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Assessing macroeconomic uncertainties for an emerging economy

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ASSESSING MACROECONOMIC UNCERTAINTIES FOR AN EMERGING ECONOMY

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S. Raja Sethu Durai

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Abstract

This study constructs the macroeconomic uncertainty indices for an emerging economy, India, and considers other macroeconomic uncertainty indices to evaluate their relative effectiveness in terms of tracing the business cycles and finding out the transmission channels consistent with theory. The study estimates a series of VAR models using quarterly data to identify different uncertainty channels of aggregate demand and supply. The derived measures of uncertainty are higher around recessions and other structural changes like demonetization and GST implementation in India. Further, the empirical results show that the effects of uncertainty shocks to different domestic variables are consistent with the supply side of the real-option channel, the demand side of the investment channel, and the precautionary channel. Finally, to understand the effects of international spillover, this study measured the impact of US uncertainty on domestic variables, and the results suggest that US uncertainty has much more impact than domestic uncertainty, suggesting a significant international spillover effect of uncertainty in the Indian economy. These findings provide a holistic examination of how uncertainty affects macroeconomic activity from an emerging economy perspective. The results also suggest that the news-based economic policy uncertainty index, which is widely used in developed countries has not properly captured the state of economic uncertainty in India.

Keywords: business cycles, economic uncertainty, emerging market economy, spillover

JEL Classification: D80, E32, E66, P50

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1. INTRODUCTION

The importance of economic uncertainty in policy making is well documented in the literature (see, for example, Issing 2002; King 2010). Recent studies on the business cycle identified macroeconomic uncertainty as one of the key drivers in frequent business cycle fluctuation (Stock and Watson 2012; Bloom et al. 2018). As observed by Bloom (2014), uncertainty rose during the financial crisis period of 2008, and its likely role in shaping the subsequent global recession focused policy attention on this topic, and such attention is evidenced by the introduction of Fan chart¹ forecasts of output and inflation across central banks. Also, reading the minutes of the central banks' monetary policy committee (MPC) reveals that policy makers dwell much on the future course of macroeconomic uncertainty before pressing the change button onto the policy instrument. However, measuring true uncertainty is a difficult task as it is neither directly observable nor quantifiable. The literature on uncertainty, therefore, developed proxy measures of uncertainty and adopted the broader definition of uncertainty, combining the Knightian notion of risk and uncertainty. With this broader definition, many proxy measures of uncertainty have been proposed, mostly since the 2008 financial crisis, and research on uncertainty is still evolving.

The proxy measures of uncertainty are broadly classified under finance-based measures, news-based measures, forecast-based measures, and measures of dispersion among forecasters. Bloom (2009) first suggested the realized stock market volatility and the Chicago Board Options Exchange implied volatility index (VIX) as proxy measures of uncertainty for the US. The VIX is derived from the call and options prices, so it is said to be a forward-looking indicator of market uncertainty. The idea is that market volatility is more volatile during a period of increased macroeconomic uncertainty. Several studies have used the stock market volatility measures as an uncertainty proxy to assess the effect of uncertainty shocks. However, the VIX is useful for capturing uncertainty originating from the financial sector rather than the uncertainty of the real economy. In their study, Bekaert, Hoerova, and Lo Duca (2013) decomposed the VIX index of implied volatility on the Standard & Poor's 500 stock index into a risk aversion component and an uncertainty component and examined the effect of monetary policy on both these components.

Baker, Bloom, and Davis (2016) developed a news-based economic policy uncertainty index (EPU) for the US. The EPU index is built upon searching keywords associated with uncertainty in relevant newspaper articles and is thus expected to capture the state of uncertainty discussed in the media. Following their methodology, many studies have attempted to develop such indices for a large number of countries, including India (Bhagat, Ghosh, and Rangan 2016). The news-based indicators assume that in the period of uncertainty, the number of counts in the articles related to economic uncertainty would surge, which could be interpreted as a signal of heightened uncertainty in an economy. At first glance, such a measure looks practical for capturing major economic events of uncertainty, but they not only often emerge after events but also do not disentangle the effect of purely economic uncertainty from that of more general uncertainty news. Particularly in developing countries' media, sociopolitical uncertainty-related events are seen as a more dominant discourse, and often such uncertainty may die off without any economic recession. Some studies consider the cross-sectional variance of forecasts given by forecasters to be an indicator of *ex ante* uncertainty (Bachmann, Elstner, and Sims 2013; Banerjee, Kearns, and Lombardi 2015). However,

¹ Fan charts, first introduced by the Bank of England, depict the probability distribution of forecasts, with information on the risk factors affecting the forecasts and the uncertainties surrounding them.

one major drawback of such a measure is that it reflects differences of opinion rather than an economic uncertainty, so it potentially presents a misleading picture of uncertainty.

More recently, with the advancement of uncertainty research, an econometric approach has been developed, focusing on the variance of the forecast errors. In this line, Scotti (2013), using Bloomberg forecast data, built an index of uncertainty based on the surprise component of the data releases relative to the forecasts. Jurado, Ludvigson, and Ng (2015) derived macroeconomic uncertainty measures using the information on the common volatility of forecasts of a large number of economic series. They argued that it is the predictability that matters for economic decision-making and, therefore, the variance of forecast errors and not the dispersion that would provide better statistics for constructing uncertainty measures. Rossi and Sekhposyan (2015), hereafter RS, extended this notion of uncertainty in a more general way and proposed a measure of uncertainty using the US Federal Reserve Bank's survey data of forecasts of professional forecasters. This index is based on relating the realized forecast error to the historical distribution of forecast errors of a variable. This measure has several advantages, as described by RS. It is based on the unconditional likelihood of the observed outcome and so not dependent on any parametric model, which is very useful for emerging economies where the availability of large sample data is a major problem. Several studies provide evidence on the macroeconomic effect of uncertainty for advanced countries. Among others, Bloom (2014) shows that uncertainty is highly countercyclical, and developing countries exhibit more uncertainty than developed countries. Indeed, the burgeoning literature on uncertainty has identified broad channels of uncertainty transmission such as real option, precautionary, and risk premia channel through which the uncertainty shocks affect the economy.

The prime focus of this paper is to construct measures of macroeconomic uncertainty using RS's methodology and compare them with other measures of uncertainty for India in terms of tracing the transmission channels and mapping with business cycles. The main contributions of this study are twofold. First, it identifies different propagation channels of uncertainty by estimating a series of vector autoregression models with suitable proxy variables by which respective channels of uncertainty transmission are assessed for alternative proxy measures of uncertainty. Second, it assesses the uncertainty measures and relates them to the business cycles in India. An attempt is made in this study to provide a holistic evaluation of the effect of macroeconomic uncertainty from an emerging economy perspective.

The study is organized as follows. Section 2 describes the data and method used for the construction of uncertainty indices and also provides a criterion for choosing a data set for constructing a forecast-based macroeconomic uncertainty index. Section 3 presents the analysis of the macroeconomic effect of uncertainty, and the final section concludes with policy implications.

2. MEASURING MACROECONOMIC UNCERTAINTY

2.1 Data

The availability of the data drives the choice of sample period and frequency. The uncertainty indices are computed using quarterly data for the period 2008Q1 to 2018Q2. These uncertainty indices are built upon the forecast errors made by professional forecasters. The forecast data are compiled from the RBI's various issues from a survey of professional forecasters (SPF). The median forecast of GDP growth,

inflation rate, and exchange rate over one-quarter and four-quarter horizons are used for constructing uncertainty indices. The corresponding actual data for the variables are then used to generate forecast errors and uncertainty indices. The study uses survey data on the Business Expectations Index (BEI). These data are collected from various issues of the RBI quarterly survey of Industrial Outlook.² The details on other variables used in the study are given in Appendix Table A.1.

2.2 Uncertainty Indices

We outline below various uncertainty measures used in the analysis.

2.2.1 Uncertainty Index based on Forecast Error Distributions

The forecast-based uncertainty is based on the notion that the large forecast errors in the economic predictions are an indication of macrocosmic uncertainty. Along the same lines, the uncertainty index proposed by RS suggests that if the probability of observing a forecast error of $\theta\%$ is very unlikely, for example, in the 99th quantile of the historical distribution of forecast errors, and the actual observed forecast error value is indeed $\theta\%$, then it is indicative of substantial uncertainty. Following the methodology of RS, the overall uncertainty index (U_{t+h}^*) is derived as follows: Let us define the forecast error made over the h -step-ahead at time t as: $e_{t+h} = y_{t+h} - E_t(y_{t+h})$, $t = 1, 2, \dots, T - h$, with T standing for total sample size. Further, let $f(e)$ denote the probability distribution function of the forecast errors, e_{t+h} . Given e_{t+h} and $f(e)$, U_{t+h} is calculated as:

$$U_{t+h} = \int_{-\infty}^{e_{t+h}} f(e) de$$

The value of U_{t+h} by construction lies between zero and one. To obtain information about upside uncertainty (U_{t+h}^U) and downside uncertainty (U_{t+h}^D), the normalized version of U_{t+h} is computed as follows:³

$$U_{t+h}^U = \frac{1}{2} + \max\left\{U_{t+h} - \frac{1}{2}, 0\right\} \text{ and } U_{t+h}^D = \frac{1}{2} + \max\left\{\frac{1}{2} - U_{t+h}, 0\right\}$$

The upside uncertainty, $U_{t+h}^U > 0.5$, will be observed only when the realized value exceeds the expected value, and the downside uncertainty, $U_{t+h}^D > 0.5$, only when the realized value goes below the expected.⁴ Lastly, the overall uncertainty index is defined as:

$$U_{t+h}^* = \frac{1}{2} + \left|U_{t+h} - \frac{1}{2}\right|.$$

² The BEI is a weighted average index derived from the quarterly net responses of businesspeople on the situation of nine indicators related to the manufacturing sector. These indicators are as follows: overall business situation; production; order books; inventory of raw material; inventory of finished goods; profit margin; employment; exports; and capacity utilization.

³ Since at any given time either positive or negative forecast errors are observed, the normalized version of the U_{t+h} provides the information on the upside (positive) and downside (negative) uncertainty.

⁴ The definitions of positive and negative shocks depend on the variable under study. In the case of GDP, upside uncertainty implies positive shocks.

The uncertainty values for all normalized indices thus lie between 0.5 and 1. Using this methodology, we derive two economic uncertainty indices as follows:

- (i) *Domestic macroeconomic uncertainty index (SPFGDP_U)*: The literature broadly defines fluctuations in the business cycle in terms of changes in GDP. We derive the uncertainty index using the SPF error of GDP variable and consider it to be an indicator of domestic macroeconomic uncertainty.
- (ii) *i) Open economy uncertainty index (SPFMACRO_U)*: Additionally, we derive a wider open macroeconomic uncertainty index using the SPF forecast information from other macro variables. It is obtained by computing RS uncertainty indices of GDP, exchange rate, and inflation rate separately, and then the average of the derived indices is defined as an open economy uncertainty index. This broader index, in addition to domestic uncertainty, is expected to capture uncertainty emanating from the external sector.

2.2.2 The Implied Volatility Index (VIX)

Bloom (2009) proposed the VIX as a measure of uncertainty and it is widely used as a proxy for uncertainty in the literature. This measure is considered an expectation indicator of market volatility and is computed using data from the call and options prices of stock indexes such as S&P 500 options contracts for the US or Nifty options for India. We derived a quarterly average of VIX uncertainty for India using the average of daily data compiled from the NSE website and called it “AVIX_U.”

2.2.3 News-based Economic Policy Uncertainty (EPU) Index

The EPU index was developed by Baker, Bloom, and Davis (2016) for the US as the frequency of newspaper articles referring to terms related to economic and policy uncertainty. This idea of a newspaper-based uncertainty index is subsequently expanded to calculate categories-wise uncertainty indices like monetary policy uncertainty, fiscal policy, and trade policy indices. We obtained India’s news-based economic policy uncertainty (IPU) index from the website given in Appendix A. We used the quarter end as well as a three-month average of IPU data in the analysis.

2.3 Assessing the Data Set for an Uncertainty Index

The uncertainty-based business cycle theory postulates that the existence of common variations across many data series is required for measures of macroeconomic uncertainty (Jurado, Ludvigson, and Ng 2015). We use the bias, variance, and covariance decomposition of the mean square error (MSE)⁵ to assess whether a professional forecast of a variable under inquiry is useful for constructing a macroeconomic uncertainty index. Table 1 presents the decomposition for one-quarter-ahead forecast error data.⁶

⁵ The mean square error of forecasts (MSE) is decomposed into three sources: the bias proportion, which measures how far the mean of the forecast is from the mean of the actual series; the variance proportion, which measures how far the variation of the forecast is from the variation of the actual series; and the covariance proportion, which measures unsystematic error, the error remaining after taking into account bias and variance proportion. For further details on computation, see Sharma and Bicchai (2018).

⁶ Similar results are found for the four-quarter-ahead forecast data.

Table 1: Mean Square Error Decompositions

	Bias Proportion	Variance Proportion	Covariance Proportion
SPFGDP	0.02	0.01	0.97
SPFINF	0.03	0.00	0.97
SPFEXC	0.12	0.03	0.85

Note: SPFGDP denotes a survey of professional forecast series gross domestic product, SPFINF denotes a survey of professional forecasts on inflation, and SPFEXC denotes a survey of professional forecast series on rupee-US dollar nominal exchange rate.

Source: Authors' calculations.

The results show that the bias and variance proportions are very insignificant for SPF-based forecasts, suggesting that the model of professional forecasters provides a good estimate of the underlying data-generating process. They further reveal that there is neither systematic bias nor any variance (uncertainty) about the forecast of individual series, but all the errors are due to the covariance proportions. These covariance proportions must be associated with the common variations of uncertainty fluctuation that exists across the many macroeconomic data series affecting them at the same time. The SPF-based forecast errors can thus be considered reliable data for generating macro uncertainty indices.

Table 2: Cross-Correlations of Uncertainty Measures

	SPFGDP_U	SPFINF_U	SPFEXC_U	SPFMACRO_U	AVIX_U
SPFINF_U	0.48 (0.00)				
SPFEXC_U	0.27 (0.08)	0.20 (0.22)			
SPFMACRO_U	0.77 (0.00)	0.73 (0.00)	0.70 (0.00)		
AVIX_U	0.35 (0.02)	0.47 (0.00)	0.20 (0.18)	0.46 (0.00)	
IPU	0.28 (0.06)	0.06 (0.67)	0.09 (0.56)	0.20 (0.20)	0.27 (0.08)

Note: SPF uncertainty measures are based on one-quarter-ahead forecast error. *P-values* of cross-correlations are in parenthesis.

Source: Authors' calculations.

The inferences from the MSE results can be corroborated by findings of cross-correlation of uncertainty measures. The results in Table 2 show that SPF-based uncertainty measures have a significant positive correlation among them and with AVIX_U, suggesting that the forecast error of professional forecast data includes the common variations of cyclical fluctuations. Further, it appears that SPF-based uncertainty indices are correlated more closely with AVIX_U than IPU, indicating the existence of common underlying uncertainty between them. Overall, the forecast error of SPF can be considered useful data for generating macroeconomic uncertainty indices.

3. ANALYZING MACROECONOMIC UNCERTAINTY

The following sections provide an assessment of uncertainty proxies, described in the previous section, mapping with the business cycles in India.

3.1 Recession and Uncertainty

One of the stylized facts about uncertainty is countercyclical behavior, which is high during recessions and low in normal times. However, in India, like the US, where the NBER officially defines recession dates, there is no agency that formally announces the dates of a recession. We, therefore, use recession dates identified for India in a study by Pandey, Patnaik, and Shah (2017), hereafter PPS,⁷ and track some stylized behaviors of various uncertainty measures against these recession dates (see Figures 1 to 5).

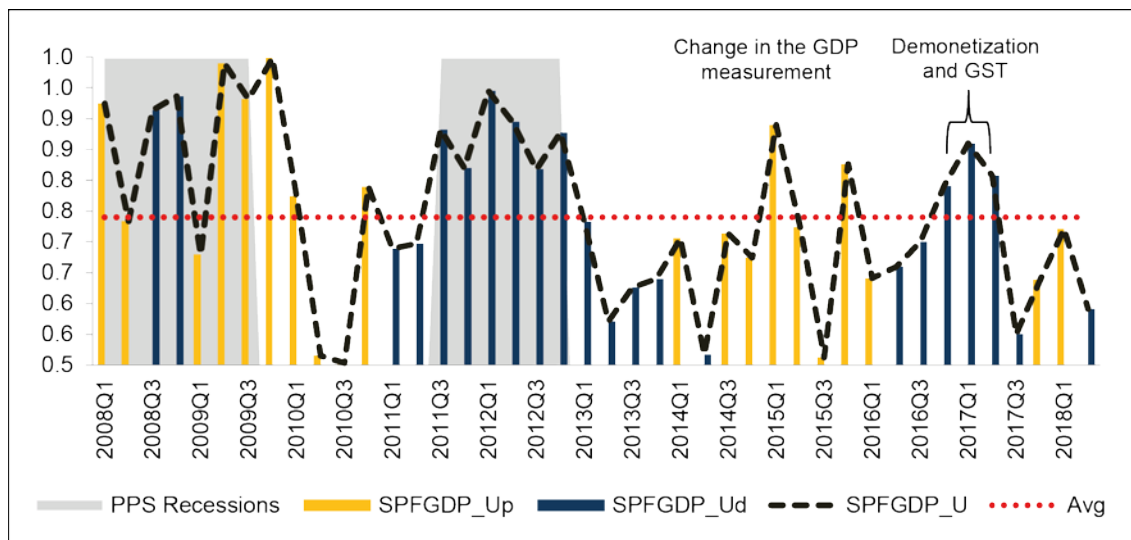
Figure 1 shows that the domestic macroeconomic uncertainty closely captures two recession episodes as the SPFGDP_U values are persistently above their average during the recession periods. It also spikes above the average on another two occasions – notably, the upside uncertainty spike during the time of demonetization, indicating that forecasters are uncertain about the actual growth rate resulting in an underestimation of the growth rate, while on another occasion, the downside uncertainty spikes around GST implementation, suggesting that forecasters overestimated the growth rate. On both occasions, however, the uncertainty does not persist in subsequent periods, thereby ruling out recessions. The open economic uncertainty (SPFMACRO_U) in Figure 2 shows some variability with a higher mean value than the SPFGDP_U, reflecting additional uncertainty stemming from the forecast bias of the exchange rate.

The implied volatility index (AVIX_U) in Figure 3 illustrates that the financial crisis of 2008 was picked up a priori and observed as starker and more persistent. In contrast, the IPU index in Figure 4 exhibits substantial uncertainty during the second recession period but very low uncertainty during the financial crisis period. Thus, this finding underlines that the two measures may capture two different types of uncertainty: AVIX_U could be a better proxy for the uncertainty that originates from the financial market, whereas India's IPU measure may be better at capturing a broader policy uncertainty. Looking at the IPU spike in Figure 4 and related events in India suggests that noneconomic events broadly drive it. For instance, in the second recession period between 2011Q3 and 2012Q1, there was a series of political events and scams, such as the coal scam and the 2G spectrum scam, which, along with a nationwide anti-corruption protest, were the primary reasons for the rise in the IPU index and were further amplified by global economic events such as the Fed tantrum policy and the Greek sovereign debt crisis. Thus, when compared with two popular measures, namely the finance-based VIX and news-based IPU, the SPF-based index, as shown in Figure 5, provides a good proxy indicator of macroeconomic uncertainty. It not only meaningfully enfolds both the recession periods but it also rises in other specific economic events

⁷ The authors show that their identified recession dates are robust to the methods used and to the choice of the business cycle indicator. We, therefore, consider the recession dates identified by this study for the analysis. For further details refer to Pandey, Patnaik, and Shah (2017).

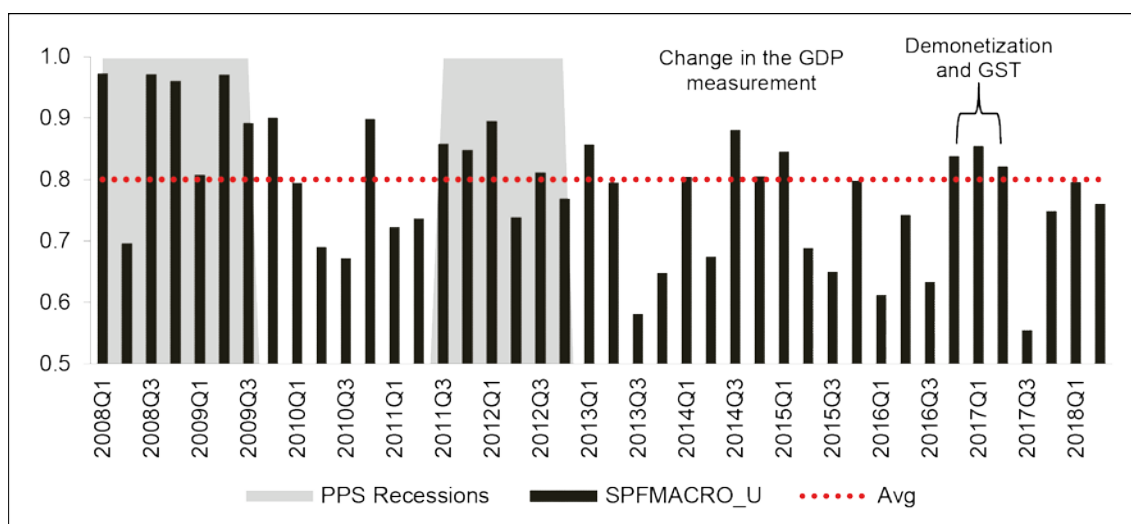
such as government switching the GDP measurement from the factor cost to GVA methodology,⁸ demonetization, and GST.

Figure 1: Plot of SPFGDP_U Uncertainty with PPS Recession Dates



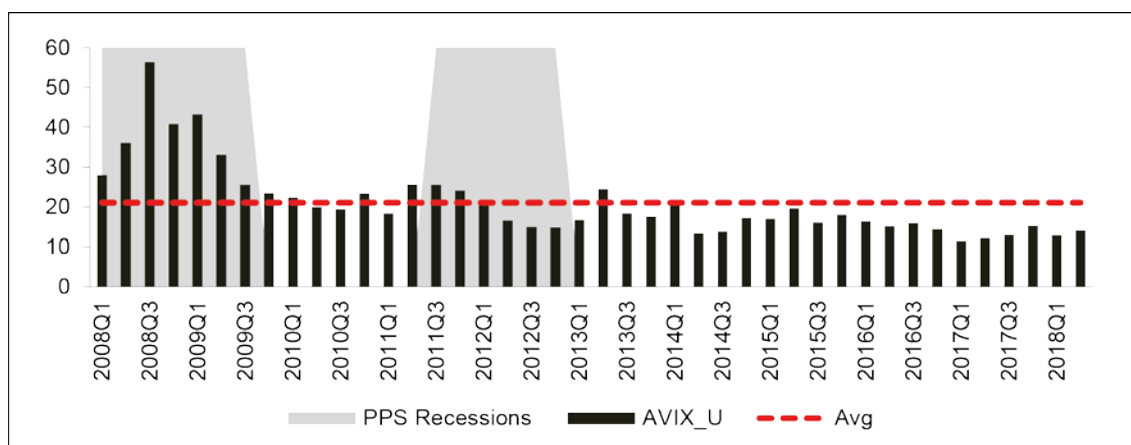
Note: The shaded area denotes the PPS recession dates, and the horizontal dotted line is the mean value of SPFGDP_U. Source: Authors' calculations.

Figure 2: Plot of SPFMACRO_U Uncertainty with PPS Recession Dates

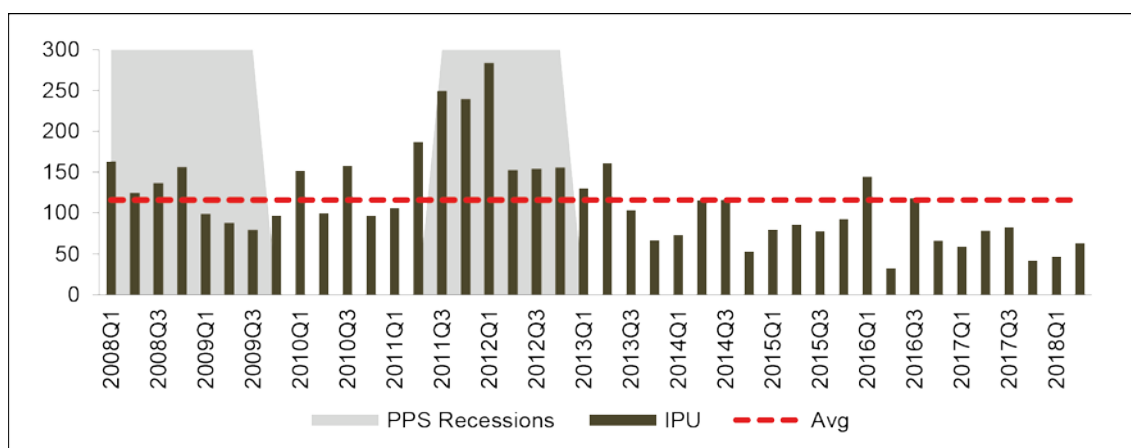


Source: Authors' calculations.

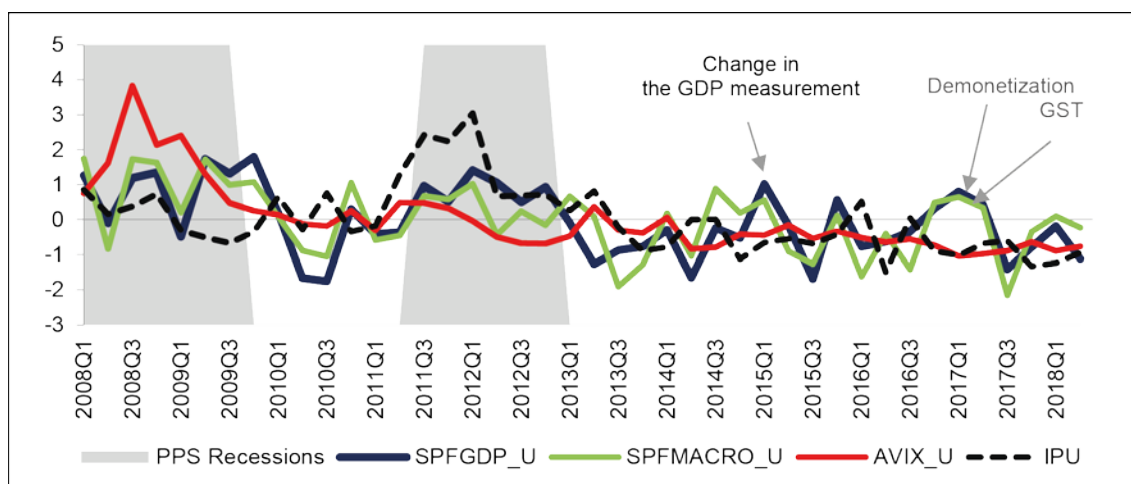
⁸ From January 2015 onward, India's official statistical agency, the Central Statistics Office, started measuring India's GDP growth by gross value-added at basic prices, replacing the previously followed factor cost method of measuring it.

Figure 3: Plot of AVIX_U Uncertainty with PPS Recession Dates

Source: Authors' calculations.

Figure 4: Plot of IPU Uncertainty with PPS Recession Dates

Source: Authors' calculations.

Figure 5: Plot of Measures of Uncertainty with PPS Recession Dates

Note: The left axis measures standardized uncertainty series.

Source: Authors' calculations.

3.2 Transmission Channels of Uncertainty Shocks

There are many transmission channels through which uncertainty shocks spread into the economy. The uncertainty shocks affect both aggregate demand and supply side of the economy through different propagation channels. The literature offers three broad channels, namely the real options channel, the precautionary savings channel, and the risk premia channel of uncertainty. The “real options” channel of uncertainty predicts that heightened uncertainty affects both the demand side and the supply side of the economy. In a period of uncertainty, firms postpone costly decisions about hiring and investment, but once uncertainty subsides, the investment will catch up (Dixit and Pindyck 1994). Thus, the initial fall in investment witnesses a sharp decline in output, and the subsequent rise in investment sees a rebound in the real output (Bloom 2009). Such a horizontal “S” shape-type impulse response of output is known as “uncertainty overshoot,” namely, the bounce back in production following the initial decline after a positive uncertainty shock. The precautionary savings channel predicts that a rise in uncertainty reduces discretionary consumption and that increases household saving (Carroll 1997). Last, the risk premia channel envisages that uncertainty will adversely affect the demand and supply of a flow of funds in the financial market and predicts that persistently heightened uncertainty will raise risk premia and credit spreads, which could negatively influence the real output through low investment. Additionally, heightened uncertainty also discourages banks from supplying funds, which creates tightening credit conditions and eventually results in a decline in the real output⁹ (Haddow et al. 2013). To identify various transmission channels of uncertainty, we use the standard vector autoregressive (VAR) models with impulse response and variance decomposition. The standard VAR (p) model is described as follows:

$$X_t = A_0 + B(L)X_{t-1} + e_t$$

where X_t is the vector of endogenous variables, $B(L)$ is a matrix lag polynomial of coefficients, and $e_t \sim N(0, \Sigma)$. One problem in the VAR analysis of uncertainty is the choice of appropriate identifications and proxy variables by which respective channels of uncertainty transmission can be traced. To address this problem, we rely on recursive ordering through Cholesky decomposition of $\hat{\Sigma}$ to identify structural shocks with alternative ordering and with suitable proxy variables, as described in the following sections through which transmission channels are determined. Another problem in VAR modeling is the appearance of nonstationarity in some variables. To this end, the uncertainty literature seems to be oblivious to the stationarity of variables in analyzing the effect of uncertainty shocks. This inattention is partly because the VAR model in levels to some extent affects only the estimators’ efficiency but not consistency. Furthermore, Bjørnland (2000) pointed out that time series is not just a random walk process; it may still display transitory fluctuations around a deterministic trend. So here we estimated all VAR models in logarithmic level variables except rate variables and uncertainty indicators and included a constant and deterministic trend in the estimation with two lags identified by the Schwarz Bayesian Information Criterion.

⁹ With the lack of appropriate data on credit spreads, we do not explicitly assess the risk premia channel. However, its effects can eventually be observed in the reduced investment and industrial output.

3.3 Examining the Supply Side of the Real-option Channel of Uncertainty Shocks

A recursively ordered two-variable VAR with log of the index of industrial production (IIP) and an uncertainty measure is used one at a time to examine whether impulse responses of output to shocks to an alternative measure of uncertainty are on expected lines. Figure 6 shows the impact of uncertainty measures on industrial production, and the results show that all uncertainty measures except Baker, Bloom, and Davis (2016) IPU index show an adverse effect on future output. These findings are robust to alternative orderings and including other variables in the model. Given that the impulse response is conditional on information used in the model, we expanded the basic 2-VAR by including business expectations and inflation deviation with the following recursive ordering of the vector of the endogenous variable X' as:

$$X' = [IIP, \text{Inflation deviation}, \text{Business expectations}, \text{Uncertainty}] \quad (1)$$

In the above specification, the inflation deviation is the difference between actual inflation and the professional forecasters' inflation expectations. The business expectations (BE) are a weighted composite index of an average net response of expectations on nine determinate variables of output. Shock to BE, therefore, could be interpreted as shock to first-moment (mean) determinants of output and that uncertainty in the model can be considered as shock to the second movement of output. The equation of IIP in the VAR estimation thus stands for a representative aggregate supply curve.¹⁰ The IIP output in the model is determined by its lags, inflation deviation, business expectations, and uncertainty shocks.¹¹

The recursive ordering of the specification means that shocks to uncertainty only affect other variables with lags.¹² The relationship between expectations¹³ and uncertainty is considered to be closely linked to variables (Baker, Bloom, and Davis 2016; Perić and Sorić 2017). The changes in confidence and uncertainty are unlikely to occur independently¹⁴ (Haddow et al. 2013). Baker, Bloom, and Davis (2016) and Redl (2018) included the confidence variable in their benchmark VAR model to disentangle uncertainty (volatility) from unexpected bad news (a change in mean). The above specification allows changes in the confidence in the form of the expectations variable.¹⁵ The results of the estimation from specification (1) are shown in Figure 7. It can be seen that these impulses are similar to the two-variable VAR estimation.

¹⁰ The standard aggregate supply curve is determined by the potential output, deviations of the price level to the expected level and shocks. Specification one could be viewed as a representative form of a typical aggregate supply curve.

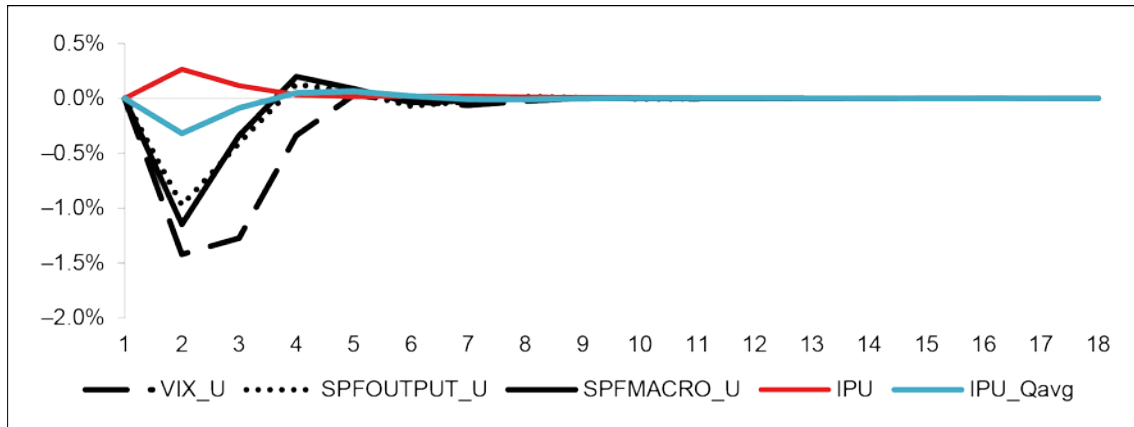
¹¹ The uncertainty shocks here implies the common variations that exist across macro variables.

¹² This assumption assumes an important policy implication that policy makers will have time to respond to the heightened uncertainty.

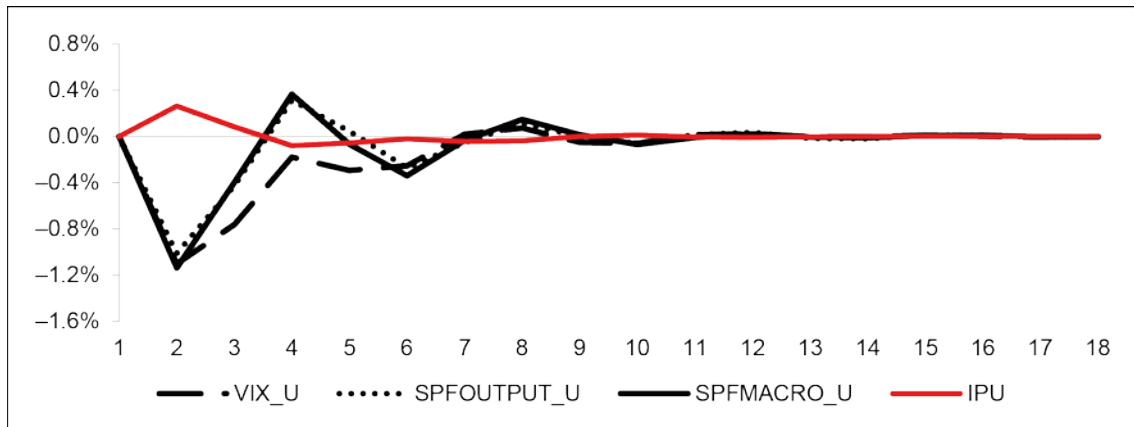
¹³ In the uncertainty literature, the confidence and the expectations are used as interchangeable terms.

¹⁴ Particularly during a crisis period, most often changes in confidence are seen as being driven by shocks to uncertainty.

¹⁵ The confidence channel is empirically traced using a survey of expectations; refer to Kamber et al. (2016).

Figure 6: Response of IIP to Alternative Uncertainty Shocks

Source: Authors' calculations.

Figure 7: Responses of IIP to Alternative Uncertainty Shocks

Source: Authors' calculations.

We check the robustness of the impulse response of the IIP in alternative VAR specifications.¹⁶ In particular, we estimate a VAR with the following recursive ordering: uncertainty, inflation deviation, and IIP gap. We also consider a VAR specification (3) that includes Nifty and Call rate, and they are ordered from fast to slow as in Baker, Bloom, and Davis (2016), i.e., placing uncertainty first assuming uncertainty shocks contemporaneously affect all variables. We also estimate VAR specification (2), which considers ordering variables from slow to fast-moving as in Jurado, Ludvigson, and Ng (2015) and Rossi and Sekhposyan (2015), i.e., putting uncertainty last assuming uncertainty responds to other variables contemporaneously. Specification (2) is taken as the baseline model.

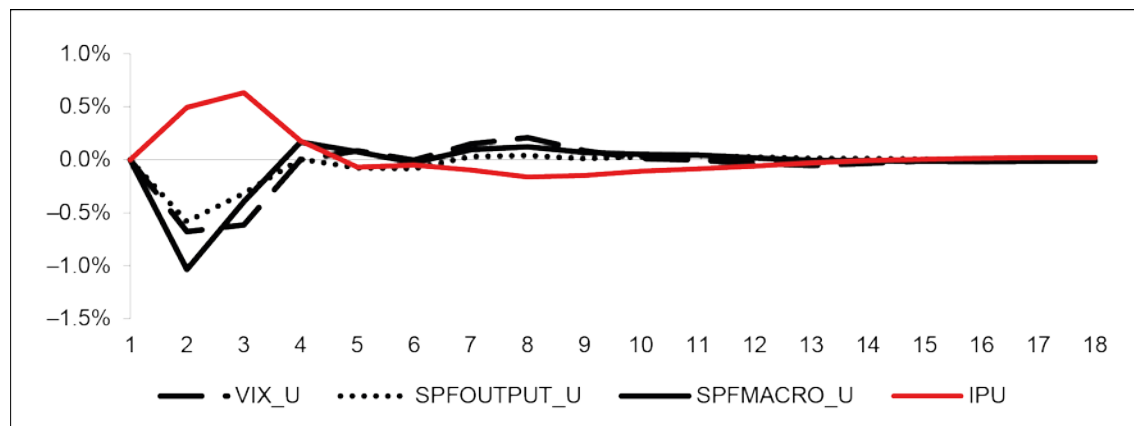
$$X' = [IIP, \text{Call rate}, \text{Business expectations}, \text{Nifty}, \text{Uncertainty}] \quad (2)$$

$$X' = [\text{Uncertainty}, \text{Nifty}, \text{Business expectations}, \text{Call rate}, \text{IIP}] \quad (3)$$

¹⁶ Bjørnland (2000) argued that the robustness of the impulse responses will be established if the extended model is consistent and is invariant to an extension of the information used.

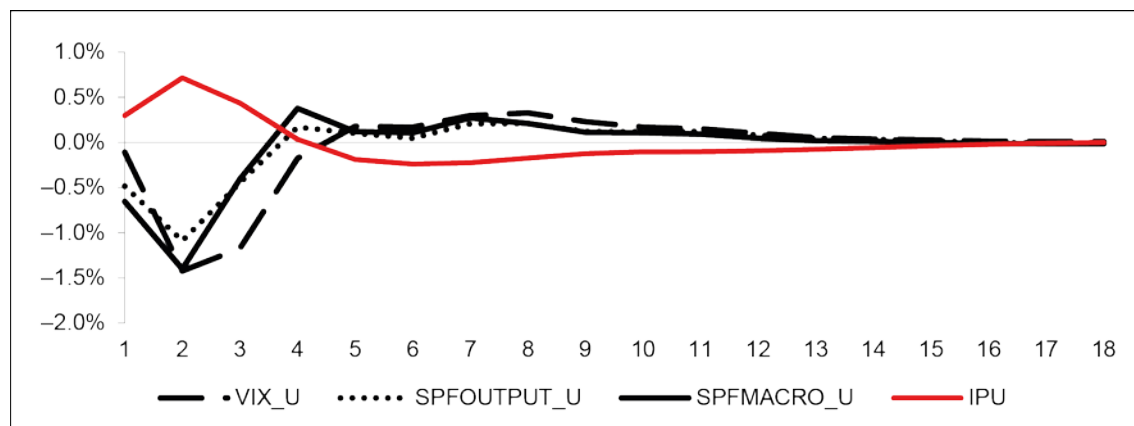
A rationale for the above specifications is that all the variables in the level are trend stationary. Appendix Table A.2 reports the results of the unit root test. It indicates that all variables are trend stationary while interest rate variables in the literature are considered stationary variables. Hence, as mentioned above, all VARs are estimated with constant and trend.

Figure 8: Responses of IIP to Alternative Uncertainty Shocks



Source: Authors' calculations.

Figure 9: Responses of IIP to Alternative Uncertainty Shocks



Source: Authors' calculations.

The impulse responses of macro variables to each uncertainty measure from the baseline estimation are reported in Appendix B. The results show that barring the IPU, the effects of a shock to AVIX_U and SPF uncertainty measures on all the variables are consistent with the predictions of the effects of uncertainty¹⁷. Figures 8 and 9 show the key results from specification 2 and 3, respectively that except for IPU uncertainty, all measures are consistent with the predictions of the supply-side channel of uncertainty. Particularly given that the quarterly growth rate of IIP averaged around 3.15% over the sample period, it is observed that the immediate fall in the production of around 1.40 percentage points is a noticeable effect. Further, the results confirm Bloom's (2009)

¹⁷ Impulse responses of macro variables from specification 3 show similar results. Further, these results do not change, regardless of the quarter end (IPU_Qend) or three-month average of the IPU index (IPU_Avg) used, as shown in Appendices B and C.

overshoot prediction of an initial fall in output following an uncertainty shock and subsequent rise over the baseline and then falling back to the baseline. Overall, the results of the supply-side channel show consistency in terms of alternative ordering and also alternative variable sets.

3.4 Examining the Demand-side Transmission Channels of Uncertainty Shocks

To identify demand-side transmission channels of uncertainty shocks, we expand the VAR model with variables relevant to the component of aggregate demand.

3.4.1 Real Options Channel of Investment

The investment channel functions on both the demand side and the supply side of an economy. It affects not only aggregate demand today but also the future productive capacity of an economy. To capture this transmission channel of uncertainty, we consider the following recursive ordering of endogenous X' variables as:

$$X' = [GDE, GFCF, \text{Project stalling rate}, \text{Business expectations}, \text{Call rate}, \text{Uncertainty}] \quad (4)$$

Here, GDE is gross domestic expenditure at constant prices,¹⁸ and GFCF is gross fixed capital formation. The project stalling rate is calculated as the total number of stalled projects as a percentage of the overall projects under implementation.¹⁹ The above specification after accounting for aggregate expenditure and other first-movement information allows us to assess the impulse responses of investment and project stalling rate to shocks to an alternative measure of uncertainty. We further propose the use of the number of projects announced in place of GFCF as it is directly linked with the wait and see decision effect of investment (Bernanke 1983).

$$X' = [GDE, \text{Number of private investment projects announced}, \text{Project stalling rate}, \text{Business expectations}, \text{Call rate}, \text{Uncertainty}] \quad (5)$$

The impulse responses of all variables from estimation 4 to each uncertainty measure are reported in Appendix C.²⁰ Again barring the IPU, the impact of AVIX_U and SPF uncertainty is broadly consistent with the theoretical effects of uncertainty. Figure 10 shows that except for the IPU, a rise in the uncertainty is associated with a decline in GFCE. The stalled project rate is an additional indicator of investment slowdown. It is expected that during a period of uncertain environment, firms often hold off on many financial decisions associated with the project. As a result, the stalled project rate may rise. The response of the project stalling rate to uncertainty shocks except for the IPU in Figure 11 supports the investment channel of uncertainty. For the robustness of these results, a VAR specification (5) is estimated by replacing GFCF in specification (4) with the number of private projects announced. A similar negative effect of uncertainty shocks on the project's announcement decisions is observed in Figure 12. The SPFMACRO_U measure has a maximum uncertainty effect on GFCF, with a peak fall noticed around

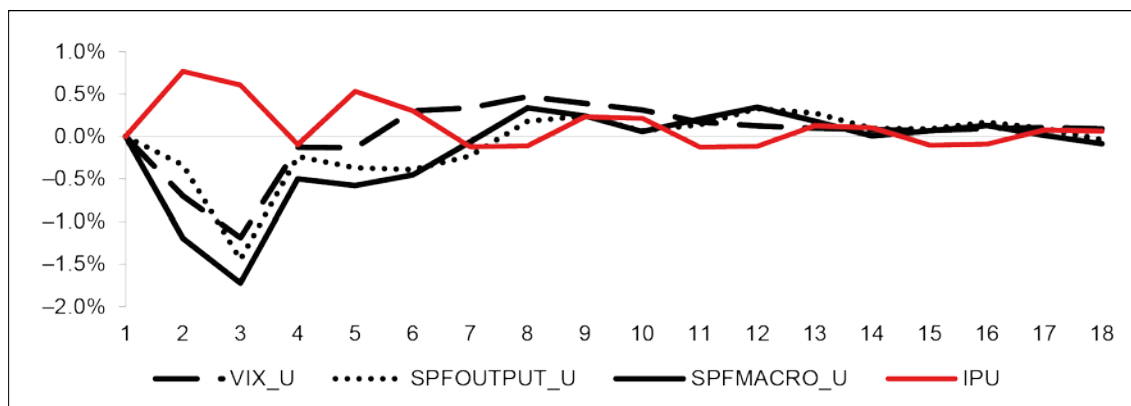
¹⁸ GDE is reported in the ordinal data source as gross domestic product at constant prices measured by the expenditure method with the base year 2011–12.

¹⁹ We consider the project stalling rate so that it can be comparable across time.

²⁰ It should be noted here that the impulse response results of all specifications from (1) to (8) for all the variables to each uncertainty measure are found to be qualitatively the same as those reported in Appendices B and C from specifications (2) and (4).

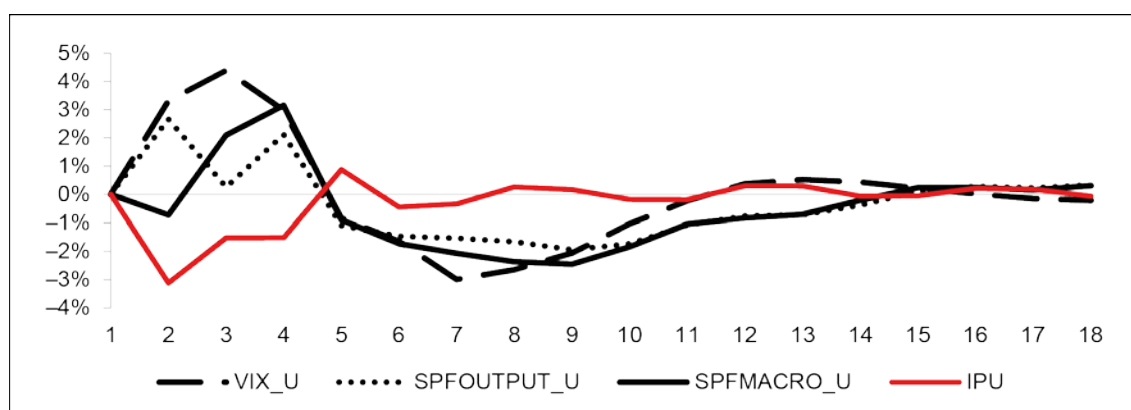
1.75% as against the average quarterly rate of GFCF of about 2% over the sample period. The result from specification 4 is robust to a VAR that includes Nifty and also robust to a VAR with the uncertainty measure ordered first and replaces GFCF with the number of projects announced.

Figure 10: Responses of GFCF to Alternative Uncertainty Shocks



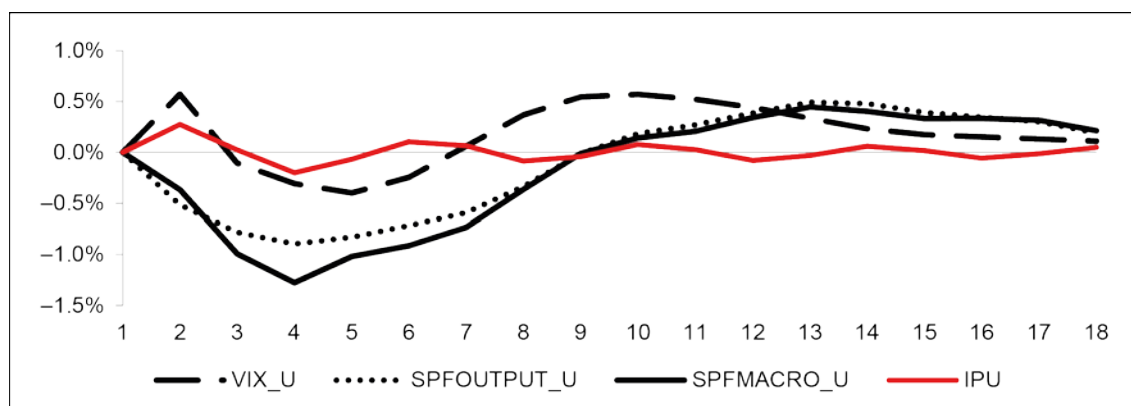
Source: Authors' calculations.

Figure 11: Responses of Project Stalling Rate to Alternative Uncertainty Shocks



Source: Authors' calculations.

Figure 12: Responses of Number of Private Investment Projects Announced



Source: Authors' calculations.

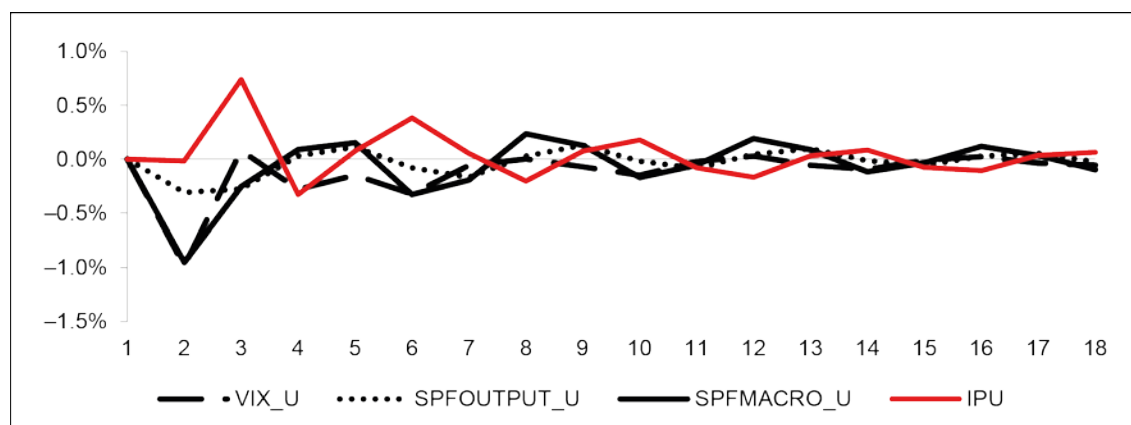
3.4.2 The Precautionary Channel of Private Consumption and Government Consumption

The precautionary saving channel of uncertainty postulates that a rise in uncertainty leads to an increase in household saving and a decrease in discretionary consumption. The consumption effect of uncertainty is expected to have two different effects: on the one hand that heightened uncertainty can induce households to postpone consumption, particularly a discretionary one, analogous to private investment channels; on the other hand, the government may increase its fiscal activity as it responds aggressively to uncertainty with increased spending to stimulate the economy. These two effects are captured using private final personal expenditure (PFPE) and final government expenditure (GFE) with the following recursive ordering of X' :

$$X' = [GDE, PFPE, \text{Business expectations}, \text{Callrate}, \text{Nifty}, \text{Uncertainty}] \quad (6)$$

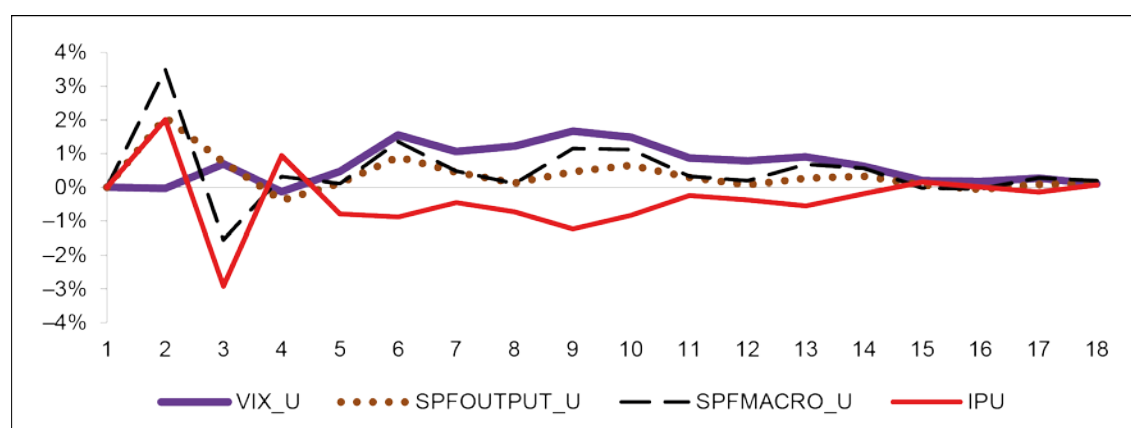
$$X' = [GDE, GE, \text{Business expectations}, \text{Callrate}, \text{Nifty}, \text{Uncertainty}] \quad (7)$$

Figure 13: Responses of PFPE to Alternative Uncertainty Shocks



Source: Authors' calculations.

Figure 14: Responses of Government Expenditure to Alternative Uncertainty Shocks



Source: Authors' calculations.

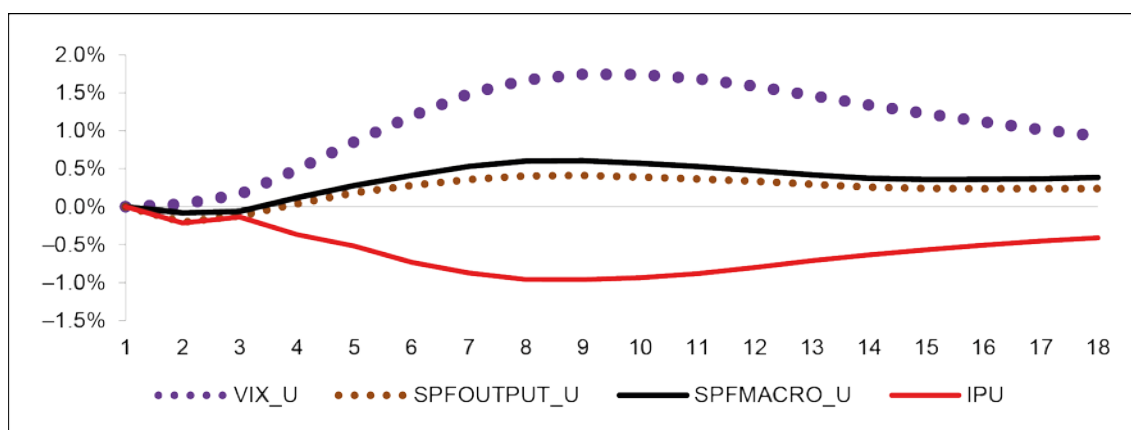
In the case of final private consumption expenditure (PFPE) response, as shown in Figure 13, it appears that its initial response to SPF and VIX uncertainty innovations is supportive of the precautionary savings channel, but it shows a relatively short-lived response – fluctuating around the baseline. This transient reaction is because the PFPE is a poor measure of discretionary expenditure, which is expected to be affected most. Therefore, we consider below a small saving as a more suitable variable to trace the precautionary savings channel. The response of government expenditure in Figure 14 is consistent with the economic prediction. However, note that the delayed response of government expenditure to AVIX_U shock is indicative of inside fiscal policy lag, but its response is persistent. This finding implies that the government does not respond instantly to uncertainty arising from the stock market until it becomes widespread and persistent.

3.4.3 The Precautionary Channel of Saving

The flip side of consumption effect is an increase in precautionary savings following a rise in uncertainty. We trace this effect by replacing PFCE in specification 6 with small saving as:

$$X' = [GDE, \text{Small saving}, \text{Callrate}, \text{Business expectations}, \text{Nifty}, \text{Uncertainty}] \quad (8)$$

Figure 15: Responses of Small Saving to Alternative Uncertainty Shocks



Source: Authors' calculations.

The saving response in Figure 15 provides evidence of the relative effectiveness of alternative measures of uncertainty. Its response to VIX- and SPF-based measures supports the precautionary savings channel prediction that the small saving rises following uncertainty shock and stays persistently at an elevated level. The highest peak impact is about a 1.75% increase for AVIX_U, followed by about 0.60% for SPFMACRO_U and 0.40% for SPFOUTPUT_U. AVIX_U uncertainty roughly triples the positive impact of uncertainty shocks on small savings. This uncertainty effect on saving is notable as the actual quarterly growth of small savings during the sample period is around 0.90%, and year-on-year growth is about 3.40%. On the other hand, the response of saving to IPU shocks shows an adverse effect, which is inconsistent with a precautionary saving channel.

3.4.4 International Spillovers Channel of Uncertainty

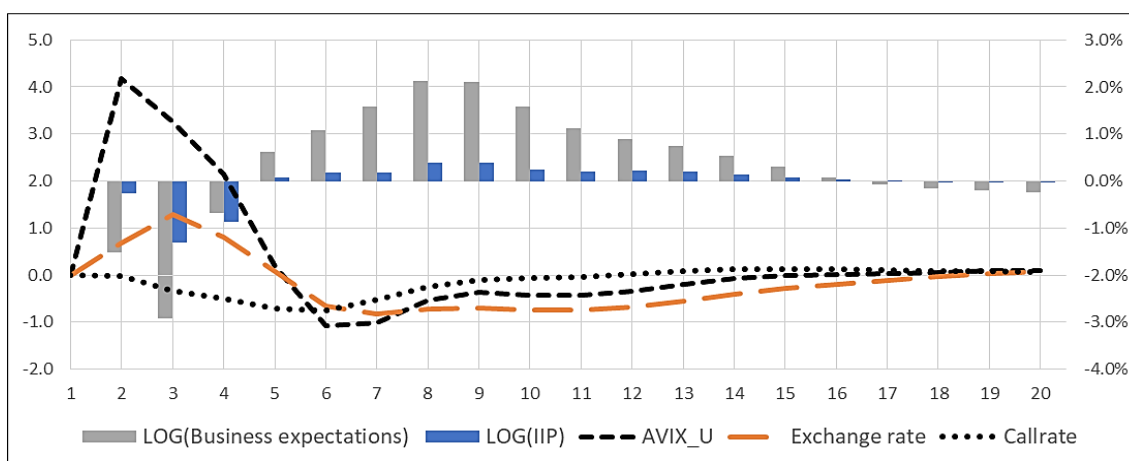
Bloom (2017) postulated that uncertainty shocks in a domestic economy might sometimes originate from a foreign country. We test this proposition by using US VIX uncertainty to assess the international spillover effect of uncertainty using the following ordering of X' :

$$X' = [\text{Foreign uncertainty, domestic uncertainty, Dollar-rupee exchange rate, Business expectations, Caltrate, IIP}] \quad (9)$$

In the above recursive VAR estimation, the foreign/US uncertainty is placed first, and then its response is restricted such that it does not respond to domestic variables, but domestic variables can respond to shocks to the US uncertainty.²¹

Figure 16 shows a substantial positive impact of US VIX uncertainty on the domestic VIX uncertainty and exchange rate, and exerts a negative effect on the level of business expectations, IIP, and call rate. These responses are similar to a VAR that uses domestic uncertainty; therefore, they are perfectly consistent with the expected theoretical channels of uncertainty. Further, the results are qualitatively not different to the use of US EPU or world EPU, suggesting that the overall story is intact. We use the variance decompositions of estimation (9) to quantify the actual role of foreign-originated uncertainty shocks in explaining the fluctuation of domestic variables, shown in Figure 17. These findings clearly demonstrate that US VIX uncertainty shocks are much more significant than India's VIX uncertainty in explaining the movements of domestic variables.

Figure 16: Responses of Domestic Variables to US VIX Uncertainty Shocks



Note: The left axis measures the rate variables, exchange rate and call rate and India's VIX uncertainty index, and the right-hand axis measures the log variables in the percentage.

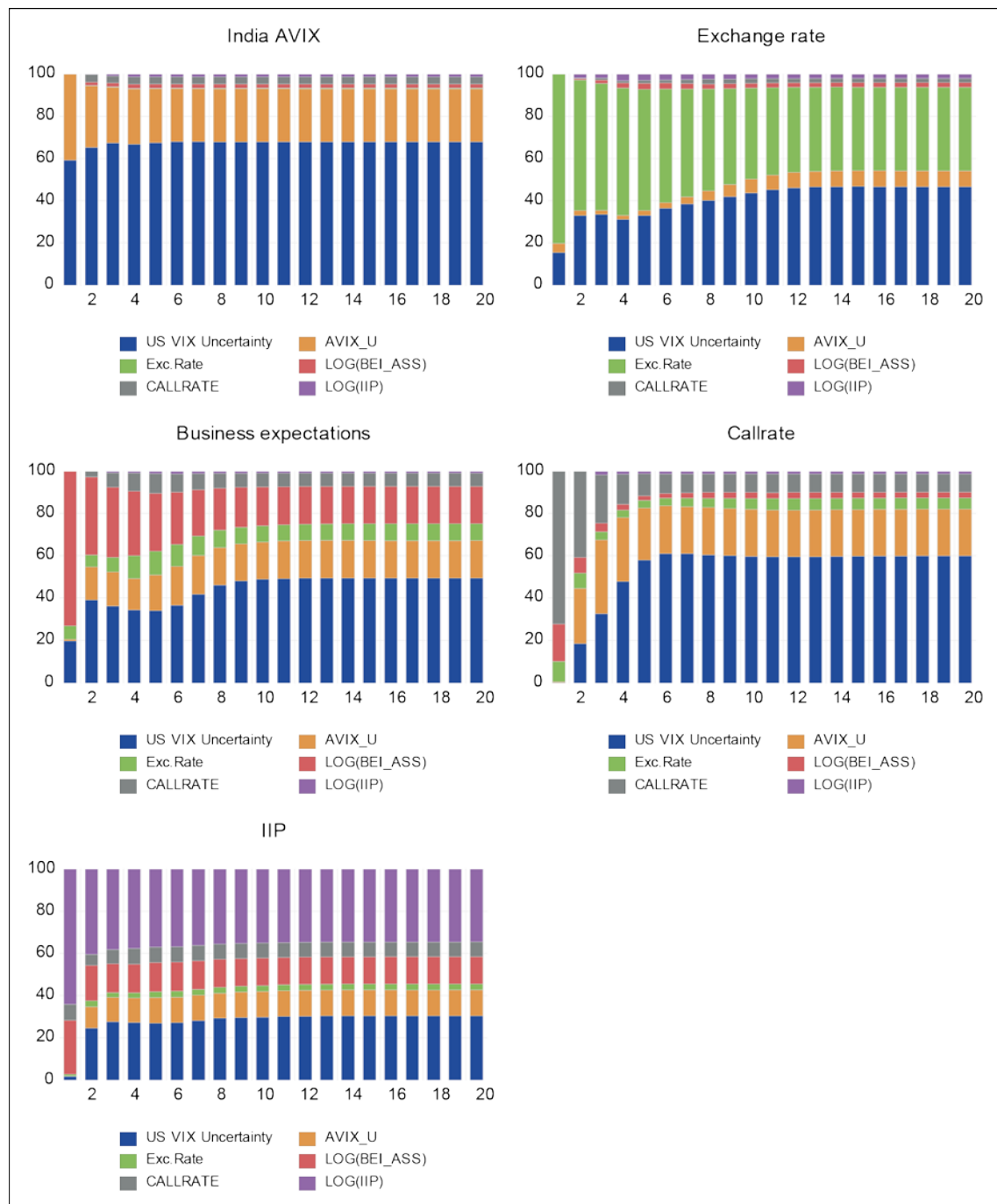
Source: Authors' calculations.

Overall, the VAR analysis of the uncertainty effect suggests that forward-looking variables are more responsive to uncertainty shocks than variables of current perceptions. The response of fiscal policy shows a considerable inside lag in recognizing the state of the economy and is found to be less effective in terms of size, although along expected lines. On the other hand, the monetary policy decisions are based on the

²¹ Specification (9) is similar to that of baseline VAR estimation (2), but it includes the exchange rate to account for uncertainty arising from the external sector.

forward-looking framework; hence, call rate responses are seen to be swift and substantial. Similarly, the reaction of business expectations appears to be more profound and substantial vis-à-vis all other responses. However, it also rebounds quickly, signifying that the expectations are data driven and so more rational. Likewise, the investment responses appear to be data driven as responses are more immediate and persistent than their counterpart consumption expenditure.

Figure 17: Variance Decompositions of Variables



Source: Authors' calculations.

4. CONCLUSION

This study constructs the macroeconomic uncertainty indices of Rossi and Sekhposyan (2015) for an emerging economy, India, and considers various other macroeconomic uncertainty indices to validate their suitability in tracing the business cycles and their consistency in shock transmission channels defined by different theoretical channels. Using quarterly data from 2008Q1 to 2018Q2, this study estimates a series of VAR models to identify different uncertainty channels of aggregate demand and supply. The derived measures of uncertainty are at a higher level around recessions and other structural changes like demonetization and GST implementation in India. Further, the empirical results also suggest that uncertainty shocks reduce industrial output, in line with the supply side of the real-option channel and correspondingly reduces the gross fixed capital formation and the number of private investment projects announced as well as raising the project stalling rate, in line with the demand-side channel of investment. Similarly, uncertainty raises household savings while reducing consumption and increasing government expenditure, which is consistent with the precautionary channel. Finally, this study also examines the international spillover of uncertainty by measuring the effects of US uncertainty measures on the domestic variables. The results show that US uncertainty has a substantial effect in explaining movements of domestic variables, much more than domestic uncertainty, suggesting a significant international spillover effect of uncertainty in the Indian economy. These findings provide a comprehensive examination of how uncertainty affects macroeconomic activity from an emerging economy perspective. The empirical results also suggest that among alternative measures, the forecast-based measure of Rossi and Sekhposyan (2015) and the market-based implied volatility measure of Bloom (2009) are found to be suitable proxies for uncertainty, while the news-based economic policy uncertainty of Baker, Bloom, and Davis (2016), which is widely used in developed countries, has not properly captured the state of economic uncertainty in India. This finding may suggest that news-based economic uncertainty indices may not be useful for developing countries since, in these countries, sociopolitical uncertainty-related events are seen to be a more dominant discourse in the media, and often such uncertainty may die off without any economic recession.

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APPENDIX A

Table A.1: Data and Sources

Variables	Source
1. US economic policy index (EPU)	http://www.policyuncertainty.com/
2. World policy uncertainty index	
3. India's economic policy index (IPU)	
4. India's implied volatility index (VIX) data	https://www.nseindia.com/
5. US VIX data	http://www.cboe.com/
6. Business expectations index (BEI) data	Reserve Bank of India quarterly survey of industrial outlook: https://www.rbi.org.in/
7. Survey of professional forecasters (SPF) data	Reserve Bank of India quarterly survey of professional forecasters (SPF): https://www.rbi.org.in/
8. Gross domestic product (GDP)	CMIE economic outlook database: https://economicoutlook.cmie.com/
9. Gross fixed capital formation (GFCF)	
10. Government expenditure (GE)	
11. Final private consumption expenditure (PFPE)	
12. Index of industrial production (IIP)	
13. Number of private investment projects announced	
14. Total number of stalled projects	
15. The overall number of projects under implementation	

Source: Authors' compilation.

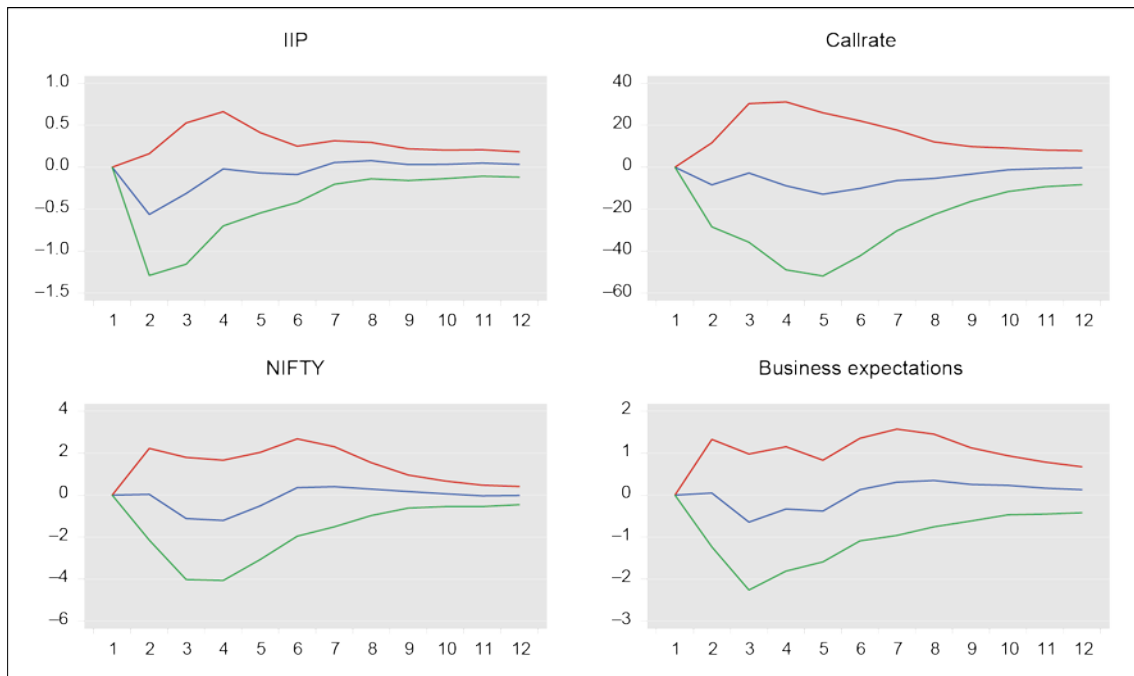
Table A.2: ADF Test Results

Variables	<i>p</i> -Values of Intercept	<i>p</i> -Values of Trend and Intercept
SPFGDP_U	0.00	0.00
SPFMACRO_U	0.00	0.00
AVIX_U	0.29	0.00
IPU	0.05	0.07
log(IIP)	0.39	0.01
log(Nifty)	0.82	0.05
log(Business expectations)	0.03	0.00

Source: Authors' calculations.

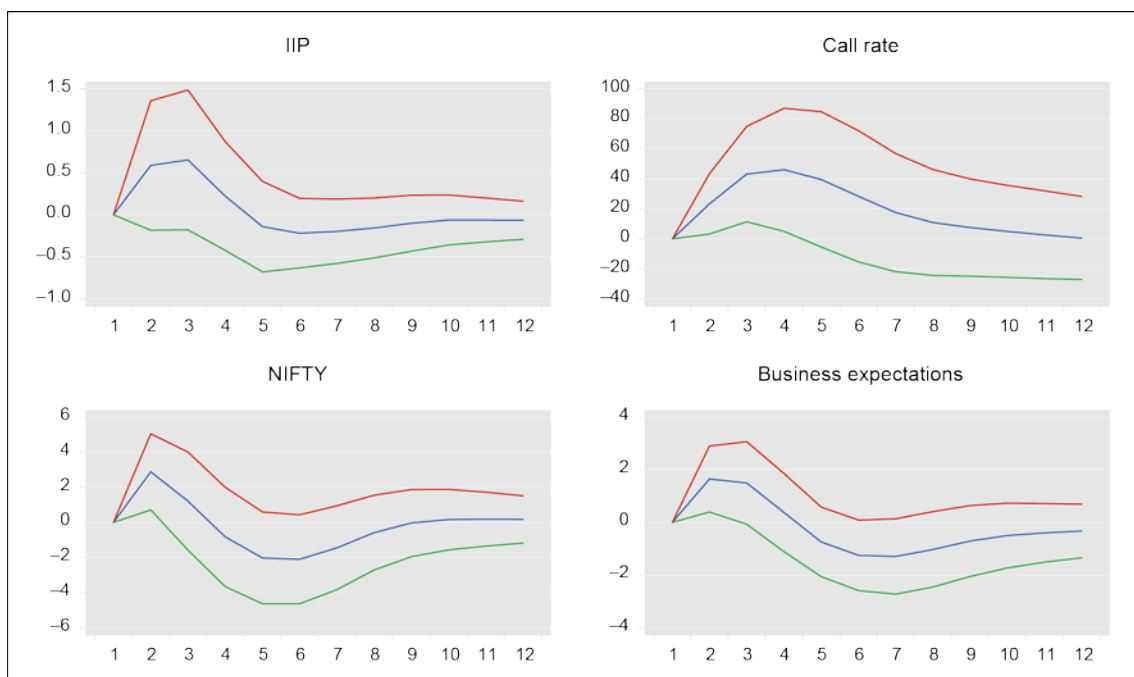
APPENDIX B: IMPULSE RESPONSES OF BASELINE SPECIFICATION (2): THE SUPPLY SIDE OF THE REAL OPTION CHANNEL

Figure B.1: Responses to SPFGDP_U Uncertainty Shocks

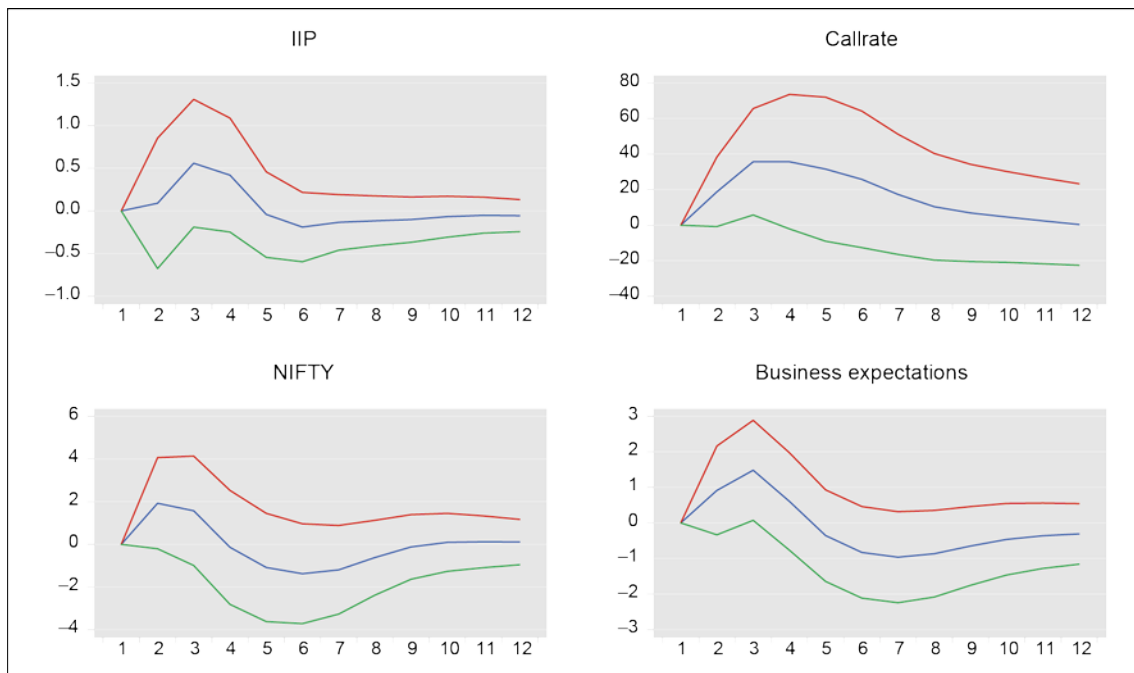


Source: Authors' calculations.

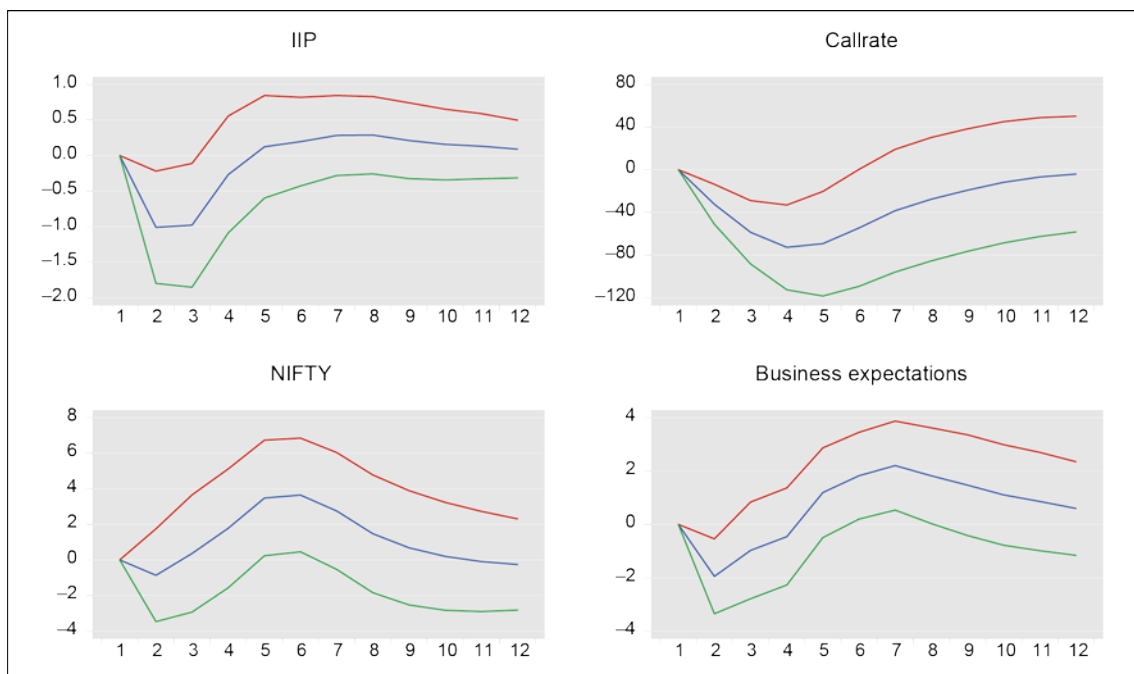
Figure B.2: Responses to IPU_Qend Uncertainty Shocks



Source: Authors' calculations.

Figure B.3: Responses to IPU_Qavg Uncertainty Shocks

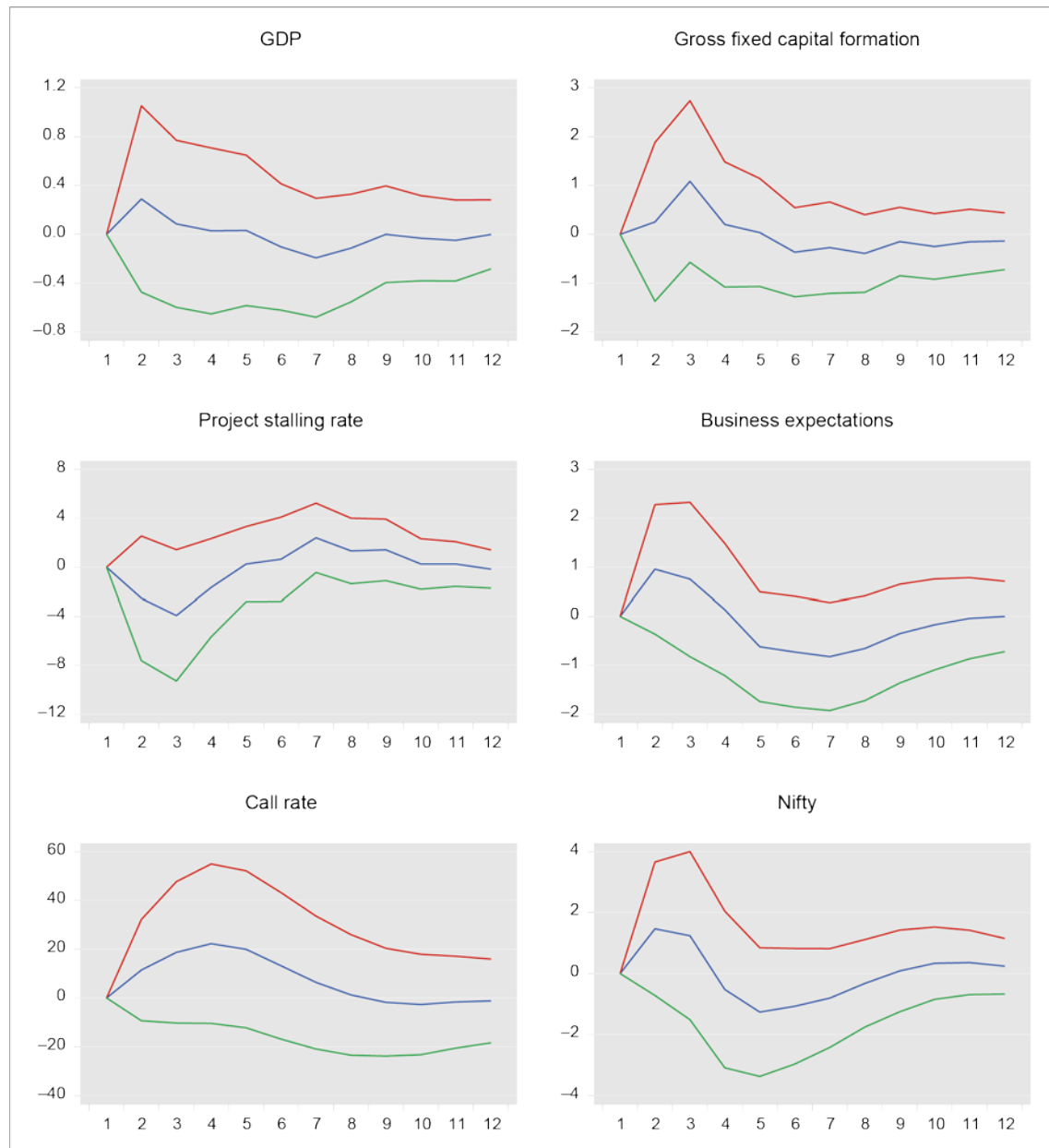
Source: Authors' calculations.

Figure B.4: Responses to AVIX_U Uncertainty Shocks

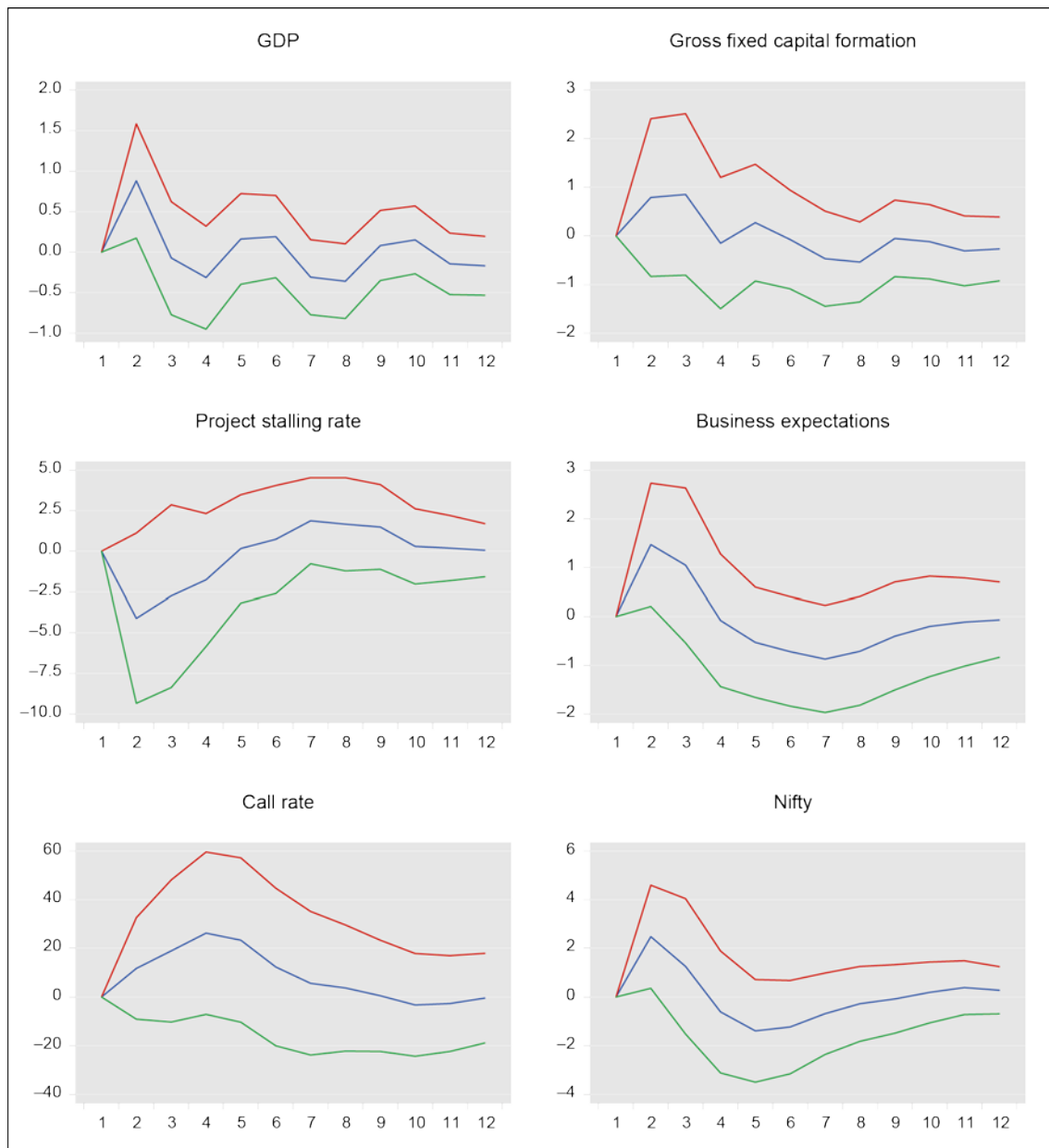
Source: Authors' calculations.

APPENDIX C: IMPULSE RESPONSES FROM THE SPECIFICATION (4): THE DEMAND SIDE REAL-OPTION CHANNEL OF INVESTMENT

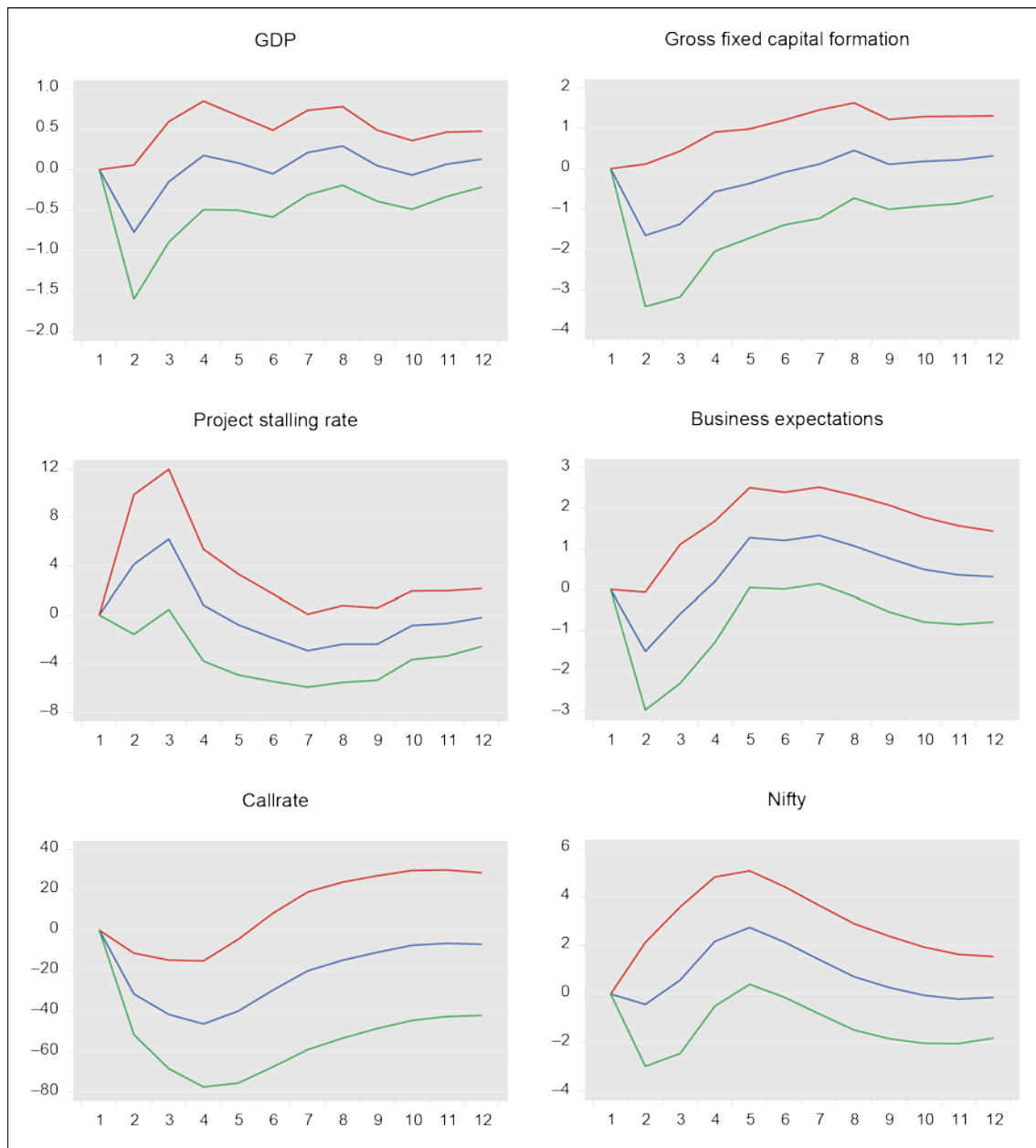
Figure C.1: Responses to IPU_Qavg Uncertainty Shocks



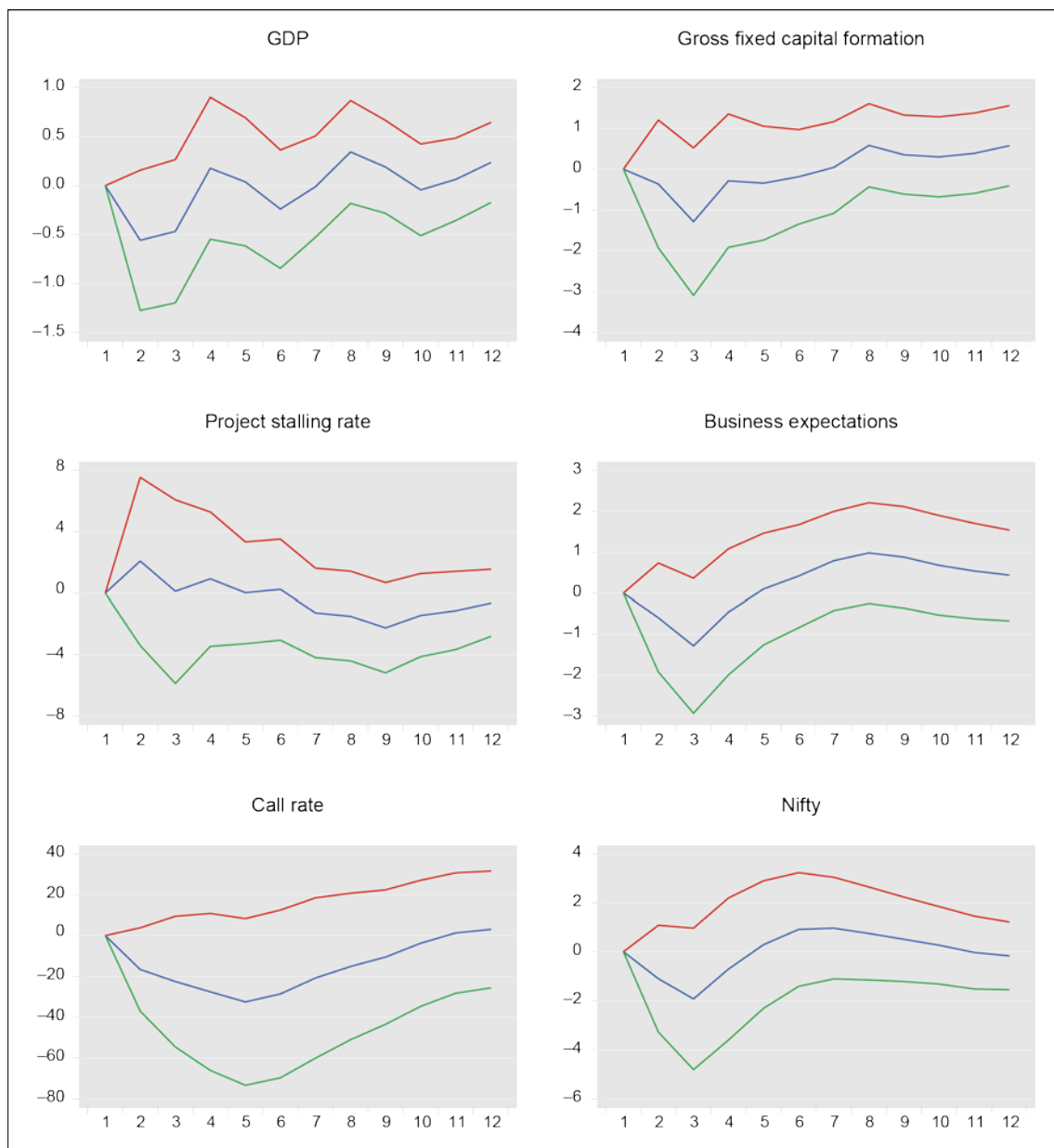
Source: Authors' calculations.

Figure C.2: Responses to IPU_Qend Uncertainty Shocks

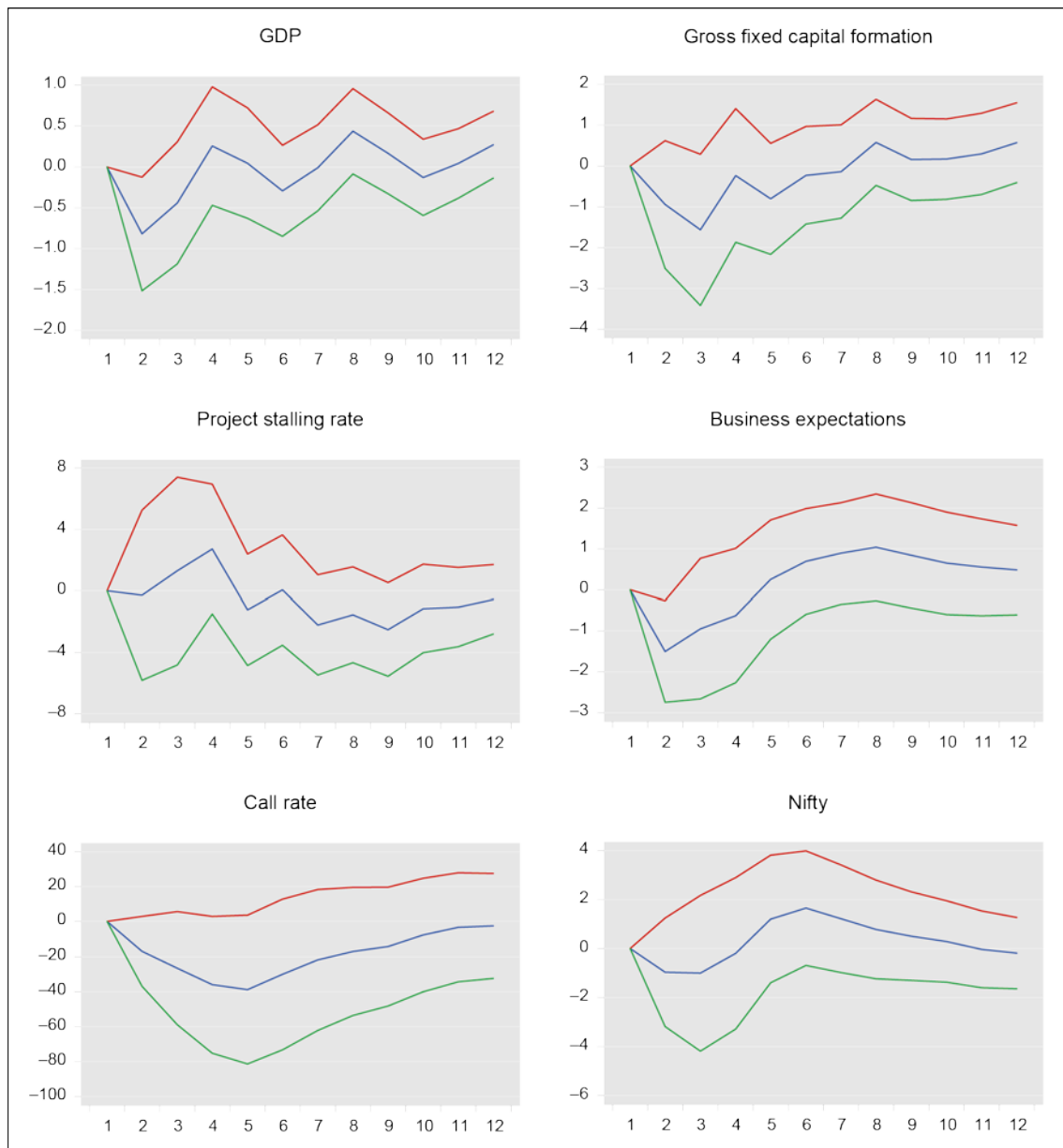
Source: Authors' calculations.

Figure C.3: Responses to AVIX_U Uncertainty Shocks

Source: Authors' calculations.

Figure C.4: Responses to SPFGDP_U Uncertainty Shocks

Source: Authors' calculations.

Figure C.5: Responses to SPFMACRO_U Uncertainty Shocks

Source: Authors' calculations.