South African Stock Return Predictability in the Context Data Mining: The Role of Financial Variables and International Stock Returns*

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Abstract

In this paper, we examine the predictive ability, both in-sample and the out-of-sample, for South African stock returns using a number of financial variables, 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. 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 explains 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.

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

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1. 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 (2010), 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 (2010), 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 (2010), following the recent work by Rapach *et al.,* (2010), suggested the need to analyze 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 (2010), 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 & Bekaert, 2007), and payout ratio (Lamont, 1998). Since we are using quite a number of predictors, we avoid of 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, continue 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.[1] 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 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 paper 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.

2. Econometric methodology

2.1 In-sample predictability

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

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 in long horizon. The predictive regression takes the form,

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

where y_t is the real stock return to holding 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 & 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 & Kim, 1993; Kirby, 1997 and Rapach and Wohar, 2006a). Recent literature, including Rapach & Wohar (2006a), Kilian (1999), Kothari & 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.

2.2 Out-of-sample predictability

Similar to Rapach and Wohar (2006a) and Rapach *et al.* (2005), we further 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 $U < 1$.[2] To formally test for

[2] 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

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.[3] 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 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:

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.

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

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

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.[4]

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.[5] 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.

2.3 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:

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

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[4] 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).

[5] 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).

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 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.[6]. 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.

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 2010:04 as the out-of-sample period for the stock returns and the other financial variables[7]. 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;

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

[7] 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.

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.[8]

[INSERT TABLE 1 HERE]

3.2 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).[9] In Table 1 we report the descriptive statistic (the mean and the standard deviations) for the stock return and each of the possible predictors.

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8 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.

9 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, or 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 2 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 2 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.

[INSERT TABLE 2 HERE]

Table 2 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 2 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 1. We use these critical values to check whether the significance of the best statistic in Table 2 is mainly due to data mining. In Table 2, the entries that remain significant after accounting for data mining are in bold, underlined and italic.

From Table 2, 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 2, 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.

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

[INSERT TABLE 3 HERE]

The results obtained using the general-to-specific model specification are reported in Table 3. 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). 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.

4. Conclusion

In this paper, 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 analyzing whether adding macroeconomic variables could help in improving the predictability of South African stock returns.

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Table 1: 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

Table 2: 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	***<u>5.309</u>***	**6.478**	**3.524**	**4.126**	**1.820**	0.353	**2.814**
	[0.233]	***<u>[0.009]</u>***	**[0.020]**	**[0.055]**	**[0.039]**	**[0.091]**	[0.209]	**[0.067]**
ENC-NEW	0.753	***<u>8.054</u>***	**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 3: 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.

Appendix **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		
	10 per cent	5 per cent	1 per cent
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		
	10 per cent	5 per cent	1 per cent
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		
	10 per cent	5 per cent	1 per cent
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		
	10 per cent	5 per cent	1 per cent
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		
	10 per cent	5 per cent	1 per cent
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		
	10 per cent	5 per cent	1 per cent
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		
	10 per cent	5 per cent	1 per cent
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 2.