# Endogenous Uncertainty and Monetary Policy*

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**Abstract**

We empirically investigate how uncertainty endogenously interacts with real activity and monetary policy, and analyze the role of endogeneity in shaping the efficacy of monetary policy using a shock restricted structural vector-autoregression model. Using the model, we show that both real and financial uncertainty endogenously react to business cycle fluctuations and to monetary policy actions. Then we provide two novel policy implications of endogenous uncertainty. First, a tighter monetary policy reduces financial uncertainty, but heightens real uncertainty. Second, endogeneity channels in uncertainty amplify the real effects of monetary policy.

Keywords: Endogenous Uncertainty, Monetary Policy
JEL Classification: C52, D80, E52

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# 1 Introduction

Following the seminal work by Bloom (2009), there has been a vast amount of literature on how uncertainty negatively affects economic activity (Bloom et al., 2018; Christiano et al., 2014; Choi, 2017). For instance, when uncertainty rises, economic agents postpone their consumption or investment decisions and wait until the uncertainty is resolved to avoid downside risk. Then, as a natural question that stems from the previous studies, it has been widely analyzed whether the effects of monetary or fiscal policy depend on the level of economy-wide uncertainty, both theoretically and empirically. However, there has been little research into the interaction between uncertainty and macroeconomic policies. Most of the previous research assumes that uncertainty is exogenously given, or at least is the most exogenous variable in the economy. However, it is a questionable assumption as private agents consider policy action as a major source of economic uncertainty.

In this paper, we try to answer the following two questions. First, how does uncertainty respond to the real activity and monetary policy? Second, how does the endogeneity of uncertainty alter the effectiveness of monetary policy? To this end, we provide a synthetic analysis of the joint dynamics of uncertainty and monetary policy using a modified shock restricted structural vector-autoregression (VAR) model, as in Ludvigson et al. (Forthcoming) ("LMN", hereafter). A preferable model for this study requires two features. First, the identification scheme needs to allow any possible degree of endogeneity in uncertainty. The identification scheme implemented in this paper is consistent with our goal, as it does not restrict the order of exogeneity nor signs of impulse responses. Instead, we just impose restrictions on the behavior of structural shocks, as in LMN. Second, we distinguish real and financial uncertainty and examine how they interact with policy action and real activity, following LMN and Jurado et al. (2015). There has been various ways to look at uncertainty or the uncertainty shock in the literature. Some researchers consider uncertainty to be a concept that originated from economic fundamentals, such as productivity (Bloom et al., 2018; Christiano et al., 2014; Park, 2019; Gilchrist et al., 2014). On the other hand, other researchers argue that uncertainty affects the economy through financial markets and can be traced by indices describing financial market conditions, such as stock market volatility (Choi et al., 2018; Caggiano et al., 2014; Bekaert et al., 2013; Basu and Bundick, 2017). This discrepancy may confuse discussions among researchers and affect the separation of the causes and consequences of uncertainty. For this reason, we separate real and financial uncertainty in a single framework to investigate causes and consequences of each type of uncertainty.

Using the model, we show that both real and financial uncertainties contemporaneously respond to fluctuations of business cycle and monetary policy, and provide two novel policy implications related to the endogeneity of economic uncertainty. First, a contractionary monetary policy shock reduces financial uncertainty, while exacerbating real uncertainty. A tight monetary policy shock may reduce financial uncertainty as the monetary authority prevents financial markets from taking on more risk and slows the piling up of financial bubbles. On the other hand, a monetary tightening may heighten real uncertainty by reducing real activity, as shown by the vast amount of monetary literature. Second, we show that the endogeneity of uncertainty amplifies the efficacy of monetary policy through a series of counter-factual studies.

More interestingly, we show that the interaction between real activity and uncertainty is the main reason for the above findings. To do so, we implement a counter-factual study by restricting the coefficients in the model so that uncertainties do not respond contemporaneously to real activity or to monetary policy, following Carriero et al. (2018). Once we shut down that channel of endogenous uncertainty, we obtain different results that are more in line with Bekaert et al. (2013): a tight monetary policy shock leads to higher financial uncertainty and lower real uncertainty followed by a sharp rebound in the counter-factual model.

Lastly, the endogeneity of uncertainty plays an amplifying role in the efficacy of monetary policy. This suggests that it is necessary to consider the endogenous feedback effects through uncertainty while evaluating the macroeconomic policy effects. The responsiveness of real activity with respect to monetary policy shocks in the benchmark model is higher than that in the counter-factual model. In particular, we show that while allowing the endogenous response of real uncertainty amplifies the real effect of monetary policy, the endogeneity of financial uncertainty dampens this effect.

**Related Literature** This paper is closely related to the uncertainty literature pioneered by Bloom (2009). The main difference between this paper and previous studies is that we investigate a model of endogenous uncertainty while previous ones considered uncertainty shocks that were independent of economic activity. Based on the exogeneity assumption, we analyze the roles of uncertainty shocks as a business cycle driver (Bloom, 2009; Bloom et al., 2018; Christiano et al., 2014) and as a source of monetary (Castelnuovo and Pellegrino, 2018; Pellegrino, 2018a,b) and fiscal policy (Berg, 2017) asymmetry.[1] To summarize these previous studies, uncertainty shocks depress economic activity and dampen the effectiveness of monetary policy all while stimulating the effectiveness of fiscal policy. This paper differs

[1] The relationships between confidence, which is a similar concept to uncertainty, and the effectiveness of fiscal policy have been studied in Bachmann and Sims (2012) and in Guimaraes et al. (2016).

from that, as we track the endogenous movements of uncertainty.

This paper is not the first paper to explore endogenous uncertainty. Bachmann and Moscarini (2011) noticed that negative first moment shocks can induce volatile and dispersed outcomes, i.e., uncertainty. Fajgelbaum et al. (2017) provided a novel framework for endogenous uncertainty through social learning and showed that vicious cycles can rise as decreased investments can reduce information flows, which are necessary to remove uncertainty. Also, Guimaraes et al. (2016) showed in a static model how fiscal policy affects the aggregate economy through the confidence channel. In their model, increased government spending signals more private investment, hence it prevents a coordination failure that would arise due to imperfect information about the fundamentals. Bekaert et al. (2013) study a similar topic to ours, as they analyze how monetary policy affects risk appetite and uncertainty. They find that a lax monetary policy decreases uncertainty. Ours differs from this, as we distinguish real and financial uncertainty. Carriero et al. (2018) is closely related to this paper. They also examine to what extend the endogenous responses of macroeconomic (real) or financial uncertainty matter for macroeconomic dynamics. They report that macroeconomic uncertainty can be considered as exogenous, but financial uncertainty is not. However, they do not consider the impact of monetary policy on uncertainty, which is the primary concern in this research.

The rest of the paper is organized as follows. Section 2 introduces the empirical strategy that allows us to investigate the relationship between uncertainty and monetary policy. section 3 explains the results obtained from our empirical analysis in detail. Section 4 concludes the paper.

## 2 Empirical Framework

In this section, we explain the empirical strategy employed in this paper to analyze the interaction between uncertainty and monetary policy and its influence on real activity. Specifically, our baseline empirical model is mainly based on that in LMN. LMN use a three-variable VAR model that consists of variables that represent real uncertainty, real activity and financial uncertainty to show whether uncertainties rise in recessions, are sources of the business cycle, or are endogenous responses to it. In this paper, we extend that model to analyze the effects of monetary policy. We use this state-of-the-art model as it is of utmost importance to carefully identify different types of uncertainties in a unified empirical framework to study the interactions among monetary policy, real activity and uncertainty.

To be precise, we build a four-variable VAR model that includes real and financial uncertainty, real activity and monetary policy indicators to analyze the impact of monetary policy. The VAR model used in this paper is basically identified by the shock restriction method applied in LMN that is originally proposed by Ludvigson et al. (2017).

## 2.1 Data

In the baseline model, we use the monthly data from October 1980 to December 2018. First of all, the estimated monthly real GDP[2] provided by two sources is used to measure the real activity in the monthly model. We use monthly estimates of GDP provided by Mark Watson, which cover January 1959 to June 2010, and from Macroeconomic Advisers by IHS Markit, which cover January 1992 to August 2019.[3] We first check that the movements from the two sources are almost the same for overlapped periods and that the correlation is close to unity. Then, we merge the datasets, with some adjustments, which eliminate any differences in the overall levels that may be caused by differences in the base years.

As measures of real and financial uncertainty, the measures proposed in Jurado et al. (2015) and LMN are used.[4] The measured uncertainties are closely related to forecasting errors. To better understand, let us define $y_{jt}^{C}$, a variable related to the real ($R$) and financial ($F$) economy, specified by the category indicator $C \in \{R, F\}$. Then, the $h$-period ahead purely unforecastable component of $y_{jt}^{C}$, conditional on all information available at time $t$, $\mathcal{U}_{jt}^{C}(h)$ is formulated in this way:

$$\mathcal{U}_{jt}^{C}(h) \equiv \sqrt{\mathbb{E}\left[\left(y_{jt+h}^{C} - \mathbb{E}\left[y_{jt+h}^{C}|I_t\right]\right)^2 |I_t\right]} \tag{1}$$

where $I_t$ represents the information set at time $t$. Then, the measured uncertainty $U_{Ct}$ is the weighted sample average of $\mathcal{U}_{jt}^{C}(h)$. We use one-month ahead forecast uncertainty ($h = 1$) as the benchmark variable following LMN, but the main results are not affected by changing the forecast uncertainty horizon to $h = 6$ or $h = 12$.

As a variable that summarizes the monetary policy stance, we use the one-year government bond yield in the baseline analysis, following Gertler and Karadi (2015). This variable is employed as the policy indicator, as it is highly correlated with the monetary policy instrument, the Federal Funds Rate (FFR), but is not subject to the Zero Lower Bound during

[2]While the Industrial Production (IP) Index is widely used in the literature for the monthly measure of real activity, we use the estimated monthly GDP as it is better to capture business cycle fluctuations.

[3]The data provided by Mark Watson is downloadable at http://www.princeton.edu/~mwatson/mgdp_gdi.html, and the later data is downloadable at https://ihsmarkit.com/products/us-monthly-gdp-index.html with details for the estimation methodologies.

[4]The uncertainty indices are downloadable at Ludvigson's website: https://www.sydneyludvigson.com/data-and-appendixes. The data appendices that explain how to construct macro, real and financial uncertainties are also available there.

the sample period.[5] Based on the choice of monetary policy variable, the monetary policy shock that measures the unexpected changes in the stance of the monetary authority is identified by introducing an auxiliary instrument variable. Specifically, the monetary policy news shock identified in Nakamura and Steinsson (2018) is employed as an instrument to help identify the monetary policy shock.

As will be explained in the subsequent subsections, we incorporate two external instruments – $S_{1t}$, the return on the S&P 500 index, and, $S_{2t}$, the log difference of the real gold price – as in LMN, to identify two types of uncertainty shocks.[6]

## 2.2 The Structural VAR (SVAR) and Identification

### 2.2.1 The Model

Let $X_t$ be the four-by-one endogenous variable. The reduced form VAR model can be expressed as

$$X_t = k_t + A_1 X_{t-1} + A_2 X_{t-2} + \cdots + A_p X_{t-p} + \eta_t \tag{2}$$

where $\eta_t \sim (0, \Omega)$ is the reduced form residual and $k_t$ is the vector of exogenous variables, including the constant, linear and quadratic time trends.[7] The lag order is chosen to be six based on LMN, but using more than six lags does not change the results.

The structural shocks $e_t$ are related to the reduced form residuals as

$$\eta_t = H\Sigma e_t = Be_t \tag{3}$$

where $e_t \sim (0, \mathbf{I_k})$ and $\Sigma$ is the diagonal variance matrix.

The endogenous variable is set as $X_t = (U_{Rt}, GDP_t, U_{Ft}, MP_t)'$. $U_{Rt}$, $GDP_t$, $U_{Ft}$ and $MP_t$ denote real uncertainty, real GDP, financial uncertainty and the monetary policy indicator. The corresponding reduced form residuals $\eta_t = (\eta_{Rt}, \eta_{GDPt}, \eta_{Ft}, \eta_{MPt})'$ can be related to the

[5] We also introduce the FFR and the shadow rate proposed by Wu and Xia (2016) as the monetary policy indicator variable in the robust check exercise. The main results, however, remain unchanged.

[6] The data source for the gold price is here: https://www.macrotrends.net/1333/historical-gold-prices-100-year-chart.

[7] We also estimate the models with one constant and with a constant and a linear trend, but the results are not affected by trend specifications.

structural shocks $e_t = (e_{Rt}, e_{GDPt}, e_{Ft}, e_{MPt})'$ as below:

$$\begin{aligned}
\eta_{Rt} &= B_{RR}e_{Rt} + B_{RGDP}e_{GDPt} + B_{RF}e_{Ft} + B_{RMP}e_{MPt} \\
\eta_{GDPt} &= B_{GDPR}e_{Rt} + B_{GDPGDP}e_{GDPt} + B_{GDPF}e_{Ft} + B_{GDPMP}e_{MPt} \\
\eta_{Ft} &= B_{FR}e_{Rt} + B_{FGDP}e_{GDPt} + B_{FF}e_{Ft} + B_{FMP}e_{MPt} \\
\eta_{MPt} &= B_{MPR}e_{Rt} + B_{MPGDP}e_{GDPt} + B_{MPF}e_{Ft} + B_{MPMP}e_{MPt}
\end{aligned} \tag{4}$$

where $B_{ij}$ is the element that belongs to $B$.[8] As is evident from the above relationships, identifying structural shocks corresponds to finding a solution for the matrix $B$. The standard covariance restrictions, which come from the covariance structure of $\eta_t$, provide $4\times(4+1)/2 = 10$ equations in $B$ and there are 16 unknowns in $B$. Hence, we need six additional restrictions to exactly identify all the structural shocks. Therefore, it is not possible to exactly identify the structural shocks without further identifying assumptions. In this paper, we do not pursue point-identification. Instead, the SVAR is set-identified by augmenting restrictions regarding the properties that structural stocks are required to possess, based on a reading of historical events as in LMN.

### 2.2.2 Shock Based Restrictions

In what follows, we introduce additional identifying assumptions that are required in order to obtain the structural relationships among endogenous variables. The key idea here is that the resulting structural shocks $e_t$ depend on the matrix $B$. Hence, by looking at the characteristics of candidate structural shocks, we can gather additional information that can be used to judge whether the candidate matrix $B$ should be accepted or discarded.

**External Variable Constraints.** First, we augment the external instrumental variables to provide more restrictions, following LMN. Specifically, the correlations between the external variables and uncertainty shocks are used to provide additional inequality constraints. The aggregate stock market return $S_{1t}$ and the log difference in the real price of gold $S_{2t}$ are required to satisfy the following restrictions:

$$\begin{aligned}
&i)\ \ c_1 = corr(e_{Ft}, S_{1t}) \leq \bar{k}_F,\ \ for\ \ \bar{k}_F < 0 \\
&ii)\ \ c_2 = corr(e_{Rt}, S_{2t}) \geq \bar{k}_R,\ \ for\ \ \bar{k}_R > 0
\end{aligned} \tag{5}$$

[8] We interpret the GDP shock as an economic driver that exogenously affects the output and that is similar to the aggregate productivity. To support our interpretation, we compare our identified GDP shock to two types of TFP series, as shown in Figure 8 in the appendix. Evidently, the three series are highly correlated and move in similar patterns.

The first constraint states that financial uncertainty shock should be negatively correlated with aggregate stock market returns. Similarly, the second one dictates that the real uncertainty shock is required to be positively correlated with the real price of gold. These restrictions are based on the broad consensus that stock market returns and the price of gold are closely related to financial and real uncertainty, respectively.

In addition, we introduce an external instrument to help identify the monetary policy shock. To be precise, it is required to have the minimal correlation $\bar{k}_{MP}$ with the monetary policy news shock identified in Nakamura and Steinsson (2018), as shown below.

$$iii)\ \ c_3 = corr(e_{MPt}, S_{3t}) \geq \bar{k}_{MP} \tag{6}$$

Finally, we also require that the overall correlation among external variables and structural shocks of interest $\sqrt{c(B)'c(B)}$ exceed a certain threshold where $c(B) = [c_1\ \ c_2\ \ c_3]'$.

$$iv)\ \ \sqrt{c(B)'c(B)} \geq \bar{k}_C \tag{7}$$

**Event Constraints.** Event constrains restrict the behavior of the structural shocks based on a reading of the times throughout history. The idea is that the produced structural shocks should be consistent with our understanding of historical events, at least during times of special interest.

1. $e_{Ft_1} > \bar{k}_1$ where $t_1$ is the period 1987:10 of the stock market crash
2. $e_{Ft_2} > \bar{k}_2$ where $t_2$ =2008:09
3. $\sum_{j=t_3} e_{GDPt} < 0$, $t_3 \in [2007:12, 2009:06]$
4. $e_{Ft_4} > 0$ at $t_4 = 2011:07$ or $t_4 = 2011:08$

The above set of restrictions demands specific signs and sizes for the identified shocks. Firstly, the identified financial uncertainty shocks in October 1987 should be large, exceeding $\bar{k}_1$ standard deviations, and positive. Second, the identified financial uncertainty in September 2008, which is the month of the Lehman collapse, should be large and exceed $\bar{k}_2$ standard deviations above the mean. The third restriction requires that the cumulative GDP shocks during the [2007:12,2009:06] period should be negative.[9] That is, the sum of real activity

[9]This restriction rules out weird cases where the GFC recession is caused by large uncertainty shocks with some positive GDP shocks which is a highly unlikely interpretation of the event.

shocks during the Great Recession may not exceed the average. The fourth one states that the financial uncertainty shock should be positive during the 2011 debt-ceiling crisis.

### 2.2.3 Implementation

The candidate solutions $\hat{B}$ are obtained by following LMN. Specifically, we initialize the solution to be the lower Cholesky factorization of $\Omega$ and then rotate it by 1,500,000 random orthogonal matrices $Q$. We keep the resulting solutions only when all restrictions given above are satisfied.

One point is worth mentioning. Although no single solution is more likely than another, we can provide one exact solution, denoted as the max-C solution, as a reference solution to the model. The max-C solution is selected based on the correlations between instruments and structural shocks. That is, the max-C solution is the solution with the highest collective correlation $\sqrt{c(B)'c(B)}$. In the subsequent sections, we use the max-C solution as the reference result and pay more attention to this specific solution.

The specific numerical bounds for the correlation – $\bar{k}_F$, $\bar{k}_R$, $\bar{k}_{MP}$ and $\bar{k}_C$ – and the event constraints – $\bar{k}_1$ and $\bar{k}_2$ – are set as below. We select $\bar{k}_F$, $\bar{k}_R$, and $\bar{k}_{MP}$ to be relatively less restrictive and are set to 0.1 for the individual correlations. For the collective correlation $\bar{k}_C$, it is required to be slightly more restrictive than the individual correlations and is set at 0.2. These conditions imply that the lower bounds of the 10% absolute correlations between external variables and structural shocks of interest are maintained, with an average absolute correlation of 12%.[10] We set the parameters regarding the event constraints to $\bar{k}_1 = 4$ and $\bar{k}_2 = 4$. The numerical values for $\bar{k}_1$ and $\bar{k}_2$ are borrowed from LMN.

We also check the sensitivity of our results to the parameters governing event constraints $\bar{k}_1$ and $\bar{k}_2$ in Appendix E. In particular, one may doubt that the results are derived based on a few solutions that satisfy a highly restrictive condition. To this end, we set $\bar{k}_1$ and $\bar{k}_2$ at lower values and allow more solutions that are not as constrained as in the baseline calibration to pass the criteria. The result suggests that our calibration is not that restrictive and that the main results of the paper are not affected by the choice of these parameters.

Finally, we emphasize the importance of identification strategy in analyzing the interaction between uncertainty and any financial variable, in particular monetary policy in this context. In Appendix G, we estimate the model using a Cholesky decomposition, which is a widely used identification scheme in the literature. For all the possible reasonable orderings, the impulse responses are qualitatively similar. We check the validity of the identification

[10]The average absolute correlation is calculated by the root-mean-square-correlation $\sqrt{\frac{1}{3}c(B)'c(B)}$ following LMN. We choose less restrictive values to accept more candidate solutions as our model is larger than theirs.

strategy by looking at the response of GDP to the monetary policy shock. We expect that any reasonable identification scheme would produce a contractionary effect on GDP, following a positive monetary policy shock. However, the responses of GDP to monetary policy do not seem reasonable. They climb immediately and then remain insignificant. These observations signal that a Cholesky decomposition does not precisely identify the structural shocks regardless of the ordering.

# 3 Results

In this section, we present the results derived from the SVAR model constructed in the previous section. To do this, the full impulse response functions are shown to gauge the effects of each structural shock. In particular, we are interested in the responses of real and financial uncertainty to the monetary policy shock, as there is little previous research on the roles of monetary policy in shaping economic uncertainty. In addition, we revisit the issue related to the endogeneity of economic uncertainty and its implications for the propagation of the other structural shocks that have been widely studied in the literature.

## 3.1 Identified Structural Shocks

Since the identification strategy heavily depends on the behavior of the identified structural shocks, it is meaningful to get a sense of the nature of the identified shocks. To do this, we depict the time series and distributions of shocks produced in the max-C solution, following LMN.[11] In the main text, we only report the identified real and financial uncertainty shocks as this research focuses on the behavior and consequences of the uncertainties. The rest of the structural shocks can be found in Appendix B. In addition, we also show that our identified structural output shock is consistent with the total factor productivity (TFP) to emphasize the validity of the identification scheme in Appendix A.

Figure 1 shows the distribution of the identified real and financial uncertainty shocks. It clearly shows that the identified shocks are non Gaussian. They are skewed and have fat tails. Their skewness and kurtosis are qualitatively similar to those in LMN. More precisely, the real uncertainty shock is positively skewed while the financial uncertainty shock is negatively skewed. Furthermore, the kurtosis of the financial uncertainty shock is about three times bigger than that of the real uncertainty shock. This supports our empirical strategy that does not require any Gaussian assumption.

[11] We show that the max-C solution is indeed a good candidate to represent identified structural shocks by providing the band of all identified shock series in Appendix C.

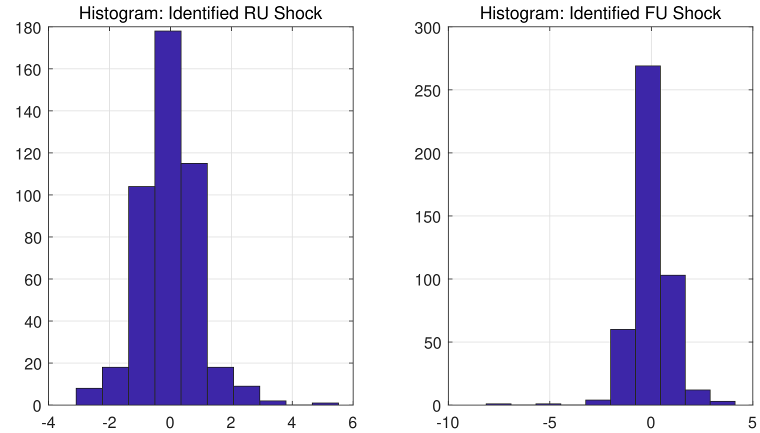
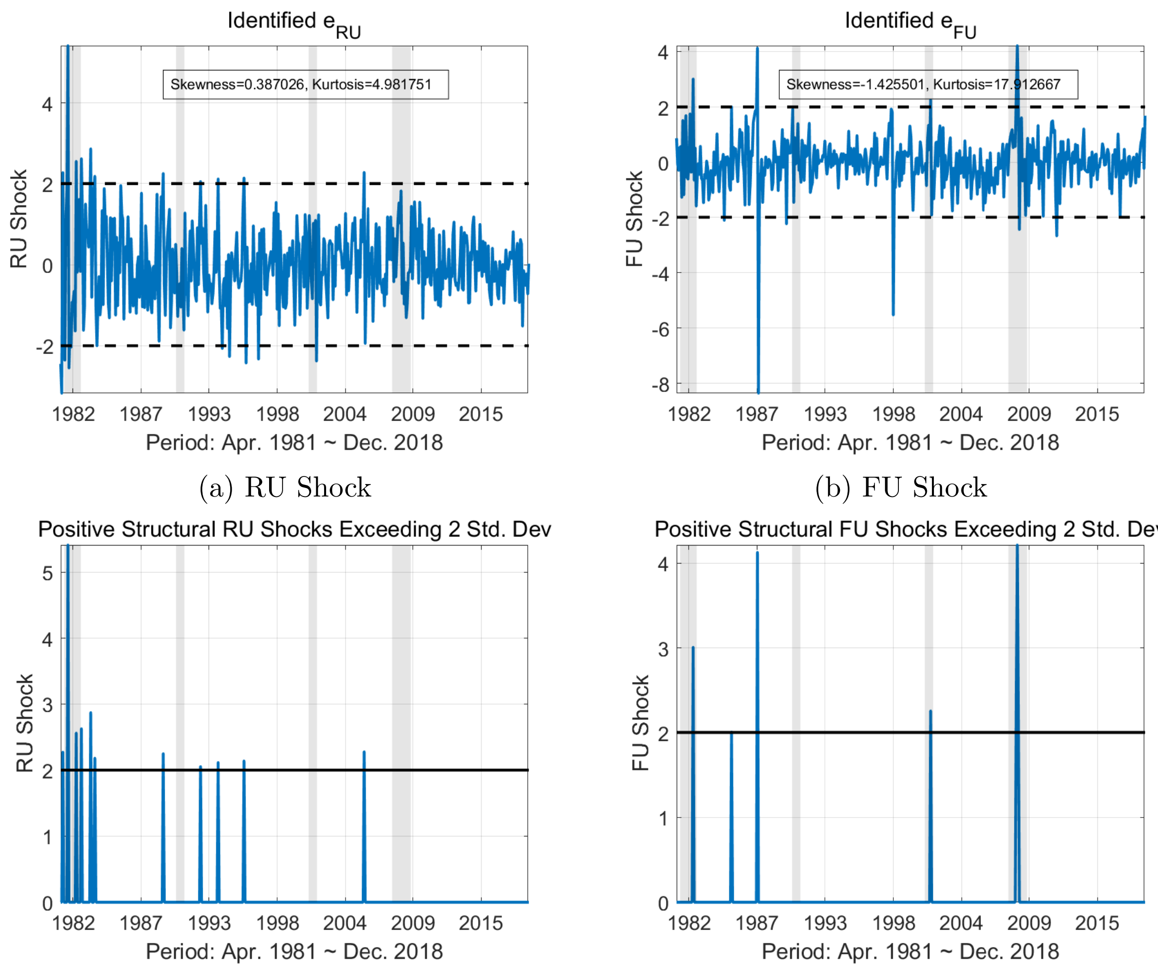



Figure 1: Distribution of identified shocks: The left panel shows the distribution of the identified real uncertainty shock and the right panel presents that of the financial uncertainty shock.

Figure 2a and Figure 2b depict the time series of real and financial uncertainty. They move similarly, but financial uncertainty is more volatile. In addition, it seems that the volatility of both series is time-varying, which means that the uncertainties are heteroskedasitic. Figure 2c and Figure 2d present the events that produce real or financial uncertainty shocks that exceed two standard deviations. Financial uncertainty exceeds four standard deviations in 1987 and 2008 due to Black Monday and to the Global Financial Crisis (GFC), as demanded by the shock restrictions. Furthermore, it also exceeds two standard deviations around 1982 (the savings and loans crisis) and 2001 (the dot-com bubble), which are not imposed by restrictions. This result also supports the plausibility of the identification strategy employed in this paper. Large real uncertainty shocks that exceed two standard deviations appear more frequently than financial uncertainty, but in general the magnitudes are smaller. In addition, spikes in real uncertainty are not synchronized with financial uncertainty. For instance, large real uncertainty shocks are absent in 1987 or 2001, while large financial uncertainty shocks are present. Overall, the general behavior of the two uncertainty shocks are in line with LMN, as expected.

## 3.2 Interactions Between Uncertainty and Monetary Policy

Figure 3 depicts the impulse responses of the SVAR model. The first row shows the responses of the endogenous variables to the real uncertainty shock. Similar to LMN, financial uncertainty goes up persistently as the real uncertainty shock hits the economy, all while this response is not being very significant. In addition, a hike in real uncertainty has a marginal consequence on real activity, and the impulse responses of GDP show a weak decline. These




(a) RU Shock

(b) FU Shock

(c) Positively Large RU Shocks

(d) Positively Large FU Shocks

Figure 2: Time series of identified shocks. Figure 2a and Figure 2b depict the time series of the identified real and financial uncertainty shocks. Figure 2c and Figure 2d highlight the shocks exceeding two standard deviations for the real and financial uncertainty shocks, respectively. The vertical shaded areas are NBER reported recession periods.

results contradict those of LMN, as they provide the result that real activity responds positively to real uncertainty. They assert that the result is consistent with the growth options theory, which has raised the possibility that some forms of uncertainty can actually increase economic activity.[12] However, the response of real activity to the real uncertainty shock derived from this research is somewhat consistent with that in Carriero et al. (2018) and in other previous studies that show that heightened uncertainty can lead to a contraction in real activity. Finally, a hike in real uncertainty leads to an expansionary monetary policy.

[12]The growth options theory postulates that a mean-preserving spread in risk generated from an unbounded upside coupled with a limited downside, can cause firms to invest and hire since the increase in the mean-preserving risk increases any expected profits. Such theories were often used to explain the dot-com boom. See Pástor and Veronesi (2006), Segal et al. (2015) and Kraft et al. (2018).

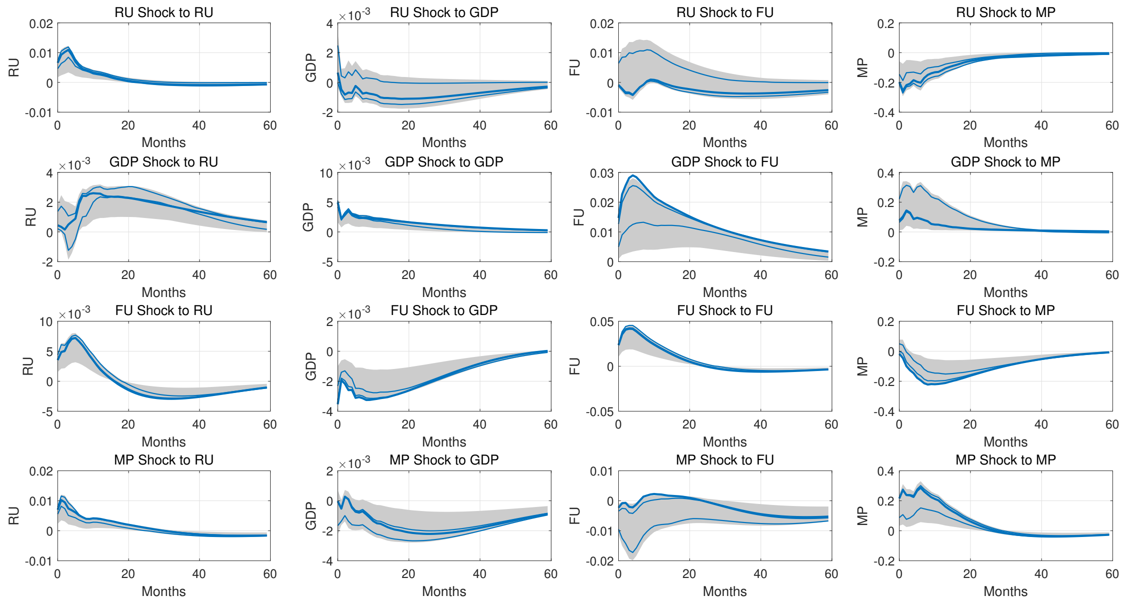



Figure 3: Impulse response functions of the monetary SVAR model: The shaded area and thin lines represent the 90% and 68% bounds for the identified solution set respectively and the solid lines represent the max-C impulse responses.

This policy action may be caused with the purpose of offsetting the economic contraction following the real uncertainty shock.

When real activity strengthens unexpectedly due to a positive GDP shock (the second row), both real and financial uncertainty tend to increase persistently, while real uncertainty undershoots initially and then spikes up quickly. These results differ from those in LMN, as they find that an increase in real activity leads to lower real uncertainty and higher financial uncertainty. A common finding that financial uncertainty increases in real activity might be understood as climbing up a boom phase of financial cycle (Brunnermeier and Sannikov, 2014; Borio, 2014; Filardo and Rungcharoenkitkul, 2016). As the economy expands, market participants take more risk and credit accumulates. These behaviors lead to financial imbalance and worsen financial cycle. Finally, monetary policy gets tighter for about 30 months following a positive GDP shock. This reaction can be understood as an ordinary monetary policy reaction to prevent the economy from becoming overheated.

The third row presents impulse responses to a positive financial uncertainty shock. Real uncertainty shows a positive hump-shaped response to the financial uncertainty shock. Combining the response of financial uncertainty to the real uncertainty shock, we can infer that these two types of uncertainties co-move and are highly related. Next, a rise in financial uncertainty leads to an immediate decline in GDP. This result is in line with many previous studies, which document that uncertainty drags down real activity (Bloom, 2009; Caggiano et al., 2014; Christiano et al., 2014; Bloom et al., 2018). As the shock depresses real activity, a monetary accommodation follows to stimulate the economy in times of recession. The monetary policy response to the financial uncertainty shock is in line with that of Bekaert et al. (2013) and Carriero et al. (2018). Central banks maintain a lax monetary policy following a rise in financial uncertainty.

The last row depicts the propagation of a positive monetary policy shock. A monetary tightening results in a slowdown in real activity, as predicted by the vast amount of monetary literature (Christiano et al., 2005). This result can be considered as additional evidence of the plausibility of our identification scheme. Real and financial uncertainty show distinct reactions to the monetary policy shock. Real uncertainty increases substantially while financial uncertainty persistently decreases. This contradicts the outcomes explored in Bekaert et al. (2013), as they predicted the opposite effects of monetary policy to financial uncertainty: a lax monetary policy action decreases financial uncertainty, while this effect is not strong. It is noteworthy that their uncertainty measure is not comparable to ours, as they built the uncertainty by decomposing the implied stock market volatility, which is also a specific measure of financial uncertainty, into a conditional variance ("uncertainty") and the rest ("risk aversion"). Furthermore, they find that the degree of risk aversion increases in the monetary policy stance. This result may be related to our result, that real uncertainty moves in the same direction with monetary policy, as a higher risk aversion leads to stronger wait-and-see behavior, which prevails under higher real uncertainty. Our findings that financial uncertainty decreases in the policy rate may be attributed to unwinding financial stress or unbalances: by increasing the policy rate, the monetary authority may prevent financial markets from bearing more risk and prevent the piling up of financial unbalances or bubbles (Rajan, 2005; Ajello et al., 2019; Adrian and Liang, 2018).

That latter result bears clear new policy implications. It is closely related to the view that a monetary authority needs to look after the financial cycle to prevent severe recessions caused by busts in the financial market (Adrian and Shin, 2008). The response of financial uncertainty hints that a tightening in the monetary policy stance may reduce risk-taking, relieve financial uncertainty and prevent the creation of bubbles. However, risk management through conventional monetary policy should be carried out cautiously, as it can also increase uncertainty related to real activities and incur immediate costs related to shrinking real activity. In sum, monetary policy seems to have a significant counter-cyclical effect in the short- to medium-run, while it also affects the build up of uncertainties.

One may concern about bias in the above results due to omitted variables which are important in conducting monetary policy such as inflation. We add core CPI into the VAR and the results are surprisingly not affected significantly. See Appendix H for details.

### 3.3 Forecasting Error Variance Decomposition

In the previous subsection, the dynamic impacts of each structural shock were illustrated based on impulse responses. As a next step, we compute to what extent each shock contributes to the historical evolution of endogenous variables by means of a variance decomposition.[13]

| SVAR: $X = (U^R, GDP, U^F, MP)'$ | | | | |
|---|---|---|---|---|
| **Fraction in Real Uncertainty** | | | | |
| | RU Shock | GDP Shock | FU Shock | MP Shock |
| $h = 1$ | 0.4103 | 0.0019 | 0.1194 | 0.4684 |
| $h = 6$ | 0.4515 | 0.0017 | 0.1909 | 0.3559 |
| $h = 12$ | 0.3999 | 0.0253 | 0.2378 | 0.3371 |
| **Fraction in GDP** | | | | |
| | RU Shock | GDP Shock | FU Shock | MP Shock |
| $h = 1$ | 0.0115 | 0.6560 | 0.3325 | 0.0000 |
| $h = 6$ | 0.0209 | 0.5811 | 0.3882 | 0.0098 |
| $h = 12$ | 0.0259 | 0.4522 | 0.4830 | 0.0389 |
| **Fraction in Financial Uncertainty** | | | | |
| | RU Shock | GDP Shock | FU Shock | MP Shock |
| $h = 1$ | 0.0012 | 0.2815 | 0.7102 | 0.0071 |
| $h = 6$ | 0.0048 | 0.3111 | 0.6828 | 0.0014 |
| $h = 12$ | 0.0031 | 0.3517 | 0.6435 | 0.0018 |
| **Fraction in Monetary Policy** | | | | |
| | RU Shock | GDP Shock | FU Shock | MP Shock |
| $h = 1$ | 0.4284 | 0.0635 | 0.0032 | 0.5049 |
| $h = 6$ | 0.3467 | 0.0911 | 0.1049 | 0.4573 |
| $h = 12$ | 0.2639 | 0.0622 | 0.2282 | 0.4457 |

Table 1: The $h$-Month Ahead Forecast Error Variance Decomposition (FEVD) for Max-C solution. The point value of FEVD is computed using the max-C solutions. The data is monthly from Apr. 1981 to Dec. 2018.

Table 1 shows the result of the variance decomposition exercise carried out for the max-C solution. From this table, we can draw some observations. First, real uncertainty may be explained subsequently by its own shock and monetary policy shock in the short-run. However, as the horizon lengthens, the fraction of real uncertainty that may be explained

[13]See Appendix D for results of historical decomposition.

by financial uncertainty increases quickly, while the share attributed to monetary policy diminishes sharply.

On the contrary, the GDP shock and the financial uncertainty shock play an important role in the evolution of the U.S. GDP. In addition, the financial uncertainty shock becomes more important with a longer horizon. Interestingly, it turns out that the influence of monetary policy on GDP with the one quarter horizon is almost zero. This result evidently illustrates the policy effect lag following shifts in monetary policy action.

Similar to the GDP case, financial uncertainty is explained almost entirely by its own shock and the GDP shock. The GDP shock becomes relatively more important with longer horizons. This result suggests that real activity and operations in the financial sector are closely intertwined. To gauge historical evolution of the relationship between the financial sector and real activity, we conduct a historical decomposition of structural shocks. It turns out that the influence of the financial uncertainty shock on GDP has been increased after 2000s. This result supports the view that the financial sector has become more influential in real activity. See Appendix D.

Finally, movements in monetary policy are largely explained by their own shock and real uncertainty in the short-run. However, the fraction of monetary policy shift that can be attributed to the financial uncertainty shock becomes substantial with a longer horizon, while the share attributed to real uncertainty diminishes quickly. This suggests that considering both the real and financial uncertainty is crucial to understanding U.S. monetary policy.

While Table 1 contains valuable information regarding the importance of each structural shock in explaining the endogenous variables, it should be understood with caution, as the decomposition is carried out based on the max-C solution. Although this solution serves as the reference solution, it should be emphasized that this solution is not more likely than the other solutions. Hence, it is necessary to have a sense of the possible range of contributions of each shock.

For this reason, Table 2 presents the 90% intervals of variance decomposition among solutions that satisfy all restrictions laid out to identify the structural shocks. Overall, the results emphasized above are intact in general. First, real uncertainty is still explained by its own shock and by the monetary policy shock in the short-run, but the role of financial uncertainty becomes as important as its own shock with a longer horizon. Second, the GDP shock and the financial uncertainty shock explain almost all variations in the evolution of U.S. GDP. However, the relative importance between the financial uncertainty shock and the GDP shock is not clear. Next, financial uncertainty is largely explained by its own shock and this is very robust among the identified solutions. Unlike the max-C solution case, the fraction of variations in the financial uncertainty that can be explained by monetary policy

| SVAR: $X = (U^R, GDP, U^F, MP)'$ | | | | |
|---|---|---|---|---|
| **Fraction in Real Uncertainty** | | | | |
| | RU Shock | GDP Shock | FU Shock | MP Shock |
| $h = 1$ | [0.2937,0.3836] | [0.0003,0.0283] | [0.1364,0.2076] | [0.4517,0.4985] |
| $h = 6$ | [0.6319,0.4129] | [0.0079,0.0202] | [0.1830,0.3096] | [0.3206,0.3839] |
| $h = 12$ | [0.3358,0.3819] | [0.0188,0.0426] | [0.2308,0.3824] | [0.2629,0.3447] |
| **Fraction in GDP** | | | | |
| | RU Shock | GDP Shock | FU Shock | MP Shock |
| $h = 1$ | [0.0005,0.1937] | [0.4935,0.6735] | [0.1218,0.3452] | [0.0110,0.1608] |
| $h = 6$ | [0.0515,0.1058] | [0.4332,0.7034] | [0.1791,0.3459] | [0.0117,0.1694] |
| $h = 12$ | [0.0685,0.0691] | [0.3092,0.6137] | [0.3030,0.4245] | [0.0142,0.1978] |
| **Fraction in Financial Uncertainty** | | | | |
| | RU Shock | GDP Shock | FU Shock | MP Shock |
| $h = 1$ | [0.0035,0.0561] | [0.0226,0.1954] | [0.7306,0.7917] | [0.0179,0.1822] |
| $h = 6$ | [0.0093,0.0437] | [0.0468,0.2215] | [0.7271,0.7846] | [0.0078,0.1594] |
| $h = 12$ | [0.0064,0.0580] | [0.0724,0.2505] | [0.6867,0.7694] | [0.0048,0.1519] |
| **Fraction in Monetary Policy** | | | | |
| | RU Shock | GDP Shock | FU Shock | MP Shock |
| $h = 1$ | [0.1300,0.8467] | [0.0369,0.4320] | [0.0009,0.0360] | [0.1155,0.4021] |
| $h = 6$ | [0.0906,0.6863] | [0.0852,0.4933] | [0.0146,0.1280] | [0.1005,0.4016] |
| $h = 12$ | [0.0699,0.5310] | [0.0573,0.4619] | [0.0465,0.2768] | [0.1349,0.4217] |

Table 2: The $h$-Month Ahead Forecast Error Variance Decomposition (FEVD) in the 90% band solutions. The data is monthly from Apr. 1981 to Dec. 2018.

turns out to be comparable to that of the GDP shock. This result suggests that monetary policy has a substantial effect on financial uncertainty. Finally, real uncertainty seems to be the most important driver of monetary policy shifts, while the exact contribution is highly uncertain. In addition, the GDP shock seems to be as important as the monetary policy shock itself. This result contrasts to that of the max-C solution case and suggests that the business cycle plays a crucial role in monetary policy shifts.

## 3.4 Role of Endogenous Responses of Uncertainties

In this subsection, we analyze the importance of the endogenous responses of uncertainties to the monetary policy shock while conducting policy analyses. Specifically, we mute any endogenous responses of real and financial uncertainty caused by changes in the other endogenous variables in order to separate the portion of the responses that stem from endogenous shifts in uncertainties. By doing this, we attempt to mimic the studies that examine the role

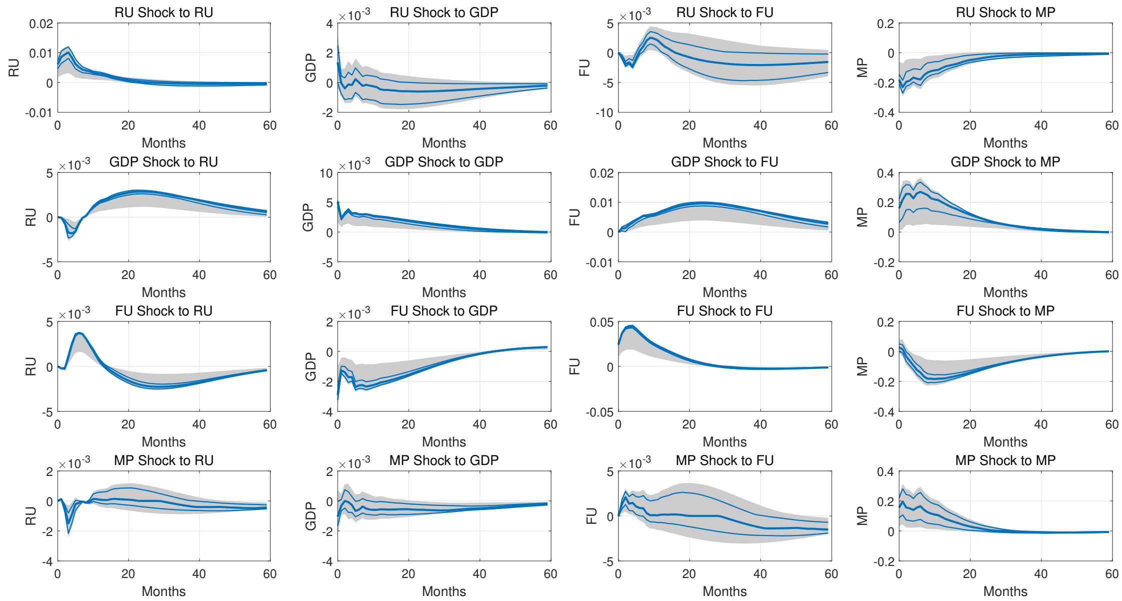



Figure 4: Impulse response functions of the SVAR model when real and financial uncertainty do not respond endogenously: The shaded area and the thin lines represent the 90% and 68% confidence band, respectively and the solid lines represent the max-C impulse responses.

of uncertainty shocks while assuming that economic uncertainty is exogenous.[14] To this end, we compare the results obtained in this subsection to those under the benchmark model. Finally, we also show whether or not ignoring the endogenous propagation of uncertainty can lead to different policy implications regarding the effectiveness of monetary policy.

As a starting point, we examine the impulse responses after shutting off all endogenous propagation channels. Precisely, the contemporaneous responses of both uncertainties to the other shocks are muted by restricting elements that govern contemporaneous responses in matrix $B$. Figure 4 presents the impulse responses derived from this exercise.

Not surprisingly, it turns out that taking endogeneity into account is important for both real and financial uncertainty. Some responses of real and financial uncertainty are qualitatively different from those obtained in the benchmark case. For instance, the initial responses of real and financial uncertainty to a positive monetary policy shock flip when the endogenous response channel is absent.

Then, we separately investigate the role of endogeneity in real/financial uncertainty in the propagation of monetary policy. That is, we shut down any contemporaneous responses of real or financial uncertainty one by one. These results also highlight the importance of

[14]Following Carriero et al. (2018), we say uncertainty is exogenous when it does not respond to the other economic shocks contemporaneously.

| Monetary Policy Multiplier: $\%\Delta GDP/\Delta MP$ | | |
|---|---|---|
| Model | Effects of Monetary Policy | $\lvert$Benchmark$\rvert$ $-$ $\lvert$Model$\rvert$ |
| Benchmark | -0.010 (-0.018, -0.005) | 0 |
| All Exogenous | -0.005 (-0.014, 0.000) | 0.005 (0.001, 0.006) |
| Endogenous RU & Exogenous FU | -0.013 (-0.031, -0.007) | -0.003 (-0.013, -0.001) |
| Endogenous FU & Exogenous RU | -0.004 (-0.007, 0.000) | 0.007 (0.004, 0.010) |

Table 3: Monetary Policy Multiplier (% changes in $GDP$ over 1% point increase in monetary policy rate): The 20-month cumulative Max-C responses of GDP divided by the 20-month cumulative Max-C responses of the monetary policy rate. The 68% confidence intervals are reported in parentheses. The first column presents the type of model and the second column shows the monetary multipliers for each case. The third column depicts the differences in the efficacy of monetary policy between the model of interest and the benchmark model.

accounting for the endogenous channels for both types of uncertainty. The detailed results can be seen in Appendix F.

One point is worth mentioning here. The observation that endogenous propagation channels are important for both real and financial uncertainty is somewhat different from the previous studies, such as LMN and Carriero et al. (2018). The former states that endogeneity matters for real uncertainty, but not for financial uncertainty, while the latter documents the opposite. There are various possible explanations that may contribute to this discrepancy. Ours uses different datasets, variables, sample period, model, identification scheme, and so on. Among these factors, we point out one important feature that may create the distinct results for each study. First, LMN lacks a policy variable. As many discrepancies are related to the policy variable, including a policy variable in a model may generate unique results. Second, Carriero et al. (2018) consider real and financial uncertainty in separate analyses. As is evident from Figure 3, the two types of uncertainty are intertwined, hence omitting one may result in a biased outcome.

Finally, we examine how the effectiveness of monetary policy changes when the endonegeity of uncertainty is overlooked. Table 3 compares the magnitudes of the real effects generated by an increase in the policy rate. To be precise, we compute the ratio of 20-month cumulative responses of monthly GDP to the 20-month cumulative responses of the monetary policy rate, all while allowing or not allowing endogenous feedback to the uncertainties.

The results in Table 3 reveal that ignoring endogenous feedback may understate the impact of monetary policy in general. That is, the real effect of monetary policy is roughly twice as large when both types of uncertainties are treated as endogenous, compared to the case that closes the endogenous channel for both of them. The last column also confirms that the difference between the two cases is significant.

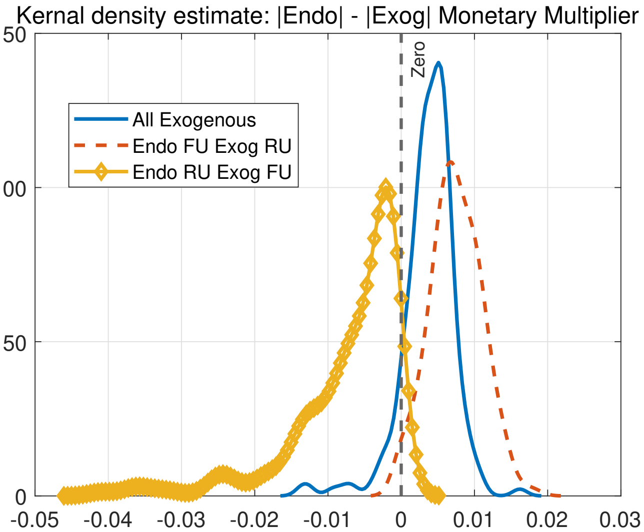



Figure 5: Kernel density estimate of the difference in responsiveness of GDP to a monetary policy shock between exogenous and endogenous uncertainty cases. The solid line represents the difference between the fully exogenous uncertainty case and the fully endogenous uncertainty case. The dashed line represents the difference between the exogenous real and endogenous financial uncertainty case and the fully endogenous uncertainty cases. The diamond line represents the difference between the exogenous financial and endogenous real uncertainty case and the fully endogenous uncertainty case.

Next, we shut down the endogeneity channels one by one to separate the influences from each uncertainty. The third and fourth rows show that while endogenous feedback of real uncertainty strengthens the real effect of monetary policy, that of financial uncertainty turns out to weaken the efficacy of monetary policy. This result is straightforward as 1. both real and financial uncertainty have negative effects on real activity, and 2. a monetary tightening aggravates real uncertainty while it improves financial uncertainty.

This suggests that it is important to consider endogenous feedback effects through uncertainty while evaluating the monetary policy effects. In addition, it also implies that the endogeneity of uncertainty should be taken into account when analyzing the state-dependent effects of monetary policy.

While monetary policy seems to be more potent when uncertainty is set to be endogenous, it is questionable whether the difference is significant. To this end, we estimate the distribution of the difference computed in possible solutions. Figure 5 shows the Kernel density estimate of the distribution across different endogeneity settings. The vertical dotted line is located at zero. If monetary policy is indeed more potent when endogeneity of uncertainty is introduced, then more mass should be concentrated at the right-hand side of the vertical line. Although there are non-trivial chances that monetary policy is more effective when the endogeneity channel is closed (the solid line), the model produces more effective monetary policy when endogeneity is allowed more than 89% of the time.

In addition, we also compute the distributions of monetary policy multiplier differences between the benchmark model and models that allow the endogeneity channel for one type of uncertainty at a time. Compared to the model in which the endogenous channel of real uncertainty is closed (the dashed line), the benchmark model produces more effective monetary policy in more than 98% of the cases. On the contrary, the model in which the channel of endogenous financial uncertainty is closed (the diamond line) provides a bigger monetary policy multiplier than the benchmark model 91.8% of the time.

In sum, allowing endogenous channels affects the consequences of monetary policy considerably. Specifically, endogenous feedback from real uncertainty strengthens the real effect of monetary policy, while that from financial uncertainty dampens the effect. While two channels create tension as they affect real activity in opposite directions, feedback from real uncertainty outweigh that from financial uncertainty.

### 3.5 Comparison with Bekaert et al. (2013)

Previous literature that studied the impact of economic policy on uncertainty is limited. One exception is Bekaert et al. (2013) (BHL, henceforth), which examines the effects of monetary policy on uncertainty. Specifically, they analyze how monetary policy affects risk appetite and uncertainty, and find that a lax monetary policy decreases uncertainty. In this subsection, we compare our results with those obtained in BHL. It is not appropriate to compare their results directly with ours, as they do not consider data after the GFC and they stop their sample in 2007. Hence, in this subsection we re-estimate the model using a shorter data sample that ends in December 2007, as in BHL.

Figure 6 contains the baseline results with a shorter sample, excluding the period after the GFC. In this case, a tighter monetary policy still heightens real uncertainty while it lowers financial uncertainty. This result contradicts with the results derived in BHL, in which financial uncertainty is increasing in the monetary policy rate. It also suggests that the main result of this research is robust to the changes in the sample period.

One additional difference that may possibly contribute to the discrepancy is the endogeneity of uncertainty in our model. Therefore, we conduct an analysis while shutting off the endogenous channel, as in subsection 3.4. The results are summarized in Figure 7. Similar to the baseline results, the signs of responses of uncertainties to the monetary policy shock flip. That is, financial uncertainty rises as monetary policy tightens, as in BHL. This exercise provides a possible explanation for the noticeably different results between this paper and

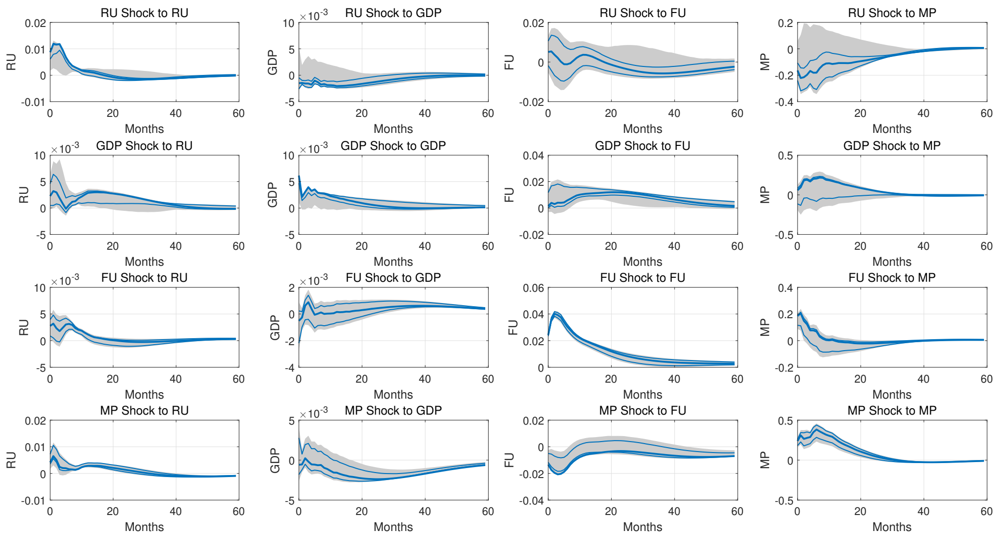



Figure 6: Comparison with BHL. Impulse response functions of the monetary SVAR model by Dec. 2007. The shaded area and thin lines represent the 90% and 68% confidence bands, respectively, and the solid lines represent the max-C impulse responses.

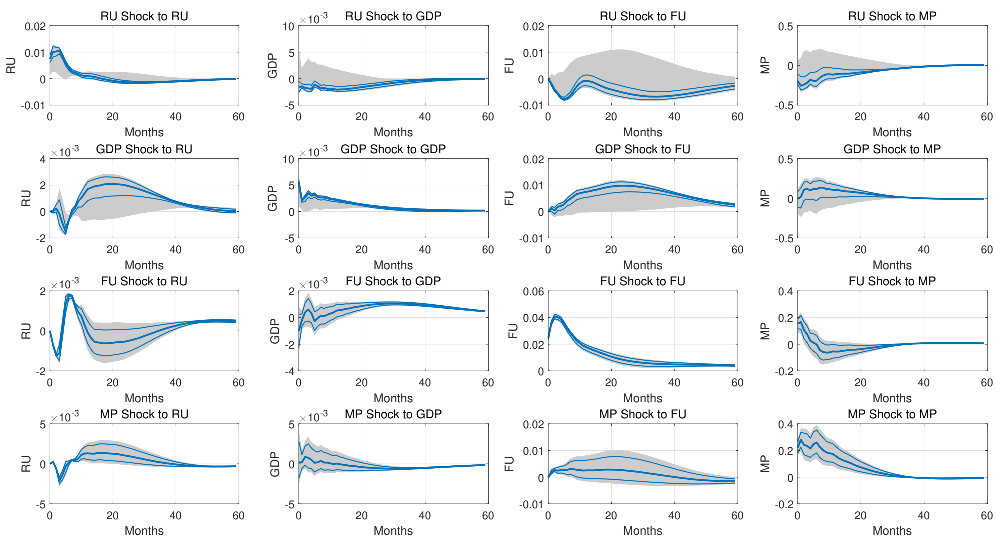



Figure 7: Comparison with BHL. Impulse response functions of the monetary SVAR model by Dec. 2007 without endogenous response of uncertainty. The shaded area and the thin lines represent 90% and 68% confidence bands, respectively, and the solid lines represent the median impulse responses.

BHL. The Cholesky decomposition used in BHL to identify the structural shocks may be too restrictive to identify the shocks related to uncertainties.

Finally, one point is worth mentioning. Both Figure 6 and Figure 7 show that financial uncertainty does not significantly drag down real activity. This result hints at the possibility that the impact of uncertainty on real activity has changed substantially since the GFC. It also calls for further research regarding the time-varying effects of uncertainty on the economy.

# 4 Conclusion

In this research, we examine how monetary policy affects the level of both real and financial uncertainty. While the economic influence of uncertainty has been widely studied after Bloom (2009), the economic forces that drive uncertainty have attracted relatively less attention. Specifically, while the role of uncertainty in shaping the effectiveness of monetary policy has been explored quite a lot, there has been little research that analyzes the impacts of monetary policy on economic uncertainty.

We find that monetary policy has a distinct effect on both real and financial uncertainty. It turns out that a tighter monetary policy dampens financial uncertainty, while injecting more uncertainty into the real sector. This result bears important policy implications and justifies an active monetary policy that targets financial stability.

In addition, we also show that accounting for the endogeneity of uncertainty does matter when analyzing the effects of monetary policy. Specifically, it is shown that implications regarding the behavior of uncertainties facing monetary policy action may alter if endogeneity is not properly taken into account. Furthermore, the impact of the monetary policy shock may be underestimated if the endogeneous responses of the uncertainties are ignored in the policy analyses.

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# Appendices

## A Comparison: Measured TFP and Identified *GDP* Shocks

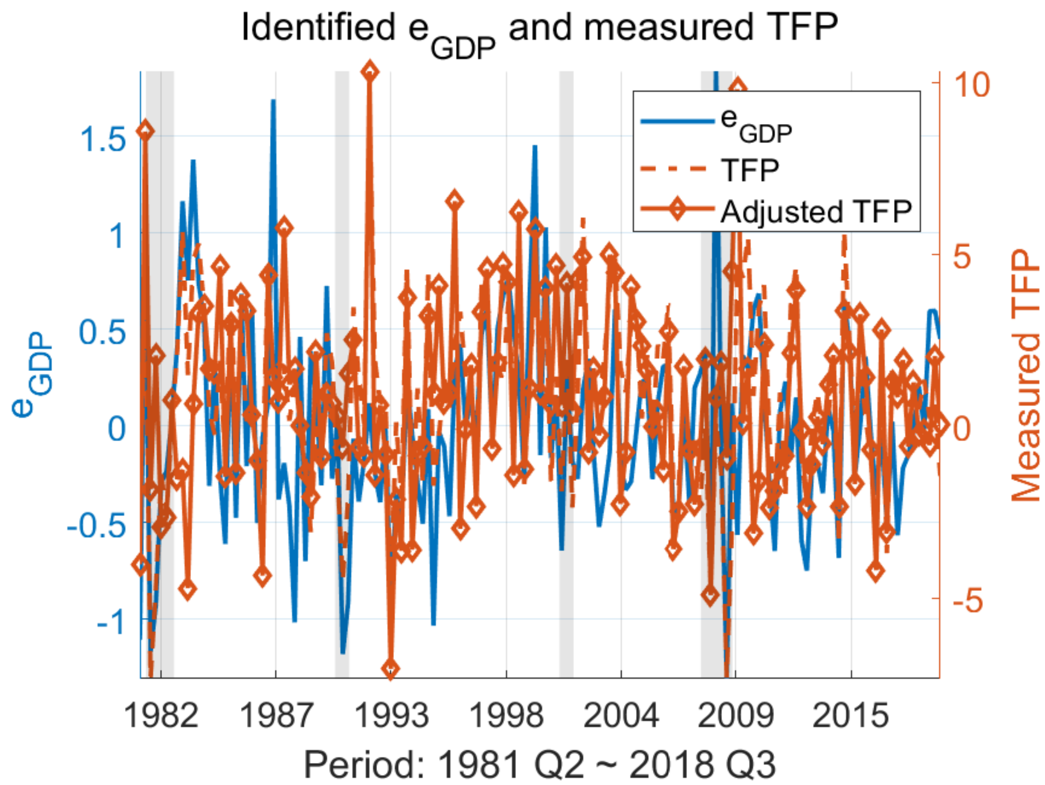
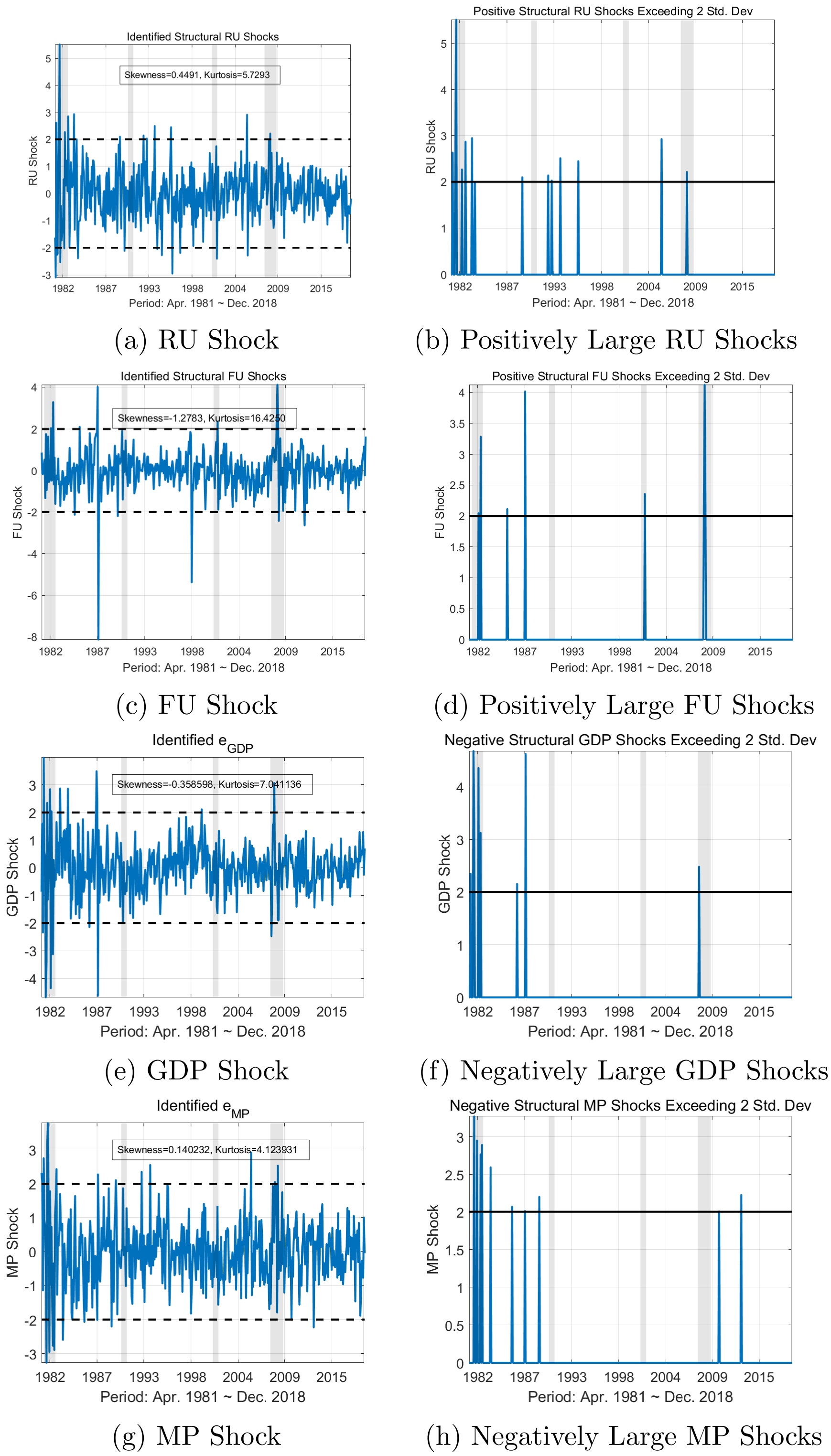



Figure 8: Comparison between identified GDP shocks and TFP. The blue solid line represents the identified GDP shocks $e_{GDP}$ of the max-C solution. The red dashed line represents the growth rate of total factor productivity (TFP), and the red diamond line represents the growth rate of utilization-adjusted TFP using estimates from Basu et al. (2006). The shaded bars represent NBER recession periods. TFP data is downloadable at https://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/. The correlation between TFP and $e_{GDP}$ is 0.5838, and that between the adjusted TFP using estimates from Basu et al. (2006) and $e_{GDP}$ is 0.3229. The data is quarterly from 1981 Q2 to 2018 Q3.

## B All Identified Shocks




(a) RU Shock
(b) Positively Large RU Shocks
(c) FU Shock
(d) Positively Large FU Shocks
(e) GDP Shock
(f) Negatively Large GDP Shocks
(g) MP Shock
(h) Negatively Large MP Shocks

Figure 9: Time series of identified shocks: Figure 9a, Figure 9c, Figure 9e, and Figure 9g depict the time series of the identified real and financial uncertainty, and GDP and monetary policy shocks, respectively. Figure 9b, Figure 9d, Figure 9f and Figure 9h highlight shocks exceeding 2 standard deviations for the real and financial uncertainty shocks, and GDP and monetary policy shocks, respectively.

## C Distributions of Identified Shocks

In this section, we provide simple evidence that the max-C solution is indeed capable of serving as the representative solution of all the identified solutions. Figure 10, which is the supplement of Figure 2a and Figure 2b, summarizes evolution of the time series of the identified real and financial shocks. The shocks identified from the max-C solution is shown as the dotted line and the shaded band contains 99% of the set identified solutions. This figure clearly shows that all the identified series move in the quite similar manner compared to the max-C solution.

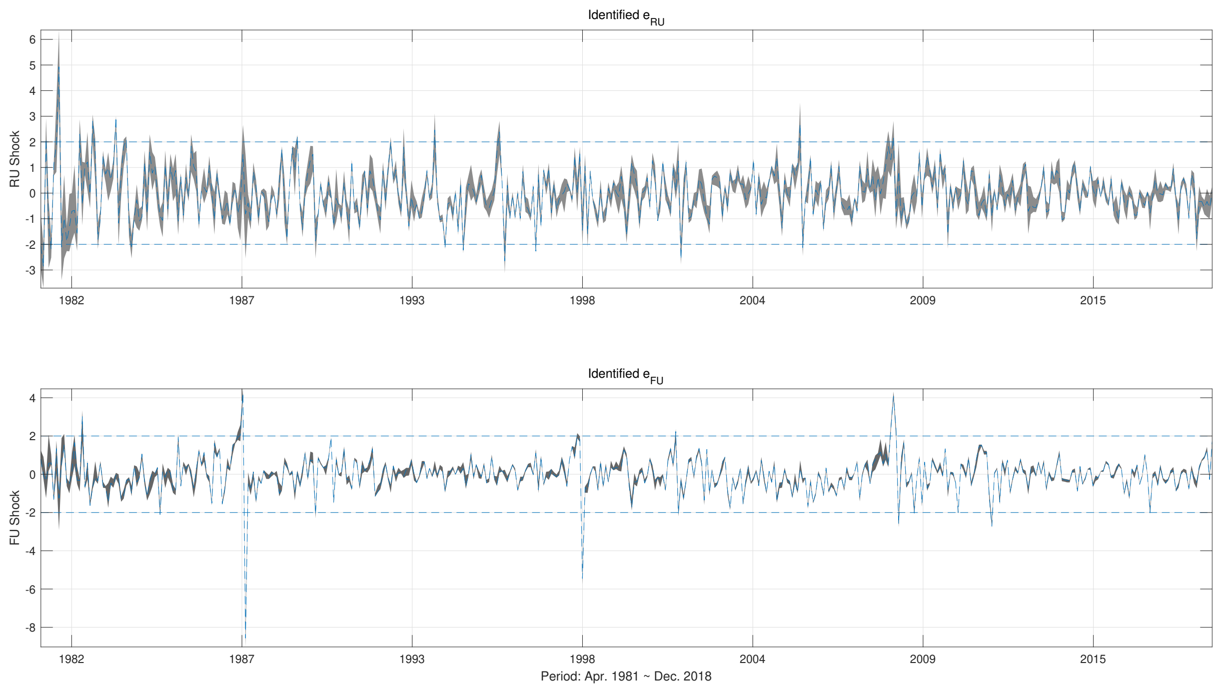
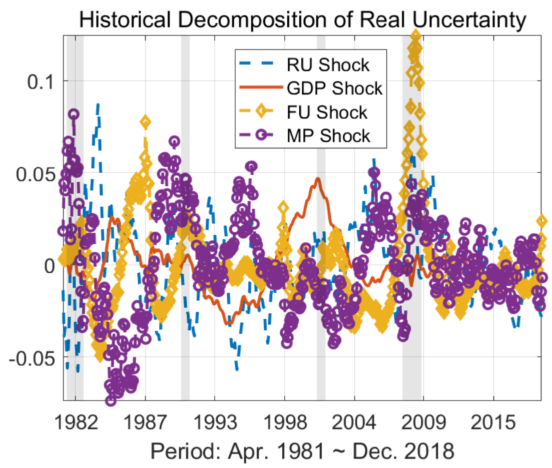


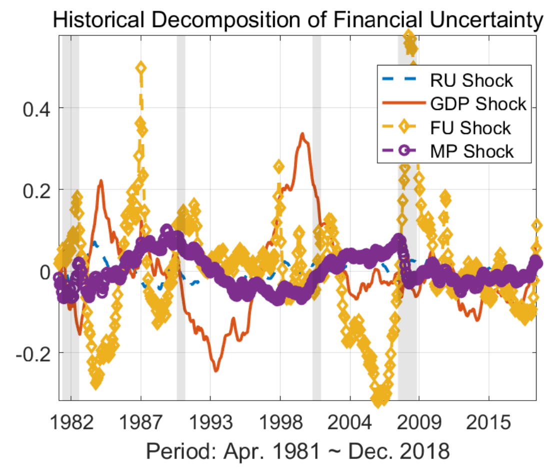

Figure 10: Time series of structural shocks of real and financial with the 99% bands. The dotted lines are max-C solutions and the shaded bands around the dotted lines are the 99% bands.

# D Historical Decomposition

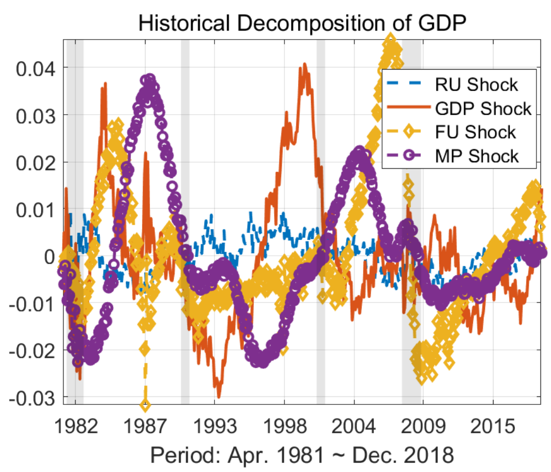
We decompose the contribution of each structural shock to historical evolution of real and financial uncertainty, real activity, and monetary policy based on the historical decomposition. Figure 11 depict the results. The dotted line, solid line, diamond-dotted line, and circle-dotted line represent the contribution of the structural real uncertainty, real activity, financial uncertainty, and monetary policy shocks, respectively. As shown in Figure 11, the importance of the structural financial uncertainty shock has increased over the sample period.



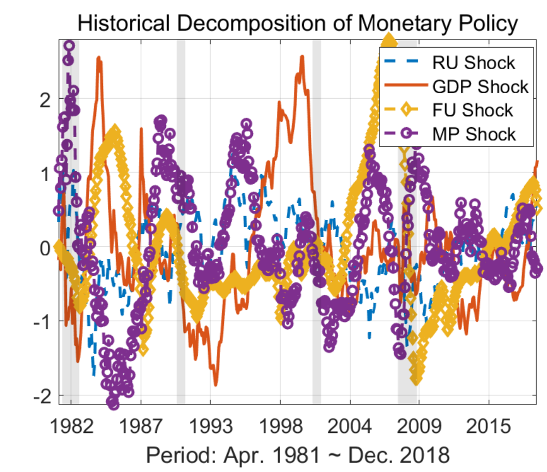

(a) HD of RU




(b) HD of FU




(c) HD of GDP



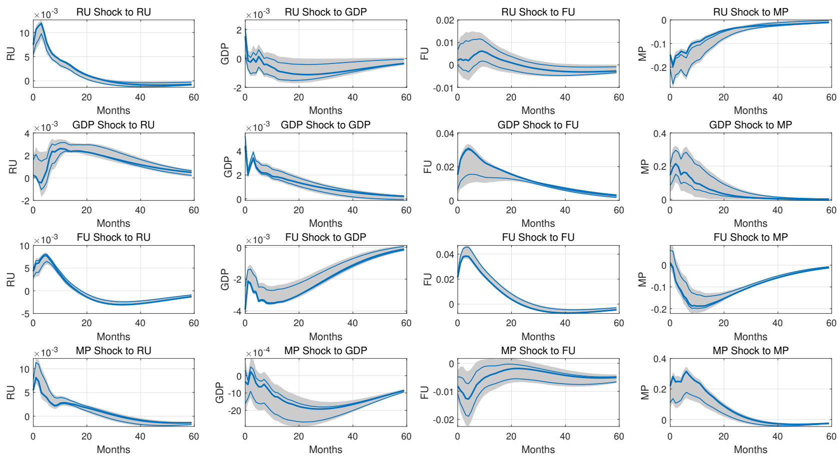

(d) HD of MP

Figure 11: Historical decomposition. Figure 11a, Figure 11b, Figure 11c, and Figure 11d depict historical contribution of the structural shock on real uncertainty, financial uncertainty, real activity, and monetary policy respectively. The shaded vertical areas represent NBER recession periods.

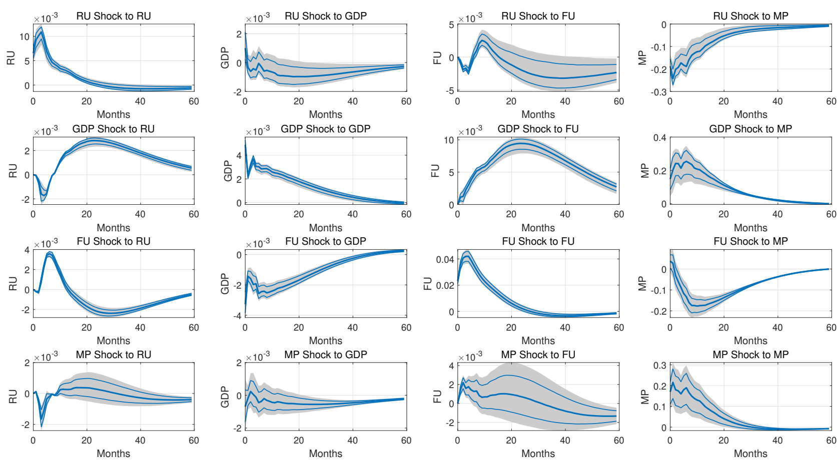
# E Robustness Check

In this section, we show that the main results – endogenous uncertainty makes monetary policy reduce financial uncertainty, but increase real uncertainty – are robust with respect to threshold values in event constraints.

Given $\bar{k}_1 = \bar{k}_2 = 4$ in the main analysis, the results in Figure 12 ($\bar{k}_1 = \bar{k}_2 = 3$) and Figure 13 ($\bar{k}_1 = \bar{k}_2 = 2.5$) imply that our results are not restrictive.

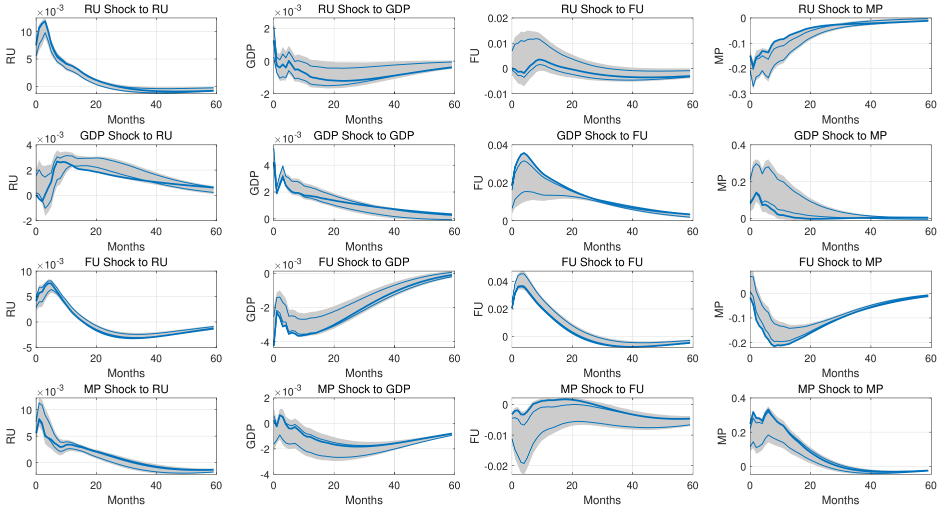



(a) Robustness Check: Impulse Response Functions for $\bar{k}_1 = \bar{k}_2 = 3$ in the benchmark model.

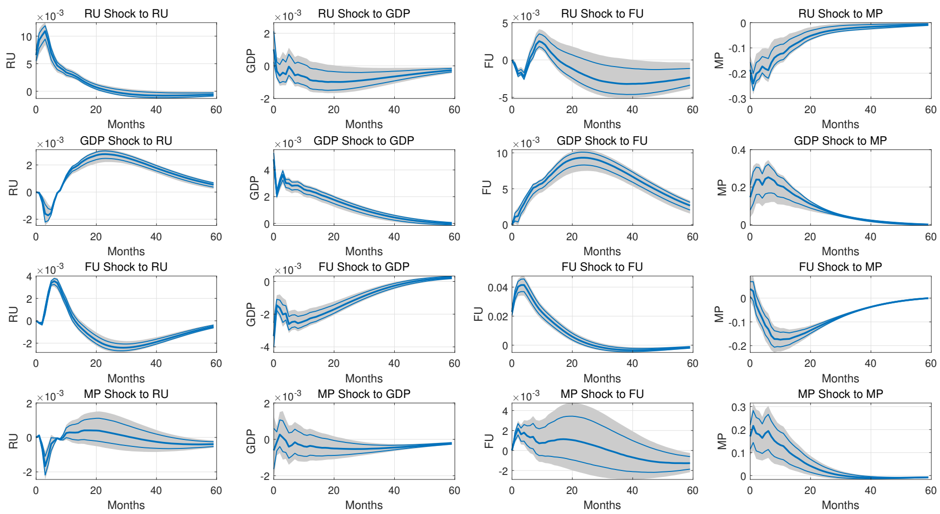



(b) Robustness Check: Impulse Response Functions for $\bar{k}_1 = \bar{k}_2 = 3$ in the counterfactual model.

Figure 12: Robustness Check: Case for $\bar{k}_1 = \bar{k}_2 = 3$. Other values are the same and $\bar{k}_1 = \bar{k}_2 = 4$ in the main analysis.




(a) Robustness Check: Impulse Response Functions for $\bar{k}_1 = \bar{k}_2 = 2.5$ in the benchmark model.

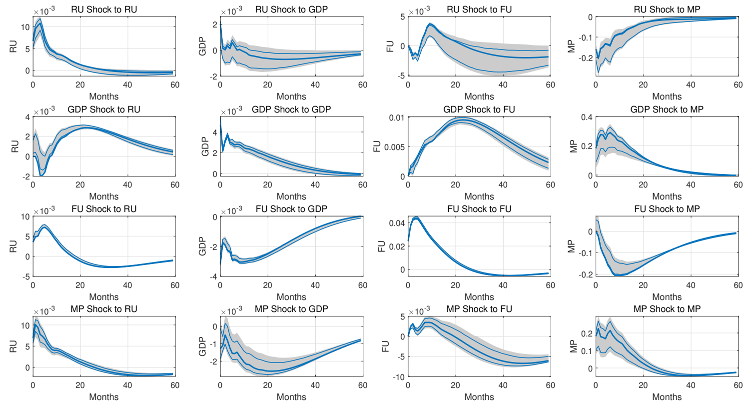



(b) Robustness Check: Impulse Response Functions for $\bar{k}_1 = \bar{k}_2 = 2.5$ in the counter-factual model.

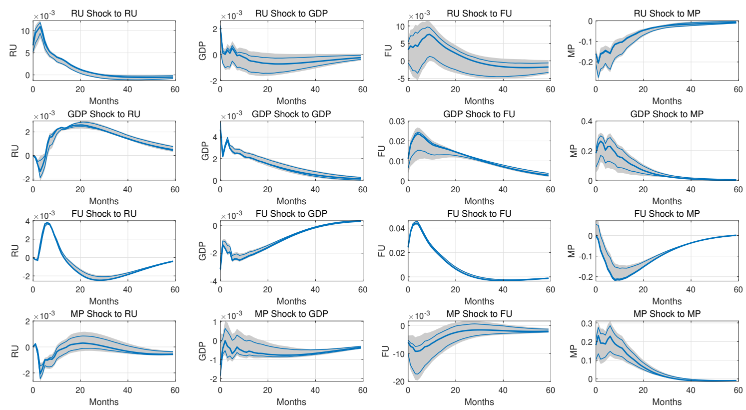
Figure 13: Robustness Check: Case for $\bar{k}_1 = \bar{k}_2 = 2.5$. Other values are the same and $\bar{k}_1 = \bar{k}_2 = 4$ in the main analysis.

# F Decomposing Endogenous Channels of Real and Financial Uncertainty

We shut down the endogenous channels of real and financial uncertainty one at a time to isolate the influence of allowing endogeneity for each type of uncertainty. Figure 14a is the impulse response functions of the SVAR model when we do not allow endogenous financial uncertainty but do allow endogenous real uncertainty, and Figure 14b represents the opposite case. Our interest is to see how real and financial uncertainty responds to the contractionary monetary policy shocks in each case. First, as shown in Figure 14a, while the response of real uncertainty is qualitatively the same with the benchmark model, that of financial uncertainty is opposite once we shut down the endogenous feedback channel of financial uncertainty. Similarly, Figure 14b shows that while the response of financial uncertainty is the same with the benchmark model, that of real uncertainty becomes the opposite once we shut down the endogenous feedback channel of real uncertainty.




(a) Impulse response functions of the SVAR model when financial uncertainty does not respond endogenously but real uncertainty does. The shaded area and the thin lines represent 90% and 68% confidence bands, respectively, and the solid lines represent the max-C impulse responses.




(b) Impulse response functions of the SVAR model when real uncertainty does not respond endogenously but financial uncertainty does. The shaded area and the thin lines represent 90% and 68% confidence bands, respectively, and the solid lines represent the max-C impulse responses.

Figure 14: Figure 14a represents the case of exogenous financial uncertainty, and Figure 14b represents the case of exogenous real uncertainty.

# G Recursive Identification

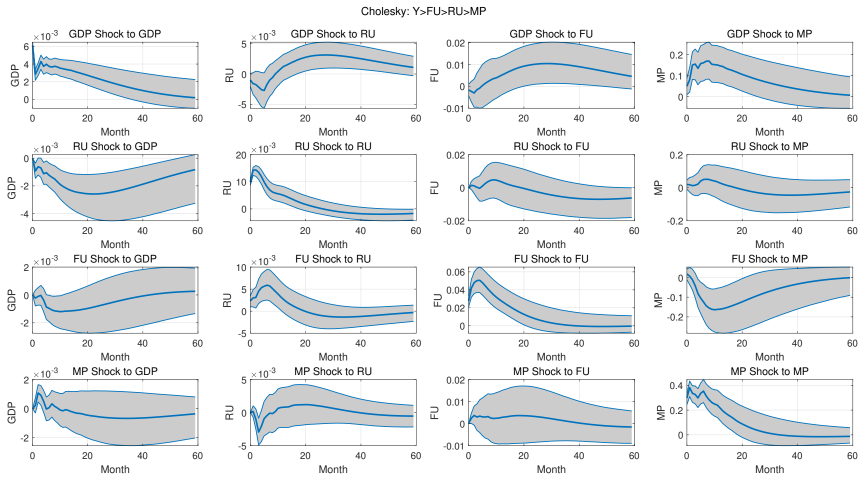



Figure 15: Cholesky Decomposition with the recursive ordering Y,FU,RU,MP

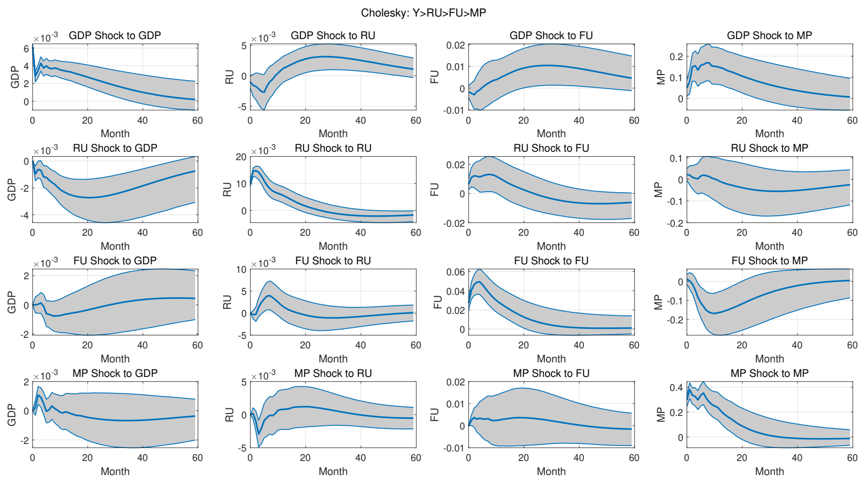



Figure 16: Cholesky Decomposition with the recursive ordering Y,RU,FU,MP

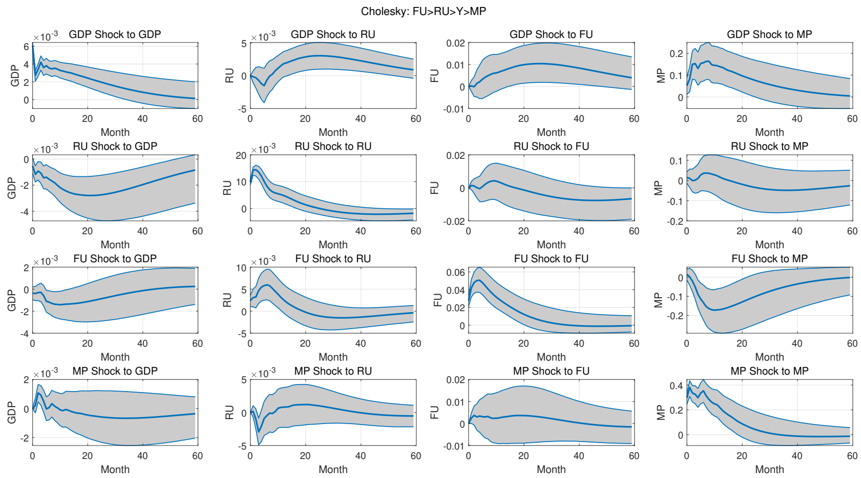



Figure 17: Cholesky Decomposition with the recursive ordering FU,RU,Y,MP

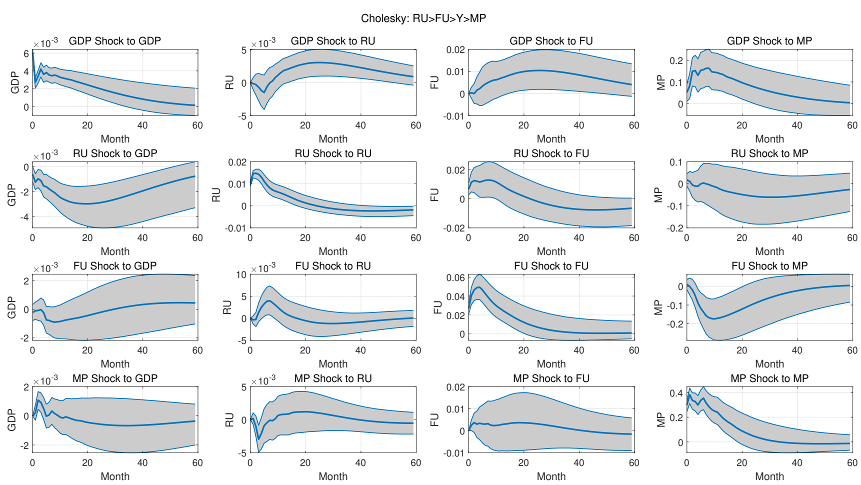



Figure 18: Cholesky Decomposition with the recursive ordering RU,FU,Y,MP

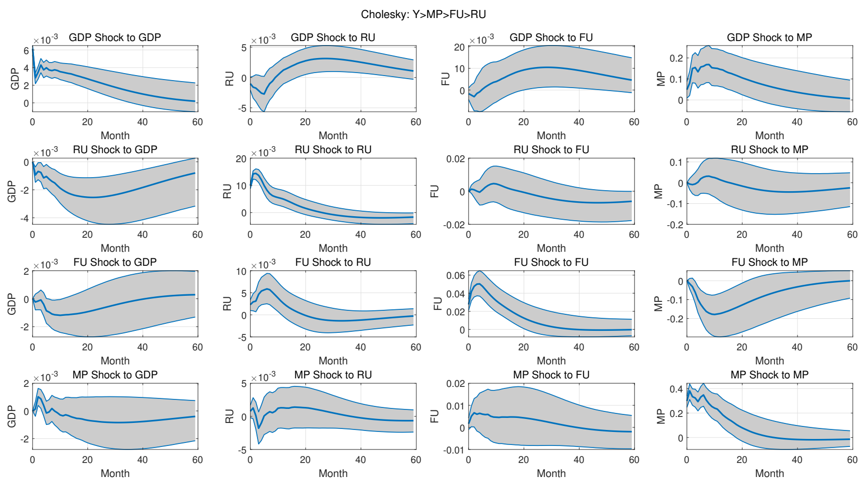



Figure 19: Cholesky Decomposition with the recursive ordering Y,MP,FU,RU

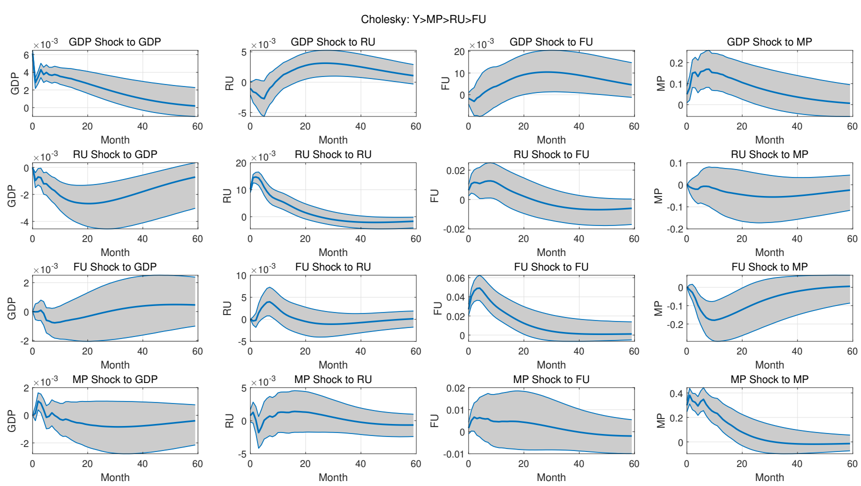



Figure 20: Cholesky Decomposition with the recursive ordering Y,MP,RU,FU

# H Five-variable VAR Analysis: Consumer Price Index (CPI)

As an additional robust check, we introduce a measure of inflation into the VAR and assess whether the main results are vulnerable to omitted variable bias. In this exercise, we use core consumer price index as the measure of inflation. To add more endogenous variable, it is required to include more identifying restrictions. In this analysis, we choose to add more restriction regarding the GDP shock rather than the newly included inflation shock. It is sufficient because we only need to identify four structural shocks for the five variable SVAR: one structural shock left can be automatically identified as a residual. Based on the observation discussed in Appendix A, we introduce an additional correlation restriction:

$$corr(e_{GDPt}, S_{4t}) \geq \bar{k}_{GDP} \tag{8}$$

where $S_{4t}$ is an appropriate instrument. Based on Appendix A, we use TFP and utilization-adjusted TFP as the instrument for the GDP shock. For the value of the threshold $\bar{k}_{GDP}$, we choose 0.3.

The result is summarized in Figure 21 and Figure 22. In sum, the impulse responses of the four initial endogenous variables are not affected considerably.

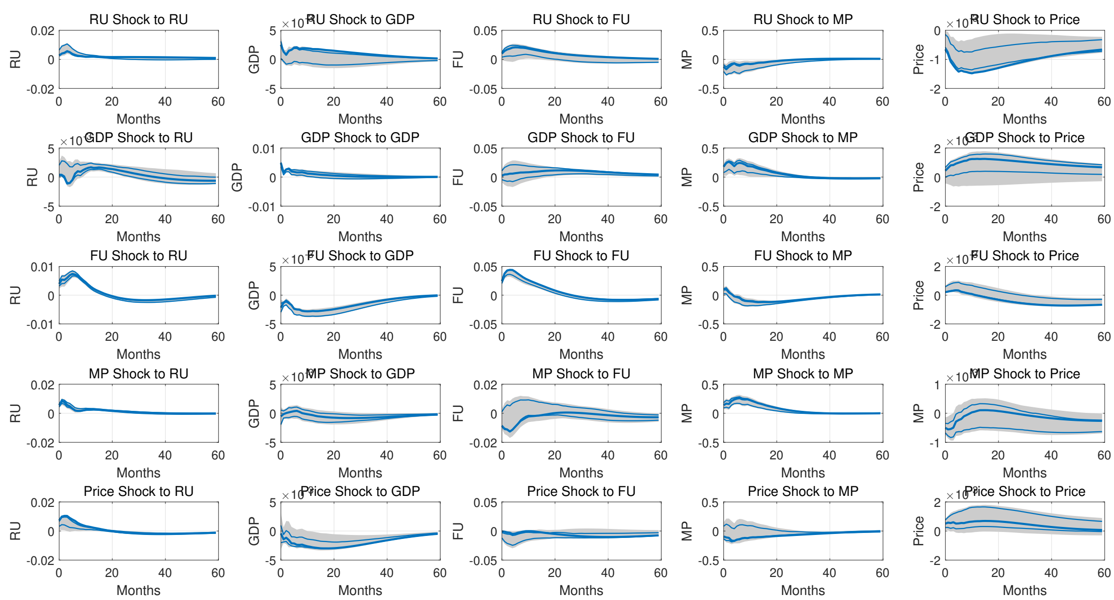


Figure 21: Impulse Responses in the 5-variable VAR while using TFP as the instrument for the GDP shock

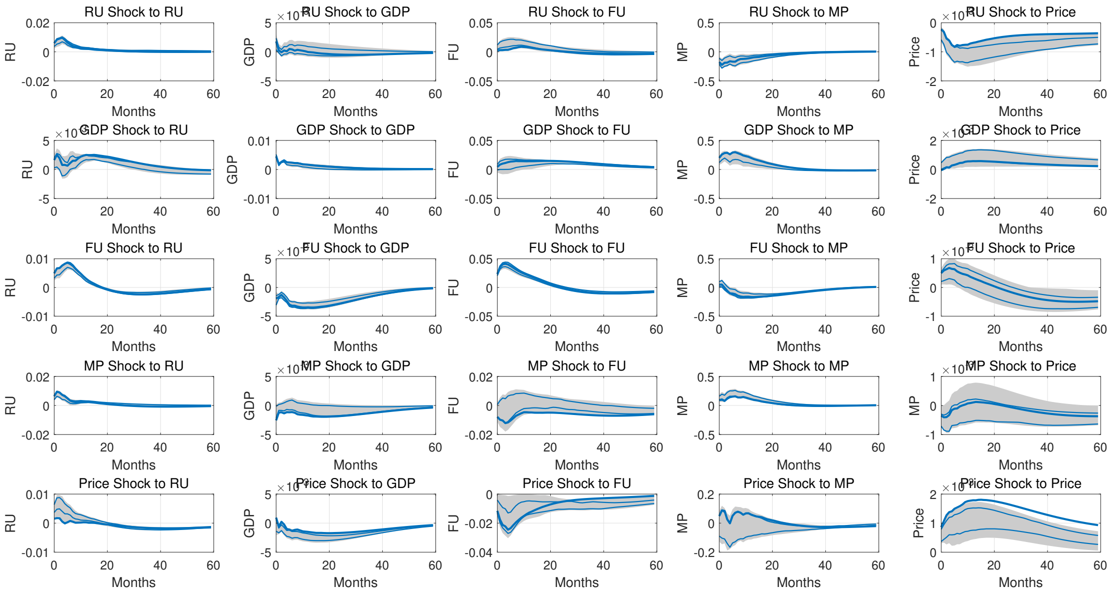



Figure 22: Impulse Responses in the 5-variable VAR while using utilization-adjusted TFP as the instrument for the GDP shock