Density Forecasts and the Evolution of Macroeconomic Uncertainty in India

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Abstract

This paper estimates uncertainty shocks using density forecasts from the Reserve Bank of India's Survey of Professional Forecasters (2008–2023). These forecasts enable a direct measurement of unobservable uncertainty in real-time, as the first difference in the second moment of the densities. In addition, we propose a forecast calibration test based on the predictive sequential principle. We report five key findings: (i) macroeconomic uncertainty in India has been on a decline since 2008; (ii) shocks to uncertainty derived from density forecasts compare favorably with other popular measures, viz. Economic Policy Uncertainty and VIX; (iii) prequential tests indicate forecasts to be calibrated; (iv) uncertainty is affected primarily by negative news and is variance rational, and (v) it captures demand shocks even after controlling for global uncertainty shocks, in contrast to EPU and VIX, which are primarily driven by supply shocks. Distinguishing these shocks is crucial for optimal monetary policy.

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1 Introduction

High levels of uncertainty have adverse real economic effects: they tend to suppress real economic activities and complicate the price-setting behavior of firms (Fernández-Villaverde et al. (2011)). Given the detrimental effects of uncertainty, measuring it has become an important endeavor for economists. Ahir et al. (2025) noted that there are three popular measures of uncertainty, financial markets-based measures (VIX Index), text-based measures such as Economic Policy Uncertainty (EPU), and survey-based uncertainty measures. This paper focuses on a survey-based measure derived from density forecasts for India.

Not all surveys lend themselves to providing measures of uncertainty. Some surveys obtain only point forecasts, which do not provide direct information about how confident forecasters are about their point estimates. However, density forecasts require forecasters to provide not just point estimates, but also their views about the entire probability distribution of outcomes. Hence, the change in the second moment of the distribution provides a natural measure of forecast uncertainty.

An example of such a dataset is the U.S. Survey of Professional Forecasters (SPF), which has regularly collected information on density forecasts since 1968 and has been increasingly used for the direct measurement and analysis of uncertainty. For example, Lahiri & Sheng (2008) use the US SPF data to measure uncertainty. In addition, they had decomposed it as the sum of forecaster disagreement and the perceived variability of future shocks. Similarly, Campbell (2007) analyzes the US SPF to document a general decline in uncertainty during the Great Moderation. In the European context, Abel et al. (2016) uses the ECB SPF to construct a measure of uncertainty based on individual histograms, forecast dispersion, and forecast accuracy.

Professional forecasters offer deeper insights into future outcomes because they closely monitor current economic conditions, target specific variables, and align their analyses with relevant forecasting horizons. In contrast, text-based measures derived from published materials often capture the opinions of their authors rather than objective economic assessments. The VIX on the other hand, captures the sentiment of the financial sector. Consequently, an uncertainty measure derived from professional macroeconomic forecasts serves as a useful supplement to other uncertainty measures.

Forecast evaluation of density forecasts requires going beyond the standard tests of bias and efficiency. It requires evaluating the validity of these forecasts across each individual bin. We comprehensively evaluate the validity of these forecasts and test for bias and efficiency. In addition, we propose a calibration test based on Dawid (1984)'s Predicting Sequential Principle (prequential) that allows for a bin-by-bin forecast evaluation.[1]

This paper introduces an uncertainty measure based on density forecasts for India -

[1]Density forecasts and their performance have been extensively investigated using data from U.S. and the euro area. See Diebold et al. (1997) for a classic study using US SPF data. Also see Tay & Wallis (2000), Bauwens et al. (2004), Lahiri & Liu (2006), Hall & Mitchell (2007), Amisano & Giacomini (2007), Clements (2018) and Schick (2024).

a large emerging market economy. We use a relatively understudied data on the density forecasts collected by the Reserve Bank of India (RBI) and construct a time series of aggregate macroeconomic uncertainty. The density forecasts are collected as a part of RBI's Survey of Professional Forecasters (SPF). To our knowledge, this is the first paper to analyze density forecasts for India and explore how they can be used in policy making.[2]

We identify the key drivers of macroeconomic uncertainty and show that negative information shocks computed from fixed-target forecasts significantly amplify uncertainty. Additionally, we uncover a strong relationship between subjective uncertainty and forecast revisions, with elevated periods of uncertainty leading to theoretically expected larger forecast errors, cf. Del Negro et al. (2022).

In addition, we examine the effect of uncertainty shocks on the dynamics of Indian macroeconomic aggregates. Recent studies underscore the impact of uncertainty shocks on business cycles. Fernández-Villaverde & Guerrón-Quintana (2020) and Houari (2022) analyze their effects in the U.S., using financial, macroeconomic, and policy uncertainty measures. Gupta (2024) finds that interest rate alone is inadequate for managing global uncertainty shocks under flexible inflation targeting.[3] A notable difference in our approach is the use of an uncertainty measure derived from SPF density data.

Similar to the evidence in the literature from other countries, we show that uncertainty has significant negative effects both in short- and medium-term on real economic outcomes. In addition, we highlight the differences in these three uncertainty measures, as SPF-U uncertainty is found to capture demand shocks whereas VIX and text-based EPU measures are better at capturing supply-driven shocks. Our results imply that in response to an increase in SPF uncertainty, policymakers must reduce policy rates. In contrast, an increase in uncertainty measured via EPU or VIX requires a policy response that balances two conflicting objectives of stabilizing output and price stability. Our findings are broadly generalizable to other large emerging market economies that follow inflation targeting regimes.

The structure of the paper is as follows. In section 2 we describe the data. Section 3 evaluates the RBI-SPF density forecasts through standard tests for bias and forecast efficiency. In addition, we introduce a novel calibration test designed to assess forecast accuracy at the bin level, providing a more granular evaluation of density forecasts. Section 4 introduces our proposed measure of uncertainty and compares it with widely used benchmarks. In section 5, we explore the determinants of uncertainty in terms of past forecast errors and forecast revisions over horizons as ex ante "news." In section 6 we estimate a standard structural vector autoregressive model (SVAR) to evaluate the dynamic effects of uncertainty shocks on macroeconomic variables. Section 7 concludes.

[2]Patra et al. (2023) use SPF data to measure uncertainty. However, they use point and not density forecasts in their analysis. Also see Singh & Bandyopadhyay (2024) for a discussion on disagreement.

[3]Also see Patra et al. (2023), Kumar et al. (2021), Das & Kumar (2018) and Swallow & Céspedes (2011)

2 Data

For our analysis, we rely on the density forecasts collected by the Reserve Bank of India as part of its Survey of Professional Forecasters (SPF). India's SPF data is based on similar survey for the US – which was initially known as the ASA-NBER survey.[4] Beginning with the 2014Q2 (28th Round), the survey frequency was increased to bimonthly in order to better align with the schedule of monetary policy deliberations.

The density forecasts for GDP growth are fixed target forecasts with a total of eight forecast horizons.[5] Professional forecasters report an initial probability distribution two years before the end of target year. In each subsequent period, as new information arrives, professional forecasters update their previous forecasts. We use the aggregate probability densities since RBI does not provide individual density forecasts, but aggregates them to provide aggregate histogram forecasts as part of its data release.[6]

In addition to growth densities, SPF also collects density forecasts for inflation. During the early part of the survey, SPF collected forecasts on Wholesale Price Index (WPI) inflation. However, due to the changes in nominal anchor for monetary policy in mid 2010s, RBI solicited density forecasts for CPI inflation rate in the latter period. Furthermore, for inflation forecasts, there were shifts in fixed vs. rolling-forecast horizons for inflation. Due to these changes, the overall sample period for inflation forecasts is limited. As a result, we report only a few findings on inflation and instead concentrate primarily on growth forecasts.

An important source of information for professional forecasters while drawing their initial forecasts is historical data. We report the historical RGDP and CPI inflation in Figure 1 starting from 1951 onwards. Average growth rates have increased from three per cent during the first three decades (1950-1979) to around six per cent since then (see Table 1). While both output and inflation have historically exhibited considerable volatility, economic growth has become notably more stable over the past three decades. A reasonable initial guess for professional forecasters would be that output would grow at the recent historical average of six percent per year. This expectation is reflected in the professional forecasts, which we analyze in greater detail using density-based projections.

In Figure 2, we report the mean point forecasts for GDP growth rates obtained from density forecasts at each forecast horizon for different years. The last value in the chart corresponds to the outturn value for the target variable. Note that we do not find much horizon specific effects. Analysis of variance reveals that horizon dummies explain only 6.7% of the total variation in GDP point forecasts over time. Extraordinary shocks to GDP growth dwarf any possible horizon effects in these data. In addition, we find

[4]Starting with June of 1990, the Federal Reserve Bank of Philadelphia started conducting the US SPF. Prior to this transition, analysis of SPF density forecasts were reported in Zarnowitz & Lambros (1987), Lahiri & Teigland (1987) and Lahiri et al. (1988).

[5]To ensure comparable data over time, we drop the two additional rounds that were introduced after the 28th round. Thus, we end up with four survey rounds within a year that align with the original quarterly frequency of the survey.

[6]We use the word "aggregate" to avoid the confusion with "consensus" professional forecasts collected by Consensus Economics Inc.

that for most years, the initial forecasts aligned within a narrow range of 6 – 8 per cent, which is consistent with India's recent high growth experience and converged well to the final values at the one-quarter horizon. These dynamics are similar to the evidence reported by Isiklar & Lahiri (2007) for advanced economies.

As forecasting rounds expands, and economic shocks are realized, forecasters update their forecasts for the same target (see Figure 3). Forecast revisions, especially at the initial forecast rounds (horizons 7 – 5) are close to 0 except for 2009 (economic slowdown) and 2015 (drought year). The precipitous fall in GDP forecasts for target year 2020 due to the COVID-19 epidemic is reflected in 2019Q4 and 2020Q1. Forecasters would make larger revisions when new information about the target variable is available. Preliminary estimates for current year's GDP growth rates are released around forecast horizons 4 and 3 in India. Not surprisingly, forecasters make larger revisions at these forecasting horizons by incorporating new information.[7]

Four Parameter Beta Distribution

Density forecasts are reported as histograms in SPF. Early studies assumed the probability mass to be concentrated at the mid-point of each bin of a histogram. In addition, the density forecasts have open-ended intervals at the extreme tails of the distribution. Recent literature has used an alternative approach of fitting normal distributions given that the true underlying distributions for inflation and GDP are continuous and unimodal, cf. Giordani & Söderlind (2003). We resolve these issues by fitting generalized beta distributions as proposed by Engelberg et al. (2009).[8] The measures of central tendency and dispersion can be obtained from the fitted distributions. This approach has previously been successfully applied to professional forecasts.[9]

Assuming that density forecasts have a unimodal distribution that belongs to the generalized beta family, we estimate the parameters of the distribution by minimizing the sum of the squared distances between each point on the empirical distribution and that of the beta distribution. The generalized beta function that we use has four parameters, two shape parameters (a, b) and two support parameters (l, u). To ensure that the distribution is unimodal, we constrain both a and b so that they are greater than unity.

The choice of support varies across different quarters. For survey rounds where the open-ended intervals receive zero probability, the support is constrained to the lower and the upper-bound of the closed intervals. For these rounds, only the shape parameters (a, b) have to be estimated. There are some quarters where one of the open-ended bins receive a positive probability, and some quarters both of the open-ended bins receive a positive probability. In these cases, additional support parameters have to be estimated.

[7]See Isiklar & Lahiri (2007) for a discussion on timing of data releases and their effect on forecast revisions.

[8]The Jarque & Bera (1980) test for normality is rejected in all cases at the 5% significance level except for Dec. 2007, Jan 2008, Dec. 2008, June 2009 and Sept 2009.

[9]See Andrade et al. (2014) and Lahiri & Wang (2021).

There are several advantages to the choice of generalized beta distribution. The conventional method of assuming the probability mass to be distributed at the mid-point violates the assumption of a globally continuous distribution of the target variable with a peak. Furthermore, the four-parameter beta distribution is highly flexible, allowing it to accommodate different shapes when imposed on histograms, particularly when histogram displays excess skewness or kurtosis. The third advantage is that by generalizing the support to *(l, u)*, fitting a four-parameter beta distribution addresses the open-ended intervals.

Specifically, we minimize:

$$\sum_{i=1}^{n} [\mathrm{Beta}(s_i; a, b, l, u) - F(s_i)]^2 \tag{1}$$

where s_i is the upper end of response interval i and $F(s_i)$ is the share of responses in intervals 1 to i.

$$\mathrm{Beta}(s_i; a, b, l, u) = \begin{cases} 0, & \text{if } s_i \le l \\ \frac{1}{B(a,b)} \int_l^{s_i} \frac{(x-l)^{a-1}(u-x)^{b-1}}{(u-l)^{a+b-1}} \, dx, & \text{if } l < s_i \le u \\ 1, & \text{if } s_i > u \end{cases}$$

where $B(a,b) = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}$ is the beta function and $\Gamma(\cdot)$ is the gamma function. This distribution generalizes the support of a standard beta distribution from $(0,1)$ to (l,u). The estimation is carried out for each quarter using the survey responses from SPF density forecasts.

3 Forecast Properties and Calibration Tests

In this section, we present important characteristics of the Indian SPF density forecasts. We propose a calibration test that allows for bin-by-bin examination of forecast calibration. Our tests establish these forecasts to be reasonable and consequently appropriate for deriving a robust measure of uncertainty.

Forecast Bias and Efficiency

Professional forecasts have been extensively studied in literature with an explicit focus on their properties such as bias and efficiency, cf. Conrad & Lahiri (2025).[10] Typical bias and efficiency tests have used point forecasts. As forecasting period evolves, forecasters undertake several revisions in an effort to incorporate new information. Consequently, forecast errors tend to be larger at longer horizons, gradually diminishing over time as successive forecasts incorporate increasingly rich and timely information. Following Holden & Peel (1990), we test for bias in forecasts by examining whether the forecast errors have a mean of zero—a sufficient, though not necessary, condition for unbiasedness. The estimated constant term for RGDP and inflation were 0.56 (p-value = 0.33) and 0.00 (p-value = 0.99), respectively, indicating that the forecasts

[10]See Nordhaus (1987), Lahiri & Wang (2013) , Loungani (2001) and Isiklar et al. (2006).

are statistically unbiased.

Furthermore, in Figure 4, we report the mean absolute forecast error (MAFE) for both target variables over available horizons. We treat the first moment of densities as our point forecast to compute MAFE. As shown in Figure 4, for both RGDP and inflation, MAFE falls steadily as the forecast horizon declines; however, the decline over horizons is modest.

In addition to the bias, an equally important issue is whether forecasts are efficient in terms of utilizing new information. An early test for this idea was proposed by Nordhaus (1987) who in one of his formulations tests whether current forecast revisions are correlated with past forecast revisions. If forecasts were fully efficient, then there should be no systematic correlation between current forecast revision and past forecast revisions. To test this hypothesis, we estimate the following model:

$$f_{t,h} - f_{t,h+1} = \alpha + \beta\left(f_{t,h+1} - f_{t,h+2}\right) + \varepsilon_{t,h} \tag{2}$$

where $f_{t,h}$ is the h-period ahead point forecast ($h = 8, 7, \ldots, 1$), and t stands for the target year. Under the null hypothesis of forecast efficiency, all relevant information is incorporated into the forecast through forecast revision. Therefore, $\alpha = 0$ and $\beta = 0$ under efficiency.

As reported in Table 2, forecast efficiency test indicates the growth forecasts to be efficient as there is limited evidence of serially correlated forecast revisions. The coefficient on lagged forecast revisions is statistically insignificant and reasonably close to 0. This result holds even when the Covid period observations are excluded from the sample.[11]

Calibration Test

The bias and efficiency tests discussed in the previous subsection focus on the point forecast from density data. There are several forecast evaluation tests that have been developed in case of density forecasts. For instance, Diebold et al. (1999) provides an early test of forecast densities using probability integral transforms (PITs). In contrast, efficiency tests developed by Mincer & Zarnowitz (1969) and later extended by Patton & Timmermann (2012) have relied on using the first moment from the distributions.[12]

We propose an alternative approach for testing density forecasts that adopts the prequential principle advocated in Dawid (1984) and utilized in Lahiri & Wang (2013). A key difference between our approach and the tests of first and second moments of density forecasts is that the prequential approach allows for a bin-by-bin test of calibration in addition to a global measure of calibration.

[11] We did not report the corresponding results for inflation due to relatively small sample size with fixed target forecasts collected by the survey.

[12] Also see Manzan (2021) for a discussion of efficiency tests using the second moment of SPF density data in the context of a Bayesian Learning Model.

Dawid (1984)'s Predictive Sequential Principle (prequential) states that the performance of the sequence of forecasts, in relation to the sequence of outcomes, should not depend on the process of generation of these forecasts. The underlying principle was used in a different context by Lahiri & Wang (2013) to test whether US-SPF recession forecast probabilities were calibrated.[13]

We begin by treating the outturn of the target variable within a given interval as a binary event that takes value 1 when true and 0 otherwise. At each forecasting horizon, professional forecasters assign a probability that the target variable would belong to a given interval. Before assigning probability to a given interval for a target variable, the forecaster has all available information, including the value of the target variable in preceding periods. Therefore, a rational forecaster is expected to know the probability of the target variable belonging to an interval based on historical data.

We aggregate the total assigned probabilities to each interval over time. That is, the SPF reports the assigned probability $\pi_{j,t}$ for the target variable x_{t+h} belongs to interval j. The aggregate total assigned probability to a given interval is given by:

$$\pi_j = \sum_{t=1}^{T} \pi_{j,t} \tag{3}$$

Each forecast interval is associated with a pair comprising the average assigned probability of the target variable falling within the interval and the empirical frequency of its realizations therein over the sample. The underlying process of forecast and data generations is assumed to be the same across time under the null.[14]

Formally, let there be J intervals for the target variables and for each $j = 1, 2, \ldots, J$ there is an assigned forecast probability π_j. For each interval, the count of the number of times target variable lies within a given interval j is given by o_j. Most macroeconomic variables are subject to revisions over time as new information becomes available. Such information is not available with professional forecasters at the time of making their forecasts, and therefore, a calibration test that compares assigned probabilities with actual occurrence based on revised data would be dubious. The appropriate test would require the comparison of assigned probabilities with vintage data of target variables. The distinction between vantage and revised data is an important issue particularly for evaluating growth forecasts given that Indian GDP series undergoes several revisions.

The assigned forecast probabilities are transformed into relative probabilities denoted by $\bar{r}_j$ and given by $\bar{r}_j = \frac{\pi_j}{\sum_{j=1}^{J} \pi_j}$ where j represents the given class interval and π_j is the given frequency for class interval j. Similarly, a relative occurrence is defined as $\bar{o}_j$ and given by $\bar{o}_j = \frac{o_j}{\sum_{j=1}^{J} o_j}$. For perfectly calibrated forecasts, $\bar{o}_j = \bar{r}_j$. The null hypothesis

[13]Also see Seillier-Moiseiwitsch, F. and Dawid, A. P. (1993) for a detailed discussion on prequential test.

[14]Our sample period for pre-covid years comprises of 13 years, and therefore, 13 observations for the target variable of GDP growth rate. However, the effective sample size for our test is larger since probability is assigned to the target variable at each horizon (h) for a given target year. This increases the effective sample to TH.

is that the sequence of occurrence is generated by the same joint distribution that generates the forecasts, and that there are no differences between these two relative measures.

Under the null hypothesis, we define the test statistic as $\bar{r}_j - \bar{o}_j$, which follows a Normal distribution with variance w_j. The variance of the binary outcome under the null hypothesis is given $w_j = \bar{o}_j(1 - \bar{o}_j)$ suggesting the N (0, 1) test statistic Z_j given by $Z_j = \frac{r_j - \bar{o}_j}{\sqrt{w_j}}$. For a test of global calibration over all bins, the test statistic is defined as $\sum_{j=1}^{J} Z_j^2$. The intuition for this test comes from the fact that some of the class intervals are more likely than others, and therefore, the probability densities assigned by professional forecasters should reflect this. The overall performance of the forecasts across all j is evaluated using the test statistic $\sum Z_j^2$, which is asymptotically distributed as a chi-squared distribution χ^2 with $J - 1$ degrees of freedom.

While implementing the test, we group forecast intervals to four class intervals due to relatively sparse probabilities for some forecast intervals. Following the recommendation of Seillier-Moiseiwitsch, F. and Dawid, A. P. (1993), bins with less than seven observations were consolidated with adjoining bins. A similar approach was necessary in the empirical examples of both Seillier-Moiseiwitsch, F. and Dawid, A. P. (1993) and Lahiri & Wang (2013).

We report the results of the calibration test in Tables 3 and 4. The critical value for Chi-Square with 3 degrees of freedom at 0.05 significance level is 7.82 and therefore whenever the overall Chi-Square value is greater than 7.82, we reject the null hypothesis of calibrated forecasts. Since the calculated Chi-Square values were only 0.26 for GDP and 0.10 for inflation, our key conclusion from our test is that the forecasts are calibrated, with the important caveat that due to data sparsity, we consolidated few adjoining bins for our calculation. Thus, with a battery of tests, we conclude that the density forecasts from SPF provides a reasonable measure of ex-ante macroeconomic uncertainty.

4 Measuring Uncertainty using Density Data

In this section, we compare the uncertainty measure obtained from density data with other popular measures of uncertainty. As mentioned earlier, the Reserve Bank of India provides data on aggregate densities. That is,

$$f_c(y) = \frac{1}{n} \sum_{i=1}^{n} f_i(y) \tag{4}$$

where $f_c(y)$ is the aggregate probability density and $f_i(y)$ is individual i's assigned probability for the target variable Y being equal to y. A widely used convention in the literature is to treat the average of individual forecast uncertainties as a proxy for aggregate uncertainty, thus requiring individual densities. However, following the fully articulated Bayesian approach of Draper (1995), the uncertainty of a combined forecast is the sum of average individual uncertainty and disagreement.[15] That is,

$$\sigma_c^2 = \frac{1}{n}\sum_{i=1}^{n}\sigma_i^2 + \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - \hat{y}_c)^2 \tag{5}$$

where σ_c^2 is the variance of the aggregate density, $\hat{y}_i$ is the mean point forecast for individual i, $\hat{y}_c$ is the mean point forecast for the consensus distribution, and σ_i^2 is individual i's forecast uncertainty (individual density variances). Thus, as motivated by recent research, we define uncertainty as the second moment of the consensus density cf. Lahiri et al. (2022). Consequently, we compute the second moment of the fitted four-parameter beta distribution on aggregate growth densities as our measure of macroeconomic uncertainty.

Other popular measures of uncertainty include the economic policy uncertainty measures by Baker et al. (2016), VIX or those that rely on GARCH-type models. A criticism of the model-based measures of uncertainty is that forecast uncertainty can often be determined by several factors outside the model specification as shown by Lahiri & Liu (2006).

We begin by benchmarking the uncertainty measure derived from density forecasts against established indicators. A popular measure is the VIX index which captures the annualized 30-day volatility of S&P 500 and is constructed by averaging the weighted prices of a specified group of S&P 500's call and put options. Given that Chicago Board Options Exchange (CBOE) – VIX is a measure of US stock market volatility, we interpret it as an alternative measure of global stock market volatility. A similar VIX that is based on the annualized 30-day volatility of India's NIFTY Index option prices (NIFVIX) is a measure of Indian stock market volatility.[16]

We use the Ahir et al. (2022) Economic Policy Uncertainty Index (EPU) for India as a text-based uncertainty measure which is developed using the same principle as in Baker et al. (2016). The construction of the uncertainty measure relies on the frequency with which the word "uncertainty" features in the Economist Intelligence Unit (EIU) Country reports.

Figure 5 compares the SPF uncertainty index (SPF-U) with the Ahir et al. (2022) EPU Index for India and the Indian VIX Index. Note that unlike the EPU and VIX indices, the uncertainty measure derived from the Survey of Professional Forecasters (SPF) are horizon-specific. However, as we pointed out before, the horizon effects are small as they are dwarfed by the total variability in the target variable over time. In these data, the horizon dummies explain only 5.5% of the total variation in the uncertainty series. In the analysis that follows, we control for the effect of horizons using dummies and generate a consistent series of nowcast-equivalent uncertainty over 2008Q1-2023Q3 at a quarterly frequency. Furthermore, all three uncertainty measures are harmonized for comparability, with their base values normalized to 100 in the first quarter of 2008.

[15] See Wallis (2005) and Lahiri & Sheng (2008) for alternative approaches to derive the same result.

[16] In this paper, we use VIX for NIFVIX and CBOE – VIX for US VIX. Both these measures have a very high correlation (0.77).

Irrespective of the choice of uncertainty measure, we observe a significant decline in uncertainty during the pre-pandemic period. Relatively stable economic environment has contributed to the secular decline in uncertainty during this period. All these measures rose sharply during the COVID-19 pandemic, with the VIX leading the other two indicators. Because stock markets react instantaneously to news, the VIX index consistently reflects higher levels of uncertainty throughout the sample period compared to the SPF-based measure. This is reflective of greater volatility surrounding stock markets relative to the stable growth recorded by India during this period. However, both VIX and EPU underestimated the measure of macroeconomic uncertainty surrounding output during the COVID pandemic. Broadly, these measures follow similar trends, however, the short-run dynamics of them differ on account of the different coverage of these two measures. The conceptual differences in these measures have been emphasized in recent research (see Houari (2022), Fernández-Villaverde & Guerrón-Quintana (2020) and Berger et al. (2020)).

An important distinction between these measures is that they capture different aspects of uncertainty. VIX for example is based on stock market volatility. Similarly, EPU focuses on policy uncertainty. In contrast, uncertainty series derived from SPF directly measures uncertainty surrounding forecasts of economic conditions as perceived by professional forecasters. This makes it a comprehensive measure for estimating multi-period macroeconomic uncertainty considering that forecast uncertainty is also a function of forecasting horizons.

5 Uncertainty and Information Shocks

To understand the dynamics of forecast uncertainty, we analyze its key determinants in terms of temporally varying forecast difficulty as indicated by forecast errors and revisions. A notable advantage of fixed target forecasts is the availability of a sequence of forecast revisions over the forecasting period.

Following Lahiri & Liu (2006),we examine the role of past forecast errors and contemporaneous information shocks in explaining uncertainty. Larger forecast errors may make the forecaster more uncertain regarding their forecasts while new information can often be interpreted differentially by forecasters resulting in higher disagreement. Both factors can contribute to elevated levels of uncertainty thereby compounding challenges faced by monetary policymakers. We present our results in Table 5. Our dependent variable in uncertainty from the density data. We begin with a simple specification with forecast errors on the right-hand side. Consistent with our expectations, there is a positive pass-through of previous forecast errors on current uncertainty. We then consider a simple AR (1) specification to test for persistence. We find uncertainty to be persistent with a coefficient of 0.53 on uncertainty's lagged values.

Drawing on Manzan (2021), we test whether macroeconomic news captured through forecast revisions leads to changes in uncertainty. Specifically, in column 3, we include past forecast errors, lagged values of uncertainty and contemporaneous forecast revisions on the right-hand side. Forecast errors are categorized based on whether the revisions were positive or negative. In our context, positive revisions reflect a favorable information shock, whereas negative revisions indicate an adverse information shock. The coefficient on lagged uncertainty remains large and highly significant (0.50, $p < 0.001$), indicating strong persistence in uncertainty over time. We interpret the result as evidence that uncertainty is not simply a short-lived phenomenon but rather displays substantial persistence over time. The coefficient on lagged forecast errors is negligible (–0.01) and fails to reach statistical significance. This suggests that in multi-period forecasting, past errors do not meaningfully influence current uncertainty once other factors such as previous forecast revisions are accounted for.

The most notable result in this specification is the asymmetric impact of forecast revisions. While positive revisions have no significant effect on uncertainty (coefficient: 0.06), negative revisions (representing adverse information shocks) are associated with a statistically significant effect on uncertainty (coefficient: –0.22, $p < 0.001$). The negative forecast revisions are numerically negative by definition; therefore, these results are interpreted as negative forecast revision increases uncertainty by 0.22. Our results are not very different from those in Lahiri & Liu (2006) as we find a lower coefficient on absolute forecast errors. The relatively lower coefficient on absolute forecast errors strengthens the argument presented in Lahiri & Liu (2006) against the use of observed variance from ARCH-type models conditional on past forecast errors as a measure of forecast uncertainty in multiperiod contexts.

Recent work by Del Negro et al. (2022) highlights a critical distinction in how professional forecasters perceive uncertainty, and its effect on forecast errors. Batchelor & Dua (1996) defined this relationship as 'variance rationality'. Del Negro et al. (2022) argue that under rationality, more uncertain forecasters should systematically make larger forecast errors, particularly when compared to "confident" forecasters.

In our analysis, we extend this inquiry examining the relationship between uncertainty and forecast errors. Following their specification, we estimate a log-log regression treating log of absolute forecast errors as the dependent variable and log of the variance derived from fitting a four-parameter beta distribution on the SPF data as the independent variable. The estimated coefficient reflects how much realized forecast errors (i.e., ex-post uncertainty) are influenced by changes in ex-ante forecast uncertainty. A coefficient of one suggests a one-to-one link, consistent with rational expectations. Our estimates indicate that subjective uncertainty contains expected information about future forecast errors. We estimate a coefficient of 0.99 (se=0.23) for growth and 0.69 (se=0.32) for inflation uncertainty. Our results are consistent with Del Negro et al. (2022) as we are unable to reject the noisy rational expectations hypothesis.

6 Macroeconomic Effects of Uncertainty Shocks

As stated earlier, management of economic uncertainty is an important aspect of modern monetary policymaking. However, given various measures of uncertainty, a relevant issue is to examine which of these might be more relevant for monetary policymakers. In this section, we demonstrate that each of these uncertainty measures captures a distinct and valuable dimension of uncertainty. Rather than serving as substitutes, they function as useful supplements.

Conventional approach to obtain uncertainty shock relies on either econometric model (such as forecast errors or volatility), use proxy variables such as EPU index or VIX. However, the use of these variables have their own limitations. For example, given that VIX measures volatility in the stock market, it is difficult to determine the direction of causality as uncertainty shocks can trigger aggregate fluctuations as much as aggregate fluctuations could influence stock market volatility. Similarly, Patra et al. (2023) show that standard text based EPU measures or Google trends-based uncertainty measures do not comprehensively cover all the sectors of the economy and therefore are not comprehensive measures of the true underlying macroeconomic uncertainty.

We take a distinct approach to measuring uncertainty, drawing on Berger et al. (2020), and define uncertainty shocks as the first difference in second moment shocks in real time. Several studies have examined how uncertainty shocks affect macroeconomic variables. For example, Fernández-Villaverde & Guerrón-Quintana (2020) discuss the relationship between uncertainty shocks and business cycle in the US. Houari (2022) explores the effects of financial, macroeconomic and policy uncertainty shocks on US macroeconomic variables to highlight the heterogenous effects of different uncertainty measures. They find EPU shocks on all variables to be less significant than those of VIX and Macroeconomic Uncertainty Shocks. In addition, they find that VIX generates the highest impact on all components for the US economy.[17] Using VIX-type uncertainty indices, Gupta (2024) theoretically analyzes the issue of optimal monetary policy in a small open economy using a new Keynesian DSGE Model for a panel of 14 economies (7 AEs and 7 EMs), and finds that households respond to uncertainty by lowering their consumption spending in response to uncertainty shocks.

In addition, recent papers have explored the effects of uncertainty shocks on emerging market economies and have observed substantial heterogeneity in the response of macroeconomic variables to such shocks. For instance, Kumar et al. (2021), Das & Kumar (2018) and Swallow & Céspedes (2011)) establish that emerging market economies exhibit greater sensitivity to uncertainty shocks compared to advanced economies.[18]

To examine the effects of uncertainty shock on macroeconomic variables, we estimate a Structural Vector Autoregressive Model (SVAR). The estimated SVAR model takes the form:

$$y_t = A_1 y_{t-1} + B_1 u_t, \quad \text{with } u_t \sim \mathcal{N}(0, \Sigma) \tag{6}$$

where y_t is a $k \times 1$ vector of k variables in period t, A_1 is a $k \times k$ coefficient matrix, B_1 is a $k \times k$ matrix, u_t is a $k \times 1$ vector of errors which have a multivariate normal distribution with zero mean and a $k \times k$ variance-covariance matrix, Σ.

[17] Also see Berger et al. (2020), who find stock market volatility to be followed by economic contractions and that forward looking uncertainty measures have limited effects on economy. They argue that while volatility matters, realized volatility drives contractions instead of implied volatility.

[18] Also see Lanzilotta et al. (forthcoming).

In terms of macroeconomic variables, we include output, inflation, investment (measured by Gross Fixed Capital Formation or GFCF), the central bank policy rate, and the exchange rate. Our primary objective is to estimate the impact of uncertainty shocks on each of these five macroeconomic aggregates. To this end, we estimate the model separately for each of the three uncertainty measures to assess its distinct effect on the selected variables. Accordingly, our baseline specification is a six-variable structural VAR (SVAR(6)) model. To distinguish between domestic and international uncertainty shocks, we estimate an additional model that incorporates the CBOE VIX (US VIX) as a proxy for global uncertainty, resulting in a seven-variable structural VAR (SVAR(7)) specification. Impulse responses generated from the SVAR (p) model help unravel the heterogeneous effects of domestic and international shocks on standard macroeconomic variables. Using impulse-response functions, we estimate the dynamic effects of uncertainty shocks on macroeconomic variables - Real GDP Growth Rate (RGDP), Real Investment Growth Rate (RGFCF), CPI Inflation (CPI), Exchange Rates (USD-INR) and Policy Rates (Policy Rate).[19]

We use three different measures for uncertainty in order to evaluate these different uncertainty measures; 1) the SPF variance from the fitted four parameter beta distribution – which measures macroeconomic uncertainty, 2) the EPU Index for India developed by Ahir et al. (2022) which measures policy uncertainty and 3) US VIX which is a measure of global financial volatility. These variables are non-stationary, and therefore we compute the log-change relative to previous period to convert them into a stationary series.

Unlike the standard VAR model where the variance-covariance matrix is symmetric, a structural VAR model imposes identification restrictions on Σ. As a standard practice in the literature, we impose Cholesky restrictions on this system by applying equality constraints using the lower triangle and diagonal matrix. Pratap & Priyaranjan (2023)[20] used a similar model to estimate the effects of uncertainty shocks on macroeconomic variables in India. Their uncertainty shocks were derived from Google Trends data.

In Figure 6 we report the cumulative orthogonal impulse response functions of an SPF Uncertainty shock from the SVAR (7) and SVAR (6) models. The key difference between these two models is the inclusion of CBOE VIX as an additional variable in the former model to capture the effects of global uncertainty explicitly. These results suggest that the inclusion of global uncertainty in the SVAR model does not materially alter the impulse responses to a unit SPF shock.

Theoretically, increased uncertainty should have a negative effect on real GDP growth rate, which holds true for the uncertainty measure derived from the SPF Data. Furthermore, the inclusion of CBOE VIX lowers the cumulative effect of an SPF shock on inflation and GDP growth rates which suggests possible spillovers of global shocks into the SPF shocks that are accommodated once CBOE VIX is included in the model.

In Figure 7, we report the cumulative orthogonal impulse response functions of

[19]Table 6 provides detailed description of variables used for the SVAR model.

[20]An alternative 3-variable VAR model with inflation, output gap and policy rate as endogenous variable with uncertainty as an exogenous variable was used by Patra et al. (2023).

uncertainty shocks derived from the CBOE VIX (US VIX) and India Economic Policy Uncertainty from a SVAR (7) model. The effect of EPU shock on RGDP is muted while VIX has the largest effect on RGDP. Pratap and Priyaranjan (2023) using Indian data report a similar muted effect of EPU Shock on real GDP. The reported results are consistent with similar findings for India (see Patra et al. (2023), Pratap & Priyaranjan (2023) and Bhagat et al. (2016)).

The effect of uncertainty shocks on inflation is more complex, particularly as uncertainty shock driven by concerns regarding negative demand would result in a reduction in price levels, while a supply shock would imply an increase in price levels. Several authors have adopted a similar approach to distinguish between supply and demand shocks. For example, Choi et al. (2024) used the response of inflation to show US consumer confidence shocks are consistent with supply-side explanations (news-shocks). Figures 6 and 7 suggest that SPF-U shocks result in a decline in inflation while CBOE VIX shocks have a positive effect on inflation. This implies that SPF-U is capturing demand shocks, while CBOE VIX captures supply shocks. EPU shocks on the other hand have an initial positive effect on inflation, but the effect is muted and dissipates within four quarters. Gupta (2024) shows that under flexible prices, uncertainty shocks would result in lower inflation which is consistent with the evidence obtained here for SPF-U shocks.

The results on the effect of uncertainty shocks on exchange rates suggests SPF-U shocks result in slower depreciation of the rupee while the opposite is true for CBOE VIX uncertainty shocks. These results are explained by the distinction between demand and supply shocks as a demand shock implies a reduction in current account deficit which would alleviate depreciation pressures on domestic currency.

Similarly, heightened financial volatility as captured by the VIX would influence capital flows instantaneously, and this would be reflected in the exchange rate. Gupta (2024) highlights the importance of exchange rates interventions as a potent policy tool to respond to uncertainty shocks. This is consistent with India's official exchange rate regime of managed float regime whereby the central bank to routinely intervenes in order to maintain a stable currency. Our findings of relatively small cumulative effect of an SPF-U shocks are consistent with India's managed float exchange rate regime which prevent a systemic sharp appreciation or depreciation of the exchange rate.

Consistent with the discussion above, SPF-U shocks result in a decline in policy rates as monetary policy authorities respond to a demand shock by lowering the policy rate. The results from the SVAR (7) model are internally consistent and similar to findings reported by other studies that have used EPU Index or other uncertainty measures. The distinction between demand driven uncertainty shocks vs. supply driven uncertainty shocks has important implications for policymakers. With demand-driven uncertainty shocks, central banks respond by cutting interest rates. However, supply induced uncertainty shocks presents a policy dilemma as they have to use just one instrument to meet conflicting objectives of full employment or price stability. As such, distinguishing between demand- and supply-driven uncertainty is essential for determining appropriate policy interventions.

7 Conclusion

Heightened uncertainty has significant adverse real economic effects, making its measurement an important endeavour for economists. Three different types of uncertainty measures have emerged over the last decade based on survey data, text-based data, and stock market volatility. This paper focuses on a survey based measure derived from density forecasts from India's Survey of Professional Forecasts (SPF). While several authors have analyzed SPF data from US and Euro Area, India's SPF data has been relatively understudied. SPF density data are reported in discrete intervals with upper and lower-tail truncation. We fit a four-parameter beta distribution for each round of the survey as an alternative to imposing distributional assumption on the intervals.

We evaluate density forecasts in terms of their bias and efficiency properties. In addition, we evaluate the validity of these forecasts across each individual bin following Dawid (1984)'s *Predictive Sequential* (prequential) principle which allows bin-by-bin test for forecast calibration. The underlying principle behind the test is to compare the average relative probabilities issued by forecasters with the empirical probability of the target variable belonging to a given discrete interval. Our findings with Indian density forecasts corroborate evidence from the U.S. and Euro Area SPF datasets, indicating that the forecasts exhibit properties of efficiency and statistical calibration.

We next turn to constructing an uncertainty measure using SPF data using the second moment of the fitted beta distributions. We compare the SPF-U with other popular uncertainty measures, viz., stock market volatility (VIX) and the text-based economic policy uncertainty index (EPU). Each of these three measures displays similar declining trend since 2008 with subtle differences in their short-run dynamics. We show that compared to SPF, both VIX and EPU underestimated macroeconomic uncertainty during the pandemic.

In addition, we examine the determinants of uncertainty and find it to be highly persistent. Furthermore, we show that negative information shocks are a major driver of uncertainty in India. Since in multi-period forecasting, past forecast errors represent dated information, they do not turn up to be statistically significant in explaining uncertainty in the presence of forecast revisions. Remarkably, consistent with noisy rational expectation hypothesis, we find that ex-ante uncertainty has a direct and significant bearing on subsequently observed forecast errors indicating variance rationality, cf. Del Negro et al. (2022).

Lastly, using a SVAR model, we show that, unlike conventional uncertainty measures like EPU or VIX, uncertainty derived from density forecasts comprehensively captures output uncertainty. An important distinction between these measures is that SPF-U captures demand-driven shocks whereas both VIX and EPU reflect supply-driven fluctuations. Our results imply that increasing SPF-U calls for lower policy interest rates, whereas increases in EPU or VIX-based uncertainty require balancing output stabilization with price stability. Policymakers would do well to monitor these uncertainty measures as useful supplements for the purpose of timely and appropriate monetary policy interventions.

A Tables

Table 1: Average GDP Growth Rate

	Real GDP Growth Rate	
	Mean	St. Dev.
1950-79	3.6	3.3
1980-89	5.7	1.9
1990-99	5.8	2.2
2000-09	6.3	2.1
2010-19	6.6	1.5
2010-23	5.9	3.8

Notes – We report the real GDP growth rate series with the base year 2004-05

Table 2: Efficiency Test: Nordhaus Test for GDP Forecasts

	Dec 07 - Jan 23	Dec 07 - Jan 20
Lagged Forecast Revision	0.10	-0.09
	(0.12)	(0.11)
Constant	-0.01	0.02
	(0.19)	(0.07)
N	103	85

Table 3: Calibration Test for Growth

Interval	**Avg. Assigned Prob.**	**Actual Occurrence**	**Rel. Prob.**	**Rel. Occurrence**	**Var**	**N(0,1)**	**Chi-Square**
Below 4%	6	30	0.04	0.19	0.15	-0.39	0.15
4–6%	26	20	0.16	0.13	0.11	0.12	0.01
6–8%	93	69	0.59	0.44	0.25	0.30	0.09
Above 8%	34	40	0.21	0.25	0.19	-0.08	0.01
Overall	158	158					**0.26**

Note: Sample period is December 2007 to January 2023.

Table 4: Calibration Test for Inflation

Interval	**Avg. Assigned Prob.**	**Actual Occurrence**	**Rel. Prob.**	**Rel. Occurrence**	**Var**	**N(0,1)**	**Chi-Square**
Below 4%	11.89	14.81	0.15	0.19	0.15	-0.09	0.01
4–6%	37.00	34.56	0.47	0.44	0.25	0.06	0.00
6–8%	21.49	14.81	0.27	0.19	0.15	0.22	0.05
Above 8%	8.62	14.81	0.11	0.19	0.15	-0.20	0.04
Overall	79	79					**0.10**

Note: Sample period is December 2007 to January 2023.

Table 5: Growth Uncertainty and Lagged Forecast Errors

	Uncertainty at time t		
	(1)	**(2)**	**(3)**
Forecast Errors at time $t-1$	0.05***		-0.01
	(0.01)		(0.02)
Uncertainty at time $t-1$		0.53***	0.50***
		(0.11)	(0.09)
Forecast Revision at time t			
Positive Revision at time t			0.06
			(0.25)
Negative Revision at time t			-0.22***
			(0.05)
Constant	0.48***	0.29***	0.23***
	(0.05)	(0.07)	(0.06)
Adjusted R^2	0.28	0.28	0.69
N	45	61	45

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
1) Forecast errors are four-quarter lagged as the last available GDP data for the target variable corresponds to the previous fiscal year. Consequently, professional forecasters are only aware of the forecast errors made four quarters ago. We use the absolute value of forecast errors as the dependent variable.
2) Forecast Revisions at time t = forecast made for time t at horizon h – forecast made for time t at horizon $h+1$.
3) Sample period corresponds to December 2007 – January 2022 with quarterly frequency.

Table 6: Variable Description for SVAR

Variable	**Description**	**Growth Rate**
GDP Growth Rate	Quarterly Real GDP Growth Rate	Year-over-year
Investment Ratio (Growth)	Quarterly Real Gross Fixed Capital Formation as a percentage of Real GDP	Year-over-year
Inflation	Consumer Price Inflation	Year-over-year
Exchange Rate	USD–INR exchange rate	Quarter-over-quarter
Policy Rate	RBI's repo rate	Quarter-over-quarter
Uncertainty Measure	Uncertainty derived from Beta Distribution for Growth	Quarter-over-quarter
	Economic Policy Uncertainty Index	Quarter-over-quarter
	Volatility Index	Quarter-over-quarter

B Figures

Figure 1: Historical GDP Growth and CPI Inflation

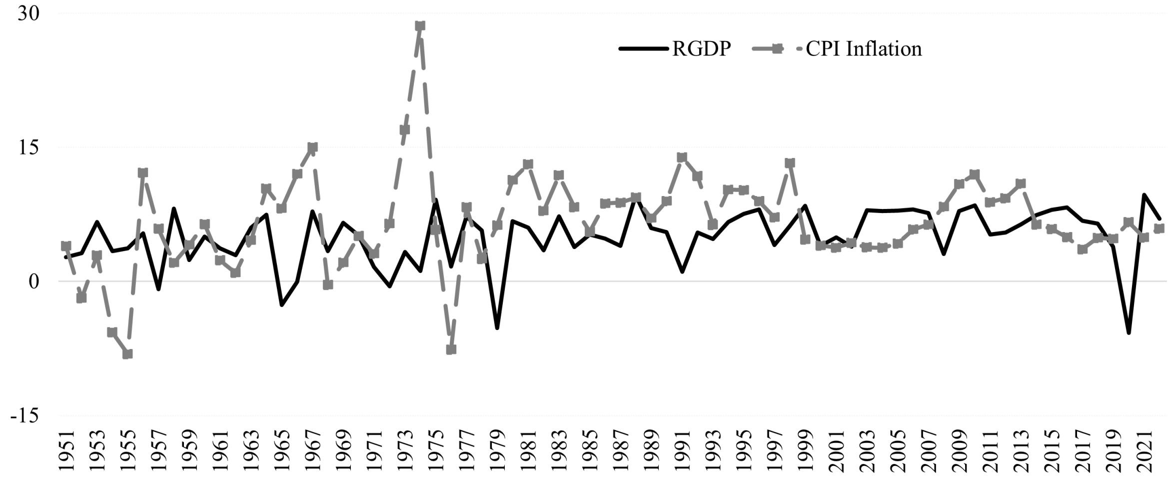


Figure 2: SPF Mean GDP Growth Rate Forecasts

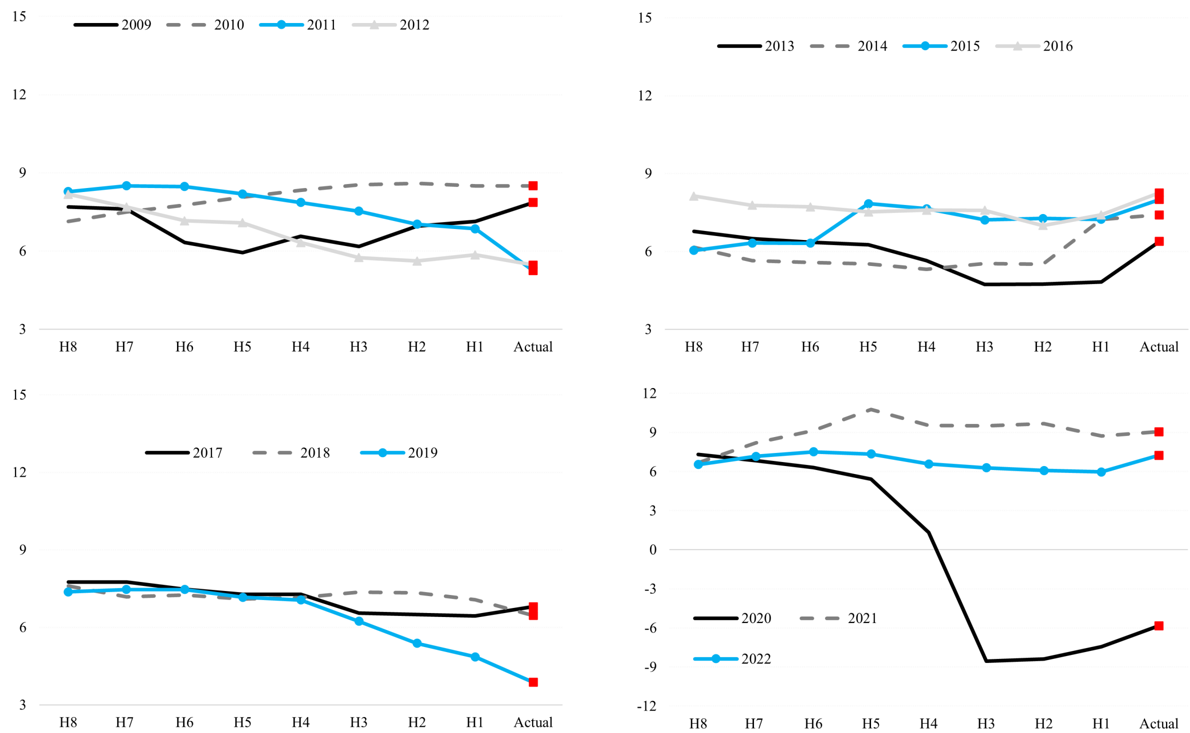


Figure 3: Forecast Revisions (RGDP)

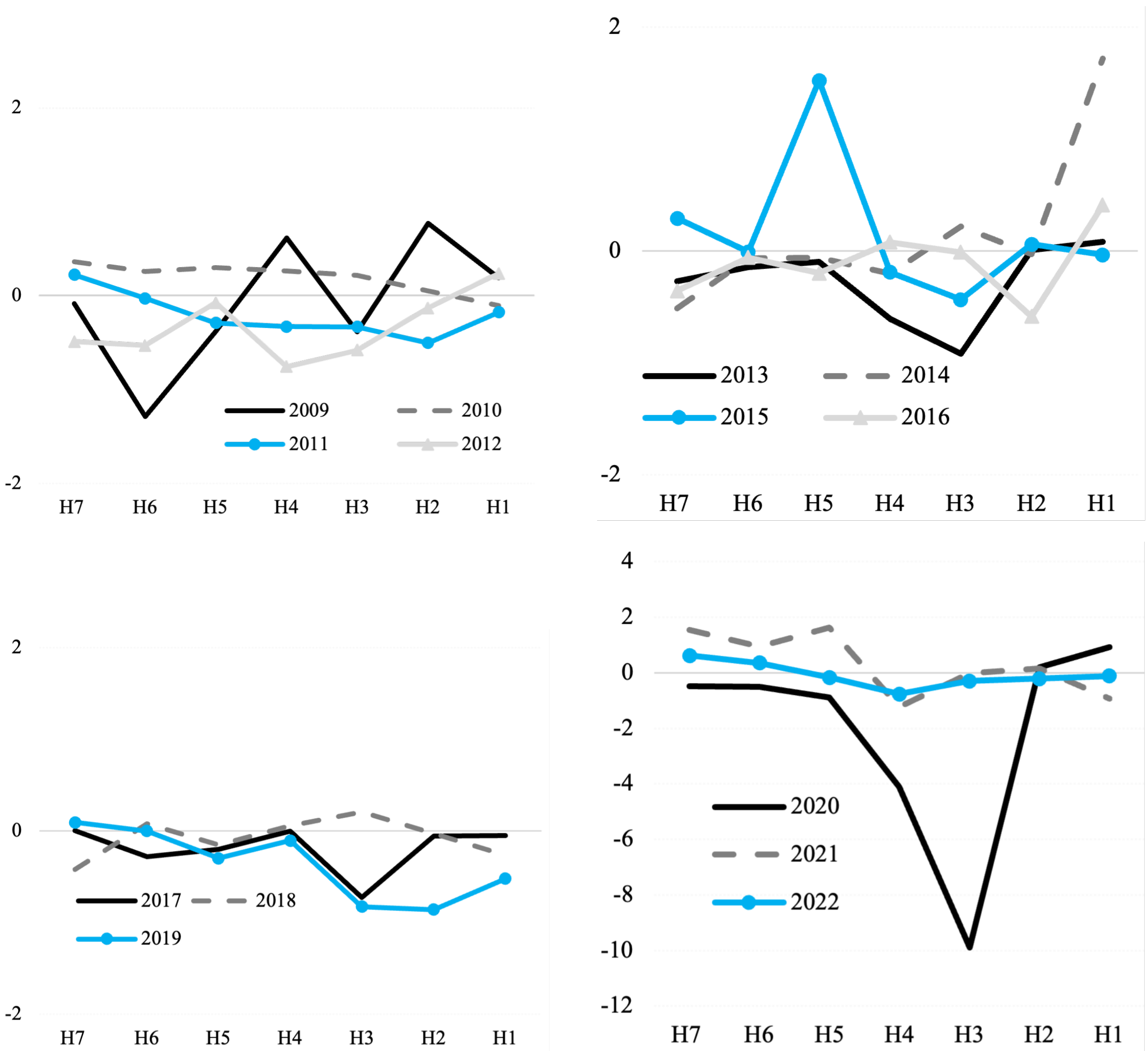


Figure 4: Mean Absolute Forecast Error by Horizons

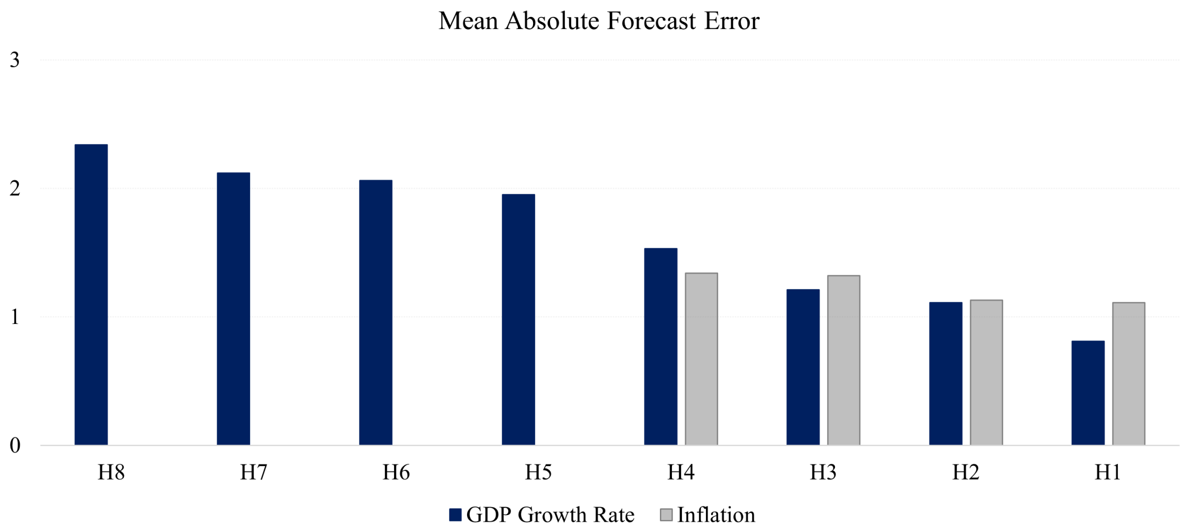


Figure 5: SPF & Other Uncertainty Measure

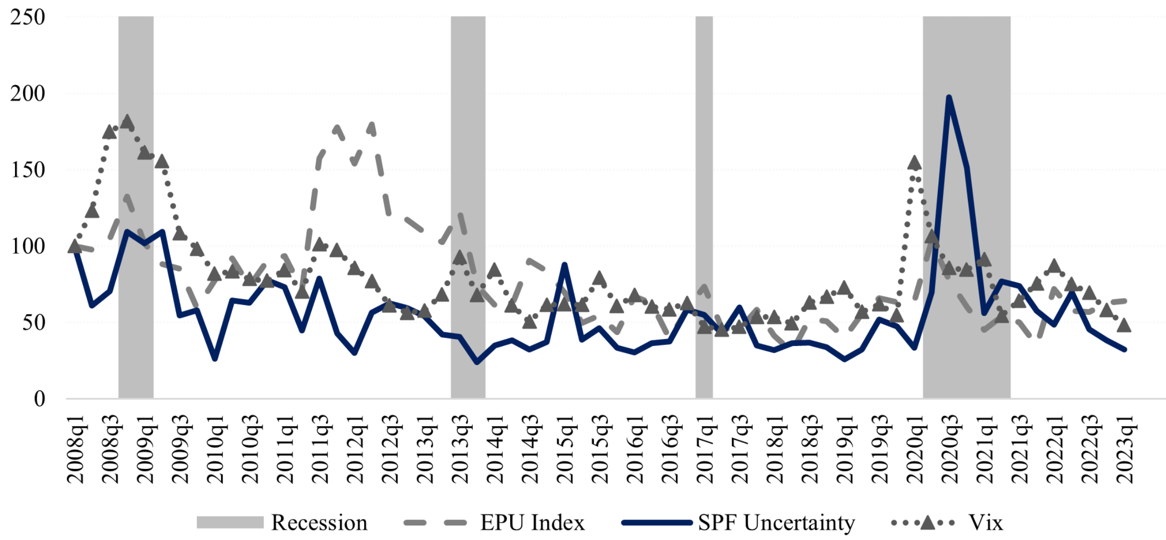


Figure 6: COIRFs of SPF Uncertainty Shock from SVAR (7) and SVAR (6)

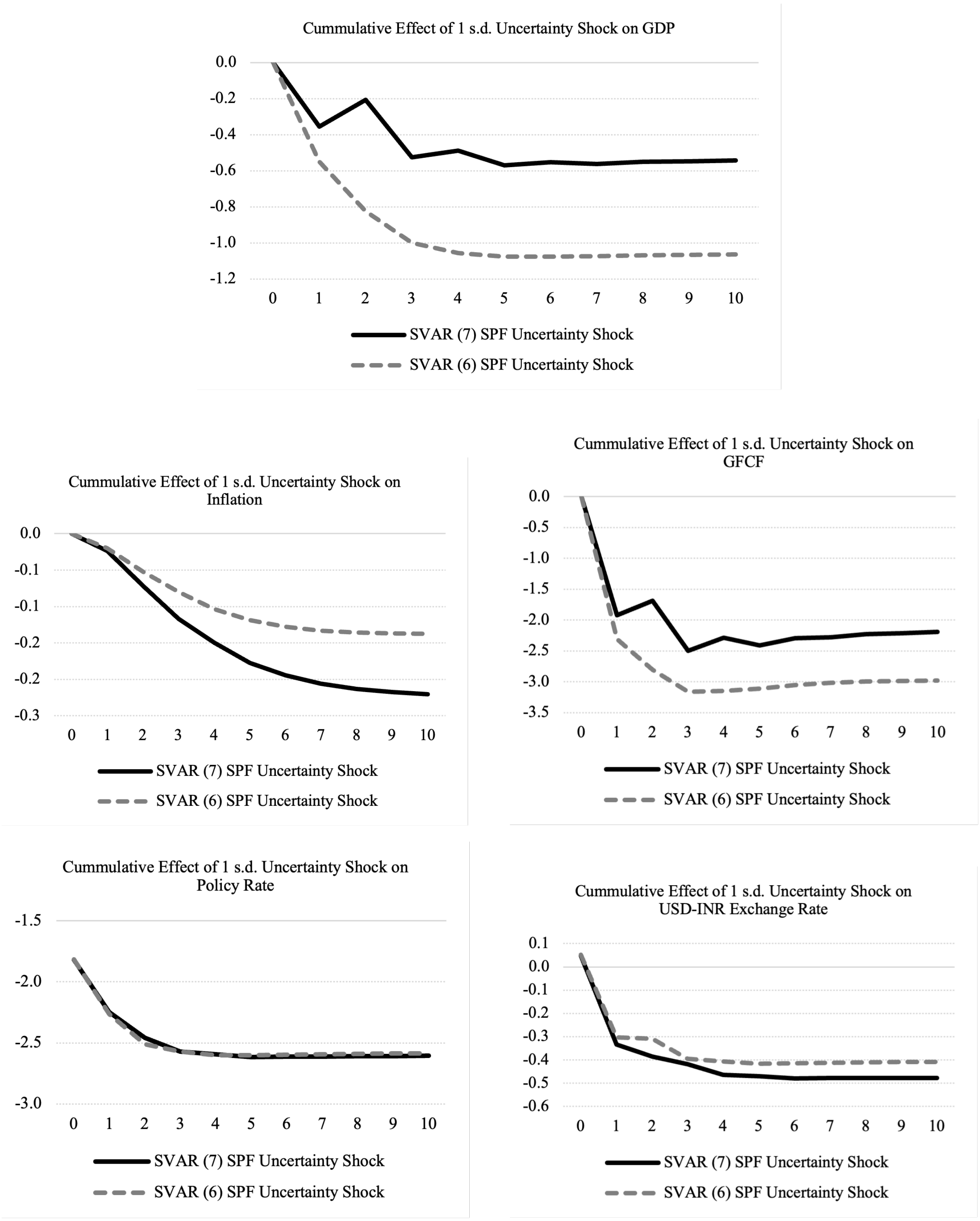
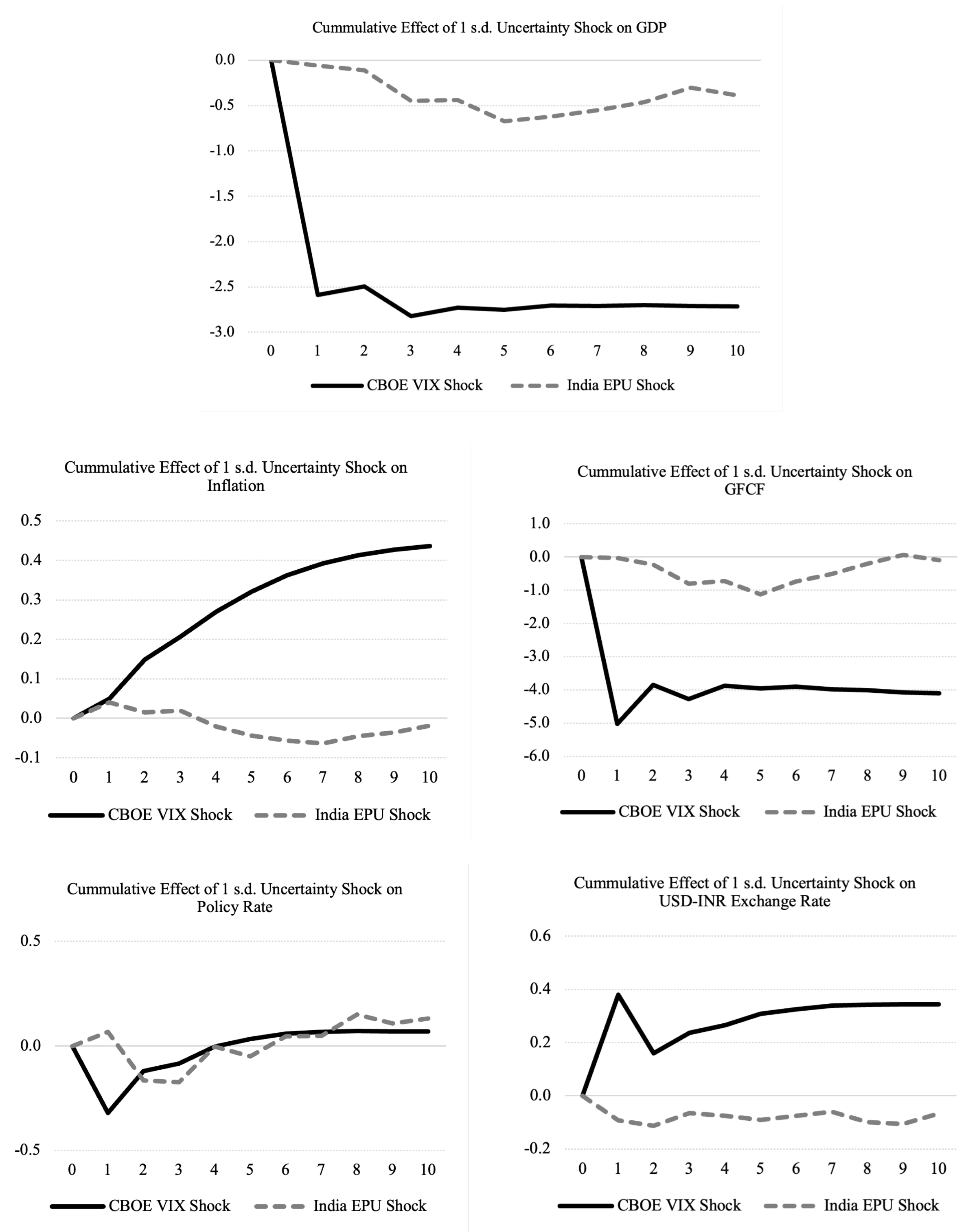


Figure 7: COIRFs of US VIX and India EPU Shocks



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