PREDICTABILITY OF EMERGING MARKET ERP CONDITIONAL ON ECONOMIC POLICY UNCERTAINTY

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INTRODUCTION

- Expectation about the magnitude of equity risk premium (ERP) is a key determinant of investment flows in an economy
- 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
- Welch and Goyal(2008) show that individual predictors fail to generate superior out-of-sample forecasts, relative to the unconditional (historical) mean ERP
- Rapach et al.(2010) point out that the mean forecast of individual predictors generates superior out-of-sample predictability relative to individual predictors

Emerging Markets ERP

- Nearly all studies on ERP predictability have focused on developed markets; their findings may therefore be less relevant for predicting emerging market ERP
- Emerging market's ERP may be influenced by additional factors (e.g., degree of market integration) that do not arise in the case of developed markets
- There is a rich body of research that has pointed out that equity returns in emerging markets are affected by the degree of market integration (Bekaert (1995); Bekaert and Harvey (2003); Buckberg (1995); De Jong and De Roon (2005); C. R. Harvey (1995); Henry (2000))
- In this paper, we present a benchmark study for predicting an emerging market's ERP

EMERGING MARKETS ERP

- We look at 3 potential factors other than the standard set of predictors employed in predicting ERP of developed markets: -
  - **Economic Policy Uncertainty (EPU)** - Risk premium demanded by investors vary with the level of EPU (e.g., Harvey(2004), Damodaran (1999, 2020b))
  - **Foreign institutional investor (FII) flows** – Portfolio rebalancing by foreign investors reflect changing expectations about ERP (e.g., Ananchotikul and Zhang (2014), Acharya et al.(2022), Coval and Stafford (2007), and Jotikasthira et al.(2012))
  - **S&P 500 to NIFTY 500 ratio** - Foreign investors in emerging markets often engage in trend chasing investment strategies (Brennan and Cao (1997), Froot and Ramadorai (2008), among others), which affects asset price formation in emerging markets

Predictors and Sources

Variables	Data Source
Short Term Treasury Rate (TBILL 3M)	Bloomberg and FBIL
Long Term Government Bond Rate (GBOND 10YR)	Bloomberg
Default Spread (DEF SPREAD)	Bloomberg (Calculated)
Term Spread (TERM SPREAD)	Bloomberg (Calculated)
INFLATION	Bloomberg
Book to Market Ratio (BOOK MKT)	Bloomberg
Earnings to Price Ratio (EARN PRICE)	Bloomberg
Dividend to Price Ratio (DIV PRICE)	Bloomberg
Dividend Yield (DIV YIELD)	Bloomberg
Dividend Payout Ratio (DIV PAYOUT)	Bloomberg
Cash Flow to Price Ratio (CF PRICE)	Bloomberg
NIFTY500 Variance (NIFTY VAR)	Bloomberg (Calculated)
S&P500 to NIFTY500 Ratiio (S&P NIFTY RAT)	Bloomberg
Percent change in FII flows (FII PER CHG)	Bloomberg (Calculated)

The Model

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

- Ordinary least squares (OLS) regression model applied to training data using the recursive window approach, starting with an initial sample size of 75 months
- Generate a series of one-step-ahead ERP forecasts (for each predictor) where the starting estimation date is fixed, but additional observations are added one at a time
- 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 each predictor
- Mean Combination Forecast (MEAN COMB) is the average of forecasts made by the individual predictors for each month in the OOS period

DYNAMIC EPU-CONDITIONED PREDICTOR (DYN EPU-COND PRED)

- We conjecture that prediction of an emerging market's ERP can be improved by conditioning on the level of domestic economic policy uncertainty
- 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

DYNAMIC EPU-CONDITIONED PREDICTOR (DYN EPU-COND PRED)

- We classify each month's EPU in the OOS period as belonging to a low, moderate, or high uncertainty regime, which is the forecasted EPU regime for the next month
- Each month's EPU belongs to one of three regimes, identified from the distribution of EPU values from July 2004 to month $t-2$, where $t-1$ denotes the current month
- Values below the 20th percentile indicate low uncertainty while values above 80^{th} percentile indicate high uncertainty. Values between the 20th and 80th percentile capture periods of moderate uncertainty
- 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

Dynamic EPU-Conditioned Predictor (DYN EPU-COND PRED)

- Since we cannot know, 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 16×16×16 (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)
- The optimal forecasting strategy is to classify the level of uncertainty in the economy 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

Forecast Evaluation

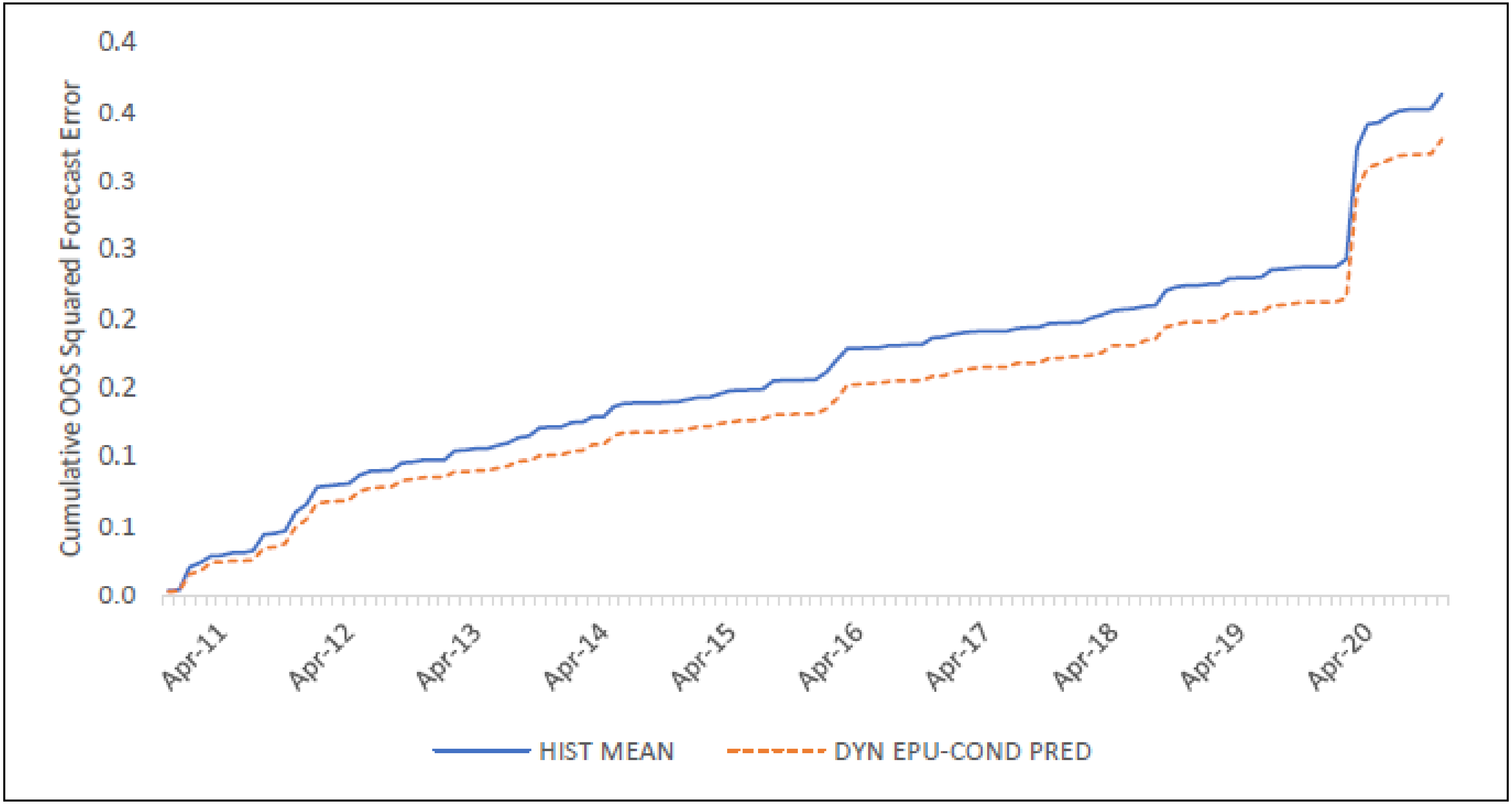
- We compare the forecast accuracy of the predictors relative to *HIST MEAN*, using the R^2_{OS} statistic, proposed by Campbell and Thompson(2008)
- Positive value of R^2_{OS} implies that the predictor has lower mean square prediction error (MSPE) than *HIST MEAN*
- Clark and Mccraken(2001) show that the statistic has a nonstandard distribution when forecasts are generated from nested models, as is our case
- To obtain more precise p-values for the one-sided (right tail) hypothesis test, we employ the nonparametric bootstrap procedure
- This involves resampling the OOS forecasts with replacement followed by inference from the resulting sampling distribution of MSPE

Results – Out-of-Sample performance

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**

DYN EPU-COND PRED is the combination of DIV PAY, CF PRICE, and S&P NIFTY RAT during periods of low, moderate, and high uncertainty, respectively

RESULTS – OUT-OF-SAMPLE FORECAST ERROR



How Large are the Forecasting Gains?

- We compute the following two measures to quantity the profitability of trading strategies based on ERP forecasts of the predictors: -
  - **Utility gains** (Rapach et al.(2010)) - Utility gains of a representative investor, where the gain is w.r.t. the utility realized from the trading strategy based on *HIST MEAN*
  - **Sharpe ratio** - Ratio of the sample mean and sample standard deviation of the monthly excess returns generated from the trading strategy
- The representative mean-variance optimizing investor is assumed to have a power utility function with a coefficient of relative risk aversion (CRRA) of 2
- The investor holds a combination of the market portfolio and 30-day T-bills, where the portfolio weights are a function of the ERP forecasts of a given predictor (Rapach et al.(2010))
- Portfolio rebalanced monthly with the weight on the market portfolio restricted to lie between 0 and 1.5 (no shorting and leveraging beyond 50%)

RESULTS – UTILITY GAINS

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

Sharpe Ratio

- We cannot comment of the statistical significance of the realized utility gains, which is a drawback of the measure
- Alternatively, we compute the statistical significance of the Sharpe ratios generated by the predictors using the same trading strategy
- A trading strategy is profitable if its Sharpe ratio is significantly different from zero (positive or negative), since the investor can always reverse the long-short positions in the portfolio
- We also report haircut Sharpe ratios (HSR) of the trading strategies, which adjust for potential data mining (Harvey and Liu (2015))
- The haircut Sharpe ratio is imputed from multiple testing p-values (as opposed to p-values of single tests) following Benjamin and Hochberg(1995) and Benjamin and Yekutieli(2001)
- The haircuts depend on the original Sharpe ratios; the larger Sharpe ratios are penalized less compared to smaller Sharpe ratios

Results – Haircut Sharpe Ratios

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** **

Robustness Tests

- We conduct the following robustness tests: -
  - Choose initial sample sizes of 60 and 90 months under the recursive window approach
  - Use alternative EPU thresholds of (10, 90) and (30, 70) percentiles for identifying periods of low, moderate, and high uncertainty
- These modifications have no significant effect on the main results, although they affect the identification of low, moderate, and high uncertainty regimes

ROBUSTNESS TESTS – DEVELOPED MARKET

- We repeat the analysis for the US equity market, proxied by the S&P 500 Total Returns Index
- We choose the set of predictors which lie at the intersection of our analysis for the Indian market and Rapach et al. (2010) analysis for the US market
- We also construct the Dynamic EPU-Conditioned predictor for the US market in the same way we did for the Indian market using the (20, 80) percentile threshold
- Although, we identify a unique combination of predictors that generates the highest forecast accuracy, this combination is not robust to alternative EPU thresholds
- *TBILL 3M* is the only predictor which is robust in the high uncertainty regime, consistent with the flight-to-safety phenomenon (Adrian, Crump, and Vogt (2019); Baele, Bekaert, Inghelbrecht, and Wei (2020); He, Krishnamurthy, and Milbradt(2019); Nagel (2016))

CONCLUSION

- We contribute to the literature by proposing a new predictor (S&P 500 to NIFTY 500 ratio) which outperforms the unconditional ERP forecast
- 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
- Moreover, the Dynamic EPU-Conditioned predictor generates the highest utility gains as well as the highest Sharpe ratio of 0.57
- This study 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

THANK YOU