On the statistical and economic performance of stock return predictive regression models: An international perspective

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Abstract

The predictability of stock returns is assessed in ten countries using the linear predictive regression framework. We use recently developed out-of-sample statistical tests and include both valuation ratios and interest rates as predictive variables. Contrary to previous studies, we explicitly address the issue of the small-sample bias, deal with trading profitability, and employ several risk-adjusted metrics. When statistical forecastability is found, it cannot be exploited to consistently deliver abnormal returns across countries and investment horizons. We hold the view that returns are predictable to some extent but show that such forecasts are not useful for portfolio advice.

Keywords: predictability, profitability, efficiency, out-of-sample.

JEL classifications: C15, C22, C53, G14.

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1 Introduction

Numerous studies have investigated the predictability of US stock returns using regression models. In these models, single- or multi-period real (excess) stock returns are regressed on variables deemed relevant. Early work such as Fama and French (1988, 1989) and Campbell and Shiller (1988) generally find strong evidence of stock return predictability. However, two serious econometric problems are ignored in these seminal papers: the overlapping observations problem and the small sample bias. The overlapping observations problem occurs when multi-period returns are computed, which leads to serial correlation in the disturbance term. The small-sample bias (i.e. the bias in finite samples of the predictive variable's slope estimate) is due to the near persistence and/or endogeneity of the predictive variable. Consequently, the distribution of the t-statistic for the predictive variable's slope estimate deviates from its usual form. Basing inferences on standard asymptotic results can therefore lead to considerable size distortions when testing the null hypothesis of no predictability.

While these econometric problems have been somewhat addressed, the vast majority of papers still rely exclusively on in-sample (IS) tests of stock return predictability. This raises concerns of data mining. Out-of sample (OOS) tests exploit observations not used in the estimation of the model itself to address data mining issues. The few recent studies that use OOS tests of return predictability provide contradictory evidence. While Rapach and Wohar (2006) and Campbell and Thompson (2008) find some OOS evidence of predictability, Goyal and Welch (2008) do not. All in all, it is challenging to argue for stock return predictability in the US.

The few studies of stock return predictability in non-US data often rely on non-robust econometric methods. Ferson and Harvey (1993) consider various aspects of predictability in international stock returns. The datasets span a fair amount of countries, but the overall time span is limited to the 1969-1992 period and most results are thus based on regressions that use less than 20 years of data. In addition, no robust econometric methods are used. Ang and Bekaert (2007) analyze predictability in stock returns for four different countries in addition to the U.S. Their international sample dates back to 1975. Polk, Thompson, and

Vuolteenaho (2006) use an international sample consisting of 22 countries with observations dating back to 1975. However, they only analyze the predictive ability of their cross-sectional beta-premiums and do not consider traditional forecasting variables. Rangvid, Rapach, and Wohar (2005) do test the predictive ability of forecasting variables outside the US: They find that interest rate variables have some ability in predicting international stock returns. However, they exclusively focus on macro variables and do not consider valuation ratios. In addition, no study on international data explicitly addresses the issue of the small-sample bias in the OLS slope estimate by using either the Stambaugh (1999) or Lewellen (2004) correction approach.

This brief review shows that the extant literature is mainly concerned with testing for the existence of return predictability in population. Another issue is whether a practitioner could have constructed a portfolio that earns above-average, raw or risk-adjusted returns. A practitioner does not necessarily care about the difference in statistical metrics: he is mostly interested in selecting the model that generates the highest raw or risk-adjusted returns according to some pre-defined trading rule and profit-based metric. Surprisingly, the economic significance of predictive regression models has always been measured through thought experiments (Campbell and Thompson, 2008; Goyal and Welch, 2008).

In this paper, we examine the predictability of stock returns in ten countries using the the well-established linear predictive regression model, with samples of monthly data ending in late 2005 and beginning in the early 50's or late 60's. Five traditional forecasting variables are considered: the dividend-yield, the earnings-price ratios, the short-term interest yield, the long government bond yield, and the term spread (i.e. the slope of the yield curve). We guard against potential size distortions due to overlapping observations, address the issue of the upward small-sample bias in the OLS slope estimate, and analyze the OOS forecasts using a pair of recently developed tests (see Section 2.1). In addition, we explicitly take the practitioner's point of view by designing a trading rule that can be easily implemented by the marginal investor. Since risk adjustment is essential when evaluating the usefulness of active strategies, we compute several profit-based metrics that rely upon risk-adjusted returns (see

Section 2.2).

Our results can be summarized as follows: The short-term interest yield and, to a lesser extent, the long government bond yield are the best out-of-sample predictors of stock returns. However, the out-of-sample predictive power of these variables does not appear to be economically meaningful across countries and investment horizons. First, thought experiments that rely upon out-of-sample statistics show that forecasting gains are small, underscoring the notion from the extant empirical literature that the predictive component in stock returns is small. Second, investment strategies that rely upon the return forecasts of predictive regression models also fail to deliver meaningful economic gains across investment horizons and across countries. While risk is difficult to measure and any risk adjustment is subject to criticism, most profit-based metrics converge to the same conclusions: predictive regression strategies based on interest rate variables generate the most robust economic performance in the US, Canada, and France; they mostly fail in the other countries. Taking the evidence overall, no common pattern of stock return predictability emerges across countries, be it on statistical or economic grounds.

The remainder of the paper is structured as follows. We describe the econometric methodology in Section 2. In Section 3, we present the dataset. We discuss the empirical results in Section 4 and conclude in Section 5.

2 Methodology

Various model specifications use non-parametric methods or allow predictive variables to exhibit non-linear patterns. However, specification search is a serious issue when more sophisticated model specifications are investigated. As Goyal and Welch (2008) point out, some of these models are bound to work both in-sample and out-of-sample by pure chance.

To alleviate data mining concerns, we follow Rapach and Wohar (2006) and much of the extant literature in using a linear predictive regression model. The predictive regression model can be written as:

$$y_{t,t+k} = \alpha_k + \beta_k z_t + \gamma_k y_t + u_{t,t+k} \tag{1}$$

where y_t is the real total log stock return from period $t-1$ to period t, $y_{t,t+k} = y_{t+1}+...+y_{t+k}$ is the real total log stock return from period t to $t+k$ (i.e. the k-period forward-looking return), z_t is the log of the predictive variable (i.e. the forecasting variable believed to potentially predict future real returns), and $u_{t,t+k}$ is a disturbance term. Under the null hypothesis, the z_t variable has no predictive power for future returns ($\beta_k = 0$); under the alternative hypothesis, z_t does have predictive power for future returns ($\beta_k \neq 0$). Note that we include a lagged return in Equation (1) as a control variable when testing the predictive ability of z_t.

The in-sample estimation of the regression model is done as follows: Suppose we have observations for y_t and z_t for $t = 1, ..., T$. This leaves us with $T - k$ usable observations with which to estimate the in-sample predictive regression model. The predictive ability of z_t is assessed by examining the t-statistic for $\hat{\beta}_k$, the OLS estimate of β_k in Equation (1).

To guard against potential size distortions due to overlapping observations, we follow the recent predictability literature and base inferences concerning the predictive variable's slope coefficient on a bootstrap procedure similar to the procedure in Kilian (1999).

We also apply the Stambaugh (1999) and Lewellen (2004) correction approaches to explicitly address the issue of the bias in the OLS slope estimate (i.e. predictive coefficient) that arises in small samples when the independent variable is close to a random walk. The decision to use the Lewellen or Stambaugh approach depends on whether the independent variable is close to a random walk. When it is (not), the Lewellen (Stambaugh) correction has greater power. Without prior information about the true value of the autoregressive coefficient of the first order, it makes sense to rely on both tests and to calculate an overall, joint significance level that reflects the probability of rejecting the null hypothesis ($\beta = 0$) using either test. In the empirical section, we follow Lewellen (2004) and use the modified Bonferroni upper bound to calculate the joint p-value.

2.1 Out-of-sample statistical analysis

As discussed in the introduction, we also perform OOS tests of return predictability. We first divide the total sample of T observations into IS and OOS portions, where the IS portion spans the first R observations for y_t and z_t, and the OOS portion spans the last P observations for the two variables.[1]

The first OOS forecast of the 'unrestricted' predictive regression model given in Equation (1) is generated in the following manner: estimate the unrestricted predictive regression model (Model 1) via OLS using data available up to period R; denote Model 1's OLS estimates of α_k, β_k and γ_k, using data available up to period R, as $\hat{\alpha}^1_{k,R}$, $\hat{\beta}^1_{k,R}$, and $\hat{\gamma}^1_{k,R}$. Using these OLS parameter estimates as well as y_R and z_R, construct a k-period return forecast, $y_{R,R+k}$, based on Model 1 using $\hat{y}^1_{R,R+k} = \hat{\alpha}^1_{k,R} + \hat{\beta}^1_{k,R} z_R + \hat{\gamma}^1_{k,R} y_R$. Denote the k-period return forecast error by $u^1_{R,R+k} = y_{R,R+k} - \hat{y}^1_{R,R+k}$.

OOS forecasts of the unrestricted predictive model are also generated after correcting for the bias in $\hat{\beta}$. Using Stambaugh's standard approach, construct a k-period return forecast such that $\hat{y}^{1S}_{R,R+k} = \hat{\alpha}^1_{k,R} + \hat{\beta}^{1S}_{k,R} z_R + \hat{\gamma}^1_{k,R} y_R$, where $\hat{\beta}^{1S}_{k,R}$ is Stambaugh's corrected beta coefficient estimated using data available up to period R. Correspondingly, construct a k-period return forecast such that $\hat{y}^{1L}_{R,R+k} = \hat{\alpha}^1_{k,R} + \hat{\beta}^{1L}_{k,R} z_R + \hat{\gamma}^1_{k,R} y_R$, where $\hat{\beta}^{1L}_{k,R}$ is Lewellen's corrected beta estimated using data available up to period R.

Campbell and Thompson (2008) make two interesting suggestions that we follow. First, they argue that a reasonable investor would not use a model that has a $\hat{\beta}_k$ coefficient with the theoretically incorrect sign. They truncate such coefficients to zero. Second, they argue that a reasonable investor would not have used a model that forecasts a negative equity premium. Such predictions are also truncated to zero.

The initial k-period return forecast for the 'restricted' model is generated in a similar manner, except we set $\beta_k = 0$ in Equation (1). That is, we estimate the restricted regression model (Model 0) via OLS using data available up to period R in order to have the k-period return forecast $\hat{y}^0_{R,R+k} = \hat{\alpha}^0_{k,R} + \hat{\gamma}^0_{k,R} y_R$, where $\hat{\alpha}^0_{k,R}$ and $\hat{\gamma}^0_{k,R}$ are the OLS estimates of α_k and γ_k in Equation (1) with β_k restricted to zero using data available up to period R. Denote the k-period return forecast error corresponding to the restricted model as $u^0_{R,R+k} = y_{R,R+k} - \hat{y}^0_{R,R+k}$.

[1]We actually keep 100 observations for IS estimation and compute OOS forecasts of log returns using a recursive window. The largest OOS period covers 568 months for the UK and the USA, while the smallest OOS period includes 310 months for France.

In order to generate a second set of forecasts, we update the above procedure by using data available up to period $1+R$. We use these parameter estimates and the observations for z_{R+1} and y_{R+1} in order to form unrestricted and restricted model k-period return forecasts for $y_{R+1,R+1+k}$ and their respective k-period return forecast errors, $u^1_{R+1,R+1+k}$ and $u^0_{R+1,R+1+k}$. We repeat this process through the end of the available sample, which yields two sets of $T-R-k-1$ recursive forecast errors, one each for the unrestricted and restricted regression models: $\{u^1_{t,t+k}\}^{T-k}_{t=R}$ and $\{u^0_{t,t+k}\}^{T-k}_{t=R}$.

The final step is to analyze the OOS forecasts. To formally test whether the unrestricted regression model forecasts are significantly superior to the restricted model forecasts, we report Theil's U, the DRMSE statistic, the McCracken (2007) MSE-F and the Clark and McCracken (2001) ENC-NEW statistics.

2.2 Out-of-sample economic analysis

Switching from statistical OOS predictability to a useful economic strategy can be challenging and often weeds out many candidate predictors. Among the potential pitfalls, parameter instability, transaction costs, and the fact that the strategy may expose the trader to idiosyncratic risks stand out.

To address these issues, we explore the economic significance of stock returns predictability by building the following 'predictive' investment strategy that can be easily implemented by the marginal investor. Using data available up to period R and estimating the unrestricted model (Model 1), we construct the k-period return forecast such that $\hat{y}^1_{R,R+k} = \hat{\alpha}^1_{k,R} + \hat{\beta}^1_{k,R} z_R + \hat{\gamma}^1_{k,R} y_R$. Denote the k-period T-bill interest rate available at period R as $i_{k,R}$. If $\hat{y}^1_{R,R+k} > i_{k,R}$, the investor buys stocks and sells the risk-free instrument. If $\hat{y}^1_{R,R+k} < i_{k,R}$, the investor sells stocks and buys the risk-free instrument. In order to generate the next forecast $\hat{y}^1_{R+1,R+1+k}$, we update the above procedure one period by using data available through period $1+R$, and estimate Equation (1) using OLS. This process goes on until the end of the sample is reached. We follow the same methodology to measure the economic significance of forecasts based on Stambaugh's and Lewellen's corrected OLS slope coefficients.

The above 'predictive' investment strategies are compared to three benchmark portfolios. The first benchmark is a passive, buy-and-hold portfolio that is always fully invested in stocks (BH). The two other benchmarks are active strategies. The first one compares the current level of the predictive variable to its extreme historical values (EXT). It is a naive strategy in the sense that it does not make any forecast *per se*. It consists in always investing the entire portfolio in stocks except when the current value of the predictive variable is above the 90th percentile of its unconditional distribution.[2] This strategy does not predict the date of the turning point, but it points to a probable decline in stocks. For example, a fall in stock prices may be more likely than a further rise when the price-earnings ratio is above the 90th percentile of its unconditional distribution. The second active strategy (REST) is based on the restricted model discussed above (model 0). If $\hat{y}^0_{R,R+k} > i_{R-k,R}$, the investor buys stocks and sells the risk-free instrument. If $\hat{y}^0_{R,R+k} < i_{R-k,R}$, the investor sells stocks and buys the risk-free instrument. In order to generate the next forecast $\hat{y}^0_{R+1,R+1+k}$, we update the above procedure one period by using data available through period $1 + R$, and estimate Equation (1) with β_k restricted to zero using OLS. This process goes on until the end of the sample is reached. If the restricted model delivers higher (risk-adjusted) returns than the unrestricted predictive model, the predictive variable may not bring any economic added value.

Both passive and active strategies are evaluated on the basis of raw returns (net of transaction costs). However, to compare the active and passive strategies, risk adjustment is important because active strategies are often out of the market and therefore may bear much less risk than the buy-and-hold strategies. Although there is no universally accepted method of adjusting returns for risk, we use four techniques: the Sharpe ratio (Sharpe, 1966), the X^* measure (Sweeny, 1988), the Jensen α (Jensen, 1968) and the X_{eff} measure of Dacorogna, Gençay, Müller, and Pictet (2001).

The Sharpe ratio measures the expected excess return per unit of risk for a zero-investment strategy (Campbell, Lo, and MacKinlay, 1997). It is usually measured in annual terms as a portfolio's annual excess return over the riskless rate, net of transactions costs, divided by

[2] The choice of the 90th percentile as the threshold implicitly assumes that the stock market moves 10 percent of the time far away from its fundamental value. This is consistent with the Black (1986) estimation.

its annual standard deviation. Although the active strategies may exhibit lower returns than the buy-and-hold portfolios, the lower volatility may allow the portfolio to be leveraged and to exceed the buy-and-hold return with similar risk.

Sweeney (1988) developed another risk-adjustment statistic, the X^* measure. He shows that, in the presence of a constant risk premium, an equilibrium k-period risk-adjusted return to an investment strategy would be given by:

$$X^* = \frac{1}{T_k}\sum_{t=0}^{T_k}[s_t y_{t+1}^k + (1-s_t)r_{t+1}^k] - \frac{n}{2T_k}\ln(\frac{1+c}{1-c}) - [\frac{p_1}{T_k}\sum_{t=0}^{T_k} y_{t+1}^k + \frac{p_2}{T_k}\sum_{t=0}^{T_k} r_{t+1}^k] \qquad (2)$$

where s_t is an indicator variable taking the value 1 if the strategy is in the market or 0 if the rule is in T-bills; y_{t+1}^k is the real total log return to holding stocks from period t to $t+k$; r_{t+1}^k is the real total log return to holding T-bills from period t to $t+k$; T_k is the number of k-period return observations; n is the number of one-way trades; c is the proportional transactions cost; p_1 is the proportion of the time spent in the market and p_2 is the proportion of the time spent in T-bills ($p_1 + p_2 = 1$).[3] Under the null of no market timing ability, there is no statistical difference between the actual return delivered by the active strategy and its expected return, so that X^* is not statistically different from zero. Statistically positive X^* statistics are interpreted as evidence of superior risk-adjusted returns.

According to Dacorogna, Gençay, Müller, and Pictet (2001), the performance of an active strategy should be viewed as favorable when the total return is high, the total return curve increases linearly over time, and loss periods are not clustered. The Sharpe Ratio does not entirely satisfy these requirements. First, the definition of the Sharpe Ratio puts the variance of the return into the denominator which makes the ratio numerically unstable at extremely large values when the variance of the return is close to zero. Second, the Sharpe Ratio treats the variability of profitable returns (which are unimportant to investors) the same way as the variability of losses (which are an investor's major concern). Third, the Sharpe Ratio does not take into account the clustering of profits and losses. An even mixture of profit and loss

[3]The sum of the last two terms estimates the expected return to a zero transactions-cost strategy that is randomly in the market on a fraction p_1 of the k month periods, earning the market premium, and in T-bills otherwise.

trades is usually preferred to clusters of losses and clusters of profits, provided the total set of profit and loss trades is the same in both cases.

One of the risk-adjustment measures advocated by Dacorogna, Gençay, Müller, and Pictet (2001) is the X_{eff} measure. X_{eff} measures the utility that the strategy provides to a constant absolute risk averse individual over a weighted average of return horizons. According to these authors, X_{eff} exhibits fewer deficiencies than the Sharpe Ratio. First, X_{eff} is numerically stable. Second, the return curve (which reflects the real risk of a trading strategy) is assessed through the sum of the accumulated total return and the current unrealized return of open positions. Accounting for unrealized returns avoids biases in favor of strategies with a low transaction frequency. X_{eff} reaches the value of the annualized total return if the return curve is a straight line as a function of time. For all nonlinear equity curves, $X_{eff}$is smaller than the annualized total return. The measure is:

$$X_{eff} = \overbrace{\frac{(12/k)100}{T_k}\{\sum_{t=0}^{T_k}[s_t(y_{t+1}^k - r_{t+1}^k)] - \frac{n}{2}\ln(\frac{1+c}{1-c})\}}^{(1)} - \overbrace{\frac{\gamma}{2}\frac{\sum_{i=1}^{n}\tilde{w}_i\sigma_i^2[12/(k\Delta t_i)]}{\sum_{i=1}^{n}\tilde{w}_i}}^{(2)} \quad (3)$$

where (1) is the annualized excess return to the strategy in percentage terms, net of transactions costs; (2) is the annualized cost of risk taking by the strategy; σ_i^2 is the variance of non-overlapping k-period returns over k-multiple time horizon Δt_i; $12/(k\Delta t_i)$ is the annualized factor, i.e. the number of k-period returns of length Δt_i in one year; γ is the risk aversion parameter. Dacorogna, Gençay, Müller, and Pictet (2001) recommend values of γ between 0.08 and 0.15; this paper follows Neely (2003) in setting γ equal to 0.12. The weights $\tilde{w}_i$ are determined with a weighting function that allows for the selection of the relative importance of the different horizons. The time horizons Δt_i are assumed to follow a geometric sequence (1,2,4,8,...months). The weighting function is:

$$\tilde{w}_i = \frac{1}{2 + [\ln(\frac{\Delta t_i}{3/k})]^2} \quad (4)$$

Finally, we consider the performance of active strategies according to the Jensen α, the return in excess of the riskless rate that is uncorrelated with the excess return to the market:

$$s_t[y_{t+1}^k - r_{t+1}^k] - \frac{n}{2T_k}\ln(\frac{1+c}{1-c}) = \alpha_k + \beta_{M,k}[y_{t+1}^k - r_{t+1}^k] + \epsilon_{t+1}^k \quad (5)$$

where the variables are as defined in Equation (2). If the intercept ($\hat{\alpha}$) is positive and significant, then the trading rule delivers excess returns that cannot be explained by correlation with the market.

3 Data

All data is provided by Global Financial Data (GFD) and extracted on a monthly frequency. The following stock indices are used: ASX-All Ordinaries (Australia), Toronto SE-300 (Canada), SBF-250 (France), CDAX (Germany), Nikko Securities Composite (Japan), Netherlands All-Share Index (the Netherlands), Johannesburg SE Return Index (South Africa), Affarsvrlden Return Index (Sweden), FTA All-Share (United Kingdom), S&P 500 (United States).

The total real log return to holding stocks from period $t-1$ to period t (RSR) are used to mesure y_t. The total real log return to holding t-bills from period $t-1$ to period t (RTR) are used to measure i_t. Real prices are computed by dividing nominal prices (which include income gains in GFD) by the level of the CPI.

The dividend-price ratio (DPR) is defined as the log of the sum of paid dividends during the past year, divided by the current price. The price-earnings ratio (PER) is defined as the log of the current price divided by the latest 12 months of earnings available at the time.

Following much of the extant literature, we measure interest rates as deviations from a moving average. The relative short-term interest yield (STY) is computed as the difference between the short-term interest yield and a 12-month backward-looking moving average. The relative long-term government bond yield is defined in the same way, i.e. the difference between the long-term government bond yield and a 12-month backward-looking moving average. The short-term interest rate is the 3-month T-bill rate when available; if the latter is not available, the private discount rate or the interbank rate is used. The long rate (LTY) is measured by the yield on long-term government bonds. When available, a 10-year bond is used; otherwise, the closest maturity to 10 years is relied upon. To be consistent with the computation of the one month stock returns, the short-term and long-term interest rates are also expressed on a monthly basis. Finally, the term spread (TSP) is defined as the log difference between the long-term and the short-term rate.

We use excess returns expressed in domestic currencies as it provides the international analogue of the forecasting regressions estimated for U.S. data. In addition, we avoid the pitfall that the predictability in exchange rates rather than in stock returns drives the results.

Transaction costs are evaluated following Sutcliffe (1997) estimates. As the active strategies can be easily replicated by using the corresponding T-bill and stock market futures contracts, we consider transaction costs on the futures markets. According to Sutcliffe (1997), an appropriate round-trip figure for the FTSE-100 futures is 0.116% (of the purchase and sale values). This figure is made up of a bid/ask spread (0.083%) and commissions (0.033%). To keep things simple, we assume identical costs for the two (stock and T-bill) future markets.

Table 1 reports the available sample for each country, as well as the mean, standard deviation, and coefficient of first-order autocorrelation for each variable. Regarding each of the five predictive variables, theory predicts negative β coefficients for the price-earnings ratio (PER), the short-term interest yield (STY), and the long government bond yield (LTY). Positive signs are expected for DPR and TSP. For ease of computation, we always use a one-sided lower-tailed alternative hypothesis in Section 4. Therefore, DPR and TSP are constructed in such a way that a negative β coefficient is also expected, i.e. we take the negative of DPR and the negative of TSP as predictive variables. Of particular interest is the high persistence of all the predictive variables in each country, as revealed by the AC(1) coefficients. As a consequence, the OLS slope estimate is likely to be biased and a correction approach à la Lewellen (2004) may be appropriate.

4 Empirical analysis

Table 2 reports IS regression results for Equation (1) using data from the full sample in each country. Each forecasting variable is examined successively. The predictive ability of the forecasting variables is estimated at the 1-month ($k = 1$), 3-month ($k = 3$), and 1-year ($k = 12$) horizons. IS statistical analysis is summarized by the β coefficient of Equation (1) and its level of significance. Theil's U, the MSE-F, DRMSE and ENC-NEW statistics used to evaluate the OOS statistical performance of forecasts are also reported in Table 2. To save space, we only report results when the forecasting variable is both IS and OOS statistically significant at (minimum) 10%.[4]

Tables 3 to 5 report the OOS economic results (net of transaction costs) delivered by the benchmark portfolios and the 'predictive' trading strategies, provided their statistical performance described in Table 2 was both IS and OOS significant. For each horizon, four profit-based metrics are reported: Sharpe Ratio, X^*, X_{eff}, and Jensen α.[5]

In the following discussion, we first describe the statistical results and then investigate in each country whether practitioners can exploit statistical superior OOS performance through the so-called 'predictive' investment strategy described in Section 2.2.

4.1 Australia

Table 2 shows that statistical evidence of stock return predictability in Australia is weak. The long government bond yield (LTY) is the only forecasting variable that exhibits IS significance. The IS β slope estimate for LTY is significant at the 5% level for each of the horizons considered. IS significance persists even after explicitly correcting for the small-sample bias, like in Stambaugh (1999) or Lewellen (2004). The modified Bonferroni's upper bound also suggests joint IS significance at each of the horizons considered. Significant results also characterize the OOS tests on LTY, but ENC-NEW is the only statistic that points to superior OOS forecasts at the 3- and 12-month horizons.

The economic performance of the LTY predictive regression model is evaluated through

[4] The complete tables are available upon request.

[5] We do not report excess returns to save space. The tables are nevertheless available upon request.

the investment strategy described in Section 2.2. Since LTY is not OOS significant at the 1-month horizon, no economic investigation is carried out when $k = 1$. At the 3-month horizon, both STAM and LEW models generate negative raw excess returns relative to the buy-and-hold equity portfolio (not reported). While these models perform better than the restrictive model (REST), they cannot beat the other active benchmark portfolio based on extreme values (EXT). In terms of risk-adjusted returns (Table 4), both STAM and LEW models display higher Sharpe ratios than the buy-and-hold portfolio (BH), but STAM fails to beat the EXT benchmark strategy. Although STAM and LEW models generate positive and higher X^* metrics than both the EXT and BH portfolios (under the assumption of a constant risk premium), there is no statistical significance, even at the 10% level. Furthermore, STAM and LEW models obtain negative X_{eff} metrics, indicating that riskless strategies provide constant absolute risk averse investors with greater utility over a weighted average of return horizons. While STAM and LEW generate higher X_{eff} than EXT and BH, they cannot beat REST. Finally, STAM and LEW provide the two highest positive Jensen α metrics among all the portfolios considered. However, these are not statistically and economically significant. At the 12-month horizon, the three versions (OLS, STAM, and LEW) of the predictive regression model are considered. Results are similar to those obtained at the 3-month horizon (Table 5).

Overall evidence of stock return predictability in Australia is weak. The long-term government bond yield (LTY) is the only predictive variable that displays statistical significance. Although the predictive regression model based on LTY does not perform badly in comparison to the buy-and-hold portfolio, the investor would have had to know upfront that the LTY variable was the (only) good performer among all the candidates. In addition, the LTY predictive regression model does not seem to systematically outperform the naive benchmark strategy based on extremes.

4.2 Canada

The results for Canada in Table 2 show that there is IS and OOS evidence of predictability for each of the three interest rate variables, but none for the two valuation ratios. Among the three interest rate variables, IS and OOS significance is highest for the LTY variable. When economic gains of OOS predictive power are measured through the DRMSE metric (see Goyal and Welch, 2008), such gains appear to be limited. For example, the highest economic gain would be delivered by the simple OLS regression with LTY as predictive variable. It would amount to a mere 1.6 bp/month gain, which is likely to be offset by trading costs.

The OOS economic analysis of the predictive investment strategies at the 1-month horizon reveals that excess returns are systematically positive when LTY and STY are used as predictive variables (not reported). STY predictive regression models are nevertheless the only models that deliver higher positive excess returns than the REST and EXT benchmark portfolios. Looking at Table 3, we see that each of the three interest rate variables generate higher Sharpe ratios than the buy-and-hold portfolio. However, only predictive models based on STY deliver higher Sharpe ratios than the two competing active strategies, EXT and REST. Results based on the X^* and X_{eff} metrics lead to similar conclusions: predictive models perform well relatively to the buy-and-hold portfolio, but none of them is able to beat the restrictive model, REST. Interestingly, all predictive models deliver positive and significant Jensen α's, but the only predictive models that beat both the EXT and REST competing models are the predictive regression models based on STY.

At the 3-month horizon (Table 4), LTY and TSP seem to offer economically meaningful performance. Excess returns delivered by the predictive models are positive and higher than those delivered by the REST model (not reported). Predictive models based on LTY and TSP also generate both the highest Sharpe ratios and X^* metrics among all the active and passive portfolios. Results based on the X_{eff} metric lead to similar conclusions. Finally, LTY and TSP predictive models obtain the highest Jensen α's, which are both positive and significant at the 5% level.

STY and LTY predictive regression models demonstrate some ability in outperforming the other benchmark portfolios at the 12-month horizon also. Both STY and LTY predictive models generate positive excess returns, with STY predictive models displaying the highest positive excess returns among all competing models. The highest Sharpe ratios and X^* metrics are also delivered by both STY and LTY predictive regression models (Table 5). While they cannot do better than the REST model with respect to the X_{eff} metric, they generate the highest positive and significant Jensen α's.

There is, in summary, some statistical evidence of stock return predictability in Canada, provided interest rate variables are used as predictors. Although forecasting gains appear to be limited according to statistical criteria (such as Theil's U or DRMSE), they may be translated into meaningful economic gains through the use of predictive investment strategies based on LTY and STY variables. At the 1-month horizon, however, such gains do not appear to be significantly higher than those provided by the restrictive model.

4.3 France

From Table 2, we see that statistical evidence of stock return predictability in France is limited to interest rate variables. IS and OOS significance for the LTY variable is found at each horizon and for each of the three versions of the predictive model. In contrast, the OOS predictive power of the TSP variable is revealed by the ENC-NEW statistic only and is limited to the 3-month horizon. In any case, forecasting gains appear to be limited according to statistical criteria such as Theil's U or DRMSE.

Looking at the 1-month economic performance (Table 3), LTY predictive regression models perform best. They deliver higher excess returns, Sharpe ratios, X^* metric, and Jensen α's than the competing models. Among the three different versions of the predictive regression, the best performance comes from the LEW model. The only caveat is the inability of the LTY predictive regression models to beat the restrictive model with respect to the X_{eff} metric. Although predictive regression models based on STY seem to outperform the passive buy-and-hold portfolio on a risk-adjusted basis, they are unable to systematically beat the two other active strategies, EXT and REST. At the 3-month horizon, the TSP predictive regression models fail to deliver meaningful economic gains (Table 4). In contrast, STY and LTY models perform well with respect to the five profit-based metrics. LTY is again the best predictive variable.

Similar results are found at the 12-month horizon (Table 5). Profit-based metrics (except the X_eff statistic) point to superior economic performance of the LTY predictive regression model relative to the competing passive and active strategies.

Summarizing the results for France, evidence of stock return predictability is limited to the short- and long-term interest rates. Statistical criteria point to limited forecasting gains. Nevertheless, the use of predictive investment strategies based on LTY and (to a lesser extent) STY variables may lead to meaningful economic gains, as revealed by the profit-based metrics.

4.4 Germany

Table 2 points to weak statistical evidence of stock return predictability in Germany. The short government bond yield (STY) is the only forecasting variable that exhibits both IS and OOS significance, but at the 1- and 3-month horizons only. At the 1-month horizon, the predictive strategies based on STY generate negative excess returns. The other profit-based metrics point to superior economic performance of the STY predictive regression models relative to the other benchmark portfolios (Table 3). However, both X^* and Jensen α metrics are not statistically different from zero. At the 3-month horizon, economic gains provided by the STY predictive strategies seem to be very limited (Table 4). Although these strategies generate positive and significant Sharpe ratios, they cannot do better than the buy-and-hold portfolio. In addition, no X^* metric or Jensen α, albeit positive, is significantly different from zero. Finally, the X_{eff} metric indicates that the restrictive model performs better than the unrestricted STY predictive strategies. To conclude, there is little evidence of stock return predictability in Germany, be it on statistical or economic grounds.

4.5 Japan

In Japan, all the predictive variables (but TSP) exhibit IS evidence of predictability (Table 2). OOS statistical evidence of predictability is thin for STY but remains substantial for the LTY, DPR and PER variables. Statistical criteria point to higher economic gains than in previous countries, but such gains remain small in size. For example, one of the highest economic gains would be provided at the 12-month horizon by the simple OLS regression with PER as predictive variable. According to the DRMSE statistic, this would amount to a 90 bp gain per year. Although this may not be entirely offset by trading costs, any serious market practitioner is not likely to care about the remaining extra-normal returns.

Table 3 shows the economic value (net of transaction costs) of predictive regression strategies at the 1-month horizon. Predictive regression strategies based on valuation ratios underperform the benchmark strategies. LTY predictive regression models show some positive economic performance, but these results are generally not robust across profit-based metrics: while Sharpe ratios are significant, X^* and Jensen α are not. Similar results are found at the 3-month and 12-month horizons.

Overall, IS evidence of stock return predictability is undeniable in Japan, but no substantial OOS forecasting gain is realized. In addition, predictive regression strategies based on valuation ratios fail to deliver extra-normal returns. While predictive regression models based on interest rate variables show some positive economic performance, these results are generally not robust across profit-based metrics.

4.6 Netherlands

The results for the Netherlands in Table 2 show that there is IS and OOS statistical evidence of predictability for two variables only: STY and LTY. Once again, statistical criteria point to small forecasting gains, except maybe for the LTY predictive regression models at the 3-month horizon.

The economic analysis of the predictive regression strategies at the 1-month horizon points to average performance. In particular, STY and (to a lesser extent) LTY predictive strategies are unable to consistently outperform the competing benchmark portfolios. First, they obtain lower Sharpe ratios than EXT models (Table 3). Second, they do not generate significantly superior X^* metrics than REST and EXT models. The analysis of the X_{eff} and Jensen α

metrics lead to similar conclusions. At the 3-month horizon (Table 4), the LTY predictive regression strategies are the best performers, in agreement with the statistical analysis of OOS forecasts. First, each of the three approaches (OLS, STAM, and LEW) generate the highest Sharpe ratios and X^* metrics; both of which are statistically significant. Second, they provide the highest Jensen α's, which are positive and close to significance. Third, they outperform the other benchmark portfolios with respect to the X_{eff} metric. The outperformance of the LTY predictive regression models found at the 3-month horizon disappears at the 12-month horizon (Table 5). First, they are outperformed by the buy-and-hold and extreme models with respect to the Sharpe ratio. Second, they provide negative Jensen α's and are outperformed by the EXT model. Third, they do worse than the REST model with respect to the X_{eff} metric.

To summarize, statistical evidence of stock return predictability in the Netherlands is concentrated on two variables only: STY and LTY. Economic significance is even further reduced: the only outperforming predictive regression strategies are based on the LTY variable and are limited to the 3-month horizon.

4.7 South Africa

IS evidence of predictability in South Africa is found for all variables, with the exception of TSP (Table 2). However, the OOS statistical analysis shows that such evidence is confirmed for the STY variable only. Conditioning upon IS significance, OOS evidence of predictability is not even found at the 12-month horizon. As in the preceding countries, statistical criteria point to small forecasting gains.

Turning to the economic analysis, predictive regression strategies based on the STY variable show positive and significant results at the 1-month horizon (Table 3). Besides providing the highest positive excess returns, they generate the highest Sharpe ratios, X^* metric, and Jensen α's, all of them being significant. Economic performance at the 3-month horizon is still positive but less convincing than at the 1-month horizon (Table 4). Sharpe Ratios provided by the LTY predictive regression strategies are positive and significant, but still lower than the Sharpe ratio delivered by the EXT benchmark model. Regarding the STY predictive regression strategies, they generate the highest Sharpe ratios but these are not significant. Similar observations apply to the X^* metric. The X_{eff} metric points to underperformance of the predictive regression strategies with respect to the restrictive model. Since no single variable is both IS and OOS significant at the 12-month horizon, no economic investigation is carried out.

All in all, no robust OOS evidence of stock return predictability is found in South Africa. While the STY variable is the most informative predictor, it fails to deliver superior economic results across investment horizons.

4.8 Sweden

From Table 2, we see that there is almost no IS statistical evidence of stock return predictability in Sweden. The relative short-term yield (STY) is the only predictive variable that shows both IS and OOS significance, mainly at the 1-month horizon.

STY predictive regression strategies show some positive economic performance at the 1-month horizon (Tables 3). Excluding X_{eff}, all profit-based metrics point to superior performance. However, Sharpe ratios are the only metrics that show statistical significance. At the 3-month horizon, the STY predictive regression model à la Lewellen fails to deliver any meaningful economic gain (Table 4). Since no single variable is both IS and OOS significant at the 12-month horizon, no economic investigation is carried out. In summary, predictive regression models fail to deliver any statistical or economic predictability in Swedish data.

4.9 United Kingdom

Significant IS predictive ability in the UK is found for all the variables, with the exception of TSP (Table 2). Interestingly, IS evidence of predictability found by the OLS model persists after correcting for the small sample bias in $\hat{\beta}$. It is also worth noting that both IS and OOS evidence of predictability are more obvious for valuation ratios than for interest rate variables. In any case, forecasting gains appear to be small. As the DRMSE statistic shows, the maximum potential gain is delivered at the 12-month horizon and amounts to an average of 48 bp per year only.

Looking at the 1-month economic performance (net of transaction costs), predictive regression strategies fail to outperform the benchmark portfolios (Table 3). First, they do not provide higher Sharpe ratios than EXT, the model based on extreme values of the predictive variable. In this respect, regression strategies based on valuation ratios perform worst as they are also unable to outperform BH and REST, the two other benchmark portfolios. Second, a quick inspection of the X^* metrics reveals that predictive regression strategies underperform the restrictive model. There is, in addition, no evidence of statistical significance. Similar results are found by looking at the Jensen α's. X_{eff} is the only statistic that points to some outperformance by the predictive regression strategies. However, all X_{eff} metrics are negative, suggesting that riskless strategies provide greater utility (over a weighted average of return horizons) to constant risk averse investors.

Although statistical significance remains an issue, more meaningful economic gains are provided by the predictive regression strategies at the 3-month horizon (Tables 4). The best results are obtained through the Sharpe ratios, which are all significant and higher than in the case of the benchmark portfolios. The X^* metric and Jensen α's also point to superior performance, but none of them are statistically significant. Finally, the DPR predictive regression strategy generates higher X_{eff} metrics than the benchmark portfolios, although it still displays negative values. In agreement with the results at the 1-month horizon, predictive regression strategies fail to outperform the benchmark portfolios at the 12-month horizon (Table 5). A quick inspection of the Sharpe ratios, X^* metrics, and Jensen α reveal that no predictive regression strategy is able to outperform the EXT benchmark model. X_{eff} is the only statistic that points to some outperformance by the predictive regression strategies, but X_{eff} values are all negative.

Summarizing the results for the UK, we find IS predictive ability for four (out of five) variables. Although valuation ratios exhibit undeniable OOS evidence of predictability, forecasting gains appear to be tiny. This is in general agreement with the economic performance of the predictive regression strategies. Although they sometimes generate higher economic gains than the buy-and-hold portfolio, none of them systematically outperforms the alternative benchmark strategies.

4.10 United States

All the variables exhibit some evidence of in-sample predictive ability in the US (Table 2). However, no evidence of OOS predictive ability is found for the price-earnings ratio. OOS evidence of predictability is also limited for the term spread. In any case, forecasting gains are small as indicated by the DRMSE and Theil's U statistics. This holds true whatever the predictive variable or investment horizon.

Nevertheless, the OOS economic analysis of the predictive investment strategies points to meaningful economic gains at the 1-month horizon (Table 3). In particular, predictive investment strategies based on LTY and STY outperform the benchmark portfolios with respect to all risk-adjusted metrics. Evidence of superior performance, albeit weaker, is also provided by the TSP predictive regression strategies and the OLS regression strategy based on DPR. Interestingly, predictive regression strategies generate positive X_{eff} metrics, suggesting that they provide risk averse investors with greater utility than riskless strategies.

Results at the 3-month horizons are in agreement with the 1-month observations (Table 4). The only significant difference comes from TSP, which is not OOS significant anymore. At the 12-month horizon, overall economic performance is still positive but less convincing than before (Table 5). First, no valuation ratio is investigated from an economic perspective, as they do not show both IS and OOS statistical evidence of predictability at the 12-month horizon. Second, the STY predictive regression strategies are the only ones that generate both higher Sharpe ratios and X_{eff} metrics than each of the benchmark strategies. In this respect, the EXT benchmark performs better than the TSP and LTY regression strategies. Finally, both STY and TSP regression strategies do best with respect to the X^* metric and Jensen α.

Taking the results together for the US, stock returns appear to be predictable in-sample. Such evidence does not completely vanish out-of-sample. Forecasting gains are somewhat stronger than those reported by Goyal and Welch (2008), but still appear to be limited. The economic analysis of predictive regression strategies generally confirms these findings. Nevertheless, meaningful outcomes are generated by the STY variable across each of the investment horizons.

5 Conclusion

Our out-of-sample statistical analysis shows that the short-term interest yield and, to a lesser extent, the long government bond yield are the most informative out-of-sample predictors of stock returns. Our results confirm that predictive variables in the US exhibit evidence of in-sample predictive ability as well as some reasonable out-of-sample performance. Nevertheless, the out-of-sample predictive power of these variables does not appear to be economically meaningful across countries and investment horizons.

First, thought experiments that rely upon out-of-sample statistics show that forecasting gains are small, underscoring the notion from the extant empirical literature that the predictive component in stock returns is small. According to Theil's U, the reduction in forecasting errors is never greater than 5%. Correspondingly, the DRMSE statistic shows that the highest performance across countries and investment horizons never goes above 100 bp per year, before transaction costs. Furthermore, there are cases where the only out-of-sample significant statistic is the Clark and McCracken (2001) ENC-NEW statistic designed to test for forecast encompassing. This indicates that a given predictive variable contains information that is useful in forecasting stock returns, even though no forecasting gain is realized according to mean squared error metrics.

Second, investment strategies that rely upon the return forecasts of predictive regression models also fail to deliver meaningful economic gains across investment horizons and across countries. While any risk adjustment is subject to criticism, most profit-based metrics yield the same conclusions: predictive regression strategies based on interest rate variables generate the most robust economic performance in the US, Canada, and France; they mostly fail in the other countries. Interestingly, the average performance of predictive regression strategies is similar to the one provided by the ‘extreme’ strategy, which consists in comparing the current value of the predictive variable to the 90th percentile of its unconditional distribution.

All in all, we find no common pattern of stock return predictability across countries, be it on statistical or economic grounds. Goyal and Welch (2008) argue that model instability may explain the poor performance of predictive regression models. Model instability can be reduced through the use of structural change models (by better modelling time-changing correlations, for example). However, specification search is clearly an issue as some of these models are bound to work both in-sample or out-of-sample by pure luck. In this respect, Lettau and Van Nieuwerburgh (2008) model structural change based on mean shifts in the dependent variables, not based on the forecasting regression. They confirm that, in real time, the in-sample return forecastability is hard to exploit out-of-sample due to the uncertainty of estimating the size of steady-state shifts. Nevertheless, the poor performance of predictive regression models may not come from the presence of structural breaks but from the fact that price movements cannot be traced back to visible news about dividends or cashflows, or even associated with interest rates or other observable movements in discount factors (Cochrane, 2008). As a consequence, excess return forecastability is not a comforting result since it cannot be easily exploited using predictive regression models. In this respect, we validate Cochrane’s argument: ‘One can simultaneously hold the view that returns are predictable [...] and believe that such forecasts are not very useful for out-of-sample forecasting and portfolio advice [...]’.

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Table 1: Summary statistics: Monthly Data.

Countries	Sample	RSR	RTR	PER	DPR	STY	LTY	TSP
A. Mean								
Australia	1969:07-2005:08	0.464	0.198	2.754	-1.577	0.014	-0.001	-0.140
Canada	1956:01-2005:09	0.440	0.197	2.854	-1.101	0.008	0.013	-0.265
France	1971:09-2005:10	0.536	0.218	2.812	-1.336	-0.072	-0.069	-0.192
Germany	1969:07-2005:10	0.357	0.171	2.725	-1.174	-0.020	-0.074	-0.298
Japan	1956:01-2005:09	0.531	0.075	3.286	-0.504	-0.074	-0.076	-1.036
Netherlands	1969:07-2005:10	0.775	0.348	2.343	-1.461	-0.044	-0.056	-0.346
South Africa	1960:02-2005:09	0.608	0.080	2.374	-1.265	0.040	0.029	-0.207
Sweden	1969:07-2005:09	0.740	0.191	2.603	-1.030	-0.064	-0.049	-0.216
United Kingdom	1950:01-2005:08	0.558	0.107	2.451	-1.505	0.041	0.014	-0.207
United States	1950:01-2005:07	0.625	0.092	2.718	-1.179	0.016	0.022	-0.352
B. Standard Deviation								
Australia	1969:07-2005:08	5.692	0.984	0.398	0.313	1.488	0.827	0.169
Canada	1956:01-2005:09	4.575	0.406	0.517	0.356	1.360	0.695	0.283
France	1971:09-2005:10	6.012	0.327	0.573	0.405	1.419	0.811	0.245
Germany	1969:07-2005:10	5.318	0.336	0.436	0.311	1.007	0.628	0.406
Japan	1956:01-2005:09	5.391	0.722	0.649	0.806	0.569	0.743	1.667
Netherlands	1969:07-2005:10	5.197	0.346	0.516	0.398	1.303	0.671	0.351
South Africa	1960:02-2005:09	6.414	0.572	0.316	0.324	1.678	0.913	0.212
Sweden	1969:07-2005:09	6.244	0.607	0.559	0.436	1.602	0.841	0.306
United Kingdom	1950:01-2005:08	5.213	0.611	0.463	0.283	1.319	0.737	0.414
United States	1950:01-2005:07	4.190	0.309	0.402	0.419	1.010	0.599	0.362
C. AC(1)								
Australia	1969:07-2005:08	0.048	0.259	0.979	0.984	0.890	0.902	0.943
Canada	1956:01-2005:09	0.088	0.219	0.978	0.988	0.919	0.886	0.956
France	1971:09-2005:10	0.099	0.600	0.946	0.985	0.933	0.927	0.970
Germany	1969:07-2005:10	0.064	0.270	0.979	0.979	0.926	0.907	0.981
Japan	1956:01-2005:09	0.041	0.134	0.992	0.995	0.931	0.903	0.974
Netherlands	1969:07-2005:10	0.071	0.420	0.986	0.990	0.910	0.908	0.947
South Africa	1960:02-2005:09	0.100	0.485	0.972	0.976	0.946	0.913	0.974
Sweden	1969:07-2005:09	0.140	0.230	0.951	0.984	0.894	0.919	0.951
United Kingdom	1950:01-2005:08	0.118	0.300	0.989	0.984	0.905	0.913	0.973
United States	1950:01-2005:07	0.038	0.430	0.988	0.991	0.881	0.884	0.968

RSR = log real total monthly stock returns; RTR = log real total monthly t-bills returns; PER = log price-earnings ratio; DPR = negative of the log dividend-price ratio; STY = relative treasury bill yield; LTY = relative long government bond yield; TSP = negative of the term spread. AC(1) = autocorrelation coefficient of the first order.

Table 2: In-sample and out-of-sample statistical analysis.

	k=1			k=3			k=12		
	OLS	STAM	LEW	OLS	STAM	LEW	OLS	STAM	LEW
AUSTRALIA									
LTY									
$\hat{\beta}$	-0.448^{b}	-0.481^{b}	-0.822^{bf}	-1.547^{b}	-1.587^{b}	-2.006^{be}	-5.660^{b}	-5.738^{b}	-6.522^{be}
U	1.009	1.010	1.012	1.006	1.006	1.008	1.007	1.008	1.016
MSE-F	-5.957	-6.242	-7.717	-3.775	-3.724	-5.158	-4.321	-4.775	-10.08
ENC-NEW	-1.984	-1.917	-1.388	0.586	0.918^{c}	1.863^{c}	12.65^{b}	13.26^{b}	14.26^{b}
DRMSE	-0.050	-0.052	-0.065	-0.054	-0.053	-0.074	-0.125	-0.139	-0.296
CANADA									
STY									
$\hat{\beta}$	-0.361^{b}	-0.376^{b}	-0.545^{bf}	-0.957^{c}	-0.980^{c}	-1.251^{c}	-4.736^{b}	-4.771^{b}	-5.182^{bf}
U	0.999	0.999	0.999	1.002	1.002	1.004	1.010	1.012	1.010
MSE-F	0.939^{b}	1.113^{b}	1.271^{c}	-2.069	-2.273	-3.505	-9.555	-11.35	-9.555
ENC-NEW	0.960^{b}	1.134^{b}	1.838^{b}	0.357	0.333	0.298	3.827^{c}	4.174^{c}	3.827^{c}
DRMSE	0.004^{b}	0.005^{b}	0.006^{c}	-0.018	-0.020	-0.031	-0.183	-0.218	-0.183
LTY									
$\hat{\beta}$	-0.702^{a}	-0.718^{a}	-0.998^{ad}	-1.749^{a}	-1.778^{a}	-2.277^{ad}	-4.618^{b}	-4.660^{b}	-5.382^{be}
U	0.997	0.997	0.999	0.997	0.998	1.001	1.010	1.010	1.015
MSE-F	3.289^{a}	3.109^{a}	0.998^{c}	2.544^{b}	2.254^{b}	-0.486	-9.467	-9.959	-14.37
ENC-NEW	4.789^{a}	4.992^{a}	6.822^{a}	8.052^{a}	8.253^{a}	10.32^{a}	10.17^{b}	10.31^{b}	11.54^{b}
DRMSE	0.016^{a}	0.015^{a}	0.005^{c}	0.022^{b}	0.019^{b}	-0.004	-0.181	-0.191	-0.278
TSP									
$\hat{\beta}$	-0.306^{c}	-0.315^{c}	-0.367^{c}	-0.907^{c}	-1.806^{c}	-1.970^{c}	-2.747	-2.787	-3.006
U	0.999	0.999	1.000	1.004	1.004	1.005	1.003	1.004	1.008
MSE-F	1.055^{c}	0.931^{c}	0.248	-3.734	-3.895	-4.624	-3.105	-3.703	-7.185
ENC-NEW	1.428^{b}	1.459^{b}	1.704^{b}	1.317	1.382	1.834^{c}	4.048	4.114	4.478
DRMSE	0.005^{c}	0.004^{c}	0.001^{c}	-0.033	-0.034	-0.040	-0.059	-0.070	-0.137
FRANCE									
STY									
$\hat{\beta}$	-0.639^{b}	-0.662^{b}	-0.809^{be}	-2.004^{b}	-2.037^{b}	-2.243^{be}	-6.284^{c}	-6.368^{c}	-6.870^{bf}
U	0.998	0.998	0.998	0.997	0.997	0.997	1.007	1.007	1.009
MSE-F	1.196^{b}	1.277^{b}	1.456^{b}	1.658^{c}	1.853^{c}	2.102^{c}	-4.266	-4.463	-5.118
ENC-NEW	0.955^{b}	1.053^{b}	1.356^{b}	2.070^{c}	2.248^{c}	2.655^{c}	0.662	0.678	0.756
DRMSE	0.011^{b}	0.012^{b}	0.014^{b}	0.029^{c}	0.032^{c}	0.037^{c}	-0.172	-0.180	-0.207
LTY									
$\hat{\beta}$	-0.947^{a}	-0.981^{a}	-1.217^{ad}	-2.888^{a}	-2.930^{a}	-3.212^{ad}	-8.535^{a}	-8.653^{a}	-9.431^{ad}
U	0.999	0.999	1.000	0.993	0.993	0.993	0.991	0.991	0.991
MSE-F	0.486^{c}	0.467^{c}	0.203	4.492^{a}	4.514^{a}	4.606^{a}	5.428^{b}	5.573^{b}	5.591^{b}
ENC-NEW	1.660^{b}	1.928^{b}	2.641^{b}	6.675^{a}	6.978^{a}	7.906^{a}	9.997^{b}	10.46^{b}	11.77^{b}
DRMSE	0.005^{c}	0.004^{c}	0.002	0.078^{a}	0.078^{a}	0.080^{a}	0.214^{b}	0.219^{b}	0.220^{b}
TSP									
$\hat{\beta}$	-0.391^{c}	-0.393^{c}	-0.396^{c}	-1.157^{c}	-1.178^{c}	-1.215^{c}	-3.641	-3.710	-3.817
U	1.000	1.000	1.000	0.999	0.999	1.000	0.995	0.995	0.996
MSE-F	-0.087	-0.058	-0.112	0.774	0.479	-0.107	2.951	2.756	2.205
ENC-NEW	0.557	0.584	0.587	1.913^{c}	1.856^{c}	1.757^{c}	4.441	4.479	4.536
DRMSE	-0.001	-0.001	-0.001	0.014	0.008	-0.002	0.117	0.109	0.088
GERMANY									
STY									
$\hat{\beta}$	-0.532^{b}	-0.535^{b}	-0.560^{be}	-1.606^{b}	-1.616^{b}	-1.686^{be}	-5.367^{a}	-5.413^{a}	-5.747^{ae}
U	0.997	0.997	0.997	0.995	0.995	0.995	0.998	0.998	0.997
MSE-F	1.963^{b}	2.019^{b}	2.157^{b}	3.072^{b}	3.232^{b}	3.633^{b}	1.381	1.544	1.914
ENC-NEW	1.357^{b}	1.407^{b}	1.557^{b}	2.503^{b}	2.628^{b}	2.992^{b}	2.290	2.437	2.893
DRMSE	0.016^{b}	0.017^{b}	0.018^{b}	0.047^{b}	0.050^{b}	0.056^{b}	0.048	0.054	0.067

Continued on next page

	k=1			k=3			k=12		
	OLS	STAM	LEW	OLS	STAM	LEW	OLS	STAM	LEW
				JAPAN					
PER									
$\hat{\beta}$	-0.418^{c}	-0.219^{c}	-0.189^{bf}	-1.374^{c}	-1.117^{c}	-1.077^{c}	-6.421^{b}	-6.075^{b}	-6.031^{bf}
U	0.997	1.054	1.066	0.990	1.027	1.024	0.960	0.979	0.967
MSE-F	2.733^{c}	-49.85	-59.72	10.18^{b}	-25.56	-22.79	41.69^{b}	21.17^{c}	34.03^{b}
ENC-NEW	2.413	-7.001	-5.359	8.021	-5.011	-0.530	30.91^{c}	21.46	28.91
DRMSE	0.014^{c}	-0.284	-0.346	0.098^{b}	-0.259	-0.230	0.900^{b}	0.471^{c}	0.742^{b}
DPR									
$\hat{\beta}$	-0.387^{c}	-0.120	-0.211^{c}	-1.274^{c}	-0.914	-1.029^{c}	-5.519	-5.053	-5.210
U	0.998	0.998	0.997	0.998	0.997	0.996	0.986	0.985	0.985
MSE-F	2.064^{c}	2.003^{b}	2.665^{b}	1.854	3.483^{c}	4.066^{c}	13.87	14.498^{c}	14.480^{c}
ENC-NEW	1.877	2.093^{c}	2.450^{c}	3.304	4.558	4.891	14.20	14.694	14.730
DRMSE	0.011^{c}	0.011^{b}	0.014^{b}	0.018	0.034^{c}	0.039^{c}	0.312^{c}	0.326^{c}	0.325^{c}
STY									
$\hat{\beta}$	-0.426^{b}	-0.435^{b}	-0.529^{be}	-1.366^{c}	-1.379^{c}	-1.511^{c}	-4.320^{c}	-4.368^{c}	-4.832^{bf}
U	1.005	1.005	1.006	1.013	1.014	1.016	1.020	1.021	1.028
MSE-F	-4.571	-4.778	-6.061	-12.82	-13.11	-15.07	-18.99	-20.05	-26.19
ENC-NEW	0.370	0.396	0.525	1.431	1.467	1.540	9.282^{c}	9.364^{c}	9.640^{c}
DRMSE	-0.024	-0.025	-0.032	-0.128	-0.131	-0.150	-0.449	-0.475	-0.627
LTY									
$\hat{\beta}$	-0.555^{a}	-0.559^{a}	-0.616^{ae}	-1.502^{b}	-1.514^{b}	-1.697^{be}	-2.626	-2.668	-3.253
U	0.999	0.999	0.999	0.995	0.995	0.996	0.996	0.996	0.995
MSE-F	1.473^{b}	1.461^{b}	1.011^{c}	4.800^{b}	4.815^{b}	4.070^{b}	3.995^{c}	4.227^{c}	4.769^{c}
ENC-NEW	1.640^{b}	1.661^{b}	1.643^{b}	4.376^{b}	4.437^{b}	4.468^{b}	2.762	2.931	3.598
DRMSE	0.008^{b}	0.008^{b}	0.005^{c}	0.047^{b}	0.047^{b}	0.040^{b}	0.091^{c}	0.096^{c}	0.109^{c}
				THE NETHERLANDS					
STY									
$\hat{\beta}$	-0.566^{b}	-0.577^{b}	-0.677^{be}	-1.480^{b}	-1.504^{b}	-1.736^{be}	-4.472^{c}	-4.516^{c}	-4.919^{c}
U	0.995	0.995	0.994	0.990	0.989	0.988	0.993	0.993	0.991
MSE-F	3.354^{a}	3.503^{a}	3.972^{a}	6.719^{b}	7.149^{b}	8.518^{b}	4.402	4.728	6.032^{b}
ENC-NEW	2.274^{b}	2.394^{b}	2.856^{b}	4.524^{b}	4.813^{b}	5.898^{b}	4.122	4.333	5.286^{b}
DRMSE	0.026^{b}	0.027^{a}	0.031^{a}	0.094^{b}	0.100^{b}	0.119^{b}	0.136	0.145	0.185^{b}
LTY									
$\hat{\beta}$	-0.991^{a}	-1.000^{a}	-1.079^{ad}	-2.753^{a}	-2.782^{a}	-3.0508^{ad}	-6.208^{a}	-6.272^{a}	-6.881^{ad}
U	0.991	0.991	0.991	0.961	0.960	0.958	0.967	0.965	0.959
MSE-F	6.422^{a}	6.429^{a}	6.103^{a}	27.69^{a}	28.39^{a}	29.81^{a}	22.50^{b}	23.65^{b}	28.03^{a}
ENC-NEW	7.580^{a}	7.802^{a}	8.555^{a}	23.27^{a}	24.19^{a}	27.48^{a}	19.94^{b}	20.81^{b}	24.73^{b}
DRMSE	0.050^{a}	0.050^{a}	0.047^{a}	0.370^{a}	0.379^{a}	0.397^{a}	0.665^{b}	0.697^{b}	0.819^{a}
				SOUTH AFRICA					
STY									
$\hat{\beta}$	-0.561^{b}	-0.576^{b}	-0.677^{be}	-1.464^{b}	-1.500^{b}	-1.736^{be}	-2.091	-2.155	-2.577
U	1.001	1.001	1.001	0.993	0.993	0.993	0.985	0.985	0.982
MSE-F	-0.805	-0.883	-0.959	6.388^{a}	6.399^{a}	6.783^{a}	13.77^{a}	13.79^{a}	15.78^{a}
ENC-NEW	1.052^{b}	1.027^{c}	1.070^{c}	7.639^{a}	7.792^{a}	8.448^{a}	14.80^{a}	15.14^{a}	16.90^{a}
DRMSE	-0.006	-0.007	-0.007	0.090^{a}	0.090^{a}	0.095^{a}	0.398^{a}	0.398^{a}	0.778^{a}
LTY									
$\hat{\beta}$	-0.378^{c}	-0.399^{c}	-0.6393^{c}	-1.198^{b}	-1.224^{b}	-1.518^{be}	-1.478	-1.527	-2.082
U	1.004	1.005	1.006	1.003	1.003	1.005	1.017	1.017	1.017
MSE-F	-3.703	-4.003	-5.123	-2.240	-2.468	-4.135	-14.14	-14.06	-14.299
ENC-NEW	-0.554	-0.597	-0.706	2.929^{b}	3.023^{b}	2.955^{b}	1.246	1.479	1.931
DRMSE	-0.029	-0.031	-0.040	-0.032	-0.035	-0.059	-0.428	-0.426	-0.433
				SWEDEN					
STY									
$\hat{\beta}$	-0.599^{b}	-0.619^{b}	-0.840^{be}	-0.802	-0.848	-1.377^{c}	-0.205	-0.259	-0.857
U	0.998	0.998	0.997	0.999	0.998	0.996	1.000	1.000	0.998
MSE-F	1.558^{b}	1.660^{b}	2.217^{b}	0.977	1.123^{c}	2.931^{b}	0.093	0.245	1.537
ENC-NEW	1.088^{b}	1.177^{b}	1.718^{b}	0.615	0.722	1.839^{c}	0.056	0.133	0.793
DRMSE	0.015^{b}	0.016^{b}	0.022^{b}	0.018^{c}	0.021^{c}	0.055^{b}	0.004	0.011	0.068

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	k=1			k=3			k=12		
	OLS	STAM	LEW	OLS	STAM	LEW	OLS	STAM	LEW
				UNITED KINGDOM					
PER									
$\hat{\beta}$	-0.404^{b}	-0.213^{c}	-0.068^{ae}	-1.285^{c}	-1.079	-0.925^{c}	-5.423^{b}	-5.227^{c}	-5.088^{be}
U	0.997	1.035	1.045	0.998	1.004	0.994	0.982	0.982	0.981
MSE-F	3.206^{b}	-38.05	-47.78	1.802	-4.136	6.680^{b}	20.20^{c}	20.82^{b}	21.68^{b}
ENC-NEW	2.581^{c}	-4.970	3.181	2.935	0.681	9.987^{b}	15.32^{c}	16.33^{c}	16.99^{c}
DRMSE	0.015^{b}	-0.191	-0.243	0.016	-0.037	0.058^{b}	0.376^{c}	0.387^{b}	0.403^{b}
DPR									
$\hat{\beta}$	-0.589^{a}	-0.465^{a}	-0.3130^{ad}	-1.788^{b}	-1.664^{b}	-1.510^{be}	-7.616^{a}	-7.502^{a}	-7.358^{ad}
U	0.998	1.000	0.995	0.996	1.000	0.998	0.977	0.979	0.985
MSE-F	2.857^{a}	0.498	5.278^{b}	4.970^{b}	0.521	1.975	25.97^{b}	23.76^{b}	16.87^{b}
ENC-NEW	2.692^{b}	2.206	4.981^{b}	4.807^{c}	2.422	3.423	26.67^{b}	23.04^{b}	18.63^{c}
DRMSE	0.014^{a}	0.002	0.025^{b}	0.044^{b}	0.005	0.017	0.480^{b}	0.441^{b}	0.316^{b}
STY									
$\hat{\beta}$	-0.261^{c}	-0.278^{c}	-0.563^{c}	-0.872^{c}	-0.893^{c}	-1.229^{c}	-3.661	-3.694	-4.204
U	1.003	1.003	1.006	1.006	1.006	1.008	1.038	1.039	1.045
MSE-F	-3.659	-3.873	-6.238	-6.238	-6.303	-8.559	-39.92	-40.47	-46.34
ENC-NEW	-0.158	0.005	0.350	1.698^{c}	2.009^{b}	2.560^{c}	0.515	0.698	0.984
DRMSE	-0.018	-0.019	-0.030	-0.055	-0.056	-0.076	-0.808	-0.819	-0.946
LTY									
$\hat{\beta}$	-0.430^{b}	-0.451^{b}	-0.759^{be}	-1.224	-1.254	-1.681	-3.670	-3.720	-4.431^{c}
U	1.007	1.007	1.010	1.010	1.011	1.015	1.019	1.021	1.025
MSE-F	-7.738	-8.267	-11.30	-11.42	-12.25	-16.11	-21.00	-22.28	-26.73
ENC-NEW	1.231^{b}	1.368^{b}	1.795^{b}	7.245^{a}	7.487^{a}	8.144^{a}	14.40^{a}	14.88^{a}	15.95^{a}
DRMSE	-0.037	-0.040	-0.055	-0.102	-0.110	-0.014	-0.414	-0.439	-0.531
				UNITED STATES OF AMERICA					
DPR									
$\hat{\beta}$	-0.334^{c}	-0.103	-0.097^{ad}	-1.023^{c}	-0.793	-0.792^{be}	-4.375	-4.126	-4.130
U	0.997	0.999	0.999	0.991	0.996	0.998	0.959	0.964	0.959
MSE-F	3.732^{b}	1.183	1.177	10.61^{b}	4.102	2.719	49.02^{b}	41.98^{b}	48.80^{b}
ENC-NEW	3.702^{b}	4.372^{b}	4.325^{b}	10.50^{b}	11.371^{b}	9.333^{b}	48.14^{b}	50.41^{b}	48.76^{b}
DRMSE	0.014^{b}	0.004	0.004	0.071^{b}	0.028	0.018	0.690^{b}	0.596^{b}	0.687^{b}
STY									
$\hat{\beta}$	-0.624^{a}	-0.627^{a}	-0.687^{ad}	-1.491^{a}	-1.501^{a}	-1.720^{ad}	-4.256^{b}	-4.282^{b}	-4.816^{be}
U	0.997	0.997	0.998	0.997	0.997	1.000	1.034	1.036	1.046
MSE-F	3.511^{a}	3.412^{a}	1.922^{b}	3.442^{b}	3.184^{b}	-0.251	-35.99	-37.55	-48.18
ENC-NEW	9.091^{a}	9.104^{a}	9.626^{a}	18.76^{a}	18.88^{a}	20.20^{a}	40.45^{a}	40.68^{a}	41.69^{a}
DRMSE	0.013^{a}	0.013^{a}	0.007^{b}	0.023^{b}	0.022^{b}	-0.002	-0.568	-0.594	-0.774
LTY									
$\hat{\beta}$	-0.689^{a}	-0.699^{a}	-0.903^{ad}	-1.698^{a}	-1.717^{a}	-2.108^{ad}	-3.619^{b}	-3.654^{b}	-4.353^{ae}
U	1.000	1.000	1.005	1.000	1.000	1.006	1.019	1.020	1.031
MSE-F	0.315	-0.021	-5.280	0.403	-0.105	-6.799	-20.94	-21.83	-32.57
ENC-NEW	10.95^{a}	11.06^{a}	13.08^{a}	24.33^{a}	24.57^{a}	28.12^{a}	31.87^{a}	32.27^{a}	35.11^{a}
DRMSE	0.001	-0.000	-0.020	0.003	-0.001	-0.047	-0.324	-0.337	-0.511
5. TSP									
$\hat{\beta}$	-0.402^{a}	-0.401^{a}	-0.393^{ae}	-1.109^{b}	-1.117^{b}	-1.150^{bf}	-3.662^{c}	-3.692^{c}	-3.802^{c}
U	1.011	1.011	1.011	1.033	1.033	1.036	1.070	1.072	1.083
MSE-F	-12.31	-12.26	-11.74	-35.29	-35.91	-38.64	-69.65	-72.24	-82.24
ENC-NEW	1.702^{c}	1.749^{c}	1.850^{c}	3.318	3.402	3.279	16.86^{c}	16.60^{c}	14.97^{c}
DRMSE	-0.048	-0.047	-0.045	-0.252	-0.257	-0.277	-1.155	-1.203	-1.391

The predictive variables are: PER = Price-Earnings Ratio; DPR = Dividend Yield Ratio; STY = Short-Term Yield; LTY = Long-Term Yield; TSP = Term Spread. OLS (STAM/LEW) refers to the predictive regression model (Equation 1) with no explicit (Stambaugh's/Lewellen's) correction for the small-sample bias in $\hat{\beta}$; U is Theil's U. The $a/b/c$ superscript indicates significance at the 1/5/10% level respectively, using bootstrapping. No significance test is carried out on U. An additional $d/e/f$ superscript on $\hat{\beta_{LEW}}$ indicates *joint* significance (given by the modified Bonferroni's upper bound) at the 1/5/10% level respectively (see Section 2). For example, superscript 'd' indicates joint significance at the 1% level, meaning that the null hypothesis ($\beta = 0$) is rejected by using either Stambaugh's or Lewellen's approach at the 1% level.

Table 3: Out-of-sample economic analysis, 1-month horizon ($k = 1$).

Models	AU	CN	FR	GE	JP	NL	SA	SW	UK	US
					SHARPE RATIO					
BH		0.1543	0.2457	0.1778	0.2586	0.3976	0.2139	0.4421	0.2632	0.3283
REST		0.3526^{a}	0.3830^{a}	0.0032^{c}	0.2638^{a}	0.3357^{a}	0.5753^{c}	0.3799^{a}	0.3228^{a}	0.2929^{a}
1. PER										
EXT					0.0968^{a}				0.2712^{a}	
OLS					0.1233^{a}				0.2468^{b}	
2. DPR										
EXT					0.1177^{a}				0.3244^{a}	0.2864^{a}
OLS					0.1057^{a}				0.2226^{a}	0.4144^{a}
LEW					-0.0050				0.1913^{a}	0.2192
3. STY										
EXT		0.1867^{a}	0.2336^{a}	0.1856^{a}		0.4311^{a}	0.2825	0.4650^{a}		0.3930^{a}
OLS		0.3412^{a}	0.3399^{a}	0.2025^{b}		0.3103^{a}	0.6314^{b}	0.4622^{a}		0.4539^{a}
STAM		0.3721^{a}	0.3671^{a}	0.2020^{b}		0.3080^{a}	0.6272^{b}	0.5001^{a}		0.4539^{a}
LEW		0.3831^{a}	0.3628^{a}	0.2055^{a}		0.2574^{a}	0.6431^{b}	0.5055^{a}		0.4474^{a}
4. LTY										
EXT		0.3961^{a}	0.3229^{a}		0.3529^{b}	0.4544^{a}			0.4168^{a}	0.4219^{a}
OLS		0.3642^{a}	0.4538^{a}		0.3377^{b}	0.4189^{a}			0.3582^{a}	0.4707^{a}
STAM		0.3322^{a}	0.4642^{a}		0.3406^{b}	0.4189^{a}			0.3357^{a}	0.4645^{a}
LEW		0.3551^{a}	0.5165^{a}		0.3330^{b}	0.3946^{a}			0.3665^{a}	0.5143^{a}
5. TSP										
EXT		0.1936^{a}								0.4942^{a}
OLS		0.2680^{a}								0.4888^{a}
STAM		0.2883^{a}								0.4974^{a}
LEW		0.3093^{a}								0.5110^{a}
					X^* METRIC					
REST		0.2437^{c}	0.2538	-0.0424	0.0015	0.0466	0.5909^{c}	0.1085	0.1934	0.0233
1. PER										
EXT					-0.1049				0.1157	
OLS					-0.0381				0.1566	
2. DPR										
EXT					-0.0762				0.1678^{c}	0.0452
OLS					-0.0779				0.1280	0.1633^{c}
LEW					-0.1651				0.1114	-0.0285
3. STY										
EXT		0.0475	-0.0077	0.0255		0.0558	0.1438	0.0766		0.1150^{c}
OLS		0.2181	0.2194	0.1435		0.0204	0.6453^{b}	0.2061		0.1770
STAM		0.2411^{c}	0.2433	0.1422		0.0146	0.6413^{b}	0.2554		0.1770
LEW		0.2431^{c}	0.2404	0.1434		-0.0361	0.6582^{b}	0.2651		0.1711
4. LTY										
EXT		0.2769^{a}	0.1273		0.1268	0.1063			0.1632^{c}	0.1337^{b}
OLS		0.2419	0.3286		0.1252	0.1215			0.1845	0.2015^{c}
STAM		0.2161	0.3396		0.1306	0.1215			0.1595	0.1962^{c}
LEW		0.2408	0.4022		0.1231	0.0984			0.1854	0.2387^{b}
5. TSP										
EXT		0.0653								0.2262^{b}
OLS		0.1452								0.2175^{c}
STAM		0.1591								0.2250^{c}
LEW		0.1710								0.2351^{c}

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Models	AU	CN	FR	GE	JP	NL	SA	SW	UK	US
X_{eff} METRIC										
BH		-0.9409	-1.8273	-1.6088	-1.1738	-1.0976	-2.0401	-1.9604	-1.2178	0.1513
REST		-0.1108	-0.2782	-0.9091	-1.0634	-0.6652	-0.3120	-0.4568	-0.4088	0.0938
1. PER										
EXT					-0.7846				-0.6837	
OLS					-0.7679				-0.2137	
2. DPR										
EXT					-0.6671				-0.6360	0.0946
OLS					-0.7659				-0.2210	0.1308
LEW					-0.8025				-0.1336	-0.0270
3. STY										
EXT		-0.6978	-1.8534	-1.5603		-1.0350	-1.4185	-1.8957		0.1809
OLS		-0.1812	-0.5439	-0.8004		-1.0357	-0.2780	-0.5417		0.1963
STAM		-0.1662	-0.5069	-0.7719		-1.0387	-0.2898	-0.5461		0.1963
LEW		-0.1712	-0.5294	-0.7673		-1.0866	-0.2634	-0.5286		0.1922
4. LTY										
EXT		-0.4010	-1.4850		-0.9012	-0.9890			-0.5190	0.1867
OLS		-0.2007	-0.4474		-0.8767	-0.7725			-0.3365	0.1993
STAM		-0.2405	-0.4641		-0.8733	-0.7725			-0.3468	0.1956
LEW		-0.2432	-0.4283		-0.8814	-0.7985			-0.3240	0.2214
5. TSP										
EXT		-0.6663								0.2536
OLS		-0.1885								0.1919
STAM		-0.1786								0.1968
LEW		-0.1703								0.2052
Jensen α										
REST		2.3144^b	2.8297^c	-1.7885	0.2202	0.1930	6.2680^c	1.5387	1.8754	0.3939
1. PER										
EXT					-1.5664				0.8367	
OLS					-1.1068				1.1166	
2. DPR										
EXT					-0.9499				1.6362	0.2447
OLS					-1.1440				0.8714	1.911^b
LEW					-2.4382				0.1114	-0.3633
3. STY										
EXT		0.6922	-0.2158	0.1831		0.7526	1.9877	0.5224		1.2219
OLS		2.3231^b	2.3568	0.9667		-0.5548	7.2748^c	2.5281		2.2098^b
STAM		2.6262^b	2.7184	0.9639		-0.5896	7.2407^c	3.0760		2.2098^b
LEW		2.7533^b	2.6651	1.0153		-1.3123	7.4695^c	3.1544		2.1356^c
4. LTY										
EXT		3.5630^a	1.7140^b		1.8090^c	1.2949^c			3.1195^b	1.7609^b
OLS		2.7630^b	3.9918^b		1.6217	1.3688			2.2955	2.4353^c
STAM		2.4416^c	4.1629^b		1.6684	1.3688			2.0305	2.3675^c
LEW		2.7197^b	4.9375^b		1.5501	1.0221			2.3962	2.9193^b
5. TSP										
EXT		0.8123								2.5473^b
OLS		1.5925^c								2.6420^b
STAM		1.7696^c								2.7310^b
LEW		1.9612^c								2.8713^b

The predictive variables are: PER = Price-Earnings Ratio; DPR = Dividend Yield Ratio; STY = Short-Term Yield; LTY = Long-Term Yield; TSP = Term Spread. OLS (STAM/LEW) refers to the predictive regression model of Equation (1) with no explicit (Stambaugh's/Lewellen's) correction for the small-sample bias in $\hat{\beta}$. REST is the restricted model, where $\beta = 0$ in Equation (1). EXT compares the current level of the predictive variable to the 90th percentile of its unconditional distribution, as defined in Section 2.2. The $a/b/c$ superscript indicates significance at the 1/5/10% level respectively, using bootstrapping. AU = Australia; CN = Canada; FR = France; GE = Germany; JP = Japan; NL = Netherlands; SA = South Africa; SW = Sweden; UK = United Kingdom; US = United States.

Table 4: Out-of-sample economic analysis, 3-month horizon ($k = 3$).

Models	AU	CN	FR	GE	JP	NL	SA	SW	UK	US
					SHARPE RATIO					
BH	0.2617	0.1442	0.2419	0.1706	0.2331	0.3931	0.1985	0.3875	0.2448	0.3154
REST	0.0341^c	0.2296^a	0.1551^a	0.0603^b	0.2213^a	0.3051^a	0.1605	0.3117^a	0.2681^a	0.3137^a
1. PER										
EXT					0.1257^a				0.2894^a	
OLS					0.1035^a					
LEW									0.3412^a	
2. DPR										
EXT					0.1095^a				0.3158^a	0.3237^a
OLS									0.3325^a	0.3108^a
LEW					0.0109^a					0.1059^a
3. STY										
EXT			0.2360^a	0.1742^a		0.3854^a	0.2267	0.3622^a	0.2369^a	0.3496^a
OLS			0.3801^a	0.1608^b		0.3038^a	0.3191		0.3075^b	0.4844^a
STAM			0.3653^a	0.1630^b		0.2973^a	0.3191		0.3034^b	0.4817^a
LEW			0.3551^a	0.1606^b		0.2949^a	0.3177	0.2218^a	0.3217^b	0.4813^a
4. LTY										
EXT	0.2800^a	0.2954^a	0.2829^a		0.3093^a	0.3881^a	0.2800^a			0.4295^a
OLS		0.3592^a	0.4724^a		0.3188^b	0.5055^a	0.2455^b			0.4589^a
STAM	0.2749^b	0.3478^a	0.4832^a		0.3188^b	0.5055^a	0.2628^b			0.4589^a
LEW	0.2855^a	0.3398^a	0.5031^a		0.3211^b	0.5048^a	0.2821^b			0.4653^a
5. TSP										
EXT		0.1868^a	0.2436^a							
OLS			0.0781^a							
STAM			0.0762^a							
LEW		0.4149^a	0.0985^a							
					X^* METRIC					
REST	-0.2234	0.3476	0.0142	-0.0732	-0.0624	-0.0120	0.3021	0.1625	0.1751	0.0915
1. PER										
EXT					-0.1978				0.4457	
OLS					-0.1552					
STAM										
LEW									0.5099	
2. DPR										
EXT					-0.2158				0.5125	0.2200
OLS									0.5943	0.2533
STAM										
LEW					-0.4326					0.0128
3. STY										
EXT			0.0092	0.0514		0.0243	0.2513	-0.0761	0.0154	0.2401
OLS			0.8252^c	0.2519		0.0601	0.8846		0.2966	0.6655^c
STAM			0.7875^c	0.2533		0.0343	0.8846		0.2888	0.6591^c
LEW			0.7462^c	0.2392		0.0278	0.8774	-0.2045	0.3503	0.6607^c
4. LTY										
EXT	0.1336	0.5704^b	0.2565		0.3145	0.1025	0.6247^b			0.4166^b
OLS		0.6976^c	1.0341^b		0.3810	0.7160^b	0.5874			0.5560^c
STAM	0.3611	0.6784^c	1.0825^b		0.3810	0.7160^b	0.6555			0.5560^c
LEW	0.3971	0.6614^c	1.1686^b		0.3966	0.7244^b	0.7394			0.5670^c
5. TSP										
EXT		0.2095	0.1259							
OLS			-0.2354							
STAM			-0.2474							
LEW		0.6448^b	-0.1821							

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Models	AU	CN	FR	GE	JP	NL	SA	SW	UK	US
X_{eff} METRIC										
BH	-6.5390	-5.6090	-10.355	-9.4915	-7.7828	-7.1826	-12.068	-14.206	-7.4931	0.5377
REST	-0.9213	-0.9933	-4.3605	-4.6580	-7.9263	-6.4529	-5.2002	-4.4906	-2.4984	0.4457
1. PER										
EXT					-4.2439				-4.6037	
OLS					-4.3151					
LEW									-3.3703	
2. DPR										
EXT					-4.1970				-4.7009	0.4204
OLS									-1.3564	0.3511
LEW					-4.3167					0.0123
3. STY										
EXT			-10.361	-9.2785		-7.1802	-9.6392	-13.844	-5.4991	0.5689
OLS			-5.0791	-6.2839		-6.8457	-5.7911		-2.5275	0.7671
STAM			-5.1685	-6.2525		-6.9059	-5.7911		-2.5465	0.7620
LEW			-5.2782	-6.5724		-6.9211	-5.7874	-5.5974	-2.5629	0.7611
4. LTY										
EXT	-5.1447	-3.3990	-9.4194		-6.8606	-7.2194	-10.407			0.6634
OLS		-1.5667	-3.8927		-6.6043	-5.3013	-6.8847			0.6681
STAM	-2.7569	-1.5982	-3.9071		-6.6043	-5.3013	-6.7901			0.6681
LEW	-2.7263	-1.6433	-3.9532		-6.5829	-5.3117	-6.7352			0.6695
5. TSP										
EXT		-3.8930	0.1259							
OLS			-0.2354							
STAM			-0.2474							
LEW		-0.8222	-0.1821							
Jensen α										
REST	-0.6112	1.3754	-0.0102	-0.9951	-0.2815	-0.8948	0.5287	1.0003	1.4438	0.5010
1. PER										
EXT					-0.6908				1.4424	
OLS					-1.2059					
LEW									2.3157	
2. DPR										
EXT					-0.8777				1.8189	0.8598
OLS									2.1044	0.9448
LEW					-2.3144					0.0629
3. STY										
EXT			-0.0942	0.1202		-0.0745	1.1090	-0.5330	0.2029	0.6571
OLS			3.1739	0.3140		-0.9435	3.1817		1.9187	2.6309^{c}
STAM			2.9579	0.3492		-1.0424	3.1817		1.8678	2.6000^{c}
LEW			2.8010	0.2922		-1.0830	3.1557	-0.7764	2.0949	2.5942^{c}
4. LTY										
EXT	0.6394	2.4753^{c}	0.9993		1.4753	0.1000	2.2565^{c}			1.9631^{c}
OLS		2.9344^{b}	4.6069^{b}		1.7087	2.7913	1.8363			2.3921^{c}
STAM	1.1278	2.8274^{b}	4.7823^{b}		1.7087	2.7913	2.1658			2.3921^{c}
LEW	1.2703	2.7519^{b}	5.1041^{b}		1.7626	2.7807	2.5178			2.4716^{c}
5. TSP										
EXT		0.8751	0.1528							
OLS			-1.4395							
STAM			-1.4991							
LEW		2.8258^{b}	-1.1797							

The predictive variables are: PER = Price-Earnings Ratio; DPR = Dividend Yield Ratio; STY = Short-Term Yield; LTY = Long-Term Yield; TSP = Term Spread. OLS (STAM/LEW) refers to the predictive regression model of Equation (1) with no explicit (Stambaugh's/Lewellen's) correction for the small-sample bias in $\hat{\beta}$. REST is the restricted model, where $\beta = 0$ in Equation (1). EXT compares the current level of the predictive variable to the 90th percentile of its unconditional distribution, as defined in Section 2.2. The $a/b/c$ superscript indicates significance at the 1/5/10% level respectively, using bootstrapping. AU = Australia; CN = Canada; FR = France; GE = Germany; JP = Japan; NL = Netherlands; SA = South Africa; SW = Sweden; UK = United Kingdom; US = United States.

Table 5: Out-of-sample economic analysis, 12-month horizon ($k = 12$).

Models	AU	CN	FR	GE	JP	NL	SA	SW	UK	US
					SHARPE RATIO					
BH	0.2554	0.1208	0.2155		0.2048	0.3754			0.2177	0.2855
REST	0.0547^{c}	0.1426^{a}	0.1651^{a}		0.2148^{a}	0.2574^{a}			0.1889^{b}	0.2224
1. PER										
EXT					0.2104^{a}				0.3232^{a}	
OLS					0.1847^{a}				0.1700^{b}	
STAM					0.1330^{a}				0.1854^{a}	
LEW					0.1765^{a}				0.1937^{a}	
2. DPR										
EXT									0.3814^{a}	
OLS									0.3080^{a}	
STAM									0.2622^{a}	
LEW									0.2041^{a}	
3. STY										
EXT		0.1736^{a}			0.2616^{b}	0.3582^{a}				0.3518^{a}
OLS		0.3144^{a}			0.2603^{c}					0.4064^{a}
STAM		0.3179^{a}			0.2603^{c}					0.4064^{a}
LEW		0.3173^{a}			0.2624^{c}	0.3144^{a}				0.4146^{a}
4. LTY										
EXT	0.3178^{a}	0.1922^{a}	0.2320^{a}			0.3596^{a}			0.3447^{a}	0.3716^{a}
OLS	0.3057^{a}	0.2613^{a}	0.2749^{a}			0.3269^{a}				0.3288^{a}
STAM	0.2910^{a}	0.2613^{a}	0.2765^{a}			0.3316^{a}				0.3233^{a}
LEW	0.2941^{a}	0.2547^{a}	0.2872^{a}			0.3288^{a}			0.2938^{a}	0.3351^{a}
5. TSP										
EXT										0.4235^{a}
OLS										0.4104^{a}
STAM										0.4110^{a}
LEW										0.4122^{a}
					X^{*} METRIC					
REST	-0.5563	0.6335	0.6808		0.0948	-0.8827			-0.0387	-0.4770
1. PER										
EXT					0.9312				2.7838^{c}	
OLS					0.8596				0.9605	
STAM					-0.1509				1.0822	
LEW					0.6081				1.0598	
2. DPR										
EXT									3.4415^{a}	
OLS									2.2942^{b}	
STAM									1.8861^{c}	
LEW									1.4159^{c}	
3. STY										
EXT		0.7173			1.2151	-0.0301				1.0397^{c}
OLS		2.3122^{b}			1.2519					1.6997^{c}
STAM		2.4114^{b}			1.2519					1.6997^{c}
LEW		2.3929^{b}			1.3067	0.7292				1.8012^{c}
4. LTY										
EXT	1.1918	1.1114^{c}	0.5971			0.3498			1.1980^{b}	0.3716^{a}
OLS	0.9239	1.7838^{c}	2.0686^{c}			1.0560				0.3288^{a}
STAM	0.8125	1.7838^{c}	2.0804^{c}			1.1284^{c}				0.3233^{a}
LEW	0.8538	1.7154^{c}	2.2615^{c}			1.0945			1.2047	0.3351^{a}
5. TSP										
EXT										1.8447^{c}
OLS										1.8526^{c}
STAM										1.8511^{c}
LEW										1.8795^{c}

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Models	AU	CN	FR	GE	JP	NL	SA	SW	UK	US
X_{eff} METRIC										
BH	-46.264	-44.843	-85.727		-74.605	-66.644			-70.729	2.3526
REST	-1.3800	-9.6962	-44.503		-73.679	-56.744			-26.241	1.4467
1. PER										
EXT					-40.026				-38.658	
OLS					-31.145				-4.880	
STAM					-47.944				-6.6716	
LEW					-44.656				-6.0122	
2. DPR										
EXT									-35.939	
OLS									-14.507	
STAM									-12.066	
LEW									-10.318	
3. STY										
EXT		-27.997			-63.774	-66.969				2.5811
OLS		-10.817			-61.897					2.7060
STAM		-11.586			-61.897					2.7060
LEW		-11.335			-61.849	-57.305				2.7514
4. LTY										
EXT	-33.446	-29.396	-82.519			-66.662			-27.2493	2.6397
OLS	-10.301	-12.128	-45.090			-61.494				2.1317
STAM	-10.578	-12.128	-45.109			-61.237				2.0808
LEW	-10.471	-12.292	-46.383			-61.779			-19.8503	2.1028
5. TSP										
EXT										3.0766
OLS										2.4480
STAM										2.4517
LEW										2.5035
Jensen α										
REST	0.0317	0.7408	0.3672		0.0864	-1.1040			0.6478	-0.4822
1. PER										
EXT					0.7951				2.3150^c	
OLS					0.5808				0.6991	
STAM					-0.7680				0.8373	
LEW					0.0951				0.8854	
2. DPR										
EXT									3.1976^a	
OLS									2.0744^c	
STAM									1.5738	
LEW									1.0080	
3. STY										
EXT		1.0564			1.2246	-0.2100				1.1448
OLS		2.5344^b			1.2457					2.0231
STAM		2.6037^b			1.2457					2.0231
LEW		2.5896^b			1.2863	-0.3621				2.1185
4. LTY										
EXT	1.4400	1.3258	0.4087			-0.1177			2.6784^c	1.4866
OLS	1.7482	2.0073^c	1.9612			-0.3578				1.1550
STAM	1.6002	2.0073^c	1.9890			-0.2580				1.1018
LEW	1.6324	1.9451^c	2.1632			-0.3025			2.0009	1.2911
5. TSP										
EXT										2.0853^b
OLS										2.1635^b
STAM										2.1695^b
LEW										2.1715^b

The predictive variables are: PER = Price-Earnings Ratio; DPR = Dividend Yield Ratio; STY = Short-Term Yield; LTY = Long-Term Yield; TSP = Term Spread. OLS (STAM/LEW) refers to the predictive regression model of Equation (1) with no explicit (Stambaugh's/Lewellen's) correction for the small-sample bias in $\hat{\beta}$. REST is the restricted model, where $\beta = 0$ in Equation (1). EXT compares the current level of the predictive variable to the 90th percentile of its unconditional distribution, as defined in Section 2.2. The $a/b/c$ superscript indicates significance at the 1/5/10% level respectively, using bootstrapping. AU = Australia; CN = Canada; FR = France; GE = Germany; JP = Japan; NL = Netherlands; SA = South Africa; SW = Sweden; UK = United Kingdom; US = United States.