Macroeconomic Variables and South African Stock Return Predictability[#]

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Abstract

We examine both in-sample and out-of-sample predictability of South African stock return using macroeconomic variables. We base our analysis 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. For the in-sample test, we use the *t*-statistic corresponding to the slope coefficient of the predictive regression model, and for the out-of-sample tests we employ the MSE-F and the ENC-NEW test statistics. When using multiple variables in a predictive regression model, the results become susceptible to data mining. To guard against this, we employ a bootstrap procedure to construct critical values that account for data mining. Further, we use a procedure that combines the in-sample general-to-specific model selection with tests of out-of-sample forecasting ability to examine the significance of each macro variable in explaining the stock returns behaviour. In addition, we 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.

Keywords: Stock return predictability; Macro variables; In-sample tests; Out-of-sample tests; Data mining; General-to-specific model.

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1. 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, 2011) 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 (2011) 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. Realising that, 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, 2006), 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 analyzing both in- and out-of-sample stock return predictability. They show that, with in-sample 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. 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 assets-pricing models and represent priced factors in Arbitrage Pricing Theory (Ross, 1976), besides playing a role in affecting future investment opportunities and consumption. 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 paper is organized as follows: Section 2 describes the econometric; Section 3 discusses the data and the results obtained from the models, while, Section 4 summarises our core findings and concludes.

2. Econometric methodology

2.1 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,

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

where y_t is the log real return to holding stock from period $t-1$ to period t, $y_{t+1}^{k} = y_{t+1} + \ldots + y_{t+k}$ 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 $t = 1,\ldots,T$. 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 & 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}.[1] 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 & 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 & Wohar (2006), Kilian (1999), Kothari & 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.

2.2 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 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 $\hat{y}_{0,R+1}^{k} = \hat{\alpha}_{0,R} + \hat{\gamma}_{0,R} \cdot y_R$.

[1] 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.

The forecast error corresponding to the restricted predictive model are denoted by $\hat{\mu}^{k}_{0,R+1} = y^{k}_{R+1} - \hat{y}^{k}_{0,R+1}$

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^{k}_{R+2} and their forecast errors, $\hat{\mu}^{k}_{1,R+2}$ and $\hat{\mu}^{k}_{0,R+2}$. We repeat this process for the entire available sample, resulting in two sets of $T-R-K+1$ recursive forecast errors. – with $\{\hat{\mu}^{k}_{1,t+1}\}_{t=R}^{T-k}$ for the unrestricted predictive regression model and $\{\hat{\mu}^{k}_{0,t+1}\}_{t=R}^{T-k}$ 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^{k}_{t+1} 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,

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

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

where: $\hat{MSE}_i = (T-R-k+1)^{-1}\sum_{t=R}^{T-k}(\mu^{k}_{i,t+1})^2$, 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.[2] 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:

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

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 tests 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.[3]

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

[2] Clements and Hendry (1998) discuss forecast encompassing in detail.
[3] 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).

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.[4] 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 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.

2.3 Diffusion index regression

Using factor analysis we were able to summarise the information contained in the 12 macro variables into one[5] 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.

2.4 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:

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

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 include 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

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4 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).

5 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.

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).

3. Empirical results

3.1 Data analysis

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;
Relatively 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;
Relatively 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.[6] 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

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

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 1 reports the descriptive statistics (mean and standard deviation) for each of the macro variables.

Table 1: 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

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

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 2. Specifically, Table 2 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 2 are generated using the bootstrap procedure described above and the brackets-bold entries indicate significant at the 10% confidence level.

The results reported in Table 2 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

Table 2: 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.

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 & 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

Table 3: 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 2 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 3 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 3 to check if the significance of the best statistics reported in Table 2 is due primarily to data mining.

From Table 2, 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 3, 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 2. 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 Tables 2, 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 2 indicate that the reduction in MSE is significant in a number of cases.

In Table 4 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 increases with the horizons, since at a 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

Table 4: 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 brackets; bold entries indicate significance at 10 per cent level

according to RMSE criterion. This means that the predictable component in South African stock returns (using macro variables) is relatively small.

3.3 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).[7] 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. 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 5. 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-

[7] We would like to thank an anonymous referee for pointing this out to us and suggesting the use of a real-time analysis.

Table 5. 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.

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.

3.4 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 consistence 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 6 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 6 are generated using the bootstrap procedure described above and the brackets-bold entries indicate significance at the 10% confidence level.

Table 6: 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 6 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[8] in general, which tends to suggest that combining information tends to improve the forecasting gains.

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

Because of concerns of data mining, we also use the critical values presented in Table 3 to make inferences on the test statistics obtained when using the diffusion index. From Table 6, 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.[9]

4. Conclusion

In this paper, 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 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 only 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-

[9] 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.

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 paper, and that in Gupta and Modise (2012 a, b), 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 need 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 analyze stock return predictability in a nonlinear framework, as in Qi (1999), Gallagher and Taylor (2001) and McMillan (2001).

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