Is Uncertainty the Same Everywhere? Advanced Versus Emerging Economies*

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Abstract

Considering the frequency of uncertainty shocks, this study examines various uncertainties across countries. Recent literature shows conflicting evidence on whether these uncertainties are supply- or demand-driven shocks. Using quarterly data from the United States and India, this study shows that although uncertainty shocks are demand shocks in advanced economies (e.g., the United States) with a contractionary output effect, they behave as supply shocks in emerging economies (e.g., India) with an inflationary effect. In contrast to the United States, asymmetry in India results from a high and positive correlation between uncertainty and oil price shocks. This study distinguishes between international and domestic uncertainty for India and finds a significant spillover of international uncertainty.

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Furthermore, the study shows that domestic uncertainty also relates to the primary sector, where rainfall emerges as a source of domestic uncertainty, thereby contributing to the inflationary effect. Therefore, uncertainty shocks influence monetary policy response differently.

JEL classification: E31; E32; E52; E57

Keywords: Penalty Function; India; Uncertainty; Inflation; SVAR; Supply Shock; Demand Shock

1 Introduction

Following the 2008-2009 global financial crisis, numerous macroeconomic studies have focused on uncertainty. The ongoing COVID-19 pandemic has further stressed the importance of understanding the sources and transmission of uncertainty shocks. In a seminal work, Bloom (2009) showed that heightened uncertainty adversely affects new hiring and investments by firms, thereby affecting resource reallocation and causing significant output and employment cost in the short run. A pause in hiring and investment by firms is similar to the real options channel proposed by Dixit and Pindyck (1994). Considering that investments are mostly irreversible, firms are buying a put option and giving up the call option (i.e., an option to invest at a lower cost later). During high uncertainty, the value of the call option increases and firms consider waiting and watching increasingly optimal (Bernanke, 1983). Therefore, during high uncertainty, the real options channel implies that investment does not increase despite declining interest rates because of precautionary savings.

Several studies have introduced uncertainty in different manners in new Keynesian models to explore the transmission of an uncertainty shock in an economy. As entrepreneurs face uncertainty in converting capital to effective capital, Christiano et al. (2014) call the magnitude of this uncertainty as risk. Their estimation suggested that the risk shock is the most crucial factor driving the United States (US) business cycle.

Basu and Bundick (2017) introduced demand uncertainty to households' discount factor in a new Keynesian model. They showed that the decline in output, hours, consumption, and investment in the model because of the demand uncertainty shock was similar to the VAR evidence on the effect of uncertainty shock on these variables.

Bloom (2009) stated that the real effect of uncertainty increases because of increased inactivity as more firms wait and watch. Conventionally, uncertainty increases financial distortions and credit risk, thereby reducing investment. Gilchrist et al. (2014) described these two channels in a general equilibrium model and showed that both channels affect investment. Arellano et al. (2019) suggested that during increased uncertainty, firms reduce their inputs to minimise risk, which exacerbates the wait-and-watch problem. Baum et al. (2009) showed that macroeconomic uncertainty reduces the optimal leverage for firms; therefore, investment declines through this channel as well. Not only do existing firms reduce their investment but also more firms could fail during high uncertainty, thereby exacerbating the real effects of uncertainty (see Byrne et al., 2015). The leverage channel can also work through banks. Istiak and Serletis (2020) argued that during high uncertainty, shadow banks significantly reduce their leverage, which is likely to disrupt the financial market and flow of credit to firms, thereby reducing investment. Using a new Keynesian model, Leduc and Liu (2016) showed that the uncertainty shock is similar to a demand shock. Fasani and Rossi (2018) argued that the results in Leduc and Liu (2016) are driven by the inaccurate specification of the Taylor rule, and once the specification is corrected, the uncertainty shock behaves as a supply shock. Alternatively, the Taylor rule is important for the uncertainty shock to be termed as demand or supply shock in the new Keynesian model (see Annicchiarico and Rossi, 2015).

It is unclear ex-ante whether these uncertainties are demand or supply shocks. The inference regarding the supply and demand can be made after identifying the exogenous component of respective uncertainties and observing their transmission in the economy. If it moves inflation and output in the same direction, then it is a demand shock, and if the exogenous component moves them in the opposite direction, then it is a supply shock. These studies have considered either country-specific or global uncertainty without making any distinction between the two. Any increase in global or domestic uncertainty negatively impacts the macroeconomy; however, the nature of the shock determines its effects. Therefore, this study compares the transmission of uncertainty shocks in advanced and emerging economies. The study considered the US and India as advanced and emerging economies, respectively. Our choice of these two countries follows the study by Bhattarai et al. (2021).

We argue that local uncertainty observed for emerging economies is not completely domestic uncertainty because of a possible spillover of international uncertainty into local uncertainty. Zhang et al. (2019) found a significant spillover of the US uncertainty to the Chinese economy, including the economic policy uncertainty index in China. International uncertainty causes an outflow of capital and represents weak external demand, which is an important source of growth for emerging economies. Moreover, sharp movements in oil prices may engender international uncertainty, thereby significantly affecting oil-dependent economies. Our impulse responses justify this result because we find a significant effect of the international uncertainty shock on domestic uncertainty.

This study, first, identifies uncertainty shocks for India and the US by using Cholesky decomposition and penalty function approaches. Our impulse-response-based identification (the penalty function method) is related to Faust (1998), Uhlig (2005), Mountford and Uhlig (2009), Barsky and Sims (2011), Kurmann and Otrok (2013), and Caldara et al. (2016). Our penalty function identifies the uncertainty shock as one that causes consecutive four quarters of positive response in uncertainty and causes maximum increase in uncertainty over one year. The responses of output and inflation show a demand-driven uncertainty shock in the US and a supply-led uncertainty shock in India. Holtemoller and Mallick (2016) showed that inflation frequently originates as a supply shock in India unlike in advanced economies where inflation has primarily been a demand concern. This study uses vector auto-regression (VAR)-based responses to classify shocks as demand and supply shocks similar to that in small and medium-scale new Keynesian models with representative households (Ireland, 2011).

To understand why the uncertainty shock is a supply shock in India, we estimate the VAR models by replacing the uncertainty shock with oil prices for both countries. The transmission of the oil price shock in India is similar to that of the economic policy uncertainty (EPU) shock. The correlation between EPU and oil price shock is high, which implies that oil price uncertainty transmits as a supply shock because Indian EPU significantly reflects oil price movements. For the US, the response of inflation because of the oil price shock is in contrast to the response caused by the EPU shock. We further find that the response of food inflation is substantially higher due to EPU shock than the oil price shock. Our subsequent analysis suggests that the EPU shock comprises other sources of domestic uncertainty, such as rainfall. Considering that Indian agriculture depends on monsoon, this result is consistent with our expectations.

We then extend the VAR model for India and include the US uncertainty, thereby identifying two shocks: international and domestic. We use an additional restriction that international and domestic uncertainty shocks are orthogonal while identifying both shocks. The response of domestic variables shows that both uncertainty shocks behave as supply shocks for India, where the effect of domestic uncertainty is most pronounced in the primary sector of the economy, and international uncertainty in other sectors of the economy. The Appendix presents the forecast error variance decomposition of domestic variables because of domestic and international uncertainty shocks. The domestic uncertainty shock is a significant driver of food inflation, which explains more than 40% of the forecast error variance of food inflation over 20 quarters. International uncertainty is relatively more important for nonfood inflation. Using another measure of uncertainty, the results in the Appendix show that our primary result, uncertainty shocks are demand shocks in an advanced economy and a supply shock in an emerging economy, still remains consistent.

Accordingly, this paper is presented as follows. Section 2 describes the data and explains the methodology. Section 3 compares the transmission of uncertainty shocks in India and the US. Section 4 disentangles domestic and international uncertainty for India. Section 5 presents the concluding remarks.

2 Data and Empirical Framework

2.1 Data

The EPU index used in the study follows Baker et al. (2016). The baseline VAR model for both India and the US is estimated using the respective EPU index, real gross domestic product (GDP), consumer price index (CPI), and short-term nominal interest rate, that is, the Treasury bill rate for 15-91 days. In particular, we use real GDP (billions of Chained 2012 US Dollars), CPI for all urban consumers (all Items in US City, Average), and 3-month treasury bills secondary market rate for the US. For India, we use CPI for industrial workers. The study period involved 1997:Q2 to 2019:Q1. All variables are seasonally adjusted and in log, except for interest rates.

Figure 1 gives the EPU index for India and the US. For India, the EPU index is available from 2003 onward. Both uncertainty indices have a similar pattern. During the financial crisis, uncertainty increased in both India and the US; however, during Taper Tantrum in 2013, the uncertainty increased in India and decreased in the US. Moreover, divergence in these two indices can be recently observed. In addition, we use another measure of global uncertainty (VIX) for robustness. VIX data for India are available from 2009 onward; therefore, using Indian VIX provides a small study sample. We use the US VIX as a measure of global uncertainty for India considering the high correlation of 0.624 between the US and Indian VIX indices (see the Appendix). Other variables are from the Reserve Bank of India and Federal Reserve Bank of Saint Louis for India and the US, respectively. We estimate several extended VAR models for India. In these estimations, we use the food price index, nonfood price index, global oil price, and agricultural output. We further use rainfall deficiency data obtained from Indiastat.

The nonfood price index for India is not directly given and is estimated from CPI and food price index for base years 1982 and 2001 (see the Appendix). Figure 2 presents the nine-quarter moving average of inflation, food inflation, and nonfood inflation.

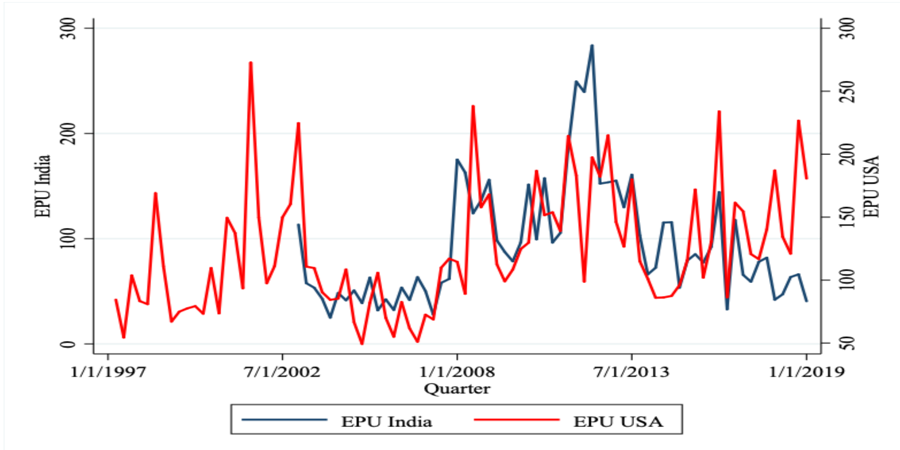


Figure 1: Economic policy uncertainty in the United States and India

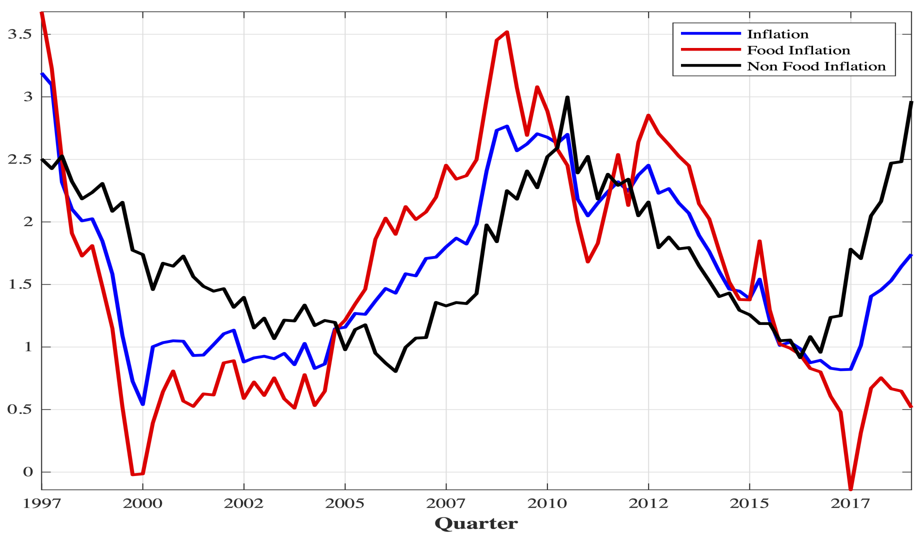


Figure 2: Nine-quarter moving average inflation

The oil price index has been obtained from the Federal Reserve Bank of Saint Louis. The EPU index in the US (international uncertainty) and India are significantly correlated. We argue that there are possible spillovers from international to local uncertainty in India. Therefore, we do not refer to the local uncertainty shock in India as the domestic uncertainty shock. The domestic uncertainty shock is obtained by eliminating the movement in local uncertainty because of international uncertainty, which is achieved by estimating a structural VAR model that includes international uncertainty.

2.2 Empirical Framework

This study identifies VAR models by using Cholesky factorization and the Uhlig penalty function method. Because Cholesky factorization is well-recognized, we omit this discussion but explain the Uhlig penalty function method. A reduced-form VAR model is given as follows:

$$Y_t = B_1 Y_{t-1} + B_2 Y_{t-2} + ... + B_p Y_{t-p} + u_t$$

where Y_t is a vector, and B_i are the reduced form coefficients. Based on this autoregressive model, the moving average representation is as follows:

$$Y_t = C(L) u_t$$

u_t are reduced-form shocks and are likely to be correlated. . Because they have limited economic meaning, we obtain the Cholesky decomposition of the reduced-form co-variance matrix: $(\sum = u_t u_t' = AA')$ which implies a recursive ordering. Structural shocks can be assumed as uncorrelated and as having unit variance; thus, $u_t = A\nu_t$.

$$\sum = u_t u_t' = A\nu_t \nu_t' A' = AA'$$

The structural moving average based on the Cholesky decomposition is as follows:

$$Y_t = C(L) A \nu_t$$

The Cholesky decomposition is not the only possible decomposition of the reduced-form co-variance matrix. There are numerous possible decompositions. In general, one can assume an orthonormal matrix Q, and the aforementioned decomposition can be written as follows:

$$\sum = AQQ'A' = AA'$$

Now the structural shocks would be different and is given by $u_t = AQ\tilde{v}_t$. The corresponding structural moving average is given by:

$$Y_t = C(L)AQ\tilde{\nu}_t$$

Matrix Q needs to be identified. We identify selected columns of Q given by $q_j = Q\ e_j$ where e_j denotes the jth column of I_n. We define the uncertainty shock as an innovation that generates the largest increase in a given measure of uncertainty for the first year. In the baseline case, we identify the uncertainty shock for India and the US separately; therefore, we identify the first column of Q. We consider uncertainty as the first variable in VAR for simplicity. Therefore, our objective is to solve the following optimization problem:

$$\Psi(q_1) = \sum_{l=0}^{3} -\frac{e_1' C(L) A q_1}{\omega_1}$$

Subject to

$$e_1' C(L) A q_1 > 0$$

The penalty function should be minimized. The second constraint ensures that the response of uncertainty caused by the first shock is positive. In the extended models for India, we identify two shocks: two columns of Q. The uncertainty index in the US is the first variable in the VAR, whereas uncertainty in India is the second variable. The first column is identified as earlier, which helps realize the international uncertainty shock. The identification of the second column requires additional conditions. The objective is to solve the following additional optimization problem:

$$\Psi(q_2) = \sum_{l=0}^{3} -\frac{e_2' C(L) A q_2}{\omega_1}$$

Subject to

$$e_2'C(L)Aq_2 > 0$$

$$Q_1^* q_2 = 0$$

As an objective function, the penalty function should be minimized. The first constraint ensures that the response of local uncertainty in India is positive because of the second shock, termed as the domestic uncertainty shock in this study. The second constraint ensures that the identified international and domestic uncertainty shocks are orthogonal (Caldara et al., 2016). ω_1 and ω_2 are standard deviations of the reduced form shocks and e_1 and e_2 are selection vectors (selecting the target response). We assume $l = 3$, that is, we identify shocks engendering a maximum increase in uncertainty over one year.

3 Country-Specific Uncertainty and Oil Price Shock in India and the United States

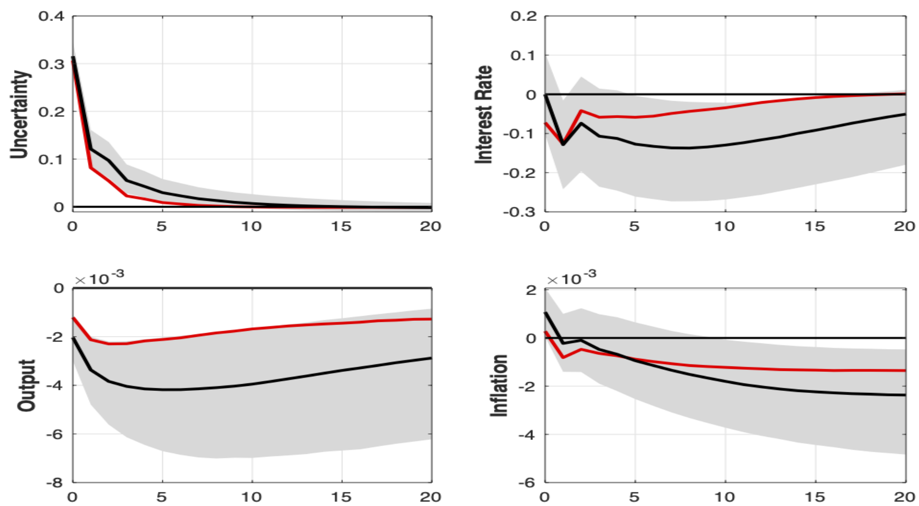


Figure 3: The response of model variables because of uncertainty (EPU) shock in the United States. Red and black lines show the shock identified by the Cholesky decomposition and Uhlig penalty function methods, respectively. The shaded area is the 68% confidence interval for the response produced by the identified shock by using the penalty function method.

This section presents country-wise VAR models for India and the US. Figure 3 presents the response of model variables engendered by the identified uncertainty shock in the US.

Both the Uhlig and Cholesky decomposition methods provide a similar response of the model variables; however, the identified uncertainty shock by using the Uhlig penalty function approach is more persistent and has a larger contractionary effect on the output than the shock identified by using Cholesky decomposition. Moreover, the shock identified by using the penalty function method has a persistent effect on inflation and interest rate.

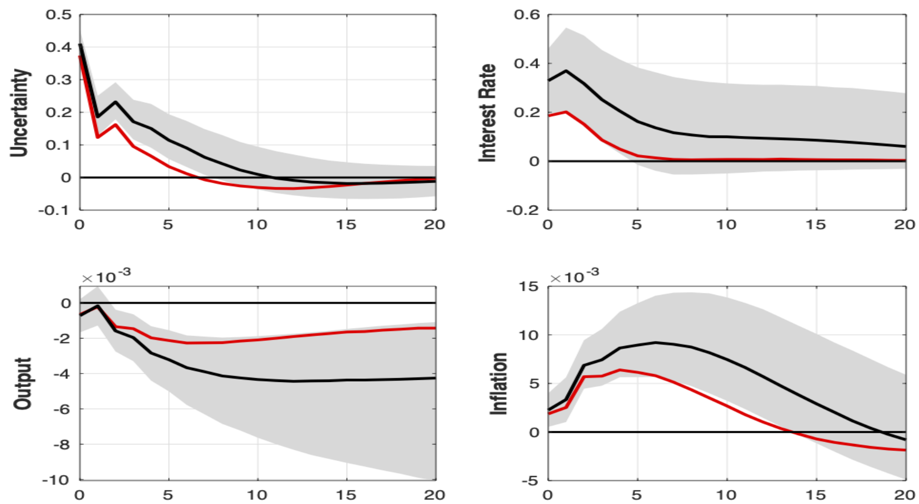


Figure 4: Response of model variables caused by uncertainty (EPU) shock in India. Red and black lines show the shock identified by the Cholesky decomposition and Uhlig penalty function methods, respectively. The shaded area is the 68% confidence interval for the response produced by the identified shock by using the penalty function method.

Because the uncertainty shock reduces output, inflation, and interest rate- although the effect is not very clear in the beginning for inflation-the uncertainty shock behaves as a demand shock in the US (an advanced economy). Figure 4 presents the response of model variables engendered by the uncertainty shock in India. The shock identified by using the penalty function method is more persistent and causes a more persistent increase in the interest rate and inflation. Furthermore, the effect on output persists even after 20 quarters. The nature of the responses shows that the uncertainty shock transmits as a supply shock in India (an emerging economy). Because the uncertainty shock behaves as a supply shock in India, it must be capturing some dominant supply shocks faced by the Indian economy. The oil price shock becomes an important supply shock for India because of the dependence on imported oil[1]. Therefore, we estimate the VAR again by replacing the country-specific uncertainty shock with common global oil price shock[2].

[1]https://economictimes.indiatimes.com/news/economy/foreign-trade/indias-oil-imports-at-near-3-year-high-in-december/articleshow/80348206.cms?from=mdr

[2]https://fred.stlouisfed.org/series/POILBREUSDM

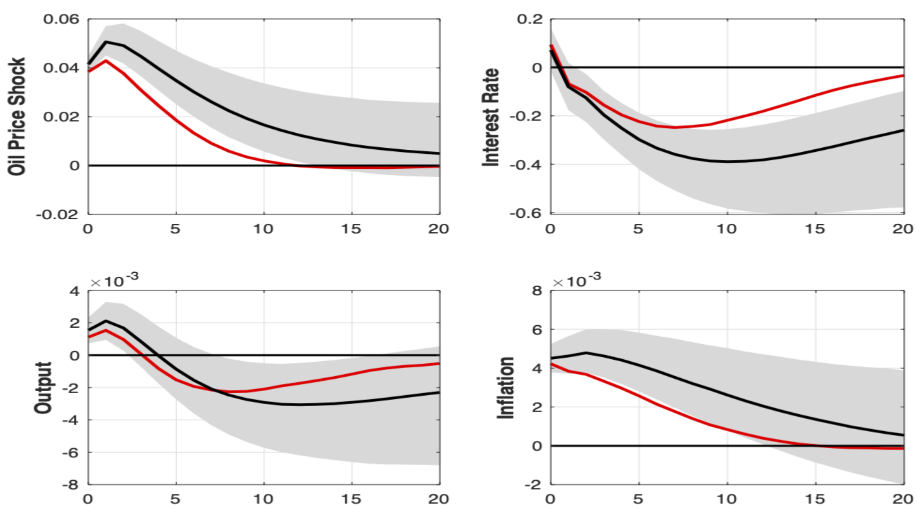


Figure 5: Response of model variables because of oil price shock in the US. Red and black lines show the shock identified by the Cholesky decomposition and Uhlig penalty function methods, respectively. The shaded area is the 68% confidence interval for the response produced by the shock identified by using the penalty function method..

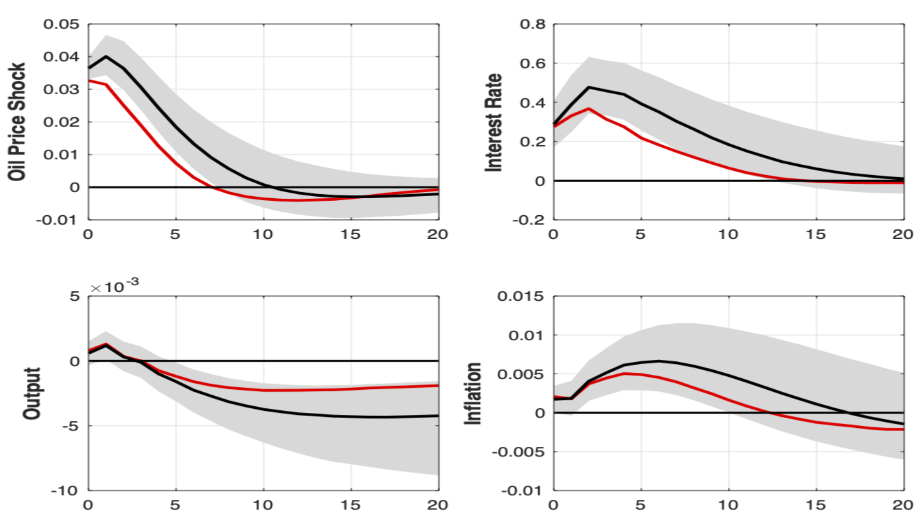


Figure 6: Response of model variables caused by the oil price shock in India. Red and black lines show the shock identified by the Cholesky decomposition and Uhlig penalty function methods, respectively. The shaded area is the 68% confidence interval for the response produced by the identified shock by using the penalty function method.

Figures 5 and 6 show the responses of the macro variables in the US and India caused by the global oil price shock identified using country-specific VAR. The oil price shock identified in this study is probably a combination of the oil demand and oil supply shock, as argued by Kilian (2009) and Caldara et al. (2019). The responses of output and inflation for the US suggest that it is probably a demand shock in the beginning. We do not disentangle the oil price shock into the demand and supply shocks because from the Indian perspective, they are less important. As a small economy, India is not likely to increase oil prices by demanding more oil. Therefore, higher oil prices are anticipated to behave like a supply shock for India. Figure 6 shows that the oil price shock reduces output and increases inflation. Therefore, oil shock predominantly transmits as a supply shock in India, and the responses caused by the oil price shock are similar to the EPU shock. In the case of the United States, we find that the oil price shock has a different effect on inflation compared with the effect of the EPU shock on inflation. One can further argue that EPU shock is predominantly a demand shock in the US and a supply shock in India.

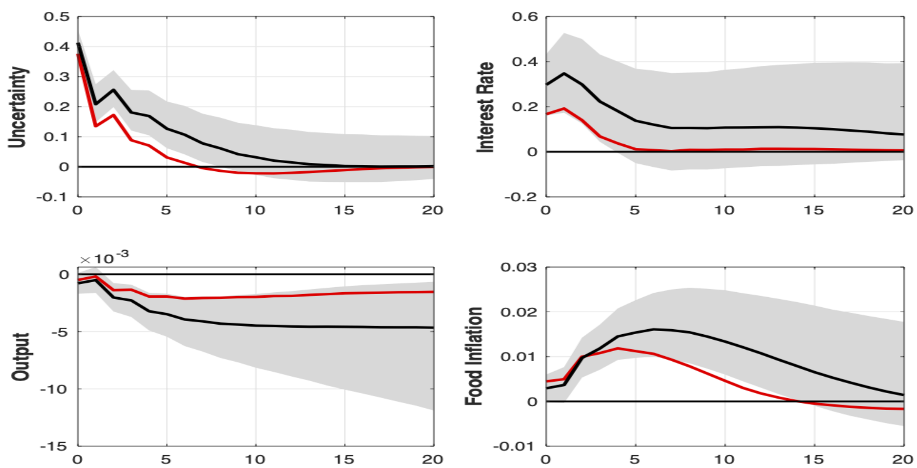


Figure 7: Response of model variables caused by the uncertainty (EPU) shock in India. The model is estimated with the food price index. Red and black lines show the shock identified by the Cholesky decomposition and Uhlig penalty function methods, respectively. The shaded area is the 68% confidence interval for the response produced by the identified shock using the penalty function method.

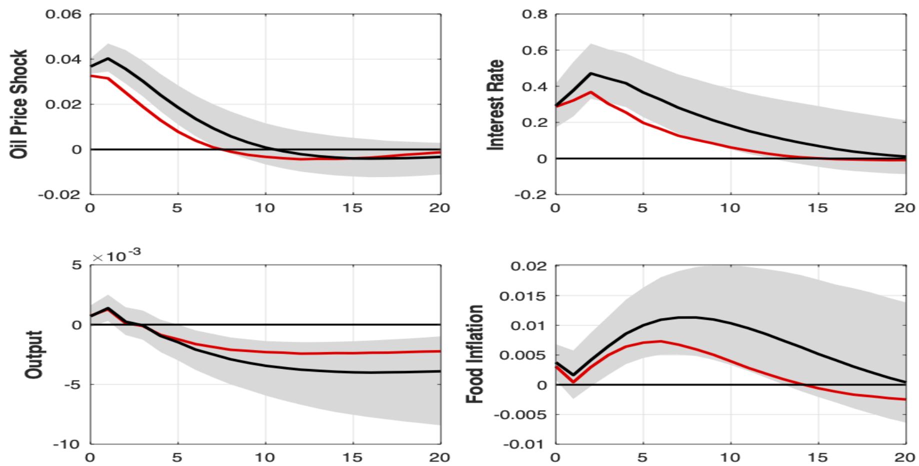


Figure 8: Response of model variables caused by the oil price shock in India. The model is estimated using the food price index. Red and black lines present the response of the shock identified by the Cholesky decomposition and Uhlig penalty function methods, respectively. The shaded area is the 68% confidence interval for the response produced by the identified shock by using the penalty function method.

We further estimate the VAR model for India by using the food and nonfood price indexes with both EPU and oil price. These models help understand the disaggregated response of inflation caused by the EPU and oil price shocks. Figures 7 and 8 show the responses of macro variables in India caused by the global oil price and EPU shocks for the models estimated with the food price index. The responses engendered by the oil price and EPU shocks are similar. In particular, both these shocks increase food inflation. Figures 9 and 10 show the responses of macro variables in India caused by the global oil price and EPU shocks for models estimated with the nonfood price index. The responses caused by oil price and EPU shocks are also similar. Furthermore, both shocks increase nonfood inflation. The EPU shock has a significantly higher effect on food inflation than on nonfood inflation. Both shocks have a similar effect on nonfood inflation. Based on the response of food inflation and considering that EPU shock is likely to contain some other sources of domestic uncertainty, the following section explores this topic in detail.

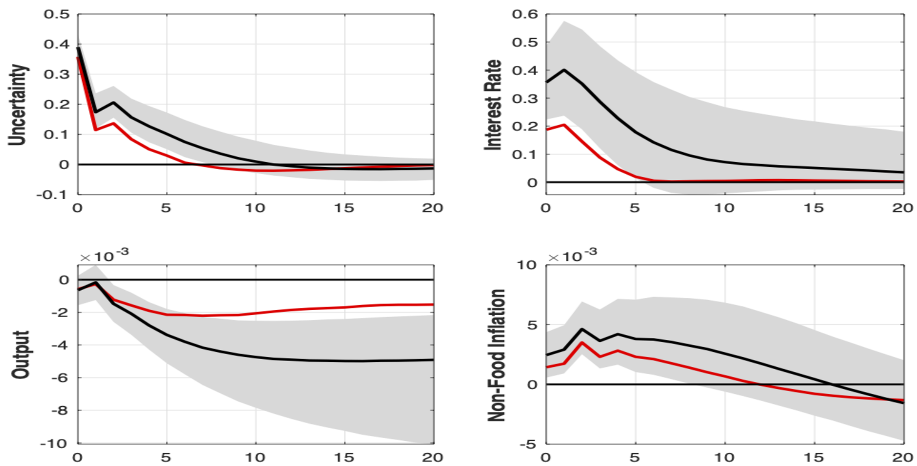


Figure 9: Response of model variables engendered by the uncertainty (EPU) shock in India. The model is estimated using the nonfood price index. Red and black lines show the response of the shock identified by the Cholesky decomposition and Uhlig penalty function methods, respectively. The shaded area is the 68% confidence interval for the response produced by the identified shock by using the penalty function method.

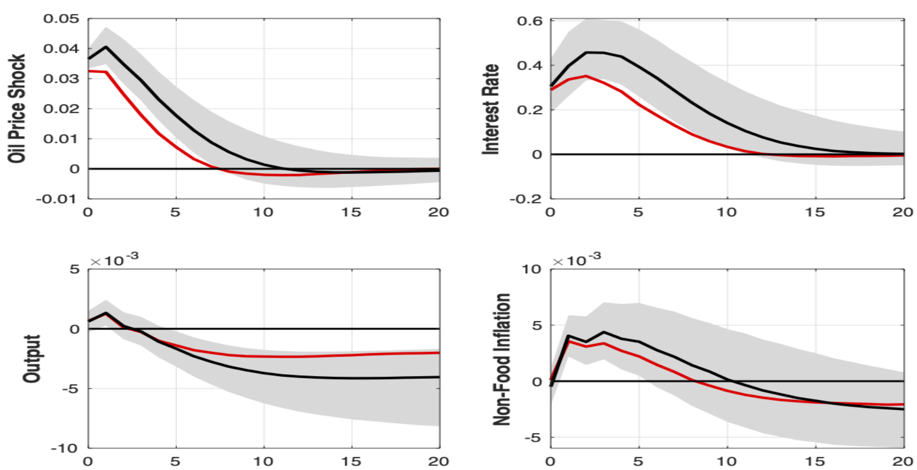
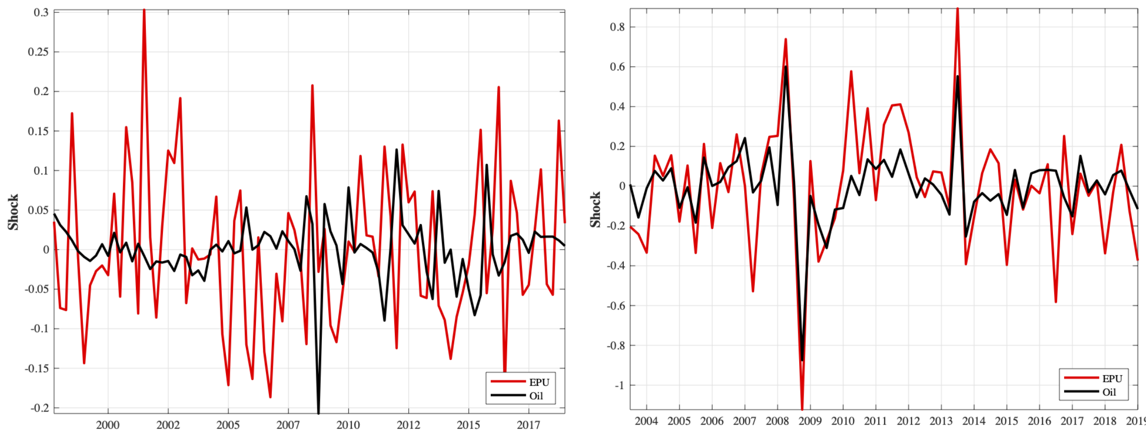


Figure 10: : The response of model variables caused by the oil price shock in India. The model is estimated with the nonfood price index. Red and black lines give the response of the shock identified by the Cholesky decomposition and Uhlig penalty function methods, respectively. The shaded area is the 68% confidence interval for response produced by the identified shock by using the penalty function method.

Figure 11: EPU and Oil Price Shock in India and the United States

(a) US (b) India



Source: Shocks have been obtained using country specific VAR containing four variables.

Figure 11 shows the EPU and oil price shocks for India and the United States. As anticipated, there is a high correlation between EPU and oil price shocks in India (approximately 0.80); therefore, the EPU shock behaves as a supply shock in India and generates similar responses as those by the oil price shock. In case of the US, the correlation is low and negative (approximately â0.15). The construction of EPU suggests that a similar methodology is used in these two countries for the construction of the respective indexes[3] [4] Therefore, oil prices are probably mentioned in Indian newspapers because of Indiaâs

[3]The US EPU is constructed using search results from 10 leading US newspapers, namely USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the Houston Chronicle, and the WSJ. It is based on the count of articles comprising at least one term from each of these three groups. First, "uncertainty" or "uncertain," second "economic" or "economy," and third "congress," "legislation," "white house," "regulation," "federal reserve," or "deficit." Further, it contains data on tax code expiration and economic forecaster disagreement. `https://www.policyuncertainty.com/us_monthly.html`

[4]EPU in India is constructed in a similar manner based on seven Indian newspapers, namely The Economic Times, the Times of India, the Hindustan Times, the Hindu, the Statesman, the Indian Express, and the Financial Express. It is based on the number of articles containing at least one term from each of these three sets. The first set is "uncertain," "uncertainties," or "uncertainty." The second set is "economic" or "economy." The third set comprises policy relevant terms, such as

dependence on them and is considered in the EPU.

4 International and Domestic Uncertainty Shocks in India

4.1 Disentangling International and Domestic Uncertainty

Because international uncertainty (the US uncertainty) can have a significant spillover in India, we extend the VAR model to include the US and local uncertainty in India. We identify international and domestic uncertainty shocks for India.

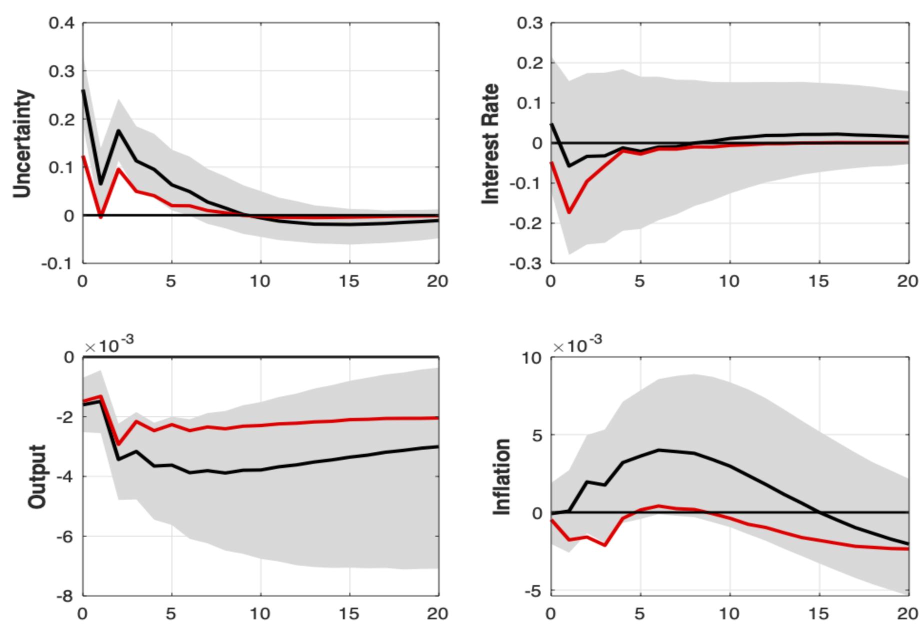


Figure 12: Response of domestic variables caused by the international uncertainty shock. Red and black lines show the response of the shock identified by the Cholesky decomposition and Uhlig penalty function methods, respectively. The shaded area is the 68% confidence interval for the response produced by the identified shock using the penalty function method.

"regulation," "central bank," "monetary policy," "policymakers," "deficit," "legislation," and "fiscal policy." https://www.policyuncertainty.com/india_monthly.html

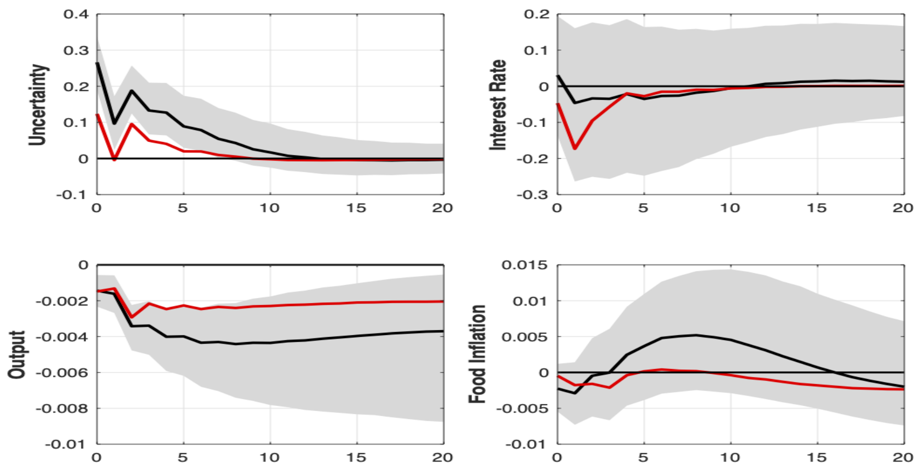


Figure 13: Response of domestic variables caused by the international uncertainty shock. Red and black lines show the response of the shock identified by the Cholesky decomposition and Uhlig penalty function methods, respectively. The shaded area is the 68% confidence interval for the response produced by the identified shock using the penalty function method.

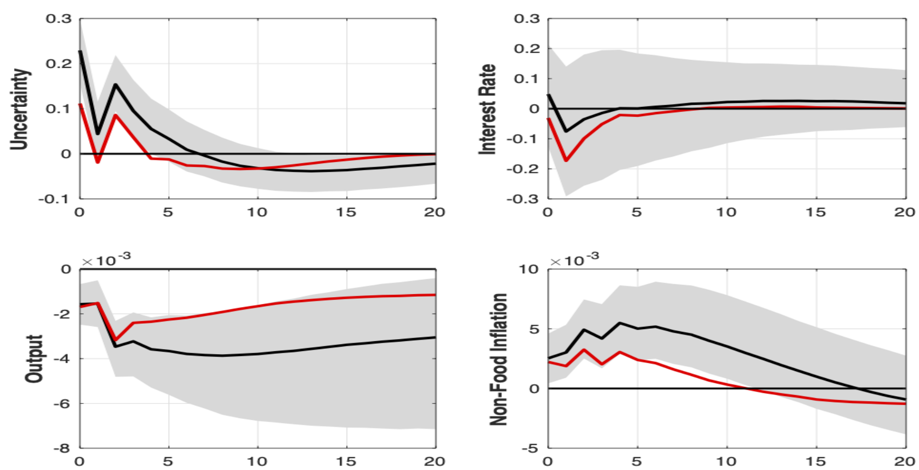


Figure 14: Response of domestic variables caused by the international uncertainty shock. Red and black lines show the response of the shock identified by the Cholesky decomposition and Uhlig penalty function methods, respectively. The shaded area is the 68% confidence interval for the response produced by the identified shock using the penalty function method.

These two shocks are orthogonal by construction in both the Cholesky decomposition and Uhlig penalty function methods. The ordering of the variables is as follows: international uncertainty, local/domestic uncertainty in India, interest rate, real GDP, and CPI. We estimate two models where we replace CPI with the food and nonfood price index.

Figures 12-14 show the responses of the domestic variables engendered by the international uncertainty shock from these three models. As argued previously, there is a significant spillover from international uncertainty to domestic uncertainty. International uncertainty shock increases domestic uncertainty, and the effect is significant for up to 10 quarters.

Furthermore, the Uhlig penalty function estimates have a persistent spillover from international uncertainty to domestic uncertainty. Among the estimated three models, we observed a persistent and significant contractionary effect of the international uncertainty shock on output. In all the three models, the effect on the interest rate is negative but not significant. Inflation increases because of the international uncertainty shock; however, the effect is not significant. These three models show that international uncertainty significantly increases nonfood inflation.

International uncertainty probably reflects the oil price shock, and considering that the Indian economy is heavily dependent on imported oil, the nonfood inflation could be increasing because of the international uncertainty shock. Moreover, if we consider nonfood inflation and output, then international uncertainty behaves as a supply shock because it increases nonfood inflation and reduces the domestic output.

As argued previously, the international uncertainty shock could occur during weak global demand, which reduces the domestic output through this international linkage. Figures 15, 16, and 17 show the responses of domestic variables engendered by the domestic uncertainty shock from these models. The domestic uncertainty shock lasts for approximately 10 quarters. Furthermore, the penalty function method estimates a more persistent uncertainty shock, and the response of the domestic variables to the shock estimated by using the penalty function method is also more persistent.

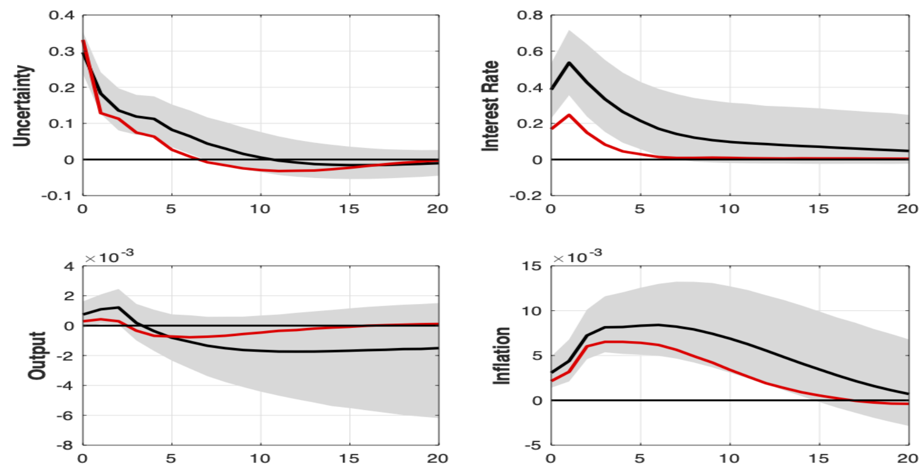


Figure 15: Response of domestic variables caused by the domestic uncertainty shock. Red and black lines show the response of the shock identified by the Cholesky decomposition and Uhlig penalty function methods, respectively. The shaded area is the 68% confidence interval for the response produced by the identified shock using the penalty function method.

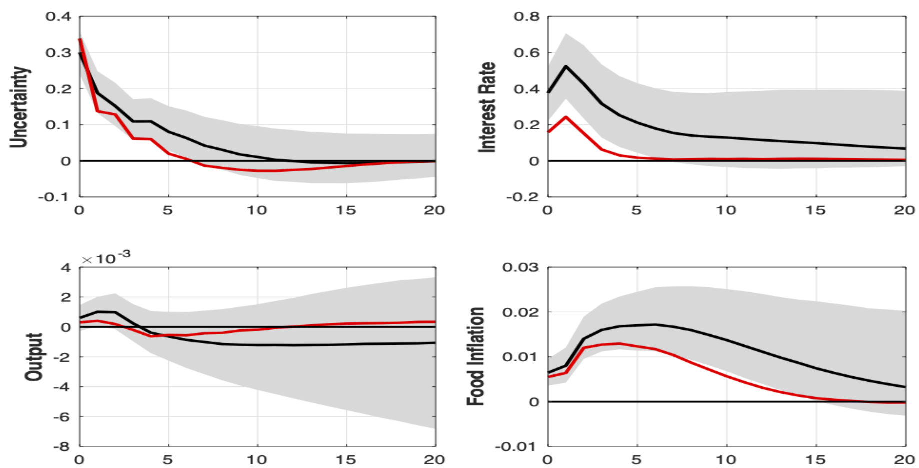


Figure 16: Response of domestic variables engendered by the domestic uncertainty shock. Red and black lines show the response of the shock identified by the Cholesky decomposition and Uhlig penalty function methods, respectively. The shaded area is the 68% confidence interval for the response produced by the identified shock by using the penalty function method

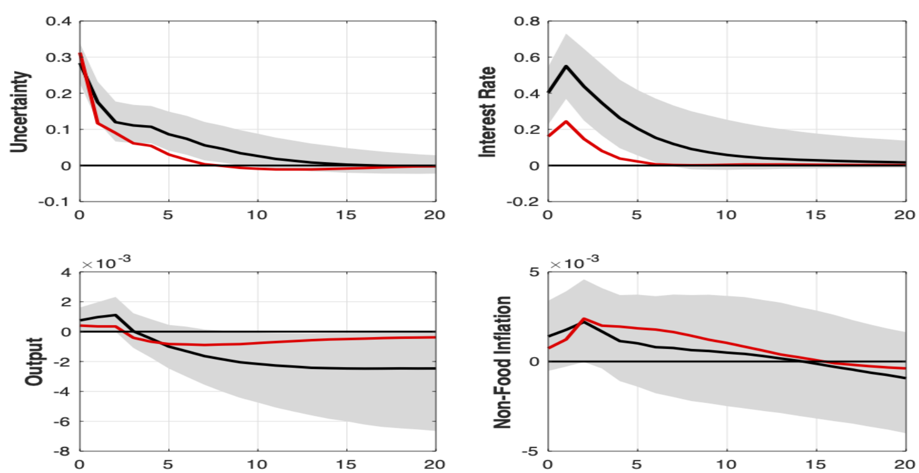


Figure 17: Response of domestic variables caused by the domestic uncertainty shock. The shaded area is the 68% confidence interval for the response produced by the identified shock by using the penalty function method. The red and black lines show the response of the identified shock by using the Cholesky decomposition and Uhlig penalty function methods, respectively.

Significant differences are noted between the responses of domestic variables engendered by international and domestic uncertainty shocks. Domestic uncertainty shock has no significant effect on output unlike the international uncertainty shock. Moreover, the interest rate increases significantly because the domestic uncertainty shock increases inflation, which decreases, although insignificantly, after the international uncertainty shock. Consumer inflation increases after the domestic uncertainty shock, and the maximum effect is a 0.75% increase in inflation. The response of inflation is persistent and lasts for more than 3 years.

The responses in figures 16 and 17 suggest another significant difference in the transmission of international and domestic uncertainty shock. The international uncertainty shock has a significant positive impact on nonfood inflation. The domestic uncertainty shock has a significant positive impact on food inflation. The maximum impact on food inflation is observed after a year and at the same time when the maximum effect on inflation is observed. Furthermore, the maximum impact on food inflation is approximately twice the maximum impact on inflation. The response of nonfood inflation is positive because of the domestic uncertainty shock; however, but it is not significant.

Thus far, results suggest that international uncertainty reduces output and increases nonfood inflation, whereas domestic uncertainty increases food inflation and interest rate. In other words, domestic uncertainty operates through the primary sector of the economy, whereas international uncertainty operates through other sectors of the economy.

4.2 Rainfall Shock Versus Domestic Uncertainty Shock

International uncertainty is contractionary and increases inflation because of several factors; however, it does not affect food inflation because food items are protected, and prices in India are primarily determined by the domestic supply of food items.

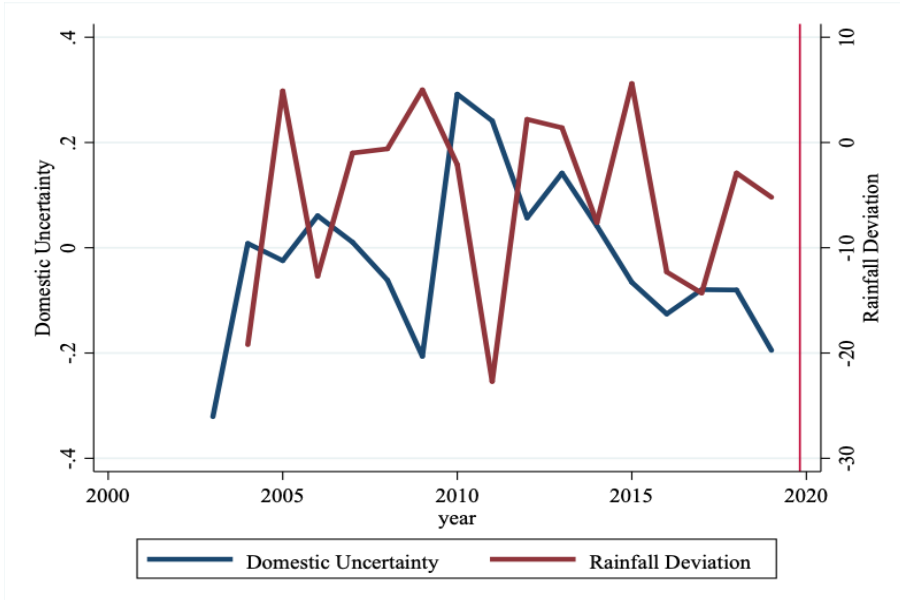


Figure 18: Domestic uncertainty shock and rainfall shock: Domestic uncertainty shock is identified by using the penalty function method for the VAR model with food inflation.

Our identified international uncertainty shock does not influence food prices, thereby further confirming that shocks have been accurately identified in this study. Because domestic uncertainty affects food inflation, it may increase the domestic supply shock. Because Indian agriculture depends on favorable monsoon, a rainfall shock can influence domestic food supply. Therefore, we estimate the rainfall shock as a deviation of actual rainfall from normal rainfall and map it against the identified domestic uncertainty shock (domestic uncertainty estimated with the food price index).

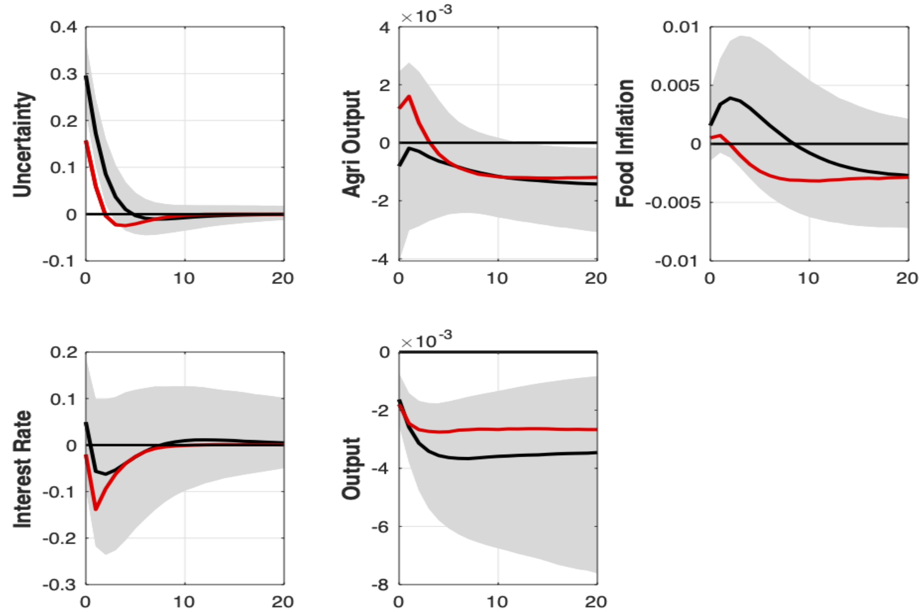


Figure 19: Response of domestic variables caused by the international uncertainty shock. Red and black lines show the response of the shock identified by the Cholesky decomposition and Uhlig penalty function methods, respectively. The shaded area is the 68% confidence interval for the response produced by the identified shock by using the penalty function method.

The domestic uncertainty shock is correlated with the rainfall shock, although the correlation is weak (Figure 18). The negative deviation of rainfall is associated with a higher value of domestic uncertainty. Given few observations available for the rainfall shock because most of the rainfall in India occurs during monsoon (June-September), we have used annual observations for the rainfall shock from 2003 onward, which is mapped with the sum of the domestic uncertainty shock for that year. Consequently, the domestic uncertainty shock is observed through agricultural output because it increases food inflation. Therefore, we extend the VAR model by introducing agricultural output. The ordering of the variables is as follows: international uncertainty, local uncertainty, agricultural output, food inflation, interest rate, and output. We identify international and domestic uncertainty shocks by using the Cholesky decomposition and penalty function as earlier.

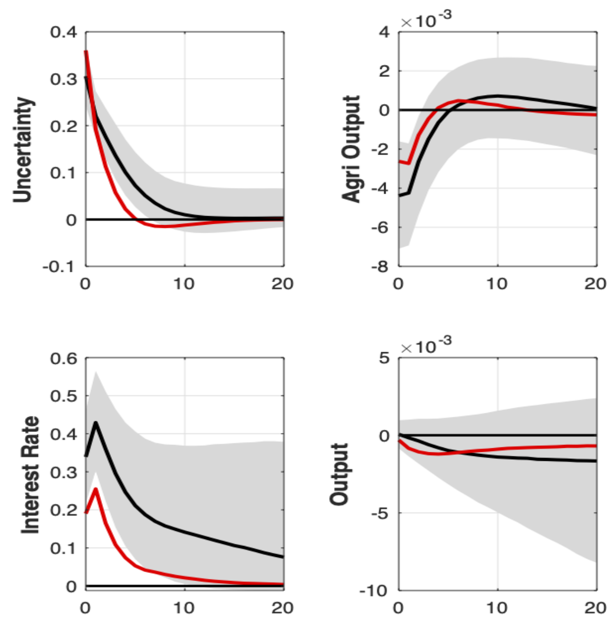


Figure 20: Response of domestic variables engendered by the domestic uncertainty shock. Red and black lines show the response of the shock identified by Cholesky decomposition and Uhlig penalty function methods, respectively. The shaded area is the 68% confidence interval for the response produced by the identified shock by using the penalty function method.

Figures 19 and 20 show the responses of model variables engendered by international and domestic uncertainty shocks. Furthermore, a significant spillover is observed from international to domestic uncertainty. The international uncertainty shock does not significantly affect agricultural output and food inflation. International uncertainty decreases the interest rate; however, the effect is not significant at the conventional level of significance. However, international uncertainty reduces output, and the effect is significant.

The domestic uncertainty shock decreases agricultural output. Although the effect does not last for more than two quarters, it is significant. Moreover, domestic uncertainty significantly increases food inflation and interest rate. The effect on food inflation is more persistent than that on agricultural output. The persistence of high food inflation in India is because of slow price adjustment owing to a two-tier pricing mechanism (i.e., government-administered pricing in the agricultural sector and market-determined pricing in the nonagricultural sector). Therefore, the rainfall shock is a source of domestic uncertainty, which reduces agricultural output and increases food inflation. This result signifies that the central bank is responding to a source of inflation over which it has limited control. Therefore, domestic uncertainty acts as a supply shock in the Indian economy. International uncertainty increases nonfood inflation and reduces output. Thus, international uncertainty is associated with movements in international oil prices and real effective exchange rate.

4.3 International Uncertainty - Oil Price and Exchange Rate

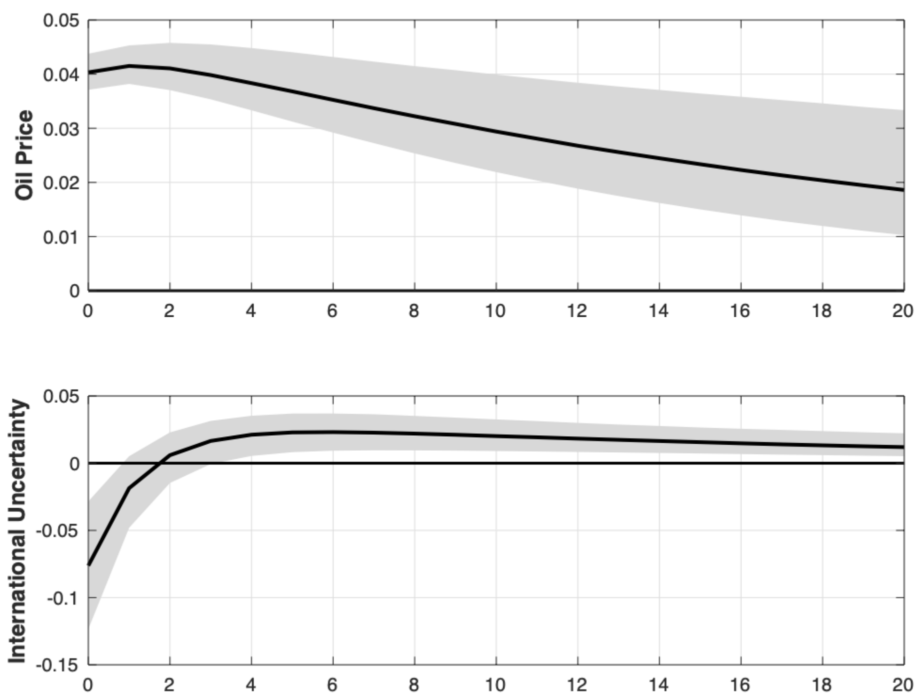


Figure 21: Response of international uncertainty engendered by the oil price shock. Black line shows the response of the shock identified by using the Uhlig penalty function method. The shaded area is the 68% confidence interval for the response produced by the identified shock by using the penalty function method.

The international uncertainty shock is associated with two primary international variables: oil prices and exchange rates. These variables are likely to have real effects. Therefore, this section estimates a bivariate VAR with oil price and international uncertainty and with the real effective exchange rate (REER) and international uncertainty. We identify the oil price shock and real exchange rate shock by using the Uhlig penalty function method. Cholesky identification is not used because the ordering between these two variables, namely international uncertainty and oil price, could be misleading because of their likely contemporaneous relationship. The same argument holds for the VAR model with international uncertainty and the REER.

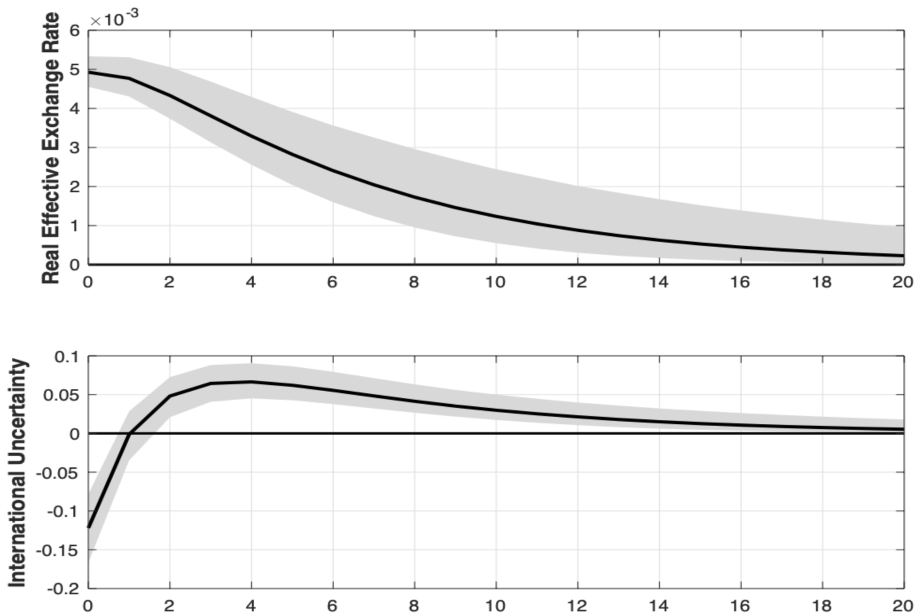


Figure 22: Response of international uncertainty caused by REER shock. The black line shows the response of the shock identified by the Uhlig penalty function method. The shaded area is the 68% confidence interval for the response produced by the identified shock by using the penalty function method.

Figure 21 shows the response of oil price and international uncertainty engendered by the oil price shock. The estimated oil price shock is persistent, and it reduces international uncertainty; however, the effect is not significant. Beyond the second quarter, the oil price shock significantly increases international uncertainty. Figure 22 shows the response of REER, and international uncertainty engendered by the REER shock. The REER shock is less persistent than the oil price shock and reduces international uncertainty on impact, which is significant. However, beyond the second quarter, the REER shock significantly increases international uncertainty. These bivariate results suggest that international uncertainty should be incorporating the movement in oil price and the REER. This justifies our choice of variables in the VARs estimated in the previous section because our objective was to estimate the effect of international uncertainty, and we believe that international uncertainty could arise for several reasons, including movement in oil prices and the REER.

5 Conclusions

An ongoing debate in the literature discusses the impact of uncertainty shocks. This study compares the nature of such uncertainty shocks in an advanced economy with an emerging economy. Uncertainty (EPU) shocks behave in a similar way to a demand shock in an advanced economy and a supply shock in an emerging economy. International uncertainty spills over into local uncertainty in a domestic economy. We disentangle local uncertainty in a domestic economy into international and domestic uncertainty shocks. The domestic uncertainty shock reduces agricultural output and increases food inflation, whereas international uncertainty shock reduces output and increases nonfood inflation. Both these measures of uncertainties behave like supply shocks: domestic uncertainty limited to primary sector and international uncertainty related to other sectors.

The response of macro variables engendered by the EPU shock in India is similar to the responses owing to the oil price shock. In the case of the US, the response of inflation engendered by the oil price shock is opposite to that of the response caused by the EPU shock. The correlation between EPU and the oil price shock is high and positive in India, whereas it is low and negative in the US. This suggests that the newspaper-based EPU index picks up more oil price movements in India than the US because of Indiaâs greater dependence on imported oil. We find that the response of food inflation caused by the EPU shock is stronger than that caused by the oil price shock. Our analysis suggests that the EPU shock involves another source of domestic uncertainty, that is, rainfall. Considering that Indian agriculture still depends on monsoon, this result is consistent with expectations.

This study has crucial policy implication. The study shows that the domestic uncertainty shock is similar to the inflationary supply shock, and the central bank responds to this uncertainty by increasing the interest rate. The increase in the interest rate negatively affects the real economy. The results show that inflation originates from the supply side, which should be considered for improved monetary policy decisions. It reduces variability in the interest rate arising from the frequent policy interventions. At the same time, the policy response in emerging economies cannot have lower interest rates owing to the uncertainty shock because it is a supply shock unlike in advanced economies.

References

[1] Annicchiarico, B. and Rossi, L., 2015. Taylor rules, long-run growth and real uncertainty. Economics Letters, 133, pp.31-34.

[2] Arellano, C., Bai, Y. and Kehoe, P.J., 2019. Financial frictions and fluctuations in volatility. Journal of Political Economy, 127(5), pp.2049-2103.

[3] Baker, S.R., Bloom, N. and Davis, S.J., 2016. Measuring economic policy uncertainty. The Quarterly Journal of Economics, 131(4), pp.1593-1636.

[4] Barsky, R.B. and Sims, E.R., 2011. News shocks and business cycles. Journal of Monetary Economics, 58(3), pp.273-289.

[5] Basu, S. and Bundick, B., 2017. Uncertainty shocks in a model of effective demand. Econometrica, 85(3), pp.937-958.

[6] Baum, C.F., Stephan, A. and Talavera, O., 2009. The effects of uncertain nonfinancial leverage of nonfinancial firms. Economic Inquiry, 47(2), pp.216-225.

[7] Bernanke, B.S., 1983. Irreversibility, uncertainty, and cyclical investment. The Quarterly Journal of Economics, 98(1), pp.85-106.

[8] Bhattarai, K., Mallick, S.K. and Yang, B., 2021. Are global spillovers complementary or competitive? Need for international policy coordination. Journal of International Money and Finance, 110, 102291.

[9] Bloom, N., 2009. The impact of uncertainty shocks. Econometrica, 77(3), pp.623-685.

[10] Byrne, J.P., Spaliara, M.E. and Tsoukas, S., 2016. Firm survival, uncertainty, and financial frictions: is there a financial uncertainty accelerator? Economic Inquiry, 54(1), pp.375-390.

[11] Caldara, D., Fuentes-Albero, C., Gilchrist, S. and Zakrajsek, E., 2016. The macroeconomic impact of financial and uncertainty shocks. European Economic Review, 88, pp.185-207.

[12] Caldara, D., Cavallo, M. and Iacoviello, M., 2019. Oil price elasticities and oil price fluctuations. Journal of Monetary Economics, 103, pp.1-20.

[13] Christiano, L.J., Motto, R. and Rostagno, M., 2014. Risk shocks. American Economic Review, 104(1), pp.27-65.

[14] De la Fuente Moreno, A., 2014. A mixed splicing procedure for economic time series. Estadistica Espanola, 56(183), pp.107-121.

[15] Dixit, A.K., and Pindyck, R.S., 1994. Investment under uncertainty. Princeton University Press.

[16] Fasani, S. and Rossi, L., 2018. Are uncertainty shocks aggregate demand shocks? Economics Letters, 167, pp.142-146.

[17] Faust, J., 1998, December. The robustness of identified VAR conclusions about money. In Carnegie-Rochester Conference Series on Public Policy (Vol. 49, pp. 207-244). North-Holland.

[18] Gilchrist, S., Sim, J.W. and Zakrajsek, E., 2014. Uncertainty, financial frictions, and investment dynamics (No. w20038). National Bureau of Economic Research.

[19] Ireland, P.N., 2011. A new Keynesian perspective on the great recession. Journal of Money, Credit and Banking, 43(1), pp.31-54.

[20] Istiak, K. and Serletis, A., 2020. Risk, uncertainty, and leverage. Economic Modelling, 91, pp.257-273.

[21] Holtemoller, O. and Mallick, S., 2016. Global food prices and monetary policy in an emerging market economy: The case of India, Asian Journal of Economics, 46, pp.56-70.

[22] Kilian, L., 2009. Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. American Economic Review, 99(3), pp.1053-69.

[23] Kurmann, A. and Otrok, C., 2013. News shocks and the slope of the term structure of interest rates. American Economic Review, 103(6), pp.2612-32.

[24] Leduc, S. and Liu, Z., 2016. Uncertainty shocks are aggregate demand shocks. Journal of Monetary Economics, 82, pp.20-35.

[25] Mountford, A. and Uhlig, H., 2009. What are the effects of fiscal policy shocks? Journal of Applied Econometrics, 24(6), pp.960-992.

[26] Uhlig, H., 2005. What are the effects of monetary policy on output? Results from an agnostic identification procedure. Journal of Monetary Economics, 52(2), pp.381-419.

[27] Zhang, D., Lei, L., Ji, Q. and Kutan, A.M., 2019. Economic policy uncertainty in the US and China and their impact on the global markets. Economic Modelling, 79, pp.47-56.

Appendix

Data

Uniform Series of Gross Domestic Product in India

Because of the unavailability of a continuous time series for national accounts data for India, which uses three base years (1999-2000, 2004-2005, and 2011-2012), we create a uniform series through linking procedures commonly used in literature. This approach involves a backward extrapolation of the most recent available series by using the growth rates of older series called retropolation or interpolation between the benchmark years of successive series (Fuente, 2009). Using retropolation, we calculate the log difference between the old and new series (the quarter when the new series starts, and we have data for both series for that quarter), and this difference was then added to the old series to create a uniform series, thereby preserving the growth rate of the old series. The implicit assumption is that the "error" in the older series remains constant over time, that is, it already existed at time 0 and that its magnitude, measured in proportional terms, has not changed between 0 and the start of the new series (see, De la Fuente Moreno, 2014).

Food and Non Food Price Index

We use CPI and food price index from two base years, namely 1982 and 2001. The linking factor for these two series for the general index (4.63) and food index (4.58) is given. The weight of food items in the general index is 57% for the base year 1982 and 46.2% for the base year 2001. Using this information, a continuous series of food and nonfood price index is calculated.

$$\text{General Index} = \alpha \text{Food Index} + (1 - \alpha) \text{Non Food Index}$$

where α is the weight of food items in the general index.

Forecast Error Variance Decomposition

Figures 23, 24, and 25 give the share of the international uncertainty shock in forecast error variance of the mentioned variables. These shares are obtained from three VARs containing the CPI, food price index, or nonfood price index at a time. Other variables remain the same across estimations.

We obtain the forecast error variance decomposition of domestic variables because of international and domestic uncertainty shocks. The international uncertainty shock explains approximately 15% of the forecast error variance of the domestic uncertainty shock. On impact, international uncertainty shock barely explains the forecast error variance of inflation; however, by the 20th quarter, it increases to approximately 10%. The international uncertainty shock explains approximately 20% of the forecast error variance of output and 5% of the forecast error variance of the interest rate. In addition, the international uncertainty shock explains more than 10% of the forecast error variance of nonfood inflation, whereas in case of food inflation, this share is approximately 5%.

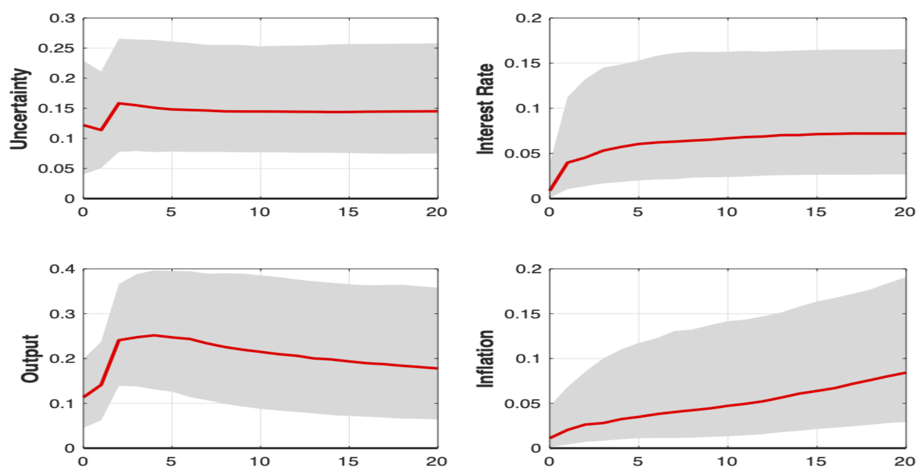


Figure 23: Share of the international uncertainty shock in the forecast error variance of domestic variables.

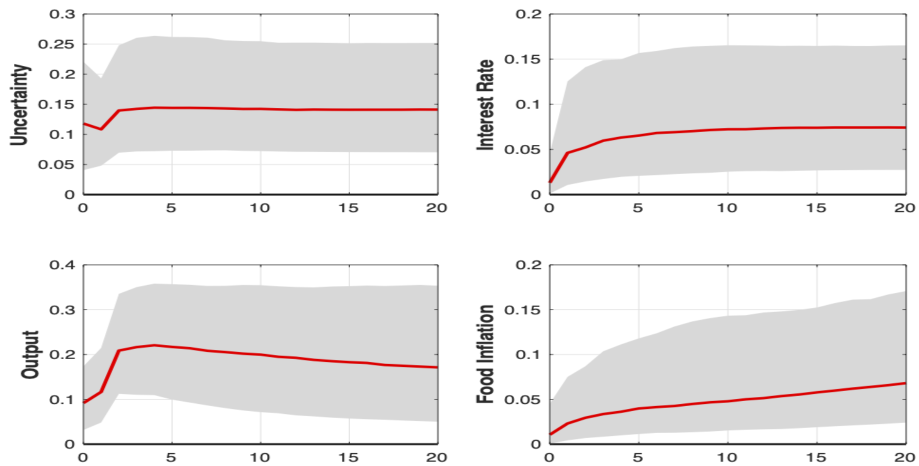


Figure 24: Share of the international uncertainty shock in the forecast error variance of domestic variables.

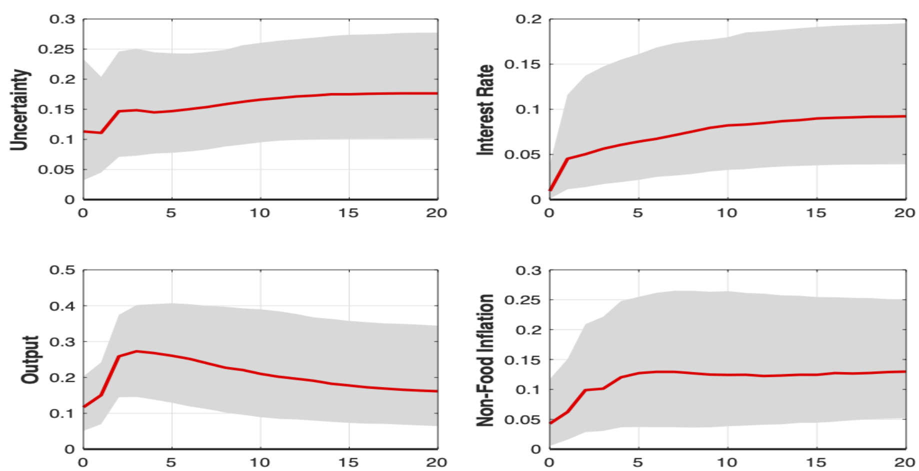


Figure 25: Share of the international uncertainty shock in the forecast error variance of domestic variables.

Figures 26, 27, and 28 present the share of the domestic uncertainty shock in the forecast error variance of the mentioned variables. These shares are obtained from three VARs comprising the CPI, food price index, or nonfood price index. Other variables remain the same across estimations. International and domestic uncertainty shocks are orthogonal to each other.

The domestic uncertainty shock explains approximately 70% of the forecast error variance of domestic uncertainty by the 20th quarter. This shock explains more than 10% of the forecast error variance of the interest rate, which is almost twice the forecast error variance explained by the international uncertainty shock. The domestic uncertainty shock explains a significantly lower amount of the forecast error variance of output than the international uncertainty shock. Furthermore, the domestic uncertainty shock is more important for inflation than the international uncertainty shock because it explains more than 30% of the forecast error variance of inflation. Considering the share of the domestic uncertainty shock in the forecast error variance of food and nonfood inflation, the domestic uncertainty shock explains a significantly higher amount of the forecast error variance of food inflation than nonfood inflation. Therefore, the domestic uncertainty shock is predominantly a food inflation shock.

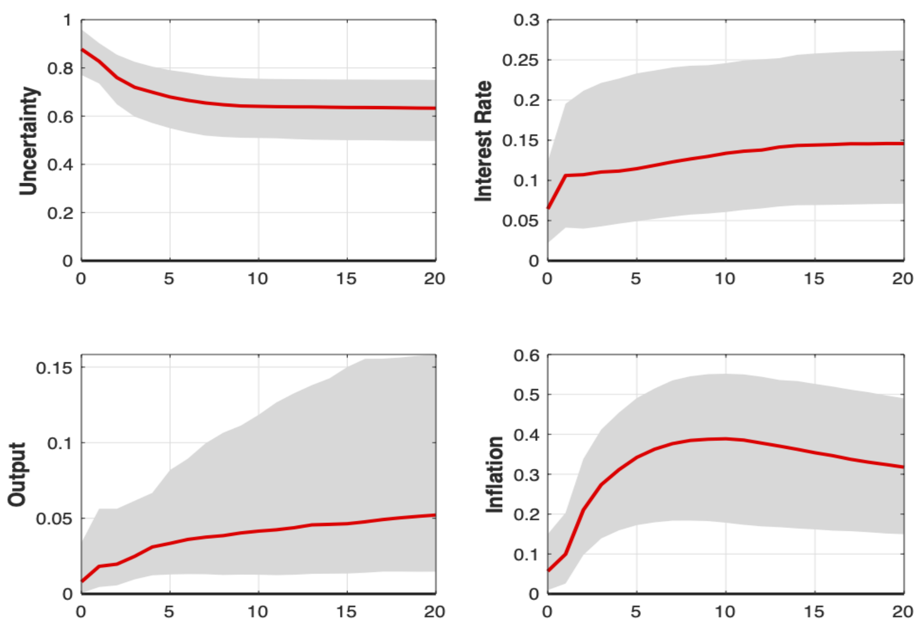


Figure 26: Share of domestic uncertainty shock in the forecast error variance of domestic variables.

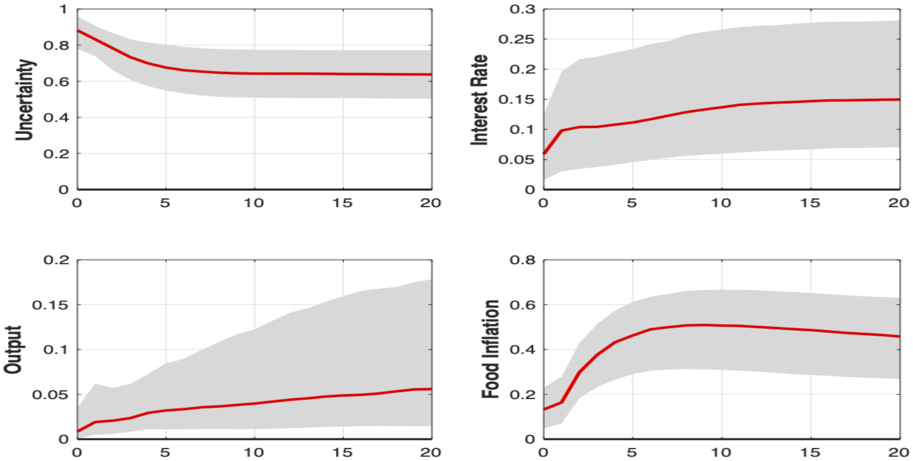


Figure 27: Share of domestic uncertainty shock in the forecast error variance of domestic variables.

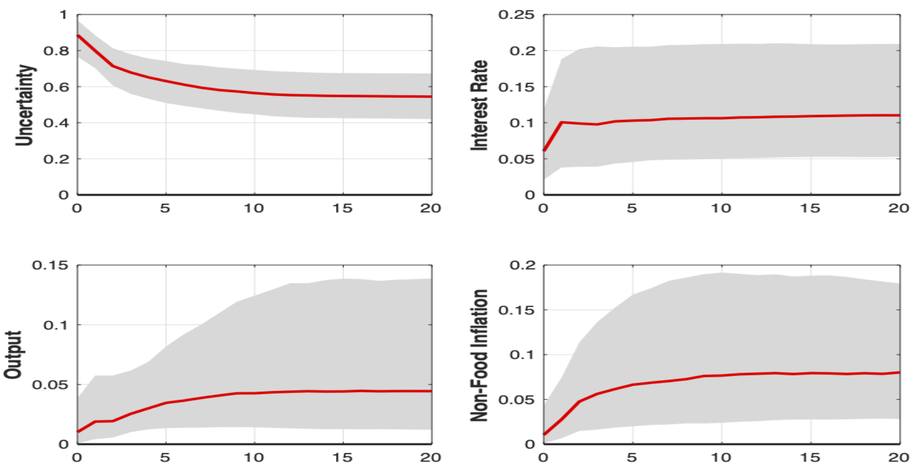


Figure 28: Share of domestic uncertainty shock in the forecast error variance of domestic variables.

Robustness Using VIX

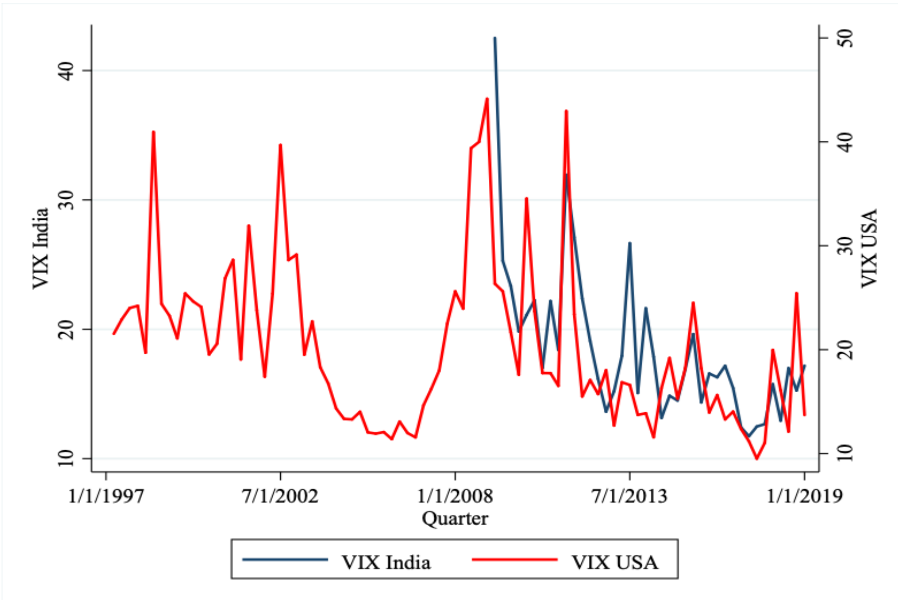


Figure 29: VIX for India and the United States - The correlation between them is 0.624.

This section provides some additional results that substantiate our result that the uncertainty shock is a supply shock in emerging economies and the demand shock in advanced economies. We use a four-variable VAR as done previously; however, now, we replace the EPU index with VIX. We use VIX from the US for both countries. Indian VIX data are available from 2009 onward and present a limited sample. Furthermore, financial markets in these economies are relatively more connected (Figure 29); therefore, VIX in the US is a good approximation of financial uncertainty in India as well. The identification is performed using Cholesky decomposition. There is no significant spillover from slow-moving real variables to fast-moving financial uncertainty. Figure 30 presents the response of model variables due to the VIX shock in the US.

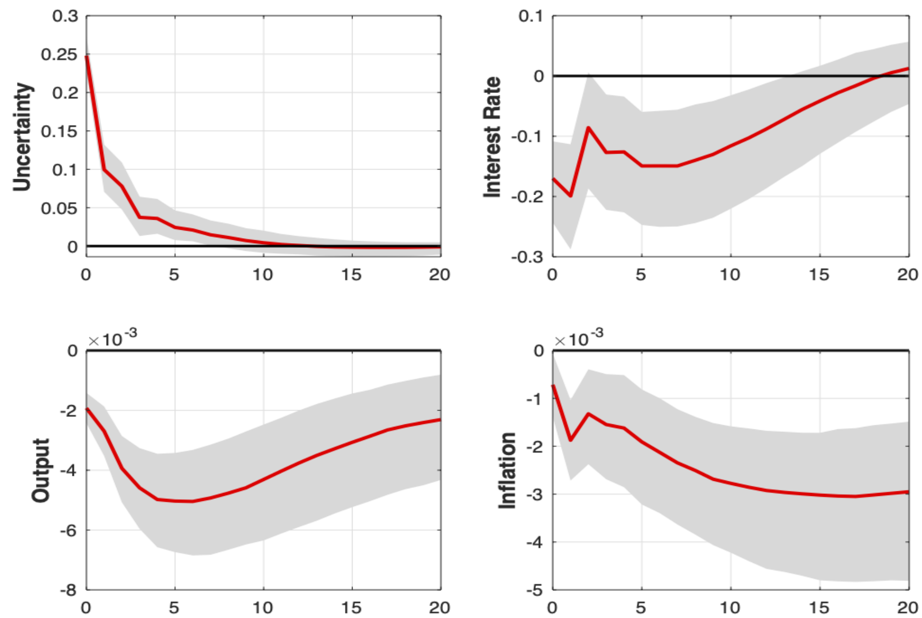


Figure 30: Response of model variables caused by the uncertainty shock in the United States. The uncertainty measure used is VIX. The shock is identified using the Cholesky decomposition. The shaded area is the 68% confidence interval for responses.

The shock reduces output and inflation in the United States, thereby suggesting a demand shock. The interest rate responds to the declining demand in the economy and represents an expansionary policy response by the federal reserve. Figure 31 presents the response of model variables caused by the VIX shock in India. This financial uncertainty shock significantly reduces output and increases inflation in India, thus indicating a supply shock. This significant output contraction enables the interest rate response to be accommodative after two quarters. However, the uncertainty shock remains a supply shock, and the central bank emphasizes loss in output, thereby reducing the interest rate. This suggests asymmetry in the Reserve Bank of Indiaâs response toward uncertainty. Although both EPU and VIX behave as supply shocks, the monetary response has been different in these two cases because India was always in the mode of monetary tightening to contain inflation when the source of inflation is the presence of supply shocks and not demand shocks (e.g., Holtemoller and Mallick, 2016), which would be further investigated in future research.

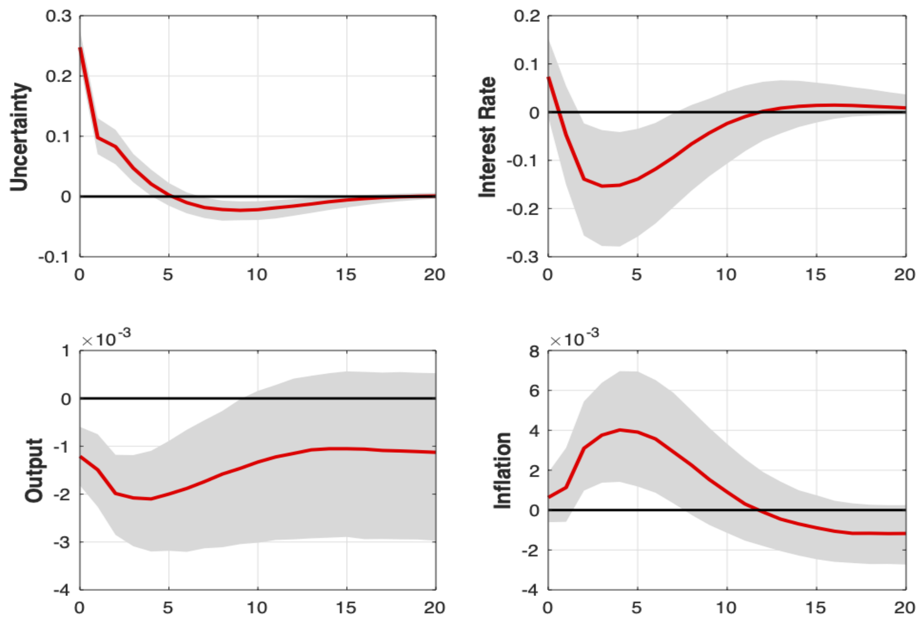


Figure 31: . Response of model variables caused by the uncertainty shock in India. The uncertainty measure used is VIX (USA). The shock is identified using Cholesky decomposition. The shaded area is the 68% confidence interval for responses.