Accepted for publication in *Journal of Asset Management* published by Palgrave Macmillan.

Forecasting Sector Stock Market Returns

David G McMillan
Division of Accounting and Finance
University of Stirling

February 2021

Abstract

We seek to forecast sector stock returns using established predictor variables. Existing empirical evidence focuses on market level data and thus sector data provides fertile ground for research. In addition to in-sample predictive regressions, we consider recursive and rolling forecasts and whether such forecasts can be used successfully in a sector rotation portfolio. The results for ten sectors and eleven predictor variables highlight that two variables, the default return and stock return variance, have significant predictive power across the stock market series. Forecast results are also supportive of these series (especially the default return), which can outperform benchmark and alternative forecast models across a range of metrics. A sector rotation strategy based on these forecasts produces positive abnormal returns and a Sharpe ratio higher than the baseline model. An examining of the sectors at each rotation reveals that a small number of dominate in the constructed portfolios.

Keywords: Sectors, Stock Returns, Forecasts, Time-Varying
JEL Codes: C22, G12

Address for Correspondence: Professor David McMillan,
Accounting and Finance Division, University of Stirling, FK9 4LA
Telephone: +44(0)1786-467309
Fax: +44(0)1786-467308
E-mail: david.mcmillan@stir.ac.uk

1. Introduction.

Given its importance in our understanding of asset price movements, the debate regarding stock return predictability continues to be a key theme in empirical finance research. Largely beginning with the work of Campbell and Shiller (1998), evidence for predictability is provided by Cochrane (2008), Campbell and Thompson (2008), Kellard et al (2010) and Maio (2013), among others. Against this view, evidence of little or no predictability is provided by Nelson and Kim (1993), Ang and Bekaert (2007), Goyal and Welch (2003), Welch and Goyal (2008), Hjalmarsson (2010) and Park (2010). In response, several papers argue that predictability is time-varying, due to breaks or market and economic regime dependence (e.g., Paye and Timmermann, 2006; Chen, 2009; Henkel et al, 2011; McMillan and Wohar, 2013; Hammerschmid and Lohre, 2018).

However, this debate has largely taken place in the context of market level stock return behaviour. An examination at the sector level, therefore, provides fertile ground for continued research into this question. As evidence of predictability is linked to asset pricing theories that in turn link stock price movements to changes in expected future cash flows and risk, this may impact across sectors differently. Further, predictability of sector stock returns informs a sector rotation investment strategy. In terms of existing work, Guidolin et al (2013), Laopodis (2016) and Pham (2020), for the US, and McMillan (2010), for the UK, consider predictability at the sector or industry level. These papers only consider in-sample predictability. While this is important, the direction of the literature is towards out-of-sample forecasting (e.g., Baltas and Karyampas, 2018; McMillan, 2021). Beller et al. (1998) do consider an out-of-sample forecasting exercise and note that forecasting models can improve portfolio allocation.

This paper examines the in-sample and out-of-sample predictive and forecast power for ten US sector stock market returns, together with a market and two style-based indices, using a range of predictor variables established in Welch and Goyal (2008). Specifically, we consider a predictive regression for each stock index across the full sample before conducting both rolling and recursive forecasts. These forecasts are used in a portfolio allocation exercise to consider their relevance for investors, notably, in terms of a sector or style rotation strategy.

This paper contributes to the literature by expanding upon the majority of previous work that considers market level evidence and on the previous limited sector level evidence by expanding the set of explanatory variables and conducted a forecasting exercise. In respect of Beller et al. (1998), this paper extends both the range of predictor variables and the data sample, including an examination of predictive power in the post-financial crisis world. It is hoped that the results presented here will be of interest not only to academics involved in understanding asset price movement but also to investors in seeking to improve their portfolio allocation.

2. Methodology.

The predictive regression equation is given by:

(1) $$r_t = \alpha + \Sigma_i \beta_i x_{i,t-1} + \varepsilon_t$$

Where r_t is the stock return, $x_{i,t}$ the predictor variables and ε_t a white noise error term.

After conducting initial full sample estimates, we undertake forecasts using both a rolling (fixed window) and a recursive (expanding window) approach. These approaches are designed to mimic investors operating in real time by updating all available information, including the data and parameter estimates. An additional advantage of the updating approaches compared to a fixed out-of-sample period is that they accommodate the presence of breaks as observations are added (and dropped) and coefficient values re-estimated.

The rolling and recursive approaches differ in how they treat older observations, either dropping them in the former approach or retaining them in the latter. In each case, we begin by estimating an initial model over a five-year (60 observation) in-sample window and then obtain the forecast for the first out-of-sample observation. To obtain the second forecast, the end of the in-sample period is rolled forward by one observation, with the starting observation also rolling forward by one observation (rolling, fixed in-sample observations, approach) or retained (recursive, expanding in-sample observations, approach). These respective processes continue through the rest of the sample period and we generate two forecast series for each stock return.

To evaluate the forecasts, we use the out-of-sample R-squared measure (see Campbell and Thompson, 2008; Welch and Goyal, 2008), which essentially compare the mean squared error (MSE) between a baseline and alternative predictive model and is given by:

(2) $$R_{oos}^2 = 1 - \left(\frac{\sum_{t=1}^{\tau}(r_t - r_t^{f_2})^2}{\sum_{t=1}^{\tau}(r_t - r_t^{f_1})^2}\right)$$

where τ is the forecast sample size, r_t is the observed return and $r_t^{f_i}$ represents the forecasts. The out-of-sample R-squared measures a baseline model, denoted f_1, against the predictor model, denoted f_2. The baseline model involves estimating a variant of equation (1) where only the constant is included (referred to as the historical mean model), while the alternative model is given by equation (1). When the R_{oos}^2 value is positive, this indicates that the predictor model has greater forecast power than the baseline model, otherwise the baseline model is preferred. To establish whether any positive out-of-sample R-squared values are statistically significant, we use the test of Clark and West (2007).

We also consider the forecast encompassing test regression given by:

(3) $$r_t = \alpha + \beta_1 r_t^{f_1} + \beta_2 r_t^{f_2} + \varepsilon_t$$

Again, r_t is the observed returns series and $r_t^{f\,i}$ the forecast series. The point of interest here is the β_2 coefficient. The forecast of the baseline, f_1, model is said to encompass the forecast of the alternative, f_2, model if β_2 is statistically insignificant. However, if β_2 is positive and statistically significant then the alternative model contains information helpful to the forecast that is not captured by the baseline model.

While the above measures capture statistical forecast performance, we also consider the economic significance of the forecasts. Here, we use the forecasts as providing trading-based signals. Where a forecast for the subsequent period return is positive, then an investor buys the stock, while if the next periods return forecast is negative, then the investor (short) sells the stock. From this process, we obtain a time series of returns that represent the outcome of the trading rule and denote this R_t.

Following Welch and Goyal (2008), Campbell and Thompson (2008) and Maio (2016), we use this trading series to compute the certainty equivalence value (CEV). This measures the change in average utility between the baseline and alternative forecasts and represents the fee an investor would be willing to pay to invest in the alternative model. Following Maio (2016), the change in CEV is calculated as:

$$CEV = E(R_t^{f_2}) - E(R_t^{f_1}) + \frac{\gamma}{2}[Var(R_t^{f_1}) - Var(R_t^{f_2})] \tag{4}$$

With $R_t^{f_2}$ the trading return obtained from the alternative predictive forecast model, $R_t^{f_1}$ the trading return from the baseline historical mean model and γ is the coefficient of relative risk aversion, set to three following Campbell and Thompson (2008) and Maio (2016).[1]

The above analysis considers each series individually, however, we can also consider an investor who is looking to diversify across different sectors and style types. Here, we examine whether the forecasts will allow an investor to improve their portfolio performance. Specifically, we first consider an investor who will switch between value and growth stocks. At each rolling and recursive step, the investor will buy the asset that has the highest forecast value, thus, switching between the two stock types. Second, we consider an equivalent process for the sectors. Again, at each step, we note the forecast values and build two portfolios, one based on only investing in the sector with the highest forecast (or highest two forecasts), and one based on a hedged portfolio of buying the highest forecast sector and selling the lowest

[1] Experimentation with different values does not change the qualitative nature of the results.

forecast sector (or buying the highest two and selling the lowest two forecasts). To examine the performance of these portfolios we calculate the mean return, the standard deviation (riskiness) and the risk-adjusted return (Sharpe ratio). We also consider a CAPM regression to obtain estimates of the alpha (abnormal return) and beta of each portfolio.

3. Data.

We obtain stock returns data for the S&P500 index, the S&P Growth and Value indices and ten sector indices from Datastream.[2] The explanatory variables are those used by Welch and Goyal (2008) and are taken from the website of Amit Goyal.[3] Specifically, this includes, dividend-price ratio, earnings-price ratio, dividend payout ratio, stock variance, book-to-market ratio, net equity issuance, long-term bond yield and return, the term structure (10-year minus 3-month government treasuries), the default return (the difference between long-term corporate and government bonds) and inflation. The data frequency is monthly, and the sample period is 1990:1 to 2018:12.

4. Empirical Results.

In-Sample Results

Table 1 presents the estimation results for equation (1) for each of the series, with the regressions conducted over the full sample. These results reveal an interesting and consistent pattern in terms of statistical significance of the predictor variables. In common with results that report no predictability, there is little evidence of wholesale statistical significance among the explanatory variables. Across the thirteen stock market series and eleven predictor variables, and thus 143 coefficient estimates, 42 (29%) exhibit statistical significance at the 5%

---

[2] The sectors are consumer discretionary (CD), consumer staples (CS), energy (EN), financials (FN), health care (HC), industrials (ID), information technology (IT), materials (MT), communication services (TL), utilities (UT).
[3] http://www.hec.unil.ch/agoyal/

(or higher), with a further 16 significant at the 10% level. Thus, statistical evidence in favour of predictability is limited.

However, within this, two variables stand out. The stock market variance variable is significant at the 1% level for twelve of the thirteen series, only being insignificant for communication services (TL). The negative coefficient suggests a rise in variance leads to a lower stock market return in the subsequent period. While this differs from the standard view of a positive risk-return relation, a negative finding is not uncommon in the literature (see, for example, Fifield et al, 2020). The default return series is significant across all thirteen stock market series. The default return is defined as the corporate bond return minus the government bond return and the positive coefficient value suggests that corporate debt and equity moves in the same direction. Thus, although there is little evidence of predictability across the range of variables, there is evidence across all series that predictability does exist from at least one variable (the default return) and from a second (stock market variance) in all but one series.

Forecast Results

While in-sample predictability, and whether a given variable exhibits a significant effect, is interesting, our main analytical focus is the out-of-sample forecast power. Thus, we run both a recursive (expanding window) and rolling (fixed window) forecast exercise for each stock market series. For the recursive forecasts we use an initial window of five-years, while for the rolling forecasts, we maintain the five-year window through the sample. To obtain the forecasts, we use four models. This includes a regression with all eleven explanatory variables, as well as regressions that includes the significant stock variance and default return variables, jointly and individually. Inevitably, the choice of using only the significant variables is driven by the results presented in Table 1 and thus can be considered subject to data mining. However, Table 1 is based on a full sample exercise, while the forecast results are obtained from subsamples. Thus, it is of interest to note whether the outperformance of these variables is maintained and could be of use in subsequent work.

Table 2 presents the results of the out-of-sample R-squared measure, the encompassing test and the CEV. In each case, the baseline regression model includes only a constant (the historical mean, HM, model), which is also obtained using a recursive or rolling window. Taking the results for the recursive forecasts (on the left-hand side of the table), we can see a distinction between the All variables forecast and the SVAR (stock variance) and DFR (default return) joint and individual forecasts and between the out-of-sample R-squared measure compared to the forecast encompassing and CEV measures.

Examining the out-of-sample R-squared values, for the All variables forecasts, these values are negative for all stock market series. This implies that the HM model outperforms the forecast model in each case. For the joint and individual SVAR and DFR forecasts, the values are positive for all series, except consumer services (DFR only), communications (SVAR only) and utilities (joint and DFR only) sectors. While this does imply that the forecast models outperform the HM model, the values are small, suggesting that any gain is minimal. Nonetheless, on the basis of the Clark and West test, the majority of the positive out-of-sample R-squared values are statistically significant at the 5% level or higher, except for the SVAR only forecasts where the test is only significant for the market index.

Examining the forecast encompassing test, for the All forecasts, we can see that in each case the coefficient is positive and for eight of the stock market series these are statistically significant at the 5% or higher level (with a further two significant at the 10% level). For the joint SVAR and DFR forecasts, all the coefficients are positive, with eleven significant at the 5% (or higher) level, one at the 10% level and one (TL) not significant. This pattern is broadly replicated for the SVAR only forecasts with all coefficients positive and significant (except

TL). For the DFR only forecasts, all (except Industrials, ID) have a positive coefficient, while ten are significant at the 1% level (with a further series significant at the 10% level).

For the CEV measure, a positive value indicates preference for the forecast model. For the All forecasts, we see a positive value for twelve stock market series (being negative for consumer staples, CS). For the remaining three predictive regression forecast models, the CEV is positive throughout except for CS for the SVAR only model. In addition, the CEV value for CS is relatively small for the joint and DFR only forecasts, as it is for utilities across all models.

Examining the right-hand side of Table 2, which contains the rolling forecasts, we can broadly see the same nature to the results. For the out-of-sample R-squared values, these are negative for the All forecasts, while they are all positive for the joint and individual SVAR and DFR forecasts (with two exceptions for the joint SVAR and DFR forecasts and three for the SVAR only forecasts). Again, however, these values are relatively low albeit, on the whole, statistically significant for the joint and DFR only forecasts. For the encompassing tests, the coefficients are positive (except for financials) for the All forecasts and significant at the 5% (or higher) level for six series. For the joint and individual SVAR and DFR forecasts, the encompassing coefficient is positive throughout and significant (except for CS on the joint model), including at the 1% level for all thirteen series for the DFR only forecasts. For the CEV, these values are positive across all four sets of models for all thirteen markets, indicating additional value for an investor over the HM based forecasts.

In addition to comparing the forecast models against the HM, we can compare them to each other and across the recursive and rolling approaches. On the basis of the out-of-sample R-squared values, the SVAR and DFR forecast models outperform the All model. For the latter model, the values are negative across both the recursive and rolling approach, while for the former models, the values are predominantly positive. Moreover, for the joint SVAR and DFR and DFR only models, the values are largely statistically significant. Nonetheless, it should be borne in mind that the values are relatively small.

For the encompassing tests, in terms of statistical significance the SVAR and DFR models outperform the All model. For the joint and individual SVAR and DFR models, coefficients are significant at the 5% level for at least eleven series, with all thirteen coefficients significant at the 1% level for the rolling DFR model. This compares to eight and six for the All model recursive and rolling approaches. In comparing the rolling and recursive approaches for the DFR model, the rolling approach outperforms the recursive approach based on statistical significance. However, the opposite is true for the All forecast model, with the joint SVAR and DFR and SVAR only models producing similar results. Within the forecast encompassing model, a coefficient value of one implies an unbiased forecast. The results across Table 2 suggest that the proximity of the coefficient to one is greater for the recursive approach.

For the CEV measure, a larger positive value indicates preference for a particular model. The joint SVAR and DFR rolling model has the highest CEV value for four stock market series and is second highest for a further five. The recursive version of this model also produces the second highest CEV for five series. The DFR rolling model achieves the highest CEV for seven of the thirteen stock market series and is second highest for two series. The DFR recursive model has the highest CEV for two stock market series and second highest twice. Thus, the DFR or joint SVAR and DFR model achieves the highest CEV value across all series. Moreover, this is predominantly for the rolling forecast approach, which achieves the highest CEV for eleven of the series. These results suggest that the DFR, either individually or in conjunction with SVAR, is preferred compared to the HM, All and SVAR only models, while the rolling approach is preferred to the recursive approach. Of interest, the recursive joint SVAR and DFR and individual DFR models are generally preferred to the rolling All model across each of the three forecast measures.

The results, therefore, suggest that the forecast variables are more important than the forecast method. Asset pricing models suggest that movements in stock prices depend upon expectations of discounted future cash flows. Thus, variables that proxy for cash flow and the discount rate can potentially have predictive power for stock returns. The default return and the stock variance variables are both linked to risk and this may explain their ability to forecast returns. The variance series is a direct proxy for risk as it measures the variability of stock returns. The default return series captures the difference between corporate bonds and government bonds. Where government bonds are viewed as safe, movement in this series is linked to the sensitivity of corporate bonds to changes in investor expectations of future economic conditions. Here, investors demand a higher return when such expectations decline, and this equally affects stock returns, allowing for the predictive relation.

Forecast-Based Portfolios

Table 3 presents the results of the portfolios constructed based on the forecast results. Against a S&P500 buy-and-hold portfolio, we build five alternative portfolios. First, we use the style indexes and consider an investor who will switch between value and growth stocks according to which forecast is higher. Second, we examine the forecast values for the sectors and build a sector rotation portfolio based on the highest sector forecast value at each iteration. Third, we conduct an equivalent process for the lowest sector forecast and construct a hedged portfolio that buys the highest forecast sector and sells the lowest forecast sector. For the fourth and fifth portfolios, we repeat the second and third portfolios but consider the highest and lowest two sectors in their construction (noted as high2 and hedge2 below). The mean return, standard deviation, Sharpe ratio and CAPM alpha and beta are reported in Table 3.

The results show that the style (growth and value) rotation strategy produces a similar result to the market in terms of mean return, standard deviation and Sharpe ratio, while the

CAPM alpha is near zero in magnitude and statistically insignificant and the beta approximately one. This is the same regardless of the forecast model or whether the forecasts are obtained by the recursive or rolling approach. The results for the sector rotation strategies differ from the style based strategies and we see a similar pattern across the recursive and rolling approaches and across the high and hedge strategies (including high2 and hedge2).

For these portfolios, we see that the mean return is higher than for the S&P500 and style strategies, but equally, so is the standard deviation.[4] This results in a slightly mixed view from the perspective of the Sharpe ratio across the different approaches. Across the All and SVAR only forecasts, the sector Sharpe ratios are not consistently higher than the buy-and-hold S&P500 Sharpe ratio. For the All forecasts, the Sharpe ratios are higher for the recursive portfolios but typically lower for the rolling portfolios. For the SVAR only forecasts, the high and high2 portfolios exhibit a higher Sharpe ratio, while both hedged portfolios have a lower ratio. The Sharpe ratios for the joint SVAR and DFR and DFR only portfolios are higher than for the S&P500. In each case, the hedged portfolios achieve a higher Sharpe ratio than the high only portfolios (except for the recursive joint forecast). The overall highest Sharpe ratio is achieved by the sector hedge2 for the DFR only forecast using the rolling regression approach.

Inevitably, these portfolios are not fully diversified as they involve investing in one or two sectors (and shorting one or two sectors) at each iteration. Thus, we also consider whether the lack of full diversification leads to any benefit in terms of the abnormal return or additional risk in the context of a CAPM regression. Table 3, therefore, includes the CAPM alpha and beta, with the alpha indicating whether an abnormal return is achieved and the beta indicating whether the portfolio is riskier than the market. Across the 32 portfolios (recursive and rolling, high, hedge, high2 and hedge2, for the All and joint and individual SVAR and DFR forecast

[4] Except for the SVAR recursive forecasts, where the mean value of the hedged portfolios is lower than for the S&P500 and style portfolios.

models), we observe that the value of alpha is positive, indicating the potential for additional return. Moreover, the majority of the alphas are statistically significant at the 5% level or higher, with only the rolling All and recursive DFR high portfolios and the recursive and rolling SVAR high and hedge portfolios insignificant (the rolling All hedge and recursive SVAR high2 and hedge2 are only significant at the 10% level). Of additional interest, the alpha for the hedged portfolios are greater than the equivalent value for the high only portfolios.

In comparing recursive against rolling and the All forecasts against the SVAR and DFR forecasts, we can see that the alphas are higher for the recursive forecasts for the All model and are generally higher for the rolling forecasts for the joint and individual SVAR and DFR models. Overall, the DFR based rolling, hedge portfolio achieves the highest alpha, although the values for the recursive version, together with the joint SVAR and DFR models are broadly similar. The alpha for the SVAR only model is noticeably lower. As with previous results, therefore, the DFR model is generally preferred. In terms of the CAPM beta values, for the high portfolios these are all reasonably close to one indicating that they broadly reflect market risk. The hedge portfolios have a beta value close to zero as expected of such a portfolio and, indeed, several are slightly negative.

It is also of interest to consider the sectors that appear in the high and low portfolios. Table 4 presents the number of times a sector is forecast to have the highest or lowest (or second highest or lowest) return and thus will be present in one of the portfolios. It is evidence that there is notable consistency in the dominant sectors between the alternative approaches, although there are some differences between the All and joint and individual SVAR and DFR models, with the latter arguably more concentrated in fewer sectors. In comparing sectors that have the maximum or minimum return forecast, we can see that several sectors typically have more minimum (low) than maximum (high) forecasts. This includes Financials, Materials, Telecoms and Utilities (and Consumer Staples for the All model forecasts). For sectors that exhibit more maximum than minimum forecasts, we can note Consumer Discretionary, Energy, Health Care and IT. In terms of the sectors that appear the most, Energy and IT dominate, while Utilities (albeit more in the minimum column) also appears often. Industrials, in contrast, appears least as the maximum or minimum forecast, which, alternatively, suggests that such forecasts are in the middle of the range. These results suggest than an investor could focus on a relatively small number of sectors when constructing a portfolio, buying, for example, from only consumer discretionary, energy, health care and IT and selling from only financials, materials, telecoms and utilities.

This also raises a further question that relates to portfolio construction. Table 4 reveals that each of the sectors exhibit both maximum and minimum forecasts, hence, this involves trading activity (turnover) within each of the portfolios (with attendant trading costs). To illustrate, Figure 1 plots the highest and lowest forecast sectors for the individual DFR forecasts, both recursive and rolling over the sample period. As is evident from the figure (and Table 4) there is switching between sectors for both the highest and lowest forecasts, which would indicate trading by a portfolio manager. However, there is also evidence that the same sector achieves the highest or lowest forecast in consecutive periods such that no trading is required. Across the recursive and rolling forecasts the same sector achieves the highest forecast in consecutive periods 120 and 109 times respectively. The same sector exhibits the lowest forecast in consecutive periods 133 times for both the recursive and rolling approaches. Thus, between 38% and 46% of the sample the high or low sector does not change. Hence, while there will be a significant amount of trading, it will not occur each period.[5]

5. Summary and Conclusions.

[5] A 0.5% trading cost would reduce average returns by around 0.3% based on the number of trades required for the long only portfolios and around 0.5% for hedged portfolios (based on when both buy and sell trades occur). For investors, the presence of such transaction costs may erode any gains identified above.

This paper seeks to consider the forecast power for stock market sectors of a common set of predictor variables. The established literature focusses on market index behaviour and thus sector indices provide fertile ground to examine predictability that informs both market participants and our understanding of market behaviour. Using eleven forecast variables established within the literature, we conduct recursive and rolling forecasts. We consider not only the forecast power of the variables but also the ability of the forecasts to be used in a portfolio rotation strategy. Using monthly US data over the period from the start of 1990 to the end of 2018, we examine ten sector and two style stock indices as well as the market index.

In-sample results for the thirteen stock market series, with eleven predictor variables, reveals that only one variable, the default return, is significant for all series, while a second variable, stock market variance, is significant for twelve series. Thus, these results support the general view that while stock market predictability is not widespread there is some evidence in favour of it. The out-of-sample results support the view that predictor variables can provide stock return forecasts that outperform the historical mean, although the specific nature of that depends on the variable set and the forecast metric used. Moreover, the forecasts can be used in a sector rotation strategy to outperform a stock index buy-and-hold. Notably a forecast model that includes only the default return achieves the highest Sharpe ratio as well as a significantly positive alpha in a CAPM regression.

The results presented here should be of interest to both academics and investors. For academics, we are interested in whether stock markets can be predicted. While at a simplistic level, market efficiency would suggest not, our models of stock price behaviour suggest a relation with factors that proxy for expected future cash flows and risk. For investors, we are interested in whether predictability aids decision-making and in this case a sector rotation strategy. Our results support the view that predictability is found but is not widespread in the variables considered. Moreover, while we consider ten sectors, a potential sector portfolio is driven by a subset of them. Nonetheless, an ability to outperform the market is apparent.

References

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

Baltas, N. and Karyampas, D. (2018). Forecasting the equity risk premium: The importance of regime-dependent evaluation. Journal of Financial Markets, 38, 83-102.

Beller, K.R., Kling, J.L. and Levinson, M.J. (1998). Are industry stock returns predictable? Financial Analysts Journal, 54, 42-57.

Campbell, J.Y. and Shiller, R.J. (1988). The dividend-price ratio and expectations of future dividends and discount factors. Review of Financial Studies, 1, 195-228.

Campbell, J.Y. and Thompson, S.B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? Review of Financial Studies, 21, 1509-1531.

Chen, L. (2009). On the reversal of return and dividend growth predictability: A tale of two periods. Journal of Financial Economics, 92, 128-151.

Clark, T.E. and West, K.D. (2007). Approximately normal tests for equal predictive accuracy in nested models. Journal of Econometrics, 138, 291-311.

Cochrane, J. (2008). The dog that did not bark: A defense of return predictability. Review of Financial Studies, 21, 1533-1575.

Fifield, S.G.M., McMillan, D.G. and McMillan, F.J. (2020). Is there a risk and return relation? European Journal of Finance, forthcoming.

Goyal, A. and Welch, I. (2003). Predicting the equity premium with dividend ratios. Management Science, 49, 639-654.

Guidolin, M., McMillan, D.G. and Wohar, M.E. (2013). Time-Varying Stock Return Predictability: Evidence from US Sectors. Finance Research Letters, 10, 34-40.

Hammerschmid, R. and Lohre, H. (2018). Regime shifts and stock return predictability. International Review of Economics and Finance, 56, 138-160.

Henkel, S.J., Martin, J.S. and Nardari, F. (2011). Time-varying short-horizon predictability. Journal of Financial Economics, 99, 560-580.

Hjalmarsson, E. (2010). Predicting global stock returns. Journal of Financial and Quantitative Analysis, 45, 49-80.

Kellard, N.M., Nankervis, J.C. and Papadimitriou, F.I. (2010). Predicting the equity premium with dividend ratios: Reconciling the evidence. Journal of Empirical Finance, 17, 539-551.

Maio, P. (2013). The FED model and the predictability of stock returns. Review of Finance, 17, 1489-1533.

Laopodis, N.T. (2016). Industry returns, market returns and economic fundamentals: Evidence for the United States. Economic Modelling, 53, 89-106.

McMillan, D.G. (2010). Present value model, bubbles and returns predictability: Sector-level evidence. Journal of Business Finance and Accounting, 37, 668-686.

McMillan, D.G. (2021). Forecasting US stock returns. European Journal of Finance, 27, 86-109.

McMillan, D.G. and Wohar, M.E. (2013). A panel analysis of the stock return dividend yield relation: predicting returns and dividend growth. Manchester School, 81, 386-400.

Nelson, C.R. and Kim, M.J. (1993). Predictable stock returns: the role of small sample bias. Journal of Finance, 48, 641-661.

Park, C. (2010). When does the dividend-price ratio predict stock returns? Journal of Empirical Finance, 17, 81-101.

Paye, B. and Timmermann, A. (2006). Instability of return prediction models. Journal of Empirical Finance, 13, 274–315.

Pham, Q.T.T. (2020). Stock return predictability: Evidence across US industries. Finance Research Letters, (in press)

Welch, I. and Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. Review of Financial Studies, 21, 1455-1508.

Table 1. In-Sample Estimation Results

Series	DP	EP	DE	SVAR	BM	NTIS	LTY	LTR	TS	DFR	INF	R-Sq.
SP500	-0.724	0.631[c]	0.024[c]	-2.991[a]	-0.061	0.058	0.027	0.180	-0.021	0.871[a]	-0.935	0.251
Growth	-0.331	0.548	0.021[c]	-2.867[a]	-0.065	0.065	-0.024	0.186[c]	-0.037	0.837[a]	-0.999	0.208
Value	-1.200[c]	0.727[c]	0.027[b]	-3.165[a]	-0.055	0.046	0.087	0.181	0.003	0.897[a]	-0.955	0.252
CD	-2.184[b]	0.640	0.044[b]	-4.890[a]	-0.030	-0.099	0.241	0.130	0.365[c]	0.886[a]	-2.138[b]	0.261
CS	-0.759	0.600[a]	0.023[a]	-2.584[a]	-0.051	-0.124	0.158	0.228[b]	0.097	0.340[b]	-0.794	0.149
EN	-3.190[b]	0.920[c]	0.037[c]	-3.399[a]	-0.021	-0.136	0.423[c]	0.203	0.247	1.412[a]	1.526	0.203
FN	-2.236[b]	0.847	0.046[b]	-4.957[a]	-0.051	0.117	0.203	0.296	0.036	1.191[a]	-1.299	0.254
HC	-0.765	0.672[b]	0.025[a]	-2.753[a]	-0.066	-0.068	0.104	0.157	-0.132	0.660[a]	-0.712	0.171
ID	-1.456[c]	-0.753	0.028[c]	-3.828[a]	-0.061	-0.199	0.251	0.108	0.295	1.070[a]	-2.099[b]	0.251
IT	-0.186	0.428	0.028	-3.930[a]	-0.064	0.209	-0.092	-0.013	-0.041	1.200[a]	-1.625	0.150
MT	-0.232[b]	1.377	0.044[b]	-4.332[a]	-0.030	-0.222	0.306	0.082	0.414[c]	1.024[a]	-1.834[c]	0.249
TL	-1.427	0.470	0.023	-1.169	0.054	0.480[c]	-0.159	0.166	-0.483	0.853[a]	-0.479	0.093
UT	-1.195	0.626[c]	0.019[a]	-2.190[a]	-0.027	-0.034	0.027	0.568[a]	-0.054	0.600[a]	-0.153	0.166
5 (10%)	4 (2)	2 (4)	7 (4)	12	0	0 (1)	0 (1)	2 (1)	0 (2)	13	2 (1)	

Notes: The series are S&P500 (SP500), S&P Growth (Growth, S&P Value (Value), Consumer Discretionary (CD), Consumer Staples (CS), Energy (EN), Financials (FN), Health Care (HC), Industrials (ID), Information Technology (IT), Materials (MT), Communication Services (TL) and Utilities (UT). The explanatory variables are dividend-price ratio (DP), earnings-price ratio (EP), dividend payout ratio (DE), stock variance (SVAR), book-to-market ratio (BM), net equity issuance (NTIS), long-term bond yield (LTY) and return (LTR), the term structure (TS; 10-year minus 3-month government treasuries), the default return (DFR; the difference between long-term corporate and government bonds) and inflation (INF). The entries are coefficient values from equation (1), with the subscripts a, b, c relating to the 1%, 5% and 10% significance level based on Newey-West *t*-statistics. The final row details the number of significant coefficients in each column.

Table 2. Forecast Results

	Recursive Forecasts						Rolling Forecasts					
	All Variables			SVAR + DFR Only			All Variables			SVR + DFR Only		
Series	OOS R2	Enc	CEV	OOS R2	Enc	CEV	OOS R2	Enc	CEV	OOS R2	Enc	CEV
SP500	-0.176	0.392[b]	2.611	0.151[a]	0.794[a]	3.014	-0.625	0.180[b]	3.141	0.084[a]	0.625[a]	4.717
Growth	-0.146	0.411[a]	2.212	0.121[c]	0.759[a]	3.024	-0.501	0.237[a]	3.774	0.084[a]	0.651[a]	4.206
Value	-0.256	0.335[b]	3.736	0.139[b]	0.784[a]	3.042	-0.881	0.088	2.413	0.042[a]	0.542[a]	4.594
CD	-0.204	0.379[a]	5.244	0.126[b]	0.770[a]	5.178	-0.881	0.078	3.385	0.035[a]	0.440[b]	6.192
CS	-0.220	0.214	-0.543	0.025	0.719[b]	0.697	-0.795	0.012	0.731	-0.188	0.149	0.564
EN	-0.001	0.492[a]	4.313	0.136[c]	0.981[a]	5.200	-0.739	0.262[a]	5.297	0.102[c]	0.615[a]	9.014
FN	-0.374	0.238[c]	2.790	0.127[c]	0.594[c]	4.492	-1.803	-0.072	1.521	0.089[b]	0.345[c]	7.402
HC	-0.348	0.225	0.161	0.099[c]	0.849[a]	2.027	-1.088	0.063	1.115	0.040[b]	0.570[a]	1.183
ID	-0.133	0.427[a]	4.389	0.184[b]	0.826[a]	6.147	-0.479	0.289[a]	4.994	0.157[c]	0.742[a]	7.138
IT	-0.212	0.355[a]	5.339	0.092[b]	0.664[a]	8.755	-0.532	0.227[a]	4.822	0.066[c]	0.642[a]	10.408
MT	-0.119	0.404[b]	5.248	0.152[b]	0.845[a]	7.336	-0.463	0.281[a]	5.339	0.142[b]	0.700[a]	7.577
TL	-0.309	0.136	1.469	0.002	0.282	0.824	-0.828	0.062	2.662	0.001	0.508[a]	2.995
UT	-0.264	0.253[c]	0.386	-0.062	0.381[a]	0.860	-0.850	0.046	1.063	-0.037	0.373[a]	1.152

Notes: Series names as in Table 1. Forecasts are obtained from equation (1) including either all (eleven) predictor variables or just the default return. Entries are the out-of-sample R-squared (equation (2)), the value of β_2 from the forecast encompassing regression (equation (3)) and the certainty equivalent value (equation (4)). The superscripts *a*, *b* and *c* relate to statistical significance at the 1%, 5% and 10% levels.

Table 2 cont

	Recursive Forecasts						Rolling Forecasts					
	SVR			DFR			SVR			DFR		
Series	OOS R2	Enc	CEV	OOS R2	Enc	CEV	OOS R2	Enc	CEV	OOS R2	Enc	CEV
SP500	0.106[a]	0.774[a]	1.882	0.010[a]	0.869[a]	2.709	0.088[c]	0.650[a]	3.408	0.111[a]	0.738[a]	5.148
Growth	0.087	0.750[a]	1.741	0.079[a]	0.830[a]	2.191	0.052	0.594[a]	1.955	0.095[a]	0.728[a]	5.443
Value	0.105	0.793[a]	1.846	0.091[a]	0.848[a]	4.152	0.096	0.687[a]	2.558	0.104[a]	0.724[a]	5.042
CD	0.094	0.866[a]	1.769	0.108[a]	0.811[a]	6.642	0.086	0.842[a]	2.683	0.114[a]	0.753[a]	8.075
CS	0.056	0.966[a]	-0.177	-0.009	0.404	0.374	0.014	0.607[c]	0.638	0.006[b]	0.529[a]	0.796
EN	0.068	0.836[a]	1.938	0.104[a]	1.248[a]	6.878	0.001	0.507[a]	2.419	0.120[a]	0.849[a]	6.293
FN	0.105	0.806[b]	1.996	0.088[a]	0.930[a]	5.582	0.089	0.587[c]	3.442	0.090[a]	0.728[a]	8.526
HC	0.083	0.919[a]	0.193	0.059[b]	0.879[a]	1.871	0.073	0.679[a]	0.350	0.060[b]	0.687[a]	2.591
ID	0.080	0.723[a]	2.594	0.142[a]	-0.911[a]	5.417	0.039	0.557[a]	3.679	0.141[a]	0.761[a]	6.487
IT	0.031	0.582[a]	3.596	0.086[a]	0.741[a]	12.106	-0.001	0.495[a]	3.974	0.099[a]	0.762[a]	11.917
MT	0.058	0.769[a]	2.983	0.127[a]	0.921[a]	7.203	0.027	0.544[a]	3.199	0.121[a]	0.748[a]	6.200
TL	-0.009	0.392	0.361	0.003[c]	0.521[c]	3.435	-0.005	0.410[a]	0.152	0.036[b]	0.610[a]	2.506
UT	0.008	0.606[a]	0.513	-0.058	0.067	0.006	-0.041	0.366[a]	0.998	0.002[b]	0.436[a]	0.581

Notes: Series names as in Table 1. Forecasts are obtained from equation (1) including either all (eleven) predictor variables or just the default return. Entries are the out-of-sample R-squared (equation (2)), the value of β_2 from the forecast encompassing regression (equation (3)) and the certainty equivalent value (equation (4)). The superscripts *a*, *b* and *c* relate to statistical significance at the 1%, 5% and 10% levels.

Table 3. Portfolio Forecast Results

	Recursive Forecasts					Rolling Forecasts				
Portfolios	Mean	Std Dev	Alpha	Beta	Sharpe	Mean	Std Dev	Alpha	Beta	Sharpe
SP 500 Buy and Hold	0.653	4.261	-	-	0.153	0.653	4.261	-	-	0.153
ALL Variable Forecasts										
Growth & Value	0.634	4.700	0.002	1.005	0.135	0.658	4.689	0.002	1.001	0.140
Sector High	1.506	6.481	0.009[a]	0.987	0.232	0.874	7.183	0.002	1.09	0.121
Sector Hedge (H-L)	1.342	7.412	0.015[a]	-0.190	0.181	0.651	7.838	0.007[c]	-0.067	0.083
Sec. High 2	1.544	5.816	0.009[a]	0.964	0.265	1.086	5.971	0.004[b]	1.045	0.182
Sec. Hedge 2 (H-L)	1.291	5.080	0.013[a]	-0.096	0.254	0.753	5.742	0.008[a]	-0.022	0.131
SVAR + DFR Forecasts										
Growth & Value	0.700	4.627	0.001	0.988	0.151	0.658	4.677	0.001	0.999	0.141
Sector High	1.516	5.690	0.010[a]	0.897	0.266	1.770	7.042	0.011[a]	1.030	0.251
Sector Hedge (H-L)	1.699	6.858	0.018[a]	-0.193	0.248	2.182	8.104	0.023[a]	-0.199	0.269
Sec. High 2	1.314	4.898	0.008[a]	0.866	0.264	1.392	5.548	0.007[a]	0.962	0.251
Sec. Hedge 2 (H-L)	1.465	4.911	0.016[a]	-0.167	0.298	1.630	5.662	0.018[a]	-0.215	0.288

Notes: The portfolios are a S&P500 buy-and-hold, a style (growth and value) rotation based on the highest growth or value forecast, two sector rotations, a long only portfolio based on the highest sector forecast and a hedged portfolio based on the highest minus the lowest forecast. The entries are the mean and standard deviation for each portfolio as well as the CAPM regression alpha and beta values and the Sharpe ratio. A 3-month Treasury bill is used as the risk-free rate. The superscripts *a*, *b* and *c* relate to statistical significance at the 1%, 5% and 10% levels.

Table 3 cont

	Recursive Forecasts					Rolling Forecasts				
Portfolios	Mean	Std Dev	Alpha	Beta	Sharpe	Mean	Std Dev	Alpha	Beta	Sharpe
SP 500 Buy and Hold	0.653	4.261	-	-	0.153	0.653	4.261	-	-	0.153
SVAR Only Forecasts										
Growth & Value	0.730	4.630	0.001	0.990	0.158	0.654	4.651	0.001	0.994	0.141
Sector High	0.961	6.157	0.003	1.027	0.156	1.108	6.952	0.005	1.012	0.159
Sector Hedge (H-L)	0.537	7.243	0.007	-0.189	0.074	0.701	7.934	0.009	-0.245	0.088
Sec. High 2	0.861	4.972	0.003[c]	0.944	0.173	1.156	5.315	0.006[a]	0.918	0.217
Sec. Hedge 2 (H-L)	0.543	5.211	0.006[c]	-0.165	0.104	0.818	5.819	0.010[b]	-0.266	0.141
DFR Only Forecasts										
Growth & Value	0.714	4.675	0.001	0.999	0.153	0.655	4.786	0.001	1.024	0.137
Sector High	1.156	6.773	0.005	1.120	0.171	1.308	6.801	0.007[b]	1.020	0.192
Sector Hedge (H-L)	1.785	7.437	0.017[a]	0.217	0.240	1.938	7.610	0.020[a]	-0.043	0.255
Sec. High 2	1.243	5.634	0.006[a]	1.039	0.221	1.311	5.144	0.007[a]	0.967	0.255
Sec. Hedge 2 (H-L)	1.463	5.450	0.014[a]	0.038	0.268	1.548	5.080	0.015[a]	0.041	0.305

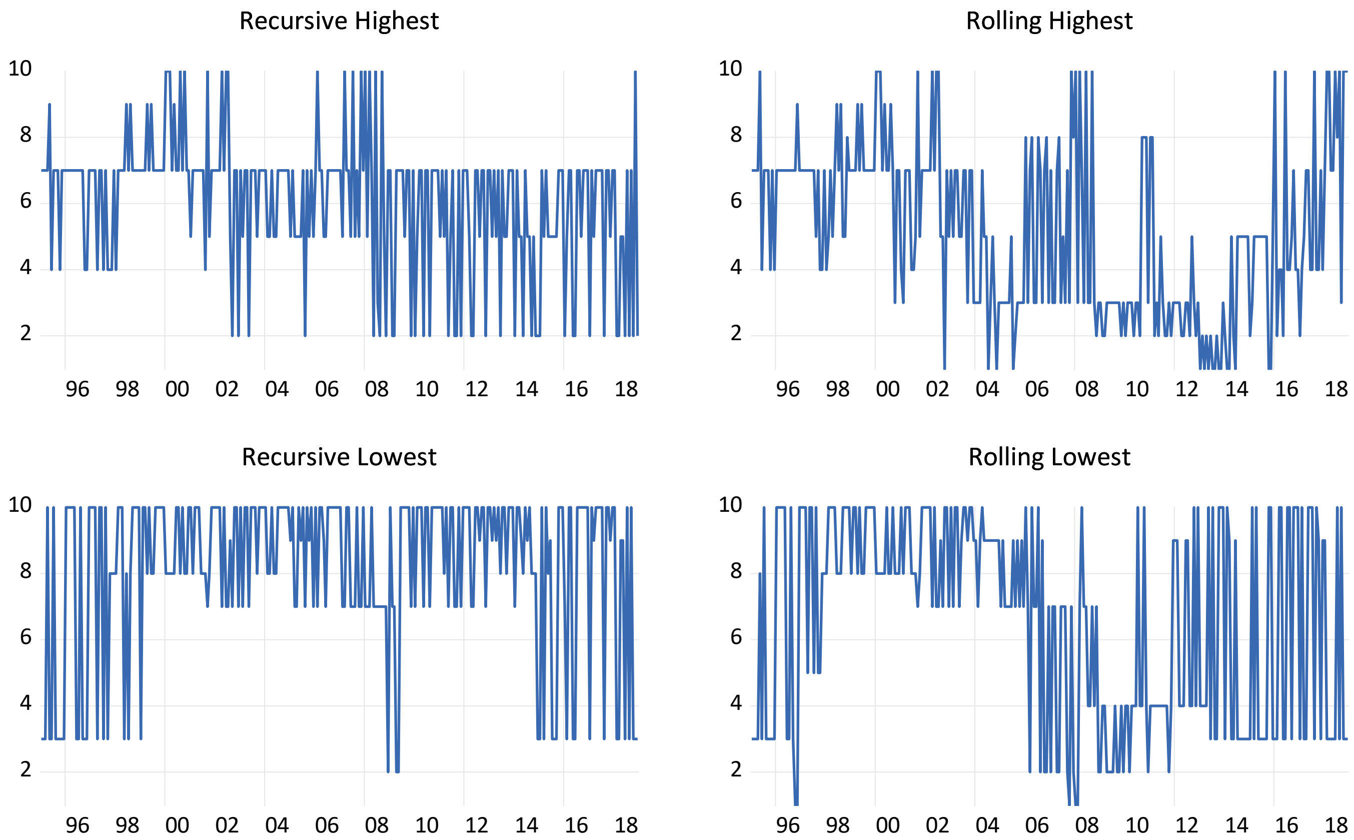
Notes: The portfolios are a S&P500 buy-and-hold, a style (growth and value) rotation based on the highest growth or value forecast, two sector rotations, a long only portfolio based on the highest sector forecast and a hedged portfolio based on the highest minus the lowest forecast. The entries are the mean and standard deviation for each portfolio as well as the CAPM regression alpha and beta values and the Sharpe ratio. A 3-month Treasury bill is used as the risk-free rate. The superscripts *a*, *b* and *c* relate to statistical significance at the 1%, 5% and 10% levels.

Table 4. Number of Maximum and Minimum Forecasts

	All Variable Forecasts				SVAR + DFR				SVAR				DFR Only Forecasts			
	Recursive		Rolling		Recursive		Rolling		Recursive		Rolling		Recursive		Rolling	
	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min
CD	25 / 25	6 / 21	19 / 30	6 / 14	0 /30	1 /30	20 / 16	6 / 18	0 / 0	1 / 17	30 / 27	3 / 25	0 / 35	0 / 28	16 / 28	5 / 27
CS	16 / 28	21 / 37	6 / 24	22 / 43	35 / 46	1 / 47	21 / 37	16 / 26	8 / 39	0 / 0	13 / 27	4 / 19	38 / 46	3 / 56	27 / 39	21 / 18
EN	60 / 19	40 / 21	71 / 27	44 / 24	3 / 38	29 / 33	86 / 23	48 / 30	13 / 26	27 / 29	83 / 28	50 / 19	1 / 31	39 / 54	64 / 20	52 / 33
FN	17 / 26	42 / 37	21 / 36	17 / 22	16 / 62	3 / 11	16 / 39	22 / 9	1 / 122	14 / 5	11 / 56	27 / 12	11 / 51	0 / 7	21 / 36	35 / 15
HC	28 / 43	6 / 15	19 / 21	16 / 21	51 / 56	0 / 2	36 / 32	8 / 11	72 / 50	0 / 0	33 / 45	2 / 3	52 / 66	0 / 0	37 / 64	4 / 5
ID	7 / 37	7 / 10	3 / 21	6 / 14	0 / 4	0 / 7	0 / 3	1 / 14	0 / 0	0 / 13	0 / 2	2 / 18	0 / 3	0 / 2	0 / 1	0 / 7
IT	71 / 29	57 / 26	58 / 44	48 / 22	148 / 6	41 / 14	56 / 22	25 / 33	168 / 29	15 / 9	60 / 17	14 / 41	162 / 15	46 / 5	80 / 27	32 / 19
MT	9 / 21	13 / 32	24 / 25	26 / 35	0 / 8	43 / 37	8 / 56	28 / 35	0 / 3	47 / 32	12 / 56	41 / 19	0 / 9	35 / 56	13 / 39	26 / 35
TL	35 / 34	27 / 54	31 / 27	52 / 51	13 / 17	61 / 53	21 / 21	57 / 71	18 / 13	99 / 67	20 / 12	84 / 58	6 / 12	15 / 66	7 / 18	29 / 84
UT	20 / 26	69 / 35	36 / 33	51 / 42	22 / 21	109 / 54	24 / 29	77 / 41	8 / 6	85 / 116	26 / 18	61 / 79	18 / 20	150 / 15	23 / 16	84 / 45

Notes: Entries are the number of times each sector achieves the highest and lower forecast value / second highest and lowest forecast value.

Figure 1. Highest and Lowest Forecast for DFR Forecasts Across Sectors



Notes: Sectors on the vertical axis are: 1 - consumer discretionary (CD); 2 - consumer staples (CS); 3 - energy (EN); 4 - financials (FN); 5 - health care (HC); 6 - industrials (ID); 7 - information technology (IT); 8 - materials (MT); 9 - communication services (TL); 10 - utilities (UT).