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

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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 prices 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 price 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.

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1. Introduction

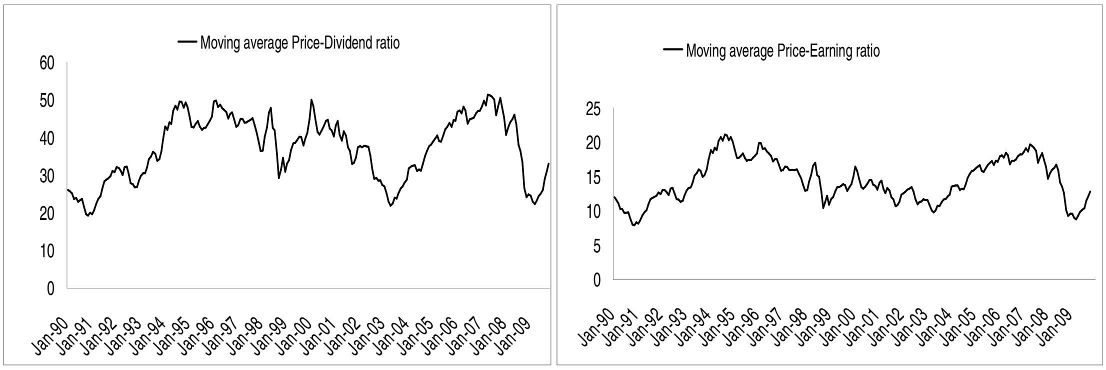
Forecasting stock prices is amongst one of the most important research questions in financial economics. In addition, there exists international evidence that asset prices, including stock prices, not only help in predicting output and inflation by acting as leading indicators (Stock and Watson, 2003), 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, 2006; Rapach and Strauss, 2006, 2007;; Pavlidis et al. 2009 and Das et al. 2010 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 (over various horizons) on a variable thought to be capable of explaining the future path of stock prices. Even though the predictive regression model suffers from a variety of econometric problems (Mankiw and Shapiro, 1986; Stambaugh, 1986, 1999; Nelson and Kim, 1993; Kirby, 1997), the general consensus is that valuation ratios (price-dividend and price-earnings ratios) based on measures of fundamental values, can, in fact, forecast stock prices (Fama and French, 1988; Campbell and Shiller, 1988, 1998; Campbell, 1999, 2000 and Rapach and Wohar, 2005). However, an interesting pattern seem to emerge from these studies, in the sense that evidence for significant stock price 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 prices 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 growth rate of real stock price with the log-value of either price-dividend or price-earnings ratio acting as the explanatory variable. The size and power properties of the long-horizon regression tests are then 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 price growth rates in a non-linear framework. As with the linear model, Monte Carlo simulations are used to measure the size and power properties of the non-linear framework. Note the parsimonious ESTAR framework allows for non-linear mean reversion in the relevant valuation ratio and is quite straightforward in terms of economic interpretation. The remainder of the paper is organized as follows: Section 2 discusses that data and presents the results of real stock price 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.

2. 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 & 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. 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 prices over the period of 1990:01-2009:08. Figure 1 shows the plots of the two valuation ratios. Note all the required data were obtained from the South African Reserve Bank and Statistics South Africa.[2]

Figure 1: One year moving sum of valuation ratios



We examine whether the valuation ratios are useful for forecasting changes in real stock prices 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[3]:

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

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 through the *t*-statistic corresponding to the OLS estimate of β_k, denoted by $\hat{\beta}_k$. When $k > 1$, the observations for the growth rate of real stock prices 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

[2] 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.

[3] 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 $z_t = p_t - e_t$.

[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., $\beta_k = 0$, 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.[4] 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 $\beta_k = 0$ against the one-sided alternative hypothesis of $\beta_k < 0$, 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.

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

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

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

In Table 2, we present the size and power properties of the predictive regression tests at the nominal 10 percent level, reported in Table 1, based on Monte Carlo simulations.[5] As can be seen from columns 2 and 4 of Table 2, size distortions are not an issue for our

[4] Refer to Rapach and Wohar (2005) for further details.

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 growth rate of real stock prices, based on valuation ratios.

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

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

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

3. 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 growth rate of the real stock prices, we decided to test for non-linearity formally to confirm our findings. Given this, we consider the following 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:

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

where μ_z is the mean of z_t and u_t is an independently and identically distributed error term with mean zero and variance σ^2. The transition function for the above ESTAR model is defined by $\exp\left[\gamma(z_{t-1} - \mu_z)^2\right]$ meaning that if $\gamma < 0$ the mean reversion will be stronger the larger the deviation (in absolute terms) of p_t from f_t. For each valuation

[5] Refer to Rapach and Wohar (2005) for further details.

ratio, equation (2) is estimated using nonlinear least squares (NLLS). As z_t is stationary under the null hypothesis that $\gamma = 0$, one must be careful when assessing the significance of $\hat{\gamma}$, the NLLS estimate of γ. Hence, following Rapach and Wohar (2005), we use a bootstrap procedure to calculate a *p*-value for the NLLS *t*-statistic corresponding to $\hat{\gamma}$. Based on the estimation $\hat{\gamma}$=-0.12 and -1.78 respectively for the price-dividend and price-earnings ratios, with the corresponding *t*-statistics and *p*-values in parentheses being -1.54 (0.49) and -1.68 (0.40). The estimates of $\hat{\gamma}$<0 are insignificant based on the boot-strapped *p*-values for the NLLS *t*-statistics, suggesting no evidence of non-linearity. However, as indicated by van Dijk et al. (2002), precise estimate of $\hat{\gamma}$ is often unlikely. Given this, and to directly compare a linear to a non-linear specification for z_t, we also tested the null hypothesis of a linear AR model specification against the alternative hypothesis of an ESTAR specification based on the Lagrange multiplier test of Granger and Tersävitra (1994) . Given the parsimonious ESTAR specification in equation (2), this boils down to estimating the following regression:

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

And testing the joint significance of α_3 and α_4. For both the price-dividend and price earnings ratio, we could not reject the null hypothesis of linearity at the 10 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 growth rate of real stock prices 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 decided to go ahead and estimate the predictive regression models for both the price-dividend and price-earnings ratios under the assumption of non-linear data-generating process, the results of which have been reported in Table 3. As with the predictive regressions under the assumption that the valuation ratios follow a linear data-generating process, we find no-evidence of predictability at horizons 1 through 60, when we assume that z_t follows an ESTAR process. In addition, the *p*-values obtained now are higher than the corresponding *p*-values reported in Table 1, which assumes linear data-generating process for z_t. This should not come as surprise since we do not find any evidence of non-linearity of z_t.

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

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

Note: See note to Table 1.

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

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

Note: See note to Table 2.

Finally, Table 4 presents the size and power properties of the predictive regressions in a non-linear framework. Clearly, as with the linear framework, there is no evidence of size distortions, based on 500 Monte Carlo replications with 500 bootstrapped replications per Monte Carlo replication. To investigate the power in a non-linear framework, we follow the method outlined in Kilian and Taylor (2003) and assume a non-linear process for the fundamental. It is important to highlight that the power of the test will depend on the specific form of the alternative model (Kilian and Taylor, 2003). We use a general-to-specific approach to obtain a relatively parsimonious model for the dividends and earnings process, with the general specification including twelve lags each of Δd_t and Δe_t. Once we obtained the specific forms[6] for Δd_t and Δe_t, we follow the bootstrapping

[6] Our specific formulations for the dividend and earnings were:
$\Delta d_t = \gamma_0 + \gamma_1 \Delta d_{t-1} + \gamma_2 \Delta d_{t-2} + \gamma_3 \Delta d_{t-5} + \gamma_4 \Delta d_{t-7} + \gamma_5 \Delta p_{t-2} + \gamma_6 \Delta p_{t-8} + \gamma_7 \Delta p_{t-10} + \gamma_8 \Delta p_{t-12} + u_{1,t}$ and
$\Delta e_t = \gamma_0 + \gamma_1 \Delta e_{t-1} + \gamma_2 \Delta e_{t-2} + \gamma_3 \Delta e_{t-5} + \gamma_4 \Delta e_{t-6} + \gamma_5 \Delta p_{t-10} + u_{1,t}$.

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 prices in South Africa.

4. **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 prices 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 growth rate of real stock prices 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. 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 price growth rates in a non-linear framework. As with the linear model, Monte Carlo simulations are used to measure the size and power properties of the non-linear framework. 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 growth rate of future real stock prices 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. Given that stock prices serve as a leading indicator and, hence, carries useful information for policy makers as to where the economy might be heading, future research would aim to investigate not only in-sample, but also out-of-sample predictability of real stock returns based on a wider set of financial and macroeconomic variables (Rapach et al., 2005, 2010a, b, c; Rapach and Wohar, 2006; Ludvigson and Ng, 2007, 2009, forthcoming; Goyal and Welch, 2008). 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. It would also be worthwhile to analyze the role played by stock returns of major trading partners of South Africa in explaining the future path of the growth rate of real stock prices (Rapach et al., 2010b). In addition, one might also want to delve into multifractal (Balcilar, 2003) and long memory models (Franses and van Dijk, 2000; Balcilar, 2004) to capture stock return movements.

References

Ang, A. & Bekaert, G. 2007. Stock return predictability: is it there? *Review of Financial Studies,* 20(3): 651-707.

Apergis, N. & Miller, S.M. 2004. Consumption Asymmetry and the Stock Market: Further Evidence. *University of Connecticut, Department of Economics, Working Paper* No. 2004-19.

Apergis, N. & Miller, S.M. 2005a. Consumption Asymmetry and the Stock Market: Further Evidence. *University of Connecticut, Department of Economics, Working Paper* No. 2005-57.

Apergis, N. & Miller, S.M. 2005b. Consumption asymmetry and the stock market: New evidence through a threshold adjustment model. *University of Connecticut, Department of Economics, Working Paper* No. 2005-08.

Apergis, N. & Miller, S.M. 2006. Consumption asymmetry and the stock market: Empirical evidence. *Economics Letters*, 93(3): 337-342.

Balcilar, M. (2003). Multifractality of the Istanbul and Moscow stock market returns. Emerging Markets Finance and Trade, 39(2): 5-46.

Balcilar, M. (2004). Persistence in Inflation: Does Aggregation Cause Long Memory? Emerging Markets Finance and Trade, 40(5): 25-56.

Berkowitz, J. & Giorgianni, L. 2001. Long-horizon exchange rate predictability? *Review of Economics and Statistics,* 83: 81–91.

Campbell, J.Y. & Shiller, R.J. 1988. Stock prices, earnings, and expected dividends. *Journal of Finance,* 43: 661–676.

Campbell, J.Y. 1999. Asset prices, consumption, and the business cycle. *In Handbook of Macroeconomics*, (1), Taylor, J. Woodford, M. edited. North-Holland: Amsterdam.

Campbell, J.Y. 2000. Asset pricing at the millennium. *Journal of Finance,* 55: 1515–1567.

Campell, J.Y. & Shiller, R.J. 1998. Valuation ratios and the long-run stock market outlook. *Journal of Portfolio Management,* Winter: 11-26.

Das, S., Gupta, R. & Kanda, P.T. 2010. *Bubbles in House Price and their Impact on Consumption: Evidence for South Africa.* University of Pretoria, Department of Economics Mimeo.

Fama, E.F. & French, K.R. 1988. Dividend yields and expected stock returns. *Journal of Financial Economics,* 22: 3–25.

Goyal, A. & Welch, I. 2008. A Comprehensive Look at the Empirical Performance of Equity Premium Prediction. *Review of Financial Studies,* 21: 1455–508.

Kilian, L. & Taylor, M.P. 2003. Why is it so difficult to beat the random walk forecast of exchange rates? *Journal of International Economics,* 60: 85–107.

Kilian, L. 1999. Exchange rates and monetary fundamentals: what do we learn from long-horizon regressions? *Journal of Applied Econometrics,* 14: 491–510.

Kirby, C. 1997. Measuring the predictable variation in stock and bond returns. *Review of Financial Studies,* 10: 579–630.

Lettau, M. & Ludvigson, S.C. 2001. Consumption, Aggregate Wealth, and Expected Stock Returns. *Journal of Finance*, 56(3): 815-849.

Lettau, M. & Ludvigson, S.C. 2004. Understanding Trend and Cycle in Asset Values: Reevaluating the Wealth Effect on Consumption. *American Economic Review*, 94(1): 276-299.

Lettau, M., Ludvigson, S.C. & Steindel, C. 2002. Monetary Policy Transmission through the Consumption-Wealth Channel. *FRBNY Economic Policy Review*, May: 117-133.

Ludvigson, S.C. & Ng, S. 2007. The Empirical Risk-Return Tradeoff: A Factor Analysis Approach . *The Journal of Financial Economics*, 83:171-222.

Ludvigson, S.C. & Ng, S. 2009. Macro Factors in Bond Risk Premia. *The Review of Financial Studies*, 22(12): 5027-5067.
Ludvigson, S.C. & Ng, S. Forthcoming. A Factor Analysis of Bond Risk Premia. *Handbook of Applied Econometrics*.
Mankiw, N.G. & Shapiro, M.D. 1986. Do we reject too often? *Economic Letters,* 20: 134–145.
Nelson, C.R. & Kim, M.J. 1993. Predictable stock returns: the role of small sample bias. *Journal of Finance* 48: 641–661.
Newey, W. & West, K.J. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica,* 55: 703–708.
Ng, S. & Perron P. 2001. Lag-length selection and the construction of unit root tests with good size and power. *Econometrica,* 69: 1519–1554.
Pavlidis, I.E., Peel, D. & Spiru, A. 2009. Bubbles in House Price and their Impact on Consumption: Evidence for the US. *Lancaster University Management School, Working Paper* No. 2009/025.
Rapach, D. & Strauss, J.K. 2006. The Long-Run Relationship Between Consumption and Housing Wealth in the Eighth District States. *Federal Reserve Bank of St. Louis Regional Economic Development*, 2(2): 140-147.
Rapach, D. & Strauss, J.K. 2007. Habit Formation, Heterogeneity, and Housing Wealth Affects Across U.S. States. *Missouri Economics Conference*.
Rapach, D. & Wohar, M.E. 2005. Valuation ratios and long-horizon stock price predictability. *Journal of Applied Econometrics*, 20: 327-344.
Rapach, D. & Wohar, M.E. 2006. In-Sample vs. Out-of-Sample Tests of Stock Return Predictability in the Context of Data Mining. *Journal of Empirical Finance*, 13(2): 231-247.
Rapach, D., Neely, C.J., Tu, J. & Zhou, G. 2010a. Out-of-Sample Equity Premium Predictability: Economic Fundamentals vs. Moving-Average Rules. *St. Louis University, Department of Economics*, Mimeo.
Rapach, D., Strauss, J. & Zhou, G. 2009. Out-of-Sample Equity Premium Prediction: Combination Forecasts and Links to the Real Economy. *Review of Financial Studies*, 23(2): 821-862.
Rapach, D., Strauss, J.K. & Zhou, G. 2010b. International Stock Return Predictability: What is the Role of the United States? *St. Louis University, Department of Economics*, Mimeo.
Rapach, D., Strauss, J.K., Tu, J. & Zhou, G. 2010c. Industry Return Predictability: Does it Matter Out of Sample? *St. Louis University, Department of Economics*, Mimeo.
Rapach, D., Wohar, M.E & Rangvid, J. 2005. Macro Variables and International Stock Return Predictability. *International Journal of Forecasting*, 21(1): 137-166.
Stambaugh, R.F. 1986. Biases in regressions with lagged stochastic regressors. *University of Chicago, Graduate School of Business Working Paper* No. 156.
Stambaugh, R.F. 1999. Predictive regressions. *Journal of Financial Economics,* 54: 375–421.
Stock, J.H. & Watson, M.W. 2003. Forecasting Output and Inflation: The Role of Asset Prices. *Journal of Economic Literature,* 41: 788-829.
Teräsvirta, T. 1994. Specification, estimation and evaluation of smooth transition autoregressive models. *Journal of the American Statistical Association,* 89: 208–218.
van Dijk, D., Teräsvirta, T. & Franses, P. 2002. Smooth transition Autoregressive models – A survey of recent developments. *Econometric Review*, 21(1): 1-47.
van Dijk, D. & Franses, P. 2000. Non-linear time series models in empirical finance. *Cambridge University Press, Cambridge, United Kingdom*.