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Can the information content of share repurchases improve the accuracy of equity premium predictions?

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- We study the role of actual share repurchases in predicting UK and French equity premia.
- To relate to markets with less stringent disclosure requirements we also use proxy repurchase data.
- Actual share repurchases do not lead to better equity premium predictions.
- The predictive content of proxies is not in line with that of actual repurchase data.
- Results based on economic value are consistent with the statistical results.

1. Introduction

A number of studies in the return predictability literature has documented the poor out-of-sample performance of the dividend-price ratio and other variables when used to predict stock returns in the US context (see Bossaerts and Hillion 1999; Goyal and Welch 2003, 2008). A very recent and small body of work posits the view that the weak out-of-sample performance of the dividend-price ratio in the US may be due to the fact that dividends alone are not representative of the true cash flow to shareholders (see Robertson and Wright 2006; Boudoukh et al. 2007). This work links the loss of the dividend-price ratio's predictive power to the fact that firms substitute share repurchases for dividend payments. For instance, Boudoukh et al. (2007, p. 880) argue that "repurchases should be taken into account when relating yields to expected returns". Hence, they construct the total payout ratio, a measure that adjusts the dividend-price ratio for share repurchase activity and demonstrate that it outperforms the dividend-price ratio in terms of predictive ability.

Furthermore, recent work suggests that share repurchases have also become an increasingly popular and important way of providing cash payouts to shareholders in countries other than the US (von Eije and Megginson, 2008; Haw et al., 2011). However, regulations governing share repurchases are not uniform across countries (Kim et al., 2004). For example, the actual number of repurchased shares and the price paid are not always disclosed (Gonzalez and Gonzalez, 2004; Haw et al., 2011). Therefore, lack of disclosure requirements in some markets could result in researchers and investors having to rely on monthly or quarterly proxies to measure share repurchase activity (Stephens and Weisbach, 1998; Chung et al., 2007). Nevertheless, these proxies tend to produce inaccurate estimates of actual repurchase data (Banyi et al., 2008).

The linkage between share repurchases and return predictability suggested in the recent US literature combined with the growing importance of share repurchases as a payout method outside the US market raises two important questions: Can share repurchases add useful information in predictive regressions with the equity premium outside a US setting? Furthermore, to what extent can the imprecise calculation of share repurchases lead to a spurious relationship between the total payout ratio and the equity premium due to lack of disclosure requirements in some countries? Our study seeks to answer these questions and offers important new evidence within an international stock return predictability setting.

The contribution of this paper is threefold. First, we examine whether actual share repurchases via the total payout ratio variable can enhance the ability of the dividend-price ratio to predict the equity premium in the UK and France stock markets. These two markets are the largest in terms of capitalisation and the ones with the highest repurchase activity in Europe (von Eije and Megginson, 2008). For both countries, our sample covers all listed companies (active and delisted) reported in DataStream and spans the period 1990:01-2010:06. To our knowledge, this is the first study to investigate the predictive content of share repurchases within a cross-country framework. Such framework allows us to extend the existing evidence which is limited and focused only on the US market.

Second, we investigate whether the imprecise calculation of share repurchases can affect inferences in terms of predictability. Firms in the UK and France are required to disclose the number of repurchased shares and the price paid not long after the transaction is completed. Our dataset is particularly advantageous within this context as it allows us to employ actual repurchase data and to overcome any measurement problems associated with share repurchases. Therefore, we are able to evaluate the predictive content of share repurchases with more

accuracy. We additionally construct a proxy measure of the total payout ratio which involves readily available data from DataStream and can be easily constructed in international markets where there is lack of disclosure requirements. This enables us to assess whether the predictive content of proxy repurchase data is in line with that of the actual repurchase data.

Third, we move beyond a purely statistical context and evaluate the economic significance of return predictability. This is particularly important as out-of-sample statistical significance does not necessarily translate into economic gains for investors (Leitch and Tanner, 1991). In a mean-variance framework, we compare the out-of-sample performance of a dynamic portfolio strategy that uses the historical moving average of the equity premium (benchmark strategy) relative to a dynamic portfolio strategy that uses either the dividend-price ratio, the total payout ratio or the proxy of the total payout ratio.

Our key findings can be summarized as follows. First, by employing a battery of in-sample and out-of-sample tests of predictive accuracy, including the Goyal and Welch (2003) graphical method, we show that the total payout ratio is a useful predictor of UK and French equity premia. However, it fails to outperform the dividend-price ratio in both markets. This new finding in the return predictability literature implies that the predictive performance of the total payout ratio may be driven by the information conveyed by the dividends rather than the actual share repurchase activity.

Second, we demonstrate that the predictive content of the proxy repurchase data is not in line with that of the actual repurchase data. In particular, the proxy measure of the total payout ratio is found to be the weakest predictive variable in the UK market, but the strongest in the French market. This lack of association in the predictive performance between the total payout

ratio and its proxy counterpart suggests that inferences in predictability may be misleading if they are based on proxy measures of repurchase activity.

Finally, the results based on economic value are in line with the corresponding results derived from the statistical analysis. This gives further support to the view that first, repurchase activity does not enhance the predictive content of the dividend-price ratio in the two largest European stock markets and second, measuring repurchase activity with an error is likely to result in a predictive performance which is not in line with that of the underlying actual data.

The paper is organised as follows. Section 2 provides a description of our data and the screening procedure followed. Section 3 presents the methodological approach and Section 4 discusses the empirical findings. Finally, Section 5 concludes.

2. Data Description

Monthly data for all companies listed on the UK and French stock exchanges covering the period from 1990:01 to 2010:06 are obtained from the Thompson Financial DataStream. To account for survivorship bias, our sample includes companies that subsequently failed, merged or were delisted. Collecting data at the firm level enables us to construct the total payout ratio (as defined in equation (2) below) which is not readily available at an aggregate level. Following Griffin et al. (2010) and Lee (2010) we apply a screening process to our international dataset that excludes non-common stocks, such as preferred stocks, warrants, unit or investment trusts, American Depository Receipts (ADRs), Global Depository Receipts (GDRs) or cross listings. In addition, all stocks not listed on the exchanges of the reference country are deleted (Griffin et al., 2010; Ince and Porter, 2006). Our dataset contains stocks from 3,756 UK and 1,538 French firms with

the respective numbers of firm-month observations being 393,084 and 188,278. Moreover, to filter out potential recording errors embedded in DataStream we follow Ince and Porter (2006) and apply a similar screening procedure to stock returns.¹

The dependent variable in our predictive regressions is the equity premium which is commonly defined as the difference between the log of the value-weighted total market return, $r_{m,t} = \log(1 + R_{m,t})$, and the log return on a risk-free three-month Treasury bill, $r_{f,t} = \log(1 + R_{f,t})$.

Our paper employs two variables with the purpose to predict the equity premium, namely the dividend-price ratio and the total payout ratio. The dividend-price ratio is defined as:

$$(1) \quad DP_t = \log \left[\frac{D_t}{MCAP_t} \right],$$

where dividends, D_t , are defined as twelve-month moving sums of dividends paid on common stocks listed on the stock exchange while $MCAP_t$ denotes the total market capitalisation. These data are from the Thompson Financial DataStream.

The total payout ratio on the other hand, can be expressed as:

$$(2) \quad TPO_t = \log \left[\frac{D_t + REP_t}{MCAP_t} \right],$$

where REP_t is defined as the twelve-month moving sum of the total amount of actual share repurchases. The data on the actual value of share repurchases are drawn from Zephyr, a database maintained by Bureau Van Dijk.

In addition, we construct a second measure of the total payout ratio denoted by *proxy-TPO*, which is based on estimated values of share repurchases instead. Specifically, we estimate share repurchases using the monthly decrease in shares outstanding reported by

¹ Returns for months t and $t-1$ are set to missing if $(1+R_t)(1+R_{t-1}) - 1 < 50\%$ where R_t is the return for month t , and at least one of the two returns is greater than 300% (see also Lee, 2010).

DataStream adjusted for distribution events such as stock splits and stock dividends (see, *inter alia*, Stephens and Weisbach, 1998; Banyi et al., 2008). A few other approaches for estimating share repurchases do exist (e.g., Stephens and Weisbach, 1998) but data for their construction in the UK and France are available only at an annual or a semi-annual frequency. Therefore, adopting these approaches, which have their own inherent problems (Banyi et al., 2008), would substantially limit our dataset. Additionally, the proxy we use can be easily applied to other markets with data limitations (either regarding actual repurchase data or components required for constructing proxies for measuring repurchase activity). Our proxy measure of the total payout ratio is expressed as:

$$(3) \quad \text{proxy-TPO}_t = \log \left[\frac{D_t + REP_t^*}{MCAP_t} \right],$$

where REP_t^* is defined as the twelve-month moving sum of the total amount of estimated share repurchases. We are particularly interested in this measure since our aim is to also examine whether predictability results are affected when having to rely on estimated rather than actual data on share repurchases.

For completeness, Figure 1 shows the graphs of all variables under consideration.² The UK dividend-price ratio shows a declining trend between 1990 and 2000 (with the exception of 1994-1996) where it resumes a positive trend until mid-2003. Thereafter, a decline occurs until 2007 where it bounces back until 2009. The two measures of the UK payout ratio show relatively different patterns and the proxy measure is above the one which is based on actual data throughout the entire period. In France, the variables exhibit a similar behaviour and no pronounced changes occur during 1990-1999. On the other hand, they all experience a sharp decline post-1999 and jump back up in mid-2000. These changes may be associated with

² A table of descriptive statistics is available upon request.

changes in stock returns and perhaps they are linked to the ability of the considered variables to convey useful out-of-sample information. Finally, it is worth mentioning that, unlike the UK case, the proxy measure of repurchase activity understates actual repurchases in France.³

[Insert Figure 1 around here]

3. Methodology

3.1. In-sample predictive ability

Typically, empirical studies on stock return predictability employ the following in-sample predictive regression specification:

$$(4) \quad y_t = a + \beta x_{t-1} + \varepsilon_t, \quad t = 1, \dots, T,$$

where $y_t = r_{m,t} - r_{f,t}$ denotes the log excess return (i.e. the equity premium), as defined in Section 2, x_{t-1} is the lagged predictive variable of interest, known at the beginning of the return period, and ε_t is the regression's disturbance term. In our case, x can be either the dividend-price ratio, the total payout ratio or the proxy measure of the total payout ratio.

If expected returns are constant, it is easy to show that β must be zero in equation (4). This is the null hypothesis of no predictability (or the “random walk” hypothesis). Hence, the alternative hypothesis of predictability predicates that $\beta \neq 0$. In practice, the one-sided alternative hypothesis is the more interesting one as it incorporates more economic content (Inoue and Kilian, 2004). The predictive ability of x_{t-1} is assessed by examining the statistical

³ Other than share repurchase activity, there are various factors that can affect the number of shares outstanding and so, the proxy measure may exhibit a different behaviour across countries. These include seasoned equity offerings (SEOs), mergers, the exercise of employee stock options, conversion of convertible securities, purchase or sale of stock by the corporation for employee benefit programs, and warrant exercises.

significance of $\hat{\beta}$, the OLS estimate of β in equation (4), as well as the goodness of fit measure, R^2 .

3.1.1. Bootstrap procedure

To account for potential small sample biases and data mining concerns, we follow much of the recent literature and base our in-sample inferences on a non-parametric bootstrap procedure which imposes the null of no predictability for obtaining appropriate p -values (see Nelson and Kim, 1993; Mark, 1995; Kilian, 1999; Rapach and Wohar, 2006).

The data are generated according to the following system:

$$(5) \quad y_t = a_0 + u_{1t},$$

$$(6) \quad x_t = b_0 + b_1 x_{t-1} + \dots + b_p x_{t-p} + u_{2t},$$

where the disturbance vector $u_t = (u_{1t}, u_{2t})'$ is identically distributed with covariance matrix Σ .

Once the above system is estimated via OLS, with the lag order (p) in equation (6) chosen by the Akaike information criterion (AIC),⁴ the residuals $\hat{u}_t = \{(\hat{u}_{1t}, \hat{u}_{2t})'\}_{t=1}^{T-p}$ are stored for sampling. We then generate 10,000 bootstrapped time-series by sampling with replacement from the residuals, $\{\hat{u}_t\}_{t=1}^{T-p}$ (for a more detailed description, see Rapach and Wohar, 2006). Using these bootstrapped time-series we obtain an empirical distribution for the t -statistic corresponding to $\hat{\beta}$ in the in-sample predictive regression. The p -value of the t -statistic is the proportion of the bootstrap statistics that are higher than the statistic obtained using the original sample. With this bootstrap procedure we are able to preserve both the autocorrelation structure of the predictor variables,

⁴ We consider a maximum number of four lags.

hence being consistent with the Stambaugh (1999) specification, and the contemporaneous correlation between the disturbances in the original sample.

3.2. Out-of-sample performance

3.2.1. Conventional approach

The focal point of our study is the out-of-sample forecasting power of the employed variables since out-of-sample tests are generally considered to be less susceptible to data mining and they are also of particular interest to a real-time investor. Following a recent strand of return predictability papers (e.g., Goyal and Welch, 2008; Rapach et al., 2010; Kellard et al., 2010) we use an expanding estimation window and generate one-month-ahead out-of-sample forecasts of the equity premium recursively.

In more detail, let R denote the number of in-sample observations and let P denote the number of out-of-sample forecasts. The first out-of-sample forecast for the x variable predictive regression model is generated in the following manner. Initially, we estimate equation (4) via OLS using data available through period R . Then, the first forecast for the equity premium is constructed as $\hat{y}_{1,R+1} = \hat{\alpha}_{1,R} + \hat{\beta}_{1,R}x_R$ where $\hat{\alpha}_{1,R}$ and $\hat{\beta}_{1,R}$ are the OLS parameter estimates of α and β in equation (4) using data available through period R . Consequently, the first out-of-sample forecast error is given by $\hat{\varepsilon}_{1,R+1} = y_{1,R+1} - \hat{y}_{1,R+1}$. In order to generate a second set of forecasts, we update the above procedure by using data available through period $R+1$ and obtaining the corresponding OLS parameter estimates. This process is repeated until all available observations are used. On the other hand, each month in the out-of-sample period, our

benchmark model computes the up-to-date equity premium average which gives the respective forecasts for the next month's equity premium.

We report the statistics on the out-of-sample prediction errors obtained in different sample periods. In particular, we document the mean, standard deviation and root mean square error (RMSE) of equity premium prediction errors resulting from each competing model. The next step is to compare the out-of-sample forecasts derived from the conditional models against the corresponding forecasts derived from the historical moving average model, which serves as our benchmark model. If the financial variable under consideration manages to outperform the prevailing moving average then this implies that it adds useful information and improves predictive ability.

As explained in the introduction, the aim of this paper is to examine whether share repurchases can enhance the dividend-price ratio's predictive performance, as well as to explore potential differences in the predictive performance between the total payout ratio and its proxy measure. Therefore, once we assess individual predictive performance, we additionally compare forecasts between the variables themselves.

3.2.2. Testing for equal predictive accuracy

An important facet of the above approach is that the model with the smallest forecast error is not necessarily superior to the other competing models. Hence, we need to formally examine whether the identified RMSE differences are significantly different from one another in a statistical sense. To address the issue, we employ the Diebold and Mariano (1995) (DM) statistic which tests for equal predictive accuracy.

When comparing forecasts between non-nested models (such as between models of two different variables), the DM statistic has a standard normal asymptotic distribution (see West, 1996). However, when comparing forecasts from nested models, McCracken (2007) shows that the DM statistic follows a non-standard limiting distribution and provides asymptotically valid critical values for various combinations of in-sample and out-of-sample proportions (π) and exclusion restrictions (k_2). In our study, this case applies when we compare the benchmark historical moving average model against the conditional models which are based on the considered financial ratios. Hence, for valid inference we use asymptotic critical values tabulated in McCracken (2007).

3.2.3. Further examination of the out-of-sample performance: A graphical approach

This section offers a brief overview of the graphical approach which is introduced by Goyal and Welch (2003) as a complementary measure for equity premium and stock return prediction. This technique could enhance our evidence regarding the out-of-sample performance and more importantly, it might reveal hidden aspects of predictive ability which cannot be captured by the more conventional methods. The graphical procedure makes it easy to detect if and when predictability has occurred throughout the out-of-sample period. Specifically, it plots the cumulative sum-squared error differences between two competing models allowing us to observe the relative performance at any point in time. If we denote it by $SSED_T$ for a sample of T observations, its algebraic expression is as follows:

$$(7) \quad SSED_T = \sum_t^T [SE_t^{\text{unconditional model}} - SE_t^{\text{conditional model}}],$$

where SE_t stands for the squared out-of-sample prediction error in observation t . With respect to the unconditional benchmark model, the prevailing up-to-date moving average serves as the forecast of the next month's excess return. In order to obtain the conditional prediction errors, we carry out recursive regressions with the lagged variable x being the single predictor of the following month's excess return (see Section 3.2.1). A positive point in the graph indicates that the predictive variable has performed better so far. Furthermore, a positive slope suggests a consistently superior performance during a given period.

4. Empirical Results

4.1. In-sample results

Table 1 presents the results of the univariate predictive regressions described in Section 3.1. In order to give a more complete view of the in-sample performance of our predictive variables, we also present results for an arbitrarily chosen sub-period which includes observations up to 2005.

[Insert Table 1 around here]

Regarding the full sample period, the bootstrap p -values suggest that the dividend-price ratio is a significant in-sample predictor of the UK equity premium. The total payout ratio is also found to be significant but produces a lower R^2 .⁵ The proxy measure of the total payout ratio shows a weaker in-sample predictive performance in terms of the produced R^2 s (e.g., an R^2 of 2.73% as opposed to 12.33% for the dividend-price ratio and 6.30% for the total payout ratio) but it is also found to be significant at all conventional levels. Using data up to 2005:01, we find that the overall picture is similar although the corresponding t -statistics and R^2 s are relatively

⁵ In the tables that follow, the TPO measure includes all share repurchases consummated by the firms in our sample. However, our results are also robust to a subset which includes only the open market repurchases.

smaller. However, the proxy of the total payout ratio is statistically insignificant during this period. These findings indicate that during the last five years of the sample, changes in the considered variables are likely to be associated with changes in UK excess returns.

On the other hand, our univariate regressions reveal a different pattern when we use data from France. Both over the full period and with data up to 2005, the proxy measure of the total payout ratio produces the highest t -statistics and R^2 s and the dividend-price ratio follows. Interestingly, the total payout ratio is the weakest in-sample predictor in this case. Nevertheless, all variables retain good statistical significance with the bootstrap p -values ranging from 0.01 to 0.06. These results are not uncommon in the return predictability literature.

Comparing the results between the two markets, we observe that a higher degree of in-sample predictability exists in the UK when the dividend-price ratio and the total payout ratio are employed as predictors. Moreover, the dividend-price ratio exhibits a stronger performance compared to the total payout ratio across markets. Finally, the proxy measure of the total payout ratio shows a predictive performance which is not in line with that of the underlying actual data. In particular, it is found to be a stronger candidate than the total payout ratio in France, but weaker in the UK.

4.2. Out-of-sample results

In-sample statistical significance may be a first indication of predictive performance but this does not mean that the variables under consideration will also be successful predictors of stock returns out-of-sample. Therefore, the real test of a model is whether it can produce good forecasts of future stock returns, and outperform the historical moving average model, using only currently available data. Table 2 tabulates the forecast error statistics obtained from recursive

regressions that employ the lagged variables considered in this study to produce one-month-ahead forecasts of the equity premium. In order to evaluate the out-of-sample performance in a more comprehensive manner, we also divide the full out-of-sample period (i.e. 2000:01-2010:06) into two sub-periods, each spanning approximately five years.

[Insert Table 2 around here]

The dividend-price ratio is found to be the most prominent candidate for predicting the UK equity premium. It produces the lowest RMSE's across all periods suggesting that the information content of share repurchases is not yet able to enhance the dividend-price ratio and strengthen its predictive power in the UK context. Out-of-sample predictability seems to be more pronounced during the last five years of the sample where the dividend-price ratio model yields a RMSE of 11.94%, the total payout ratio yields 12.56% and the proxy payout measure yields 12.84%, as opposed to the RMSE of 13.15% from the benchmark model. Turning to the French market, Table 2 shows that all variables maintain a good out-of-sample performance and outperform the historical moving average across all periods. For instance, during the full out-of-sample period the benchmark model produces a RMSE of 11.12%, the dividend-price ratio model produces a RMSE of 11.02%, the total payout ratio model produces a RMSE of 11.04% while the total payout ratio proxy model yields the smallest RMSE of 10.87%.

A consistent finding across markets is that the actual repurchase data do not convey additional useful information so as to enhance the forecasting power of the dividend-price ratio. A plausible explanation for this finding could be that dividend policies are independent of share repurchase policies in the UK and France. Therefore, share repurchases may not be substitutes for cash dividends and their information content may not be relevant for predicting the equity

premium (Boudoukh et al., 2007).⁶ On the other hand, the proxy measure of the total payout ratio produces the best forecasts across all periods in France, which is in sharp contrast to the UK findings. This result is a first indication that researchers should be cautious when using proxy payout measures in out-of-sample tests.

Overall, the above findings are congruent with our in-sample results in the sense that first, the total payout ratio does not seem able to outperform the dividend-price ratio and second, the predictive content of proxy share repurchases is not in line with that of the actual repurchase data.

4.3. Diebold and Mariano (1995) test results

The identified differences in Section 4.2 above do not necessarily suggest that the competing models produce forecasts which are also different in a statistical sense. Therefore, before we reach our final conclusion we conduct a formal test of equal predictive accuracy. As such, Table 3 tabulates the computed DM statistics when we compare each conditional variable model to the naive benchmark model across different periods. As we are equally interested in the out-of-sample performance of the total payout ratio relative to its proxy measure and to the dividend-price ratio, we report results of the produced DM statistics when making comparisons between the conditional models in Table 4.⁷

[Insert Table 3 around here]

[Insert Table 4 around here]

⁶ Of course there are other reasons for firms to repurchase their own shares (see Lakonishok et al., 1995).

⁷ Calculating a modified version of the Diebold and Mariano (1995) test, suggested by Harvey et al. (1997) and a more recent test proposed by McCracken (2007), do not materially affect our results. The former is used to correct for small size distortions compared to the original DM test and the latter has been proven to be a more powerful statistic in extensive simulation experiments.

Table 3 suggests that during the full out-of-sample period (i.e. 2000:01-2010:06) and also during the two sub-sample periods, the dividend-price ratio and the total payout ratio significantly outperform the historical moving average at all conventional levels. The proxy measure of total payout ratio also outperforms the benchmark model during the full out-of-sample period and during the last five years of the sample. However, it does not produce statistically different forecasts from the benchmark model during the first sub-period which spans 2000:01-2005:01.

Regarding the French market, all conditional models manage to outperform the historical moving average model during the full out-of-sample period. In particular, the total payout ratio proxy is found to be a better predictor at all conventional levels while the other two candidates outperform the naive model at the 5% level. During the first five years of the out-of-sample period predictability is somewhat weaker and all predictive variables produce statistically different forecasts compared to the historical moving average at the 10% significance level. Finally, in the last five years of the sample, only the dividend-price ratio and the proxy measure of the total payout ratio significantly outperform the historical moving average (at 5% and 1% levels respectively).

Clearly, the above results suggest that in both markets the dividend-price ratio model captures predictability at any period, even where the total payout ratio model fails to do so. Therefore, the question of interest is whether the identified differences between the conditional models are also statistically significant. Perhaps more importantly, we need to address the issue of whether a proxy measure is an adequate substitute of the more accurate total payout ratio when used in predictive regressions.

Table 4 reveals that, apart from one sub-period in France, forecasts derived from the dividend-price ratio model are always statistically superior to the ones derived from the total payout ratio model. This result suggests that dividends convey more useful information for predicting the equity premium than actual share repurchases. As mentioned earlier, this may be an indication that share repurchases do not substitute for dividends in the UK and France and thus their information content might not be useful for predicting stock returns.

The total payout ratio model produces significantly different forecasts compared to its proxy counterpart in both markets (between 1% and 5% levels). This is a particularly important finding given that the proxy measure produced the highest RMSE's using UK data but the lowest RMSE's using French data. Therefore, our study suggests that extra caution should be given when constructing total payout yields based on a proxy measure of share repurchases for the purposes of predicting stock returns.

With the aim to further explore the out-of-sample performance of our predictive variables, we turn to the graphical diagnostic suggested by Goyal and Welch (2003) which will allow us to observe predictability in a more dynamic framework.

4.4. Additional out-of-sample evidence: the graphical procedure

Figure 2 shows the relevant graph when the diagnostic method of Goyal and Welch (2003) is applied to our UK and French data. The cumulative sum-squared error differences are plotted for all models under consideration.

[Insert Figure 2 around here]

With respect to the UK market, Figure 2i) suggests that the dividend-price ratio and the total payout ratio have an almost identical predictive performance between 2000 and the first

quarter of 2006. The graph line of the diagnostic test shows an upward tendency during that period suggesting a better performance of the two variables relative to the historical moving average. The graph line for the total payout ratio then experiences a decline until 2009. Interestingly, in both cases the slope becomes very steep between the first quarter of 2009 and the end of the sample, in 2010:06, indicating that predictability is more pronounced in this period. During the same period, the dividend-price ratio conveys more information as the corresponding line is at a much higher level compared to the one derived from the total payout ratio. On the other hand, the proxy measure of the total payout ratio exhibits the worst performance as suggested by the graph line which is almost identical to the zero line for the most part of the sample. It is not until 2009 where it starts to consistently outperform the benchmark model. Overall, the graphical procedure gives support to the previous reported findings in terms of relative predictive performance throughout the out-of-sample period and also reveals that predictability is stronger from 2009 onwards.

Turning to the French market in Figure 2ii), we observe that for all three variables, the graph line is always above zero and exhibits a similar pattern until the third quarter of 2008. Performance seems balanced during the first five years with almost equal fractions of positive and negative slope tendencies. As of 2006, we observe a steady upward trend which leads to an even more distinct and sharp positive slope (starting at the end of 2008 and ending mid-2009) in the case of the proxy measure of the total payout ratio, and to a steady decline in the case of the other two conditional models at the beginning of 2009. Finally, the depicted graph line corresponding to the proxy measure concludes with a decline during 2010, albeit at a much higher level compared to the dividend-price ratio and the total payout ratio. Overall, throughout the out-of-sample period the line corresponding to the total payout ratio proxy measure is

consistently above the lines obtained from the other two variables and this is more evident during the last two years of the sample. This confirms that the proxy measure performs differently across markets and also yields different results compared to the total payout ratio which employs actual share repurchases. These findings raise some concerns regarding the reliability of the proxy-TPO as a predictive variable.

As a final remark, the relatively stronger return predictability we detect in the later years of our sample is broadly in line with recent work that suggests a weaker performance of the historical moving average and a better predictive ability of the conditioning variables during recessions (see Henkel et al., 2011).

4.5. Further analysis of predictability: economic significance

Finding statistical significance in terms of predictive ability does not necessarily mean that there is also economic significance. In this section, we analyze the performance of different investment strategies conditioned on our predictive variables and we study their economic significance within each market. In particular, we compare each strategy from the perspective of an investor who faces an investment opportunity set spanned by the market portfolio and a riskless asset. Our goal is to assess how the predictability results presented in the previous sections are affected when economic value is accounted for. In other words, we seek to answer (i) which conditional model can also lead to economically sensible predictions and (ii) what is the impact of using a proxy measure for the total payout ratio on investment decisions.

4.5.1. The framework for measuring economic significance

Consider an investor whose goal is to maximise a mean-variance utility function. The investor dynamically rebalances her portfolio which comprises of one risky asset (i.e. the market portfolio) and the risk-free asset. For a given level of initial wealth, the investor's optimization problem can be expressed as follows:

$$(8) \quad \max_{w_{t+1}} u \left\{ E_t(r_{p,t+1}), \text{Var}_t(r_{p,t+1}) \right\},$$

where w_{t+1} denotes the time-varying proportion of the portfolio allocated to the risky asset, and $r_{p,t+1}$ is the return of the portfolio which equals:

$$(9) \quad r_{p,t+1} = r_{f,t+1} + w_{t+1}(r_{m,t+1} - r_{f,t+1}),$$

where $r_{m,t+1}$ is the return on the risky asset in period $t+1$ and $r_{f,t+1}$ is the return on the risk-free asset. The utility function we assume is (see also Marquering and Verbeek, 2004):

$$(10) \quad u(\cdot) = E_t(r_{p,t+1}) - \frac{1}{2} \gamma \text{Var}_t(r_{p,t+1}),$$

where the coefficient γ measures the investor's degree of risk aversion. The solution to the above maximization problem leads to the following optimal portfolio weight on the risky asset:

$$(11) \quad w_{t+1}^* = \frac{1}{\gamma} \frac{E_t(r_{m,t+1}) - r_{f,t+1}}{\text{Var}_t(r_{m,t+1})}.$$

Equation (11) shows that the optimal weights for the different investment strategies will vary to the extent that the conditional moments obtained from our predictive models will vary.

The realized Sharpe ratio is a commonly employed performance measure to assess economic significance. However, Goetzmann et al. (2007) show that this measure can be open to manipulation and suggest an alternative manipulation-proof measure that overcomes this

problem. Therefore, we adopt their approach and calculate the risk-adjusted return of each conditional strategy relative to the benchmark strategy as shown in equation (12):

$$(12) \quad \Theta = \frac{1}{(1-\gamma)} \left\{ \ln \left[\frac{1}{T} \sum_{t=0}^{T-1} \left(\frac{r_{p,t+1}^C}{r_f} \right)^{1-\gamma} \right] - \ln \left[\frac{1}{T} \sum_{t=0}^{T-1} \left(\frac{r_{p,t+1}^B}{r_f} \right)^{1-\gamma} \right] \right\},$$

where $r_{p,t+1}^C$ denotes the gross portfolio return of the conditional strategy based on any of our three predictive variables, and $r_{p,t+1}^B$ is the gross portfolio return resulting from the benchmark strategy. In line with our statistical analysis, the benchmark strategy uses the historical moving average of the equity premium to construct one-step-ahead forecasts. The estimates of Θ are reported in annualized basis points (bps).

4.5.2. Empirical evidence on the economic significance

This section addresses the important question of whether a dynamic strategy based on each of the conditioning variables can lead to economic gains relative to the benchmark strategy.

Table 5 shows the computed performance measure Θ with respect to all considered variables for a mean-variance investor who invests in a domestic market, be it the UK or France. In line with the out-of-sample analysis from the previous sections, the results are presented for the full period and for the two sub-periods, each spanning approximately five years. As in Goetzmann et al. (2007) and Della Corte et al. (2010) the risk aversion coefficient γ is assumed to be 3.⁸

[Insert Table 5 around here]

⁸ We have also considered investors with $\gamma \in \{2, 4, 6\}$ and our conclusions are robust to different levels of risk aversion.

The results suggest that large economic gains can be made in the UK by adopting a dynamic trading strategy which utilises the information content of the dividend-price ratio (DP). This can be demonstrated by the large value of Θ which shows that the DP model generates 172 annual bps relative to the benchmark model during the full out-of-sample period. The total payout ratio (TPO) results in an annual economic gain of 124 bps during this period. However, the proxy measure of the total payout ratio (proxy-TPO) leads to an annual loss of 26 bps. The ranking of the above strategies remains the same if we consider each of the two out-of-sample sub-periods. In particular, DP and TPO always produce the highest economic gains and more so during the last five years of the sample (with annual gains of 241 bps and 146 bps respectively). The proxy-TPO manages to outperform the naive strategy only in the last five years with annual gains of 59 bps.

In France, all conditional strategies outperform the benchmark strategy and yield positive economic gains. In this case however, it is the proxy-TPO that generates the highest premium relative to the benchmark model across all periods. For example, it generates economic gains of 73 bps during the full out-of-sample period as opposed to 28 bps for the DP and 22 bps for the TPO. During the first five-year period the TPO model leads to higher gains compared to the DP model while the opposite is true during the second sub-period.

Overall, the results presented in this section are consistent with the statistical results reported in the previous sections and suggest that the economic performance of each predictive variable is in line with its statistical performance. This gives further support to our findings and strengthens our main conclusions.

5. Conclusion

A small body of literature suggests that the total payout ratio, a measure which adjusts the dividend-price ratio for share repurchases, can lead to better predictions of the equity premium within the US market (e.g., Robertson and Wright, 2006; Boudoukh et al., 2007). The current paper contributes to this literature in three ways. First, we construct this new variable and assess its predictive performance against the dividend-price ratio within an international setting. To our knowledge, this is the first study to investigate the predictive content of share repurchases outside the US context. In particular, we apply a prediction testing framework to monthly data derived from the two largest European stock markets (both in terms of size and repurchase activity), the UK and France, and cover all listed firms between the 1990:01-2010:06 period. Second, we offer some important new evidence by including both actual and estimated repurchase data in our analysis. Specifically, we assess the predictive performance of the total payout ratio when compared against a proxy total payout measure which can be easily constructed in markets where there are repurchase data limitations. Third, in departure from a purely statistical context, our paper further investigates predictability in terms of economic significance and evaluates the performance of a mean-variance portfolio optimization strategy based on each of the conditional predictive models relative to the historical moving average model.

In-sample and out-of-sample statistical tests suggest that an element of predictability exists in both markets. Out-of-sample performance is assessed by means of conventional tests and also by employing the Goyal and Welch (2003) graphical diagnostic. Our results suggest that the total payout ratio, although a successful predictor of the equity premium, does not manage to outperform the dividend-price ratio in any of the considered markets. This important new finding

implies that share repurchase policies may be independent of dividend policies in the two largest European stock markets and hence, share repurchases do not substitute for dividend payments. Consequently, the information content of repurchases may not be relevant for predicting the equity premium.

On the other hand, we find no association between the predictive performance of the total payout ratio and its proxy counterpart. This lack of association indicates that the predictive content of proxy repurchase data is not in line with that of the actual repurchase data. Therefore, caution should be taken when repurchase activity is represented by proxies in order to predict excess returns. Finally, we find that there is consistency between the statistical evidence of predictability and the evidence based on economic value, substantiating the robustness of our conclusions under different frameworks of analysis.

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Abstract

We adjust the dividend-price ratio for share repurchases and investigate whether predictive power can be improved when constructing forecasts of UK and French equity premia. Regulations in the two largest European stock markets allow us to employ actual repurchase data in our predictive regressions. Hence, we are able to overcome problems associated with markets characterised by less stringent disclosure requirements, where investors might have to rely on proxies for measuring repurchase activity. We find that predictability does not improve either in a statistical or in an economically significant sense once actual share repurchases are considered. Furthermore, we employ a proxy measure of repurchases which can be easily constructed in international markets and demonstrate that its predictive content is not in line with that of the actual repurchase data.

JEL Classification: C22, C53, G12, G17

Keywords: Stock return predictability; Dividend-price ratio; Share repurchases; Out-of-sample tests; Economic value

Tables

Table 1 In-sample univariate regressions: $r_{m,t} - r_{f,t} = \alpha + \beta x_{t-1} + \varepsilon_t$

x_{t-1}	β	R^2 %	S.E.%	β	R^2 %	S.E.%
	UK			France		
Full Sample 1990:01-2010:06						
DP_{t-1}	0.172	12.33	7.93	0.024	2.43	9.94
<i>t</i> -statistic	(5.845)			(2.458)		
<i>p</i> -value	[0.000]			[0.010]		
TPO_{t-1}	0.106	6.30	8.20	0.012	0.74	10.02
<i>t</i> -statistic	(4.040)			(1.349)		
<i>p</i> -value	[0.000]			[0.059]		
<i>proxy-TPO</i> $_{t-1}$	0.074	2.73	8.35	0.031	3.23	9.89
<i>t</i> -statistic	(2.610)			(2.847)		
<i>p</i> -value	[0.007]			[0.009]		
Sample Period 1990:01-2005:01						
DP_{t-1}	0.064	3.70	5.81	0.018	2.60	7.84
<i>t</i> -statistic	(2.613)			(2.180)		
<i>p</i> -value	[0.009]			[0.013]		
TPO_{t-1}	0.058	2.80	5.84	0.013	1.65	7.88
<i>t</i> -statistic	(2.263)			(1.728)		
<i>p</i> -value	[0.017]			[0.041]		
<i>proxy-TPO</i> $_{t-1}$	0.007	0.05	5.92	0.022	3.18	7.82
<i>t</i> -statistic	(0.291)			(2.419)		
<i>p</i> -value	[0.363]			[0.010]		

Table 1 presents the results of the following univariate regression:

$$r_{m,t} - r_{f,t} = \alpha + \beta x_{t-1} + \varepsilon_t$$

where the predictive variable, x , can be either the dividend-price ratio (DP), the total payout ratio (TPO) or the total payout ratio proxy (*proxy-TPO*). For each OLS regression, the estimated coefficients are given in the first row. Figures in parentheses and square brackets denote *t*-statistics and *p*-values respectively. The *p*-values are computed using the bootstrap procedure described in Section 3.1.1 based on 10,000 repetitions. 0.000 indicates < 0.001 . S.E. is the standard error of the regression residuals. Results are also reported with respect to a sub-period which uses data up to 2005.

Table 2 Out-of-sample performance

Forecast error statistic	Historical moving average %	Dividend-price ratio %	Total payout ratio %	Total payout ratio proxy %
UK				
<u>Full sample 2000:01-2010:06</u>				
Mean	0.50	0.77	0.32	0.68
Standard Deviation	10.29	9.39	9.85	10.07
Root Mean Square Error	10.26	9.38	9.81	10.05
<u>Sub-sample 2000:01-2005:01</u>				
Mean	-1.51	-0.80	-1.09	-1.49
Standard Deviation	5.61	5.46	5.48	5.61
Root Mean Square Error	5.77	5.47	5.54	5.76
<u>Sub-sample 2005:02-2010:06</u>				
Mean	2.38	2.24	1.64	2.72
Standard Deviation	13.03	11.82	12.55	12.64
Root Mean Square Error	13.15	11.94	12.56	12.84
France				
<u>Full sample 2000:01-2010:06</u>				
Mean	0.34	1.92	1.73	1.81
Standard Deviation	11.16	10.89	10.95	10.76
Root Mean Square Error	11.12	11.02	11.04	10.87
<u>Sub-sample 2000:01-2005:01</u>				
Mean	-1.14	1.45	1.29	1.83
Standard Deviation	5.93	5.61	5.65	5.44
Root Mean Square Error	6.00	5.75	5.75	5.69
<u>Sub-sample 2005:02-2010:06</u>				
Mean	1.72	2.37	2.15	1.79
Standard Deviation	14.37	14.20	14.27	14.08
Root Mean Square Error	14.36	14.29	14.33	14.09

This table presents the properties of the equity premium prediction errors obtained from four competing models: The historical moving average model, a model which employs the lagged dividend-price ratio, and two other models which employ the lagged total payout ratio using either actual or estimated data on share repurchases. The full out-of-sample period spans 2000:01-2010:06. For a more in-depth evaluation, results are also reported for arbitrary splits of the sample, each spanning approximately five years. All models use available data starting from 1990:01. Boldface indicates superior performance (i.e. more accurate forecasts).

Table 3 Diebold and Mariano (1995) statistics

Sample Period	Dividend-price ratio model	Total payout ratio model	Total payout ratio proxy model
UK			
2000:01-2010:06 (full sample)	2.68 ^{***}	2.46 ^{***}	1.83 ^{***}
2000:01-2005:01	2.56 ^{***}	1.90 ^{***}	0.16
2005:02-2010:06	2.48 ^{***}	2.18 ^{***}	1.84 ^{***}
France			
2000:01-2010:06 (full sample)	1.17 ^{**}	0.98 ^{**}	2.06 ^{***}
2000:01-2005:01	0.73 [*]	0.79 [*]	0.77 [*]
2005:02-2010:06	1.29 ^{**}	0.63	2.39 ^{***}

Table 3 shows the computed Diebold and Mariano (1995) test statistics across different periods. These statistics are employed to test whether the reported RMSE performances between the predictive variables and the historical moving average in Table 2, are statistically different from one another. A positive value indicates that the conditional model performs better than the historical moving average model. Asterisks *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 4 Diebold and Mariano (1995) statistics between predictive variables

Sample Period	Dividend-price ratio vs Total payout ratio	Total payout ratio vs Total payout ratio proxy
UK		
2000:01-2010:06 (full sample)	-2.77 ^{***}	-2.40 ^{***}
2000:01-2005:01	-1.96 ^{**}	-1.48 [*]
2005:02-2010:06	-2.70 ^{***}	-1.98 ^{**}
France		
2000:01-2010:06 (full sample)	-1.34 [*]	1.88 ^{**}
2000:01-2005:01	0.08	0.46
2005:02-2010:06	-2.77 ^{***}	1.84 ^{**}

Table 4 shows the computed Diebold and Mariano (1995) test statistics across different periods to assess whether the reported RMSE performances between the predictive variables in Table 2, are statistically different from one another. A negative (positive) value indicates that the first model performs better (worse) compared to the second model. Asterisks *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 5 Out-of-sample economic significance

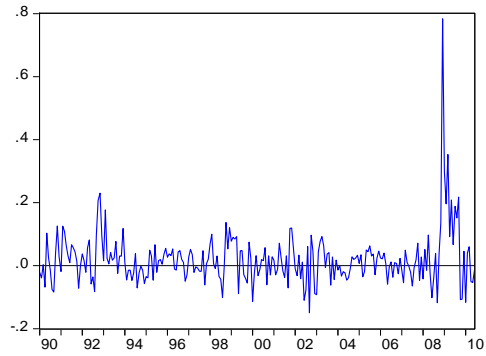
Sample Period	Dividend-price Ratio	Total payout ratio	Total payout ratio proxy
UK			
2000:01-2010:06 (full sample)	172	124	-26
2000:01-2005:01	104	101	-110
2005:02-2010:06	241	146	59
France			
2000:01-2010:06 (full sample)	28	22	73
2000:01-2005:01	23	31	85
2005:02-2010:06	32	15	62

This table reports the estimated Θ s (see Section 4.5.1) which measure the economic significance of a dynamic strategy based on each considered predictive variable, namely the dividend-price ratio (DP), the total payout ratio (TPO) and the total payout ratio proxy (proxy-TPO) relative to a benchmark strategy which uses the historical moving average of the equity premium to construct one-step-ahead forecasts.

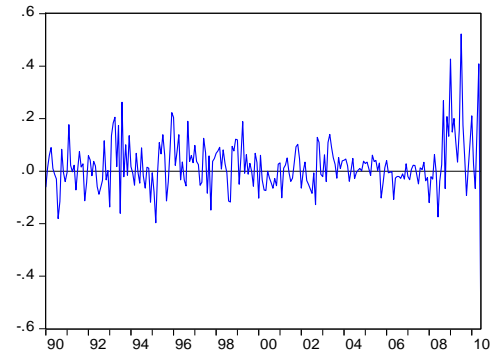
Figures

Figure 1 Time series graphs

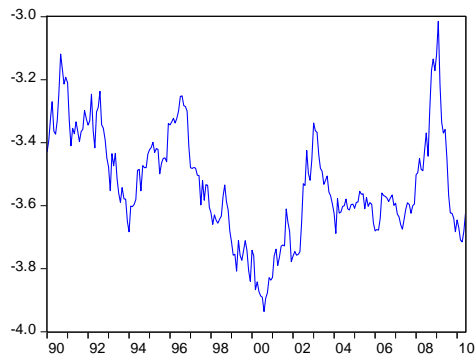
i) The log equity premium (UK)



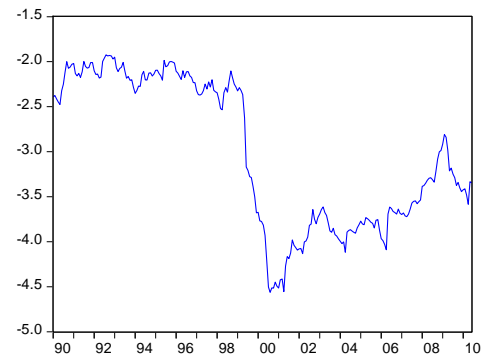
iv) The log equity premium (France)



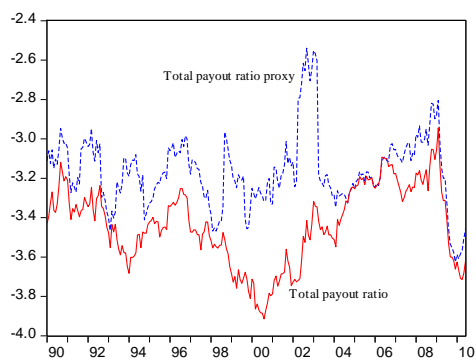
ii) The log dividend-price ratio (UK)



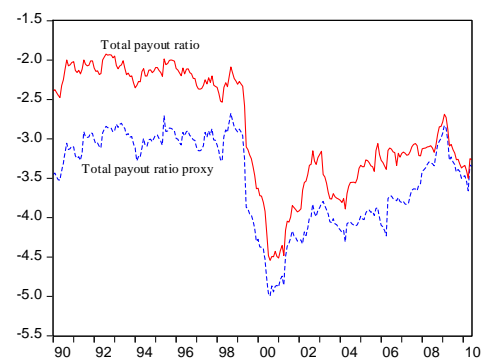
v) The log dividend-price ratio (France)



iii) Total payout ratios (UK)



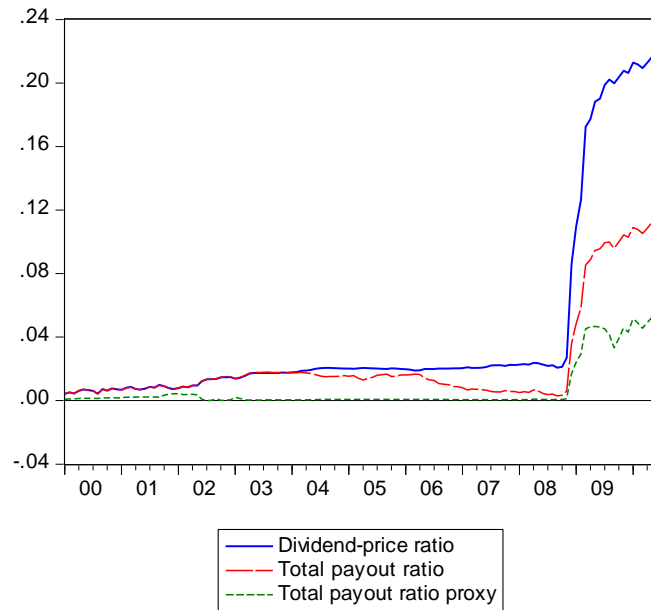
vi) Total payout ratios (France)



The above graphs depict the time series of the log equity premium, the log dividend-price ratio and the two measures of the total payout ratio in the UK and France. All variables are explained in Section 2.

Figure 2 Graphical representation of cumulative relative out-of-sample performance

i) UK market



ii) French market

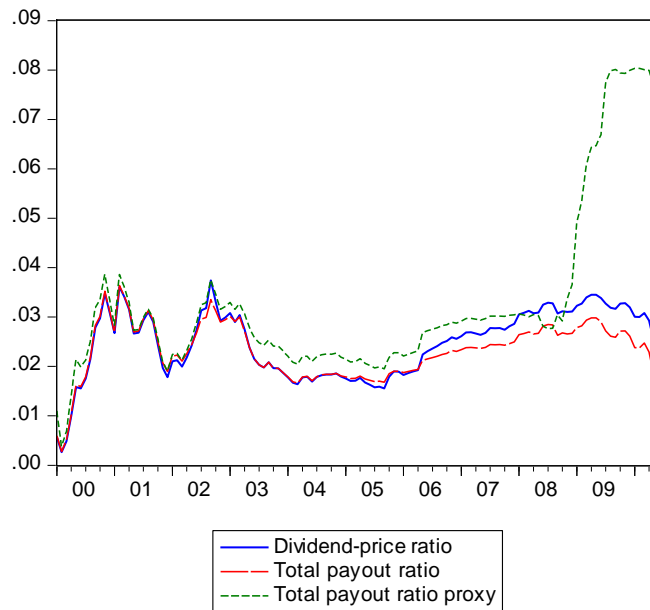


Figure 2 presents the out-of-sample graphical procedure of Goyal and Welch (2003) when applied to the UK and France (see Section 3.2.3 for a detailed description). The method is presented for all models under consideration when compared to the historical moving average model. The out-of-sample period spans 2000:01-2010:06.