Predicting the UK Equity Premium with Dividend Ratios: An Out-Of-Sample Recursive Residuals Graphical Approach

Neil Kellard[†], John Nankervis and Fotis Papadimitriou

Department of Accounting, Finance and Management and Essex Finance Centre
University Of Essex

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Abstract

The purpose of this paper is to evaluate the ability of dividend ratios to predict the UK equity premium. Specifically, we apply the Goyal and Welch (2003) methodology to equity premia derived from the UK FTSE All-Share index. This approach provides a powerful graphical diagnostic for predictive ability. Preliminary in-sample univariate regressions reveal that the UK equity premium contains an element of predictability. Moreover, out-of-sample the considered models outperform the historical moving average. In contrast to similar work on the US, the graphical diagnostic then indicates that dividend ratios are useful predictors of excess returns. Finally, Campbell and Shiller (1988) identities are employed to account for the time-varying properties of the dividend yield and dividend growth processes. It is shown that by instrumenting the models with the identities, forecasting ability can be improved.

JEL Classification: C22, C32, C53
Keywords: Equity Premium, Return Predictability, Dividend Ratios, Out-of-Sample Prediction

[†] Corresponding author: Essex Finance Centre, Department of Accounting, Finance & Management, University of Essex, Wivenhoe Park, Colchester, CO4 3SQ, United Kingdom. Tel: +44 1206 874153, Fax: +44 1206 873429. E-mail: nkellard@essex.ac.uk

1. Introduction

Undoubtedly, the predictability of stock market returns is one of the most controversial and intensely debated issues in empirical finance. A voluminous literature around the issue has evolved during the last two decades, rendering its overall assessment extremely difficult or, perhaps, an elusive goal. The variety of markets and the different sample periods that have been examined, in conjunction with the numerous and complicated methodologies that have been employed to address the question of whether returns are predictable, have failed to yield a general consensus.

Interestingly, researchers have identified a large number of financial variables that might be used to predict stock returns. The most popular candidates are the dividend-to-price ratios and the dividend yields (Rozeff, 1984; Campbell and Shiller, 1988a; Fama and French, 1988; Hodrick, 1992; Lewellen, 2004), the earnings-to-price ratios (Campbell and Shiller, 1988b; Campbell and Shiller, 1998; Lamont, 1998), the book-to-market ratios (Kothari and Shanken, 1997; Pontiff and Schall, 1998), short-term interest rates (Hodrick, 1992; Ang and Bekaert, 2003), yield spreads (Keim and Stambaugh, 1986; Campbell, 1987; Fama and French, 1989), and more recently the consumption-wealth ratio (Lettau and Ludvigson, 2001).

In many studies, the statistical significance of predictability is judged according to the t-statistics and R^2s of predictive regressions. However, finding statistical significance is not conclusive evidence that predictability is economically significant. Additionally, a serious concern is that most predictive variables behave as highly persistent variables and also are not exogenous but lagged endogenous. This can lead to violation of the standard OLS assumptions and to biases in the estimated coefficients. Thus, using standard critical values, we tend to over reject the null hypothesis of no predictability and this explains why early studies have been challenged and criticised for the validity of their results.

Many authors have stressed the importance of simulation methods such as the bootstrap technique which can be used in order to account for possible biases and Monte Carlo experiments which can be used to evaluate the robustness of results. For example, Goetzmann and Jorion (1993) stress that previous studies have failed to recognize the serious biases arising from regressions on lagged dependent variables. Using bootstrapping, as well as Monte Carlo simulations, they find that OLS estimates are biased upwards due to overlapping observations and conclude that there is no strong evidence of predictability. In a similar study, Nelson and Kim (1993) use simulation evidence and examine the bias of the coefficient estimates when the predictor variable is endogenous and the bias of the standard errors in the case of overlapping periods. The main finding of their study is that both sources of small sample bias are significant and large enough to vitiate the claim that dividend yields are predictors of stock returns. Ferson, Sarkissian and Simin (2003) show that data mining interacts with spurious regression bias and the two effects underpin each other leading to invalid results. Their simulations suggest that many of the regressions in the literature which are based on individual predictive variables may be spurious.

Another issue that makes the overall assessment of return predictability rather difficult and raises concerns of data mining is the fact that the extant literature relies primarily on in-sample tests. It is typically believed however, that out-of-sample tests are able to correct for this and to provide a measure against data mining. Interestingly, this “conventional wisdom” has been challenged by a few researchers. For example, Inoue and Killian (2004) and Rapach and Wohar (2006) both show that, if appropriate tests are employed, in-sample and out-of-sample tests are equally reliable. Rapach and

Wohar (2006) argue that the case for a predictable component in stock returns is strengthened by this result[1].

As shown above, given the number of potential biases, it is perhaps not surprising that no consensus has been reached over the issue of return predictability. In a departure from the above literature, Goyal and Welch (2003) employ a simple, recursive residuals (out-of-sample) graphical approach to assess equity premium prediction. An attractive attribute of this methodology is that it allows the identification of different periods of predictability. In other words, the out-of-sample performance of the dividend ratios can be decomposed, allowing detection of which month or year they succeed (or fail) in predicting the equity premium. The graphical diagnostic employed makes it easy to observe the relative performance of different forecasting models. The methodology is straightforward to implement and provides a powerful complement to those methods seeking to compute the appropriate standard errors of a test statistic**.** Goyal and Welch (2003) examine the comparative performance of the dividend yields and dividend-price ratios against the unconditional equity mean of the US equity premium. Their graphical diagnostic, covering the period 1926 to 2002, indicates that the presumed predictive ability of the dividend ratios is a "mirage", any predictive ability dependent on only two years, 1973 and 1974.

This paper adopts the Goyal and Welch (2003) methodology to examine whether dividend ratios are useful predictors of the UK equity premium. Recent studies using more conventional methods (see, *inter alia*, McMillan, 2003, and Pesaran and Timmermann, 2000) suggest that dividend yields may have some predictive power in the UK context. The graphical diagnostic will allow us to re-

[1] This argument is based on the notion that typically, in-sample tests provide more evidence of return predictability than out-of-sample.

examine these claims, and if supported, observe dynamically when predictability has occurred. Our empirical application relies on the FTSE All Share index which is the most commonly used index with respect to stock return predictability in the UK market. The data set constructed contains monthly observations covering the period from 1975 to 2004.

Our study adds to an emerging literature that is linked to the UK market, in contrast to the overwhelming majority of the extant literature focusing primarily on the US market. Strikingly we find strong support for the predictability of the UK equity premium. This is found using the graphical diagnostic and conventional in-sample and out-of-sample tests. In particular the graphical diagnostic highlights the period from the late 1990s onward as highly predictable. Moreover, with the purpose of delving deeper into our main predictive variable, the dividend ratio, we employ the Campbell and Shiller (1988) theory to account for the time-varying properties of the dividend yield and dividend growth processes. It is shown that by instrumenting models with the Campbell and Shiller identities, forecasting ability can be yet further improved.

The paper is organized as follows: Section 2 provides information on the data set and describes the main variables as well as the transformations used in the empirical analysis. Section 3 presents the methodology while section 4 offers the results and discusses the empirical findings. A final section concludes our study.

2. Data

The FTSE All Share, or to give its full name, "The Financial Times Actuaries All Share Index" is the most comprehensive UK stock market index. In our study, monthly data is employed on this index, covering the period from 1975:02 to 2004:10. All data were obtained from Datastream, the starting date representing the extent of data availability from that databank. The use of a monthly frequency is particularly advantageous, allowing the examination of intra-annual predictability.

A number of variables are relevant to the study. Firstly, and as is common in the literature, log returns on the index are used:

$$r_{m,t} = \log[R_{m,t}] = \log[(P_t + D_t) / P_{t\text{-}1})] \quad (1)$$

where P is the stock index level and D the paid dividends. Next, the log returns on the three-month risk-free Treasury bill (called $R_{f,t}$) are calculated:

$$r_{f,t} = \log[1 + R_{f,t}] \quad (2)$$

The dividend-price ratio DP_t is the log of the aggregate dividends D_t divided by the aggregate stock market value P_t:

$$DP_t = \log[D_t / P_t] \quad (3)$$

whilst the dividend yield ratio DY_t is defined:

$$DY_t = \log[D_t / P_{t\text{-}1}] \quad (4)$$

Finally, the equity premium is denoted by EQP_t and is the return on the stock market ($r_{m,t}$) minus the return on a short-term risk-free treasury bill ($r_{f,t}$):

$$EQP_t = r_{m,t} - r_{f,t} \quad (5)$$

Table 1 provides the descriptive statistics for the series. For the entire sample period, the average log equity premium was 5.29%; the average dividend yield was 4.32%

and the average dividend-price ratio was 4.28%. In common with the vast majority of previous work, the augmented Dickey and Fuller (1979) test suggests the presence of a unit root in the dividend ratios. For completeness, Figure 1 plots the time series of the equity premium and the dividend ratios.

[Insert Table 1 around here]

[Insert Fig. 1 around here]

3. Methodology

3.1 In-Sample Predictability

In order to evaluate the in-sample predictive ability, we estimate the following predictive regression model:

$$EQP_t = \alpha + \beta x_{t\text{-}1} + \varepsilon_t \qquad (6)$$

where the lagged predictive variable $x_{t\text{-}1}$ can be either the lagged dividend-price ratio $(DP_{\text{t-1}})$ or the lagged dividend yield ($DY_{t\text{-}1}$). The predictive ability of x_t is assessed by examining the t-statistic corresponding to $\hat{\beta}$, the OLS estimate of β in equation (6), as well as the goodness of fit measure, R^2. The null hypothesis tested is that of no predictability, i.e. $\beta = 0$ against the alternative that there is predictability, i.e. $\beta \neq 0$.

3.2 Out-of-Sample Predictability

A market timing investor would be interested in knowing if s/he could take advantage of the dividend ratios in order to predict the equity premium. Thus, the question is how the "conditional dividend-ratio models" would perform when compared to the "unconditional historical equity premium model" (the prevailing simple moving average). As in Goyal and Welch (2003), forecasting regressions are estimated only with then-available data. Both the conditional models and our naïve benchmark model are estimated as recursive forecasts to predict one-month-ahead equity premia.

Our next goal is to compare the out-of-sample forecasts from the dividend model predictive regressions against the historical mean. If the conditional dividend ratio model outperforms the prevailing moving average then this implies that the dividend ratios add useful information and improve predictive ability. First we report the statistics on the out-of-sample prediction errors obtained in different sample periods. In particular we document the mean, the standard deviation, the root mean square error (RMSE) and the mean absolute error (MAE) of equity premium prediction errors. Finally, we compute the Diebold and Mariano (1995) test statistic for equal predictive accuracy.

3.3 A Graphical Evaluation Method for the Out-of-Sample Performance

Following Goyal and Welch (2003), we employ a graphical method as a complementary diagnostic for equity premium and stock price prediction. The procedure consists of plotting the cumulative sum-squared error from the unconditional model minus the cumulative sum-squared error from the dividend ratio model (denoted by $Net-SSE_T$). Expressed algebraically:

$$Net\text{-}SSE_T = \sum_{t}^{T}[SE_t^{\Pr evailing\ Mean} - SE_t^{Dividend\ Model}] \tag{7}$$

where SE_t is the squared out-of-sample prediction error in observation t. The unconditional SE is obtained when the prevailing up-to-date equity premium average is used to forecast the following month's equity premium. The conditional prediction errors of the dividend models are obtained from recursive regressions with either $DP_{t\text{-}1}$ or $DY_{t\text{-}1}$ as the sole predictor of the following month's equity premium. Clearly, a positive value indicates that the dividend ratio model has outperformed the unconditional model so far. In addition, a positive slope indicates that the dividend model had lower forecasting error in a given month (i.e. superior performance).

Although graphing recursive residuals is relatively simple, Goyal and Welch (2003) stress its neglect by the literature implies some possible insights regarding predictability have typically been overlooked. In particular, the methodology allows for a more dynamic identification of predictability. Time periods where dividend ratios succeed (or fail) in predicting the equity premium relative to the prevailing mean can be clearly observed. As a consequence the graphical procedure can be used to enhance information derived from more conventional summary measures. As noted in the introduction, Goyal and Welch (2003) claim the graphical diagnostic reveals any predictability shown by US summary measures is caused primarily by outliers. On the other hand, it is possible that when the summary measures indicate no predictability, the graphical procedure may reveal pockets of forecastability which are hidden when an averaging procedure is employed.

3.4 Instrumenting the Changing Dividend-Ratio Process

Goyal and Welch (2003) argue that changes in dividend ratio autocorrelation and in the ability to predict changes in dividend growth could themselves imply changes in the dividend ratio ability to predict the equity premium. These process changes can be used to enhance the dividend ratio forecasting coefficients for the equity premium. To explain this in more detail consider the Campbell and Shiller (1988) approximate present value relation with time-varying expected returns. Assuming that dividends and returns follow log-linear processes, the approximation begins with the following identity:

$$1 \equiv (1+R_{m,t+1})^{-1}(1+R_{m,t+1}) \Rightarrow$$
$$1 \equiv (1+R_{m,t+1})^{-1}(1+\frac{P_{t+1}+D_{t+1}-P_t}{P_t}) \equiv (1+R_{m,t+1})^{-1}\frac{P_{t+1}+D_{t+1}}{P_t} \tag{8}$$

After some algebra, we find that the log dividend-price ratio can be approximated by the following relationship:

$$d_t - p_t \approx r_{m,t+1} - \Delta d_{t+1} - k + \rho(d_{t+1} - p_{t+1}) \tag{9}$$

or if we isolate returns on the LHS:

$$r_{m,t+1} \approx (d_t - p_t) - \rho(d_{t+1} - p_{t+1}) + \Delta d_{t+1} + k \tag{10}$$

Now taking covariances with DP_t and dividing by the variance of DP_t we have:

$$\frac{Cov(r_{m,t+1,}DP_t)}{Var(DP_t)} \approx 1 - \rho\,\frac{Cov(DP_{t+1},DP_t)}{Var(DP_t)} + \frac{Cov(\Delta d_{t+1},DP_t)}{Var(DP_t)}$$
$$\Rightarrow \beta_{r_{m,t+1},DP_t} \approx 1 - \rho\,\beta_{DP_{t+1},DP_t} + \beta_{\Delta d_{t+1},DP_t} \tag{11}$$

The new model employs equation (11)[2]. To estimate (11) we initially carry out recursive estimations of the following regressions which correlate the dividend-price ratio and the dividend growth with the lagged dividend-price ratio:

$$DP_{t+1} = \alpha_0 + \alpha_1\, DP_t \tag{12}$$

$$\Delta d_{t+1} = \gamma_0 + \gamma_1\, DP_t \tag{13}$$

Once we have obtained the recursive coefficients α_1 and γ_1 from the above regressions, we can use (11) to calculate the instrumented beta β_1 as follows:

$$\beta_1 = 1 - \rho\,\alpha_1 + \gamma_1 \tag{14}$$

Accordingly, using the above instrumented beta, the indirect Campbell and Shiller forecasts are constructed as follows:

$$r_{m,t+1} = \beta_0 + \beta_1\, DP_t$$

[2] Note that these approximations work only for returns and not for equity premia and also for dividend-price ratios but not dividend yields.

$$\beta_1 = 1 - \rho\alpha_1 + \gamma_1$$

On the other hand, direct forecasts (the straight dividend model) are constructed simply by using the equation:

$$r_{m,t+1} = \beta_0 + \beta_1 DP_t$$

and obtaining the recursive beta coefficients.

4. Results

4.1 In-Sample Fit

Table 2 tabulates the results of the univariate regressions that associate the log equity premium with the lagged dividend-price ratio (DP_t) and the lagged dividend yield (DY_t).

[Insert Table 2 around here]

Prior to 1995, the dividend ratios had significant forecasting power (with the dividend yield appearing more reliable) and the predictive ability actually increases as we extend the sample period into 2004. The t-statistics, both plain and Newey-West adjusted for heteroskedasticity and autocorrelation, vary between 1.90 and 4.08. For the whole sample, the dividend-price ratio and the dividend yield retain good statistical significance (the t-statistics are 3.76 and 4.08 respectively). Such results are not untypical of those found in the literature.

4.2 Out-of-Sample Forecasts

Obviously, a trader or other interested party would not be able to use the in-sample results to forecast the equity premium. As such Table 3 displays statistics on the out-of-sample prediction errors when only then-available data are used to construct forecasts. The errors from the dividend models are obtained from recursive regressions that employ the lagged dividend-price ratio and the lagged dividend yield as predictors for the equity premium.

[Insert Table 3 around here]

Strikingly, both the dividend-price ratio and the dividend yield appear to outperform the historical moving average across all periods. This is particularly noticeable during the 2000-2004 sample period where the RMSE for our naive benchmark model is 6.11% whilst for the dividend-price ratio it is 5.36% and for the dividend yield it is 5.35%. Clearly, we need to examine whether these identified differences are statistically significant. Table 4 reports the computed Diebold and Mariano (1995) statistics for different out-of-sample periods.

[Insert Table 4 around here]

For the full sample the dividend ratio models significantly outperform the historical moving average at the 5% level of significance (with the DM statistics being 2.13 for the dividend- price model and 1.70 for the dividend yield model). These results add to the small body of work suggesting, that perhaps in contrast to the US, a degree of predictability exists in UK stock returns (see, *inter alia*, McMillan, 2003). Furthermore, although an arbitrary division of the sample, the DM tests indicates that the predictability is strongest in the 2000-2004 period. To investigate the dynamic nature of UK stock return predictability in more detail we turn to the graphical procedure.

4.3 A Graphical Evaluation Method for the Out-of-Sample Performance

Figure 2 depicts the relevant graph of the recursive residuals diagnostic test that is described in section 3.3.

[Insert Fig. 2 around here]

The graph shows that, relative to the historical mean, both the dividend-price and the dividend yield do not exhibit superior performance during the 1993-1994 period. Additionally, towards the end of 1998 and until mid-1999 the slope is strongly negative indicating a superior performance of the historical mean. However, during 1994-1996 and particularly post-1999, the graph line reveals an upward tendency (i.e. the slope is positive) which prevails until the end of the sample, in 2004, suggesting a better performance of the dividend models. The usefulness of the graphical diagnostic in this context is clear: it confirms the predictability results from the conventional measures and clarifies that the period from the late 1990s onward is highly predictable.

4.4 The Instrumented Model

Goyal and Welch (2003) indicate that it might be possible to enhance the dividend-ratio forecasting coefficients by instrumenting the model to account for the time-varying properties of the dividend yield and dividend growth processes. To our knowledge this has not been applied in a UK context. To that end we apply the methodology outlined in section 3.4. Initially, Figure 3 plots the time series of the naïve stock return betas and the instrumented Campbell-Shiller (CS) based betas[3].

[Insert Fig. 3 around here]

The CS betas show a decline during the decade 1990-2000 and are typically slightly lower than the ordinary betas. However the trend reverses from 2000 and reveals an upward tendency while at the same time the CS betas are slightly higher than the ordinary betas.

[3] For the estimation of the CS betas in equation (11), ρ can be calibrated to be about 0.96 for the UK market.

Table 5 shows how the prevailing mean, the straight dividend model and the instrumented dividend model perform when predicting stock returns. The forecast error statistics are calculated with respect to the period from 1990:01 to 2004:10 (i.e. our out-of-sample period). Note that direct forecasts in Table 5 are comparable to those in Table 3 with the only difference being that the former forecasts stock returns themselves while the latter is constructing forecasts of excess stock returns.

[Insert Table 5 around here]

The results indicate that both models manage to outperform the prevailing stock return moving average. The RMSE for the prevailing mean model is found to be 4.59% as opposed to 4.03% for the straight dividend model and 3.99% for the instrumented model. In addition, the DM statistics for the straight dividend model and the instrumented model are 3.03 and 3.25 respectively, indicating superior performance against the historical moving average model, both at 1% and 5% levels of significance.

Furthermore, when we compare the straight dividend model against the Campbell and Shiller based model (i.e. the instrumented model) we find that they are statistically different from one another with the latter exhibiting better performance (the DM statistic is 4.9). The last result establishes the fact that we can improve predictive ability using the Campbell and Shiller (1988) accounting identities. In other words, taking into consideration the time-varying properties of the dividend yield and dividend growth processes by instrumenting our model, we can enhance forecasting coefficients and improve out-of-sample performance. Again, this new result for the UK is in sharp contrast with Goyal and Welch (2003) and the US context.

5. Conclusion

A relatively small body of literature suggests that a degree of predictability exists in UK equity premia. To extend this work, the current paper primarily employs a recursive residuals (out-of-sample) graphical approach. This methodology allows for a more dynamic identification of predictability, revealing the actual time periods where dividend ratios succeed (or fail) in predicting the equity premium. Its usefulness was first illustrated by Goyal and Welch (2003). They show graphically that the supposed predictive ability of post-war US dividend ratios is essentially dependent on a few outlier observations.

Our empirical application relies on the well known UK FTSE All Share stock market index and uses monthly data covering the 1975:02-2004:10 period. Firstly, preliminary in-sample univariate regressions show that, prior to 1995, the dividend ratios had significant forecasting power and extending the sample into 2004, the predictive ability actually increases. Secondly, as far as the conventional out-of-sample performance is concerned, forecast error statistics and Diebold-Mariano (1995) tests indicate that dividend ratio models outperform the unconditional historical equity premium model (the prevailing simple moving average) across all periods. These preliminary results can be seen as further confirmation of the literature that suggests dividend ratios can be employed to predict UK equity premia.

To analyse the dynamic nature of UK equity premia predictability we next turn to the graphical procedure. The general idea is to plot (against time) the cumulative sum-squared error from an unconditional model minus the cumulative sum squared error from a dividend ratio model. An upward tendency in the graph line therefore suggests the better performance of the dividend ratio models. Goyal and Welch (2003) stress that although a simple procedure, its neglect by the literature may have left useful information regarding predictability uncovered. When the methodology is applied to our UK data, pockets of forecastability are shown to exist before the late 1990s. Most strikingly however, the methodology identifies that the period from the late 1990s onward as consistently predictable. This new result adds significantly to the information set regarding UK equity premia predictability: for example, revealing that unlike the US case, predictability is not the result of outlier observations.

Finally, in an effort to improve the predictability of UK equity premia, we employed Campbell and Shiller (1988) theory to instrument the forecasting model. Specifically, we account for the time-varying properties of the dividend ratio and dividend growth processes. To our knowledge this has not been applied in a UK context. In contrast to Goyal and Welch (2003) we find that the relevant descriptives of forecast errors and the Diebold and Mariano (1995) statistics reveal that the Campbell and Shiller (1988) identities can further improve the forecasting ability of UK dividend ratios!

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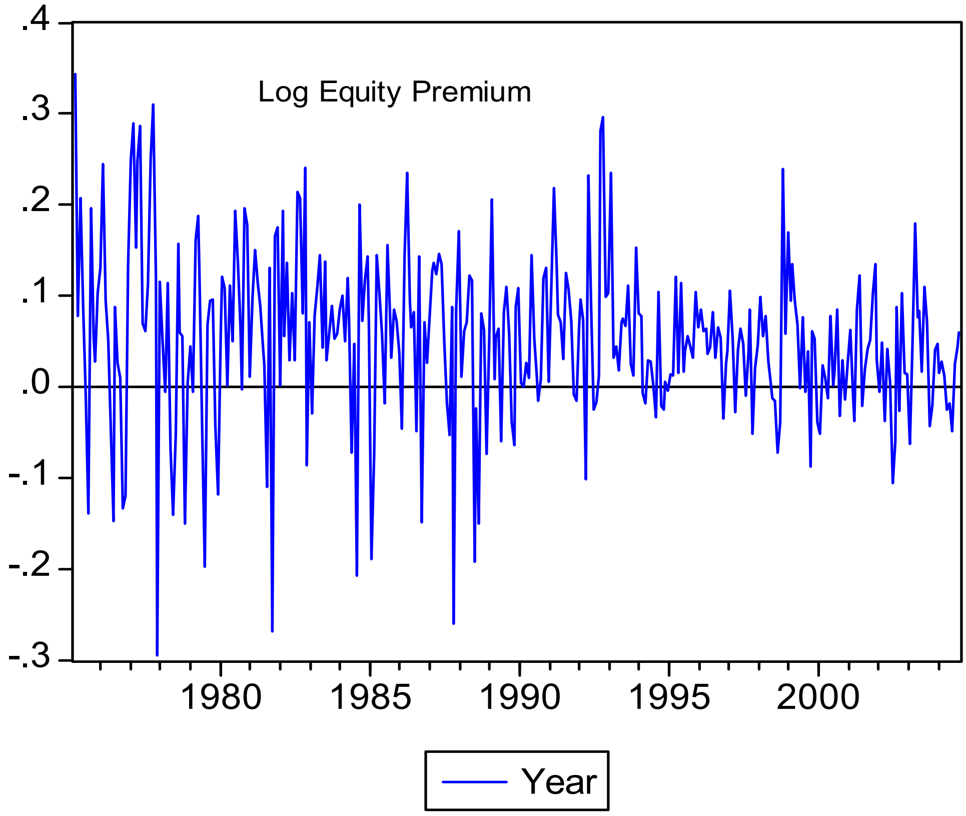
APPENDIX

1 FIGURES

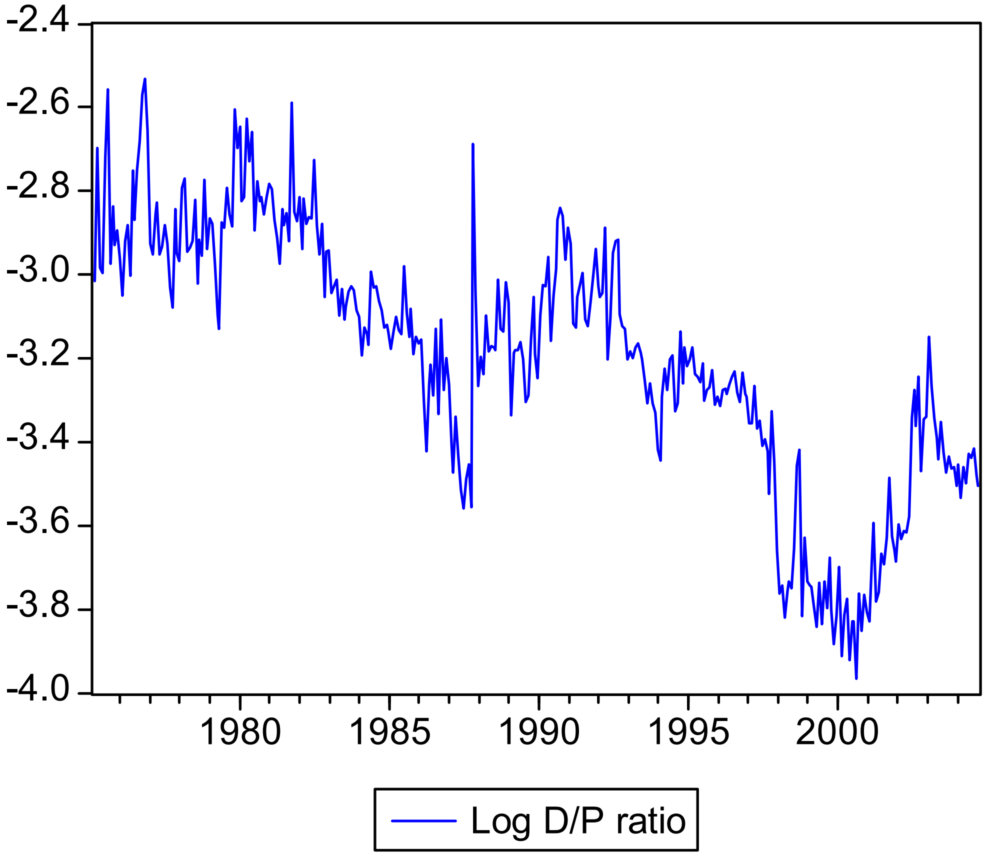
Figure 1 Time Series Graphs

Explanation: The following 3 graphs plot the time series of the log equity premium, the log dividend-price ratio and the log dividend yield respectively. All variables are described in section 2 and in Table 1.

a) The Log Equity Premium



b) The Log Dividend-Price Ratio



c) The Log Dividend Yield

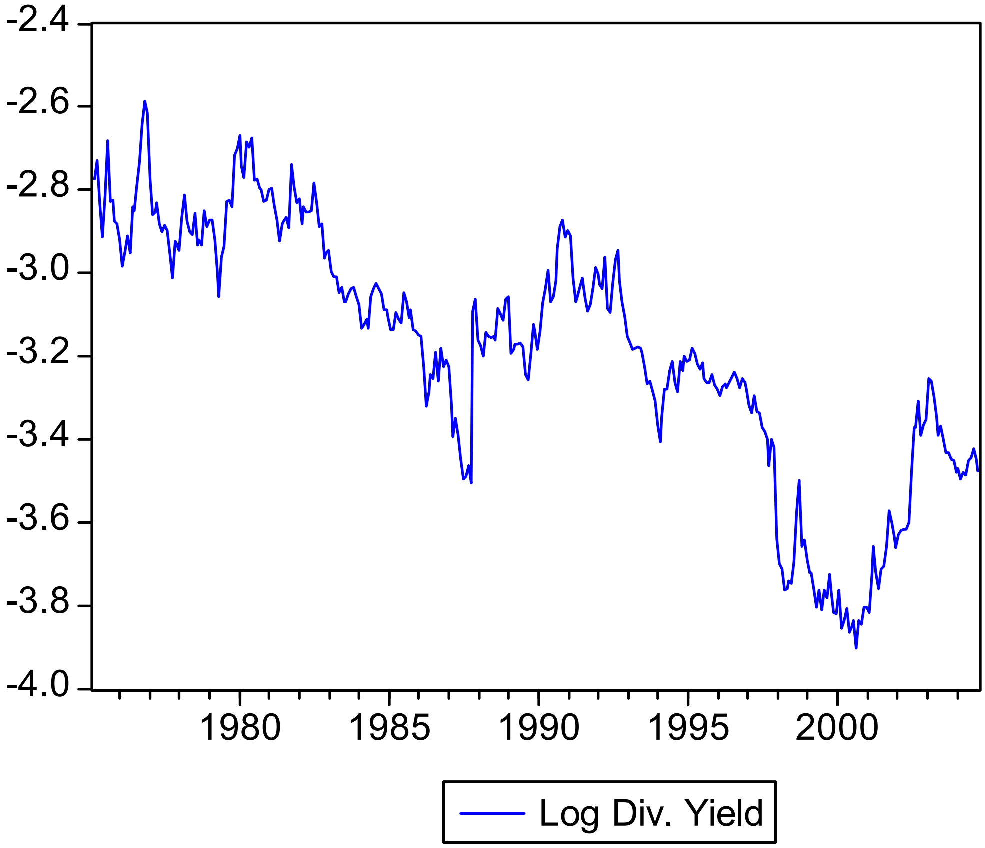
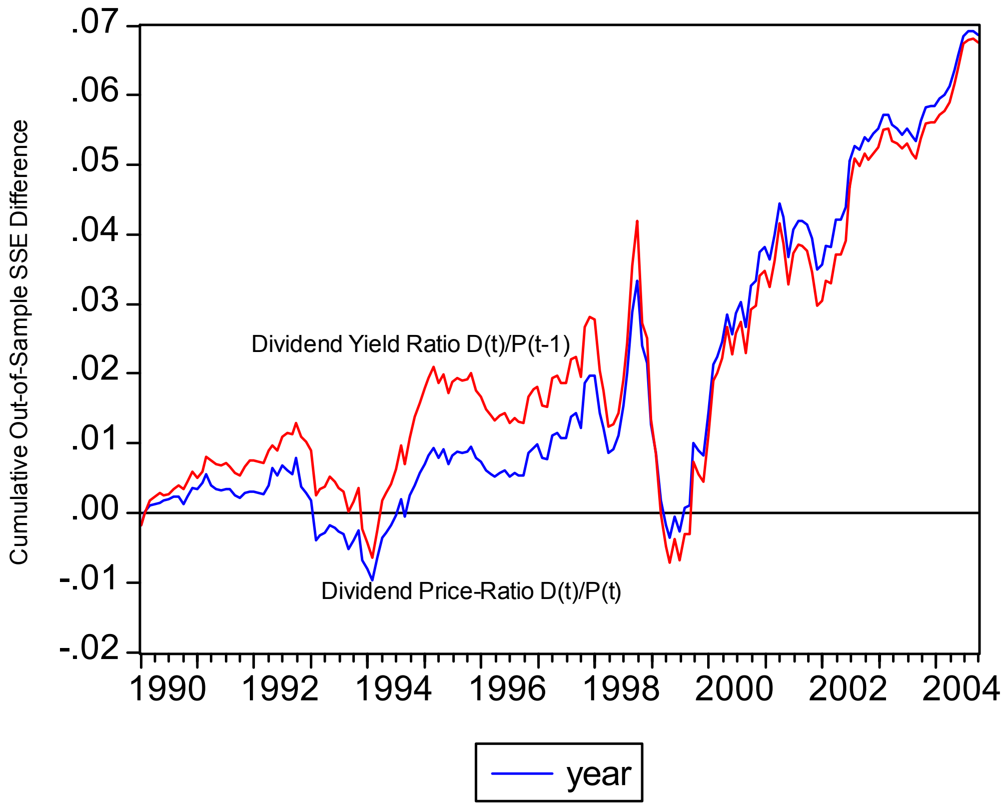


Figure 2 Cumulative Relative Out-Of-Sample, Sum-Squared Error Performance

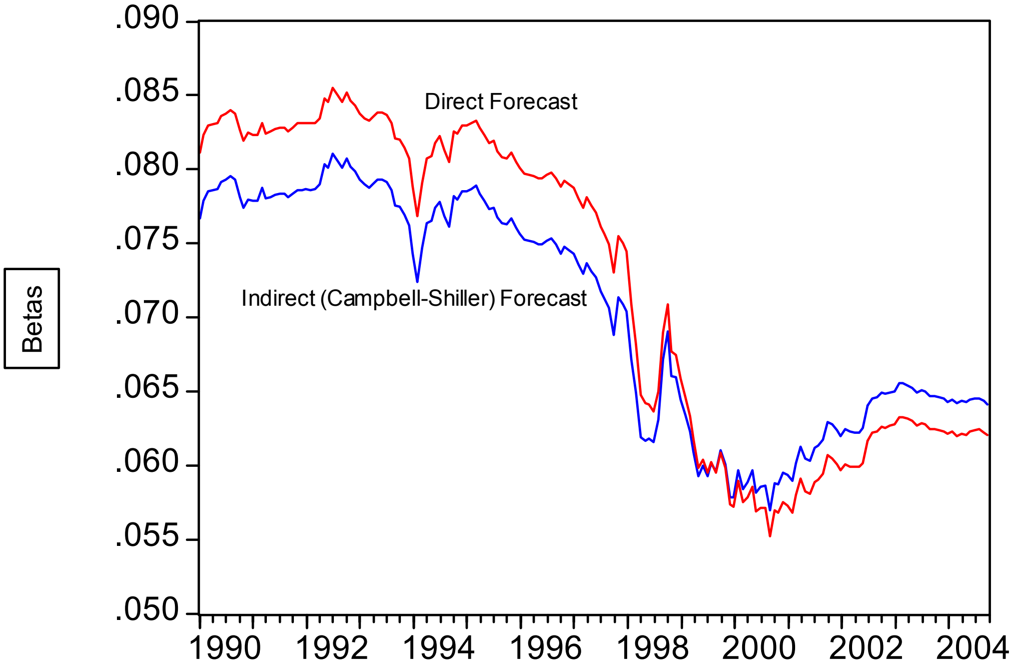


Explanation: This figure plots $Net\text{-}\mathrm{SSE}_T$ which is the cumulative sum-squared error from the unconditional model minus the cumulative sum-squared error from the dividend ratio model. 1990:01 – 2004:10 is the out-of sample period. In particular, it plots:

$$Net\text{-}SSE_T = \sum_t^T [SE_t^{Prevailing\ Mean} - SE_t^{Dividend\ Model}]$$

Where SE_t is the squared out-of-sample prediction error in observation t. The unconditional SE is obtained when the prevailing up-to-date equity premium average is used to forecast the following month's equity premium. The conditional prediction errors of the dividend models are obtained from recursive regressions with either $DP_{t\text{-}1}$ or $DY_{t\text{-}1}$ as the sole predictor of the following month's equity premium.

Figure 3 Campbell-Shiller Betas



Explanation: This figure plots the recursive beta coefficients of forecasts using the dividend-price ratio as a regressor. Direct forecasts are constructed using the equation $r_{m,t+1} = \beta_0 + \beta_1 DP_t$. Campbell-Shiller forecasts are constructed using:

$$DP_{t+1} = \alpha_0 + \alpha_1 DP_t$$
$$\Delta d_{t+1} = \gamma_0 + \gamma_1 DP_t$$
$$\beta_1 = 1 - 0.96\alpha_1 + \gamma_1$$
$$r_{m,t+1} = \beta_0 + \beta_1 DP_t$$

The recursive betas are calculated using the entire history of data available. Figure 3 plots these betas only for the period from 1990:01 to 2004:10.

2 TABLES

Table 1 Descriptive statistics

	Mean	Sdev.	Median	Min	Max	Skew	Kurt	JqBr	ADF
Sample 1975:02-2004:10									
$r_{m,t}$	5.08	5.25	5.24	-33.95	29.12	-0.86	12.25	1311.44	-17.92
EQP_t	5.29	9.16	5.55	-29.48	34.39	-0.24	4.59	41.17	-16.26
DP_t	-3.20	0.31	-3.17	-3.97	-2.53	-0.42	2.60	13.05	-1.996
DY_t	-3.19	0.30	-3.15	-3.90	-2.58	-0.51	2.51	19.09	-1.832
Δd_t	0.68	7.66	0.98	-37.5	46.43	0.12	8.51	449.38	-14.46

Explanation: All series are described in section 2. $r_{m,t}$ is the log return on the UK FTSE-All Share stock market index from month t-1 to t. The equity premium EQP_t subtracts the equivalent log return on a 3-month treasury bill. $DP(t)$ is the dividend-price ratio, i.e. the log of the dividend D_t divided by the stock market price P_t. The dividend yield DY_t divides by P_{t-1} instead. Δd_t is the change in log dividends from month t-1 to t. All variables are in percentages.

Table 2 In Sample Univariate Regressions $EQP_t = \alpha + \beta x_{t-1} + \varepsilon_t$

x_{t-1}	α	β	R^2 %	R^2 adj.%	s.e.%	N
Sample Period 1975:4-1995:4						
DP_{t-1}	0.290	0.076	2.16	1.75	10.09	241
t-stat	[2.89]	[2.30]				
NW t-stat	[2.37]	[1.90]				
DY_{t-1}	0.370	0.103	3.40	2.99	10.02	241
t-stat	[3.45]	[2.90]				
NW t-stat	[2.89]	[2.46]				
Sample Period 1975:4-2000:4						
DP_{t-1}	0.228	0.055	2.57	2.24	9.36	301
t-stat	[3.72]	[2.81]				
NW t-stat	3.15]	[2.43]				
DY_{t-1}	0.254	0.063	3.22	2.90	9.33	301
t-stat	[4.04]	[3.16]				
NW t-stat	[3.40]	[2.71]				
Sample Period 1975:4-2004:10						
DP_{t-1}	0.236	0.058	3.85	3.57	8.88	355
t-stat	[4.8]	[3.76]				
NW t-stat	[4.11]	[3.32]				
DY_{t-1}	0.253	0.063	4.49	4.22	8.85	355
t-stat	[5.11]	[4.08]				
NW t-stat	[4.36]	[3.60]				

Explanation: Table 2 presents the results of the following univariate regression:

$$EQP_t = \alpha + \beta x_{t-1} + \varepsilon_t$$

For each regression the estimated coefficients are given in the first row while the OLS t-statistics and the Newey-West adjusted t-statistics are given in the second and third row respectively.

Table 3 Out-of-Sample Performance: Forecast Errors

	Prevailing Mean %	Dividend-Price ratio model %	Dividend Yield model %
Full sample 1990:01-2004:10			
Mean	**-1.45**	0.49	0.96
Standard Deviation	6.51	6.35	**6.31**
Root Mean Square Error	6.65	**6.36**	**6.36**
Mean Absolute Error	5.15	4.81	**4.79**
First Subsample 1990:01-1995:01			
Mean	**0.03**	0.91	1.27
Standard Deviation	7.85	7.72	**7.55**
Root Mean Square Error	7.79	7.71	**7.60**
Mean Absolute Error	6.09	6.00	**5.79**
Second Subsample 1995:02-2000:02			
Mean	-1.66	**1.03**	1.73
Standard Deviation	5.67	**5.61**	5.63
Root Mean Square Error	5.86	**5.66**	5.85
Mean Absolute Error	4.33	**4.25**	4.37
Third Subsample 2000:03-2004:10			
Mean	-2.80	-0.57	**-0.21**
Standard Deviation	5.45	**5.37**	5.38
Root Mean Square Error	6.10	5.35	**5.34**
Mean Absolute Error	5.00	**4.13**	**4.14**
Subsample 1990:01-2000:01			
Mean	**-0.70**	1.04	1.56
Standard Deviation	6.84	6.71	**6.63**
Root Mean Square Error	6.85	**6.76**	6.78
Mean Absolute Error	5.16	5.11	**5.07**

Explanation: All series are described in section 2 and Table 1. This table presents the properties of the equity premium prediction errors from the naïve model that uses only the prevailing historical mean equity premium as a forecast and another model that uses the dividend-price ratio or the dividend yield as a predictor. Both models use all prevailing data beginning in 1975:02. Bold-face values denote superior performance.

Table 4 Diebold and Mariano (1995) statistics

	Dividend-Price ratio model	Dividend Yield model
1990:01-2004:10 (full sample)	**2.13**	**1.70**
1990:01-1995:01	0.80	1.40
1995:02-2000:02	0.57	0.07
2000:03-2004:10	**2.75***	**2.47***
1990:01-2000:01	0.66	0.43

Explanation: This Table tabulates the computed Diebold and Mariano (1995) statistics across different periods. The Diebold and Mariano (1995) statistic tests whether the RMSE performances reported in Table 3 are statistically different from one another. Boldface indicates significance at the 5% significance level. Star indicates significance both at 5% and 1%.

Interpretation: For the full sample the dividend-price ratio models significantly outperform the historical moving average at the 5% significance level. During the last period of our sample, both dividend ratios perform better than the unconditional mean both at 5% and 1%

Table 5 Instrumented Dividend-Ratio Forecasts for Returns

Forecast Error statistic	Prevailing Mean %	Straight Dividend Model %	Instrumented Dividend Model
Mean	-1.90	0.20	0.17
Standard Deviation	4.19	4.04	4.00
Root mean square error	4.59	4.03	3.99
Mean absolute error	3.44	3.12	3.09

Explanation: This table reports the results of stock return prediction from a model that uses the prevailing average stock return as a forecast and two other models:
Direct forecasts (the straight dividend model) are constructed using the equation

$$r_{m,t+1} = \beta_0 + \beta_1 DP_t$$

Indirect Campbell –Shiller based forecasts (the instrumented model) are constructed using:

$$DP_{t+1} = \alpha_0 + \alpha_1 DP_t$$

$$\Delta d_{t+1} = \gamma_0 + \gamma_1 DP_t$$

$$\beta_1 = 1 - 0.96\alpha_1 + \gamma_1$$

$$r_{m,t+1} = \beta_0 + \beta_1 DP_t$$

The recursive betas are calculated using the entire history of data available. The descriptives of forecast errors involve only the period of 1990:01-2004:10. Note that direct forecasts in Table 5 are comparable to those in Table 3, with the only difference that Table 5 forecasts stock returns instead of excess stock returns. For this period we also calculated the Diebold and Mariano (1995) statistic which measures the statistical difference between RMSEs from two models and is asymptotically normally distributed.

Interpretation: The forecasting ability indeed does improve using the Campbell–Shiller identities. Diebold and Mariano (1995) statistics for the two models are 3.03 and 3.25 indicating that both models significantly outperform the prevailing moving average out-of-sample. When the straight dividend model is compared to the instrumented model, the Diebold and Mariano (1995) statistic is found to be 4.09 and this demonstrates that the Campbell–Shiller based betas manage to improve predictive ability.