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News and The Business Cycle: The Effects of News Based Uncertainty Shocks

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Abstract

I use two news-based indicators- News-based policy uncertainty and Equity-Market volatility as a measure for both policy-Specific uncertainty and general economic uncertainty for the period 2000 to 2022. Next, to determine the effects of these shocks in the business cycles, I simulate the response of the different macroeconomic variables (GDP, Inflation, Exchange rate, Interest rate, M1 aggregate) to these shocks. The results, using an SVAR model, indicate that both general and policy-related uncertainty shocks slow down the level of economic activity, with Volatility shocks having a more severe and instantaneous impact on the economy. The result supports Alexopoulos et al. (2009). However, it seems that the response to the news on uncertainty is quicker. This is shown by the fact that peak on the IRFs of Alexopoulos & Cohen (2015) occurred only after 12 months for most variables, however IRF in my model suggests that the response peak out in less than six months. It must be because of the online access to print media now compared to 2007 when Alexopoulos & Cohen (2015) collected the data.

Introduction

Business cycle researchers have spent most of their focus on identifying the reasons for cyclical fluctuations in the economy. Though business cycle models place much emphasis on the technology or innovation shocks, empirical works such as Gali (1999), Gali & Rabanal (2004) and Christiano et al. (2004) do not find evidence that technology shocks account for most of the fluctuations. They conclude that only a small proportion of the business cycle fluctuations is explained by technology shocks. In light of this result, researchers have focused on other sources such as monetary shocks, fiscal shocks, and oil shocks[I].

Recent developments in the empirical literature have focused on policy-uncertainties affecting. Business cycles in the economy. This premise is supported by the fact that economic policies are designed to stabilize, promote economic growth and prosperity, and employment. The importance of economic policies can be underlined by the statements of IMF (2012) and IMF (2013) stating that economic activities and subsequently economic indicators are guided by fiscal, regulatory, and monetary policy decisions. In the wake of the great recession, policy-induced uncertainty has become so important to economic research and literature that it is even believed that the uncertainty models might often foreshadow the future economic path[II]. IMF (2013) pointed out that uncertainties in the US and European monetary, fiscal, and economic policies were responsible for the Great Recession in 2008-09 and slow recoveries afterward. Although the former statement was supported, the latter argument of slow recovery because of policy uncertainty was challenged by Bloom (2009). For this, Bloom (2009) used a model with a time-varying second moment and firm-level data to suggest that uncertainty shocks generate sharp recessions followed by swift rebounds.

One of the major developments in uncertainty models is the new index of economic policy uncertainty (EPU) by Baker et al. (2016). The index is built from three components. The first is the coverage of policy-related economic uncertainty in major newspapers.

[I] see for example, Christiano et al. (1999), Schmitt-Grohe & Uribe (2004) for monetary policy, Christiano & Eichen- baum (1992) for fiscal policy and Hamilton (1983) for oil price shock

[II] For example see the discussion on the website measuring uncertainty index following the work of Bloom (2009) https://www.policyuncertainty.com/methodology.html

The reports by the Congressional Budget Office (CBO) on the number of federal tax code provisions set to expire in future years are used as the second component. As a proxy for uncertainty, the disagreement among economic forecasters is used as the third component.

The relationship between EPU and real variables like investment, employment, and output is analyzed by Baker et al. (2016) using a VAR setup. The results suggested that policy uncertainty can be linked with higher stock price volatility and lower investment and employment in sectors sensitive to economic policy such as national defense, health care, and finance.

Istrefi & Piloiu (2013) argues a positive association between policy-induced uncertainty shocks and long-term inflation expectations. They further argue that uncertainty in the economy is guided by fiscal policy-related instead of monetary policy-related shocks. Beckmann & Czudaj (2017) also model the economic policy uncertainty and its role in expectations in the financial market. They achieve this by estimating the impact of policy uncertainty on exchange rate expectations and professional forecast errors. They find that policy uncertainty affects forecast errors more than the perceived expectations and that the effect of uncertainty in market expectations is not recorded accurately. Both Istrefi & Piloiu (2013) and Beckmann & Czudaj (2017) use the index generated by Baker et al. (2016) as the measure of uncertainty in their papers.

The policy-based uncertainty index of Baker et al. (2016) is a relatively new measure of uncertainty. Traditionally, uncertainty is measured by market volatility. Alexopoulos et al. (2009) use stock price volatility as market volatility. They then generate an uncertainty index similar to Baker et al. (2016) from New York Times' articles. The results suggest, that both measures of uncertainty generate short, sharp recessions and recoveries. Both papers argue that the newspaper-based index accounts for a significant proportion of the variance in most variables. The authors argue this happens because newspaper-based uncertainty shocks more effectively and extensively capture the uncertainty level changes in the economy.

This paper builds on the work of Alexopoulos et al. (2009) and Alexopoulos & Cohen (2015) that use stock market volatility and a news-based index to model the effect of each uncertainty measure on different macroeconomic variables. However, we now with availability of better measures of uncertainties. These new measures can be tested again to see if we can shed new light on how the macroeconomic variables responds to uncertainty shock.

I use the policy-based uncertainty index and US equity market volatility developed by Baker et al. (2016) 3 to test the reaction of macroeconomic fundamentals for each of these uncertainties. I say this because the uncertainty measure of Alexopoulos & Cohen (2015) is built on the newspaper articles of New York Times. But Baker et al. (2016) build their uncertainty index from 10 different newspaper which might have better confidence to capture wider range and also with precision the uncertainty in the economy. Moreover, the volatility measure in Alexopoulos & Cohen (2015) is the volatility of the Standard and Poor (S&P) 500 for the period pre-1986 and the VXO, the implied volatility index of the S&P 100 30 day options of the CBOE post-1986[III].

This paper is focused on the response of the monetary authorities to the news on uncertainty. By doing this I fulfill three objectives:

I attempt to see the effects of two uncertainty measures on the economic cycles and analyze the effects of the two different measures of uncertainties.

I seek to show that these shocks might be an important tool to explain and analyze a significant proportion of cyclicity in the US economy.

Measuring Uncertainty

This section describes the two different measures of uncertainty, I applied in the analysis- The news-based policy uncertainty and Equity market volatility. The news-based policy uncertainty (Baker et al., 2016) is an index generated based on the search results from ten large newspapers[IV].

[III] https://www.policyuncertainty.com/index.html

[IV] USA Today, the Los Angeles Times, the Chicago Tribune, the New York Times, the Washington Post, the Miami Herald, the Boston Globe, the Dallas Morning News, the San Francisco Chronicle, and the Wall Street Journal

The search is for a monthly frequency of articles with the following terms: "uncertainty" or "uncertain"; "economic" or "economy"; the second term searching is one of the following policy terms: "congress", "deficit", "Federal Reserve", "legislation", "regulation" or "white house" (including variants like "un- certainties", "regulatory" or "the Fed"). It means that to be counted in the uncertainty index, an article must comprise the terms in all three categories involving uncertainty, the economy, and policy. The normalized economic policy uncertainty index representing the volume of news articles focusing economic policy uncertainty is built from these search results.

A challenge in building the index is the changing proportions of articles for any given paper over time. For the news-based policy uncertainty index, this problem is addressed by calculating the ratio of the number of articles discussing policy uncertainty to the total number of articles for a certain paper and month. This results in a series of count-article ratios for each paper. The ratio is then normalized such that it has a unit standard deviation over the given period of time.

The next step is to aggregate the normalized values over papers in each month such that we obtain a multi-paper index. The multi-paper index generated as such is again re-normalized over the given period of time to an average value of 100.

The second measure of uncertainty is the News-based Equity Market Volatility (EMV) tracker collected from eleven major U.S. newspapers[V]. The steps taken for creating the overall volatility tacker are:

Three categories (EMV) for the index is defined as follows:

E: economic, economy, financial
M: stock market, equity, equities, "Standard and Poors" (and variants)
V: volatility, volatile, uncertain, uncertainty, risk, risky

The Time Series plot of the log value for both news-based equity market volatility and policy uncertainty index are presented below:

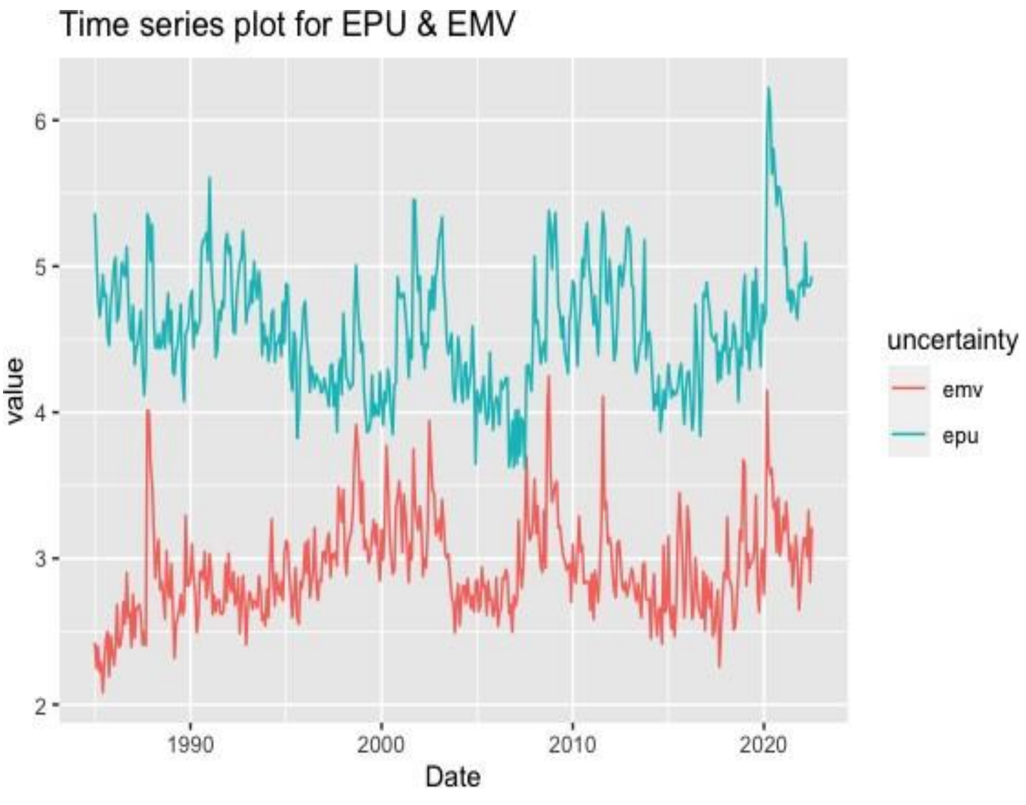

Figure 1: Time Series plot (log value) for EMV and Policy-Uncertainty Index

[V] The newspaper in the list are:Boston Globe, Chicago Tribune, Dallas Morning News, Houston Chronicle, Los Angeles Times, Miami Herald, New York Times, San Francisco Chronicle, USA Today, Wall Street Journal, and Washington Post

One of the concern over the two uncertainty selected for the analysis is that both the measures might be capturing the same type of uncertainty or at least be heavily correlated. Visual inspection of the two uncertainty variables shows that they are not very correlated. To be certain, I use Pearson correlation test and the correlation is 0.3240869(p-value 1.729e-12). Thus, we can argue that although the correlation between the two indices is significant- meaning that the true correlation is not equal to zero, there is only a weak/moderate correlation between them.

Data

The SVAR models are estimated from the macroeconomic data from the International Financial Statistics database (International Monetary Fund) and FRED data from St. Louis Federal Reserve. The data for the News-Based uncertainty is taken from the Economic Policy Uncertainty website[VI] based on Baker et al. (2016). The data is monthly for the period of February 2000 to July 2022. All variables with the exception of interest, exchange and unemployment rates are transformed to log level. The table below presents a summary of data used in the paper:

Table 1: Summary of Data used in the model

Variable	Sample:February2000toJuly2022
Equity-Market volatility	Newspaper-based Volatility tracker
Industrial Production	Manufacturing (NAICS), Index 2012=100, Monthly, Seasonally Adjusted
Interest Rate	Treasury Bill rate:Percent per annum
Exchange Rate	National currency per SDR
M1 Aggregate	Money-Nationalcurrency,billions
Consumer Prices	Consumer price index, all items, 2010=100
Unemployment	Unemployment Rate, Percent, Monthly, Seasonally Adjusted
NewsUncertainty	NewsBasedPolicyUncertaintyIndex

3.1 Unitroot

The unit root test is performed for testing if the data is stationary or non-stationary. I perform the Dickey-Fuller test on the data for the presence of unit root, time trend, or drift term. Enders (2008) suggests that the Dickey-Fuller unit root test can be performed as follows:

$$\Delta y_t = \alpha_0 + \gamma * y_{t-1} + \alpha_2 t + e_t \quad (1)$$

The hypotheses are:

$\tau_3: \gamma = 0$

$\emptyset_3: \gamma = \alpha_2 = 0$

$\emptyset_2: \alpha_0 = \gamma = \alpha_2 = 0$

(1) The hypotheses are:

As shown in Table 2, I test all three hypotheses mentioned above. The presence of unit root is tested in the first hypothesis; the second hypothesis tests for the presence of unit root and, a drift term; and the third hypothesis tests for unit root, time trend, and a drift term. As seen in the table, the test fails to reject all three null hypotheses for all variables except EMV, interest rate and CPI. This means that for the three variables EMV, Interest rates and CPI we can conclude that, and. Thus, these variables have unit roots, no time trend, and no drift term. The presence of unit roots means that the variables are non-stationary. For the remaining variables we reject all three hypotheses concluding that, and. Thus, we can conclude that the variables do not have unit root but we are inconclusive about drift and the trend.

[VI] https://www.policyuncertainty.com/index.html

Variable	Sample:January2000toJuly2022		
	τ_3	$\emptyset_2$	$\emptyset_3$
EquityMarketVolatility	-4.959	8.220	12.330
IndustrialProduction	-2.478	2.212	3.090
Unemploymentrate	-3.045	3.235	4.851
M1Aggregate	-1.104	2.779	1.889
Exchangerate	-2.171	2.572	3.841
Interestrate	-4.292	6.292	9.229
ConsumerPriceIndex	-7.420	18.361	27.541
News-BasedPolicyUncertainty	-3.625	4.430	6.645

Table 2: Dicky-Fuller Unit root test for Unit Root- TEST STATISTICS

	1%	5%	10%
τ_3	-3.99	-3.42	-3.13
$\emptyset_2$	6.15	4.71	4.05
$\emptyset_3$	8.34	6.30	5.36

Table 3: Dicky-Fuller Unit root test for Unit Root-Critical Values

The Economic Framework

This section describes the setup of a structural VAR model analyzing the macroeconomic system with US data. In a structural model with K number of variables, where the structural shocks are uncorrelated, the VAR model is as follows (Enders, 2008):

In reduced-form VAR model with K variables is as follows:
Where, $A_0 = B^{-1}\Gamma_0$, $A_1 = B^{-1}\Gamma_1$ and $u_t = B^{-1.}$

From the reduced form equation and structural form equation, we can conclude that the relationship b etween the error terms and the structural shocks is $Bu_t = A.$ Here, A_i's are (K × K) matrices containing the coefficients of the VAR model and $u_t = (u_{1t}, ...u_{kt})'$ is a vector of the unobservable error term. Again, the covariance matrix is given as E($^{)}$= .

Here, are stochastic vectors that are assumed to be independent with (0,*)* and E(*)=0* ∀ . ^{K} × 1 vector of innovations with (0,*)* and and E(*)=0* ∀*s t.*

The transformation of the innovation vector allows the researchers to analyze the change of element e_t in the system dynamics. In a short-run SVAR model, identification is obtained by placing restrictions on A and B, which are supposed to be non-singular.

Structural Shocks

SVAR model is used to test the effects of news shocks on the economic variables. The VAR model is used to determine the Structural shocks by converting the reduced form VAR into Structural VAR. The identification of structural shocks is done by placing Cholesky restrictions on the VAR model. The number of restrictions is chosen according to Lu¨tkepohl & Kr¨atzig (2004).

As we can see in the model in the economic framework section, I use the type A-model. The A-model assumes that the covariance matrix is diagonal. This means that it only contains the variances of the error term - and contemporaneous relationships between the observable variables are described by an additional matrix A. The A-Matrix is restricted such that the lower triangular of the matrix is zero. The number of restrictions is calculated by the standard formula (K(K − 1)/2. Since I identify the shocks using a Cholesky decomposition, the ordering of the variables is important. Uncertainty measure of equity market volatility is placed first accounting for the belief of other shocks responding instantly to this shock[VII].

[VII] This order in gassumptionisconsistent with Alexopoulosetal.(2009)andBloom(2009)

For the most part, subsequent ordering is customary. For instance, Christiano et al. (1997) placed quantitative variables (output and employment) ahead of the money aggregate, exchange rate, and Treasury bill rate, and ordered the price variables after them. Alexopoulos et al. (2009) argue that this choice considers the standard assumption that these shocks affects prices swiftly, but variables measuring quantities adjusts gradually. Finally, I arrange the news-based policy uncertainty shocks last. This is supported by Beaudry & Portier (2006), who argue that any news regarding productivity is supposed to capture information on future productivity and hence, should affect other variables with a lag. In my paper, I use news-based policy uncertainty that picks up information on future uncertainty. Hence it affects the economic variables with some lags, justifying the ordering of policy uncertainty.

The inclusion of the exchange rate in the model is of particular interest. Cologni & Manera (2008) point out the fact that most VAR literature has typically omitted exchange rates from their analysis. They argue further that inclusion of exchange rate is important for at least two reasons. First is the important role of exchange rates on monetary policy stance under any external shock, and the second is the manifestation of domestic monetary policy shock in exchange rate innovations as authorities often target exchange rates.

For selecting the lag length, I used four different criteria. I got the following results from different lag length criteria and choose AIC as appropriate criterion. The first reason to choose this criterion is that AIC and FPE both select the same number of lags. The second reason is based on Wooldridge (2016) suggesting that the thumb rule for selecting the lag length should be “1 or 2 lags typically used with annual data; usually 4 or 8 with quarterly data and with monthly data, 6, 12, or maybe even 24 are used”. This statement was used as reference and as I used monthly data, I chose the highest lag from the lag selection from different criteria.

Table 4: Number of Lags for various selection criteria

Selection	AIC(n)	HQ(n)	SC(n)	FPE(n)
Lags	3	2	1	3

Results

The change in news-based policy uncertainty and Equity market volatility may have some vital consequences. It is worthwhile to study the impact of these shocks on the economy and how they influence the business cycles. To test these issues, I ran a structural vector autoregression with a short-run Cholesky restriction to identify the shocks. To analyze the response of macroeconomic fundamentals to the uncertainty shocks, the IRF of the variables are presented.

The impulse response function as shown in the figure, illustrates that the shocks predominantly translate into significant responses in the economy. It can be said that a standard deviation news- based policy uncertainty shock will have an adverse effect in the economy, as it can been seen that Unemployment rises and production falls. For all variables except M1 aggregate and exchange, the extremum is around the fifth month. The economic agents respond to the shock by accumulating money aggregate as measured by M1 money, and a rise in money aggregate is seen in the response. As for the interest rates, it can be seen that the interest rates fall gradually and bottoms out around 5th month and then gradually moves back to the long run equilibrium. The response of the inflation is also interesting. It is seen that the inflation falls in response to news on policy uncertainty. We can assume that this is because of the market inactivity on light of the uncertain future, but we need further analysis to conclude that.

The IRF plots for the Equity-market volatility shock demonstrates a significant differences when compared to the Policy uncertainty shocks. It can be said that the qualitative effects of the volatility shocks are similar to the News-based policy uncertainty shock. This be because both shocks produces a negative response of the macroeconomic variables. However, the responses are significant for the EMV shocks. Moreover, it can also be said that the effects of market volatility are more immediate on economic variables. In News-based policy uncertainty, the extremum was around five months; however, we see the extremum at around 3 months for market volatility shock. However, the effects of volatility shocks although significant are much smaller compared to the policy uncertainty shocks. The IRF response of the unemployment, production, interest rates and the exchange rates to the news on market volatility is significant.

The IRFs of the macroeconomic variables in response to both News-based policy uncertainty shocks and the News-bases Equity market volatility shock show that the response of the variables are more significant to Equity-market volatility. The IRF response of the unemployment, production, interest rates and the exchange rates to the news on market volatility is significant. The peak and trough both are bigger for the response for news-base economic policy uncertainty shock.

This result seems to support Alexopoulos et al. (2009), who argue that the results of news shocks and volatility shocks are similar, and news shocks outperform the volatility shocks. However, there are a few points to consider here. First, the results of Alexopoulos et al. (2009) has qualitative similarity but are different in some respect. The differenes can be elaborated on the fact that the news shocks used by Alexopoulos et al. (2009) is different from the news-based policy uncertainty shock in this paper. Moreover, the volatility shocks they used is volatility in Standard and Poor

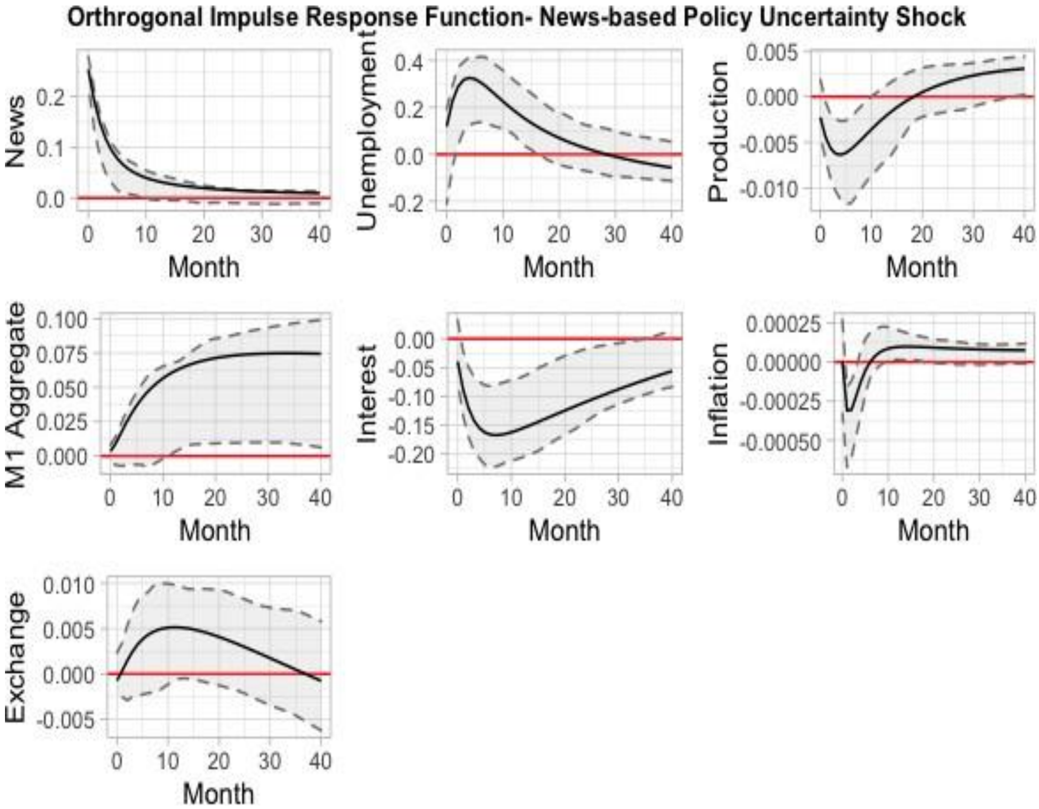

Figure 2: IRF from the SVAR Model with Policy Uncertainty shock

S&P 500) index and the VXO Index but the equity market volatility in this paper is a News-based Equity market volatility. This News-based Equity market volatility considers any news on volatility in both the general economic conditions and policy-related issues. Another way to look into the difference between the market volatilities in the two papers is the fact that the volatility used in this paper is a first-moment uncertainty and the volatility used in Alexopoulos et al. (2009) is a second-moment of uncertainty. Hence, there are some differences with Alexopoulos et al. (2009) but the conclusion remains the same i.e., Uncertainty shocks, regardless of the measure, depresses the economy driving it to sharp short-lived recessions by lowering industrial production and increasing unemployment. The recession is further supported by the fact that the prices are falling and the Federal Reserve lowers interest rates to fight the effects of uncertainty shock.

Robustness

The economic news may affect the results of the event study regressions in subsequent lags. However, the selection of the lags based on different criteria suggest only 3 lags at maximum for the data.

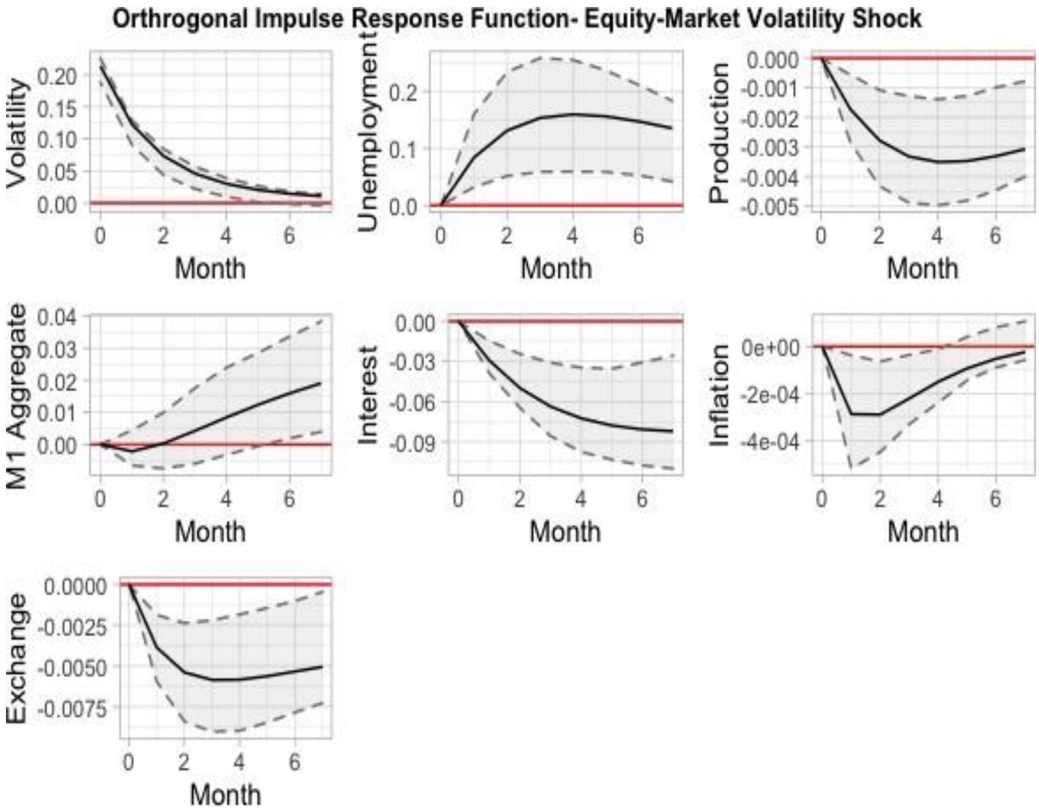

Figure 3: IRF from the SVAR Model with EMV shock

Moreover, the ordering of the variables in the VAR model can vary with researchers. These two problems can be significant criticism of this paper. For this, I perform two robustness checks. First, I change the ordering of the variables and perform the SVAR analysis on the new ordering to get the IRFs. Second, I increase the lag length, so that if there are effects of the news shock after more lags than the one selected by the AIC criterion, the model can capture that effect.

The second robustness test is performed by increasing the lags in the VAR model. As shown in Appendix, the qualitative results remain the same after changing the lag lengths. Hence, the results in the SVAR model are robust. Another robustness test is done by changing the ordering of just the EMV and policy uncertainty while the ordering of all other variables is fixed. Even with this ordering, it is seen that the IRF produced shows qualitatively robust results.

The ordering is changed in the robustness check according to VAR-11 model[VIII] in Jurado et al. (2015), the ordering being [Industrial production, Unemployment rate, Inflation, Exchange, Interest, Equity-Market Volatility, M1 aggregate, News-Based policy Uncertainty]. The IRF from the new ordering of the variables is qualitatively similar (Appendix 3-B). Since the qualitative results remain the same for each variable, it can be said that the model is robust.

Conclusion

To capture the effects of uncertainty shocks on the U.S. economy, I use two different indicators of aggregate and policy uncertainty, i.e., the news-based policy uncertainty index and the Equity-Market Volatility index generated based on the information contained in various newspapers. I then model the effects of those uncertainty shocks on different macroeconomic aggregates by using a simple SVAR model. The first conclusion that we can draw from the analysis is that the shocks have negative effects on the economy including production and unemployment loss. This result is also supported by Baker et al. (2016), Alexopoulos et al. (2009) and Alexopoulos & Cohen (2015). The analysis also reveals that volatility shocks have a more significant effect on the aggregates, than the news-based policy uncertainty shocks and is relatively instantaneous. However, the response to policy uncertainties is relatively less instantaneous.

[VIII] The ordering is also very close to Christiano etal.(2005)

The major difference from Alexopoulos & Cohen (2015) is how quick the variables responds to news on uncertainty. When Alexopoulos & Cohen (2015) shows that the response of the variables might take more than 12 months to respond to the news shocks on uncertainty, in my model it peak out in less than six months.

This must be because of how print media works now compared to 2007 until which Alexopoulos & Cohen (2015) collected his data. Now, people get the print media online and is widely available for sharing in social media. So, it can be argued that the diffusion of news is quicker and effective now as compared to the period before 2007. The result of quicker response is closer to Baker et al. (2016) for unemployment and industrial production variables with policy uncertainty shocks. Baker et al. (2016) uses more recent data until 2013. So, argument about diffusion of news seems valid. However, it is also a possibility that since I am using the same shock as of Baker et al. (2016), I am getting responses similar to them.

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Appendix A: IRF with 12 lags in VAR model

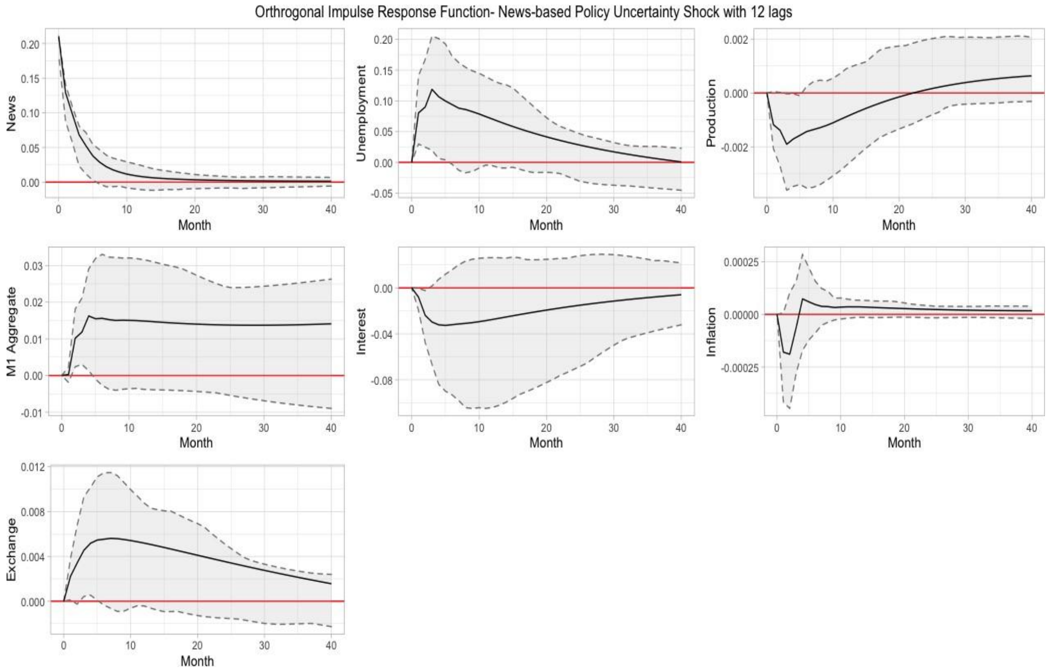

Figure 4: IRF from the SVAR Model with Policy Uncertainty shock with 12 lag in VAR analysis

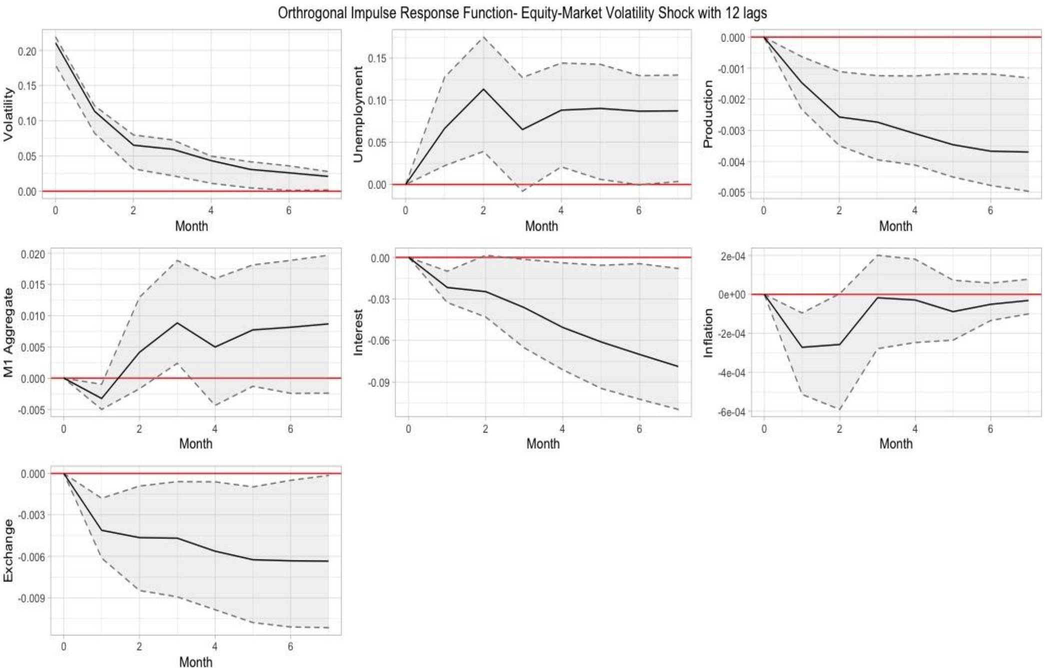

Figure 5: IRF from the SVAR Model with EMV shock with 12 lag in VAR analysis

Appendix B: IRF with EPU and EMV reversed in VAR model

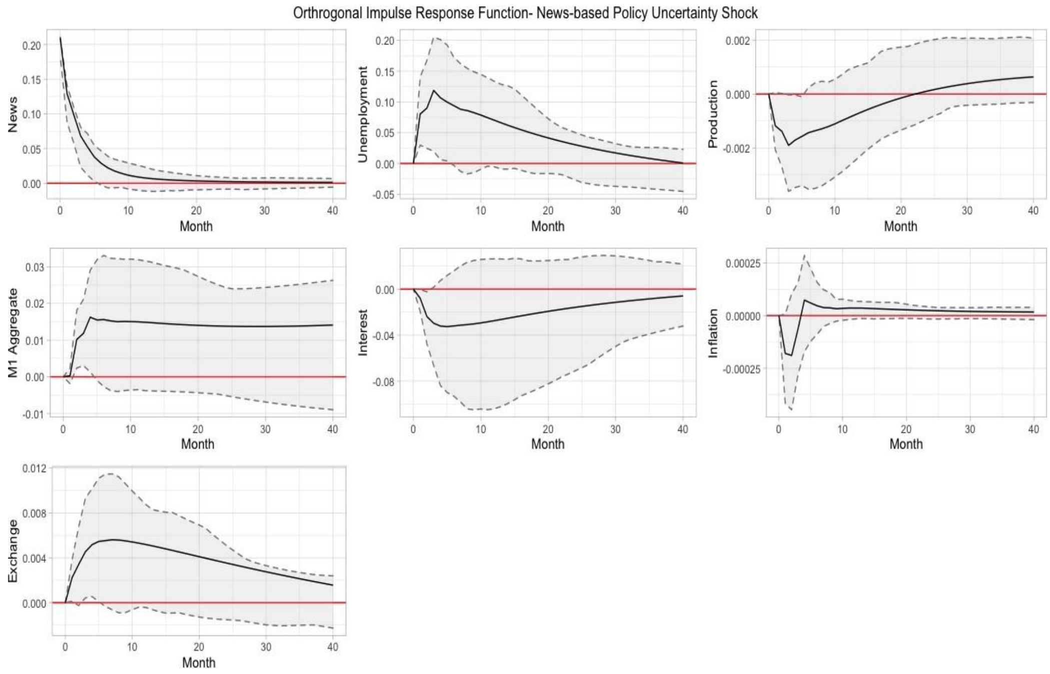

Figure 6: IRF from the SVAR Model with Policy Uncertainty shock with reverse ordering

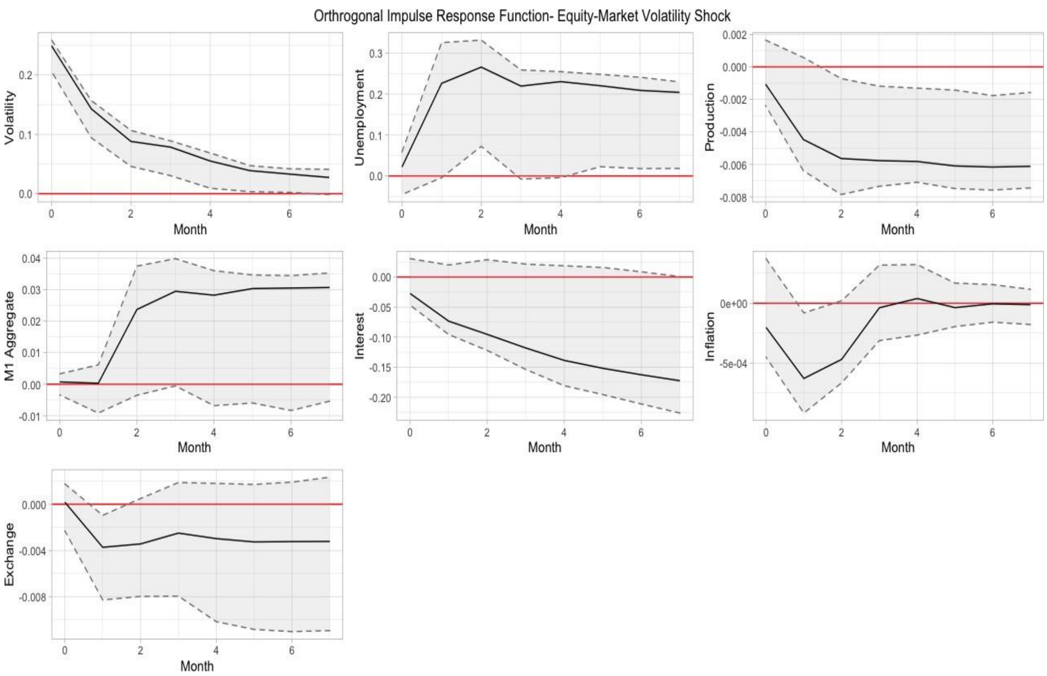

Figure 7: IRF from the SVAR Model with EMV shock with reverse ordering

Appendix C: IRF with EPU and EMV in VAR-11 model

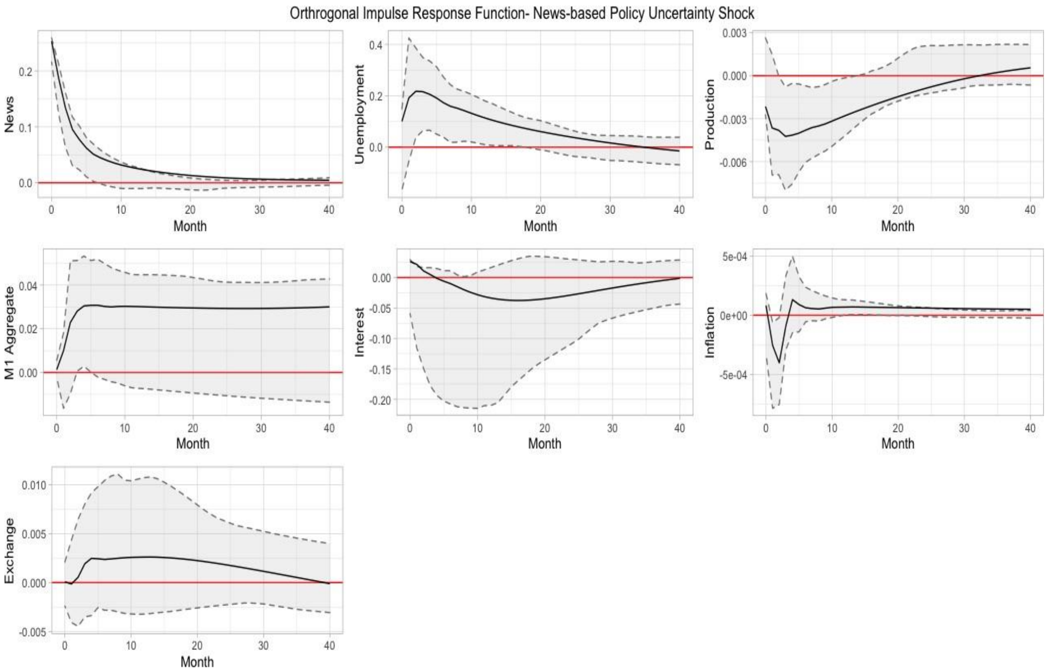

Figure 8: IRF from the SVAR Model with Policy Uncertainty shock with VAR-11 ordering

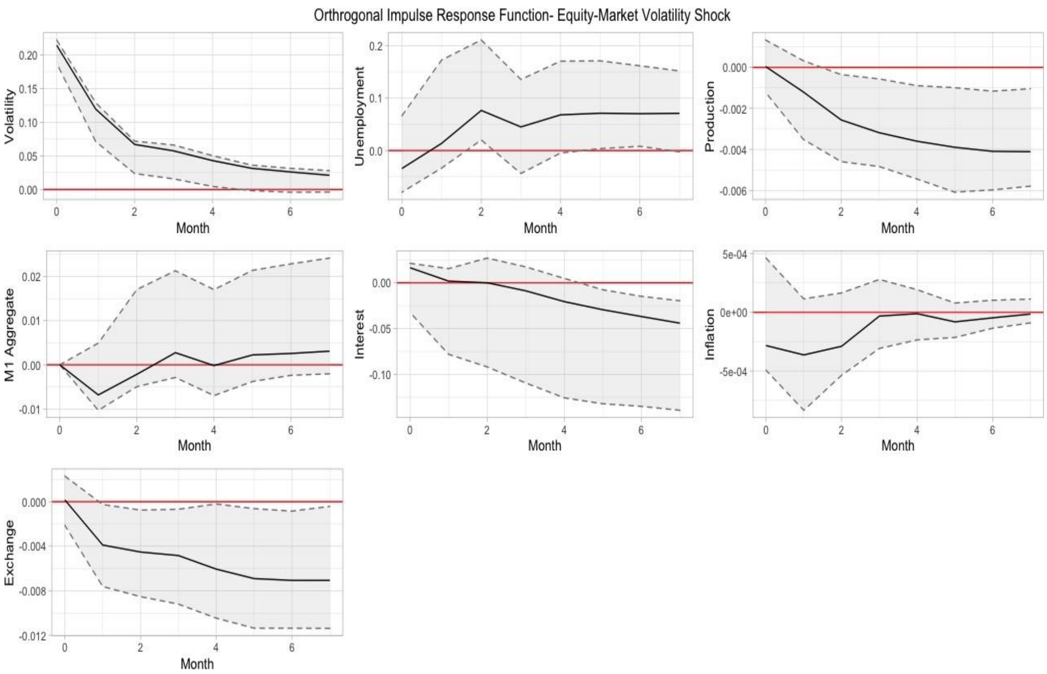

Figure 9: IRF from the SVAR Model with EMV shock with VAR-11 ordering