Valuation ratios and stock return predictability in South Africa: Is it there?♣

Rangan Gupta* and Mampho P. Modise**

Abstract

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

JEL classifications: C22, C32, C53, G12.

Key words: Predictive regression; Monte Carlo simulation; Nonlinear mean-reversion.

Introduction

Forecasting stock returns is amongst one of the most important research questions in financial economics. In addition, there exists international evidence that asset prices, including stock prices, not only help in predicting output and inflation by acting as leading indicators (Stock and Watson, 2003), but also that there are major (asymmetric) spillovers from the stock markets to the real sector of the economy (for some recent evidence, refer to, Lettau and Ludvigson, 2001, 2004; Lettau et al. 2002; Apergis and Miller, 2004, 2005a, b and 2006; Rapach and Strauss, 2006, 2007; Pavlidis et al. 2009 and Das et al. forthcoming amongst others). Hence, obtaining accurate predictions of stock prices cannot be understated. In general, stock price predictions are based on a predictive regression model, which essentially amounts to regressing the growth rate of real stock price, i.e., stock returns, (over various horizons) on a variable thought to be capable of explaining the future path of stock prices. Even though the predictive regression model

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* Corresponding author. Contact details: Professor, Department of Economics, University of Pretoria, Pretoria, 0002, South Africa. Phone: + 27 12 420 3460, Email: Rangan.Gupta@up.ac.za.

** Graduate Student, Department of Economics, University of Pretoria. Contact details: Department of Economics, University of Pretoria, Pretoria, 0002, South Africa. Email: mamphomodise@yahoo.com.

suffers from a variety of econometric problems (Mankiw and Shapiro, 1986; Stambaugh, 1986, 1999; Nelson and Kim, 1993; Kirby, 1997), the general consensus is that valuation ratios (price-dividend and price-earnings ratios) based on measures of fundamental values, can, in fact, forecast stock prices (Fama and French, 1988; Campbell and Shiller, 1988, 1998; Campbell, 1999, 2000 and Rapach and Wohar, 2005). However, an interesting pattern seem to emerge from these studies, in the sense that evidence for significant stock return predictability is only observed at long, and not short, horizons. In other words, the hypothesis that the current value of price-dividend and price-earnings ratios are uncorrelated with changes in future stock price changes can only be rejected at longer horizons. Two possible explanations for such a pattern are non-linearity in the data and possible increase in statistical power at longer-horizons when considering a linear framework (Rapach and Wohar, 2005).

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

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

[1] We would like to thank one of the anonymous referees for pointing this out to us.

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

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

Predictive regression in a linear framework

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

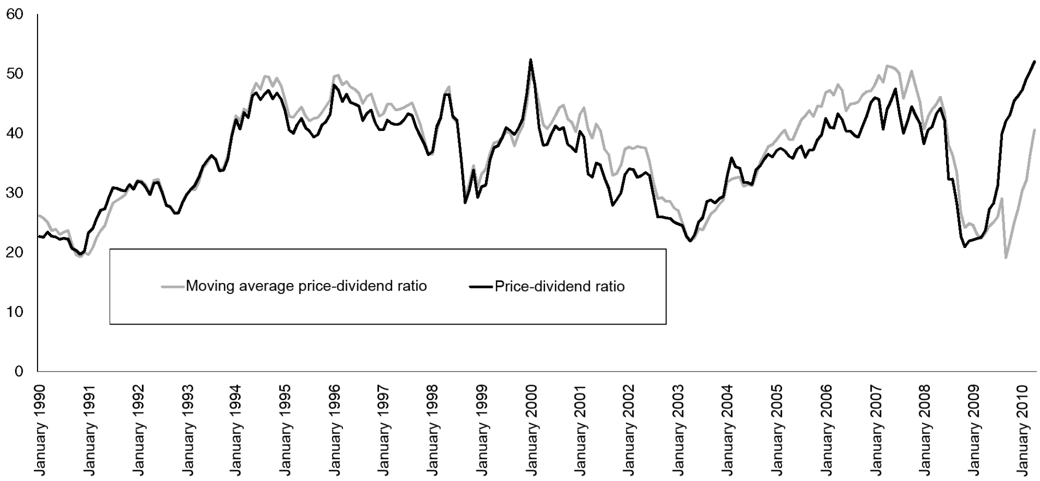

Figure 1. Actual and moving average of price-dividend ratio, 1990–2010

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

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

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

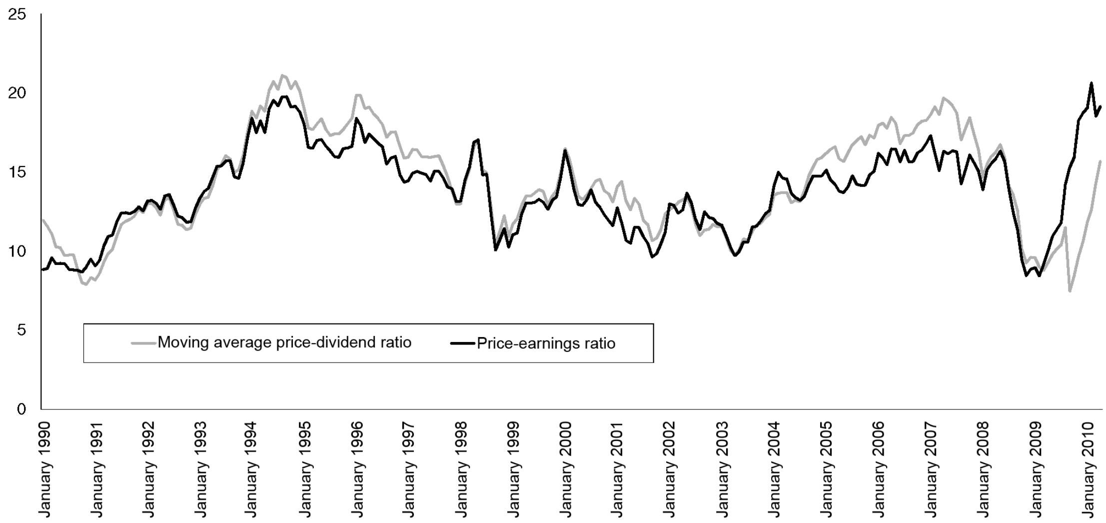

Figure 2. Actual and moving average of price-earnings ratio, 1990–2010

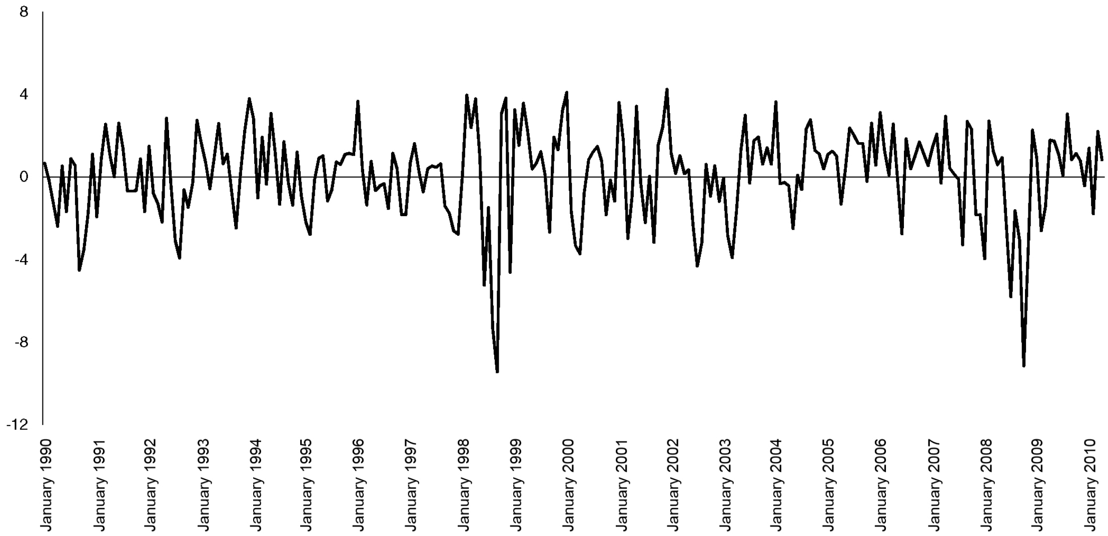

Figure 3. Real stock returns, 1990–2010

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

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

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

where p_t represents real stock prices in log-levels; z_t is the relevant log-value of the valuation ratio; $\Delta p_{t+k}^{k} = p_{t+k} - p_t$; and, ε_{t+k}^{k} is the error term. More specifically, $z_t = p_t - f_t$; while, f_t represents log of real dividends (d_t) or log of real earnings (e_t). Following Ang & Bekaert (2007), we consider $k = 1,...,60$ months in equation (1). The predictive ability of z_t in a predictive regression, such as equation (1), is assessed

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

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

Note: Values in parentheses are bootstrapped *p*-values.

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

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

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

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

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

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

Predictive regression in a nonlinear framework

Since we found no predictability based on linear predictive regressions, we decided to analyze if our results change, when we consider a parsimonious ESTAR model specification, as in Rapach and Wohar (2005). Note, even though our result of no predictability at the one-step-ahead translates to no predictability at any horizon implied that the valuation ratios are linearly related to the real stock returns, we decided to test for non-linearity formally to confirm our findings. Given this, we consider a parsimonious ESTAR specification for the price-dividend and price-earnings ratio, originally outlined in Kilian and Taylor (2003) for analyzing nominal exchange rate deviations from purchasing power parity fundamentals that incorporates the idea of risky arbitrage. At this stage, it must be pointed out that ESTAR models are only one of the many possible non-linear models that can be used. For instance Markov-switching models are very popular in analyzing stock returns at monthly frequencies (see Franses and van Dijk (2000) for details on various non-linear frameworks used in the literature to model stock returns). However, it was not our intent to undertake an extensive analysis of how well different classes of nonlinear models fit the data.[7] Instead, we wanted to investigate a parsimonious nonlinear model with a straightforward economic interpretation as follows: When both noise traders and arbitrageurs exist in a model, the demand for assets by noise traders is based on beliefs not justified completely by news on fundamentals. While, arbitrageurs form fully rational expectations about the returns to holding an asset and can, in turn, potentially profit from the mistaken beliefs of noise traders. However, arbitrage is risky in these models, since mistaken beliefs of noise traders may cause asset prices to deviate from their underlying fundamentals for considerable periods of time. In this situation, even though the asset prices they will ultimately return to a level in line with the fundamentals, an arbitrageur may have to borrow to trade or be compared to other financial advisors. And then, if the mispricing persists, the arbitrageur can suffer serious losses or fare poorly relative to other advisors. Kilian and Taylor (2003) hypothesize that the risk to arbitrage decreases as the asset becomes increasingly overvalued or undervalued, leading to disproportionately quicker adjustment toward the equilibrium, while, smaller deviations are likely to persist longer.

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

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

where μ_z is the mean of z_t and u_t is an independently and identically distributed error term with mean zero and variance σ^2. The transition function for the above ESTAR model is defined by $\exp[\gamma(z_{t-1} - \mu_z)^2]$ meaning that if $\gamma < 0$ the mean reversion will be stronger the larger the deviation (in absolute terms) of p_t from f_t. For each valuation ratio, equation (2) is estimated using nonlinear least squares (NLLS). As z_t is stationary under the null hypothesis that $\gamma = 0$, one must be careful when assessing the significance of $\hat{\gamma}$, the NLLS estimate of γ. Hence, following Rapach and Wohar (2005), we use a bootstrap procedure to calculate a *p*-value for the NLLS *t*-statistic corresponding to $\hat{\gamma}$. Based on the estimation $\hat{\gamma}$=-0.12 and -1.78 respectively for the price-dividend and price-earnings ratios, with the corresponding *t*-statistics and *p*-values in parentheses being -1.54 (0.49) and -1.68 (0.40). The estimates of $\hat{\gamma}$<0 are insignificant based on the boot-strapped *p*-values for the NLLS *t*-statistics, suggesting no evidence of non-linearity.

[7] The readers are referred to Table 4 in Gupta and Modise (2010) for further details.

However, as indicated by van Dijk et al. (2002), precise estimate of $\hat{\gamma}$ is often unlikely. Given this, and to directly compare a linear to a non-linear specification for z_t, we also tested the null hypothesis of a linear AR model specification against the alternative hypothesis of an ESTAR specification based on the Lagrange multiplier test of Granger and Tersävitra (1994) . Given the parsimonious ESTAR specification in equation (2), this boils down to estimating the following regression:

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

Table 3. Estimation results for the predictive regression model under the assumption of a nonlinear data-generating process

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

Note: Values in parentheses are bootstrapped *p*-values.

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

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

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

	$z_t = p_t - d_t$		$z_t = p_t - e_t$	
Horizon (*k*)	**Size**	**Power (β_1 = –0.003)**	**Size**	**Power (β_1 = 0.002)**
1 month	0.10	0.02	0.08	0.2
3 months	0.09	0.05	0.10	0.29
6 months	0.09	0.11	0.11	0.26
9 months	0.11	0.17	0.10	0.24
12 months	0.10	0.25	0.10	0.24
18 months	0.08	0.33	0.11	0.24
24 months	0.07	0.40	0.11	0.22
36 months	0.07	0.43	0.10	0.22
48 months	0.09	0.38	0.13	0.24
60 months	0.07	0.35	0.11	0.22

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

earnings process, with the general specification including twelve lags each of Δd_t and Δe_t. Once we obtained the following specific forms for Δd_t and Δe_t:

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

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

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

Conclusion

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

Contrary to the extant literature, where one tends to obtain predictability of the real stock price growth rate at least at the long-horizon, we fail to reject the null of no-predictability at both short- and long-horizons. The pertinent question now is: Why is that valuation ratios for South Africa are found to have no predictability for stock returns? To explain our results, we rely on the findings of Ang and Bekaert (2007). These authors too provided international evidence of the lack of predictability of stock returns based on valuation ratios, when considered purely on their own. However, when the predictive regressions were supplemented with the short-term interest rate, valuation ratios were found to predict the path of future stock returns. Ang and Bekaert (2007) then went ahead to built a present value model which showed that short-term interest rate movements, along with the discount rate, play a major role in explaining the variation in the valuation ratios, which, in turn, helped them to explain the above set of observations in the data. Such an explanation seems to hold true even for South Africa, in light of the recent evidence provided by Gupta and Modise (2010). In this paper, the authors forecast both in- and out-of-sample stock returns based on a wide set of financial variables, including valuation ratios, as well as international stock returns of South Africa's major trading partners. The authors, just like Ang and Bekaert (2007), observe that though the price-dividend and price-earnings ratios have no predictability both in- and out-of-sample in univariate predictive regression models similar to those considered here. However, when a general-to-specific modeling approach is followed to take account of all the variables used in the forecasting exercise, the valuation ratios show up consistently in the specific model, along with the short-term interest rate, term spread and international stock returns. More importantly, the specific model is now found to contain significant predictive ability both in and out-of-sample.[8]

Given that stock prices serve as a leading indicator and, hence, carries useful information for policy makers as to where the economy might be heading, future research would aim to investigate not only in-sample, but also out-of-sample predictability of real stock returns[9] based on a wider set of financial and macroeconomic variables (Choudhry, 2004; Chancharoenchai et al., 2005; Rapach et al., 2005, 2010a, b, c; Rapach and Wohar, 2006; Ludvigson and Ng, 2007, 2009, forthcoming; Carvalhal and de Melo Mendes, 2008; Goyal and Welch, 2008, Cakmakli and van Dijk, 2010) by extracting factors to serve as explanatory variables in predictive regression models or even based on Bayesian vector autoregressive models, with both these approaches capable of handling huge data sets involving hundreds of variables. In addition, one might also want to delve into multifractal (Balcilar, 2003), long memory models (Franses and van Dijk, 2000; Balcilar, 2004) and even non-linear models[10] (Qi, 1999; McMillan, 2001) to capture stock return movements.

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

[9] We would like to thank the anonymous referees for pointing out to us that, over and above the dynamic adjust of the predictors being non-linear, it is possible that the predictive relation itself is non-linear.

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