day Treasury bill rate and a 12-month backward-looking moving average;
Term spread: Difference between long-term government bond yield and the 90-day Treasury bill rate;
Relative money market rate: Difference between the prime rate and the 12-month backward-looking moving average;
DAX (log-level): The real stock returns for Germany, computed as the first difference of the real DAX (Deutscher Aktien-Index) – a blue chip stock market index consisting of the 30 major German companies trading on the Frankfurt Stock Exchange;
CAC (log-level): The real stock returns for France, computed as the first difference of the real CAC 40 (the benchmark French stock market index);
S&P 500 (log-level): The real stock returns for the US, computed as the first difference of the real S&P 500, which is the free-float capitalisation-weighted index of the prices of 500 large-cap common stocks;
FTSE 100 (log-level): The real stock returns for the United Kingdom, computed as the first difference of the real FTSE 100 all-share index, which is a capitalisation-weighted index of around 100 companies traded on the London Stock Exchange;
NIKKEI (log-level): The real stock returns for Japan, computed as the first difference of the real Nikkei 225 stock index for the Tokyo Stock Exchange;
Hang-Seng (log-level): The real stock returns for Hong Kong, computed as the first difference of the real Hang Seng Index, which is a free float-adjusted market capitalisation-weighted stock market index;
Real effective exchange rate: First difference in log-levels of real effective exchange rate index;
Broad money supply growth rate: First difference in the log-levels of real broadly defined money stock;
Narrow money supply growth rate: First difference in the log-levels of real narrowly defined money stock;
The inflation rate: First difference in the log-levels of the consumer price index;
Industrial production growth rate: First difference in the log-levels of industrial production;
Employment growth rate: First difference in the log-levels of employment;
World oil production growth rate: First difference in the log-levels of the world oil production; and
Crude oil price growth rate: Refiner acquisition cost of imported crude oil growth rate in real terms. To obtain the rand denominated price, we use the rand/dollar exchange rate, and then deflate the nominal value using the consumer price index to obtain the real crude oil price.

The monthly data is obtained from the South African Reserve Bank, Statistics South Africa, Bloomberg and the US Energy Information Administration[44]. Following Rapach *et al.* (2005), we measure interest rate variables as deviations from a backward-moving average. This is because, if real interest rates play a crucial role in determining stock returns, then measuring the interest rate as deviations from a backward-looking moving average tends to make the nominal interest rate effectively a real interest rate. That is, the behaviour of expected inflation is such that most of the fluctuations in the relative nominal interest rate reflect movements in the relative real component. All the variables were tested for unit roots. Based on standard tests, only inflation rate was nonstationary, hence the first difference was used in the analysis.

4.2 Structural breaks for bivariate and multivariate models of South Africa's equity premium

Table 17 presents the estimation results for Equation (1) based on the 23 explanatory variables for the bivariate predictive regressions as well as the results for the multivariate regressions.[45] The reported results in Table 17 are for the SupF, $\hat{J}$, QLR_T, WDmax and the SupFT test statistics.[46] For the bivariate regressions, the coefficients for all variables are positive with the exception of financial share prices, industrial share prices, payout ratio, long

[44] The mean (standard deviation) for the variables is as follows: Allshare: 1.309 (21.675), Financials share prices: 0.006 (0.039): Industrial share prices: 0.006 (0.039), Price-dividend ratio: 0.377 (0.084), Price-earnings ratio: 0.146 (0.031), Payout ratio: 0.388 (0.037), Long term bond: 0.185 (0.908), Treasury bill rate: 0.246 (1.366), Term-spread: 0.858 (1.932), Money market rate: 0.236 (1.418), DAX: 0.002 (0.028), CAC 40: 0.001 (0.025), S&P 500: 0.001 (0.019), FTSE 100: 0.001 (0.019), NIKKEI: -0.002 (0.028), Hang Seng: 0.003 (0.033), REER: 0.000 (0.013), Broad money supply: 0.005 (0.006), Narrow money supply: 0.005 (0.017), Inflation: 0.003 (0.002), Industrial production: 0.000 (0.012), World oil production: 0.000 (0.004), Oil price: 10.109 (38.477), and Employment rate: -0.001 (0.002).
45 To facilitate comparisons across variables, we divide the explanatory variable by its standard deviation before it enters Equation (1).
[46] The results for the coefficient, R2, WDmax (10% and 5%) and SupF (2|1, 3|2 and 4|3) are available from the authors upon request.

term bond, real effective exchange rate and inflation which have negative signs. Using the t-test statistic and the 10% significance level, the slope coefficient is significant for all variables except financial share price, industrial share price, payout ratio, long term bond, Treasury bill rate, US S&P 500, real effective exchange rate, broad money supply, inflation and world oil production. As is common in the literature, the R^2 statistics show that even when a variable has a significant effect on future equity premium, the predictable component in equity premium tends to be relatively small. Nevertheless, even a small predictable component in equity premium can have important implications for asset-allocation decisions (Kandel and Stambaugh, 1996). Andrews (1993) $SupF$ statistics for testing the null hypothesis of no structural change are reported in column (2) while the corresponding p-values are reported in column (3) of Table 17. As indicated in Section 2 above, we use 15% trimming and generate p-values using the Hansen (2000) heteroskedastic fixed regressor bootstrap. The null hypothesis of no structural change is rejected at 1% significant level in all 23 bivariate predictive regression models. The endogenously selected breakpoints are reported in column (4). The break points for price earnings ratio, price dividend ratio, payout ratio and employment rate occur in 1999:06, 2001:09, 2002:10 and 2005:06 respectively. For the money market and Treasury bill rate, the breakpoint occurs in 2004:03. The breakpoints for the rest of the variables occur in either 2003:11 or 2003:12. Column (5) of Table 17 reports the Elliott and Müller (2003) $\hat{J}$ statistics. Again, we are able to reject the null hypothesis of structural stability in all the 23 predictive regression models. We report the Rossi (2005) QLR_T statistic for each bivariate predictive regression model in column (6) of Table 17. This statistic is designed to be optimal for testing the joint null hypothesis that β_0 and β_1 are constant over time and equal to zero in Equation (1), meaning, a test of no predictability over the entire sample. The null hypothesis is rejected for all of the bivariate predictive regression models.

Next, we employ the Bai and Perron methodology in order to test for multiple structural breaks, and the results are reported in Table 17. Using the $SupF_T(l+1|l)$ statistics and the Bai and Perron sequential procedure, there is evidence of a single structural break for all the variables, as the $SupF_T(1|0)$ statistics are significant. The $SupF_T(2|1)$ statistics are also significant for all variables except employment, suggesting two structural breaks for the other models. Out of the 23 predictive regressions, 8 show at least 5 structural breaks (see Table 17, column 10). Given that the sequential procedure can have low power in the presence of multiple breaks, we also consider the Bai and Perron double maximum procedure, following the recommendation of Bai and Perron (2004). The results are reported in columns 7 and 8 of Table 17. The entire statistics are significant for each of the 23 predictors.

We further investigate the stability of multivariate predictive regression models of equity premium. A difficulty with multivariate predictive regression models of equity premium is selecting the predictors to include in the model. Following Rapach and Wohar (2006), we specify multivariate predictive regression models using the AIC and SIC, with all 23 of the individual variables analysed in the previous section considered as potential predictors. These results are presented lower panel of Table 17. The AIC selects five variables – price-earnings ratio, term spread, money market rate, Hang Seng and employment rate – to include in the multivariate predictive regression model, while the SIC selects three predictors – price-earnings ratio, money market and employment rates Each of the selected variables enters significantly with R^2 statistics of 0.56 and 0.58 for the model selected by AIC and SIC respectively. This indicates a high predictive power of the multivariate models. The $SupF$ statistic based on the heteroskedastic fixed-regressor bootstrap, as well as the $\hat{J}$ statistics are significant at the 1% level, indicating structural instability in the multivariate models selected by both the AIC and SIC. Also, the null hypothesis of no predictability over the entire sample is rejected as the QLR_T statistic is significant for both models. For the two multivariate models, there is strong and significant evidence of structural breaks in both cases. Using the $SupF_T(l+1|l)$ statistics and the Bai and Perron sequential procedure, we find strong evidence of structural breaks for the models selected by both the AIC and the SIC – four breaks are detected for each model. Similar to the Bai and Perron sequential procedure, the Bai and Perron double maximum procedure indicates multiple breaks for the two multivariate models, as the $UD\max$ and the $WD\max$ statistics are significant.

The results for the Bai (1997) subsample procedure for both bivariate and multivariate predictive regressions are reported in Table 18. The Bai (1997) subsample procedure for the bivariate regressions indicates a single significant break for the employment rate, so that there are no breaks in addition to the one reported in Table 17 for this variable. For Financial share price, S&P 500, FTSE 100, NIKKEI, Hang Seng, M3, and inflation, the Bai (1997) subsample procedure in Table 18 detects two significant structural breaks. Four significant breaks were detected for payout ratio, money market rate, DAX, CAC 40 and narrow money supply. For the remaining 10 variables, there is evidence of three significant breaks according to the Bai (1997) subsample procedure in Table 18. The break points occur mostly in 1993, 1994, 1996, 1999, 2003, 2004 and 2007 at different months. There is also strong and significant evidence of structural breaks in the multivariate regressions.

The observed structural breaks so far can now be explained based on certain events that took place in South Africa at different times. The first structural break (in 1993/1994) marks the change to the first democratic government. This period was viewed as a crisis mainly because the closing years of the apartheid government proved extraordinarily expensive and economically crippling [Rustomjee (2006)]. The outgoing administration left escalating fiscal deficits, considerably high levels of domestic indebtedness by the private sector and high levels of debt service costs. The increasingly poor quality of expenditure and an inability to reduce the structural inflationary pressures intensified the crisis. The installation of the democratic administration was coupled with significant outflows, affecting the financial sector negatively [Rustomjee (2006)].

The second year that exhibits a structural break for a number of predictive regression models is 1996. Structural breaks in 1996 may have been caused by the introduction of the democratic government's economic strategy – GEAR (Growth, Employment and Redistribution). This was the basic macroeconomic policy of the South African government. Both global and domestic investors were very critical of the new policy introduces by the government resulting in large capital outflows and as a result, excessive volatility in the economy. The main criticisms included the focus being on macroeconomic variables instead of microeconomic reforms and the lack of consultation preceding its tabling in parliament [Naidoo *et al.* (2008)].

Not surprising, the late 1990s and the early 2000s exhibit structural breaks because of a number of events in the country. Firstly, because of its sophisticated financial markets and substantial private capital flows, South Africa was fully exposed to contagion from the world financial crisis. The weakening of investor confidence in May 1998 and the ensuing downward pressure on the rand was exacerbated by the monetary authorities' large-scale intervention in the foreign exchange market and the uneven stance of monetary policy [Harris (1991)]. Secondly, the political situation also brought uncertainty for South Africa as 1999 was a year when Thabo Mbeki took over Nelson Mandela and the government also announced that Tito Mboweni will take over would take over the then governor of the South African Reserve Bank, Chris Stals. Thirdly, the government announced that South Africa will be adopting an inflation targeting in 2000. Fourthly, the crisis that began in Argentina flooded to other emerging economies with developed financial markets, and South Africa was not immune to it. Prior to the 2001 currency crisis, South Africa was experiencing large short-term capital flows which increased its vulnerability. When investors globally started taking out their money from riskier financial markets – emerging markets mainly – the rand depreciated significantly as this caused panic for South African investors resulting in a currency crisis.

The year 2003 is broadly seen as a start of the global boom that ended in 2007. The US finally recovered from the IT bubble experienced in prior years and economic growth was increasing around potential growth, while the Japanese authorities nationalised a major bank in response to the earlier financial crisis. The global market for securitized assets grew rapidly and investors began demanding more emerging market equities. Asian countries were growing fast, especially China. South Africa was also growing noticeably, with inflation rate moderating to single digits and macro stability maintained. Growth was mainly driven by household consumption, investment, financial and business services, construction, and trade. The budget deficit and the current account were also under control. The 2005 break dictated for employment could be as a result of the redefinition of the measure of employment by Statistics South Africa during this period. The current financial crisis – which started in the US housing market – is a result of the structural breaks for 2007.

Table 19 reports multiple regime bivariate predictive regression model estimation results for models based on each of the 23 predictors. The number of breaks is selected according to the Bai and Perron double maximum procedure, and the breakpoints correspond to the global minimizers in Equation (11). For the financial shares prices, the absolute value of the slope coefficient increased significantly as we move from the first regime, which ends in 1993:5, to the third regime which ends in 1999:10 but declined in the fourth and fifth regimes and slightly increased in the last regime. The slope coefficient was only significant in regime 3. The R^2 recorded for this model is relatively low – the highest R^2 is recorded for the third regime (0.04) – suggesting that financial share prices have weak predictive power. A similar trend is also observed for industrial share prices. We note that the end period for regime 5 which corresponds to the beginning point for regime 6 occur in 2007:10 and this period corresponds to global financial and economic crisis. Therefore, the observed decline in the slope coefficients of financials and industrial share price is not surprising. Even for the industrial share prices, the R^2 values for the different regimes are low, suggesting weak predictive power for the variable. Turning to the price-dividend ratio, it is interesting to note that the slope coefficient is significant in each of the five regimes. The first regime ends in 1994:10, and the slope coefficient grows as we move from the first to the third regime, declined to 22.6 in regime 4 which begins in 2001:08 and to 18.3 in the 5th regime. The 1994 break date corresponds to a period of change to democratic government in South Africa. The 2001 break date corresponds to the currency crisis in 2001. This trend is also seen in the behaviour of the R^2 values for the different regimes. For the first regime, the R^2 value is 0.78, and then declines to 0.4 in the third regime. The R^2 value for the fourth regime rises to 0.78 (the highest R^2 value for the regime in our analysis). The R^2 values show that the price-dividend ratio has a very strong predictive power for the different regimes. For the price-earnings ratio, the slope coefficient is significant in each regime and again grows as we move from the first to the last regime, which begins in 2006:09. There is a slight decline in the second regime which ends in 1999:06. The R^2 values for the price-earnings ratio are the highest for the first regime (0.72), second regime (0.62) and the third regime (0.64), while it remains high for the fourth regime (0.67). In general, our results highlight the importance of valuation ratios as predictors of the behaviour of equity premium in South Africa.

With respect to the payout ratio, the slope coefficient (in absolute value) was 9.53 in regime 1. This increased to 17.5 in regime 2, declined to 7.26 in regime 3, increased to 9.74 and 17.8 in regime 4 and 5 respectively. The slope coefficient was significant in all the regimes. The payout ratio shows a relative strong predictive power only during the third and fourth regimes – with the R^2 values of 0.34 for both regimes. A similar trend holds for long term bond, Treasury bill rate and term spread with the exception that their coefficients were insignificant in one or two of the regimes. For the money market rate, the absolute value of the coefficient was 6.1 in the first regime which ends in 1993:06. By the end of regime 2 in 1996:10, it increased to 22.1. The value declined afterwards until it was 1.17 in the last regime which began in 2007:10. The slope coefficients were significant except for the last regime. Although the predictive power is not as strong as for the valuation ratios, most interest rate variables have some predictive power in some regime. The R^2 values are particularly large in the second and third regimes and, to some extent, the fourth regime. The highest R^2 values are associated with the money market interest rates (0.48) and the term spread (0.46) in the second regime.

The same pattern holds for inflation rate except that inflation's slope coefficient was insignificant in the first and last regimes. For the real effective exchange rate, the slope coefficient declined in absolute value for five regimes except in regime 4 which begins in 2003:12 and ends in 2007:10. For employment rate, the slope coefficient increases from 7.7 in regime 1 which ends in 2005:06 to 20.1 in regime two which begins in the same period. All our results indicate 2005:06 as a break point for employment rate. This could be as a result of the redefinition of the measure of employment by Statistics South Africa. The interpretation for the rest of other variables in the predictive regression models of equity premium follows in similar fashion. The R^2 values for most of these variables are low, suggesting weak predictive power. In general, the estimation results in Table 19 show that most of the variables exhibit structural breaks in 1993/94 at the end of the first regime and in 2007 at the beginning of the last regime. This is not surprising as the 1993/94 break period marks the beginning of democratic rule in South Africa, while the 2007 break period marks the beginning of global financial crisis. Further, the results show that the predictive ability of many variables varies considerably over time, indicating that failure to account for structural breaks in predictive regression models of equity premium can lead one to substantially overestimate or underestimate predictive ability during certain periods.

Table 20 presents estimation results for the multivariate regression model selected by the AIC over the four regimes defined by the structural break dated by the Bai and Perron global minimizer in Equation (11). The breakpoints occur in 1994:10, 1999:6, 2007:10. The R^2 values for the model are significantly high for the different regimes (0.87, 0.80, and 0.78, respectively) – showing significant predictive power. Five regimes were defined by the structural breaks for the model selected by SIC. The breakpoints occur in 1994:10, 1996:6, 2002:10 and 2007:10 – with R^2 values of 0.84, 0.78, 0.46, 0.85 and 0.74, respectively. The multivariate regression models selected by AIC and SIC have significant predictive power compared to most bivariate regression models in our analysis.

Overall, there is strong evidence of a multiple structural breaks in the bivariate and multivariate regressions models, with the structural break formal tests providing significant evidence of structural instability. Also, the R^2 results show that the predictive ability of many variables varies considerably over time, indicating that failure to account for structural breaks in predictive regression models of equity premium can lead one to substantially overestimate or underestimate predictive ability during certain periods.

5. Conclusion

In this Chapter, we test for structural breaks over 1990:01-2010:12 using a large number of predictive regression models for South Africa's equity premium. We test for structural breaks using procedures developed by Andrews (1993), Bai (1997), Bai and Perron (1998, 2003a, 2004), Hansen (2000), and Elliott and Müller (2003). We find strong evidence of structural breaks in bivariate predictive regression models of equity premium based on all 23 financial and macroeconomic variables included. The evidence points to a single structural break in bivariate models of equity premium based on the employment rate. For the remaining 22 variables, there is a minimum of two significant structural breaks. We also find strong evidence of structural breaks in a multivariate predictive regression model of equity premium. Our findings show that that the degree of predictability of equity premium can differ widely across the regimes defined by the structural breaks. The main conclusion of this study is that structural breaks appear prevalent in predictive regression models of South Africa's equity premium. The extensive evidence of structural breaks in the predictive regression models of equity premium in South Africa indicates the need for out-of-sample forecasting schemes that take explicit account of potential structural breaks in predictive regression models as this may improve asset allocation decisions by investors.

Table 17: Structural Break results for different tests for both bivariate and multivariate predictive regressions

Predictor	SupF	p-values	Breakpoint	$\hat{j}$		QLR_T^*		UDmax		WDmax(1%)		SupFT(1|0)		SupFT(5|4)	
Bivariate															
Financials share prices	24.5510	0.00000	Nov-03	-41.1945	***	23.8840	***	105.1734	***	142.9314	***	20.4565	***	14.9064	**
Industrial share prices	24.6580	0.00000	Nov-03	-41.4933	***	26.3290	***	105.3256	***	143.2946	***	20.5168	***	13.6881	**
Price-dividend ratio	37.4860	0.00000	Sep-01	-94.4847	***	22.8270	***	156.3601	***	255.1225	***	37.5857	***	-	
Price-earnings ratio	54.7100	0.00000	Jun-99	-95.7312	***	25.6560	***	122.7763	***	162.5686	***	54.8475	***	-	
Payout ratio	37.8660	0.00000	Oct-02	-68.1151	***	24.0350	***	131.5673	***	180.6476	***	31.1606	***	-	
Long term bond	24.0500	0.00100	Nov-03	-51.2929	***	21.8050	***	108.4992	***	167.6851	***	20.0061	***	28.3566	***
Treasury bill rate	38.2960	0.00000	Mar-04	-57.4139	***	22.6000	***	114.5130	***	175.6970	***	30.4589	***	14.5683	**
Term-spread	46.5900	0.00000	Dec-03	-65.8827	***	25.1120	***	149.2796	***	188.8418	***	35.4489	***	12.5397	**
Money market rate	39.0660	0.00000	Apr-04	-56.3957	***	21.6390	***	119.0094	***	180.5249	***	30.4241	***	12.2607	*
DAX	32.6580	0.00000	Dec-03	-44.3585	***	24.9830	***	104.4272	***	140.6728	***	27.5571	***	10.7416	
CAC 40	36.2300	0.00000	Dec-03	-46.4948	***	48.7630	***	105.4711	***	142.3325	***	30.7511	***	11.2789	
S&P 500	35.2390	0.00000	Dec-03	-48.1456	***	28.1760	***	108.2999	***	143.1709	***	29.7070	***	10.8527	
FTSE 100	32.0780	0.00000	Dec-03	-44.3029	***	21.4490	***	106.2471	***	141.1502	***	27.0599	***	10.6881	
NIKKEI	27.4180	0.00000	Nov-03	-39.7958	***	26.9090	***	100.2465	***	133.4406	***	23.3562	***	10.3113	
Hang Seng	27.0130	0.00000	Dec-03	-41.2414	***	31.4640	***	104.5888	***	139.2395	***	22.4342	***	10.3482	
REER	24.7000	0.00000	Nov-03	-40.4566	***	24.1530	***	105.4499	***	142.3387	***	20.5473	***	10.5243	
Broad money supply	32.0680	0.00000	Nov-03	-42.2690	***	23.8100	***	101.5727	***	136.4723	***	27.5434	***	9.8307	
Narrow money supply	25.5160	0.00000	Nov-03	-40.7558	***	25.7030	***	105.7844	***	141.9093	***	21.2170	***	10.4572	
Inflation	27.3050	0.00000	Nov-03	-43.0966	***	22.0980	***	101.7370	***	139.7537	***	23.6646	***	22.3836	***
Industrial production	27.3720	0.00000	Nov-03	-43.5660	***	22.5840	***	107.5528	***	141.2462	***	23.1550	***	10.5591	
World oil production	24.9860	0.00000	Nov-03	-40.2767	***	25.8310	***	111.2198	***	149.6535	***	20.7829	***	11.8584	*
Oil price	27.2020	0.00000	Nov-03	-53.3435	***	30.4070	***	106.9355	***	165.7511	***	23.4830	***	8.8287	
Employment rate	31.2840	0.00000	Jun-05	-42.0349	***	33.5940	***	65.1676	***	82.4384	***	29.2502	***	3.8997	
Multivariate															
Model selected by AIC	65.5659	0.00000	Jun-95	-166.074	***	33.594	**	151.5384	***	237.1871	***	70.2386	***	14.3997	
Model selected by SIC	47.1277	0.00000	Dec-93	-149.3	***	28.317	***	124.1554	***	151.7522	***	103.4028	***	-	

***, **, * represents 1%, 5% and 10% confidence intervals

Table 18: Bai (1997) subsample analysis, bivariate and multivariate predictive regression models

Predictor	Sample	*SupF*	p-values	Breakpoint
Bivariate				
Financials share prices	1990:01 - 2010:12	24.5510	0.0000	3-Nov
	1990:01 - 2003:11	8.7860	0.1070	Sep-96
	2003:11 - 2010:12	64.4780	0.0000	7-Sep
Industrial share prices	1990:01 - 2010:12	24.6580	0.0000	3-Nov
	1990:01 - 2003:11	9.7800	0.0850	Sep-96
	2003:11 - 2010:12	64.0410	0.0000	7-Sep
Price-dividend ratio	1990:01 - 2010:12	37.4860	0.0000	1-Sep
	1990:01 - 2001:09	102.8100	0.0000	Oct-94
	2001:10 - 2010:12	71.6300	0.0000	6-Nov
Price-earnings ratio	1990:01 - 2010:12	54.7100	0.0000	Jun-99
	1990:01 - 1999:06	152.1300	0.0000	Oct-94
	1999:07 - 2010:12	56.4270	0.0000	6-Oct
Payout ratio	1990:01 - 2010:12	37.8660	0.0000	2-Oct
	1990:01 - 2002:10	26.5460	0.0000	Jun-99
	2002:11 - 2010:12	58.0180	0.0000	7-Jun
	1990:01 - 1999:06	71.2440	0.0000	May-93
Long term bond	1990:01 - 2010:12	24.0500	0.0010	3-Nov
	1990:01 - 2003:11	20.6250	0.0010	Dec-94
	2003:12 - 2010:12	75.4240	0.0000	7-Oct
Treasury bill rate	1990:01 - 2010:12	38.2960	0.0000	4-Mar
	1990:01 - 2004:04	28.5300	0.0000	Nov-94
	2004:05 - 2010:12	54.7870	0.0000	7-Oct
Term-spread	1990:01 - 2010:12	46.5900	0.0000	3-Dec
	1990:01 - 2003:12	19.8290	0.0010	May-93
	2004:01 - 2010:12	85.4180	0.0000	7-Oct
Money market rate	1990:01 - 2010:12	39.0660	0.0000	4-Apr

	1990:01 - 2004:04	15.3690	0.0080	Oct-96
	2004:05 - 2010:12	54.2200	0.0000	7-Oct
	1990:01 - 1996:10	74.8280	0.0000	Jun-93
DAX	1990:01 - 2010:12	32.6580	0.0000	3-Dec
	1990:01 - 2003:12	9.4030	0.0760	Sep-96
	2004:01 - 2010:12	60.2220	0.0000	7-Jun
	1990:01 - 1996:09	28.6350	0.0000	May-93
CAC 40	1990:01 - 2010:12	36.2300	0.0000	3-Dec
	1990:01 - 2003:12	8.6340	0.1120	Oct-96
	2004:01 - 2010:12	57.5440	0.0000	7-Oct
	1990:01 - 1996:10	29.6860	0.0000	May-93
S&P 500	1990:01 - 2010:12	35.2390	0.0000	3-Dec
	1990:01 - 2003:12	8.2960	0.1210	Oct-96
	2004:01 - 2010:12	65.3820	0.0000	7-Oct
FTSE 100	1990:01 - 2010:12	32.0780	0.0000	3-Dec
	1990:01 - 2003:12	8.1560	0.1420	Oct-96
	2004:01 - 2010:12	63.7550	0.0000	7-Oct
NIKKEI	1990:01 - 2010:12	27.4180	0.0000	3-Nov
	1990:01 - 2003:11	8.6770	0.1130	Oct-96
	2003:11 - 2010:12	57.5340	0.0000	7-Oct
Hang Seng	1990:01 - 2010:12	27.0130	0.0000	3-Dec
	1990:01 - 2003:12	7.9710	0.1760	Sep-96
	2004:01 - 2010:12	63.3640	0.0000	7-Oct
REER	1990:01 - 2010:12	24.7000	0.0000	3-Nov
	1990:01 - 2003:11	9.1750	0.0960	Oct-96
	2003:11 - 2010:12	64.0930	0.0000	7-Oct
	1990:01 - 1996:10	27.5960	0.0000	May-93
M3	1990:01 - 2010:12	32.0680	0.0000	3-Nov

	1990:01 - 2003:11	8.8670	0.1090	Sep-96
	2003:11 - 2010:12	52.4950	0.0000	7-Oct
M1A	1990:01 - 2010:12	25.5160	0.0000	3-Nov
	1990:01 - 2003:11	9.0340	0.0870	Oct-96
	2003:11 - 2010:12	62.9320	0.0000	7-Oct
	1990:01 - 1996:10	30.8220	0.0000	May-93
Inflation	1990:01 - 2010:12	27.3050	0.0000	3-Nov
	1990:01 - 2003:11	8.2730	0.1390	Apr-93
	2003:11 - 2010:12	61.6480	0.0000	7-Oct
Industrial production	1990:01 - 2010:12	27.3720	0.0000	3-Nov
	1990:01 - 2003:11	9.0790	0.0950	Sep-96
	2003:11 - 2010:12	75.8060	0.0000	7-Oct
	1990:01 - 1996:09	28.8380	0.0000	May-93
World oil production	1990:01 - 2010:12	24.9860	0.0000	3-Nov
	1990:01 - 2003:11	8.6560	0.1030	Sep-96
	2003:11 - 2010:12	74.5210	0.0000	7-Oct
Oil price	1990:01 - 2010:12	27.2020	0.0000	3-Nov
	1990:01 - 2003:11	43.4530	0.0000	Nov-94
	2003:11 - 2010:12	69.0250	0.0000	7-Oct
Employment rate	1990:01 - 2010:12	31.2840	0.0000	5-Jun
	1990:01 - 2005:06	5.7110	0.3710	May-93
Multivariate				
Model selected by AIC	1990:01 - 2010:12	47.1277	0.0000	Dec-93
	1990:01 - 1995:06	49.9929	0.0000	Oct-94
	1994:01 - 2010:12	54.6002	0.0000	Jul-99
	1999:07 - 2010:12	43.2950	0.0000	7-Oct
Model selected by SIC	1990:01 - 2010:12	65.5659	0.0000	Jun-95
	1990:01 - 1995:07	68.3705	0.0000	Oct-94

	1995:08 - 2010:12	55.7325	0.0000	Jul-99
	1999:07 - 2010:12	30.1886	0.0000	7-Oct

Table 19: Bai and Perron (1998, 2003a, 2004) multiple regime bivariate predictive regression model estimation results

	Regime 1						Regime 2					
	$\hat{\beta}_0$	S.E	$\hat{\beta}_1$	S.E	R^2	End point	$\hat{\beta}_0$	S.E	$\hat{\beta}_1$	S.E	R^2	End point
Financials share prices	-8.468	2.229	-0.119	2.600	0.0004	May-93[Sep-92, Sep-93]	11.124	2.716	-2.922	2.741	0.0376	Sep-96[May-96, Jan-97]
Industrial share prices	-8.086	2.236	-1.820	2.606	0.0127	May-93[Sep-92, Sep-93]	11.092	2.712	-2.827	2.695	0.0330	Sep-96[May-96, Jan-97]
Price-dividend ratio	-64.126	5.487	17.745	1.432	0.7176	Oct-94[Aug-94, Nov-94]	-132.351	17.826	23.951	3.387	0.5424	Jul-98[Sep-97, Aug-98]
Price-earnings ratio	-61.530	5.237	14.781	1.182	0.7203	Oct-94[Aug-94, Dec-94]	-80.862	7.830	13.602	1.503	0.6192	Jun-99[May-99, Jul-99]
Payout ratio	99.644	40.378	-9.537	3.557	0.1649	May-93[Jan-93, Jul-93]	-180.346	20.161	17.259	1.947	0.1233	Jun-99[Mar-99, Oct-99]
Long term bond	-6.251	2.162	-7.099	2.609	0.1500	May-93[Aug-92, Sep-93]	9.929	2.618	-1.289	1.758	0.0141	Oct-96[Apr-96, Feb-97]
Treasury bill rate	-4.330	2.739	-7.412	3.244	0.1129	May-93[Jan-93, Jun-93]	16.750	2.249	18.246	3.140	0.3955	Sep-96[Jul-96, Nov-96]
Term-spread	-8.587	2.201	0.608	2.314	0.0006	May-93[Aug-92, Jun-94]	-9.346	1.442	12.109	1.140	0.4649	Dec-03[Oct-03, Feb-04]
Money market rate	-6.055	2.513	-6.004	4.039	0.0597	Jun-93[Feb-93, Aug-93]	16.008	2.115	21.222	3.355	0.4818	Oct-96[Jul-96, Dec-96]
DAX	-8.493	2.103	3.724	2.251	0.0626	Jun-93[Sep-92, Sep-93]	10.240	2.707	1.466	3.835	0.0226	Sep-96[Dec-95, Apr-97]
CAC 40	-8.510	2.115	3.113	2.069	0.0513	May-93[Sep-92, Sep-93]	10.104	2.628	0.318	3.233	0.0000	Oct-96[Dec-95, May-97]
S&P 500	-8.623	2.170	1.589	2.391	0.0101	May-93[Oct-92, Sep-93]	11.323	2.625	-8.157	4.612	0.0709	Oct-96[Feb-96, May-97]
FTSE 100	-8.533	2.174	0.593	1.905	0.0024	May-93[Sep-92, Sep-93]	10.238	2.649	-1.276	3.361	0.0014	Oct-96[Dec-95, Jun-97]
NIKKEI	-8.358	2.215	0.500	1.666	0.0013	May-93[Sep-92, Oct-93]	10.060	2.620	1.246	2.683	0.0008	Oct-96[Dec-95, Jun-97]
Hang Seng	-9.024	2.199	3.148	2.920	0.0281	May-93[Sep-92, Sep-93]	10.281	2.665	1.672	2.522	0.0108	Oct-96[Dec-95, Apr-97]
REER	-8.264	2.183	-4.930	6.937	0.0111	May-93[Sep-92, Sep-93]	10.055	2.656	-0.383	4.053	0.0001	Oct-96[Dec-95, Jun-97]
M3	-8.091	2.464	-0.698	2.041	0.0023	May-93[Sep-92, Sep-	9.256	3.931	1.252	3.110	0.0073	Oct-96[Nov-95, Apr-

						93]						97]
M1A	-7.700	2.184	-2.698	1.827	0.0484	May-93[Sep-92, Sep-93]	9.582	2.811	1.236	2.482	0.0060	Oct-96[Dec-95, Jun-97]
Inflation	-14.838	5.200	3.128	2.339	0.0485	May-93[Dec-92, Jul-93]	-4.507	5.606	11.953	4.050	0.1922	Sep-96[May-96, Dec-96]
Industrial production	-8.521	2.173	-0.533	2.005	0.0015	May-93[Sep-92, Sep-93]	10.418	2.685	0.013	2.876	0.0000	Sep-96[Dec-95, May-97]
World oil production	-8.536	2.169	-0.638	1.421	0.0053	May-93[Sep-92, Sep-93]	10.275	2.754	0.857	4.042	0.0012	Sep-96[Dec-95, Apr-97]
Oil price	-0.781	2.630	-12.689	4.494	0.1305	Nov-94[Jul-94, Sep-95]	-9.586	1.449	7.764	1.169	0.2880	Nov-03[Sep-03, Jan-03]
Employment rate	2.920	1.429	7.701	1.263	0.1487	Jun-05[Apr-04, Jul-06]	14.263	2.375	20.107	2.293	0.5307	Dec-2010

90% confidence intervals for the endpoints are given in square brackets. Regime 1 begins in 1990:01.

Table 19: Bai and Perron (1998, 2003a, 2004) multiple regime bivariate predictive regression model estimation results, contd

	Regime 3						Regime 4					
	$\hat{\beta}_0$	S.E	$\hat{\beta}_1$	S.E	R^2	End point	$\hat{\beta}_0$	S.E	$\hat{\beta}_1$	S.E	R^2	End point
Financials share prices	-14.283	2.516	4.440	2.677	0.0432	Oct-99[Aug-98, Jul-00]	-1.911	2.454	-3.927	2.709	0.0379	Dec-03[Oct-03, Apr-04]
Industrial share prices	-14.021	2.478	4.908	2.618	0.0554	Oct-99[Jun-98, Aug-00]	-2.029	2.491	-2.239	2.571	0.0144	Dec-03[Oct-03, Apr-04]
Price-dividend ratio	-132.898	23.535	27.364	4.962	0.3927	Aug-01[Jun-01, Nov-01]	-84.253	6.239	22.606	1.456	0.7784	Oct-06[May-06, Dec-06]
Price-earnings ratio	-94.066	8.137	23.187	1.805	0.6442	Sep-06[Mar-06, Jan-07]	-92.921	9.575	19.090	1.908	0.6670	Dec-2010
Payout ratio	71.410	13.695	-7.267	1.360	0.3428	Nov-03[Sep-03, Jan-04]	127.948	23.356	-9.745	2.214	0.3441	Sep-07[Apr-07, Oct-07]
Long term bond	-10.399	2.130	9.000	1.786	0.3048	Jul-01[Mar-01, Oct-01]	2.772	2.325	-16.115	2.725	0.4478	Aug-04[Jun-04, Oct-04]
Treasury bill rate	-15.538	1.887	6.392	1.089	0.4182	Oct-99[Apr-98, May-00]	-3.882	2.396	6.331	2.345	0.1404	Dec-03[Oct-03, Mar-04]
Term-spread	27.217	1.776	-4.215	2.540	0.1016	Oct-07[Jun-07, Nov-07]	-10.098	3.277	14.981	3.339	0.3040	Dec-2010
Money market rate	-8.862	1.724	6.211	1.236	0.2209	Dec-03[Oct-03, Feb-04]	25.684	1.455	-3.589	2.194	0.1240	Oct-07[Apr-07, Nov-07]
DAX	-7.232	1.903	0.801	1.494	0.0018	Dec-03[Oct-03, Mar-04]	24.784	1.620	3.293	3.012	0.0006	Oct-07[Apr-07, Nov-07]
CAC 40	-7.318	1.928	0.906	1.622	0.0026	Dec-03[Oct-03, Mar-04]	24.958	1.576	3.256	3.202	0.0012	Oct-07[Apr-07, Nov-07]
S&P 500	-7.177	1.929	-0.740	1.644	0.0032	Dec-03[Oct-03, Mar-04]	25.477	1.531	0.364	3.085	0.0042	Oct-07[May-07, Nov-07]
FTSE 100	-7.233	1.926	0.270	1.803	0.0001	Dec-03[Oct-03, Mar-04]	25.304	1.543	1.638	3.116	0.0003	Oct-07[Apr-07, Nov-07]
NIKKEI	-6.942	1.925	2.591	2.133	0.0153	Dec-03[Oct-03, Mar-04]	25.140	1.522	2.530	2.476	0.0100	Oct-07[Apr-07, Nov-07]
Hang Seng	-7.258	1.885	2.195	1.586	0.0197	Dec-03[Oct-03, Mar-04]	25.088	1.587	2.404	3.150	0.0023	Oct-07[Apr-07, Nov-07]
REER	-7.236	1.926	-0.205	1.684	0.0002	Dec-03[Oct-03, Mar-04]	25.506	1.492	-0.443	1.401	0.0009	Oct-07[Apr-07, Nov-07]
M3	-7.494	2.342	0.384	1.719	0.0010	Dec-03[Oct-03, Mar-	21.382	2.298	3.563	1.560	0.1225	Oct-07[Mar-07, Nov-

						04]						07]
M1A	-7.693	1.983	1.578	1.763	0.0079	Dec-03[Oct-03, Mar-04]	25.309	1.575	0.717	1.752	0.0001	Oct-07[Apr-07, Nov-07]
Inflation	-6.645	3.512	-7.327	2.672	0.1366	Oct-99[Dec-98, Apr-00]	-7.505	3.418	5.556	2.621	0.0796	Dec-03[Oct-03, Mar-04]
Industrial production	-7.131	1.885	2.511	1.836	0.0182	Dec-03[Oct-03, Mar-04]	25.729	1.526	-0.274	1.720	0.0000	Sep-07[Apr-07, Oct-07]
World oil production	-7.365	1.917	1.224	1.791	0.0042	Dec-03[Oct-03, Mar-04]	25.680	1.460	-3.384	2.187	0.0792	Oct-07[Apr-07, Nov-07]
Oil price	20.878	1.800	9.042	2.553	0.2643	Oct-07[Apr-07, Nov-07]	-10.281	3.826	7.582	3.032	0.1413	Dec-2010
Employment rate					-						-	

90% confidence intervals for the endpoints are given in square brackets. Regime 1 begins in 1990:01.

Table 19: Bai and Perron (1998, 2003a, 2004) multiple regime bivariate predictive regression model estimation results, contd

	Regime 5						Regime 6					
	$\hat{\beta}_0$	S.E	$\hat{\beta}_1$	S.E	R^2	End point	$\hat{\beta}_0$	S.E	$\hat{\beta}_1$	S.E	R^2	End point
Financials share prices	25.554	1.497	-0.433	1.365	0.0049	Oct-07[Apr-07, Nov-07]	-8.025	4.051	-1.362	3.246	0.0062	Dec-2010
Industrial share prices	25.556	1.504	-0.297	1.344	0.0034	Oct-07[Apr-07, Nov-07]	-8.257	4.112	0.252	3.566	0.0000	Dec-2010
Price-dividend ratio	-86.645	9.817	18.311	2.019	-						-	
Price-earnings ratio					-						-	
Payout ratio	178.216	73.357	-17.782	7.014	-						-	
Long term bond	28.334	1.674	-2.450	2.543	0.0009	Oct-07[May-07, Nov-07]	-8.815	3.872	-10.509	5.596	0.4492	Dec-2010
Treasury bill rate	25.646	1.474	-2.985	2.450	0.0945	Oct-07[Apr-07, Nov-07]	-7.096	4.257	-3.692	4.805	0.0236	Dec-2010
Term-spread					-						-	
Money market rate	-7.781	4.317	-1.170	4.267	-						-	
DAX	-7.514	3.883	6.786	3.682	-						-	
CAC 40	-6.717	3.911	6.798	3.424	-						-	
S&P 500	-7.102	3.837	5.866	2.701	-						-	
FTSE 100	-7.426	3.858	5.900	2.964	-						-	
NIKKEI	-7.273	4.038	4.005	3.349	-						-	
Hang Seng	-8.013	3.965	4.082	3.407	-						-	
REER	-8.211	4.042	0.149	3.081	-						-	
M3	-8.024	5.008	-0.344	5.718	-						-	
M1A	-8.781	4.186	3.356	6.674	-						-	
Inflation	24.743	2.490	0.967	2.494	0.0117	Oct-07[Apr-07, Nov-07]	-6.145	5.135	-1.840	2.862	0.0072	Dec-2010
Industrial production	-7.319	3.668	9.312	3.537	-						-	Dec-2010
World oil production	-8.353	3.924	8.480	5.695	-						-	Dec-2010
Oil price					-						-	
Employment rate					-						-	

90% confidence intervals for the endpoints are given in square brackets. Regime 1 begins in 1990:01.

Table 20: Bai and Perron (1998, 2003a, 2004) multiple regime multivariate predictive regression model estimation results

	Regime 1				Regime 2				Regime 3			
	$\hat{\beta}_0$	$\hat{\beta}_1$	R^2	End point	$\hat{\beta}_0$	$\hat{\beta}_1$	R^2	End point	$\hat{\beta}_0$	$\hat{\beta}_1$	R^2	End point
Model selected by AIC	-0.235 (0.020)		0.8706	Oct-94[Aug-94, Nov-94]	-0.232 (0.024)		0.7991	Jun-99[Apr-99, Jul-99]	-0.183 (0.016)		0.7768	Oct-07[Feb-07, Mar-08]
Price-earnings ratio		0.059 (0.005)				0.038 (0.005)				0.043 (0.003)		
Term spread		-0.027 (0.005)				0.001 (0.004)				0.015 (0.003)		
Money market rate		-0.002 (0.002)				0.003 (0.003)				0.003 (0.004)		
Hang Seng		0.004 (0.003)				0.002 (0.002)				-0.002 (0.004)		
Employment rate		-0.004 (0.004)				-0.010 (0.004)				0.010 (0.003)		
Model selected by SIC	-0.151 (0.014)		0.8353	Oct-94[Aug-94, Nov-94]	-0.236 (0.019)		0.7820	Jun-99[Apr-99, Aug-99]	-0.055 (0.048)		0.4649	Oct-02[Jun-02, May-03]
Price-earnings ratio		0.038 (0.003)				0.039 (0.003)				0.016 (0.012)		
Money market rate		-0.027 (0.006)				0.009 (0.002)				0.019 (0.005)		
Employment rate		-0.002 (0.005)				-0.009 (0.003)				0.021 (0.008)		

Standard errors are given in parenthesis; 90% confidence intervals for the endpoints are given in square brackets. Regime 1 begins in 1990:01.

Table 20: Bai and Perron (1998, 2003a, 2004) multiple regime multivariate predictive regression model estimation results, contd

	Regime 4				Regime 5			
	$\hat{\beta}_0$	$\hat{\beta}_1$	R^2	End point	$\hat{\beta}_0$	$\hat{\beta}_1$	R^2	End point
Model selected by AIC	-0.048 (0.044)							
Price-earnings ratio		0.010 (0.009)						
Term spread		0.033 (0.006)						
Money market rate		-0.001 (0.007)						
Hang Seng		0.006 (0.008)						
Employment rate		0.030 (0.009)						
Model selected by SIC	-0.264 (0.018)		0.8542	Oct-07[Feb-07, Dec-07]	-0.169 (0.036)		0.7373	Dec-2010
Price-earnings ratio		0.060 (0.004)				0.035 (0.007)		
Money market rate		0.021 (0.004)				0.0036 (0.007)		
Employment rate		0.008 (0.003)				0.031 (0.003)		

Standard errors are given in parenthesis; 90% confidence intervals for the endpoints are given in square brackets. Regime 1 begins in 1990:01.

CHAPTER 8: OUT-OF-SAMPLE EQUITY PREMIUM PREDICTABILITY IN SOUTH AFRICA: EVIDENCE FROM A LARGE NUMBER OF PREDICTORS[47]

1. Abstract

This Chapter uses a predictive regression framework to examine the out-of-sample predictability of South Africa's equity premium, using a host of financial and macroeconomic variables described in Chapters 2, 3 and 4. We employ various methods of forecast combination, bootstrap aggregation, diffusion index and Bayesian regressions to allow for a simultaneous role of the variables under consideration, besides individual predictive regressions and assess both their statistical and economic significance. Our results show that forecast combination methods and diffusion indices improve the predictability of equity premium relative to the AR(1). However, the Bayesian regressions outperform all other models both in terms of statistical (forecasting) and economic (utility) gains.

[47] Forthcoming in Emerging Markets Finance and Trade

2. Introduction

Forecasting stock market behaviour has received great attention in recent years from both academics and policy-makers. The current uncertainties regarding the economic performance of the major global economies (especially the United States and the Euro zone) and the likelihood that the global economy may experience a double-dip recession has continued to emphasise the importance of predicting the behaviour of leading indicators (including stock returns) accurately. Stock and Watson (2003) and Forni *et al.* (2003), amongst others, show that stock prices act as leading indicators in helping predict the behaviour of output and inflation in the economy. In this regard, recently, Gupta and Hartley (forthcoming) have highlighted similar abilities of stock prices for South Africa.

Literature proposes numerous financial and macroeconomic variables as possible predictors of stock markets behaviour including valuation ratios (Gupta and Modise, 2012a,b), such as price-earnings ratio (Campbell and Shiller 1988, 1998; Demirtas and Zirek, 2010; Wu *et al.,* 2012) and price-dividend ratio (Fama and French 1988, 1989); payout ratio (Lamont, 1998); interest rates (Ang and Bekaert, 2001; Campbell, 1987; Cao, 2012); the term spread (Campbell, 1987); stock returns of South Africa's major trading partners (Rapach *et al.*, 2010a); the inflation rate (Fama, 1981); money stock (Geske and Roll, 1983); industrial production and the employment rate (Rapach *et al.*, 2005); world oil production and the refiner acquisition cost of imported crude oil (Peersman and Van Robays, 2009); as well as industrial and financial stock returns (Jiang *et al.*, 2009; Rapach *et al.*, 2011; Neely *et al.*, 2011). Although most studies focus on in-sample tests and conclude that there is significant evidence of return predictability, Rapach *et al.,* (2005) and Goyal and Welch (2008) show that these potential predictors are unable to deliver consistently superior out-of-sample forecasts of equity premium relative to a benchmark; autoregressive model of order one or a random walk model respectively.

In highlighting the importance of out-of-sample tests for evaluating equity premium predictability, Pesaran and Timmermann (1995) demonstrate the relevance of model uncertainty and parameter instability for stock return forecasting. Model uncertainty recognises that the best model and its corresponding parameter values are generally unknown. Parameter instability suggests that the best model, if selected, can change over time. Model uncertainty and parameter instability are highly relevant for equity premium forecasting because of the connection between business-cycle fluctuations and equity premium predictability since these factors are also relevant to macroeconomic forecasting. The substantial model uncertainty and parameter instability surrounding the data-generating process for equity premium render out-of-sample predictability challenges. To address these, literature provides forecasting tools that deliver statistical and economically significant out-of-sample gains. To improve out-of-sample equity premium based on these variables, to address the model uncertainty and to deal with parameter instability, we propose four approaches – bagging forecasts, combination of model forecasts, principal component and Bayesian regressions – based on monthly data with the in-sample covering the period from 1990:01 to 1996:12, while the out-of-sample covering the period from 1997:01 to 2010:12. While, the starting date and the end point of the data sample is contingent on data availability, the choice of the out-of-sample period is driven by the fact that this period encompasses a host of domestic and global events that are likely to have affected the South African stock market. The out-of-sample period covers events such as the Asian financial crisis, South Africa's decision to move to an inflation targeting regime in 2000, the currency crisis in late 2001, and finally the US sub-prime crisis.

The first approach we use applies bootstrap aggregating (bagging) to a general-to-specific procedure based on a general dynamic linear regression model with the 23 possible predictors. Following Rapach and Strauss (2010), we construct the bagging forecasts using a moving-block bootstrap. The second approach is to combine individual forecasts using a number of different methods proposed in recent financial literature. There is evidence (see Bates and Ganger, 1969 and Rapach *et al.*, 2010b) showing that combining individual forecasts tends to outperform the individual forecasts themselves. Forecast combination methods are proven to generate consistent and significant out-of-sample gains and link out-of-sample predictability to the real economy (Rapach *et al.*, 2010b and Kong *et al.*, 2009). We analyse combination forecasts formed as weighted averages of the 23 individual predictive regression model forecasts for a period starting from 1997:01. The methods we consider include: simple averages, discounting (Stock and Watson, 2004), clusters (Aiolfi and Timmermann, 2006), and principal components (Neely *et al.,* 2011). Note, in addition to forecast combination via principal components, we also look at forecasting capabilities of predictive regressions based on principal components extracted from the entire data set. Our last approach is to assess the out-of-sample predictability of equity premium of South Africa using the Bayesian regression methods under the Gaussian and double-exponential priors used by De Mol *et al.* (2008). De Mol *et al.*

(2008) show that forecasts produced by Bayesian regression models are highly correlated with principal component forecasts and perform equally well, if not better, for a wide range of prior choices.

To test the out-of-sample forecasts, we employ the out-of-sample R^2 statistic, R_{OS}^2, developed by Campbell and Thompson (2008), which measures the reduction in the mean squared forecast error (MSFE) for a predictive regression forecast relative to a benchmark forecast (Rapach *et al.*, 2010b and Kong *et al.*, 2009). Because the R_{OS}^2 does not explicitly account for the risk borne by an investor over the out-of-sample period, we follow Marquering and Verbeek (2004), Campbell and Thompson (2008), Goyal and Welch (2008), and Wachter and Warusawitharana (2009) and compute realised utility gains for a mean-variance investor on a real-time basis. Goyal and Welch (2008) show that out-of-sample criteria are crucial in assessing equity premium predictability. Additionally, we provide statistical explanations for the relatively good out-of-sample performance of forecast combination regarding the equity premium. Using forecast encompassing tests we are able to explain the econometric sources of the benefits of forecast combination. In our analysis, however, we only compare the forecasts from our best model (which happens to be the Lasso: LARS) with forecasts from individual regressions and other combination models.

For individual regressions, our results emphasise the importance of interest rate variables in explaining the behaviour of equity premium, relative to the bench mark AR(1) model. The interest rate variable that exhibit highest utility gains is the term spread, which is around 12 per cent at an annualised rate. Barring the inflation rate, no other variable show significant forecasting gains over the out-of-sample relative to the AR(1) model As expected, combining information across individual regressions outperforms individual forecasts themselves and our results show the following; firstly, constructing principal components using the original data and combining those principal components improves the out-of-sample predictability for equity premium in South Africa. Secondly, various combining methods also provide significant out-of-sample gains relative to the benchmark random walk model – with the cluster combining methods and principal component combining methods outperforming other combining methods that we consider. Also interestingly, even though the performance of the bagging model is quite poor, when we take the mean of bagging forecasts and principal component forecast combination methods, the performance markedly improves to the extent that, the model outperforms all the various forecast combination methods. Thirdly, predictive regressions based on the second principal component perform better than forecast combination methods. But, the Bayesian regression forecasts outperform the individual regression forecasts, the bagging model, the alternative combining methods and principal component regressions. The utility gains for the Bayesian regression forecasts are significantly higher than for the other combination model forecasts and the individual regression models – with the LASSO:Landweber having the highest utility gain of 65.35 per cent at an annualised rate. The forecast encompassing test results further substantiate the importance of the Bayesian regressions in explaining South African equity premium behaviour. The remainder of the Chapter is structured as follows: The econometric models are described in Section 2; Section 3 provides the data and discusses the results obtained from the different models; and Section 4 concludes.

3. Econometric methodology

3.1 Predictive regression

We analyse the South African equity premium using a standard predictive regression framework, expressed as:

$$r_{t+1} = \alpha + \beta z_t + \gamma r_t + \mu_{t+1} \tag{1}$$

where r_{t+1} is the equity premium, z_t is the variable whose predictive ability is of interest and μ_{t+1} is the disturbance term. The variable z_t has predictive power when $\beta \neq 0$. We include the lagged equity premium as a control variable when testing the predictive ability of z_t since the estimated value of $\gamma = 0.93$, with a p-value of 0.00. We further divide the total sample of T observation for r_t and z_t into an in-sample portion comprising the first m observations (1990:01 to 1996:12) and an out-of-sample portion made up of the last q observation (1997:01 to 2010:12). The initial out-of-sample forecast of the equity premium based on the predictor z_t is given by:

$$\hat{r}_{i,m+1} = \hat{\alpha}_{i,m} + \hat{\beta}_{i,m}\hat{z}_{i,m} + \hat{\gamma}_{i,m}\hat{r}_{i,m} \tag{2}$$

where $\hat{\alpha}_{i,m}$, $\hat{\beta}_{i,m}$ and $\hat{\gamma}_{i,m}$ are the OLS estimates of α, β and γ in equation 1. The period is then updated by using data available through $m + 1$ in order to generate a second set of forecasts, given by:

$$\hat{r}_{i,m+2} = \hat{\alpha}_{i,m+1} + \hat{\beta}_{i,m+1}\hat{z}_{i,m+1} + \hat{\gamma}_{i,m+1}\hat{r}_{i,m+1} \tag{3}$$

This process is repeated through to the end of the out-of-sample period, generating a series of q out-of-sample forecasts of the equity premium based on $z_{i,t}$, $\{\hat{r}_{i,t+1}\}_{t=m}^{T-1}$.
There has emerged a consensus amongst financial economists suggesting that equity premium tends to be unpredictable and, as a result, could be approximated by a random walk model (Pesaran, 2003). Consequently, our random walk model is defined similar to Campbell and Thompson (2008) and Goyal and Welch (2008) as the historical average of the equity premium. The historical average that serves as a natural benchmark forecast model corresponding to a constant expected equity premium is defined as follows: $\bar{r}_{t+1} = \sum_{j=1}^{t} r_j$. But given the high and significant persistence of the equity premium as discussed above and as suggested by one of the referees, we use the AR(1) model obtained by setting $\beta = 0$ in (1) as our benchmark:
However, following the literature, we report, in Appendix 8.1, results from all the models relative to the historical average as well.

3.2 Bagging forecasts

To define the bagging forecasts we follow a procedure in Inoue and Kilian (2008) and Rapach and Strauss (2010). We specify the bagging model of a one-month-ahead forecast horizon as:

$$r_{t+1} = \alpha + \gamma r_t + \sum_{i=1}^{n} \beta_i z_{i,t} + \mu_{t+1} \quad (4)$$

We estimate r_{t+1} via OLS, using equation 4 with data from 1990:01 through to time t and compute the *t*-statistics corresponding to each predictor. The $z_{i,t}$ variables with *t*-statistics less than 1.645 in absolute value are dropped from equation 4 and the model is re-estimated. The forecast of r_{t+1} is obtained by regressing only the included $z_{i,t}$ variables value into the re-estimated equation 4 and setting the disturbance term to its expected value of zero.
We construct the bagging forecasts by means of a moving-block bootstrap. Basically we generate a large number *B* of pseudo-samples of size *t* by randomly drawing blocks of size *s* (with replacement) from the observations of the equity premium and possible predictors from 1990:01 through to time *t*. We estimate equation 4 using the pretesting procedure to determine the predictors to include in the forecasting model. As specified earlier, r_{t+1} is forecast by adding only the included $z_{i,t}$ variables and values into the re-estimated version of the forecasting model. Even with the moving-block bootstrap, the disturbance term is set to its expected value of zero. The bagging model forecast corresponds to the average of the *B* (which is set to 100) forecast for the bootstrap pseudo-sample. The out-of-sample period comprises of a series of p recursive simulated out-of-sample forecasts using the bagging procedure. The recursive out-of-sample forecast therefore takes the form: $\{\hat{r}_{BA,t+1}\}_{t=R}^{T-1}$, where *R* corresponds to the in-sample for the entire data set of *T* observations.

3.4 Combination forecasts

Following Bates and Granger (1969) and Rapach and Strauss (2010), we use information across individual forecasts via forecast combining methods since combining individual forecasts is known to outperform the individual forecasts themselves. We consider a number of combining methods, and some of these models require a hold-out period to calculate the weight used to combine the individual regression forecasts. For the hold-out period, we use the first P_0 out-of-sample observations (the first five years in our case). With the exception of the Bayesian models, the combination forecasts of r_{t+1} made at time *t*, $\hat{r}_{CB,t+1}$, are a linear combination of the individual regressions constructed above, meaning:

$$\hat{r}_{CB,t+1} = \sum_{i=1}^{n} w_{i,t} \, \hat{r}_{i,t+1} \quad (5)$$

where $\sum_{i=1}^{n} w_{i,t} = 1$.
The weights are constructed using the start of the hold-out period to time *t*. We use a post hold-out period for each of the combining methods (with the exception of the Bayesian models and the simple combining methods), meaning we have a $P_1 = P - P_0$ combination forecast for evaluation. Below is a full discussion on each of the combining forecast models.

3.4.1 <u>Simple combining methods</u>

Following Stock and Watson (2003 and 2004), we look at three combining methods which tend to work well in forecasting using a large number of potential predictors. We assess the mean, median and the trimmed mean. The mean is defined as: $w_{i,t} = \frac{1}{n} (i = 1, \dots, n)$ in equation 5. The median combining method is simply defined as the sample median of $\{\hat{r}_{i,t+1}\}_{i=1}^{n}$. We define the trimmed mean combination forecast as $w_{i,t} = 0$ for the individual forecast with the smallest and largest forecasts at time *t* and $w_{i,t} = \frac{1}{(n-2)}$ for the remaining individual forecasts in equation 5.

3.4.2 Discount MSFE combining methods

In a discount MSFE, the weights in equation 5 are a function of recent historical forecasting performance of the individual regression models (Rapach and Strauss, 2010 and Stock and Watson, 2004) and are defined as: $w_{i,t} = \rho_{i,t}^{-1} / \sum_{j=1}^{n} \rho_{j,t}^{-1}$, where

$$\rho_{i,t} = \sum_{s=R}^{t-1} \psi^{t-1-s} (r_{s+1} - \hat{r}_{i,s+1})^2 \qquad (6)$$

In this model the discount factor is given by ψ. When $\psi = 1$, there is no discounting and equation 5 produces the optimal combination forecast for the case where the individual forecasts are uncorrelated. A discount factor that is less than 1 places greater importance to the recent forecasting accuracy of the individual regressions. We follow Rapach and Strauss (2010) in selecting the value of the discount factors as 1.0 and 0.9.

3.4.3 Cluster combining methods

Cluster combining methods incorporate persistence in forecasting performance. The procedure we follow was developed by Aiolfi and Timmermann (2006) and used in Rapach and Strauss (2010). The initial combination forecast: $r_{(R+P_0)+1}$ is computed by grouping the individual regression forecasts over the initial hold-out out-of-sample period: $\{\hat{r}_{i,s+1}\}_{s=R}^{R+(P_0-1)}$ $(i = 1, \ldots, n)$ into *H* equal-sized clusters based on MSFE. The first cluster will include those individual regressions with the lowest MSFE values. The second cluster will have the next lowest MSFE values and so on. To construct the first combination forecast, we average the individual regression forecasts of $r_{(R+P_0)+1}$ in the first cluster. The average of the individual regression forecasts of $r_{(R+P_0)+1}$ in the first cluster will be the first combination forecast. We compute the MSFE for the individual regression forecasts $\{\hat{r}_{i,s+1}\}_{s=R+1}^{R+P_0}$ $(i = 1, \ldots, n)$ to form the second combination forecast. The individual regression forecasts are then grouped into H clusters. The average of the individual regression forecasts of $r_{(R+P_0)+2}$ included in the first cluster becomes the second combination forecast. We do this procedure through the end of the available out-of-sample period. Basically we form clusters by computing MSFE using a rolling window. Since the number of clusters serves to define the size of the first cluster, as none of the clusters are used in generating the forecasts and that the greater the number of clusters, the smaller the size of the first cluster, we select $H = 2$ and $H = 3$ (following Rapach and Strauss, 2010 and Aiolfi and Timmermann, 2006).

3.4.4 Principal components combining methods

Another forecasting combination method that we use involves generating a combination forecast using the first *x* principle components of the individual regressions out-of-sample forecasts. The first *x* principal components of the uncentred second moment matrix of the individual regression forecasts are denoted by; $\hat{F}_{1,s+1}, \ldots, \hat{F}_{x,s+1}$ for $s = R, \ldots, t$. The combination forecast of r_{t+1} at time *t* based on the fitted principal components is given by the following regression:

$r_{t+1} = \phi_1 \hat{F}_{1,s+1} + \cdots + \phi_x \hat{F}_{x,s+1} + \mu_{t+1}$ with $s = R, \ldots, t-1$. The combination forecast is given by $\hat{\phi}_1 \hat{F}_{1,s+1} + \cdots + \hat{\phi}_x \hat{F}_{x,s+1}$, where $\hat{\emptyset}_1, \ldots, \hat{\emptyset}_x$ are the OLS estimates of $\emptyset_1, \ldots, \emptyset_x$. Bai and Ng (2002) developed the $\mathrm{IC_{p3}}$ information criterion to select the number of principal components. We use this criterion since other familiar information criteria such as the Akaike Information Criterion and the Schwarz Information Criterion do not always estimate the correct number of factors consistently (see Bai and Ng, 2002).

3.5 Diffusion index (principal component) regression and Bayesian regressions[48]

The use of dynamic factor analysis enables us to effectively summarise information from the 23 variables in our analysis to a small number of principal components. This helps with the problem of in-sample over-fitting when using a large number of variables (Neely *et al.*, 2011 and Ludvigson and Ng, 2007, 2009). We therefore consider the entire sample period (1990:01 to 2010:12) to construct principal components, and in turn, use these principal components individually and together instead of individual predictors (*z*) in equation 1. This model differs from

[48] Please refer to De Mol *et al.,* (2008), Belmonte *et al.,* (2011) and Korobilis (2011) for technical details on these methods.

the principal components combining method discussed earlier, whereby, we combine out-of-sample forecasts obtained from individual predictive regressions.

To select the number of factors to include in our analysis, we use an information criterion described and used in Alessi *et al.* (2010). It is crucial to select the correct number of factors, since we need the factors to be relatively small to avoid the problem of in-sample over-fitting, but not too small, thereby neglecting important information in the 23 individual predictors. The procedure that we follow selects the number of factors by correcting for the tendency of traditional criteria to overestimate the true number of factors. It is quite well-known that when the number of variables, from which principal components are to be extracted, are small relative to the number of data points, the Bai and Ng (2002) criteria does not have a minimum, and hence, cannot lead to an optimal choice of the number of factors. Based on Alessi *et al.* (2010), we extract two factors, which are found to be sufficient and efficient in summarising the information contained in the 23 possible predictors.

In order to identify these two factors, Figures 6 and 7 plots the marginal R^2 of the bivariate regression involving the two factors on each of the 23 predictors. Figures 6 and 7 show that the first constructed factor contains more information from the financial variables, whereas the second principal component contain information from the macroeconomic variables. Hence, the principal component 1 can be dubbed a financial factor, while the principal component 2 can be called the macroeconomic factor.

Figure 6: Principal component 1 – representing financial variables

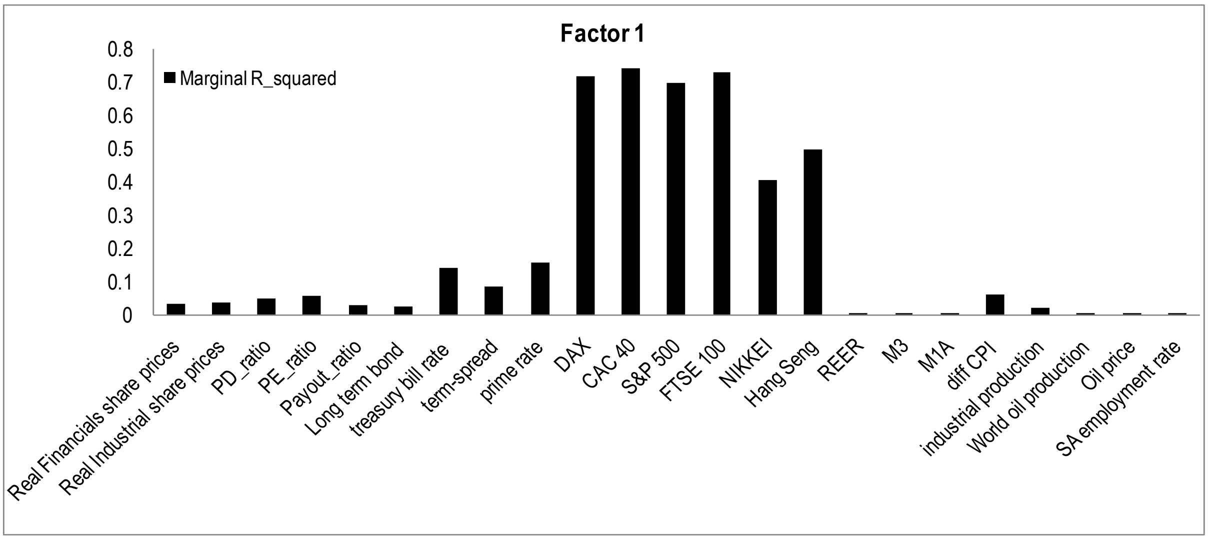
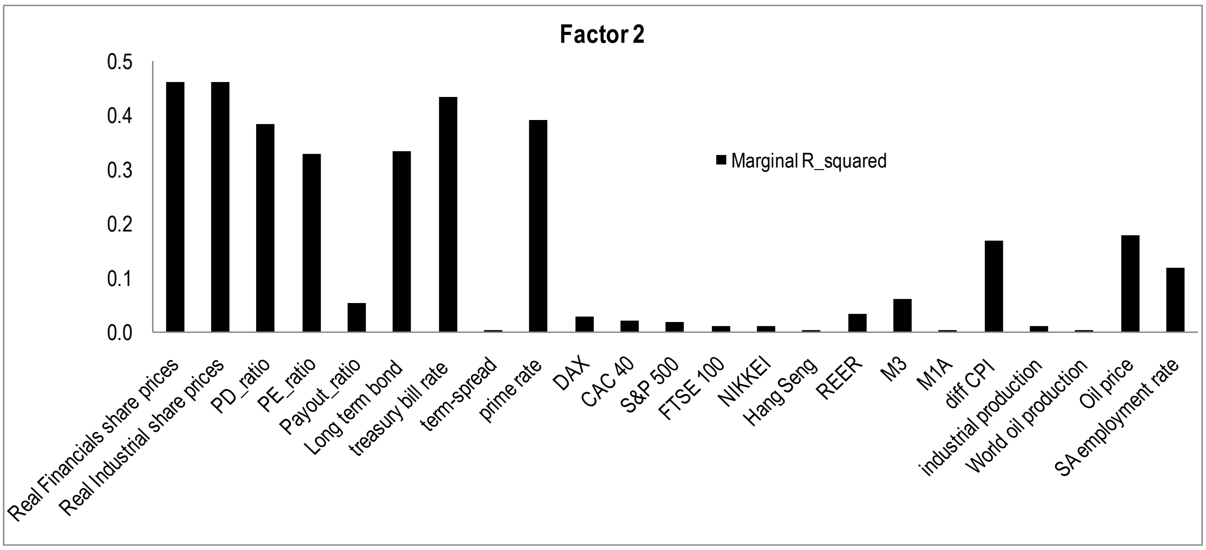


Figure 7: Principal component 2 – representing macroeconomic variables



In addition to analysing principal components based on predictive regressions, we also consider Bayesian regressions to assess the out-of-sample predictability of equity premium using all of the 23 variables together in equation 1. The use of Bayesian regressions to summarise large information sets is becoming widely used in financial literature. Pettenuzzo *et al.* (2008) use Bayesian regressions to forecast out-of-sample equity premium and find that these regressions tend to produce better forecasts than standard models. Other studies that consider the use of Bayesian regressions to forecast equity premium, although not always focusing on the out-of-sample predictive ability, include Stambaugh (1999), Avramov (2002), Cremers (2002) and Dangl and Halling (2007). Following De Mol *et al.* (2008), we choose two types of priors for the Bayesian regressions corresponding to the cases of variable aggregation and variable selection. In the case of the Gaussian prior, the maximized posterior distribution generates coefficients implying that all the predictors, including the lagged excess returns, in the panel are given non-zero coefficients. Unlike the principal component regressions, which involve regressors that are linear combinations of all variables in the panel with unit weight to the dominant ones and zero to the others, the Gaussian prior gives decreasing weight to the ordered eigenvalues of the covariance matrix of the data. On the other hand, the double-exponential prior puts more mass near zero and in the tails, and thus, induces a tendency of the coefficients maximizing the posterior distribution to be either large or zero. As a result, it leads to a sparse specification with a recovery of a few large coefficients instead of many small ones and truly zero rather than small values, resulting in variable selection rather than in variable aggregation.

Under the Gaussian prior, it is relatively simple to compute the maximiser of the posterior density, since, with independent and identically distributed (*i.i.d.*) regression coefficients, the solution amounts to solving a penalised least-squares of the coefficients (the Ridge regression problem). The double-exponential prior, on the other hand, does not have an analytical form for the maximiser of the posterior density, but under the prior of *i.i.d.* regression coefficients, the solution boils down to a Least Absolute Shrinkage and Selection Operator (Lasso) regression problem. Following De Mol *et al.* (2008) we also consider two algorithms for the Lasso regression, the least angle regression (LARS) and the iterative Landweber scheme with soft-thresholding at each iteration. Lasso regression combines variable selection and parameter estimation, with the estimator depending in a non-linear manner on the variable to be predicted. Literature shows that, although the Gaussian and the double-exponential priors are estimated differently, an out-of-sample evaluation for these methods produces similar means squared errors.

3.6 Forecast evaluation

To evaluate the out-of-sample forecasts for different models (individual regressions, combination models, bagging regression, principal component and Bayesian regressions), we use the out-of-sample R^2 statistic, R^2_{OS}. The R^2_{OS} was suggested by Campbell and Thompson (2008) and used by Rapach and Strauss (2010), Rapach *et al.* (2010b), as well as Jiang *et al.* (2009) and it compares $\hat{r}_{t+1}$ (which can either be the individual regressions, combination, bagging, diffusion index and Bayesian regressions forecasts) and the AR(1) model forecasts, $\bar{r}_{t+1}$. The R^2_{OS} is generated by:

$$R^2_{OS} = 1 - \frac{(\sum_{k=q_0+1}^{q} r_{m+k} - \hat{r}_{m+k})^2}{(\sum_{k=q_0+1}^{q} r_{m+k} - \bar{r}_{m+k})^2} \qquad (7)$$

The R^2_{OS} measures the reduction in the MSFE for the individual regressions, combination, bagging, diffusion index and Bayesian regressions forecasts relative to the AR(1) model for the equity premium. This means that the $\hat{r}_{t+1}$ forecast outperforms the AR (1) when $R^2_{OS} > 0$, while a $R^2_{OS} < 0$ suggests that the walker(1) outperforms the other models.

We further test whether the individual regressions, combination, bagging, diffusion index and Bayesian regressions forecasts have a significantly lower MSFE than the benchmark AR(1) model forecast. The null hypothesis in this case becomes $R^2_{OS} \leq 0$ against the alternative hypothesis of $R^2_{OS} > 0$. We use the MSFE-adjusted statistic developed by Diebold and Mariano (1995) and West (1996) which generates asymptotically valid inferences when comparing forecasts from nested linear models and is defined as:

$$f_{t+1} = (r_{t+1} - \bar{r}_{t+1})^2 - [(r_{t+1} - \hat{r}_{t+1})^2 - (\bar{r}_{t+1} - \hat{r}_{t+1})^2] \qquad (8)$$

We then regress $\{f_{t+1}\}_{s=m+q_0}^{T-1}$ on a constant and calculating the *t*-statistics corresponding to a one-sided (upper tail) test – with the standard normal distribution.

3.7 Forecasting encompassing test

We further use a forecasting encompassing test[49] to compare the information content in the best performing model, in terms of the highest R_{OS}^2 value, with other models. To construct the forecasting encompassing test, we start by forming an optimal composite forecast of r_{t+1} as a convex combination of the forecast from models i and j, which takes the following form:

$$\hat{r}_{t+1}^* = (1-\lambda)\hat{r}_{i,t+1} + \lambda\hat{r}_{j,t+1} \quad (9)$$

where λ is between 0 and 1. If $\lambda = 0$ (the null hypothesis) then model i forecast encompasses the model j forecast, as model j does not contain any useful information beyond that already contained in model i. However, if $\lambda > 0$ (the one sided alternative hypothesis) then model j encompasses the model i forecast. To test the null hypothesis we use a test statistic developed by Harvey *et al.* (1998). Firstly we define:

$$d_{t+1} = (\hat{\mu}_{i,t+1} - \hat{\mu}_{j,t+1})\hat{\mu}_{i,t+1} \quad (10)$$

where $\hat{\mu}_{i,t+1} = r_{t+1} - \hat{r}_{i,t+1}$ *and* $\hat{\mu}_{j,t+1} = r_{t+1} - \hat{r}_{j,t+1}$ (11)

We then define $\bar{d} = [\frac{1}{q-q_0}]\sum_{k=q_0+1}^{q} d_{R+k}$. We use the modified version of the test statistic, which is defined as:

$$MHLN = \left[\frac{q-q_0-1}{q-q_0}\right][\hat{V}(\bar{d})^{-\frac{1}{2}}]\bar{d} \quad (12)$$

with $\hat{V}(\bar{d}) = (q-q_0)^{-1}\hat{\phi}_0$ and $\hat{\phi}_0 = (q-q_0)^{-1}\sum_{k=q_0+1}^{q}(d_{R+k} - \bar{d})^2$.

In essence, our results only show the null hypothesis whether the best forecasting model encompasses the other models with an the alternative hypothesis that the forecast from the best performing model does not encompasses the other models.

3.8 Utility gains

In line with Rapach et al (2010b) and Rapach and Zhou (2012), we analyse the equity premium forecasts with profit- or utility-based metric, which provide more direct measures of the value of forecasts to economic agents. A leading utility-based metric for analysing equity premium forecasts is the average utility gain for a mean-variance investor. The first step is to compute the average utility for a mean-variance investor with relative risk aversion θ[50] who allocates his portfolio between stocks and risk-free bills based on the equity premium predictive regression forecasts. This requires the investor to forecast the variance of the equity premium. Following Campbell and Thompson (2007) and Rapach and Zhou (2012), we assume that the investor allocates the following share of his portfolio to equities during $t+1$

$$a_{i,t} = \left(\frac{1}{\gamma}\right)\left(\frac{\hat{r}_{i,t+1}}{\hat{\sigma}_{t+1}^2}\right) \quad (13)$$

where $\hat{\sigma}_{t+1}^2$is a forecast of the variance of the equity premium. The average utility level realised by the investor over the out-of-sample period is given by:

$$\hat{v}_i = \hat{\mu}_i\text{-}0.5\gamma\hat{\sigma}_i^2 \quad (14)$$

where $\hat{\mu}_i$ and $\hat{\sigma}_i^2$ are the sample mean and variance of the portfolio formed on the basis of $\hat{r}_{i,t+1}$ and $\hat{\sigma}_{t+1}^2$ over the out-of-sample forecast evaluation period. If the investor instead relies on the benchmark AR(1) model of the equity premium, he allocates the portfolio share as:

$$a_{0,t} = \left(\frac{1}{\gamma}\right)\left(\frac{\bar{r}_{t+1}}{\hat{\sigma}_{t+1}^2}\right) \quad (15)$$

to equity during $t+1$ and he will realise an average utility level of

$$\hat{v}_0 = \hat{\mu}_0\text{-}0.5\gamma\hat{\sigma}_0^2 \quad (16)$$

where $\hat{\mu}_0$ and $\hat{\sigma}_0^2$ are the sample mean and variance over the out-of-sample period formed on the basis of $\bar{r}_{t+1}$ and $\hat{\sigma}_{t+1}^2$. The difference between equation (14) and (16) represents the utility gain accruing to using the predictive regression forecast of the equity premium in place of the AR(1) forecast in the asset allocation decision. The utility gain is basically the portfolio management fee that an investor is willing to pay to have access to the additional

[49] Forecast encompassing provides a means for comparing the information content in different forecasts. Recent research by Corradi and Swanson (2006) demonstrates the size of the in-sample period relative to the out-of-sample period, type of estimation window (fixed, rolling, or recursive), and whether the models are nested or non-nested can affect the asymptotic distribution of the test statistic. Strictly speaking, all of the conditions required for the validity of the asymptotic distribution may not be met in our case, hence, our inferences based on the MHLN statistic is intended to serve as a rough guide to statistical significance.

[50] Following Rapach and Zhou (2012), we report the utility gains for $\theta = 3$ since the results are qualitatively similar for other reasonable γ values.

information available in a predictive regression model or combination, bagging, diffusion index and Bayesian regressions relative to the information in the AR(1) model alone.

4. Empirical results

The results obtained from different models are discussed in this section and reported in Tables 24 and 25. We begin by discussing the data used in the analysis.

4.1 Data

We use monthly data from 1990:01 to 1996:12 for the in-sample period and 1997:01 to 2010:12 as the out-of-sample period for the equity premium and the possible predictors. The variables are discussed below:

Equity premium: Nominal return on a stock market index (All-share index) in excess of the risk-free interest rate (the Treasury bill rate);

Financials share prices:[51] Real stock returns for the financial sector in South Africa, computed as the first difference in the log-levels of real Financial Stock Index;

Industrial share prices:[52] Real stock returns for the industries in South Africa, computed as the first difference in the log-levels of real Industrial Stock Index;

Price-dividend ratio (log-level): One-year moving sum of the ratio of nominal dividend to nominal stock prices;

Price-earnings ratio (log-level): One-year moving sum of the ratio of nominal earnings to nominal stock prices;

Payout ratio (log-level): The ratio of price-earnings to price-dividend;

Relative long-term bond yield: Difference between the long-term government bond yield and a 12-month backward-looking moving average;

Relative 90 days Treasury bill rate: Difference between the 90-day Treasury bill rate and a 12-month backward-looking moving average;

Term spread: Difference between long-term government bond yield and the 90-day Treasury bill rate;

Relative money market rate: Difference between the prime rate and the 12-month backward-looking moving average;

DAX (log-level): The real stock returns for Germany, computed as the first difference of the real DAX (Deutscher Aktien-Index) – a blue chip stock market index consisting of the 30 major German companies trading on the Frankfurt Stock Exchange;

CAC (log-level): The real stock returns for France, computed as the first difference of the real CAC 40 (the benchmark French stock market index);

S&P 500 (log-level): The real stock returns for the US, computed as the first difference of the real S&P 500, which is the free-float capitalisation-weighted index of the prices of 500 large-cap common stocks;

FTSE 100 (log-level): The real stock returns for the United Kingdom, computed as the first difference of the real FTSE 100 all-share index, which is a capitalisation-weighted index of around 100 companies traded on the London Stock Exchange;

NIKKEI (log-level): The real stock returns for Japan, computed as the first difference of the real Nikkei 225 stock index for the Tokyo Stock Exchange;

Hang-Seng (log-level): The real stock returns for Hong Kong, computed as the first difference of the real Hang Seng Index, which is a free float-adjusted market capitalisation-weighted stock market index;

Real effective exchange rate: First difference in log-levels of real effective exchange rate index;

Broad money supply growth rate: First difference in the log-levels of real broadly defined money stock;

Narrow money supply growth rate: First difference in the log-levels of real narrowly defined money stock;

The inflation rate: First difference in the log-levels of the consumer price index;

Industrial production growth rate: First difference in the log-levels of industrial production;

Employment growth rate: First difference in the log-levels of employment;

World oil production growth rate: First difference in the log-levels of the world oil production; and

Crude oil price growth rate: Refiner acquisition cost of imported crude oil growth rate in real terms. To obtain the rand denominated price, we use the rand/dollar exchange rate, and then deflate the nominal value using the consumer price index to obtain the real crude oil price.

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[51] Jiang *et al.* (2009), Neely *et al.* (2011), Rapach *et al.* (2011), amongst others, suggests that sub-sectors of the overall share index (such as financial and industrial stock prices) are also possible predictors of equity premium.

[52] See above footnote.

We used monthly data obtained from the South African Reserve Bank, Statistics South Africa, Bloomberg and the US Energy Information Administration. Further, barring the Treasury bill rate and the inflation rate, for which we use the first difference, all the other variables were found to be stationary based on standard unit roots tests. Following Rapach *et al.* (2005), we measure interest rate variables as deviations from a backward-moving average. This is because, if real interest rates play a crucial role in determining stock returns, then measuring the interest rate as deviations from a backward-looking moving average tends to make the nominal interest rate effectively a real interest rate. That is, the behaviour of expected inflation is such that most of the fluctuations in the relative nominal interest rate reflect movements in the relative real component. We also use growth rates for the other variables, all in an effort to have variables that are stationary.

4.2 Out-of-sample equity premium predictability

Table 24 reports the out-of-sample R_{OS}^2, for each of the individual predictive regression models, combining methods, bagging regression, principal component and Bayesian regression models relative to the benchmark AR(1) model. For R_{OS}^2 statistics greater than zero, the statistical significance is assessed with the Clark and West (2007) MSFE-adjusted statistics discussed earlier. The results for the utility gains for these models are also reported in Column 3 of Table 24. From Table 24, we see that only 5 (price-dividend ratio, relative Treasury bill rate, term spread, relative money market rate and the inflation rate) out of the 23 predictors used in this Chapter, produce better forecasts than the AR(1) model. Out of these 5 predictors, the R_{OS}^2 is insignificant for the price dividend ratio, while the same is significant at 1 per cent level for the other three interest rate based predictors, and at 10 per cent level for the inflation rate. Barring financial share prices, for which there is no forecasting gains relative to the AR(1) model, the remaining 18 predictors are outperformed by the AR(1) model. When we compare these results with the random walk (historical average) used as the benchmark (reported in Table A1 in Appendix 8.1), instead of the AR(1) model, we find that 18 of the 23 individual predictive regressions have positive R_{OS}^2, two of which are less than or equal to 0.26 per cent (making them statistically insignificant). The significant R_{OS}^2 (significant at least at 10 per cent level of significance) vary from 0.47 per cent for the FSTE 100 stock returns to 9.26 per cent for relative money market rate. The individual regressions for the payout ratio, DAX returns, the real effective exchange rate, the oil price and the employment growth are outperformed by the benchmark random walk model. Overall, the interest rate variables and the stock returns for some of South Africa's major trading partners exhibit some out-of-sample forecast – emphasising the importance of these variables when predicting equity premium for South Africa. Also, we find some out-of-sample predictive power from other variables, with only the employment being outperformed by the benchmark random walk model. Our results suggest that most of the variables included in our analysis contain important information for explaining the behaviour of the equity premium in South Africa, when using the historical average as the benchmark. So, we observe evidence of relatively more predictability when using a weaker benchmark (the random walk model) in some sense, instead of the AR(1) model, which accounts for high and significant persistence in the equity premium.

As far as the economic significance of the results are concerned, 12 out of 23 predictors produce utility gains relative to the AR(1) model, implying that even though some of the predictors might not produce statistical gains in terms of forecasting, implying that an investor is willing to pay a portfolio management fee to have access to the additional information available in a predictive regression model than can be obtained from the AR(1) model. Positive utility gains are obtained for financial and industrial share price, the valuation ratios, relative Treasury bill rate, term spread and relative money market rate, the stock returns based on the DAX, CAC 40 and S&P 500, oil price and employment growth. Interestingly, the highest utility gains are obtained from the interest rate variables, which in turn, also produce the highest forecasting gains. The inflation rate, however, fails to produce utility gains even after producing significant forecasting gains.

Table 21: One-month ahead forecasting and encompassing test results for the individual regressions, combining methods, bagging, principal component and Bayesian regressions:

	R^2_{OS} (per cent)	Utility gains Annual percent	Best model (LARS) Encompasses other model (p-values)		R^2_{OS} (per cent)	Utility gains Annual percent	Best model (LARS) Encompasses other model (p-values)
Individual forecasts				***Combination forecasts***			
Financials share prices	0	1.37	0.83	Principal component 1	-0.44	-3.22	0.86
Industrial share prices	-0.31	1.62	0.89	Principal component 2	3.76***	9.79	0.76
Price dividend ratio	0.03	0.50	0.90	BA model	-3.55	37.16	0.99
Price earnings ratio	-0.56	0.85	0.86	Both Principal Components 1 and 2	3.97***	3.99	0.72
Payout ratio	-1.49	-17.94	0.97	Mean	1.43**	0.50	0.84
Relative long term bond yield	-0.11	-14.79	0.87	Median	0.50*	-0.37	0.82
Relative treasury bill rate	6.76***	4.76	0.63	Trimmed mean	0.39*	0.50	0.95
Term spread	3.02***	11.89	0.79	DMSFE (delta = 1.0)	1.45**	0.42	0.88
Relative money market rate	8.07***	3.81	0.62	DMSFE (delta = 0.90)	1.61**	-0.65	0.87
DAX	-1.39	1.68	0.97	C(2,PB)	2.13***	-0.48	0.89
CAC 40	-1.04	2.37	0.95	C(3,PB)	2.86***	-2.11	0.76
S&P 500	-1.27	1.25	0.92	PC(IC_p3)	3.08***	35.90	0.74
FTSE 100	-0.83	-0.54	0.98	BA and PC(IC_p3)	3.16***	40.36	0.72
NIKKEI	-0.41	-2.94	0.83	Ridge	13.04***	58.39	0.21
Hang Seng	-0.35	-1.53	0.90	Lasso: LARS	21.70***	58.39	
Real effective exchange rate	-1.34	-2.04	0.96	Lasso: Landweber	20.93***	65.35	0.13
Broad money supply	-0.65	-3.09	0.97				
Narrow money supply	-0.41	-1.16	0.88				
Inflation	1.20*	-5.52	0.83				
Industrial production	-0.6	-1.07	0.92				
World oil production	-0.32	-0.15	0.94				
Oil price	-2.83	4.15	0.91				
Employment growth rate	-1.49	1.45	0.95				

R^2_{OS} is the Campbell and Thompson (2008) out-of-sample R^2, with ***, ** and * indicating significance at 1, 5 and 10 per cent levels respectively. The *p*-values correspond to the forecast encompassing test with the null hypothesis that the best model (Lasso: LARS) forecast encompasses the forecasts from all the other models individually.

Apart from the alternative combination model forecasts and bagging, that we discuss in section 2.3, we also use predictive regressions based on the two principal components that were extracted using the entire sample period from 1990:01 to 2010:12. We looked at these two principal components individually and also considered them simultaneously in the predictive regression model and compared the forecasts with the benchmark AR(1), as well as the random walk model. All the combination model forecasts outperform the benchmark AR(1) model significantly at least at the 10 per cent level of significance – with the R_{os}^2 varying from 0.39 per cent (trimmed mean) to 3.08 per cent (PC_IC_p3). The diffusion index approach based on the principal components yields the following results: while the AR(1) model outperforms the predictive regression based on the first principal component, forecasting gains obtained from the second principal component yields statistical gains at one per cent level of significance. This is not surprising since the second principal component mainly represents the interest rate variables, while the first principal component captures the international stock returns. Forecasting gains are even higher (and also greater than all the combination methods) when we actually use both the principal components, suggesting that information contained in the first principal component can add value to forecasting when used simultaneously with the second principal component.[53] Interestingly, even though the bagging model performs worse than the AR(1) model on its own, when we average the bagging forecasts and the forecasts obtained from the principal component combination method (IC_p3) since it performs the best among combination methods used, the model performs better than the AR(1) model.54 In fact, this model produces the highest R_{os}^2 amongst all the forecast combination methods, but cannot beat the performance of the diffusion index model based on both the principal components. As can be seen from Table A1, barring that the predictive regression model based on the first principal component also outperforms the random walk model when used as the benchmark, the remaining results are qualitatively exactly the same for the diffusion index approach, bagging and combination methods as obtained and discussed above with the AR(1) model as the benchmark.

The utility gains, reported in column 7 of Table 24, are, in general, in line with the forecasting performances of the combination, diffusion index and bagging methods. The glaring exception is the bagging model, which produces substantial utility gains of 37.16 per cent at an annualised rate, even when it performed worse than the AR(1) model in terms of forecasting. Otherwise, high utility gains are obtained from the principal component forecast combination, and simple average of the principal component forecast combination and bagging methods.

When analysing the results obtained for Bayesian regressions reported in Table 24, it is important to note the large R_{os}^2 generated by each Bayesian specifications. All the R_{os}^2 are greater than 13 per cent, with the Lasso: LARS having the highest R_{os}^2 of 21.70 per cent – and all the R_{os}^2 are significant at 1 per cent level of significance. Further, the R_{os}^2 statistics for the Bayesian regressions are greater than the largest R_{os}^2 amongst the individual predictive regressions (8.07 per cent with the relative money market rate) and the combination, bagging and diffusion index approaches (3.97 per cent for the model that combines the two constructed principal components). Amongst the Bayesian regressions, the Ridge regression has the lowest R_{os}^2 value of 13.04 per cent, but is still significantly larger than all the non-Bayesian models. Again (as seen from Table A1), as with the results under the diffusion index approach, bagging and combination methods, the results for the Bayesian regressions with the random walk model used as the benchmark is qualitatively exactly the same as obtained and discussed above with the AR(1) model as the benchmark. Note that for the Bayesian (Ridge) regression, we run the regression using the first estimation sample 1990:1-1996:12 for a grid of priors. We then choose the priors for which the in-sample fit explains a given fraction of the variance of the excess returns. In our case, the ridge regression produced the lowest MSFE when 90 per cent of the variance of the excess stock return was explained.

For the double-exponential prior under the two alternative algorithms, we select the prior that delivers a given number of non-zero coefficients at each estimation step in the out-of-sample evaluation period. We look at the cases of 1 to 24 (we now also include the lagged value of the equity premium as one of the regressors) non-zero coefficients. We found the 5 non-zero coefficients produced the minimum MSFE under the double exponential

[53] A potential drawback of the diffusion index model is that the estimated factors are designed to explain the covariation among the individual predictors themselves, without explicitly taking into account the relationship between the predictors and the targeted variable that we want to forecast. Kelly and Pruitt (2011) develop a three-pass regression filter (3PRF) to estimate the factors that are the most relevant for forecasting the target. When we used this approach in forecasting the equity premium based on two factors, we obtained significant (at 10 per cent) forecasting gains (R_{os}^2=0.83) relative to the AR(1) model, which in turn, is way less than the forecasting gains obtained from the standard diffusion index approach discussed in the main text. The details of these results are available upon request from the authors.

[54] Rapach and Strauss (2010) also obtained a similar result when forecasting employment growth for the US.

prior for both the LARS and Landweber algorithms. We therefore examine the five variables selected at the beginning (1997:01) and at the end (2010:11) of the sample out-of-sample evaluation period. There are a number of results that emerges from Table 25. Firstly, the variables that are selected by both the Lasso: LARS and the Lasso: Landweber are inconsistent across time horizons and across models. Secondly, the choice of variable selection is not entirely in line with the performance of each variables when using the R_{OS}^2 to evaluate the out-of-sample predictability. Thirdly, for both the Lasso algorithms and time periods, the variables selected include both the financial and macroeconomic variables. The above results suggest that the variables included in these algorithms are not necessarily consistent through time as a result of collinearity and hence we have temporal instability (De Mol *et al.*, 2008).

Just like the forecasting gains, the Bayesian models also produce very high utility gains when compared to the individual predictive regressions, the diffusion index approach, bagging and combination methods. The Lasso: Landweber based Bayesian regression produces the largest utility gains.

Table 22: Variables selected using the Bayesian regressions

	1997:01 (First out-of-sample period)	**2010:11 (Last out-of-sample period)**
Variables included in the Lasso: LARS model	Real Financials share prices	Real Financials share prices
	Price dividend ratio	Money market rate
	Payout ratio	S&P 500
	DAX	Industrial production
	Employment rate	Lagged Excess Returns
Variables included in the Lasso: Landweber model	Real Industrial share prices	Payout ratio
	Payout ratio	Term spread
	Money market rate	CAC 40
	NIKKEI	Oil price
	Oil price	Employment rate

We provide statistical explanations for the relatively good out-of-sample performance of the Lasso: LARS with respect to the equity premium. Through the forecast encompassing tests, we are able to show that the Lasso: LARS incorporates useful forecasting information from the macroeconomic and financial variables included in our analysis. Table 24 also reports *p*-values for the MHLN statistic applied to the out-of-sample forecasts. Each entry in the table corresponds to the null hypothesis that the Lasso: LARS forecast encompasses the forecasts for the individual regressions, the diffusion index approach, bagging and combination methods. From Table 24, it is visible that the Lasso: LARS forecast encompasses all models we consider – suggesting that it is important to combine information from individual variables using the Lasso: LARS model specification to incorporate additional information thus explaining the out-of-sample gains corresponding to the Lasso: LARS model. Not surprisingly, this is also the case when we use the historical average as the benchmark, as observed from Table A1.

Following Goyal and Welch (2008) and Rapach and Zhou (2012), Figures 8 presents the cumulative difference in squared forecast errors for the AR(1) forecast relative to the predictive regression forecast. While, Figure 9 does the same relative to the diffusion index approach, bagging, combination methods and Bayesian regressions. This is an informative tool that provides a graphical representation of the consistency and volatility of the forecasting performances of these models over time. When the curves in Figure 8 and 9 are in the positive (negative) plane then the predictive regression model, the diffusion index approach, bagging, combination methods and Bayesian regressions outperforms (is outperformed by) the benchmark AR(1) model. As pointed out in Goyal and Welch (2007), and reiterated in Rapach *et al.*, (2010b), the units on the plots are not intuitive; these plots are, however, useful in determining the how the predictive regressions, diffusion index approach, bagging, combination methods and Bayesian regressions perform in terms of MSFE relative to the benchmark AR(1) model at each point of time over the out-of-sample horizon.

The figures echo the same story as indicated by R_{OS}^2 reported in Table 24. In other words, amongst the 4 variables that show significant forecasting gains, for the relative Treasury bill rate, term spread, relative money market rate, the cumulative difference in squared forecast errors for the AR(1) forecast relative to the predictive regression forecast is consistently positive. As far as the inflation rate is concerned, the graph remains in the negative plane for most of the out-of-sample period, but high forecasting gains are registered during the "Great Recession". The high forecasting gains form the price dividend ratio during and after the financial crisis produces the positive, but insignificant R_{os}^2. Interestingly, for many of the other predictors which produces negative R_{os}^2, forecasting gains are observed based on the predictors relative to the AR(1) model during the recessionary period of 1997:1-1999:8, but not during the recession of 2007:12-2009:08. In general, the graphs are more volatile during the recession, emphasising the difficulty in predicting equity premium during downturns relative to the benchmark.

As with individual predictive regression models, the cumulative difference in squared forecast errors for the AR(1) forecast relative to the diffusion index approach, bagging, combination methods and Bayesian regressions forecast is consistently positive for all the cases, barring the bagging approach and the predictive regression based on the first principal component (financial variable) for which R_{os}^2<0. But again, for these two cases, forecasting gains are observed based relative to the AR(1) model during the recessionary period of 1997:1-1999:8, but not during the recession of 2007:12-2009:08. The graphs depict minimal volatility, irrespective of whether the economy is in an upturn or a downturn for the Bayesian regressions; thus highlighting their superiority in terms of forecasting performances.

Figure 8: Cumulative square predictive error for the AR(1) minus the cumulative square predictive error for the individual regressions

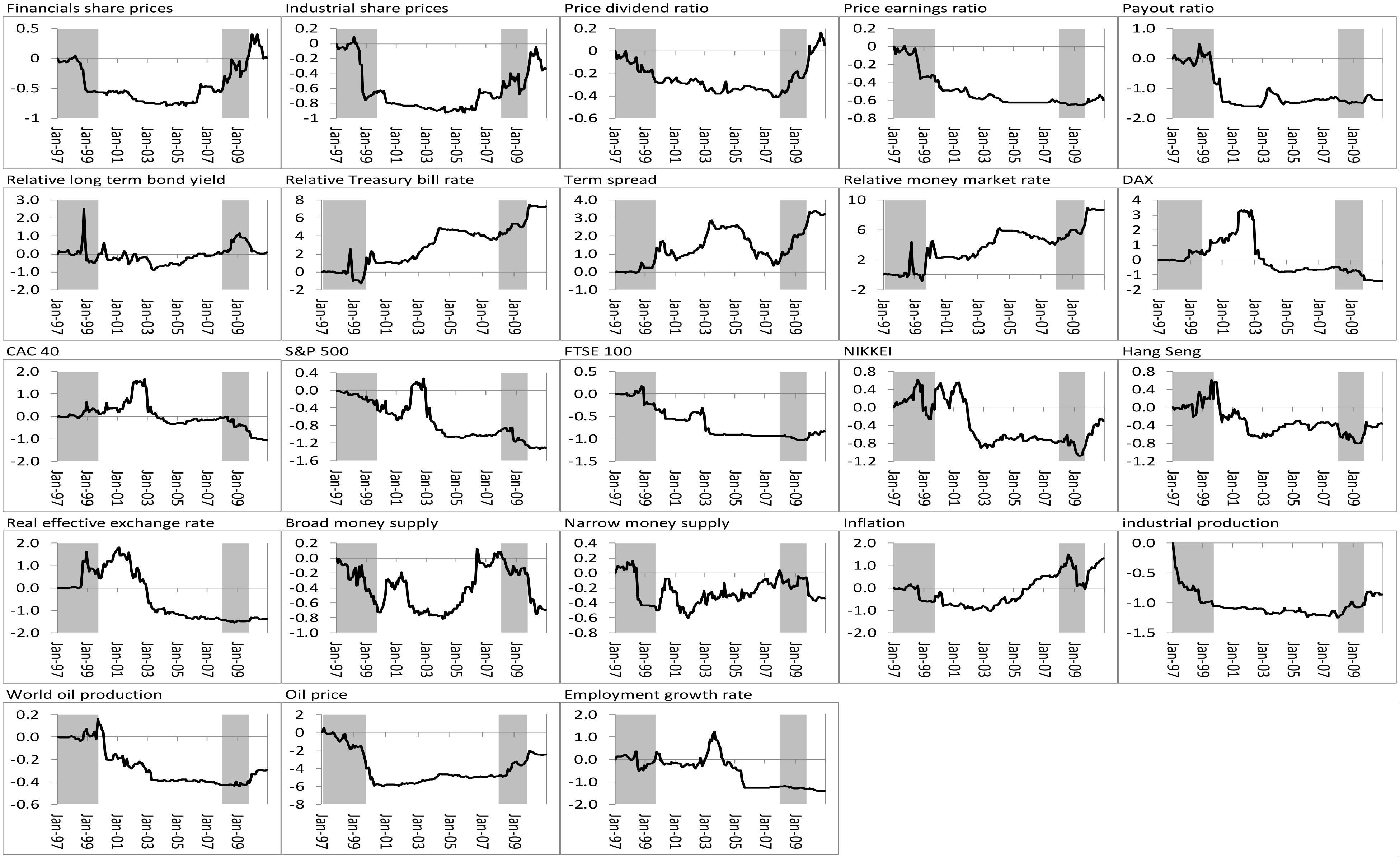
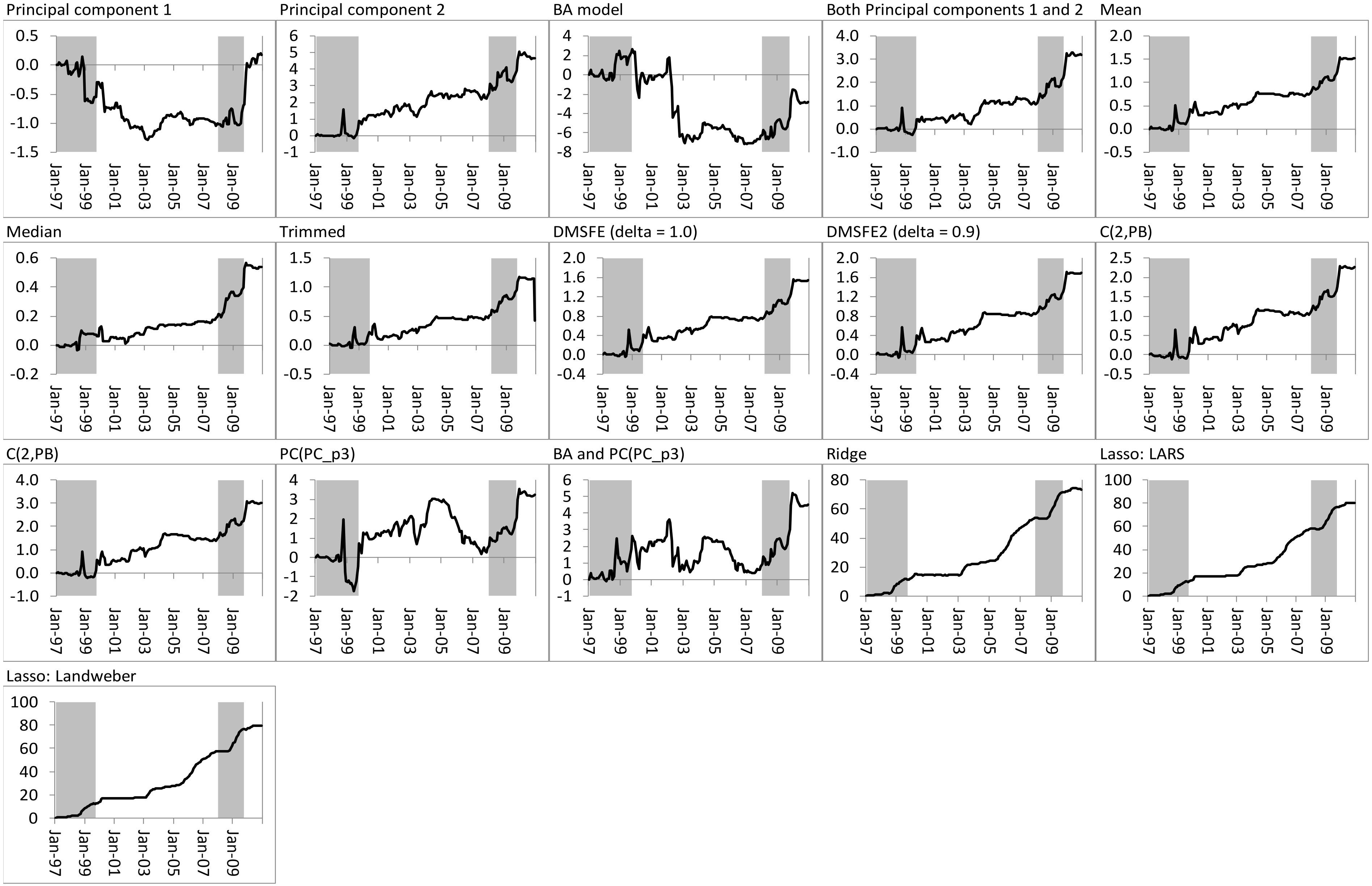


Figure 9: Cumulative square predictive error for the AR(1) minus the cumulative square predictive error for the combination models



5. Conclusion

The aim of this study is to analyse the predictability of South Africa equity premium considering financial and macroeconomic variables using monthly data from 1990:01 to 2010:12 for the out-of-sample period of 1997:01 to 2010:12 period. The literature suggest that combining individual forecasts is known to outperform the individual forecasts themselves, we therefore use a number of combination model forecasts, besides, bootstrap aggregation (bagging), principal component and Bayesian regressions to simultaneously incorporate information from 23 possible predictors. We find that only four (the relative money market rate, relative treasury bill rate, the term spread and the inflation rate) of the 23 predictors significantly outperforms the benchmark AR(1) model. However, in terms of economic significance, 12 of the 23 predictors produce positive utility gains, with term spread producing the highest utility gains of 11.89 per cent amongst the individual predictors.

As suggested in the literature, all the combination model forecasts outperform the benchmark AR(1) walk model and have R_{os}^2 that are statistically significant at least at 10 per cent level of significance. Though the bagging model performs way poorer than the benchmark, when combined with the principal component based forecast combination method (the best performing forecast combination method), the combination outperforms the AR(1) model and ends up beating all the other forecast combination methods in terms of R_{os}^2. The principal component based predictive regressions, based on the second principal component (depicting macroeconomic variables) and when involving both principal components also perform significantly better than the AR(1) model. The Bayesian regressions (Ridge, Lasso: LARS and Lasso: Landweber) are, however, found to be the standout performers, with these models outperforming forecast combination methods, bagging, the diffusion index approach and all individual predictive regressions. All the R_{os}^2 are greater than 13 per cent, with the Lasso: LARS having the highest R_{os}^2 of 21.70 per cent – and all the R_{os}^2 are significant at 1 per cent level of significance. When using forecast encompassing tests to provide statistical explanations for the relatively good out-of-sample performance of the Lasso: LARS, we find that this model forecast encompasses all other model specifications. This means that the Lasso: LARS incorporates useful forecasting information from the macroeconomic and financial variables included in our analysis. The utility gains are, in general, in line with the forecasting performances of the combination, diffusion index, bagging methods and the Bayesian regressions. The benefits of predicting the equity premium using Bayesian models are also evident in the utility gains for these models. The models have the highest utility gains compared to all other models, with the Lasso: Landweber producing the highest utility gain of 65.35 per cent at an annualised rate.

Appendix 8.1

Table A1: One-month ahead forecasting and encompassing test results for the individual regressions, combining methods, bagging, principal component and Bayesian regressions:

	R^2_{OS} (per cent)	Best model (LARS) Encompasses other model (p-values)		R^2_{OS} (per cent)	Best model (LARS) Encompasses other model (p-values)
Individual forecasts			***Combination forecasts***		
Financials share prices	1.29**	0.82	Principal component 1	0.85**	0.85
Industrial share prices	0.98**	0.88	Principal component 2	5.00***	0.76
Price dividend ratio	1.31**	0.89	BA model	-2.21	0.98
Price earnings ratio	0.74*	0.85	Both Principal Components 1 and 2	5.21***	0.72
Payout ratio	-0.18	0.96	Mean	2.70***	0.83
Relative long term bond yield	1.18**	0.86	Median	1.78***	0.81
Relative treasury bill rate	7.96***	0.63	Trimmed mean	1.67**	0.94
Term spread	4.27***	0.78	DMSFE (delta = 1.0)	2.72***	0.87
Relative money market rate	9.26***	0.62	DMSFE (delta = 0.90)	2.88***	0.86
DAX	-0.09	0.96	C(2,PB)	3.39***	0.88
CAC 40	0.26	0.94	C(3,PB)	4.11***	0.76
S&P 500	0.04	0.91	PC(IC_p3)	4.33***	0.74
FTSE 100	0.47*	0.97	BA and PC(IC_p3)	4.41***	0.72
NIKKEI	0.89**	0.82	Ridge	14.16***	0.21
Hang Seng	0.95**	0.89	Lasso: LARS	22.71***	
Real effective exchange rate	-0.03	0.95	Lasso: Landweber	21.95***	0.13
Broad money supply	0.65*	0.96			
Narrow money supply	0.89**	0.87			
Inflation	2.48***	0.82			
Industrial production	0.69*	0.91			
World oil production	0.97**	0.93			
Oil price	-1.5	0.9			
Employment growth rate	-0.18	0.94			

R^2_{OS} is the Campbell and Thompson (2008) out-of-sample R^2, with ***, ** and * indicating significance at 1, 5 and 10 per cent levels respectively. The *p*-values correspond to the forecast encompassing test with the null hypothesis that the best model (Lasso: LARS) forecast encompasses the forecasts from all the other models individually.

CHAPTER 8: CONCLUSION AND CONTRIBUTION

In recent years, forecasting stock market behaviour has received great attention from both academics and policy-makers. The current uncertainties regarding the economic performance of the major global economies and the likelihood that the global economy may experience a double-dip recession has continued to emphasise the importance of predicting the behaviour of leading indicators (including stock returns) accurately. Recent studies have also highlighted the fact that stock prices help predict the behaviour of output and inflation in South Africa. An understanding of market behaviour helps in guiding both policy and trading decisions. This thesis examines the determinants, spillovers and predictability of stock returns for the South African economy.

Literature suggests that stock returns can be determined by a number of financial and macroeconomic variables that are consider in this thesis. These include valuation ratios (price-earnings ratio and price-dividend ratio), payout ratio, interest rates, the term spread, stock returns of South Africa's major trading partners, the inflation rate, money stock, industrial production and the employment rate, world oil production, the refiner acquisition cost of imported crude oil, global activity index, industrial stock returns and financial stock returns.

The first step in this thesis was to assess the predictive power of valuation ratios. The empirical analysis starts by estimating predictive regression models for growth rate of real stock price with the log-value of either price-dividend or price-earnings ratio acting as the explanatory variable. The size and power properties of the long-horizon regression tests are then analysed using Monte Carlo simulations outlined in Kilian (1999) and Rapach and Wohar (2005). In addition to the linear predictive regression model, a parsimonious version of the exponential smooth-transition autoregressive (ESTAR) model proposed by Kilian and Taylor (1993) is used to reevaluate the predictability of the real stock price growth rates in a non-linear framework. As with the linear model, Monte Carlo simulations are used to measure the size and power properties of the non-linear framework.

The second step was to evaluate the predictive power of a group of financial variables and macroeconomic variables. The analysis uses the predictive regression to test for predictability of these variables, testing for both the in-sample and the out-of-sample periods. For in-sample predictability, the t-statistic corresponding to the slope coefficients in a predictive regression model is used. For the out-of-sample period, the MSE-F and the ENC-NEW test statistics developed by Clark and McCracken (2001) and McCracken (2004) are used. To account for data mining – since both the in-sample and the out-of-sample test statistics are subjected to data mining when one uses a large number of predictors (Inoue and Kilian, 2002) – the appropriate critical values for all the test statistics using a data-mining-robust bootstrap procedure are computed. A methodology that combines in-sample general-to-specific model selection with tests of out-of-sample forecasting ability is also considered to assess the importance of the macro and financial variables in explaining the behaviour of stock returns. Since monthly data is used to predict stock prices, it is crucial that the data used is of the same vintage, since data revisions may be detrimental in discerning causal relationships between different time series (Koenig et al., 2003). In light of this, real time data for macroeconomic variables that are consistently revised was also constructed and used to assess the determinants of stock returns in South Africa. A diffusion index approach (extracting a principal component from the macro variables) was also used to test the predictive power thereof. The third step was to investigate the dynamic relationship between different oil price shocks and the South African stock market. This was done using a sign restriction structural VAR approach and a variance decomposition approach.

The results presented in this thesis show no evidence of either short-horizon or long-horizon predictability; that is, the hypothesis that the current value of a valuation ratio is uncorrelated with real stock returns cannot be rejected at both short- and long- horizons based on bootstrapped critical values constructed from linear representations of the data. Further, it observed that the power to detect predictability in finite samples tends to decrease at long horizons in a linear framework. Though the ESTAR models of the price-dividend and price-earnings ratios show increased power, the ability of the non-linear framework in explaining the pattern of stock price predictability in the data again fails to show any promise both at short- and long-horizons. Secondly, adding more financial variables does not improve the predictive ability of the valuation ratios. Further, only the stock returns for our major trading partners and interest rate variables, world oil production and money supply have some in-sample predictive ability at certain horizons.

For the out-of-sample forecast, the stock returns of our trading partners, some interest rates variables, inflation rate and money supply show some predictive power over the horizon analysed. The diffusion index yields statistically significant results for only four specific months over the out-of-sample horizon. A real time analysis based on a subset of variables that underwent revisions, resulted in deterioration of the predictive power of these variables compared to the fully revised data. Accounting for data mining the results show that only the in-sample test statistics for most horizons remain significant (except the 24-months-ahead horizon), while, for the out-of-sample forecasts, the MSE-F and the ENC-NEW test statistics become insignificant from six-months-ahead horizon for financial variables. For macroeconomic variables and the diffusion index, when accounting for data mining, both the in-sample and the out-of-sample test statistics become insignificant at all horizons. The results we obtain from the general-to-specific model show that the valuation ratios play a crucial role in explaining movements in stock returns, despite their inability to predict stock return when using in-sample and out-of-sample test statistics.

The results in this thesis further show that for an oil-importing country like South Africa, stock returns only increase with oil prices when global economic activity improves. In response to oil supply shocks and speculative demand shocks, stock returns and the real price of oil move in opposite directions. The analysis of the variance decomposition shows that the oil supply shock contributes more to the variability in real stock prices. Different oil price shocks affect stock returns differently and policy makers and investors should always consider the source of the shock before implementing policy and making investment decisions.

The next step was to assess the spillover from stock prices onto consumption and interest rates for South Africa. This was done by estimating a three-variable TVP-VAR model comprising of real consumption growth rate, the nominal three-months Treasury bill rate and the growth rate of real stock prices. The outcome of estimated model shows that the impact of a real stock price shocks on consumption is in general positive, with large and significant effects observed at the one-quarter ahead horizon. However, there is also evidence of significant negative spillovers from the stock market to consumption during the financial crisis, at both short and long-horizons. Monetary policy response to stock price shocks has been persistent and strong – especially post-the financial liberalization in 1985, but became weaker during the recent financial crisis. Overall, the thesis provides evidence of significant time-varying spillovers on consumption and interest rate from the stock market.

The use of predictive regression models used in this thesis and the fact that these models are usually estimated using relatively long span of data, necessitates the need to test for the structural stability of the parameters in these models. The next step was therefore to test for the structural stability of both bivariate and multivariate predictive regression models for equity premium in South Africa over based on a combination of financial and macroeconomic variables. Several methodologies are employed to test for structural breaks, namely, the popular Andrews (1993) $SupF$ statistic and the Bai (1997) subsample procedure in conjunction with the Hansen (2000) heteroskedastic fixed-regressor bootstrap. The Elliott and Müller (2003) $\hat{J}$ statistic and Bai and Perron (1998, 2003a, 2004) methodologies are also used in this regard. The results show very strong evidence of at least two structural breaks in almost all bivariate predictive regression models. Evidence of structural instability in the multivariate predictive regression models of equity premium is also obtained. The results also show that the predictive ability of these variables can vary widely across different regimes.

For the final step, the two different sets of variables (macro and financial) are then combined to improve out-of-sample predictability for equity premium, three approaches are proposed. The first approach uses applies bootstrap aggregating (bagging) to a general-to-specific procedure based on a general dynamic linear regression model with the variables as possible predictors. The bagging forecasts were constructed by using a moving-block bootstrap. The second approach is to combine individual forecasts using a number of different methods proposed in recent financial literature since combining individual forecasts tends to outperform the individual forecasts themselves. The methods considered include simple averages, discounting and principal components. The last approach is to assess the out-of-sample predictability of equity premium of South Africa using the Bayesian regression methods under the Gaussian and double-exponential prior. The results show that forecast combination methods and diffusion indices improve the predictability of equity premium relative to the AR(1). However, the Bayesian regressions outperform all other models both in terms of statistical (forecasting) and economic (utility) gains.

This thesis contributes to literature in the following manner (not limited to): a first attempt to examine the predictability of real stock prices for South Africa based on valuation ratios; the first study using South African data that looks at not only in-sample, but also out-of-sample forecasting predictability using macroeconomic and financial variables; a first attempt, in the literature, to analyse the spillover effect of real stock prices on consumption and interest rate using a TVP-VAR model for the South African economy; and looking at South African data, this is a first attempt to disaggregate global oil market shocks and include oil inventories in the analysis to further identify the forward-looking element of oil price shock.

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