Predictability of Equity Risk Premium Conditional on Economic Policy Uncertainty: Evidence from an Emerging Market*

V. Ravi Anshuman†

Rajdeep Sharma‡

Prateek Jain§

July 23, 2022

*We acknowledge the helpful comments on this paper from Bidisha Chakrabarty, Partha Mohanram, and seminar participants at the 2022 International Conference on Financial Markets and Corporate Finance. We thank Arnab Biswas for providing excellent research assistance. All remaining errors are our own. Send correspondence to V. Ravi Anshuman, Indian Institute of Management, Bangalore, Bannerghatta Main Road, Bengaluru, Karnataka 560076, India. E-mail: anshuman@iimb.ac.in.

†Professor, Indian Institute of Management, Bangalore

‡Doctoral Student, Indian Institute of Management, Bangalore

§Doctoral Student, Indian Institute of Management, Bangalore

Predictability of Equity Risk Premium Conditional on Economic Policy Uncertainty: Evidence from an Emerging Market

Abstract

We show that the predictability of equity risk premium (ERP) in an emerging market is significantly influenced by local economic policy uncertainty (EPU). Using a dataset on the Indian equity market index (NIFTY 500), we propose a novel ERP predictor conditional on EPU that outperforms all other standard predictors, including the unconditional historical mean ERP, in out-of-sample predictions. More specifically, we find that selecting a combination of dividend payout ratio, cash-flow to price ratio, and S&P to NIFTY 500 ratio, conditional on EPU level being low, moderate, and high, respectively, delivers the highest forecast accuracy. Using a trading strategy based on ERP forecasts from this EPU-Conditioned predictor, investors can generate a Sharpe ratio of 0.57, which is 30% higher than the next best predictor.

JEL classification: C22, G12, G14

Keywords: Equity risk premium, Economic policy uncertainty, Out-of-Sample prediction, Sharpe ratio, India

Introduction

Expectation about the magnitude of equity risk premium (ERP) is a key determinant of investment flows in an economy. The estimate of ERP affects investment decisions of both individual investors (regarding investments in capital markets) and corporate management (regarding investments in internal projects and external acquisitions). Not surprisingly, considerable research has been expended on *predicting* ERP. Extant literature on ERP predictability has relied on a standard set of economic variables as potential predictors. These predictors reflect information contained in earnings, dividends, cash flow generating capacity, book value, interest rates, macroeconomic indicators, and volatility measures.[1]

Welch and Goyal 2008 provide a comprehensive analysis of the horse-race between different predictors of ERP.[2] They show that individual predictors fail to generate consistent out-of-sample forecasts, relative to the unconditional (historical) mean ERP. Rapach, Strauss, and Zhou 2010 also point out that the mean forecast of individual predictors is superior to any individual predictor in terms of out-of-sample predictability.

Nearly all the studies in the ERP predictability literature have focused on developed markets; their findings may therefore be less relevant for predicting emerging market ERP because the standard set of individual predictors used in developed market studies may fail to account for all the factors that drive emerging market risk premium. There is a rich body of research that has pointed out that equity returns in emerging markets are affected by the

[1]The relevant literature is as follows: earnings (Campbell and Shiller 1988b, Lamont 1998), dividends (Rozeff 1984, Campbell and Shiller 1988a, Goyal and Welch 2003, Fama and French 2021), cash flow generating capacity (Rayburn 1986, Hecht and Vuolteenaho 2006, Westerlund and Narayan 2014), book value (Kothari and Shanken 1997, Pontiff and Schall 1998, Campbell and Shiller 2001), interest rates (Ball 1978, Campbell 1987), macroeconomic indicators (Lintner 1975, Nelson 1976, Fama and Schwert 1977, Fama 1981), and volatility measures (French, Schwert, and Stambaugh 1987, Baillie and DeGennaro 1990, Campbell and Hentschel 1992).

[2]In addition to the standard set of predictors, Welch and Goyal 2008 also consider investment-capital ratio, consumption, wealth, income ratio, and aggregate net or equity issuing activity.

degree of market integration, which depends on a continuum of liberalization measures adopted over time (Bekaert 1995; Buckberg 1995; Harvey 1995; Henry 2000; Bekaert and Harvey 2003; De Jong and De Roon 2005).[3] Furthermore, given that emerging markets like Brazil, China, India, Indonesia, Russia, South Africa, and Turkey account for 26.12 percent of world-wide GDP in 2019, it would be useful to identify superior ERP predictors for emerging markets.[4]

In this paper, we present a benchmark study for *predicting* an emerging market's ERP. We not only account for the standard set of economic predictors employed in studies of developed markets but also incorporate information about specific factors that could affect the prediction of an emerging market's ERP.

There are good reasons to believe that an emerging market's ERP is influenced by additional factors that do not arise in the case of developed markets. More specifically, we look at three important factors. First, we consider economic and political uncertainty (EPU), which reflects the economic policy uncertainty and the possibility of expropriation. Fama and French 1989 and Cochrane 1999; Cochrane 2007 argue that investors require a higher risk premium during periods of increased risk aversion (e.g., during business cycle downturns). Likewise, we expect investors to demand higher risk premium during periods of higher domestic economic policy uncertainty (EPU) to compensate for the risk of investing in an emerging market.[5] This, in turn, generates equity premium predictability. Consistent with this argument, several studies (e.g., Harvey 2004, Damodaran 1999, and Damodaran 2020) have documented the role of economic and political uncertainty on equity risk premium in different countries.

[3] Stulz 1999 show that increased liberalization in emerging markets is associated with a decrease in the cost of capital. Bekaert, Harvey, and Lundblad 2007 document that liquidity is an important determinant of equity risk premiums in emerging markets in spite of increased liberalization.

[4] Source: https://data.worldbank.org/indicator/NY.GDP.MKTP.CD

[5] Kelly, Pástor, and Veronesi 2016 document that equity options prices also reflect higher political uncertainty.

We conjecture that predicting an emerging market's ERP can be improved by conditioning on the level of domestic economic policy uncertainty. The intuition behind conditioning forecasts on EPU is that while a given individual predictor's performance may be mediocre over the entire out-of-sample period, it may perform much better during periods when the level of economic policy uncertainty lies in certain range. To elaborate, it may happen that during periods of low economic and political uncertainty a particular individual predictor may systematically generate superior forecasts, whereas during periods of higher economic and political uncertainty a different individual predictor may perform better. Thus, conditioning on the current level of EPU allows us to capture conditionally superior predictors of ERP.

More specifically, we propose a new predictor, the Dynamic EPU-Conditioned predictor that is based on the EPU series (Baker, Bloom, and Davis 2016), which serves as a proxy for domestic economic and political uncertainty.[6] This predictor optimally switches to the best individual predictor, conditional on three levels of the current period's EPU (low, intermediate, and high levels of EPU). It is worth noting that we use the EPU level as an uncertainty regime indicator to estimate whether economic policy uncertainty is low, moderate, or high in a given month. This regime classification is in the spirit of Rapach, Strauss, and Zhou 2010, who do an ex-post comparison of ERP predictability during bad, normal, and good growth phases of the economic cycle.

Second, we consider the impact of foreign institutional investor (FII) flows on an emerging market's ERP. Several studies have shown that economic shocks in developed economies exacerbate risk aversion of foreign investors, thereby triggering an exodus of capital from emerging markets (Forbes and

[6]We have obtained the EPU series for India and US from Bloomberg. Bloomberg sourced this series from the website maintained by Baker, Bloom, and Davis (https://www.policyuncertainty.com/). Using the EPU series for India, Bhagat, Ghosh, and Rangan 2016 have shown that GDP growth and fixed investment in India are negatively associated with EPU.

Warnock 2012, Rey 2015). It has also been well-established in the extant literature that FIIs indulge in portfolio rebalancing in response to shocks in their home country (for instance, Ananchotikul and Zhang 2014, Acharya, Kumar, and Anshuman 2022, Coval and Stafford 2007, and Jotikasthira, Lundblad, and Ramadorai 2012). Thus, variation in foreign flows reflects changing expectations about ERP. This evidence has also been documented for the taper tantrum episode of May 2013 and the COVID-19 period when emerging markets experienced capital flight to safety (Acharya, Kumar, and Anshuman 2022). We augment the list of individual predictors by including FII flows as a potential predcitor of an emerging market's ERP.

Third, foreign investors in emerging markets often engage in trend chasing investment strategies (Brennan and Cao 1997, Froot and Ramadorai 2008, among others). This investing behavior affects asset price formation in emerging markets. We capture these incentives by using the relative performance of the Standard and Poor 500 index and the emerging market index as a potential predictor of an emerging market's ERP.

While these three factors (EPU levels, FII flows, and trend chasing strategies of FIIs) are less relevant for predicting ERP in developed markets, they play an important role in influencing an emerging market ERP. Ignoring these factors and using the same set of predictors as used in developed economies is likely to provide us with less accurate estimates of an emerging market's ERP.

We explore this research objective in the context of India, which is a well-established emerging market with credible market data.[7] To proxy for the Indian equity market, we consider the NIFTY 500 index, which is a value-weighted market portfolio that is widely used by portfolio managers as a benchmark to evaluate their portfolio performance.[8] Equity risk premium

[7]See, Vig 2013, Gormley, Kim, and Martin 2012, Narayan and Bannigidadmath 2015 among others.

[8]NIFTY 500 represents the top 500 companies based on full market capitalization and 94% of the free float market capitalization (as on March 31, 2016). Source: https://www.niftyindices.com/indices/equity/broad-based-indices/nifty-500.

is defined in terms of the excess returns of the NIFTY 500 index over and above the risk free rate. Our objective is to compare the performance of a set of predictors to determine the predictor that has the least out-of-sample forecasting errors.

We begin our analysis by employing the standard set of predictors used in studies of developed market ERP. This set includes the following twelve variables, (i) two interest rate variables: 3-month treasury bill rate and 10-year government bond yield; (ii) three macroeconomic indicators: credit default risk (default spread), term spread, and inflation; (iii) two indicators of value: book to market and earnings to price ratio; (iv) three measure of dividends: dividend to price ratio, dividend yield, and dividend payout ratio; (v) a measure of cash generating capacity: the cash flow to price ratio; and (vi) two measures of volatility: daily return volatility and variance of daily NIFTY 500 returns. Besides the standard set of predictors discussed above, we include two additional individual predictors: (i) monthly percentage change in net foreign institutional investor (FII) flows (to reflect the impact of foreign fund flows) and (ii) the relative performance of the S&P 500 to NIFTY 500 (to reflect the trend chasing incentives of foreign institutional investors (FIIs)). Finally, we also consider the following aggregated predictors that represent different ways of capturing the information contained in the individual predictor: (i) the unconditional historical mean of ERP, (ii) the mean combination of ERPs, and (iii) our proposed Dynamic EPU-Conditioned predictor.

The Dynamic EPU-Conditioned predictor is constructed, as follows. First, we classify the current month's EPU as belonging to either a low, moderate, or high uncertainty regime, based on the empirical distribution of in-sample EPU values. We then consider an ordered set of three individual predictors, where only one of the three predictors would be used to generate an ERP forecast. If the current month's EPU regime is classified as low (uncertainty), the first predictor would be used to generate the one-month ahead ERP forecast. Similarly, if the current month's EPU regime is moderate/high, the second/third predictor would be used to generate the one-month ahead ERP forecast. In brief, depending on the current month's EPU regime (low, moderate, or high), we forecast the one-month-ahead EPU using the corresponding predictor from the ordered set of predictors.

As in Welch and Goyal 2008, we conduct a horse race between the individual predictors and the Dynamic EPU-Conditioned predictor and rank them based on their out-of-sample predictive power. Our key finding is that the Dynamic EPU-Conditioned predictor outperforms the predictions based on individual predictors as well as the predictions based on the mean combination forecast, thereby highlighting the importance of economic policy uncertainty in predicting an emerging market's ERP. More specifically, our results suggest that selecting an ordered set of dividend payout ratio, cash-flow to price ratio, and S&P to NIFTY 500 ratio (corresponding to periods of low, moderate, and high EPU) generates the highest forecast accuracy.

We demonstrate the import of our findings for investment professionals by computing the economic gains of trading strategies that rely on ERP forecasts of the predictors, including the Dynamic EPU-Conditioned predictor. Corresponding to the forecasts of each predictor, we compute the Sharpe ratio (risk-adjusted return) realized by adopting the trading strategy. We rank order the predictors with statistically significant Sharpe ratios and find that the Dynamic EPU-Conditioned predictor has the highest Sharpe Ratio of 0.57. The Sharpe ratio of the Dynamic EPU-Conditioned predictor is around 30% higher than the next best predictor, the dividend payout ratio. Using an alternative approach based on assumptions about risk aversion, we show that the Dynamic EPU-Conditioned predictor generates higher utility gains of around 2.5-4 percentage points more than the next best predictor, the dividend payout ratio.

An additional contribution of our analysis is regarding the sensitivity of forecast accuracy to the window used to define the data used for prediction. In our analysis, we adopt the same methodology of OLS regression using a recursive window, as established in Welch and Goyal (2008). For robustness, we compare the forecast accuracy of recursive window approach to that of the rolling window approach (fixed window size).[9] While most papers (Welch and Goyal 2008, Rapach, Strauss, and Zhou 2010) use the recursive window approach to estimate the predictability of ERP, they do not provide any theoretical or empirical basis for using the entire available data (recursive), and not just the data relevant to the present (rolling). We establish that forecast performance under the recursive window approach is marginally superior, justifying this approach in Welch and Goyal 2008 and Rapach, Strauss, and Zhou 2010. Our study is also useful for industry stakeholders who require estimates of the market risk premium, e.g., passive mutual funds which allocate investor capital in a diversified market portfolio, investment advisors aiming to diversify their client's wealth between stocks, market portfolio and risk-free assets; and regulators computing the cost of capital in a regulated industry. The model we develop in this paper is tractable and can be used for capital budgeting, relative valuation, and portfolio management disciplines.

The rest of the paper is organized as follows. Section 1 discusses the key drivers of ERP in India. Section 2 describes the data and the variables that we use in our paper. We discuss the methodology in Section 3. In Section 4, we discuss the results. Section 5 reports the robustness tests and Section 6 concludes.

1 Key Drivers of Equity Returns in India

In this section, we discuss the related literature on key drivers of equity returns in India, other than the usual set of fundamental economic variables. We classify the literature into three strands: (i) Economic and Political Uncertainty, (ii) FII flows due to global risk aversion, and (iii) Trend chasing

[9] Clark and McCracken 2009 argue that if the earliest available data follow a different data generating process than the present economic scenario, then using the recursive approach may lead to biased parameter estimates and forecasts, as opposed to using only the data that is relevant to the present (rolling approach). Such biases can accumulate over time and may lead to large mean squared forecast errors.

strategies used by FIIs. The idea is as follows: local economic and political uncertainty is a fundamental driver of expected risk premiums in an emerging market. Furthermore, global risk aversion (VIX) and trend chasing incentives, which depend on the relative performance of S&P 500 to NIFTY 500, affect FII flows, which in turn, affect asset price formation in emerging markets. The arguments provided in this section provide justification for selecting the additional predictors of ERP beyond the standard set of predictors used in studies of ERP predictability in developed markets.

1.1 Economic and Political Uncertainty

1.1.1 Relation between EPU and ERP

Fama and French 1989 and Cochrane 1999; Cochrane 2007 argue that investors require a higher risk premium during periods of increased risk aversion (e.g. during business cycle downturns). Similarly, we expect investors to demand higher risk premium during periods of higher economic policy uncertainty (EPU) as a compensation for increased risk of investing in emerging markets. This, in turn, generates equity premium predictability. Brogaard and Detzel 2015 use the news-based measure of Baker, Bloom, and Davis 2016 and find that economic policy uncertainty (EPU) is an important risk factor for equities. Further, Adjei 2020 shows that EPU impacts market risk more during the recession periods than during the expansion periods.

1.1.2 EPU during the Global Financial Crisis

Figure 1 plots the time series of the natural logarithm of EPU values for four emerging markets (Brazil, Russia, India, and China) from July 2004 to November 2020. The EPU time series for the four countries are positively correlated and exhibit considerable volatility with a noticeable spike during the Global Financial Crisis (GFC) from mid-2007 to end-2009 and during the COVID-19 pandemic (February 2020 onwards). These periods coincided with a rise in uncertainty among market participants on the economic outlook and also lower realized ERP. This negative association of ERP and policy uncertainty suggests that EPU may contain information relevant for predicting ERP, particularly during periods of higher than average uncertainty.

1.1.3 Country Risk Premium and EPU

Damodaran 2003 argues that the country risk is a critical element in the valuation of companies which have significant operations in emerging and developing countries. This risk is priced as a component of the equity risk premium of such companies. The three components of country risk premium are political, financial, and economic risk, which are captured to some extent by the EPU time series. Moreover, Harvey 2004 shows that these risk factors are correlated with future stock returns in emerging markets. This lends further support to our hypothesis on the possible predictive power of EPU in emerging markets. Investment banks and auditing firms increasingly employ the country risk premium (CRP) for valuing firms in emerging markets (Kruschwitz, Löffler, and Mandl 2012). FIIs also closely track the CRP of emerging economies while making portfolio rebalancing decisions. Thus, any predictor which incorporates information on CRP for predicting ERP in emerging markets is likely to be superior to the one that does not. Figure 2 shows that country risk, as measured by the Bloomberg Country Risk Score, was considerably higher and more volatile over the past decade for India compared to the US.

In the context of India, the Economic Survey of India (2018-19) highlights that higher EPU discourages investment and further emphasizes the need to reduce uncertainty in the country in order to foster a favorable investment climate.[10] Since investment and asset returns are closely related, we expect that information contained in the the current level of local EPU plays an important role in driving future ERP.

[10]Source: https://pib.gov.in/Pressreleaseshare.aspx?PRID=1577013

1.1.4 EPU and Other Related Measures

There are other reliable indicators of uncertainty and risk aversion such as the Volatility Index (VIX), which also captures similar information. However, due to the lack of depth in the Indian options market, EPU is the only reliable measure with a sufficiently long history that can provide us information on the economy-wide level of uncertainty and risk aversion. To the best of our knowledge, prior research on ERP predictabilty in emerging markets has not explored the predictive power of forecasts conditioned on EPU information.

We use EPU information to classify periods into low, moderate, or high uncertainty regimes. These regimes correspond to periods when investors demand low, moderate, and high equity risk premiums. We allow for the possibility of differing predictive power of the predictors in each of the three regimes. This approach is similar in spirit to Rapach, Strauss, and Zhou 2010 who document that the predictive performance varies across different growth phases of the economic cycle. However, their findings are based on an ex-post analysis since they use NBER-dated business-cycle phases.[11] In contrast, our procedure (described in detail in Section 3) selects the optimal predictor conditional on the current level of EPU and enables one to obtain real-time ERP forecasts.

An alternative measure of regime classification could be one based on option-implied volatilty, imputed from the market prices of NIFTY 500 index options. However, due to the lack of depth in the Indian options market, EPU is the only reliable measure with a sufficiently long history that can provide us information on the economy-wide level of uncertainty. To the best of our knowledge, prior research on ERP predictabilty in emerging markets has not explored the predictive power of forecasts conditioned on EPU information.

[11]The National Bureau of Economic Research (NBER) is an American private non-profit research organization. The NBER's Business Cycle Dating Committee maintains a chronology of US business cycles. The chronology identifies the dates of peaks and troughs that frame economic recessions and expansions. Source: https://www.nber.org/research/business-cycle-dating

1.2 Foreign Institutional Investor Equity Flows

Empirical studies almost universally find a strong and statistically significant negative impact of increases in global risk aversion on portfolio flows to emerging markets (e.g., Milesi-Ferretti and Tille 2011, Fratzscher 2012, Bai 2013, Ahmed and Zlate 2014, Ananchotikul and Zhang 2014, Koepke 2018, and Rey 2015). Forbes and Warnock 2012 find that the CBOE Volatility Index (VIX) measure, a proxy for global risk aversion, consistently predicts extreme capital flow episodes in emerging and developed economies. These episodes have substantial implications for ERP as they tend to create high volatility in equity markets. Acharya, Kumar, and Anshuman 2022 study the effect of net foreign fund flows on equity returns at short horizons, using a dataset of Indian equity returns. They find that high capital inflows are associated with permanent price increase (i.e., price discovery), while outflows are associated with temporary price decline and increased volatility due to portfolio rebalancing by foreign investors. Figure 3 shows that net foreign institutional investor (FII) flows in India have become increasingly volatile over the past decade. Due to greater financial integration with the global economy, FII flows to and from India have become increasingly associated with global risk aversion, as measured by VIX. Hence, spillovers from the global financial cycle have become increasingly important for Indian equity markets.

1.3 Foreign Institutional Investors and Trend Chasing Strategies

Kumar and Mukhopadyay 2002 argue that economies of two nations may be linked through factors such as trade and investment. This is especially true for emerging economies such as India, which rely heavily on capital inflows from developed economies such as the U.S. and the Europe and are also sensitive to their policy changes such as the Fed Rate revisions (Mohanty

2014). Their results show that US equity markets (NASDAQ and S&P500) unidirectionally impact Indian stock market index, NIFTY 500. Mensi et al. 2014 find that BRICS stock markets exhibit dependence with the global stock and commodity markets (S&P index, oil, and gold). Brennan and Cao 1997 and Froot and Ramadorai 2008 provide evidence that FII flows are associated with the return differential between the U.S. and emerging stock markets, consistent with trend-following by foreign investors. Our measure of the return differential, the S&P NIFTY ratio, affects FII flows and, by extension, should be a reliable predictor of the emerging market risk premium. Figure 4 plots the time series of the FII flows and the monthly change in the S&P NIFTY ratio. The two time series are negatively correlated, consistent with trend-chasing by FIIs.

2 Data

We use Bloomberg and Financial Benchmarks India Pvt. Ltd. (FBIL) to obtain our dataset.[12] Our sample period ranges from July 2004 to November 2020. Table 1 reports the data source and ticker code for the variables used in the paper.[13]

Index Level (P_t^{PI}): Closing price level of the NIFTY 500 Price Index on the last trading day of month t.[14]

[12]From Bloomberg, we obtain daily frequency data for annualized interest rate variables such as T-bills, Government bonds, Corporate Bond etc. Since our analysis is at monthly level, we convert the frequency of observations for these variables from daily to monthly by taking the simple arithmetic mean of the daily annualized observations in a month. This gives us annualized yields at a monthly frequency.

[13]Variables start at different periods, however, since we compare an array of predictors, we choose the overlapping period.

[14] *"Nifty family of indices are price index and hence reflects the returns one would earn if investment is made in the index portfolio. However, a price index does not consider the returns arising from dividend receipts. Only capital gains arising due to price movements of constituent stocks are indicated in a price index. Therefore, to get a true picture of returns, the dividends received from the constituent stocks also need to be factored in the index values. Such an index, which includes the dividends received, is called the Total Returns Index."* For more information, please refer to: https://www1.nseindia.com/products/content/equities/indices/total_returns_index.htm

Index Level (P_t^{TRI}): Closing price level of the NIFTY 500 Total Returns Index on the last trading day of month t. This reflects the returns on the index arising from (a) constituent stock price movements and (b) dividend receipts from constituent index stocks.

Monthly Returns (R_{mt}): The natural logarithm of the ratio of NIFTY 500 total returns index level on the last trading day of the current month divided by the NIFTY 500 total returns index level on the last trading day of the previous month.[15]

$$R_{mt} = ln\left(\frac{P_t^{TRI}}{P_{t-1}^{TRI}}\right),$$

Risk-Free Rate (r_{ft}): We consider 30-day Treasury bill yield as the proxy for risk-free rate.

Equity Risk Premium (ERP_t): Equity Risk Premium is the difference between the continuously compounded monthly returns (R_{mt}) and the continuously compounded risk-free rate, i.e., $ln(1+r_{ft})$, where the annualized risk-free rate for each month is converted to a monthly figure by multiplying it with the number of calendar days in the month and dividing by 365.

$$ERP_t = R_{mt} - ln(1 + r_{ft})$$

Short Term Treasury Rate ($TBILL\ 3M_t$): The expected yield on the government issued 3-month treasury bill is taken as the proxy for the short term treasury rate.

Long Term Government Bond Rate ($GBOND\ 10YR_t$): The expected yield on the government issued 10-year bond is taken as the proxy for the long term government bond rate.

Default Spread ($DEF\ SPRD_t$): Default Spread captures the outlook on default risk in the corporate sector of the economy. For any month,

[15] *"An investor in index stocks should benchmark his investments against the Total Returns index instead of the price index to determine the actual returns vis-à-vis the index."* Source: NSE

Default Spread is the difference between the annualized yields of Corporate bond BBB l0-year index and India Government bond 10-year index.[16]

$$\begin{aligned} DEF\ SPRD_t = & (\text{Yield of Corporate bond BBB l0-year index})_t - \\ & (\text{Yield of India Government bond 10-year index})_t \end{aligned}$$

At the 10 year horizon, India Government bond is the safest investment option. BBB being the lowest investment grade (White 2010), the default spread ($DEF\ SPRD_t$) captures the yield spread at the 10-year investment horizon. This spread is expected to rise in the times of financial crises and narrow down when the economy is doing well.

Term Spread ($\boldsymbol{TERM\ SPRD_t}$): Term Spread captures the outlook on long-term inflation in the economy. For any month, term spread is the difference between the annualized yields of India Government bond 10-year index and the 3-month Treasury Bill.

$$\begin{aligned} \text{TERM SPRD}_t = & (\text{Yield of India Government bond 10-year index})_t - \\ & (\text{Yield of 3-month Treasury Bill})_t \end{aligned}$$

Inflation ($\boldsymbol{INFLATION_t}$): Inflation is the year-on-year (YoY) percentage change in the Indian Consumer Price Index.

Book Value ($\boldsymbol{BOOK\ VAL_t}$): Book Value is the market capitalization-weighted book value of the constituent stocks of the NIFTY 500 index. For the months of January to September of month t, we consider book value as of 31^{st} March of the previous calendar year and for the months of October to December of month t, we consider book value as of 31^{st} March of the same calendar year.[17]

---

[16] The India government bond 10-year index is calculated using annualized government bond yield CG I665 and Monthly Corporate bond spreads for BBB provided by The Fixed Income Money Market and Derivatives Association of India (FIMMDA). Source: Bloomberg

[17] We use lagged book values so that they are known before predicting future returns (See Basu 1983 and Fama and French 1992).

Book to Market Ratio ($\boldsymbol{BOOK\ MKT_t}$): Book to Market ratio for a given month is the natural logarithm of the ratio of Book Value to the closing NIFTY 500 Index Level for that month.

Earnings ($\boldsymbol{EARN\ TTM_t}$): We define earnings as the sum of trailing twelve months (TTM), including the current month, of market capitalization-weighted earnings of the constituent stocks of the NIFTY 500 index. Hence, TTM earnings for month t is the sum of the earnings from month t to month $t-11$.

Earnings to Price ratio ($\boldsymbol{EARN\ PRICE_t}$): Earnings to Price ratio for a given month is the natural logarithm of the ratio of TTM Earnings to the closing NIFTY 500 index level for that month.

$$EARN\ PRICE_t = ln\left(\frac{EARN\ TTM_t}{P_t^{PI}}\right)$$

Dividends ($\boldsymbol{DIV\ TTM_t}$): We define dividends as the sum of trailing twelve months (TTM), including the current month, of market capitalization-weighted dividends of the constituent stocks of the NIFTY 500 index. Hence, TTM dividends for month t is the sum of the dividends from month t to month $t-11$.

Dividend to Price Ratio ($\boldsymbol{DIV\ PRICE_t}$): Dividend Price ratio for a given month is the natural logarithm of the ratio of TTM Dividends to the closing NIFTY 500 Index Level for that month.

Dividend Yield ($\boldsymbol{DIV\ YLD_t}$): Dividend Yield for month t is the natural logarithm of the ratio of TTM dividends of month t to the closing NIFTY 500 Index Level for month $t-12$.

Dividend Payout Ratio ($\boldsymbol{DIV\ PAY_t}$): Dividend Payout ratio for a given month is the natural logarithm of the ratio of the TTM dividends to the TTM earnings of that month.

Cash Flow to Price Ratio ($\boldsymbol{CF\ PRICE_t}$): $CF\ PRICE_t$ is calculated as the trailing 12-month cash flow per share divided by the closing NIFTY 500 Index Level for month t.

Stock Variance ($\boldsymbol{NIFTY\ VAR_t}$): Stock Variance is the measure of volatility in daily returns of the NIFTY 500 Total Returns Index for that month. It is calculated for a given month as the variance of daily continuously compounded returns in the month.

S&P 500 to NIFTY 500 Ratio ($S\&P\ NIFTY\ RAT_t$): S&P NSE Ratio for a given month is calculated as the natural logarithm of the ratio of the closing index level of S&P 500 index in the U.S. to the closing index level of NIFTY 500 of India, scaled by the USD-INR exchange rate. This variable gives us a measure of the relative performance of the Indian equity market with respect to its U.S. counterpart, hence giving a sense of global outlook of Indian economy.

Net FII Flows Percentage Change ($\boldsymbol{FII\ PER\ CHG_t}$): Net FII Flows Percentage Change for month t is defined as the percentage change in the net FII flows from month $t-1$ to month t.

$$FII\ PER\ CHG_t = \frac{Net\ FII\ Flows_t - Net\ FII\ Flows_{t-1}}{|Net\ FII\ Flows_{t-1}|}$$

Economic Policy Uncertainty ($\boldsymbol{EPU_t}$): The Baker, Bloom, and Davis 2016 index of economic policy uncertainty, constructed based on the frequency of newspaper references to policy uncertainty. They construct an index from three types of underlying components. One component quantifies newspaper coverage of policy-related economic uncertainty. A second component reflects the number of federal tax code provisions set to expire in future years. The third component uses disagreement among economic forecasters as a proxy for uncertainty.[18]

Table 2 reports the summary statistics of the variables used in this paper.

[18] Refer to the ticker code: EPUCNINM Index in Bloomberg for more information.

3 Methodology

3.1 The Model

We investigate the predictability of ERP using the ordinary least squares (OLS) regression model applied to training data using the recursive window approach, starting with an initial sample size of 75 months. The recursive window approach generates a series of one-step-ahead ERP forecasts where the starting estimation date is fixed, but additional observations are added one at a time to the training data. The dependent variable is monthly ERP while the independent variables are the fourteen one-month lagged predictors (outlined in Section 2), employed one at a time (Goyal and Welch 2003).[19] Equation (1) is the representation of the OLS model for the i^{th} predictor, where the error series η_t is assumed to follow a white noise process.

$$ERP_t = \beta_0 + \beta_1 Predictor_{i,t-1} + \eta_t \tag{1}$$

From the estimated model, we generate one-step-ahead ERP forecast for each month in the out-of-sample (OOS) period. The initial estimation window starts in August 2004 and the OOS period ranges from November 2010 to November 2020. This results in 121 one-step-ahead forecasts for the i^{th} predictor. We repeat this procedure to generate ERP forecasts for all the predictors.

[19] In a given data sample, some variables might appear non-stationary. However, prior studies on ERP forecasting do not account for the possibility that our set of predictors may have stochastic or deterministic trends over time (like GDP level). Moreover, non-stationary variables cannot be expected to forecast a stationary variable such as ERP. Hence, we do not make any adjustments for non-stationarity in our sample. We thank Amit Goyal for this valuable suggestion.

3.2 ERP Predictors

3.2.1 Individual Predictors

We forecast *ERP* using fourteen predictors, namely, (i) *TBILL 3M*, (ii) *GBOND 10YR*, (iii) *DEF SPRD*, (iv) *TERM SPRD*, (v) *INFLATION*, (vi) *BOOK MKT*, (vii) *EARN PRICE*, (viii) *DIV PRICE*, (ix) *DIV YLD*, (x) *DIV PAY*, (xi) *CF PRICE*, (xii) *NIFTY VAR*, (xiii) *S&P NIFTY RAT*, and (xiv) *FII PER CHG*.

3.2.2 Mean Combination Forecast

Following Rapach, Strauss, and Zhou 2010, Welch and Goyal 2008 and Narayan and Bannigidadmath 2015, we compute the equal-weighted one-step-ahead ERP forecasts based of all predictors for each month in the OOS period. This predictor, which we call the mean combination forecast (*MEAN COMB*), is designed to capture information on all the twelve predictors while reducing the volatility of forecasts.

3.2.3 Dynamic EPU-Conditioned Predictor

We develop a procedure for constructing ERP forecasts, which are conditioned on the observed level of EPU in India. This enables us to factor in the critical role played by EPU in emerging markets ERP prediction. To start with, we classify each month's EPU in the OOS period as belonging to a low, moderate, or high uncertainty regime. This is also the forecasted EPU regime for the next month.[20] Each month's EPU belongs to one of these three regimes, identified from the distribution of EPU values from July 2004 to month $t-2$, where $t-1$ denotes the current month. More precisely, from the distribution of in-sample EPU values (from July 2004 to month $t-2$),

[20]We compare the EPU regime forecasts with the realized EPU regimes in the OOS period. The realized EPU regimes are computed from the entire distribution of EPU values from November July 2004 to December 2020, with the same EPU percentile thresholds. Our EPU forecasts demonstrate high forecast accuracy with 39%, 74%, and 64% correctly identified low, moderate, and high uncertainty regimes.

we compute the values corresponding to the 20^{th} and 80^{th} percentile. Values below the 20^{th} percentile indicate low uncertainty while values above 80^{th} percentile indicate the opposite. Values between the 20^{th} and 80^{th} percentile capture periods of moderate uncertainty. In the OOS period we identify 20, 76, and 25 months of ERP forecasts made during periods of low, moderate, and high uncertainty, respectively.[21]

Our procedure is based on the implicit assumption that, depending on the level of uncertainty, certain predictors may systematically outperform other predictors in the OOS period. For instance, ERP forecasts based on *TBILL 3M*, *BOOK MKT*, and *DIV YLD*] in the low, moderate, and high uncertainty regimes, respectively may be more accurate than forecasts based on any of the 16 individual predictor variables *alone* throughout the OOS period. Since we have no way of knowing, ex-ante, the identity of these predictors, we allow for the possibility that any of the 16 predictors may generate superior ERP forecasts in the three EPU regimes. We generate $16 \times 16 \times 16$ (4,096) possible combinations of predictors, each of which is a 3-tuple, an ordered vector consisting of three predictors, where the ordering of the predictors correspond to the EPU regimes from low to high. These 4,096 combinations consists of the 16 individual predictors (i.e., when the three predictors are the same) and 4,080 combinations of two or three distinct predictors. Among the 4,080 combinations, define the 3-tuple that generates the highest forecast accuracy as the Dynamic EPU-Conditioned Predictor (*DYN EPU-COND PRED*).

In this way, we are able to examine whether conditioning the predictor variable on the EPU regime results in superior forecast accuracy. The optimal forecasting strategy is to classify the level of uncertainty in the economy

[21]We also implemented the Markov switching model for classifying the EPU regimes into low, medium, and high uncertainty. Specifically, we fitted a 3-regime Markov switching model in each recursive window and generated one-step-ahead EPU regime forecasts. However, for the initial recursive windows, we were unable to generate stable regime estimates, which may arise if the likelihood function is flat over a subset of parameter values. This may be due to the relatively smaller sample sizes in the initial recursive windows.

into one of the three regimes and select the ERP forecast of the predictor corresponding to that regime, as identified by *DYN EPU-COND PRED*.

3.2.4 Benchmark Predictor-Historical Mean (*HIST MEAN*)

Our benchmark ERP predictor is the unconditional mean ERP, which is the average of in-sample ERP values in each recursive estimation window. For each month t in the OOS period, this average is the one-step-ahead ERP forecast (*HIST MEAN*). Consequently, we obtain 121 one-step-ahead unconditional forecasts from November 2010 to November 2020.

3.3 Forecast Evaluation

We compare the forecast accuracy of the predictors (including *MEAN COMB*) relative to *HIST MEAN* using the R^2_{OS} statistic, proposed by Campbell and Thompson 2008. If we denote $\hat{r}_t$ and $\bar{r}_t$ as the ERP forecasts of a given predictor and *HIST MEAN* in month t, then R^2_{OS} is given by:

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{P}(r_t - \hat{r}_t)^2}{\sum_{t=1}^{P}(r_t - \bar{r}_t)^2} \tag{2}$$

where P is the number of one-step-ahead OOS forecasts. A positive value of R^2_{OS} implies that the predictor has lower mean squared predictor error (MSPE) than *HIST MEAN*. We test whether this lower MSPE is statistically significant, which is equivalent to testing the null hypothesis that $R^2_{OS} \leq 0$ against the alternative hypothesis that $R^2_{OS} > 0$. The standard approach for testing this hypothesis is to use the Diebold and Mariano 1995 statistic or its small sample adjusted version proposed by Harvey, Leybourne, and Newbold 1997. However, the statistic is correctly sized only for non-nested models and is severely undersized for nested models (Diebold and Mariano 2002 and Clark and West 2007). Since the ERP forecasts of the predictors reduce to the unconditional ERP forecasts when we restrict $\beta_1 = 0$ in equation (1), we employ the MSPE-adjusted statistic suggested by Clark and West 2006 and

Clark and West 2007 which is correctly sized for comparing forecasts from nested models. The MSPE-adjusted statistic is computed as:

$$MSPE - adjusted = 1/P \sum_{t=1}^{P} \{(r_t - \bar{r}_t)^2 - (r_t - \hat{r}_t)^2 + (\bar{r}_t - \hat{r}_t)^2\} \quad (3)$$

Using the MSPE-adjusted statistic, we test whether the population MSPEs of two models are equal, which is akin to testing whether $\beta_1 = 0$ in equation (1). The statistic is computed as the difference between sample MSPEs plus an adjustment term which removes the noise in ERP forecasts introduced by estimating the additional parameter, β, when it is in fact zero in the population model. The adjustment term is the average of the squared difference between forecasts based on *HIST MEAN* and the predictor. Clark and McCracken 2001 show that the statistic has a nonstandard distribution when forecasts are generated from nested models. However, standard normal critical values yield actual sizes close to, but slightly lesser than nominal size, for large samples (Clark and West 2007). We report the p-values for the one-sided (right tail) tests, obtained from the standard normal distribution.

Given that our sample is moderately sized with 121 OOS forecasts, we estimate more precise p-values by the nonparametric bootstrap, which accounts for the possible nonstandard sampling distribution of the MSPE-adjusted statistic. Specifically, we randomly sample with replacement 10,000 times from the 121 demeaned OOS forecasts, each time computing the MSPE-adjusted statistic. Demeaning ensures that the the sampling distribution of the statistic is centered at zero, which enables us to correctly test the null hypothesis. We then calculate the area in the right tail (p-value) of the bootstrap sampling distribution corresponding to the statistic for the original sample. The nonparametric bootstrap procedure generates accurate results if the OOS forecasts are independent and identically distributed (i.i.d). The independence assumption holds in our context since optimal one-step-ahead forecasts are independent (Diebold and Mariano 1995 and Clark and West

2007). Hence, we do not employ the computationally demanding circular block bootstrap procedure of Politis and Romano 1992, which preserves the autocorrelation structure in time series data.

4 Results

We compare the ERP forecasts of the predictors with the unconditional ERP forecasts (*HIST MEAN*) to identify whether they have superior OOS forecast accuracy. The second column of Table 3 reports the R^2_{OS} of the predictors. Following Campbell and Thompson 2008 and Rapach, Strauss, and Zhou 2010, statistical significance is evaluated with the Clark and West 2007 MSPE-adjusted statistic, when R^2_{OS} is greater then zero. Even if R^2_{OS} is greater than zero and statistically significant, it may not be economically meaningful in terms of higher annual portfolio returns. Campbell and Thompson 2008 show that R^2_{OS} values as low as 0.5% (0.005) for monthly data are economically meaningful for a mean-variance investor. Since our ERP forecasts are for the one-month horizon, we use this floor value of R^2_{OS} to assess the economic significance of forecast performance.[22] We report the p-values corresponding to the standard normal distribution and the nonparametric bootstrap in columns 3 and 4, respectively. Panels A, B, and C report the results for the fourteen predictors, *MEAN COMB*, and *DYN EPU-COND PRED* respectively.

4.1 Forecast Accuracy - *DYN EPU-COND PRED*

From the 4,096 predictor 3-tuples, which are conditioned on EPU, we find that the 3-tuple, [*DIV PAY*, *CF PRICE*, *S&P NIFTY RAT*], has the highest forecast accuracy relative to *HIST MEAN*. Therefore, optimal forecasts are generated by selecting *DIV PAY*, *CF PRICE*, and *S&P NIFTY RAT* during

[22]Our R^2_{OS} estimates are of similar magnitude to those reported by Rapach, Strauss, and Zhou 2010 for the ERP predictors of the U.S equity market.

periods of low, moderate, and high uncertainty, respectively. Thus, *EPU-COND* is defined as this 3-tuple, the elements of which are selected based on the forecasted EPU regime.[23] Panel C in Table 3 shows that ERP forecasts based on *EPU-COND* have lower MSPE than *HIST MEAN* at the 1% level of significance. Moreover, the outperformance is economically significant. Among predictors which are statistically significant at the 1% level of significance, we observe that *EPU-COND* has the highest R^2_{OS}. The R^2_{OS} of *EPU-COND* is around 45% higher than the next best predictor, *DIV PAY*, which is a considerable gain in forecast accuracy achieved by conditioning ERP forecasts on EPU.

Figure 5 visually illustrates the superior forecast accuracy of *EPU-COND*. Panels A and B plot the cumulative squared forecast error (CSE) of ERP forecasts and the difference in squared forecast error relative to *HIST MEAN*, respectively. These plots help us understand the relative performance of *EPU-COND*. When the dotted orange line is below the solid blue line in Panel A, it indicates that *EPU-COND* has superior forecast accuracy compared to *HIST MEAN* till that month. We observe that *EPU-COND* outperforms *HIST MEAN* almost throughout the OOS period. When the difference in squared forecast error is positive in Panel B, it indicates that *EPU-COND* had lower absolute value of forecast error relative to *HIST MEAN* in the month. We observe a larger proportion of positive values for *EPU-COND* (61%), which is complementary evidence on the superior prediction accuracy of *EPU-COND*. We also test whether the superior forecast accuracy is driven by a particular subperiod of OOS observations. To do this, we first split the OOS period into two subperiods of equal length with the first and second subperiod ending in October 2015 and November 2020, respectively. The latter subperiod includes the turbulent period of the COVID-19 pandemic. Then, we employ the difference-in-means test on the squared forecast errors

[23]Among all 3-tuples which outperform *HIST MEAN* at the 1% level, we find that *DIV PAY*, *CF PRICE*, and *S&P NIFTY RAT* are the most frequently selected components of the 3-tuples in periods of low, moderate, and high uncertainty, respectively.

and find that the outperformance of *EPU-COND* (relative to *HIST MEAN*) is similar in the two subperiods (p-value = 0.15). This suggests that *EPU-COND* is fairly robust in the sense that its superior forecast accuracy is independent of market conditions.

4.2 How Large are the Forecasting Gains?

Till now, we have provided statistical evidence on the forecast performance of the predictors. We go one step further and compute the realized utility gains of a mean-variance investor who rebalances his or her portfolio monthly between the market portfolio and risk-free 30-day T-bills based on ERP forecasts of the predictors. The investor is assumed to have a power utility function with a coefficient of relative risk aversion (CRRA) between 1 and 3. Moreover, we restrict the weight on the market portfolio to lie between 0 and 1.5 each month, which prevents the investor from shorting the market portfolio or leveraging more than 50%. The realized utility gain for a predictor is the difference between the utility from the predictor's forecasts and the utility from the unconditional mean ERP forecasts. Since we forecast ERP at the monthly horizon, we multiple the realized utlity gain by 1200 to convert it to annualized percentage utility gain. Since the methodology on computing utility gains is common in ERP predictability literature, we do not discuss it here to conserve space. Interested readers can refer to the methodology in Campbell and Thompson 2008 and Rapach, Strauss, and Zhou 2010.

Table 4 reports the annualized utility gains of the ERP predictors for CRRA values of 1, 2, and 3. Panels A, B, and C correspond to the fourteen predictors, *MEAN COMB*, and *DYN EPU-COND PRED*, respectively. We observe that the realized utility gain is the highest for *DYN EPU-COND PRED* across all levels of relative risk aversion. The gains are 2.5-4 percentage points higher than the next best predictor *DIV PAY*, depending on the level of relative risk aversion. Interestingly, the utility gains relative to *DIV*

PAY decline as relative risk aversion increases.

As an alternative approach to computing forecasting gains, we estimate the risk-adjusted returns for the mean-variance optimizing investor, who is assumed to have a power utility function with a CRRA of 2. We use the Sharpe ratio as a measure of risk-adjusted returns as it is widely used by practitioners to backtest trading strategies. The Sharpe ratio of the trading strategy, based on ERP forecasts of a given predictor, is the ratio of the sample mean and sample standard deviation of the monthly excess returns generated from the strategy. The trading strategy involves zero net-investment (i.e., a long-short strategy) whereby the investor invests borrowed funds in a combination of market portfolio and T-bills. The proportion invested in the market portfolio varies across the individual predictors and in every month of the OOS period. We restrict the weight on the market portfolio to lie between 0 and 1.5 each month, which prevents the investor from shorting the market portfolio or leveraging more than 50%.

Although the Sharpe ratio for a sample of excess returns is easy to compute, it is a biased estimator of the population Sharpe ratio, and the size of the bias depends on the underlying data generating process of excess returns. We employ the unbiased estimator proposed by Bao 2009 to conduct two-tailed hypothesis tests on the estimated Sharpe ratios of the predictors. We say that a trading strategy, based on ERP forecasts of a given predictor, is profitable if its Sharpe ratio is significantly different from zero (positive or negative). This is because the investor can always reverse the long-short positions in the portfolio. The details of the estimation procedure and the underlying assumptions are discussed in Appendix A.

When one conducts multiple hypothesis tests, the probability of false discoveries (Type I error) is higher than the level of significance of single tests (Harvey and Liu 2015). This implies that the statistical significance of some of the Sharpe ratios may be spurious because we conduct hypothesis tests on 17 trading strategies. This multiple testing issue, also known as data mining, is common in finance research. To deal with data mining, Harvey and Liu 2015 propose an haircut to the estimated Sharpe ratios, the haircut Sharpe ratio (HSR), using the Benjamini, Hochberg and Yekutieli (BHY) procedure (Benjamini and Hochberg 1995; Benjamini and Yekutieli 2001). We follow this procedure and compute multiple testing p-values (p^M) for the estimated Sharpe ratios by inflating the p-values of the individual tests (p^S). HSR is the imputed Sharpe ratio corresponding to the (larger) multiple testing p-value.

Table 5 reports the annualized Sharpe ratios, p^S, p^M, and HSR for the trading strategies based on ERP forecasts of the 17 predictors. Panels A, B, and C correspond to the fifteen predictors (including *HIST MEAN*), *MEAN COMB*, and *DYN EPU-COND PRED*, respectively. We find that the haircut Sharpe ratio of *DYN EPU-COND PRED* is the highest at 0.57, and is around 30% higher than the next best predictor *DIV PAY*.[24] The haircuts depend on the original Sharpe ratios; the larger Sharpe ratios are penalized less compared to smaller Sharpe ratios. This is economically meaningful since the smaller Sharpe ratios are more likely to be false discoveries. Moreover, the number of statistically significant Sharpe ratios reduces from 5 to 3 after the multiple testing adjustment. Surprisingly, the Sharpe ratio of *MEAN COMB* is not statistically significant, despite its superior forecast accuracy based on the R^2_{OS} statistic. This can be attributed to the lower volatility of the mean combination forecasts (Bates and Granger 1969; Rapach, Strauss, and Zhou 2010), resulting in the inability to accurately track changes in the more volatile ERP time series.

The Sharpe ratios that we compute from the simple trading strategy help illustrate the economic gains that can be achieved through superior forecast accuracy. One can develop even more sophisticated trading strategies (e.g., by utilizing information on both the magnitude and the sign of forecast errors

[24]For the US market, Harvey and Liu 2015 document that a trading strategy based on the betting against beta (BAB) factor generates the largest haircut Sharpe ratio of 0.74 over the sample period from January 1984 to March 2012. The haircut Sharpe ratios for the other predictors in our study are also similar to those reported in Harvey and Liu 2015, although they are for the Indian market and over a different sample period.

of the predictors) to generate higher risk-adjusted returns.

5 Robustness Tests

We investigate the stability of our results through a host of robustness tests. We test whether our results hold if we: (i) employ a rolling window estimation approach which incorporates only the recent history of observations, (ii) use a more sophisticated model specification which allows for possible autocorrelation in the ERP time-series, and (iii) choose different initial in-sample estimation window length and EPU thresholds. Finally, we assess whether conditioning on EPU generates superior ERP forecasts in developed markets like the US, as is the case for an emerging market like India.

5.1 The Recursive and Rolling Window Approaches

We estimate the OLS model (Equation (1)) applied to the rolling window approach with the initial sample size of 75 months. This approach accounts for the possible time-varying data generating process of ERP and the predictors, which the recursive window approach implicitly assumes to be stable. The results under this approach (available in the online appendix) are consistent with those from our main specification.

We also compare the forecast accuracy of the predictors for the OLS model under the recursive and the rolling window approaches. Figure 6 plots the time series of ERP forecasts based on *HIST MEAN*, the benchmark predictor, under the rolling and the recursive window approach from November 2010 to November 2020. We observe that *HIST MEAN* based on the rolling window approach is more volatile than under the recursive window approach. In addition, the volatility of *HIST MEAN* based on the latter approach declines as we move through the OOS period. This is because the weight of individual in-sample ERP values in recursive window approach declines as we increase the number of observations, leading to a gradual smoothening of forecasts.

By contrast, the weight of individual in-sample ERP values is constant for ERP forecasts based on the rolling window approach.

The underlying model specification for generating ERP forecasts is the same under both the recursive and rolling window approaches. This implies that the models, which generate ERP forecasts for a given predictor under the two estimation approaches, are *not* nested. Hence, we employ the modified Diebold and Mariano 1995 test (Harvey, Leybourne, and Newbold 1997) for comparing the forecast accuracy for each predictor under the two estimation approaches. Table 6 reports the DM-statistics and p-values of the modified DM-Test. Under the null hypothesis, the MSPE of the forecasts for the predictor is the same under both the rolling and the recursive window approaches. A statistically significant positive value of the DM-statistic implies that the predictor has superior forecast accuracy under the recursive window approach. We find that forecast *DYN EPU-COND PRED* is superior under the recursive window approach at the 5% level of significance. Interestingly, *DYN EPU-COND PRED* outperforms *HIST MEAN* under the rolling window approach as well at the 1% level of significance, although the R^2_{OS} is lower. This indicates that our Dynamic EPU-Conditioned forecasts are robust to alternative estimation approaches. The sign of the DM-statistics suggest that MSPE is lower under the recursive window approach for 14 out of the 17 predictors, which justifies this approach employed by Goyal and Welch 2003, Welch and Goyal 2008, and Narayan and Bannigidadmath 2015.

5.2 Autocorrelation in OLS Residuals

The OlS model (Equation (1)) assumes that the error series η_t is a white noise process. We test for the validity of this assumption by evaluating the autoregressive integrated moving average (ARIMA) parameters of the residuals of the estimated OLS model. We find that the residuals follow an ARIMA (0,0,0) process for approximately 98% of the estimated OLS models under both the recursive and rolling window approaches. Hence, there is no marginal benefit in terms of improved in-sample fit by estimating an ARIMAX (p,d,q) model, with one lag of the predictors, as it reduces to the OLS model.

We could, in principle, improve the in-sample fit of the OLS model by dynamically selecting the optimal number of lags of the predictor in each estimation window. The optimal number of lags is the one which minimizes the Akaike Information criterion (AICc) information criterion.[25] Although this approach is more flexible, it leads to problems in statistical inference using the MSPE-adjusted statistic. More precisely, the MSPE-adjusted statistic applies specifically to hypothesis tests on forecast accuracy of nested models, where the null hypothesis is the unrestricted model with some of its parameters (beta coefficients) set to zero. For evaluating forecast accuracy of the predictors under the recursive and rolling window approaches, the number of parameters that are set to zero must be the same for all estimation windows. This is clearly not the case with the flexible OLS model as the number of parameters that are set to zero will, in general, vary across estimation windows. This makes model identification under the alternate hypothesis difficult.

5.3 Varying Sample Sizes and EPU Thresholds

We vary the initial sample size under the recursive window approach and the choice of EPU thresholds which identify low, moderate, and high uncertainty regimes. Specifically, we re-estimate model (1) choosing sample sizes of 60 and 90 months and alternative EPU thresholds, which are the (10^{th}, 90^{th}) and (30^{th}, 70^{th}) percentiles. These modifications have no significant effect on the main results, although they affect the identification of low, moderate, and high uncertainty regimes.[26]

[25]AICc is AIC with a correction for small sample size. This is necessary to prevent model overfitting.

[26]Results from these robustness tests are available in the online appendix.

5.4 Predictability of Developed Market Equity Risk Premium

In our final set of robustness tests, we repeat the entire analysis for the US equity market, proxied by the S&P 500 Total Returns Index. For ease of comparison, we choose the set of predictors which lie at the intersection of our analysis for the Indian market and Rapach, Strauss, and Zhou 2010 analysis for the US market.[27] Then, we reestimate model (1) for each of the individual predictors using the recursive window approach, starting with an initial sample size of 75 months. The initial estimation window starts in October 2000 and the OOS period is from January 2007 to December 2020. From Table 7, we observe that only two predictors, *TBILL 3M* and *DIV YLD*, deliver statistically significant superior forecast performance. The latter predictor, however, is weakly significant at the 10% level. Surprisingly, *MEAN COMB* fails to deliver superior ERP forecasts relative to *HIST MEAN*, a finding which is at odds with Rapach, Strauss, and Zhou 2010. However, the OOS period in Rapach, Strauss, and Zhou 2010 ends in December 2005, while our OOS period starts in January 2007 and includes the turbulent periods of the GFC and the COVID-19 pandemic.

We also construct the Dynamic EPU-Conditioned predictor for the US market in the same way we did for the Indian market. Specifically, we classify each month's EPU in the OOS period as belonging to a low, moderate, or high uncertainty regime using the (20^{th}, 80^{th}) percentile threshold of the in-sample empirical distribution of EPU. Then, we compute the forecast accuracy of all possible combinations of predictors ($13 \times 13 \times 13 = 2{,}197$ combinations), each of which is a 3-tuple, where the ordering of the predictors correspond to the EPU regimes from low to high. Although, we are able to identify a unique combination of predictors that generates the highest forecast accuracy, this combination is not robust to alternative choice of

[27]This selection procedure excludes *CF PRICE*, *FII PER CHG*, and *S&P NIFTY RAT*. The relative measure, *S&P NIFTY RAT*, is anyway not meaningful for the US market.

EPU thresholds. The only predictor in the combination that does not vary with the choice of EPU threshold is the 3-month T-bill yield (*TBILL 3M*) in the high uncertainty regime. The robustness and superior predictive power of *TBILL 3M* during periods of high uncertainty can be explained by the flight-to-safety phenomenon. When uncertainty shifts from moderate to high regimes, investors exit their risky investments and park their funds in safe haven assets like US treasuries (Nagel 2016; Adrian, Crump, and Vogt 2019; He, Krishnamurthy, and Milbradt 2019; Baele et al. 2020). This behaviour leads to a natural association between Treasury yield and ERP.

Therefore, we conjecture that an optimal predictor combination for the US market would be *TBILL 3M* in the high uncertainty regime and *HIST MEAN* in the other two regimes. Moreover, our analysis suggests that the procedure of conditioning ERP forecasts on EPU may work better in emerging markets compared to developed markets.

6 Conclusion

We investigate the predictability of one-month-ahead excess returns on the market portfolio by employing numerous predictors that have been suggested by prior literature. Using the OLS regression model under the recursive window approach, we generate ERP forecasts for the NIFTY 500 Index from 2010 to 2020. We contribute to the literature by proposing two additional predictors, which are expected to predict ERP in emerging markets: (i) monthly percentage change in net foreign institutional investor (FII) flows and (ii) the relative performance of the S&P 500 to NIFTY 500. We find that the latter outperforms the unconditional ERP forecast, consistent with our expectation.

We develop a novel procedure for constructing ERP forecasts, by conditioning on economic policy uncertainty. We show that forecasts generated by selecting dividend payout, cash flow to price, and the S&P to NIFTY 500 ratio in periods of low, moderate, and high uncertainty, respectively, have the highest forecast accuracy relative to the unconditional ERP forecast. We test the economic significance of the forecast accuracy by computing (i) the utility gains realized from superior forecast accuracy and (ii) the risk-adjusted returns (Sharpe ratio) realized by employing the forecast information in a simple trading strategy. We find that the Dynamic EPU-Conditioned predictor generates the highest utility gains as well as the highest Sharpe ratio of 0.57. These results hold in various robustness tests.

Past studies on ERP forecasting have almost exclusively employed the recursive window approach. We contribute to this strand of literature by providing empirical justification for preferring the recursive window estimation over the rolling window approach.

Our findings contribute significantly to the asset pricing literature, especially those related to equity risk premium prediction. This study also has important implications for industry practitioners in the realm of portfolio management and for regulators and treasury managers interested in estimating the cost of capital in Indian markets over short horizons. Instead of developing and backtesting sophisticated predictive models, an investor can simply use the OLS model and generate superior forecasts.

References

Acharya, Viral V, K Kiran Kumar, and V Ravi Anshuman (2022). "Foreign fund flows and stock returns: Evidence from India". In.

Adjei, Frederick (2020). "Effect of Economic Policy Uncertainty on Market Risk and Market Risk Premium". In: *Journal of Finance and Economics* 8.2, pp. 57–60.

Adrian, Tobias, Richard K Crump, and Erik Vogt (2019). "Nonlinearity and flight-to-safety in the risk-return trade-off for stocks and bonds". In: *The Journal of Finance* 74.4, pp. 1931–1973.

Ahmed, Shaghil and Andrei Zlate (2014). "Capital flows to emerging market economies: A brave new world?" In: *Journal of International Money and Finance* 48, pp. 221–248.

Ananchotikul, Nasha and Ms Longmei Zhang (2014). *Portfolio flows, global risk aversion and asset prices in emerging markets*. International Monetary Fund.

Baele, Lieven et al. (2020). "Flights to safety". In: *The Review of Financial Studies* 33.2, pp. 689–746.

Bai, Yan (2013). "Discussion on "Gross capital flows: Dynamics and crises" by Broner, Didier, Erce, and Schmukler". In: *Journal of Monetary Economics* 60.1, pp. 134–137.

Baillie, Richard T and Ramon P DeGennaro (1990). "Stock returns and volatility". In: *Journal of financial and Quantitative Analysis*, pp. 203–214.

Baker, Scott R, Nicholas Bloom, and Steven J Davis (2016). "Measuring economic policy uncertainty". In: *The quarterly journal of economics* 131.4, pp. 1593–1636.

Ball, Ray (1978). "Anomalies in relationships between securities' yields and yield-surrogates". In: *Journal of financial economics* 6.2-3, pp. 103–126.

Bao, Yong (2009). "Estimation risk-adjusted Sharpe ratio and fund performance ranking under a general return distribution". In: *Journal of Financial Econometrics* 7.2, pp. 152–173.

Basu, Sanjoy (1983). "The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence". In: *Journal of financial economics* 12.1, pp. 129–156.

Bates, John M and Clive WJ Granger (1969). "The combination of forecasts". In: *Journal of the Operational Research Society* 20.4, pp. 451–468.

Bekaert, Geert (1995). "Market integration and investment barriers in emerging equity markets". In: *The World Bank Economic Review* 9.1, pp. 75–107.

Bekaert, Geert and Campbell R Harvey (2003). "Emerging markets finance". In: *Journal of empirical finance* 10.1-2, pp. 3–55.

Bekaert, Geert, Campbell R Harvey, and Christian Lundblad (2007). "Liquidity and expected returns: Lessons from emerging markets". In: *The review of financial studies* 20.6, pp. 1783–1831.

Benjamini, Yoav and Yosef Hochberg (1995). "Controlling the false discovery rate: a practical and powerful approach to multiple testing". In: *Journal of the Royal statistical society: series B (Methodological)* 57.1, pp. 289–300.

Benjamini, Yoav and Daniel Yekutieli (2001). "The control of the false discovery rate in multiple testing under dependency". In: *Annals of statistics*, pp. 1165–1188.

Bhagat, Sanjai, Pulak Ghosh, and Srinivasan Rangan (2016). "Economic policy uncertainty and growth in India". In: *Economic and Political Weekly*, pp. 72–81.

Brennan, Michael J and H Henry Cao (1997). "International portfolio investment flows". In: *The Journal of Finance* 52.5, pp. 1851–1880.

Brogaard, Jonathan and Andrew Detzel (2015). "The asset-pricing implications of government economic policy uncertainty". In: *Management Science* 61.1, pp. 3–18.

Buckberg, Elaine (1995). "Emerging stock markets and international asset pricing". In: *The World Bank Economic Review* 9.1, pp. 51–74.

Campbell, John Y (1987). "Stock returns and the term structure". In: *Journal of financial economics* 18.2, pp. 373–399.

Campbell, John Y and Ludger Hentschel (1992). "No news is good news: An asymmetric model of changing volatility in stock returns". In: *Journal of financial Economics* 31.3, pp. 281–318.

Campbell, John Y and Robert J Shiller (1988a). "Stock prices, earnings, and expected dividends". In: *the Journal of Finance* 43.3, pp. 661–676.

— (1988b). "The dividend-price ratio and expectations of future dividends and discount factors". In: *The Review of Financial Studies* 1.3, pp. 195–228.

— (2001). *Valuation ratios and the long-run stock market outlook: An update.* Tech. rep. National bureau of economic research.

Campbell, John Y and Samuel B Thompson (2008). "Predicting excess stock returns out of sample: Can anything beat the historical average?" In: *The Review of Financial Studies* 21.4, pp. 1509–1531.

Clark, Todd E and Michael W McCracken (2001). "Tests of equal forecast accuracy and encompassing for nested models". In: *Journal of econometrics* 105.1, pp. 85–110.

— (2009). "Improving forecast accuracy by combining recursive and rolling forecasts". In: *International Economic Review* 50.2, pp. 363–395.

Clark, Todd E and Kenneth D West (2006). "Using out-of-sample mean squared prediction errors to test the martingale difference hypothesis". In: *Journal of econometrics* 135.1-2, pp. 155–186.

— (2007). "Approximately normal tests for equal predictive accuracy in nested models". In: *Journal of econometrics* 138.1, pp. 291–311.

Cochrane, J (2007). "Financial Markets and the Real Economy". In: *Handbook of the Equity Premium.*

Cochrane, John H (1999). "New Facts in Finance". In: *Economics* 23.3, pp. 36–58.

Coval, Joshua and Erik Stafford (2007). "Asset fire sales (and purchases) in equity markets". In: *Journal of Financial Economics* 86.2, pp. 479–512.

Damodaran, Aswath (1999). "Estimating equity risk premiums". In.

— (2003). "Country risk and company exposure: theory and practice". In: *Journal of applied finance* 13.2.

— (2020). "Equity Risk Premiums: Determinants, Estimation and Implications-The 2020 Edition". In: *Estimation and Implications-The*.

De Jong, Frank and Frans A De Roon (2005). "Time-varying market integration and expected returns in emerging markets". In: *Journal of financial economics* 78.3, pp. 583–613.

Diebold, Francis X and Robert S Mariano (1995). "Comparing predictive accuracy". In: *Journal of Business & economic statistics* 20.1, pp. 134–144.

— (2002). "Comparing predictive accuracy". In: *Journal of Business & economic statistics* 20.1, pp. 134–144.

Fama, Eugene F (1981). "Stock returns, real activity, inflation, and money". In: *The American economic review* 71.4, pp. 545–565.

Fama, Eugene F and Kenneth R French (1989). "Business conditions and expected returns on stocks and bonds". In: *Journal of financial economics* 25.1, pp. 23–49.

— (1992). "The cross-section of expected stock returns". In: *the Journal of Finance* 47.2, pp. 427–465.

— (2021). *Dividend yields and expected stock returns*. University of Chicago Press.

Fama, Eugene F and G William Schwert (1977). "Asset returns and inflation". In: *Journal of financial economics* 5.2, pp. 115–146.

Forbes, Kristin J and Francis E Warnock (2012). "Capital flow waves: Surges, stops, flight, and retrenchment". In: *Journal of international economics* 88.2, pp. 235–251.

Fratzscher, Marcel (2012). "Capital flows, push versus pull factors and the global financial crisis". In: *Journal of International Economics* 88.2, pp. 341–356.

French, Kenneth R, G William Schwert, and Robert F Stambaugh (1987). "Expected stock returns and volatility". In: *Journal of Financial Economics* 19.1, pp. 3–29.

Froot, Kenneth A and Tarun Ramadorai (2008). "Institutional portfolio flows and international investments". In: *The Review of Financial Studies* 21.2, pp. 937–971.

Gormley, Todd A, Bong Hwan Kim, and Xiumin Martin (2012). "Do firms adjust their timely loss recognition in response to changes in the banking industry?" In: *Journal of Accounting Research* 50.1, pp. 159–196.

Goyal, Amit and Ivo Welch (2003). "Predicting the equity premium with dividend ratios". In: *Management Science* 49.5, pp. 639–654.

Harvey, Campbell R (1995). "Predictable risk and returns in emerging markets". In: *The review of financial studies* 8.3, pp. 773–816.

— (2004). "Country risk components, the cost of capital, and returns in emerging markets". In: *Available at SSRN 620710*.

Harvey, Campbell R and Yan Liu (2015). "Backtesting". In: *The Journal of Portfolio Management* 42.1, pp. 13–28.

Harvey, David, Stephen Leybourne, and Paul Newbold (1997). "Testing the equality of prediction mean squared errors". In: *International Journal of forecasting* 13.2, pp. 281–291.

He, Zhiguo, Arvind Krishnamurthy, and Konstantin Milbradt (2019). "A model of safe asset determination". In: *American Economic Review* 109.4, pp. 1230–62.

Hecht, Peter and Tuomo Vuolteenaho (2006). "Explaining returns with cash-flow proxies". In: *The Review of Financial Studies* 19.1, pp. 159–194.

Henry, Peter Blair (2000). "Stock market liberalization, economic reform, and emerging market equity prices". In: *The Journal of Finance* 55.2, pp. 529–564.

Jotikasthira, Chotibhak, Christian Lundblad, and Tarun Ramadorai (2012). "Asset fire sales and purchases and the international transmission of funding shocks". In: *The Journal of Finance* 67.6, pp. 2015–2050.

Kelly, Bryan, L'uboš Pástor, and Pietro Veronesi (2016). "The price of political uncertainty: Theory and evidence from the option market". In: *The Journal of Finance* 71.5, pp. 2417–2480.

Koepke, Robin (2018). "Fed policy expectations and portfolio flows to emerging markets". In: *Journal of International Financial Markets, Institutions and Money* 55, pp. 170–194.

Kothari, Smitu P and Jay Shanken (1997). "Book-to-market, dividend yield, and expected market returns: A time-series analysis". In: *Journal of Financial economics* 44.2, pp. 169–203.

Kruschwitz, Lutz, Andreas Löffler, and Gerwald Mandl (2012). "Damodaran's country risk premium: a serious critique". In: *Business Valuation Review* 31.2-3, pp. 75–84.

Kumar, Kiran K and Chiranjit Mukhopadyay (2002). "Equity market interlinkages: Transmission of volatility-A case of US and India". In: *NSE, India Research paper, Source: www.nseindia.com.*

Lamont, Owen (1998). "Earnings and expected returns". In: *The journal of Finance* 53.5, pp. 1563–1587.

Lintner, John (1975). "Inflation and security returns". In: *The journal of finance* 30.2, pp. 259–280.

Mensi, Walid et al. (2014). "Do global factors impact BRICS stock markets? A quantile regression approach". In: *Emerging Markets Review* 19, pp. 1–17.

Milesi-Ferretti, Gian-Maria and Cédric Tille (2011). "The great retrenchment: international capital flows during the global financial crisis". In: *Economic policy* 26.66, pp. 289–346.

Miller, Robert E and Adam K Gehr (1978). "Sample size bias and Sharpe's performance measure: A note". In: *Journal of Financial and Quantitative Analysis* 13.5, pp. 943–946.

Mohanty, Madhusudan S (2014). "The transmission of unconventional monetary policy to the emerging markets-An overview". In: *BIS Paper* 78a.

Nagel, Stefan (2016). "The liquidity premium of near-money assets". In: *The Quarterly Journal of Economics* 131.4, pp. 1927–1971.

Narayan, Paresh Kumar and Deepa Bannigidadmath (2015). "Are Indian stock returns predictable?" In: *Journal of Banking & Finance* 58, pp. 506–531.

Nelson, Charles R (1976). "Inflation and rates of return on common stocks". In: *The journal of Finance* 31.2, pp. 471–483.

Politis, Dimitris N and Joseph P Romano (1992). "A circular block-resampling procedure for stationary data". In: *Exploring the limits of bootstrap* 2635270.

Pontiff, Jeffrey and Lawrence D Schall (1998). "Book-to-market ratios as predictors of market returns". In: *Journal of financial economics* 49.2, pp. 141–160.

Rapach, David E, Jack K Strauss, and Guofu Zhou (2010). "Out-of-sample equity premium prediction: Combination forecasts and links to the real economy". In: *The Review of Financial Studies* 23.2, pp. 821–862.

Rayburn, Judy (1986). "The association of operating cash flow and accruals with security returns". In: *Journal of Accounting Research*, pp. 112–133.

Rey, Hélène (2015). *Dilemma not trilemma: the global financial cycle and monetary policy independence*. Tech. rep. National Bureau of Economic Research.

Rozeff, Michael S (1984). "Dividend yields are equity risk premiums". In: *Journal of Portfolio management*, pp. 68–75.

Stulz, René M (1999). "International portfolio flows and security markets". In.

Vig, Vikrant (2013). "Access to collateral and corporate debt structure: Evidence from a natural experiment". In: *The Journal of Finance* 68.3, pp. 881–928.

Welch, Ivo and Amit Goyal (2008). “A comprehensive look at the empirical performance of equity premium prediction”. In: *The Review of Financial Studies* 21.4, pp. 1455–1508.

Westerlund, Joakim and Paresh Narayan (2014). “A random coefficient approach to the predictability of stock returns in panels”. In: *Journal of Financial Econometrics* 13.3, pp. 605–664.

White, Lawrence J (2010). “Markets: The credit rating agencies”. In: *Journal of Economic Perspectives* 24.2, pp. 211–26.

Tables and Figures

Table 1
Data Source
This table reports the data source of the raw variables used in our analysis. The third column contains the Bloomberg ticker code of the variables. Effective 3^{rd} April, 2018, The Fixed Income Money Market and Derivatives Association of India (FIMMDA) has discontinued publishing the treasury bill (T-Bill) fixings. Post 3^{rd} April, 2018, the T-Bill fixings have been migrated to Financial Benchmarks India Pvt Ltd. (FBIL).

Variables	Data Source	Variable Code
TBILL 3M	Bloomberg and FBIL	IYTB30D Index, FBTB1M Index
GBOND 10YR	Bloomberg	GIND10YR INDEX
CBOND BBB 10YR	Bloomberg	BCOPBBB0 INDEX
NIFTY 500 Price Index	Bloomberg	NSE500 INDEX
NIFTY 500 Total Return Index	Bloomberg	NSE500TR INDEX
INFLATION	Bloomberg	EHPIIN INDEX
EARN TTM	Bloomberg	TRAIL_12M_EPS_BEF_XO_ITEM
DIV TTM	Bloomberg	TRAIL_12M_DIV
BOOK VAL	Bloomberg	BOOK_VAL_PER_SH
CF PRICE	Bloomberg	PX_TO_CASH_FLOW
S&P NIFTY RAT	Bloomberg	.SPXNSEI G INDEX
FII PER CHG	Bloomberg	FIINNET INDEX
EPU	Bloomberg	EPUCNINM INDEX

Table 2
Summary Statistics
This table reports the summary statistics of the variables used in our analysis. The data is for the period from July 2004 to November 2020.

Variables	Min.	25 %ile	Median	Mean	75 %ile	Max.
TBILL 3M	0.0025	0.0046	0.0056	0.0055	0.0064	0.0093
GBOND 10YR	0.0046	0.0058	0.0064	0.0063	0.0067	0.0078
CBOND BBB 10YR	0.0077	0.0092	0.0096	0.0096	0.0100	0.0116
MONTHLY RETURNS	-0.3172	-0.0179	0.0145	0.0120	0.0521	0.2962
ERP	-0.3237	-0.0234	0.0096	0.0067	0.0469	0.2938
DEF SPRD	0.0019	0.0029	0.0032	0.0033	0.0037	0.0055
TERM SPRD	-0.0021	0.0002	0.0006	0.0008	0.0012	0.0035
INFLATION	0.0221	0.0446	0.0652	0.0679	0.0904	0.1531
BOOK MKT	0.1850	0.3222	0.3529	0.3574	0.3997	0.5911
EARN PRICE	0.0188	0.0407	0.0540	0.0542	0.0632	0.1053
DIV PRICE	0.0001	0.0002	0.0003	0.0004	0.0004	0.0019
DIV YLD	0.0001	0.0002	0.0003	0.0004	0.0004	0.0027
DIV PAY	0.0031	0.0043	0.0051	0.0061	0.0060	0.0214
CF PRICE	0.0087	0.0339	0.0442	0.0487	0.0558	0.1604
NIFTY VAR	0.0000	0.0001	0.0001	0.0002	0.0002	0.0023
S&P NIFTY RAT	104141	168848	191622	195369	219953	378830
FII PER CHG	-56.82	-0.80	0.07	2.62	1.27	225.71
EPU	27.74	59.81	83.39	95.23	122.28	283.69

Table 3
Out-of-Sample Performance of Forecast Errors
This table reports the forecast accuracy of the predictors under the recursive window approach. Panels A, B, and C report the results for the fourteen predictors, *MEAN COMB*, and *DYN EPU-COND PRED* respectively. We measure forecast accuracy by the Campbell and Thompson 2008 R^2_{OS} statistic of each predictor, reported in the second column. The statistical significance of the R^2_{OS} statistic is based on the p-value of the Clark and West 2007 MSPE-adjusted statistic. The null hypothesis is that the expected forecast error of the predictor and the unconditional ERP forecast (*HIST MEAN*) are equal against the alternative hypothesis that the expected forecast error of the predictor is lower. The p-values reported in the third and fourth columns correspond to the standard normal and the nonparametric bootstrap sampling distributions of the MSPE-adjusted statistic, respectively. ***, **, and * indicate statistical significance from the nonparametric bootstrap sampling distribution at the 1%, 5%, and 10% level, respectively.

Panel A

Predictor	R^2_{OS}	p-Value	
		Standard Normal	Bootstrap
TBILL 3M	-0.057	0.132	0.136
GBOND 10YR	-0.047	0.206	0.209
DEF SPRD	0.000	0.332	0.340
TERM SPRD	-0.018	0.138	0.143
INFLATION	-0.005	0.614	0.621
BOOK MKT	-0.032	0.536	0.531
EARN PRICE	-0.032	0.201	0.199
DIV PRICE	**0.008****	**0.015**	**0.019**
DIV YLD	-0.005	0.041	0.044
DIV PAY	**0.063*****	**0.002**	**0.004**
CF PRICE	**0.043*****	**0.005**	**0.005**
NIFTY VAR	-0.022	0.992	0.982
S&P NIFTY RAT	**0.040****	**0.028**	**0.029**
FII PER CHG	-0.525	0.043	0.067

Panel B

Predictor	R^2_{OS}	p-Value	
		Standard Normal	Bootstrap
MEAN COMB	**0.036****	**0.010**	**0.011**

Panel C

Predictor	R^2_{OS}	p-Value	
		Standard Normal	Bootstrap
DYN EPU-COND PRED	**0.091*****	**0.000**	**0.000**

Table 4
Realized Utility Gains in the Out-of-Sample Period
This table reports the annualized utility gains of a mean-variance investor with a coefficient of relative risk aversion (CRRA) of 1, 2, and 3. The investor rebalances his or her portfolio monthly between the market portfolio and risk-free 30-day T-bills based on ERP forecasts of the predictors. We restrict the weight on the market portfolio to lie between 0 and 1.5 each month, which prevents the investor from shorting the market portfolio or leveraging more than 50%. The realized utility gain for a predictor is the difference between the utility from the predictor's forecasts and the utility from the unconditional mean ERP forecasts. Panels A, B, and C correspond to the fourteen predictors, *MEAN COMB*, and *DYN EPU-COND PRED*, respectively.

Panel A

Predictor	Utility Gain (%)		
	CRRA=1	CRRA=2	CRRA=3
TBILL 3M	3.039	5.170	3.874
GBOND 10YR	1.093	4.875	3.888
DEF SPRD	-2.127	1.012	-0.728
TERM SPRD	-0.122	2.346	0.788
INFLATION	0.143	0.394	-0.414
BOOK MKT	1.171	2.195	1.172
EARN PRICE	0.009	4.583	5.336
DIV PRICE	5.105	7.064	6.990
DIV YLD	2.004	5.513	5.956
DIV PAY	8.016	9.993	9.014
CF PRICE	6.959	9.664	8.847
NIFTY VAR	-2.020	-2.049	-1.723
S&P NIFTY RAT	7.037	6.725	4.229
FII PER CHG	1.511	2.336	4.454

Panel B

Predictor	Utility Gain (%)		
	CRRA=1	CRRA=2	CRRA=3
MEAN COMB	5.217	6.159	6.389

Panel C

Predictor	Utility Gain (%)		
	CRRA=1	CRRA=2	CRRA=3
DYN EPU-COND PRED	12.113	13.394	11.573

Table 5
Risk-adjusted Returns in the Out-of-Sample Period
This table reports the annualized Sharpe ratios for the mean-variance optimizing investor, who is assumed to have a power utility function with a coefficient of relative risk aversion (CRRA) of 2. The Sharpe ratio of the trading strategy, based on ERP forecasts of a given predictor, is the ratio of the sample mean and sample standard deviation of the monthly excess returns generated from the strategy. The trading strategy involves zero net-investment (i.e., a long-short strategy) whereby the investor invests borrowed funds in a combination of market portfolio and T-bills. The proportion invested in the market portfolio varies across the individual predictors and in every month of the OOS period. We restrict the weight on the market portfolio to lie between 0 and 1.5 each month, which prevents the investor from shorting the market portfolio or leveraging more than 50%. To deal with data mining, we follow the Benjamini, Hochberg and Yekutieli (BHY) procedure (Benjamini and Hochberg 1995; Benjamini and Yekutieli 2001) and compute multiple testing p-values (p^M) for the estimated Sharpe ratios by inflating the p-values of the individual tests (p^S). We impute the haircut Sharpe ratio (HSR) from the (larger) multiple testing p-value. Panels A, B, and C report the results for the fifteen predictors (including *HIST MEAN*), *MEAN COMB*, and *DYN EPU-COND PRED* respectively. ***, **, and * indicate statistical significance from the bootstrap sampling distribution at the 1%, 5%, and 10% level , respectively.

Panel A

Predictor	SR (Annual)	p^S (Single)	p^M (Multiple)	HSR (Annual)
TBILL 3M	0.192	0.653	0.963	0.044
GBOND 10YR	0.179	0.669	0.963	0.041
DEF SPRD	-0.006	0.947	0.963	0.002
TERM SPRD	0.038	0.960	0.963	0.037
INFLATION	-0.021	0.913	0.963	-0.002
BOOK MKT	0.139	0.689	0.963	0.027
EARN PRICE	-0.026	0.963	0.963	-0.026
DIV PRICE	**0.522*****	**0.002**	**0.039**	**0.358****
DIV YLD	**0.361*****	**0.008**	0.111	0.214
DIV PAY	**0.647*****	**0.000**	**0.000**	**0.437*****
CF PRICE	**0.519****	**0.031**	0.365	0.234
NIFTY VAR	-0.129	0.646	0.963	-0.003
S&P NIFTY RAT	0.290	0.455	0.963	0.035
FII PER CHG	0.045	0.938	0.963	0.033
HIST MEAN	-0.044	0.857	0.963	-0.005

Panel B

Predictor	SR (Annual)	p^S (Single)	p^M (Multiple)	HSR (Annual)
MEAN COMB	0.191	0.749	0.963	0.067

Panel C

Predictor	SR (Annual)	p^S (Single)	p^M (Multiple)	HSR (Annual)
DYN EPU-COND PRED	**0.807*****	**0.001**	**0.018**	**0.568****

Table 6
Comparison of Forecast Accuracy - The Rolling and the Recursive Window approaches
This table compares the forecast accuracy of the predictors under the rolling and the recursive window approaches, using the modified Diebold and Mariano test (DM-Test). Panels A, B, and C report the results for the fifteen predictors (including *HIST MEAN*), *MEAN COMB*, and *DYN EPU-COND PRED* respectively. We report the DM-statistics and p-values of the MSPE point estimates in the second and third columns, respectively. Under the null hypothesis, the forecast accuracy of the predictor is the same under both the rolling and the recursive window approaches. A statistically significant positive value of the DM-statistic implies that the predictor has superior forecast accuracy under the recursive window approach. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A

Predictor	Δ MSPE Test statistic	Δ MSPE p-Value
TBILL 3M	1.178	0.241
GBOND 10YR	0.934	0.352
DEF SPRD	1.436	0.154
TERM SPRD	**1.673***	**0.097**
INFLATION	1.276	0.204
BOOK MKT	-0.594	0.553
EARN PRICE	0.343	0.732
DIV PRICE	-1.252	0.213
DIV YLD	0.433	0.666
DIV PAY	-1.394	0.166
CF PRICE	1.193	0.235
NIFTY VAR	1.086	0.280
S&P NIFTY RAT	1.320	0.189
FII PER CHG	0.090	0.929
HIST MEAN	1.162	0.247

Panel B

Predictor	Δ MSPE Test statistic	Δ MSPE p-Value
MEAN COMB	**2.144****	**0.034**

Panel C

Predictor	Δ MSPE Test statistic	Δ MSPE p-Value
DYN EPU-COND PRED	**2.475****	**0.015**

Table 7
Out-of-Sample Performance of Forecast Errors - US Market
This table reports the forecast accuracy of the predictors under the recursive window approach, for predicting the equity risk premium of the US market. Panels A and B report the results for the fourteen predictors and *MEAN COMB*, respectively. We measure forecast accuracy by the Campbell and Thompson 2008 R^2_{OS} statistic of each predictor, reported in the second column. The statistical significance of the R^2_{OS} statistic is based on the p-value of the Clark and West 2007 MSPE-adjusted statistic. The null hypothesis is that the expected forecast error of the predictor and the unconditional ERP forecasts (*HIST MEAN*) are equal against the alternative hypothesis that the expected forecast error of the predictor is lower. The p-values reported in the third and fourth columns correspond to the standard normal and the nonparametric bootstrap sampling distributions of the MSPE-adjusted statistic, respectively. ***, **, and * indicate statistical significance from the nonparametric bootstrap sampling distribution at the 1%, 5%, and 10% level, respectively.

Panel A

Predictor	R^2_{OS}	p-Value	
		Standard Normal	Bootstrap
TBILL 3M	**0.020****	**0.016**	**0.020**
GBOND 10YR	-0.017	0.026	0.022
DEF SPRD	-0.037	0.357	0.345
TERM SPRD	-0.007	0.017	0.016
INFLATION	-0.014	0.944	0.940
BOOK MKT	0.002	0.243	0.244
EARN PRICE	-0.027	0.552	0.562
DIV PRICE	-0.064	0.773	0.792
DIV YLD	**0.007***	**0.055**	**0.056**
DIV PAY	-0.048	0.468	0.477
S&P 500 VAR	-0.125	0.474	0.461

Panel B

Predictor	R^2_{OS}	p-Value	
		Standard Normal	Bootstrap
MEAN COMB	0.008	0.175	0.172

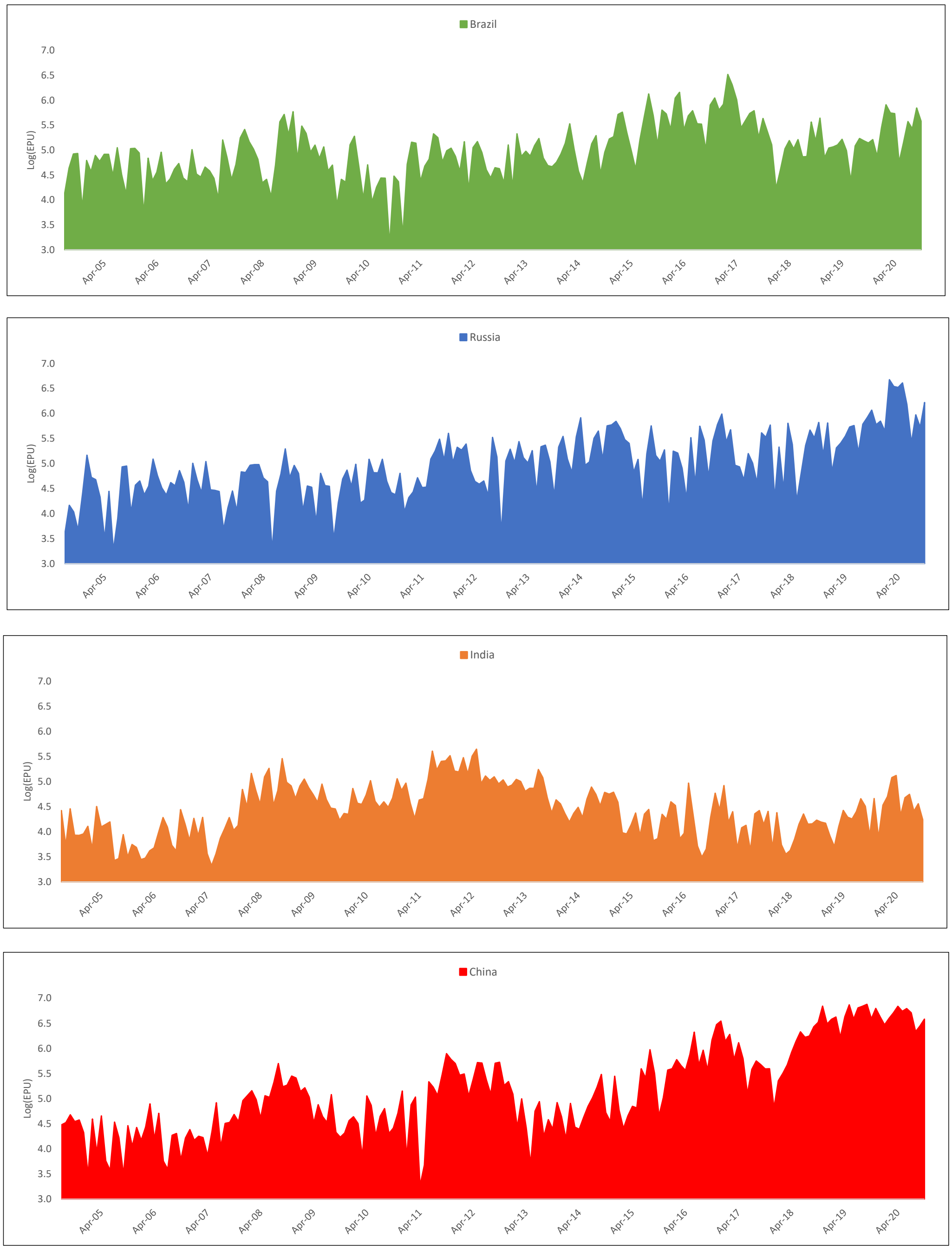


Figure 1
Economic Policy Uncertainty (EPU) Index of Emerging Markets
This figure plots the time series of the natural logarithm of EPU values for Brazil, Russia, India, and China from July 2004 to November 2020. Low and high values indicate periods of low and high uncertainty, respectively.

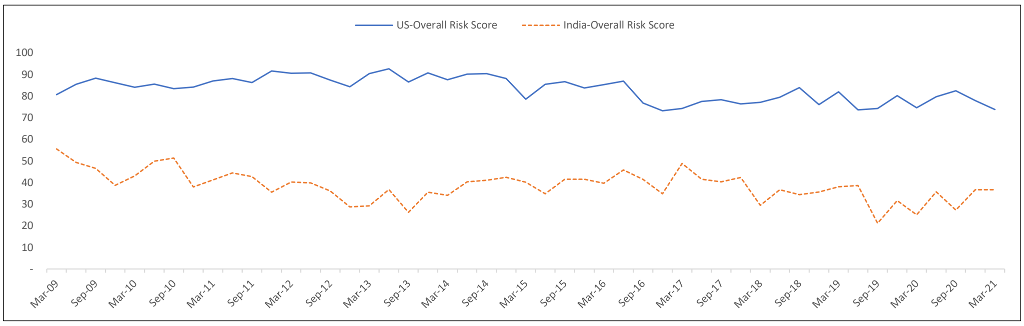


Figure 2
Bloomberg Country Risk Score
This figure plots the Bloomberg Country Risk Scores of India and the US from March 2009 to March 2021. The Bloomberg Country Risk Score is a composite of 29 indicators representing financial, economic and political risks facing investors. The score measures a country's overall risk across financial, economic and political sectors relative to the performance of other emerging and developed countries. Each risk score is calculated using a quarterly, equally-weighted, percent-rank model and is measured on a scale of 0-100. Higher scores indicate more stability and less risk.

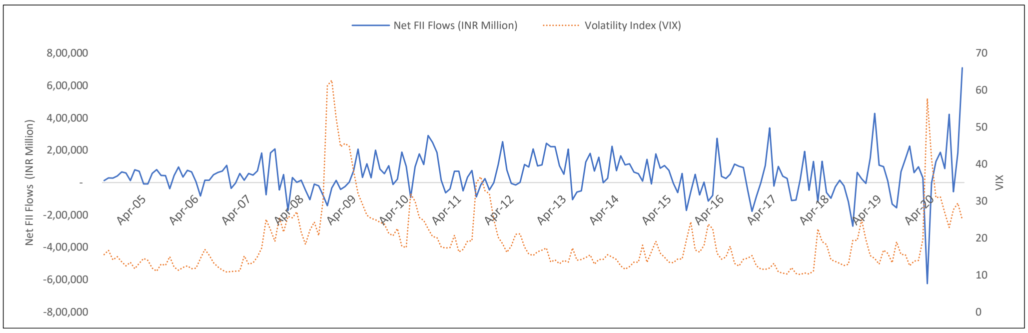


Figure 3
Net Foreign Institutional Investor (FII) Flows and Volatility Index (VIX)
This figure plots the time series of the net FII flows in the Indian equity market and VIX from July 2004 to November 2020. The time series' are negatively correlated over the sample period.

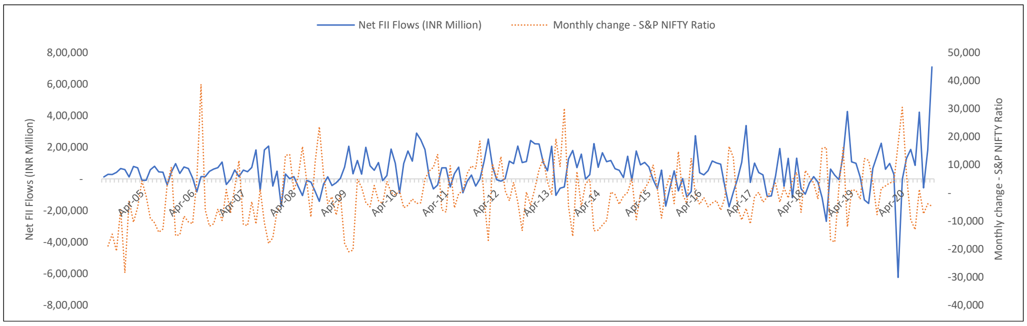
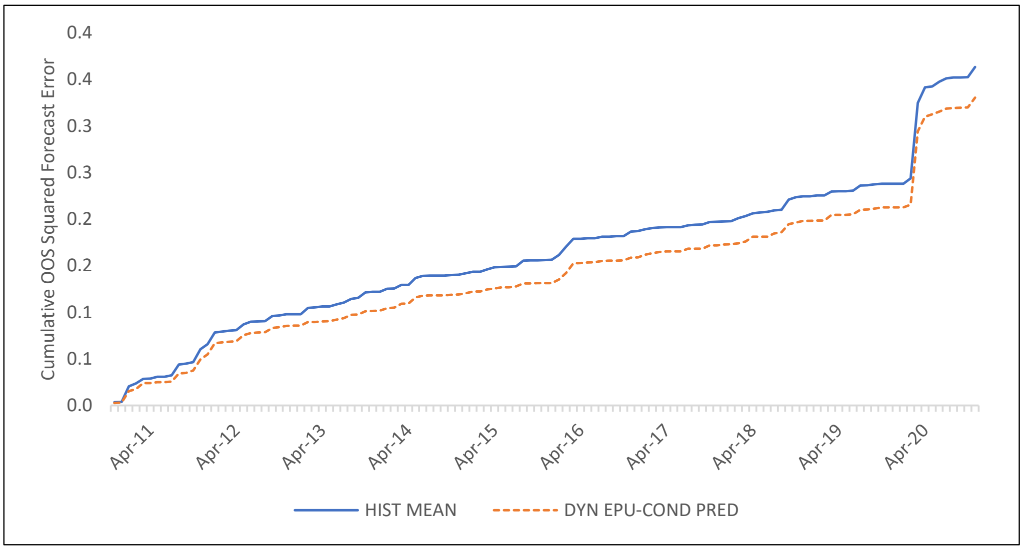
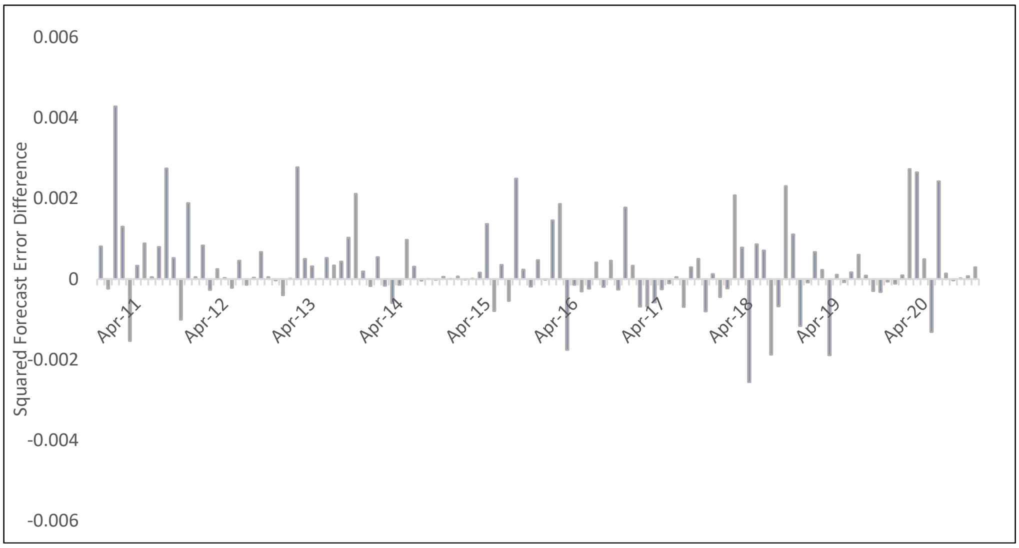


Figure 4
Net Foreign Institutional Investor (FII) Flows and monthly change in S&P NIFTY Ratio
This figure plots the time series of the net FII flows in the Indian equity market and the monthly change in the S&P NIFTY Ratio from August 2004 to November 2020. The time series' are negatively correlated over the sample period.



Panel A. Cumulative Out-of-Sample Squared Forecast Error Performance



Panel B. Out-of-Sample Squared Forecast Error Difference

Figure 5
Out-of-Sample Forecast Error Performance - *DYN EPU-COND PRED*
This figure compares the accuracy of ERP forecasts based on *DYN EPU-COND PRED* with the unconditional ERP forecast (*HIST MEAN*), under the recursive window approach. This plot helps us understand the relative performance of *DYN EPU-COND PRED*. Panels A and B correspond to the cumulative out-of-sample squared forecast error and the month-on-month difference in squared forecast error of *DYN EPU-COND PRED* and *HIST MEAN*, respectively. When the dotted orange line is below the solid blue line in Panel A, it indicates that the *DYN EPU-COND PRED* has superior forecast accuracy compared to *HIST MEAN* till that month. Positive value of the difference in squared forecast error in Panel B indicates that *DYN EPU-COND PRED* had lower forecast error than *HIST MEAN* in the month.

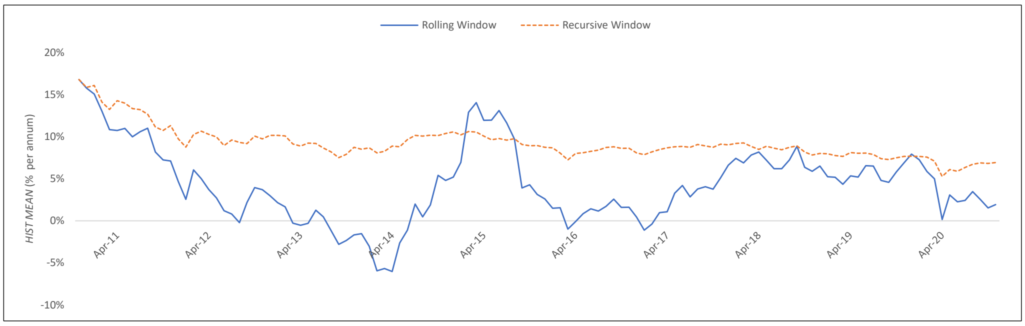


Figure 6
***HIST MEAN* - The Rolling and the Recursive Window approaches**
This figure plots the time series of unconditional ERP forecasts (*HIST MEAN*) under the rolling and the recursive window approaches from November 2010 to November 2020.

Appendix A

The Sharpe ratio, $\hat{\zeta}$, of the trading strategy based on the ERP forecasts of a given predictor is:[28]

$$\hat{\zeta} = \frac{\hat{\mu}}{\hat{\sigma}} \tag{4}$$

where $\hat{\mu}$ and $\hat{\sigma}$ are the sample mean and sample standard deviation of the monthly excess returns from the strategy.

Under the assumption that the excess returns are independently and identically distributed (i.i.d) samples from a normal distribution, $\hat{\zeta}$ is biased and the bias is proportional to the true Sharpe ratio (Miller and Gehr 1978). The mean of the sampling distribution of $\hat{\zeta}$ is:

$$\mathbb{E}[\hat{\zeta}] = \zeta\sqrt{\frac{n-1}{2}}\frac{\Gamma(\frac{n-2}{2})}{\Gamma(\frac{n-1}{2})}) \tag{5}$$

where $\Gamma(n) = (n-1)!$ is the gamma function. The bias factor, $\frac{\mathbb{E}[\hat{\zeta}]}{\zeta}$, is more than 1 and converges to 1 as the sample size, n, increases.[29] For our sample size of 121 excess returns, the bias is negligible.

The variance of $\hat{\zeta}$ is:

$$Var[\hat{\zeta}] = \frac{(1+n\zeta^2)(n-1)}{n(n-3)} - \mathbb{E}[\hat{\zeta}]^2 \tag{6}$$

For eight predictors, we strongly reject the null hypothesis that the excess returns are normally distributed using the Jarque-Bera test. Relaxing the assumption of normally distributed excess returns, but maintaining the i.i.d assumption, Bao 2009 proposes an *approximately unbiased* estimator of ζ,

[28]We drop subscript i, which indexes the predictor, for notational simplicity.

[29]For example, the bias factor is 1.08 for n=12, 1.02 for n=40, and 1.01 for n=75.

given by:

$$\hat{\zeta}_{ab} = \hat{\zeta} - \frac{3}{4n}\zeta + \frac{1}{2n}\gamma_1 - \frac{3}{8n}\zeta\gamma_2 \tag{7}$$

where γ_1 and γ_2 are the Pearson's measures of skewness and kurtosis. For a normal distribution, these parameters are all equal to zero.

The estimator is *approximately unbiased* because the exact formulae for the expectation of the estimator (equation (7)) contains higher order terms of the sample size, n. We ignore these higher order terms since our relatively large sample size of 121 observations introduces minimal approximation error in the computations, while reducing computational complexity significantly. Since $\hat{\zeta}_{ab}$ depends on unknown population parameters, we replace ζ and the γs with their corresponding sample estimates. The sample estimates of the γs are the Fisher's k-statistics.

The bias-corrected estimated Sharpe ratio, $\hat{\zeta}_{ab}$, has no known theoretical probability distribution when the distribution of excess returns is non-normal. Hence, we obtain the sampling distribution of the estimator by bootstraping the excess return series. The unbiasedness of $\hat{\zeta}_{ab}$ depends crucially on the assumption of i.i.d excess return series, which is unlikely to hold in real world data.[30] We estimate the bias, arising due to violation of the i.i.d assumption, from the bootstrap sampling distribution of $\hat{\zeta}_{ab}$. If there is no bias, the bootstrap sampling distribution would be centred on the original sample statistic, $\bar{\zeta}_{ab}$. Therefore, we estimate the bias ($\hat{B}_{ab}$) as the difference between the mean of the bootstrap sampling distribution and the original sample statistic, $\bar{\zeta}_{ab}$. The unbiased estimator of the population Sharpe ratio under a general data generating process (DGP) of excess returns is:

$$\hat{\zeta}_{gdgp} = \hat{\zeta}_{ab} - \hat{B}_{ab} \tag{8}$$

[30]Using the Box-Pierce test, we are unable to reject the joint null hypothesis of no autocorrelation in excess returns (up to 5 lags) for all the predictors, except *DIV PRICE* and *DIV PAY*. However, the Box-Pierce test examines whether the excess return series is uncorrelated rather than i.i.d, which is a stronger assumption than uncorrelatedness.

We obtain the sampling distribution of $\hat{\zeta}_{gdgp}$ by simply shifting the bootstrap sampling distribution of $\hat{\zeta}_{ab}$ by the bias, $\hat{B}_{ab}$. From the bootstrap sampling distribution, we calculate the two-tailed p-value corresponding to the original sample statistic, $\bar{\zeta}_{gdgp}$. This enables us to compute the statistical significance of the Sharpe ratios corresponding to the 17 predictors.