Financial Market Volatility and Macroeconomic Fundamentals

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Abstract

In this paper, we intend to discover the dynamic relationship between financial market volatility and macroeconomic fundamentals. Our main goal would be to shed light on the evidence that macroeconomic conditions are linked to the uncertainty in the stock market as well as in the economic-policy domain. For that, we employ a structural VAR model with bayesian sign restrictions. More specifically, we consider a bi-variate structural VAR between distinct macroeconomic variables, stock market volatility and uncertainty measures, allowing us to model any potential feedback effects between these variables, and therefore enabling us to capture the relationship between the real economy, volatility observed in the stock market as well as uncertainty in the policy domain. We obtain and utilize the data on monthly production indices, realized and implied stock market volatility, and economic policy uncertainty index for United States and India to conduct our analysis.

1 Introduction

The financial system is an integral part of an economy in today's modern world, which facilitates the transfer of funds from surplus entities to deficient entities. It is considered as a tool for economic development, mobilizing savings, and stimulating investments throughout the economy. Thus, over the years, the relation between financial markets and macroeconomic variables has received increasing attention. Macroeconomic variables here refer to GDP, private consumption expenditure, inflation, money supply, and international trade at large.

Stock markets, a more niche segment of financial markets, deal with equity instruments and play a vital role in facilitating the smooth operation of abundant capital economies by the efficient allocation of resources and the creation of liquidity for businesses and entrepreneurs. There have been several studies modeling the relationship

*This term paper was a part of the Time-series course during my master's program at Ashoka University. I am grateful to Professor Piyali Banerjee (piyali.banerjee@ashoka.edu.in) for the helpful comments and discussions.

between the stock market returns and fundamental macroeconomic variables, indicating that the two are inherently linked.

Macroeconomic fundamentals are almost always intrinsically a part of the pricing of the financial securities i.e., stock prices take into account macroeconomic factors. The investment theory, **Efficient market hypothesis (EMH**) by Eugene Fama, states that the costs of securities are fair and reflect assets' intrinsic value. Market efficiency causes existing share prices to always incorporate and reflect all relevant information. It can be divided into:

(i) Operational efficiency: Ensures all transactions are completed on time with maximum accuracy and minimum cost.

(ii) Allocation efficiency: Ensures allocation of funds to projects with the highest possible risk-adjusted returns.

(iii) Informational efficiency: Ensures that the market price of a security reflects all the information affecting the price of that security.

The concept of efficiency implies that a financial market is working effectively, and the prices are determined depending on available macroeconomic information in the market. Efficient Market Hypothesis focuses on the informational efficiency of the financial markets. The theory takes three forms of efficiency (Roberts 1967)[28].

(i) The weak Form of EMH asserts that prices fully reflect the information contained in the historical sequence of prices. It is also known as the random walk theory.

(ii) The semi-strong form of EMH asserts that current stock prices reflect not only historical price information but also all publicly available information relevant to a company's securities. Therefore, public information about a company will not yield abnormal economic profits.

(iii) The strong form of EMH asserts that all available information, both public and private, is priced into the price of a security.

Hence, EMH establishes the link from macroeconomic variables to stock prices.

On the other hand, stock market returns affect the macroeconomy through various channels. Firstly, market conditions affect the wealth of the investors, which further affect the consumer spending in the economy and thus GDP. Secondly, stock market returns are an indicator of consumer and business confidence in a country. A rise in stock market returns encourages spending in the economy. Conversely, a fall would translate to worsening the sentiments of the economy thereby contracting the consumer spending yet again. Lastly, a falling market hampers the ability of companies to procure investment necessary for new projects resulting in the shrinking of the investment activities in the economy. Although theoretically, there exists a contemporaneous relationship between the stock market and macroeconomic variables, empirical evidence suggests that this two-way relation between the stock market and macroeconomic fundamentals is not always present. A study by Kwan and Shin for the Korean stock market found that stock price indices were not a leading indicator of macroeconomic variables. The absence of such a relationship empirically as tested by various studies raises interesting questions.

The importance of studying the impact that uncertainty has on macro-economy has shifted the focus on stock return volatility. Uncertainty is a ubiquitous concern of policymakers due to its influence on the macroeconomic variables. Moreover, uncertainty arises from macro-level factors. The contemporary financial theory asserts that the stock market volatility is closely related to the movement of macroeconomic variables. This is because the stock market reflects essential information about the fundamentals. The movement of fundamentals thus explains volatility in the stock market, which in turn affects the economic development of the economy through the various channels discussed above. Levine and Zervos (1996)[23] found in a cross-country analysis that stock market development is positively and robustly linked to long-run economic growth. There exists an entire strand of literature that investigates the impact of stock market volatility on macroeconomic variables.

A step further results in linkages between financial market volatility and fundamental macroeconomic volatility, i.e., studying the determinants of financial market volatility. Most studies in this area have been mainly unsuccessful in establishing unambiguous relationships except for the recent study, which confirmed a significant positive relationship between the two using data for a large number of countries by Diebold and Yilmaz[17]. The study further established that there exists a one-way relationship, that fundamental volatility Granger causes stock market volatility but not vice versa. This study focuses on the realized volatility aspect of stock market volatility.

Nevertheless, there is a better alternative to use forward-looking volatility in the case of stock market returns and study its relation with the macroeconomic fundamentals. Option implied volatility derives the market's estimate of future volatility from traded option prices. As the option prices reflect investors' expectations of cash flows in different states of the world and at different time horizons, option implied volatility can incorporate broader information set than model-based volatility forecasts derived from realized volatility. Implied volatility is in a better position to capture the expected macroeconomic trends as perceived by the investors and signals the market's expectations for future returns. (Berger et al)[6] in their study of Uncertainty Shocks as Second-Moment News Shocks, confirmed that option implied volatility is a much better estimate for forecasting future realized volatility rather than the past values of realized volatility. Therefore, this paper incorporates implied volatility to estimate future uncertainty.

Moreover, the Chicago Board of Options Exchange (CBOE) came up with a volatility index, VIX. The index measures the market's expectation of volatility implicit in the prices of options and is traded in the market as an instrument for risk-averse investors.

Many studies on asset pricing literature have revealed that realized volatility and expected volatility (option implied volatility), though correlated, have essential differences (Anderson, Bollerslev, and Diebold)[1]. A jump in stock prices, such as a crash or the response to a particularly bad macro data announcement, mechanically generates high realized volatility. On the other hand, news about future uncertainty, such as a coming presidential election, increases expected volatility. Realized volatility can be viewed as a short-term uncertainty measure which precludes the market's instant reaction to information. Whereas, expected volatility is a relatively long-term uncertainty measure that includes a more comprehensive set of information.

Uncertainty is defined as clarity, or lack of thereof, of future economic activity. Measures of uncertainty can be divided into two categories (Moore, 2016)[25]:

(i) Finance based measure of uncertainty.

(ii) Newspaper-based measure of uncertainty.

Realized volatility and expected volatility are able to explain the economic factors of uncertainty which translate readily into stock prices. These are a **finance-based** measure of uncertainty that incorporate financial information. However, government economic policies also raise uncertainty in the economy. In fact, policy uncertainty is associated with higher stock price volatility and reduced investment and employment (Baker, Bloom, Davis, 2016)[3]. The **newspaper-based** measure of uncertainty, Economic Policy Uncertainty Index (EPU) by Baker, Bloom, and Davis[3], reflects the frequency of articles in 10 leading US newspapers that contain the following triple: "economic" or "economy"; "uncertain" or "uncertainty"; and one or more of "congress", "deficit", "Federal Reserve", "legislation", "regulation" or "White House". The index shows strong responses to events with major policy concerns thereby capturing a broader sense of uncertainty.

This paper attempts to further investigate the contemporaneous effect of economic uncertainty as measured by stock market realized volatility and options implied volatility; as well as policy uncertainty as measured by EPU on macroeconomic fundamentals and vice versa. The goal is to study the bi-directional relationship between various forms of uncertainty and the broader economy. By incorporating EPU, this paper includes a broader measure of uncertainty that encompasses non-economic parameters that seek to affect macroeconomic fundamentals.

The paper further extends this study to compare the results in a developed economy like the US with an emerging market economy like India. The reason for doing is the difference in the efficiency of the financial markets of the two economies. Efficiency here is defined as the speed with which information is incorporated into stock prices. This further would help in examining whether faster transmission of information as in US financial markets would lead to a stronger relationship with fundamentals. In addition to this, the paper seeks to observe whether the measure of uncertainty with the most robust relation with fundamentals is able to forecast macroeconomic trends.

2 Literature

Several studies in the area of financial economics have examined strong links between stock markets and macroeconomic parameters. A study by Kwona and Shin(1999)[22] investigates whether current Korean economic activities could explain stock market returns by using a cointegration test and a Granger causality test from a vector error correction model. Monthly stock prices of the value-weighted Korea Composite Stock Price Index (KOSPI) are used with the combination of macroeconomic variables, including the foreign exchange rate, the trade balance, the money supply, and the production index. The results illustrate that stock prices are cointegrated with the set of macroeconomic variables. The cointegration relation indicates direct long-run and equilibrium relation between the stock price index and macro variables. The study implies that macro information is reflected in the Korean stock prices and the relation was found to be strong in the Korean context, however, the study could not find evidence that stock price indices affect macro variables.

Similar researches have been conducted for different countries like Wongbangpo and Sharma(2002)[34] examine the interdependence of stock market and macroeconomic fundamentals in Malaysia, Thailand, Philippines, Singapore, and Indonesia. They use a VECM model to study the long run and short-run relationship between stock prices and GNP, CPI, interest rate, exchange rate, and money supply. The findings indicate that past values of fundamentals are able to predict stock prices. Moreover, the evidence suggested that there exists a causal relationship from stock prices to GNP and CPI in all 5 ASEAN countries. The observed bidirectional causality reveals that stock prices contain essential information about the condition of the macroeconomy.

Another study by Pooja Joshi (2015) [20] empirically estimated the effect of fundamental macroeconomic variables on stock prices in the context of India using the Auto Regressive Distributed Lag (ARDL) co-integration procedure and VECM is used to investigate the direction of causality. The results reassure a long-run co-integrating relationship between different macroeconomic variables and the stock prices in India. Martin K.(2004) [19] Hess analyzes the transmission mechanism of macroeconomic shocks to the stock market and explains time-varying dynamic linkages between domestic and foreign macroeconomic conditions, economic policy surprises, and financial markets in an open economy environment. The analysis displays positive stock market reactions to domestic shocks during recessions and to foreign shocks during expansions.

Eventually, the focus of research shifted from stock return indices to stock return volatility and its impact on macroeconomic variables due to policymaker's increased attention to uncertainty in the economy. Chaudiiuri & Koo (2001)[14] examine the impact of domestic macroeconomic fundamentals and international economic environments on the stock return volatility of four emerging markets in Asia: India, South Korea, Malaysia, and Thailand and identify the dynamic relations between stock return volatility and various domestic and international variables. Their research is motivated by the efficient market hypothesis. They use 12th order autoregression for each variable with 12 dummy variables to allow different monthly mean values. The advantage of including 12 dummy variables is that they are taking care of a possible seasonality problem in each variable. The results state that government expenditure turns out to be an essential factor affecting stock return volatility in Asian markets. Also, domestic macroeconomic variables and global variables were found to have explanatory power for stock return volatility. Nicholas Bloom (2009)[10] analyzes types of uncertainty shocks empirically and built a model with a time-varying second moment of the driving process and a mix of labor and capital adjustment costs. Am impact of an uncertainty shock is stimulated to generate overshoot in employment, output, and productivity growth. The results indicated that second-moment effects generate a rapid slow-down and bounce-back in economic activity, entirely consistent with the empirical evidence.

The paper by Schwert (1989)[29] analyses the relation of stock volatility with real and nominal macroeconomic volatility, economic activity, financial leverage, and stock trading activity. The study finds weak evidence that macroeconomic volatility can help to predict stock and bond return volatility. The evidence is somewhat stronger that financial asset volatility helps to predict future macroeconomic volatility. This result is contradicted by Diebold & Yilmaz(2008)[17], who investigates the links between fundamental volatility and stock market volatility for 46 countries. The research is motivated by financial economic theory, which suggests that the volatility of real activity should be related to stock market volatility. They firstly, estimate a fixed-effects model with GDP volatility depending on three lags of itself and three lags of stock market volatility, and use it to test the hypothesis that stock market volatility Granger causes GDP volatility. Next, they estimate a fixed-effects model with stock market volatility depending on three lags of itself and three lags of GDP volatility, which we use to test the hypothesis if GDP volatility does Granger cause Stock market volatility. There exists a positive cross-sectional relationship between stock market volatility and fundamental volatility. However, evidence suggested that stock market volatility does not cause GDP volatility whereas, GDP volatility does cause stock market volatility.

A more forward-looking aspect of stock market volatility i.e. implied volatility is studied further for its possible impact on macroeconomic fundamentals. Anderson, Bollerslev & Diebold(2007)[1] state that implied volatility contains more and different information than the realized volatility, thus it could be studied to further examine the impact of uncertainty in the form of stock market volatility on macro variables. Tanha, Dempsey, and Hallahan[32] examines whether implied volatility captures the beliefs of market participants about the likelihood of future states together with the preferences of market participants toward these states. In particular, the paper relates changes in option implied volatility (IV) to changes in macro-economic announcements through the impact of these announcements on the moments of the state price density (SPD) function in the context of the Australian ASX SPI 200 index futures options contracts. To examine the effect of macroeconomic announcements on the implied volatility, the log changes of implied volatility (IV) are first calculated. The regressions are performed, firstly, without considering whether an announcement carries "surprise" information, or whether the announcement carries "good" or "bad" news (yielding what we term an "unconditional" response). Thereafter, we consider the "conditional" responses by distinguishing those announcements that (i) carry "surprise" news and those that (ii) carry either good or bad news.

Finally, this paper extends the literature by Berger, Becker, and Giglio (2017) [6] who test theories by quantifying how the economy responds to identified shocks to uncertainty. The critical distinction that this paper draws is between realized volatility and uncertainty which is calculated as option implied volatility. Option market investors appear to have economically meaningful information about future uncertainty that is not contained in the time series of past realized volatility. The study concludes that changes in expected volatility uncertainty shocks appear to have no significant adverse effects on macro-variables and it is the volatility shocks that are followed by economic downturns. The empirical results are inconsistent with theories in which pure shocks to aggregate uncertainty play an essential role in driving real activity. There appear to be adverse shocks to the stock market that occur at business cycle frequencies, are associated with high realized volatility and declines in output, and are priced firmly by investors.

Another study by Chiu, Harris, Stoja, and Chin (2016)[16] takes forward this literature by decomposing the volatility of stock and bond returns into a long run persistent component and a short run transitory component and investigate the bidirectional relationships that each of these volatility components has with macroeconomic fundamentals and investor sentiment. They identify five structural shocks study endogenous responses of financial market volatility conditional on the following four adverse shocks: aggregate demand shocks; aggregate supply shocks; monetary policy shocks; and investor sentiment shocks. The second is the response of output growth, inflation, the interest rate, and investor sentiment to an adverse shock to financial market volatility. The results show the link between volatility and the real economy is, as expected, stronger for the long run persistent component of volatility than it is for total volatility. In contrast, the short-run cyclical component of volatility has a much weaker relationship with the real economy but is instead more closely associated with investor sentiment.

The paper is also related to the works of Angus Moore (2016)[25] which identifies different ways of measuring economic uncertainty as a finance-based measure of uncertainty, which is further divided into realized & implied volatility and newspaper-based measure of uncertainty. The news element of uncertainty as discussed above is measured using the work of Baker, Bloomer, and Davis[3]. They create an Economic Policy Uncertainty (EPU) Index to capture uncertainty about who will make economic policy decisions, what economic policy actions will be undertaken and when, and the economic effects of policy actions (or inaction) – including uncertainties related to the economic ramifications of "non-economic" policy matters, e.g., military actions. The index reflects the frequency of articles in 10 leading US newspapers.

A critical distinction between this paper and the previous works is that we take into account three different measures of uncertainty to measure the bidirectional impact of structural shocks on a broader economy capturing the impacts on both real economy and monetary policy. It also seeks to test the difference in the efficiency of the financial markets of a developed economy and emerging market economy by examining the difference in the results of the two economies.

3 Objective of the Paper

The main objective of this paper is to find the plausible link between the various measure of uncertainty and macroeconomic variables and thus study shocks to which measure has the most definite impact on the fundamentals i.e., which measure might be able to predict the macroeconomic trends the best. Furthermore, this paper attempts to compare the financial markets of a developed economy like the USA with an emerging market economy, India, and test whether there is any discrepancy in the relation between fundamentals and implied volatility of the two countries depending upon how developed their financial markets are. Lastly, this paper aims to give helpful insights into whether market expectations fulfill themselves by transforming from stock market volatility to changes in macroeconomic fundamentals.

4 Variables & Data Sources

For this purpose, the macroeconomic fundamentals selected are GDP, which is proxied by the IMF Production Index (IP) as the real macroeconomic variable. Monthly data for IP is obtained from International Financial Statistics (IFS). Similarly, the consumer price index is also obtained from the International Financial Statistics (IFS). As discussed above, we look into three different measures of uncertainty. Firstly, we look at the realized volatility, which is the current uncertainty in the stock market. It is calculated as the volatility for the S&P 500 index and NIFTY index for the USA and India, respectively. Daily data of the stock indices are obtained from CBOE and NSE, which is converted into monthly volatility series. Secondly, we look at the future expectation of volatility for the stock market. It is given by the VIX measure of the CBOE and India VIX given by NSE. Lastly, the Economic Policy Uncertainty Index is used to measure non-economic and policy uncertainty. Monthly data is obtained from the Federal Reserve bank of St. Louis for both the economies. The period of the analysis is limited by the availability of India VIX data, which is available from April 2009 onwards.

5 Methodology

To calculate the realized volatility from stock returns, this paper uses two methods. Firstly, it calculates unconditional volatility as a monthly standard deviation of daily data. Secondly, conditional volatility is calculated using the GARCH mean estimation model. The GARCH (Bollerslev,1986)[11] model is popular in the estimation of conditional financial volatility because of its capability of capturing time-series volatility clustering.

Several studies have shown that Asymmetric GARCH models have better predictive ability than the popularly used GARCH (1,1) model. Natchimuthu and Prakasam(2019)[15] show that for the Indian stock market, asymmetric GARCH models perform better than the symmetric models like GARCH (1,1). Awartani and Corradi (2005)[2] conclude the same result for US stock market. We use the EGARCH model to calculate conditional variances. Exponential GARCH (EGARCH) by Nelson (1991)[27] overcomes the shortcomings of the symmetric GARCH models and allows for the asymmetric effect by modeling log of conditional variance.

$$log(\sigma_t)^2 = \omega_0 + \beta_t log(\sigma_{t-1}^2) + \alpha_t|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}| + \gamma_t \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

E-GARCH models the log of variance as a function of lagged log of variance and lagged absolute residual from the mean equation. This model also allows for the asymmetrical effects of residuals on the conditional variance. Hence, a negative residual can have a different effect compared to a positive residual on the conditional variance. Here, α_t measures the volatility clustering effect and γ_t measures the asymmetry effect (Nelson, 1991)[27]. The asymmetry effect can be tested against the null hypothesis $\gamma_t = 0$. The statistical significance of the coefficient (γ_t) confirms the presence of asymmetricity. In addition, a negative coefficient (γ_t) indicates that the negative shocks have a larger impact on the conditional variance than positive shock.[12]

VAR Setup and Impulse Response

To test the relationship between the stated variables, we set up a VAR model and generate impulse response as following:

$$y_t = \beta_{10} - \beta_{11} v_t + \gamma_{11} y_{t-1} + \gamma_{12} v_{t-1} + \varepsilon_{yt}$$
$$v_t = \beta_{20} - \beta_{21} y_t + \gamma_{21} y_{t-1} + \gamma_{22} v_{t-1} + \varepsilon_{vt}$$

where:

$y_t = \begin{bmatrix} \text{IP}_t \\ \text{CPI}_t \end{bmatrix}$ i.e. Macroeconomic variables; Index of Industrial Production & Consumer Price Index

$$v_t = \begin{bmatrix} \text{rv}_t \\ \text{iv}_t \\ \text{EPUI}_t \end{bmatrix} \text{ i.e. Various measures of uncertainity}$$

Error terms are assumed to be normally distributed with mean zero and covariance matrix Σ.

[1]Note: Non-stationary variables taken, seasonality adjusted data taken. Further, stationarity of the variables is tested using Augmented Dickey-Fuller (ADF), Phillips Perron (PP), DF-GLS, and KPSS tests.

[2]Another noteworthy point about our analysis is that we have non-stationary time-series for some variables. That is is because in Sims (1980) [30], he advocated the purpose of VAR estimation is to explore real relationships between the variables, and that making a series time-stationary by differencing, any information on the long-run relationship is thrown away. That is an essential aspect of our paper. Our analysis is different in this aspect too.

$$\begin{bmatrix} 1 & \beta_{12} \\ \beta_{21} & 1 \end{bmatrix} \begin{bmatrix} \mathrm{y}_t \\ \mathrm{v}_t \end{bmatrix} = \begin{bmatrix} \beta_{10} \\ \beta_{20} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} \begin{bmatrix} \mathrm{y}_{t-1} \\ \mathrm{v}_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{vt} \end{bmatrix}$$

This can also be written as:

$$Bx_t = \Gamma_0 + \Gamma_1 x_{t-1} + \epsilon_t$$

where:

$$B = \begin{bmatrix} 1 & \beta_{12} \\ \beta_{21} & 1 \end{bmatrix}; x_t = \begin{bmatrix} \mathrm{y}_t \\ \mathrm{v}_t \end{bmatrix}; \Gamma_0 = \begin{bmatrix} \beta_{10} \\ \beta_{20} \end{bmatrix}; \Gamma_1 = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}; \epsilon_t = \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{vt} \end{bmatrix}$$

The VAR model is further reduced to standard form to get:

Pre-multiplication by B^{-1} gives,

$$x_t = A_0 + A_1 x_{t-1} + e_t \tag{1}$$

Or;

$$\begin{bmatrix} \mathrm{y}_t \\ \mathrm{v}_t \end{bmatrix} = \begin{bmatrix} a_{10} \\ a_{20} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ v_{t-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix}$$

where:

$$e_t = B^{-1}\epsilon_t; e_{1t} = \frac{\varepsilon_{yt} - \beta_{12}\varepsilon_{vt}}{1 - \beta_{12}\beta_{21}}; e_{2t} = \frac{\varepsilon_{vt} - \beta_{21}\varepsilon_{yt}}{1 - \beta_{12}\beta_{21}} \tag{2}$$

Using the stability condition we get;

$$\begin{bmatrix} \mathrm{y}_t \\ \mathrm{v}_t \end{bmatrix} = \begin{bmatrix} \overline{y} \\ \overline{v} \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}^i \begin{bmatrix} e_{1t-i} \\ v_{2t-i} \end{bmatrix}$$

Using (2);

$$\begin{bmatrix} \mathrm{y}_t \\ \mathrm{v}_t \end{bmatrix} = \begin{bmatrix} \overline{y} \\ \overline{v} \end{bmatrix} + \frac{1}{1 - \beta_{12}\beta_{21}} \sum_{i=0}^{\infty} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}^i \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} \begin{bmatrix} e_{1t-i} \\ v_{2t-i} \end{bmatrix}$$

which can be written as;

$$\begin{bmatrix} \mathrm{y}_t \\ \mathrm{v}_t \end{bmatrix} = \begin{bmatrix} \overline{y} \\ \overline{v} \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} \phi_{11}(i) & \phi_{12}(i) \\ \phi_{21}(i) & \phi_{22}(i) \end{bmatrix}^i \begin{bmatrix} e_{1t-i} \\ v_{2t-i} \end{bmatrix}$$

This is The Vector Moving Average (VMA) representation of the VAR model which can be used to examine the interaction between the uncertainty measures (v_t) and macroeconomic variables (y_t). The coefficients ϕ_i can be used to generate the effect of ε_{yt} and ε_{vt} shocks on time paths of v_t and y_t. These sets of coefficients are called impulse response functions.

SVAR

$x_t = A_0 + A_1 x_{t-1} + e_t$ is the reduced VAR equation but e_t has no economic interpretation the error terms maybe correlated across equations.

Rewriting (1) as:

$$x_t = A_0 + A_1 x_{t-1} + C\epsilon_t$$

where:

$$\mathrm{C} = B^{-1}$$

To extract C and arrive at structural shocks with economic interpretation, we assume that structural shocks are uncorrelated:

$$\mathbb{E}(\epsilon_t \epsilon_t^T) = \Omega_\epsilon = I$$

Then we can show that by using definition $e_t = C\epsilon_t$, the reduced form error covariance matrix is:

$$\mathbb{E}(e_t e_t^t) = C\mathbb{E}(\epsilon_t \epsilon_t^T)C^T$$
$$\Omega_e = C\Omega_\epsilon C^T$$
$$\Omega_\epsilon = CIC^T$$

$$\Omega_\epsilon = CC^T \tag{3}$$

(3) is essentially the identification problem of SVAR.

Identification of the SVARs is a challenging task, additional information needs to be brought in the model which imposes strict restrictions. Canova (2005)[12] explains that popular identification schemes such as the Cholesky decomposition and long-run restrictions impose 'zero-type' restrictions that cannot be easily justified by many DSGE models and are difficult to explain the economic theory.

To overcome this hurdle, Blanchard and Diamond(1990)[9], Faust (1998)[18], Canova and De Nicoló (2002)[13], and Uhlig (2005)[33] proposed that structural inference using vector auto-regressions might be based merely on prior beliefs about the signs of the impacts of certain shocks. The sign restrictions methodology curb some of the shortfalls of conventional identification techniques. They impose “sign” or “qualitative” restrictions on structural responses. This procedure makes VAR and DSGE models more comparable than with other identification strategies.

Sign Restricted Approach

In the case of the usual Cholesky decomposition, C would be a lower triangular matrix. In the sign restriction approach, C is not lower triangular. However, Cholesky decomposition is used as an intermediate step to extract B. Here, P is a Cholesky lower triangular matrix that satisfies $\Omega_\epsilon = PP^T$.

Any such matrix that meets the criteria will do and is used only for computational purposes. Then any orthogonal matrix D yields C = PD and satisfies:

$$\Omega_e = CC^T$$

$$CC^T = PDD^T P^T$$

$$PDD^T P^T = PIP^T = PP^T$$

Further, the procedure continues as follows:

Impulse responses are generated based on Givens rotation after making draws from the data. Then, whether impulse response satisfies the restrictions that are given directly to its shape is checked. If the impulse responses satisfy the given restrictions, then the impact matrix C is saved. It should be noted that there does not exist a unique C.

In the case of Uhlig’s(2005)[33] penalty function, the algorithm is based on finding an impulse vector that comes as close as possible to satisfy the imposed sign restrictions by minimizing a function that penalizes sign restriction violations and rewarding responses which satisfy the constraints, rather than being based on the acceptance and rejection of sub-draws. This reduces the uncertainty of identification by helping to accurately identify the best impulse response out of all those that satisfy the sign conditions.

Let J be the total number of sign restrictions and K be the total number response periods for which these restrictions apply. Here, the impulse vector is the vector α which minimizes the total penalty $\Psi(\alpha)$ for all constrained responses j $\in$ J at all constrained response periods k $\in$ K.

Sign restrictions are, only properly defined from a Bayesian point of view (Moon and Schorfheide,2012)[24]. Thus, the Markov chain Monte Carlo method (MCMC) is used to draw samples from the posterior distribution.

Shocks Identification

To study the bi-directional causal relationship between various measures of uncertainty and macroeconomic fundamentals, structural shocks are identified. Micro-founded macroeconomic models are used to identify the macroeconomic structural shocks (Canova and De Nicoló)[13] as:

(i) **Adverse aggregate demand shock** drives down output growth but increases inflation rate contemporaneously.

(ii) **Adverse aggregate supply shock** drives down output growth but drives up interest rates contemporaneously.

To study the impact of uncertainty measures, shocks are identified as:

(i) **Realized volatility shock**

(ii) **Implied Volatility shock**

(iii) **Policy Uncertainity shock**

The five structural shocks are orthogonal to each other by construction and help to identify the impact of uncertainty on macroeconomic variables and vice versa. The objective is to uncover the bidirectional relationship if it exists. For this, we focus first on the response of the three measures of uncertainty to the macroeconomic shocks like aggregate demand shock and aggregate supply shock. Second, we focus on the response of output growth and inflation to adverse financial market shocks. We repeat the analysis for India and compare the results. Bayesian Sign restrictions are summarized in the following table:

In the below table, we have summarized sign restrictions associated with the shocks. The five structural shocks are orthogonal by construction.

Table 1: Bayesian sign restrictions

Variables	**EPUI**	**Conditional Realized Vol.**	**Implied Vol.**	**Consumer Price Index**	**Industrial Production**
Aggregate Supply shock	?	?	?	+	−
Aggregate Demand shock	?	?	?	−	−
Realized Vol. Shock	?	+	?	?	?
Implied Vol. Shock	?	+	+	?	?
Policy Uncertainty Shock	+	?	?	?	?

Note:- The above table displays the imposed sign restrictions, which are used to identify structural shocks in our SVAR model (8). '+' refers to positive contemporaneous impact in a variable when a structural shock hits, whereas '-' refers to a negative contemporaneous impact and '0' means that the certain variable remains unaffected. '?' means that the we are agnostic about the response of the variables. Also, the five structural shocks are orthogonal to each other by construction.
The (+) & (−) sign restrictions are borrowed from the paper Chiu et al (2018)[16].

6 Results

In this section, we report the results from our VAR analysis. In our VAR analysis, we include variables such as EPUI, VIX (implied volatility), GDP (proxied through Index of Industrial Production), Inflation (proxied through Consumer Price Index), and realized volatility proxied through stock market indices. We use GDP and IIP interchangeably in our analysis.

We first examine the impulse response functions (IRFs) of the above-mentioned variables to adverse aggregate Demand and aggregate supply shock. We also explore the shocks in uncertainties indices. However, in contrast to the past literature, we measure the uncertainty shocks through variables like policy uncertainty index, realized volatility, and implied volatility. Each of our figures includes the percentage estimates of the impact along with the 68% confidence intervals for a period of five years. In the later part, we also explore the question of variance forecasting of the same variables using the same shocks i.e., how much forecasting error can be explained by a particular shock.

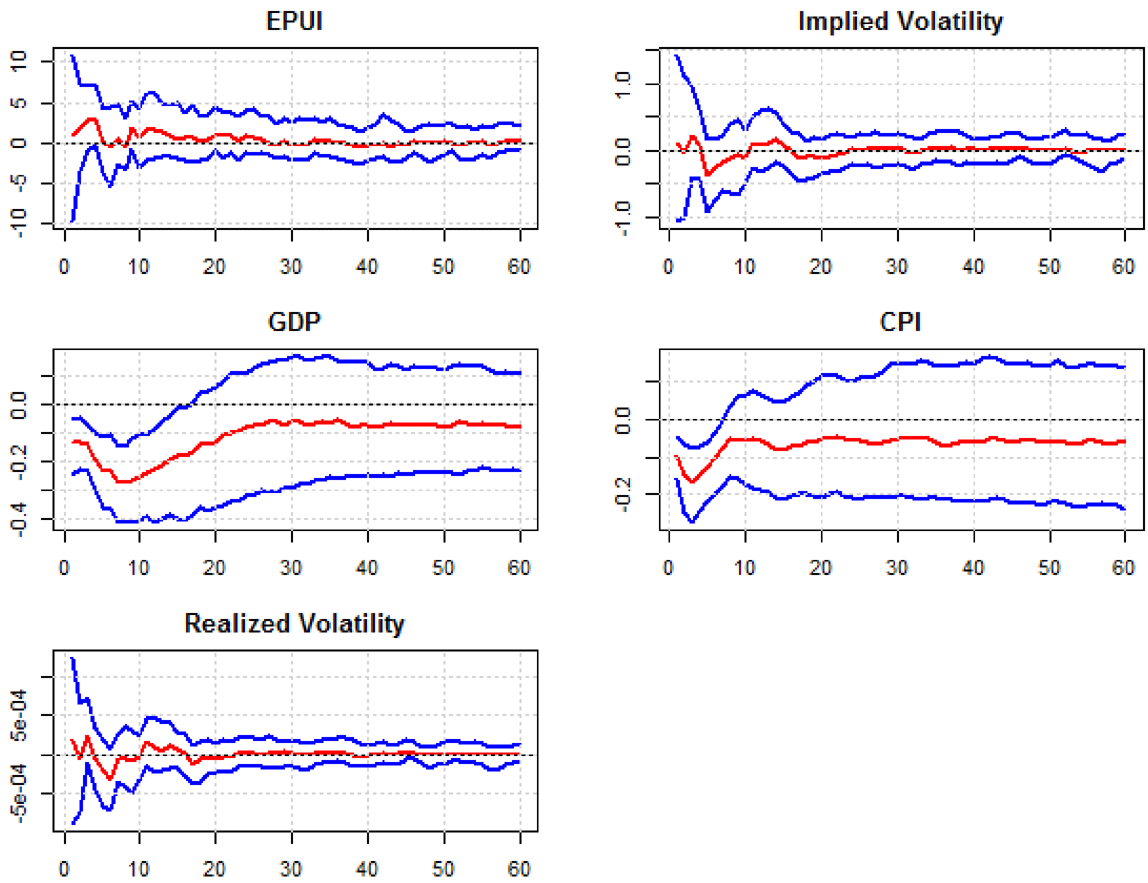

Figure 1: Impulse Responses for the Aggregate Demand Shock (US)

Fig 1 presents the responses of the five variables mentioned above to adverse aggregate demand shock on the horizon of 0-60 months. There are many components to aggregate demand in an economy. It is the sum of consumption, investments, and net exports in an economy. An adverse aggregate demand shock impacts the investment and labor demand decisions, and this affects IIP. Similarly, prices fall due to low demand and relatively high supply. As government intervenes to absorb the shock, it might create a slight increase in policy uncertainty. Albeit this will be a second-order effect, so we are agnostic about its presence. The level of demand shock decreases the profitability of investors, which in turn lowers the level of cash in the economy and hence drives down stock market prices. In general, we might see an increase in financial market volatility. In our plots, we see a minimal EPUI shock, which hovers around 10% however it rises in the next 2-3 months and gradually decreases to half in the next 2-3 months. It results in the fall of GDP by 12% and CPI falls by 10%. The shock leads to a statistically positive increase in both implied and realized volatility, which is again in consonance with earlier findings, albeit with a gradual decrease in statistical significance over time. Past literature on changes to aggregate demand presents similar findings. In Chiu et al (2018)[16], Researchers find identical results for aggregate demand shocks on macroeconomic fundamentals like GDP and inflation.

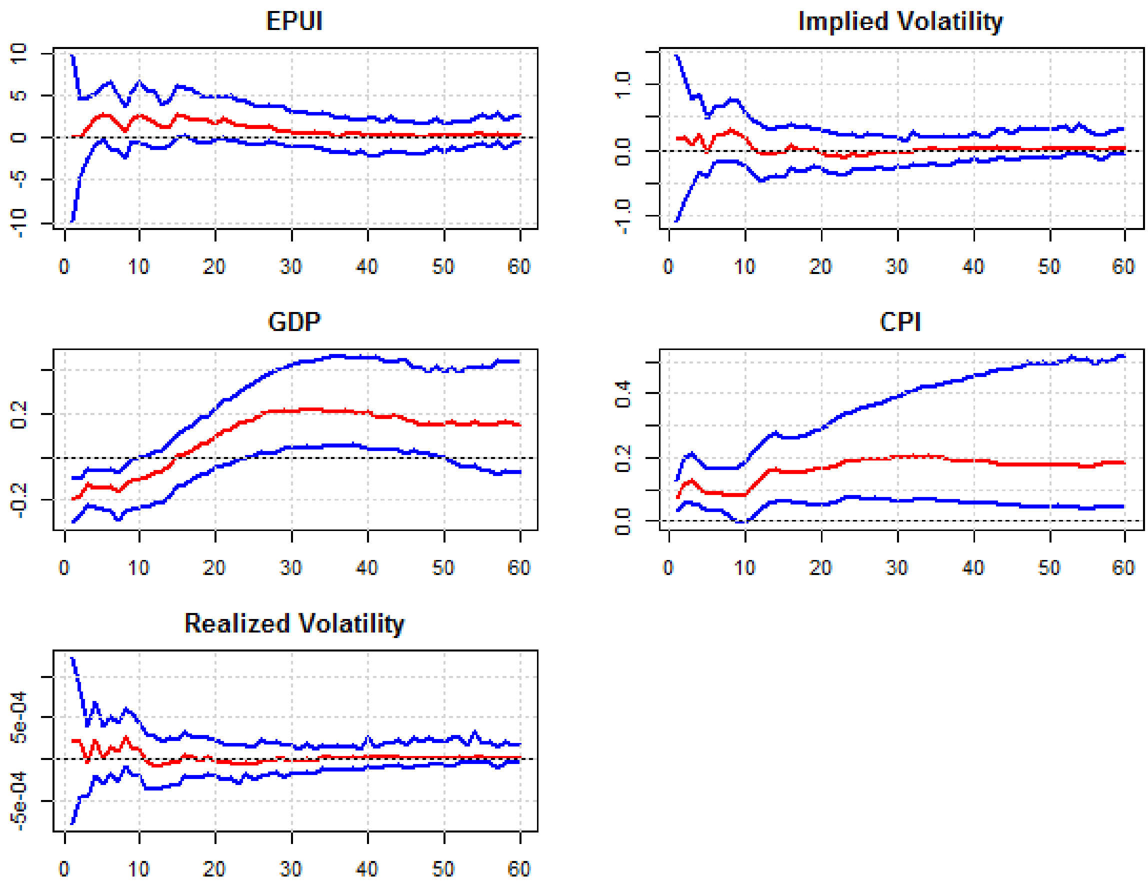

Figure 2: Impulse Responses for the Aggregate Supply Shock (US)

Fig 2 plots the impulse response point estimates for adverse aggregate supply shock on volatility indices and macroeconomic fundamentals. In the literature, IIP has been used as a proxy for aggregate supply. Aggregate supply too is affected by labor and investment decisions. Adverse supply shock creates a shortage of goods in the market resulting in higher CPI at the time of impact. Such supply shock affects the investor's profitability, which in turn affects the stock prices. This implies that there is higher volatility in the financial market. However, these uncertainties and volatility indices will have lagged or less impact because again impact will be of second order. The impact follows almost the same pattern as found for AD shock, with the only outlier being CPI. GDP plummets by 20% at the time of impact, but we observe a reversal of sign after fifteen months. Results are statistically significant at the time of impact. It yields a positive effect on implied volatility with the shock reducing to zero after ten months. It doesn't induce any contemporaneous effect on policy uncertainty. Our results are consistent with the findings in Chiu (2018) paper which finds an initial reduction for output growth (IIP) and an increase of 20% in the case of CPI.

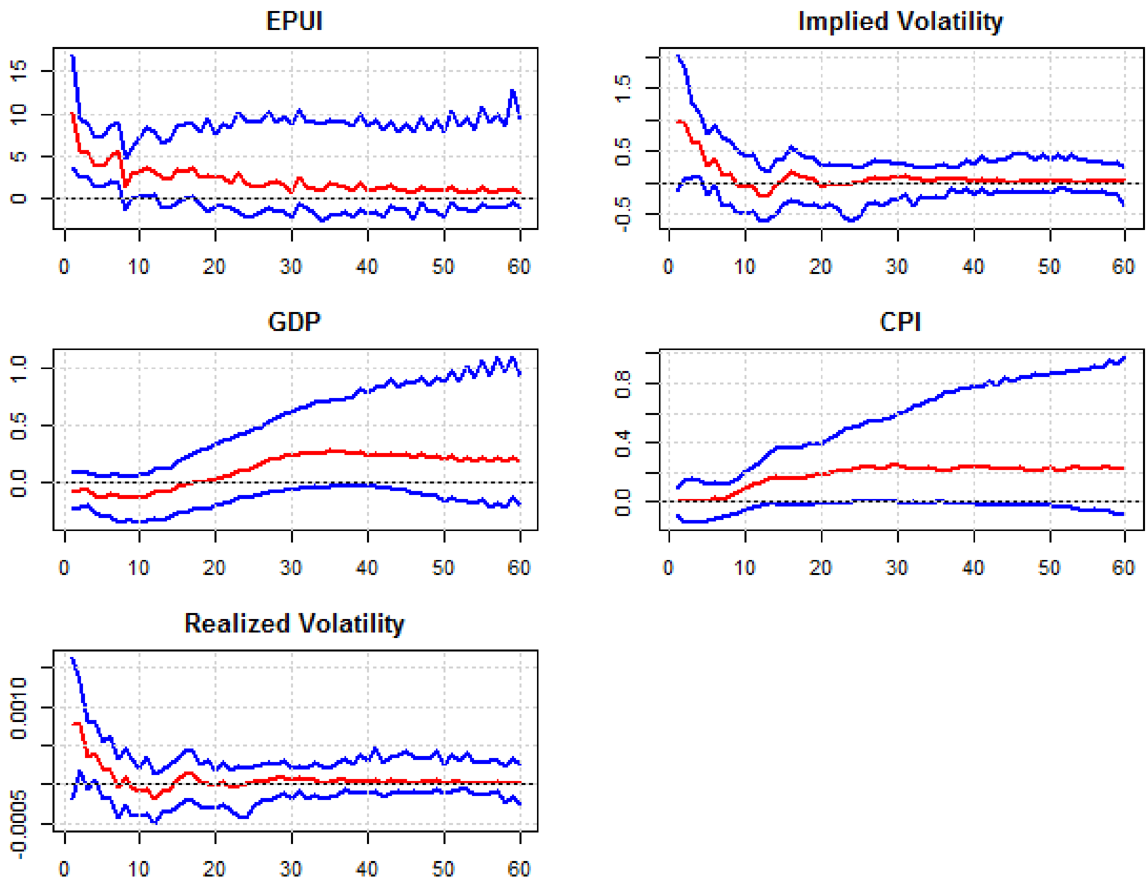

Figure 3: Impulse Responses for the Policy uncertainty Shock (US)

Fig 3 plots the IRF for a shock in uncertainty in economic policy. Greater policy uncertainty, such as the taper tantrum period in 2013, creates systematic uncertainty about the next-period economic policy of an economy. It results in a higher cost of capital. While this doesn't affect the contemporaneous price of goods, it affects investment decisions and induces precautionary savings. As a result, IIP (GDP) is negatively affected. It also affects implied volatility since future prices of stock options. An increase in uncertainty affects financial markets by lowering assets valuation and, as a result, affect Realized volatility by increasing it. Bansal (2004) [4] has provided empirical evidence in this respect. In our analysis, while such shock in uncertainty produces a minuscule contemporaneous impact on GDP, it has almost no effect on CPI at the time of impact. Nonetheless, the impact on CPI starts becoming explicit after 6-7 months and is highly substantial to the tune of 20%. It induces a one-to-one impact on both implied and realized volatility. The shock persists for twenty months for Implied volatility. V Sum [31] in his 2012 paper, explores the structural relationship between EPUI and stock returns, finds similar results for stock returns (Realized volatility). Effect of uncertainty on macroeconomic variables has been well documented in past literature like Bernanke(1983) [7] and Julio et al.(2012) [21]. Julio et al. provide empirical evidence of a negative correlation between an uncertain political environment and investments.

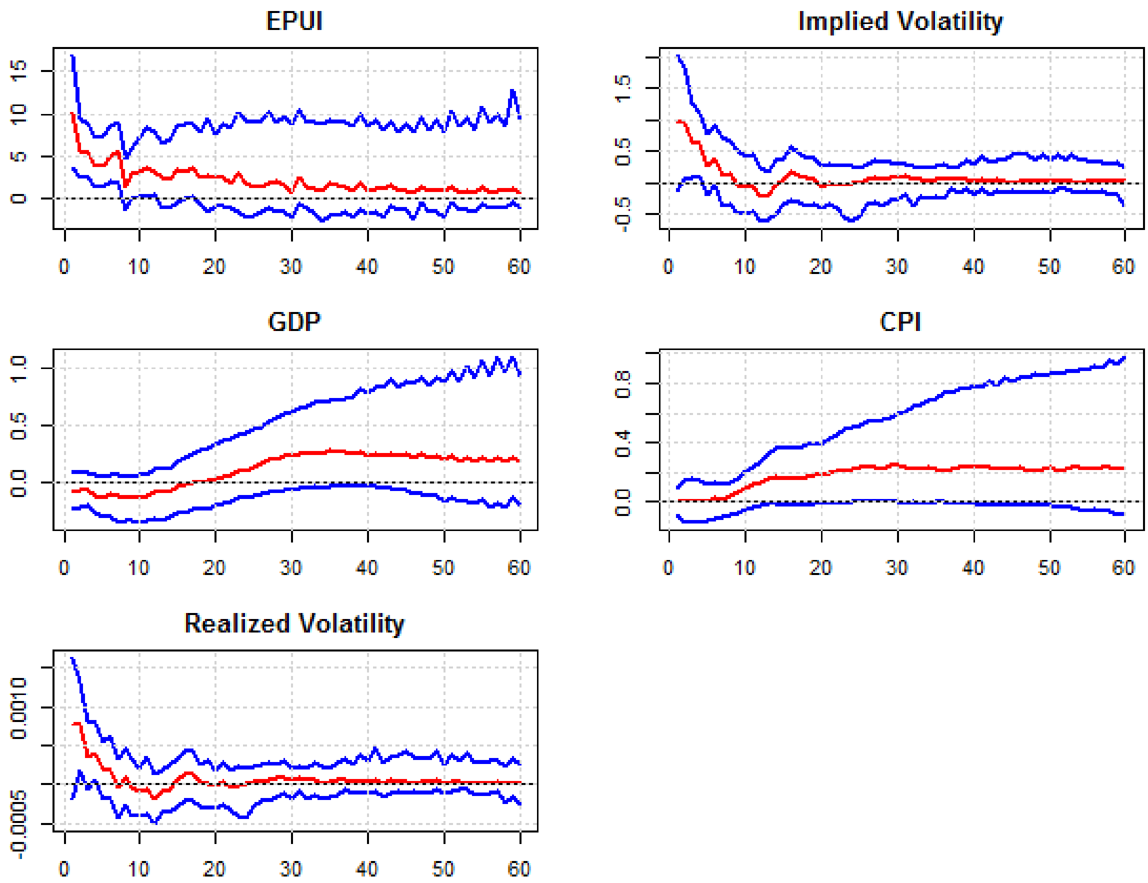

Figure 4: Impulse Responses for the Implied volatility Shock (US)

Fig 4 explores how implied volatility (measured by VIX) would impact these five variables. Implied volatility measures the volatility based on the future market's expectation of stock movement. If this volatility increases, then current stock returns too fluctuate due to the uncertainty factor. Similarly, we should observe a significant impact on EPUI due to uncertainty in market sentiment. EPUI index construction itself is based on words like "economic", "uncertainty" etc. GDP and CPI would not receive a contemporaneous impact. However, they may have a second-order impact through the effect of market sentiment on consumer spending. Basu and Bundick(2015) [5] in their paper, argue that uncertainty modeled by implied volatility induces risk-averse individuals to save more and consume less. This results in the contraction of GDP, as seen in our plot too. Bernanke(1983) [7] posits that due to uncertainty in the economic environment, firms get an incentive to freeze future investments and hiring processes. Our findings show that implied volatility response function plots are on a similar pattern to EPUI shocks. In particular, it yields a 100% increase in EPUI measure. In regards to macroeconomic fundamentals, it has a minimal effect at time zero and around it. GDP receives a negative impact of approx 10%. CPI impulse response looks very similar to the IRF plot from EPUI shock. It experiences a lagged positive impact after eight months. Realized volatility has an impact of 75% at time zero, which after a period of 20 months, fades away. Statistical significance at 68% confidence interval for the macroeconomic variables

(GDP and CPI) reduces with time and becomes insignificant at the horizon of the 60th month.

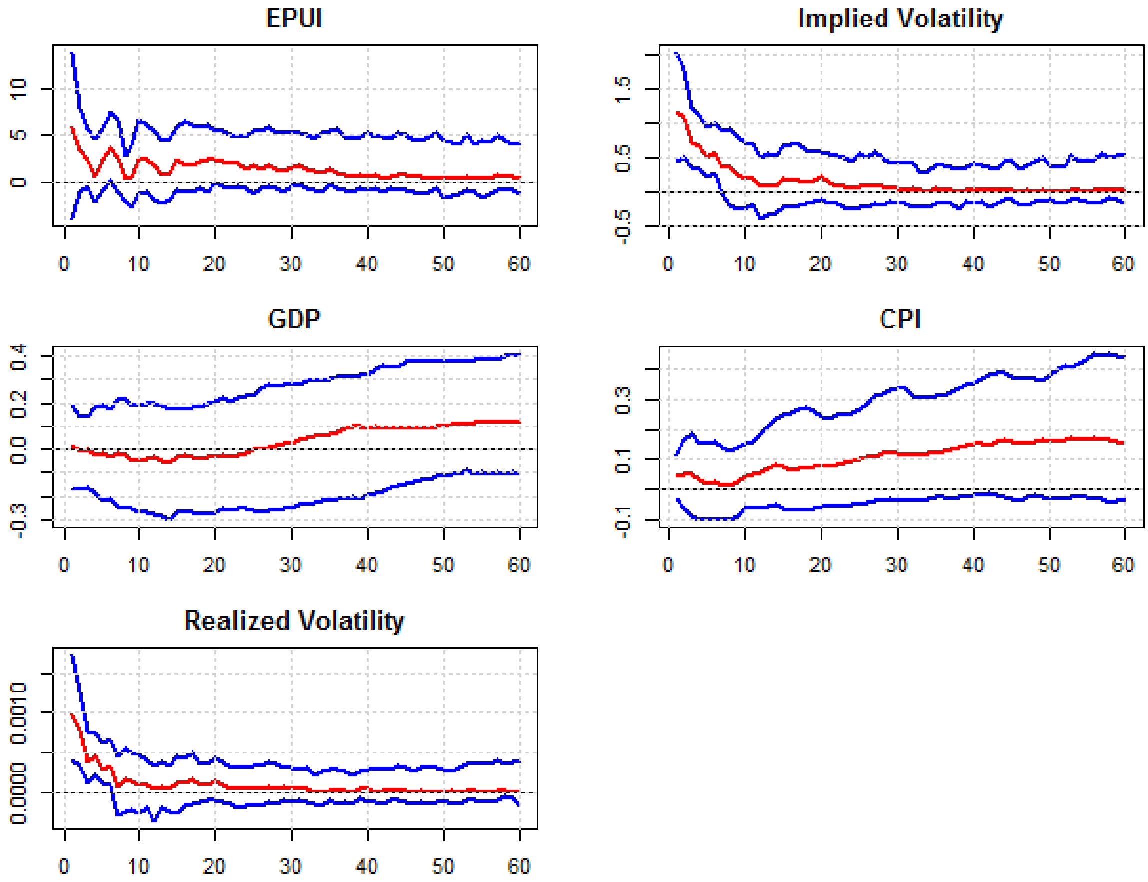

Figure 5: Impulse Responses for the Realized volatility Shock (US)

Fig 5 presents the same analysis; however, it measures uncertainty through realized volatility. Realized volatility is based on stock market returns. Stock market returns are a kind of sentiment indicator in the economy. As volatility increases, people may change their spending behavior, and GDP may fall due to demand/supply shock. These demand/supply shock will, in turn, impact CPI. An increase in Realized volatility directly affects EPUI as the EPUI index itself is constructed based on specific words related to the stock market and economic policy. Similarly, an increase in realized volatility will affect future volatility by more than one-to-one as they are highly correlated. As is expected, We find that it yields an increase of 110% and 55% increase for Implied volatility and EPUI, respectively. However, in contrast to past studies like [6], our plot shows a zero impact on IIP(GDP) at time zero. GDP has a lagged impact. Berger et al. (2020) found a statistical and economically significant negative impact on the manufacturing-based industrial production index. CPI increases by 5% at the time of impact.

India-Based analysis

In this section, we repeat our analysis for India -a developing country. Most of the literature in the VAR analysis has kept its attention limited to the developed countries, trying to figure out the dynamic response of the uncertainties to the macroeconomic variables or volatility indices like stock market returns. We add to that literature by extending the analysis to an emerging market economy. Emerging economies have relatively inefficient markets and are therefore different from developed countries in this context. Also, post-2008, economic policy uncertainty in India compared to Europe and USA [3] [8].

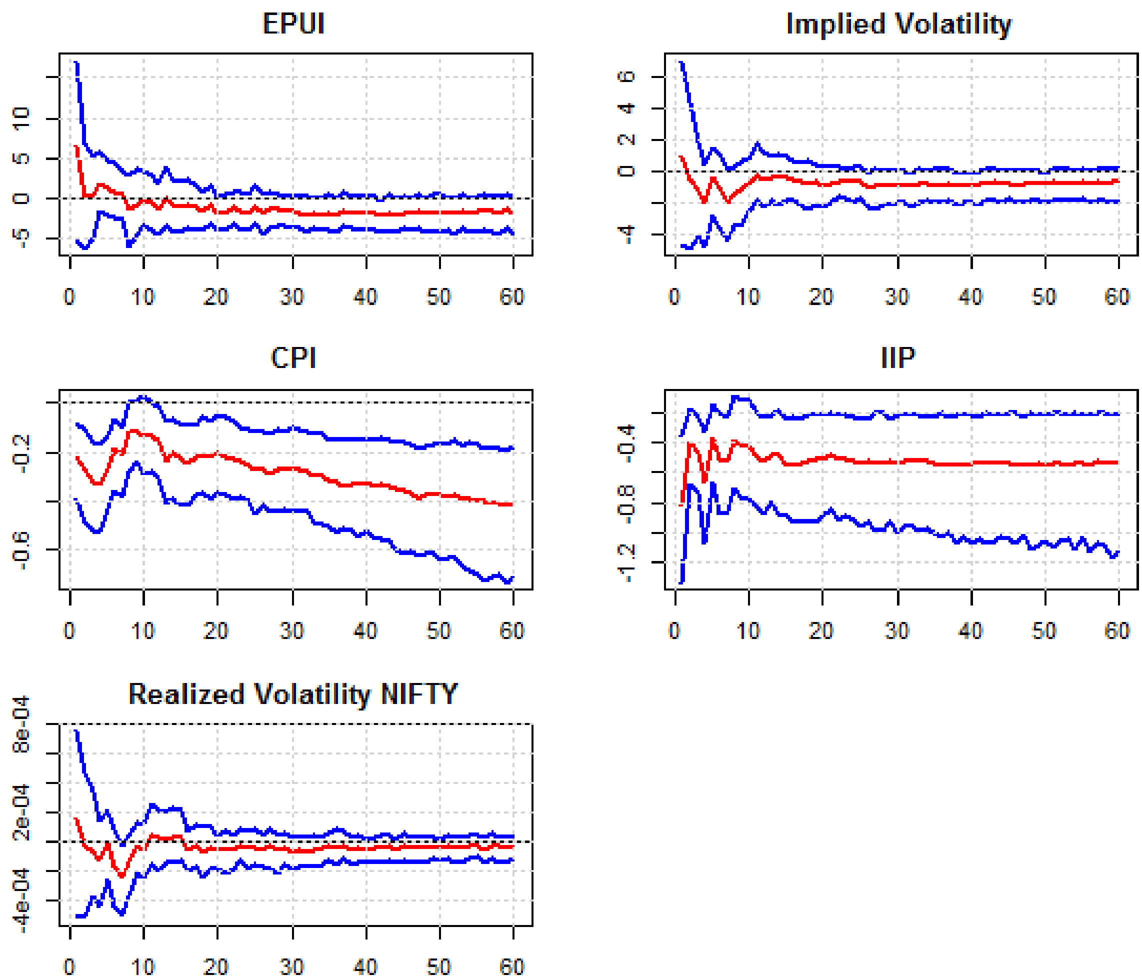

Figure 6: Impulse Responses for the Aggregate Demand Shock (India)

Fig 6 presents the result for adverse aggregate demand shock. We find that it results in an -1.5% decrease in the Industrial Production Index much. larger than -0.35% in the case of the US. In the case of implied volatility, it yields to a short-term decrease

[3] Sanjai Bhagat and Pulak Ghosh (2013) show that in case of India, EPUI fluctuates much more than its counterparts in developed world.

amounting to -0.5% but EPUI index increases by 5% bp before stabilizing. The impact on EPUI shows that India has a higher volatile EPUI index compared to the USA. This evidence is consistent with the findings of the paper by Bhagat(2013)[8].Inflation also responds negatively and the extent of the shock hovers around -0.2%. Realized volatility shows a minimal, statistically significant increase of 0.3%. Indian financial markets behave in tandem with US financial markets. This might be due to greater integration of the Indian stock market with global stock markets, so they respond accordingly to global cues. [4] [26]. However, effect to EPUI is positive in case of India but negative in case of USA.

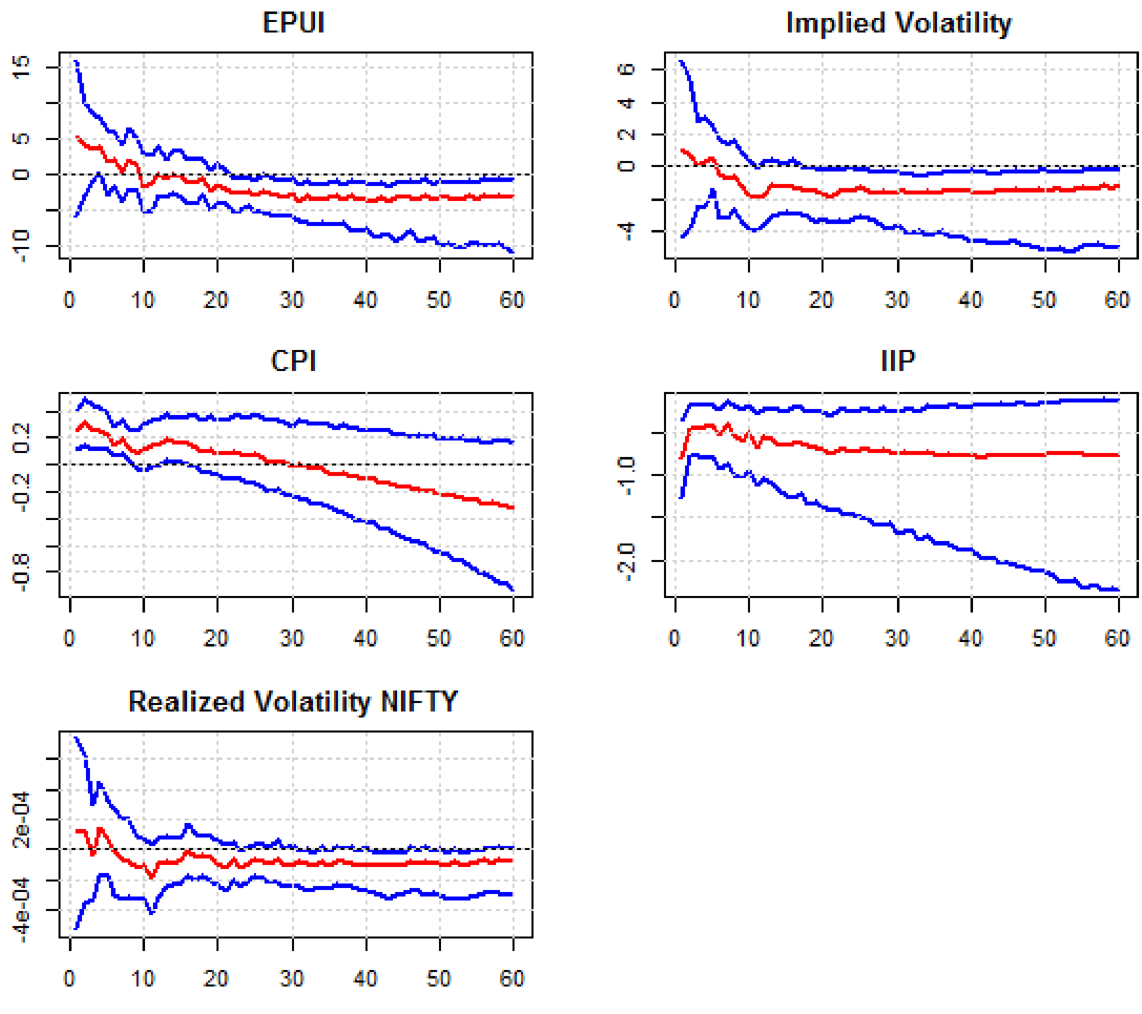

Figure 7: Impulse Responses for the Aggregate Supply Shock (India)

Fig 7 plots the IRFs, when he administer a negative aggregate supply shock. It shows a steep-negative impact on IIP in the first few months and an increase for CPI by 0.15%. Apart from this, EPUI and implied volatility undergo an increase of 12 bp

[4]Debjiban Mukherjee in his paper finds that post reforms like SEBI act, Indian stock markets are globally integrated and more affected by global situation.

and 1%, respectively. Results are significant at point of impact. Plots for uncertainties measures like EPUI, Implied Volatility and realized volatility is in sync with the results from US scenario. Chiu et al. (2018)[16] study had also found that supply shocks result in a fall in output and a rise in inflation. However, the magnitude of the impact in their analysis differs from ours. Results are statistically significant and the analysis is robust to 68% confidence intervals.

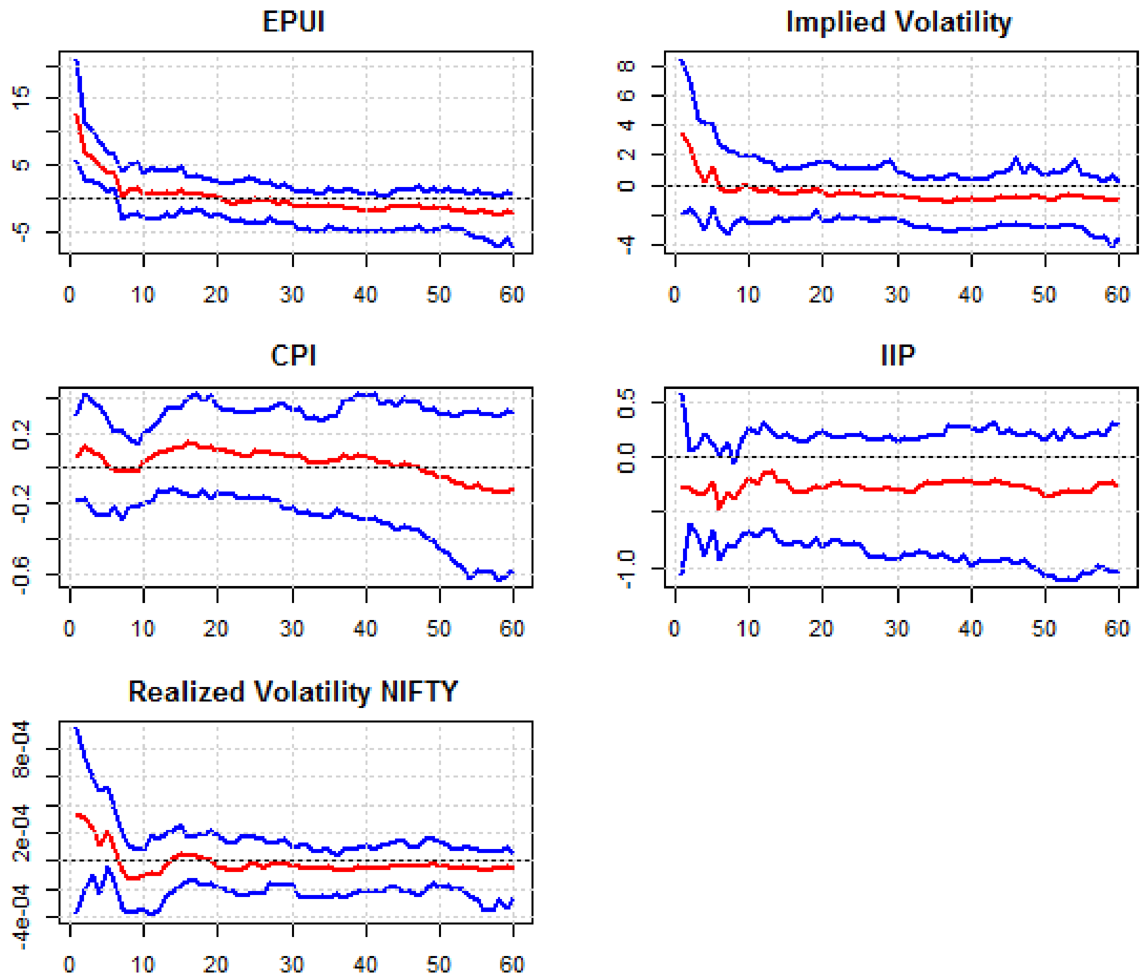

Figure 8: Impulse Responses for the Policy Uncertainty Shock (India)

Fig 8 presents impulse response plots to the shock in economic-policy uncertainty. This specific shock is particular interesting as there are very few studies that have carried out the analysis to gauge the impact of policy uncertainty on macro fundamentals. Impact on the EPUI, Implied volatility and realized volatility are very similar to the US case even in the magnitude. However, IIP and CPI show a different trend than the US, IIP undergoes a reduction of 25%, and CPI increases by 5% whereas in US case CPI doesn't observe any impact while GDP shock hovers around -10% at the time of impact. Realized volatility receives a significant shock contemporaneously but gradually settles after 12-14 months. This different trend might be due to the relatively more fluctuating EPUI of India[8].

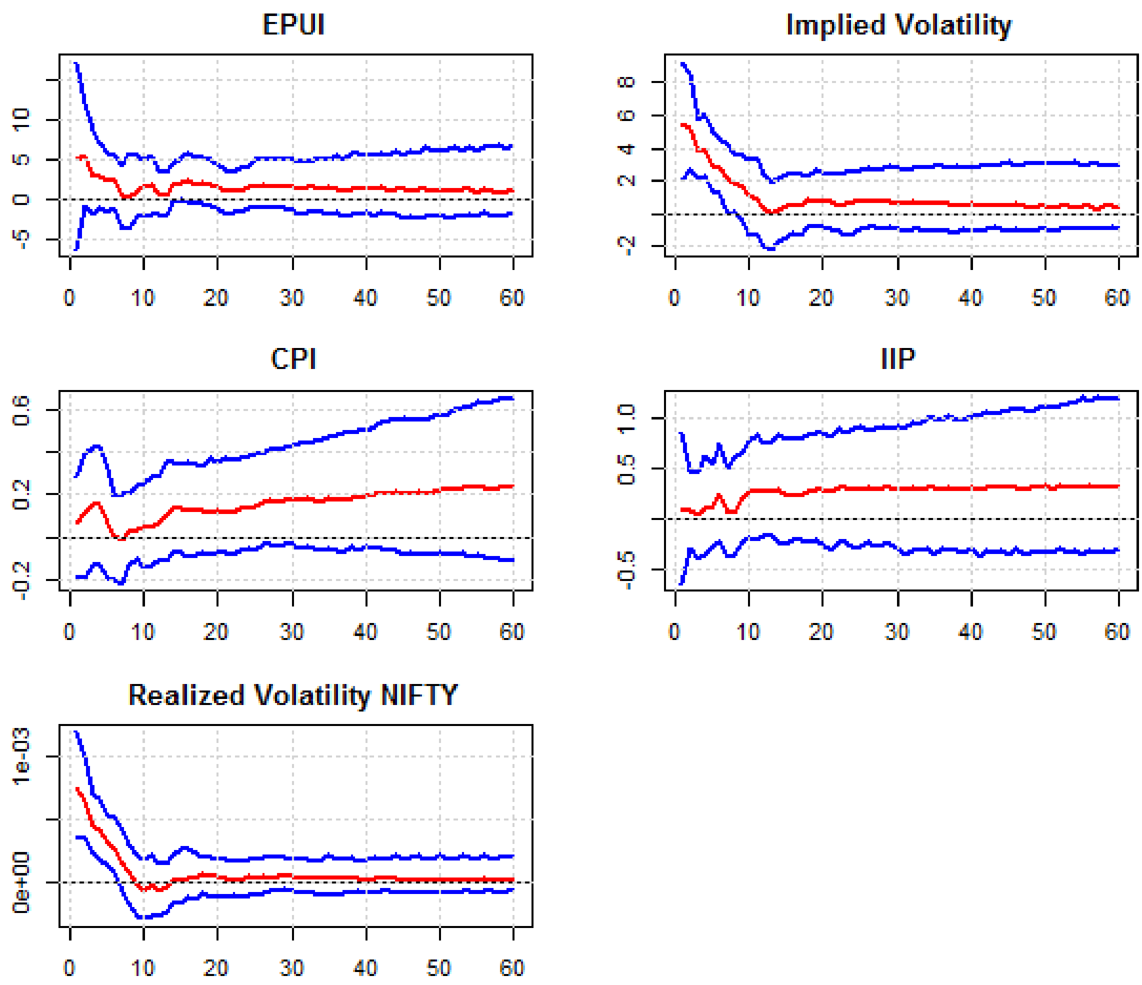

Figure 9: Impulse Responses for the Implied volatility Shock (India)

Fig 9 plots the IRFs in response to shock in Implied volatility. The impact is the same as of US for the case of Realized volatility. EPUI contemporaneous shock from this shock is half of what we observed in the US's case. Results also differ for CPI and GDP(IIP). Implied volatility shock induces a positive shock on CPI and IIP Results are marginally significant. It yields a minimal effect of 10% initially, which booms to 25% after ten months of impact. In tandem with what we have analyzed until now, the statistical significance of the shocks to IIP decreases after a time. We do not provide any explanation for the relative lower EPUI impact.

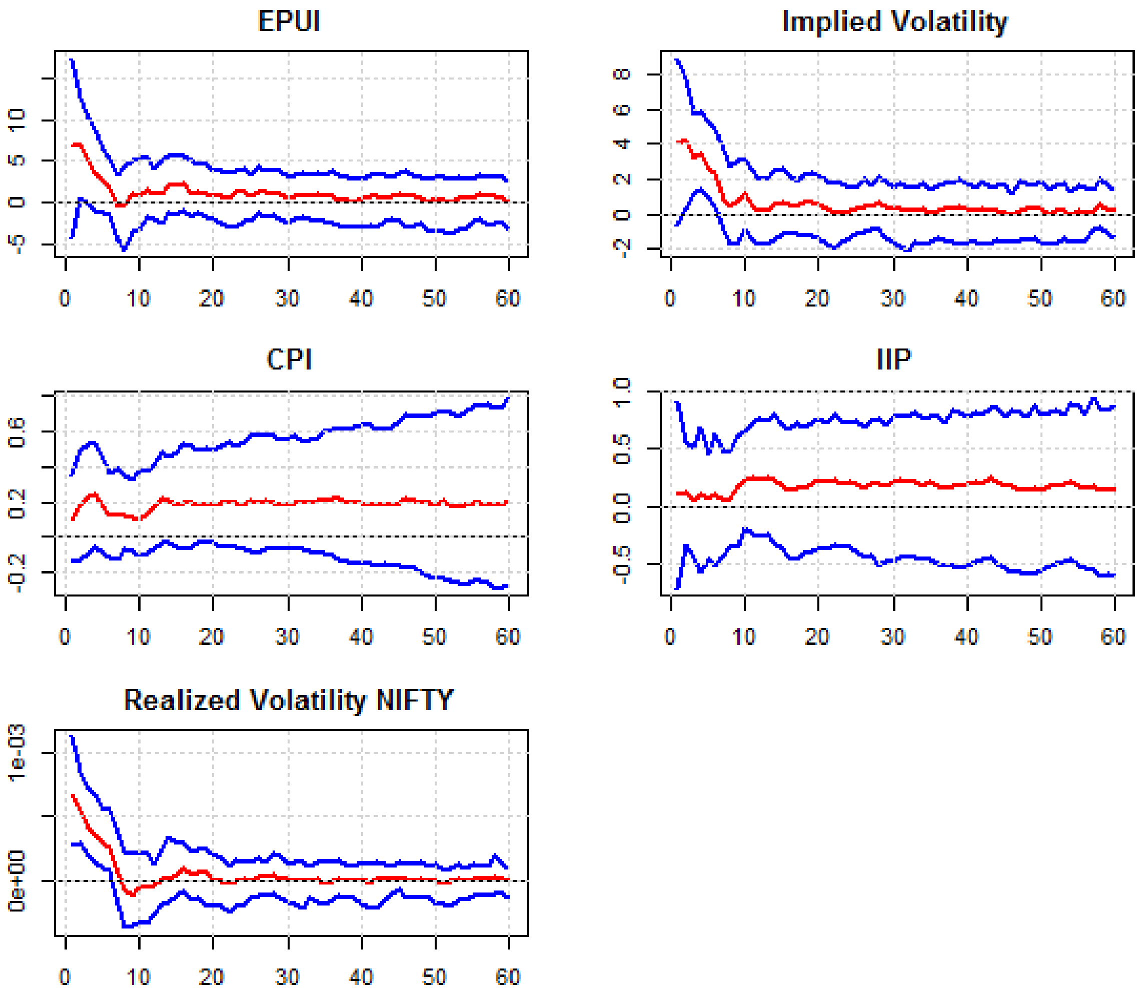

Figure 10: Impulse Responses for the Realized volatility Shock (India)

This last figure 10 plots IRFs for a shock in Realized volatility. In India, a realized volatility shock has a more stable and persistent effect on IIP(GDP) in comparison to the USA economy according to our analysis. CPI increases by 10%, EPUI by 50%, Implied Volatility increases by 40%. Realized volatility shock in India induces a very similar impact to the USA's case. A similar analysis in Berger's paper has found that volatility, be it implied or realized, has a negative association with the output growth and employment.

7 Summary

Adverse demand and supply shocks affect the USA and India in a similar way. Realized volatility has a lagged impact on IIP and CPI after a year has passed. EPUI does not impact contemporaneously, but it induces a faster effect in CPI than realized volatility.

EPUI and implied volatility's impact differs in case of India and US. In India, it create ripples in macroeconomic fundamentals like GDP and CPI even though estimates are statistically insignificant. Realized volatility has a similar impact in both US and India. Our results for EPUI align with the earlier results of V.Sum et al.(2012) where the researchers explored the relationship between stock returns and policy uncertainty.

In the appendix, we also present our results of variance decomposition where we do forecast error variance decomposition (FEVD) to see how much variance in variables is explained by demand shocks or uncertainties shocks that we used earlier.In the case of US, we see that an adverse variation in demand explains about 10-15% variation in the forecast of the uncertainties variables (EPUI, IV, RV) while in the case of macroeconomic variables like CPI and IIP, it can explain 15-20%. Realized volatility is explaining variation in the similar range. In all of the cases discussed above, we observe that forecast error variation improves after a one-year horizon or more and then becomes constant. Results for India, too, are on the same lines but with lower statistical significant estimates at 68% confidence interval.

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