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Government spending policy uncertainty and economic activity: US time series evidence

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ABSTRACT

In this paper, I empirically examine how uncertainty about government spending policy affects economic activity by using US time series data. To this end, I build government spending policy uncertainty indexes and estimate a proxy structural vector autoregression (VAR) model. The model shows that an increase in government spending policy uncertainty has negative, sizable, and prolonged effects on economic activity. Firms' external financing premiums seem to be an important transmission channel of government spending policy uncertainty shocks. The results also imply that the standard recursive VAR model systematically underestimates the adverse effect of government spending policy uncertainty. I also discuss the advantages and disadvantages of the proxy VAR versus the sign restriction VAR.

1. Introduction

What are the macroeconomic consequences of fiscal policy uncertainty? Many economists and policy makers have recently expressed concern about the adverse effects of fiscal policy uncertainty on economic activity. In the United States, for example, the debt-ceiling crisis, the federal government shutdown, and the Trump administration's plan for huge infrastructure investment have elevated government spending policy uncertainty, and many are worried about the consequent adverse effects. In Europe, there are concerns about future spending paths and tax policy owing to the escalated government debt level since the European debt crisis. Uncertainty about a consumption tax hike is one of recent biggest issues in Japan.

This study investigates the size of such adverse effects of fiscal policy uncertainty, particularly government spending policy uncertainty, and its transmission channels. To this end, I build two government spending policy uncertainty indexes for the United States and estimate the proxy structural vector autoregression (SVAR) model using those indexes and US time series data.

I build two government spending policy uncertainty indexes, a "disagreement index" and a "combined index", based on well-known uncertainty measures: the Philadelphia Fed forecasting disagreement measure and the uncertainty index provided by Baker et al. (2016). The forecasting disagreement measure has long been used in the literature to capture increases and decreases in uncertainty since the pioneering work of Bomberger (1996). The Philadelphia Fed provides a measure of forecasters' disagreements about US federal government consumption and investment based on its Survey of Professional Forecasters (SPF). Also, Baker et al. (2016) provide a category-specific uncertainty index, focusing on a specific policy, based on their newspaper method. I use their government spending policy uncertainty index.

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Next, I estimate the proxy SVAR model developed by Stock and Watson (2012) and Mertens and Ravn (2013) using the indexes. The proxy SVAR model uses external instruments to identify exogenous shocks. To identify an exogenous shock of government spending policy uncertainty, I use the defense news constructed by Ramey and Zubairy (2014) as an instrumental variable (IV). Defense news, the expected discount value of government spending induced by overseas military events, is unlikely to be related to US economic conditions. Moreover, it contains information on the future path of government spending. It may thus affect uncertainty about future government spending.

The main findings can be summarized as follows. First, government spending policy uncertainty has prolonged negative effects on economic activity and those negative effects are not negligible. An exogenous increase in government spending policy uncertainty reduces gross domestic product (GDP), private consumption, investment, labor hours, real wages, and markups but increases firms' external financing cost and price levels. The increase in price levels would be caused by an increase in firmsâ;; external financing costs and a consequent increase in marginal costs. This external financing cost channel has received relatively little attention from researchers. Pioneering research with dynamic stochastic general equilibrium (DSGE) done by Born and Pfeifer (2014) and Fernández-Villaverde et al. (2015) emphasize the countercyclical markups to explain inflation in response to fiscal uncertainty shocks rather than the cost push channel via the external financing premium.

Second, the standard recursive VAR, which is widely used in research on policy uncertainty, tends to underestimate the adverse effects of government spending policy uncertainty. The results using the recursive VAR reveal that the effects of spending policy uncertainty on economic activity are small. This result could be caused by the shortcomings of the identification strategy in the recursive VAR as pointed out by Ludvigson et al. (2015). I also discuss the advantages and disadvantages of the proxy VAR versus the sign restriction VAR.

Uncertainty has attracted renewed attention since the 2007/08 financial crisis. Bloom (2009) shows that uncertainty harms economic activity through several channels, such as the wait-and-see option channel and the precautionary saving motive, using empirical and theoretical models.[2] Since the pioneering work of Bloom (2009), several studies have tried to show how uncertainty impacts economic activity.[3] Among these, some research focus on uncertainty about specific policies. For instance, Mumtaz and Zanetti (2013) focus on monetary policy uncertainty; they use a SVAR model and US data to show that such uncertainty, measured as the time-varying volatility of monetary policy shocks, harms economic activity. Handley (2014) investigates the effects of trade policy uncertainty on firmsâ;; exporting behavior using panel data analysis.

A few studies focus on the effects of fiscal policy uncertainty. Davig and Foerster (2014) focus on the effects of uncertainty about tax policy using a calibrated DSGE model. Born and Pfeifer (2014) and Fernández-Villaverde et al. (2015) focus on uncertainty about fiscal policy. Born and Pfeifer (2014) show that monetary and fiscal policy uncertainty, measured by time-varying volatility, are not the major sources of business fluctuations using an estimated DSGE model. Fernández-Villaverde et al. (2015) show that capital tax uncertainty reduces output, private consumption, and investment, at least in the short run, through a VAR analysis and an estimated DSGE model. Ricco et al. (2016) investigate how the effectiveness of government spending varies depending on levels of government spending policy uncertainty using a nonlinear VAR model. However, they do not examine the effects of uncertainty about government spending policy itself.

Although these studies provide helpful insights on the macroeconomic consequences of fiscal policy uncertainty, most focus on tax policy uncertainty, rather than government spending policy uncertainty. Furthermore, I use a more data-driven method while they use structural models. Most significantly, I provide a new empirical strategy for identifying government spending policy uncertainty shocks.

The rest of this paper is structured as follows. Section 2 provides a detailed explanation of how I build the government spending policy uncertainty indexes. In Section 3, I briefly describe the proxy SVAR, data set, and other econometric issues. Section 4 provides empirical results, and Section 5 discusses them. Finally, Section 6 concludes the paper.

2. Government spending policy uncertainty index

This study examines the quantitative effects of uncertainty about government spending policy on economic activity. To this end, I build two indexes to measure government spending policy uncertainty levels. These indexes are based on two measures: the forecasting disagreement measure using the four-quarter-ahead real federal government spending growth rate provided by the Philadelphia Fed and the measure of government spending policy uncertainty provided by Baker et al. (2016). In the Philadelphia Fed's SPF, professional forecasters have reported their four-quarter-ahead forecasting values for the growth rate of real federal government consumption and gross investment from 1981.Q3 onwards.[4] The Philadelphia Fed provides the interquartile range of forecasting values as the cross-sectional dispersion measure. This type of forecasting disagreement measure has long been used in the literature to calculate uncertainty levels. Bomberger (1996); Boero et al. (2008); Dovern et al. (2012); Bachmann et al. (2013), and Baker et al. (2016) show that forecasting dispersion measures are useful for capturing uncertainty levels. Ricco et al. (2016) construct

[2] Lo and Rogoff (2015) claim that uncertainty is one of the reasons for the sluggish recovery in advanced and emerging countries from the 2007/08 financial crisis.

[3] See Basu and Bundick (2012); Baker and Bloom (2013); Leduc and Liu (2016), and Brogaard and Detzel (2015) among others.

[4] In the SPF, forecasters have also reported their forecast values about the level and growth rate of 32 macroeconomic variables, such as GDP, unemployment, inflation, housing price indexes, and interest rates. They have reported their forecasting values for the current quarter and up to four quarters ahead.

their government spending policy uncertainty measure based on the cross-sectional dispersion of SPF.[5] Following such studies, I use the interquartile range of forecasting values on federal government spending as a component of my government spending policy uncertainty index.

The second component is the measure of government spending policy uncertainty constructed by Baker et al. (2016). They provide both the economic policy uncertainty (EPU) index, reflecting overall EPU, and category-specific indexes, which focus on uncertainty about specific policies, such as on government spending and taxation.[6] They provide the measure of government spending policy uncertainty based on their newspaper method and it covers from 1985 onward. This method counts how frequently uncertainty-related terms about government spending policy (e.g., "federal government spending policy uncertainty", "state government spending policy uncertainty") appear in several newspapers. The more frequent such terms appear in newspapers, the higher uncertainty about government spending policy that we consider prevails.

Based on those two measures, I build two uncertainty indexes. The first is the normalized SPF dispersion measure with the standard score method (hereafter the "disagreement index"). The second is the average of the disagreement index and the normalized Baker et al. (2016)'s government spending policy uncertainty measure (hereafter the "combined index").[7] Normalization enables me to directly compare each index to the other. The advantage of the disagreement index is that the SPF measure directly relates to federal government spending policy. The defense news that I use as an instrument in the empirical analysis mainly covers the federal government military spending. For the relevance of the instrument, it is important that the uncertainty index is directly related to the federal government's spending policy. However, the index of government spending policy uncertainty created by Baker et al. (2016) is related not only to federal government spending but also to state and local government spending. Thus, the relevance of defense news for the combined index may be weak because defense news is related only to federal government spending, while the combined index contains information on state and local government spending as well. Including information unrelated to federal government spending may lower the relevance of the instrument.[8] However, the combined index also has an advantage. Although cross-sectional dispersion of forecasting values is widely used as a proxy for uncertainty, some studies, such as Lahiri and Sheng (2010), claim that forecasting disagreement measures are sometimes insufficient for capturing uncertainty levels since forecasters' disagreements may depend on idiosyncratic components, rather than economic fundamentals. The combined index can avoid this problem by adding EPU index.

The method to build two indexes is a simple process, but the indexes can complement pre-existing government spending uncertainty indexes. Ricco et al. (2016) construct their government spending disagreement index based on SPF. As mentioned, however, some studies claim that forecasting disagreement measures are insufficient for capturing uncertainty levels. The combined index can avoid this problem by adding additional information from an EPU index. Fernández-Villaverde et al. (2015) construct their capital tax volatility as a measure of capital tax uncertainty based on the stochastic volatility model and US capital tax data. Volatility is a useful and intuitive measure of uncertainty, but the construction process is fundamentally different from that used in this study. Furthermore, they do not provide government spending volatility.

Fig. 1 shows a time series plot of the two indexes and federal government shutdowns and debt-ceiling crisis events as important fiscal-related events.[9] A federal government shutdown tends to induce concerns about the future path of government spending. Thus, if the indexes capture uncertainty about government spending accurately, they should rise around those events. As Fig. 1 shows, the indexes seem to capture uncertainty caused by shutdowns and debt-ceiling crises well. For example, both indexes rose around the shutdown event in 1987 and the recent debt-ceiling crises around 2011 and 2013. Furthermore, uncertainty about government spending policy tends to increase in a recession because government spending is a policy tool used to overcome recessions. The indexes tend to rise during recessions such as that in 1981 and the recession caused by the financial crisis. Overall, both the disagreement and combined indexes seem to capture increases and decreases of government spending policy uncertainty caused by fiscal-related events.[10]

3. Econometric method and data

I use the proxy SVAR model developed by Stock and Watson (2012) and Mertens and Ravn (2013). The proxy SVAR model uses instrument variables to identify exogenous shocks, which is somewhat different from the traditional SVAR model, which uses recursive identification or sign restriction. This method has been widely used, including in several recent studies such as Gertler and Karadi (2015). Here, I briefly describe the bivariate model used for the baseline estimation.[11]

Consider the following simple bivariate reduced form VAR system:

[5] The fiscal policy uncertainty index in Ricco et al. (2016) is constructed based on the standard deviation of the forecast values as a dispersion measure. Standard deviation is also a useful indicator for capturing cross-sectional dispersion, but it is sometimes affected by outliers. I also construct an uncertainty measure based on standard deviation and estimate the proxy VAR with that index. The results are qualitatively similar and are available upon a request.

[6] Their EPU index is widely adopted in recent literature such as Fernández-Villaverde et al. (2015) and Bordo et al. (2016).

[7] This is similar to Baker et al. (2016). Their EPU index is the average of various normalized uncertainty measures.

[8] The marginal F-statistic of defense news for the EPU index is about 5, which is lower than the rule-of-thumb level.

[9] Owing to the data availability of Baker et al. (2016)'s measure, the combined index starts from the first quarter of 1985. The correlation between the two indexes is 0.85 in overlapping periods.

[10] Detailed fiscal events are shown in the Appendix A.1.

[11] See Stock and Watson (2012); Mertens and Ravn (2013), and Ramey (2016) for detailed discussions.

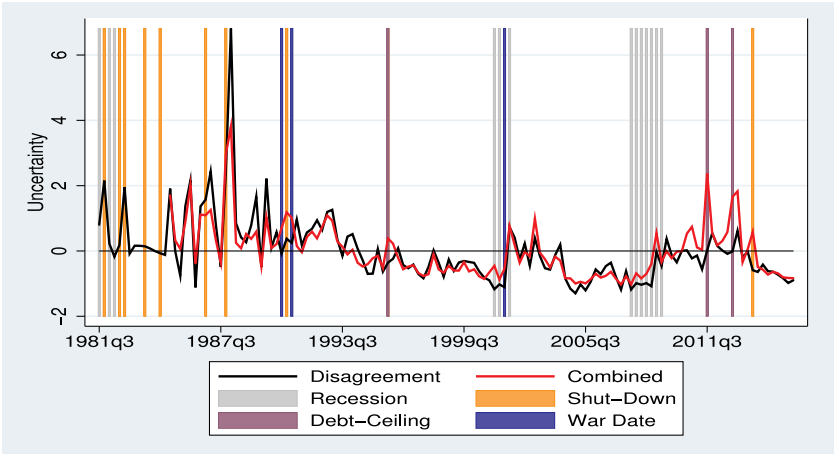


Fig. 1. Government spending policy uncertainty index. Note: The black and red solid lines indicate the disagreement index and the combined index, respectively. The gray bar indicates NBER recession dates, the orange bar federal government shut-down events, the purple bar debt-ceiling events, and the blue bar war episodes (i.e., Gulf War and 9/11). For data availability reasons, the combined index starts in 1985.Q1. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

$$\begin{bmatrix} U_t \\ Y_t \end{bmatrix} = \begin{bmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{bmatrix} \begin{bmatrix} U_t \\ Y_t \end{bmatrix} + \begin{bmatrix} \varepsilon_{U,t} \\ \varepsilon_{Y,t} \end{bmatrix} \tag{1}$$

U_t is an uncertainty index at time t, Y_t is the output, and $A(L)$ is a lag operator. $\varepsilon_{U,t}$ and $\varepsilon_{Y,t}$ are the residuals of each equation. Let $\eta_{U,t}$ be a structural shock of uncertainty which we are interested in. The goal of the identification strategy is to find a mapping from the reduced form residual (ε) to a structural shock (η). Given the usual normalization and assumption of the covariance matrix of structural shock, we obtain the following relation:

$$\begin{bmatrix} \varepsilon_{U,t} \\ \varepsilon_{Y,t} \end{bmatrix} = \begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix} \begin{bmatrix} \eta_{U,t} \\ \eta_{Y,t} \end{bmatrix} \tag{2}$$

The identification is to find the mapping (b_{12}, b_{21}) in Eq. (2). There are several ways to achieve this. For example, the recursive structure simply assumes $b_{12} = 0$. Then we can obtain the unbiased estimator of b_{21} using Cholesky decomposition. The assumption ($b_{12} = 0$) means that we do not allow contemporaneous changes in uncertainty to other shocks. This identification strategy is widely used in the literature on uncertainty. In the proxy SVAR, the information from an external instrument variable is used. Suppose that Z_t satisfies the following two conditions:

$$E[Z_t \eta_{U,t}] \neq 0 \tag{3}$$

$$E[Z_t \eta_{Y,t}] = 0 \tag{4}$$

These two conditions are similar to the usual conditions that any IV should satisfy. Eq. (3) means that Z_t should be contemporaneously correlated with a structural uncertainty shock. Eq. (4) indicates that Z_t should be independent to other structural shocks contemporaneously. If we have Z_t, it is straightforward to identify b_{12}, b_{21} with the following 3 steps:

Step 1. Estimate the reduced form VAR model (Eq. (1)) and obtain residual ε.

Step 2. Regress $\varepsilon_{Y,t}$ on $\varepsilon_{U,t}$ with Z_t as an instrument. We obtain the unbiased estimator of b_{21} through this regression. Let the residual of this regression be ν_t.

Step 3. Regress $\varepsilon_{U,t}$ on $\varepsilon_{Y,t}$ with ν_t as an instrument. We obtain the unbiased estimator of b_{12} through this regression.

The reduced form innovation $\varepsilon_{U,t}$ consists of two parts: a structural uncertainty shock and other shocks. Because Z_t is related only to a structural uncertainty shock, we can isolate a structural uncertainty shock from reduced form innovation $\varepsilon_{U,t}$ through certain regressions with Z_t.

The advantage of this strategy is that we do not rely on the assumption that $b_{12} = 0$. This allows uncertainty to vary contemporaneously in response to other shocks. Ludvigson et al. (2015) point out that it is important to allow this contemporaneous feedback channel of uncertainty to other shocks.

This procedure can be easily extended for VAR with additional variables. Consider the following multivariate reduced form VAR system:

$$\begin{bmatrix} U_t \\ \mathbf{X}_t \end{bmatrix} = \begin{bmatrix} A_{11}(L) & \mathbf{A}_{12}(L) \\ \mathbf{A}_{21}(L) & \mathbf{A}_{22}(L) \end{bmatrix} \begin{bmatrix} U_t \\ \mathbf{X}_t \end{bmatrix} + \begin{bmatrix} \varepsilon_{U,t} \\ \boldsymbol{\varepsilon}_{X,t} \end{bmatrix} \tag{5}$$

where X_t is a $k \times 1$ vector; $\mathbf{A}_{12}(L)$, $\mathbf{A}_{21}(L)$, $\mathbf{A}_{22}(L)$ are matrix of polynomial in lag operator; and $\varepsilon_{X,t}$ is a $k \times 1$ error term matrix. For

convenience, I define $\varepsilon_{X,t} = [\varepsilon_{X,1t}, \varepsilon_{X,2t}, ..., \varepsilon_{X,kt}]'$.

Similar to the bivariate case, the mapping between reduced form residuals to structural shocks is defined as follows:

$$\begin{bmatrix} \varepsilon_{U,t} \\ \varepsilon_{X,t} \end{bmatrix} = \begin{bmatrix} 1 & \mathbf{b}_{12}' \\ \mathbf{b}_{21} & \mathbf{C} \end{bmatrix} \begin{bmatrix} \eta_{U,t} \\ \eta_{X,t} \end{bmatrix} \tag{6}$$

where $\mathbf{b}_{12}$, $\mathbf{b}_{21}$ are the $k \times 1$ matrix. $\eta_{X,t}$ is the $k \times 1$ matrix for structural shocks. $\mathbf{C}$ is the $k \times k$ matrix in which all diagonal elements are one. Similar to the bivariate case, the goal is to identify $\mathbf{b}_{12}$ and $\mathbf{b}_{21}$.[12]

Suppose Z_t satisfies the following conditions:

$$E[Z_t \eta_{U,t}] \neq 0 \tag{7}$$

$$E[Z_t \eta_{X,t}] = \mathbf{0} \tag{8}$$

where $\mathbf{0}$ is the $k \times 1$ zero matrix. As in the bivariate case, the first condition indicates the relevance of the proxy variable, and the second condition indicates the exogeneity of the proxy variable. Then, the identification can be achieved by the following procedure:

Step 1. Estimate the reduced form VAR model (Eq. (5)) and obtain residual ε.

Step 2. Regress each $\varepsilon_{X,it}$, $i = 1, 2, ..., k$ on $\varepsilon_{U,t}$ with Z_t as an instrument. We obtain the unbiased estimator of $\mathbf{b}_{21}$ through this regression. Let the residual matrix of those regressions be $\zeta_t = [\zeta_{1,t}, \zeta_{2,t}, ..., \zeta_{k,t}]'$ where $\zeta_{i,t}$ is the residual from the regression of $\varepsilon_{X,it}$ on $\varepsilon_{U,t}$ with Z_t as an IV.

Step 3. Regress $\varepsilon_{U,t}$ on $\varepsilon_{X,t}$ with ζ_t as an instrument. We obtain the unbiased estimator of $\mathbf{b}_{12}$ through this regression.[13]

In the estimation, I use the defense news constructed by Ramey (2011) and updated by Ramey and Zubairy (2014) as an IV for the government spending uncertainty index. Defense news, which is identified by reading several newspapers, captures the expected discount value of the US federal government's military spending induced by military events such as the 9/11 attacks and purely political events. Thus, defense news is unlikely to be related to US domestic economic conditions. Furthermore, defense news contains information on expected government spending and may reduce uncertainty about future government spending.

It is important to examine how closely defense news, as an instrument for government spending policy uncertainty, is related to the government spending policy uncertainty indexes.[14] To test the relevance of defense news as an instrument, I conduct a formal first-stage F-test similar to that conducted by Stock and Watson (2012) and Ramey (2011). Table 1 summarizes the results. All marginal F-statistics are well above the rule-of-thumb level of 10 suggested by Staiger and Stock (1997). The results indicate that defense news is a relevant instrument for the estimation. By construction, defense news contains information on the future path of government spending. For professional forecasters, this can be a useful resource for predicting future government spending, which can reduce disagreements or uncertainty on future government spending paths among forecasters. It may be a reason for the high relevance shown in Table 1.

Most of the macroeconomic variables in the estimation (such as GDP) come from the Bureau of Economic Analysis. Nominal variables are transformed into real per capita terms using population and the GDP deflator. Other variables - such as labor hours, wage, and markups - come from the St. Louis Fed. Labor hours are transformed into per capita terms using population; wage data are transformed into real terms using the GDP deflator. Markups are measured as the inverse value of the labor share, following Fernández-Villaverde et al. (2015). Moreover, the Atlanta Fed provides the shadow federal fund rate, and the defense news comes from Ramey's website. Finally, I use GZ spread, which is the cross-sectional average of the credit spread constructed by Gilchrist and Zakrajšek (2012), to capture firms' external financing costs. Most of the data start in 1981.Q3 and end in 2015.Q4. The data span is dictated by the availability of defense news and the government spending policy uncertainty measure of Baker et al. (2016). Finally, I use the simple average of monthly frequency data in each quarter.[15]

4. Results

4.1. Main results

The estimation results are as follows. To mitigate potential problems induced by the short data span, I keep the model as simple as possible. I start with the bivariate model as a benchmark case and focus on the effects of uncertainty on GDP. Then, I present the results with the extended model to investigate the detailed effects and transmission channels of uncertainty shocks. The bivariate model includes four lags of the uncertainty index, the log of real per capita GDP, and a constant term. The choice of lag length is based on the likelihood ratio (LR) test and Akaike information criteria (AIC).[16]

Fig. 2 shows the bivariate model results. The left panel presents the results with the disagreement index, and right panel presents the results with the combined index. In Fig. 2, the black solid line represents the response of real per capita GDP in the proxy SVAR.

[12] Since I am interested only in identifying uncertainty shocks, it is not necessary to identify all off-diagonal elements in $\mathbf{C}$.

[13] According to Paul (2017), impulse response functions estimated from a VAR in which proxy variables are treated as exogenous variables (the so-called "VAR-X" model) are asymptotically equivalent to an impulse response function estimated from a proxy VAR.

[14] Montiel Olea et al. (2012) show that show that inference and consistency problems occur in proxy SVAR models with weak IVs.

[15] Appendix A.2 provides detailed data sources.

[16] For the estimation, I use the MATLAB codes of Mertens and Ravn (2013)

Table 1
Marginal F-Statistics for the IV Relevance test. Note: The bivariate model includes a constant, four lags of the log of real per capita GDP, and the uncertainty index. The extended model includes a constant, two lags of the log of real per capita GDP, the log of real per capita consumption, the log of real per capita gross fixed investment, the (shadow) federal funds rate, and the uncertainty index.

	Bivariate model	Extended model
Disagreement index	29.32	19.16
Combined index	13.62	11.65

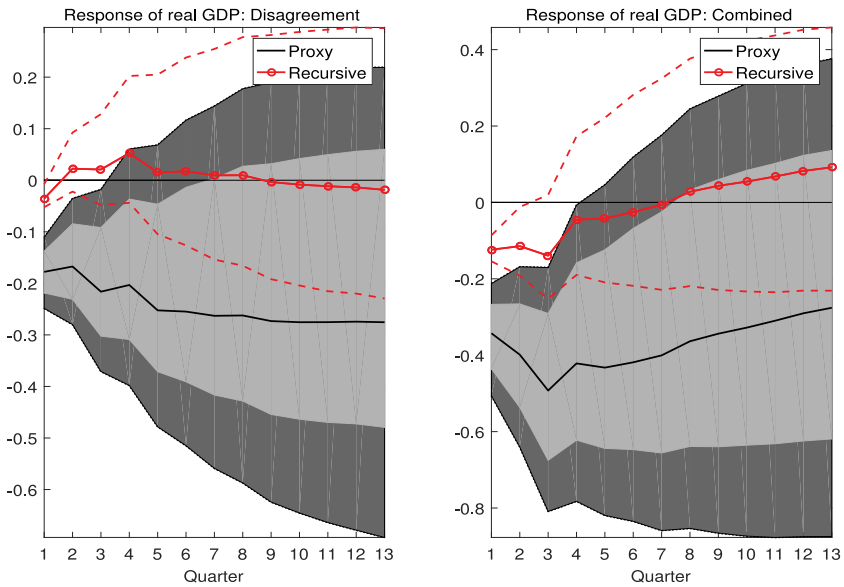


Fig. 2. Response of GDP to government spending uncertainty shock: Bivariate VAR. Note: The black solid and red dotted lines indicate the impulse response of the log of real per capita GDP to a one-unit increase in government spending policy uncertainty in the proxy VAR and recursive VAR, respectively. The light gray and dark gray lines indicate 68% and 90% confidence bands for the response in the proxy VAR, and the dashed line indicates 90% confidence bands for the response in the recursive VAR. Confidence bands are constructed by the bootstrap method with 10,000 replications. The y-axis indicates the percentage change in the log of real per capita GDP, and the x-axis indicates quarters. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The red dotted line is the response of real per capital GDP in the recursive VAR model as a benchmark. In the recursive VAR model, the uncertainty index is ordered first. Light gray and dark gray indicate 68% and 90% confidence bands, respectively, for the response in proxy VAR, and the dashed line indicates 90% confidence bands for the response in recursive VAR. To compute the confidence bands, I use the wild bootstrap method with 10,000 replications, following Mertens and Ravn (2013). A shock is defined as a one-unit increase in the uncertainty index, and the GDP response is calculated as a percentage change. In 2009.Q1, the disagreement index and combined index rose by one unit owing to the new fiscal stimulus package (American Recovery and Reinvestment Act, ARRA). Thus, the one-unit increase in uncertainty indexes can be roughly interpreted as a shock induced by the ARRA.

The implications of the results shown in Fig. 2 are twofold. First, an increase in government spending policy uncertainty has a negative effect on GDP; the size of that effect is not negligible. GDP immediately falls around 0.2% (disagreement index) - 0.35% (combined index), and this negative effect is statistically significant, at least in the short run. How large is that adverse effect? The combined index rose from 0 to 2.3 2011.Q3 owing to the debt-ceiling crisis. Based on the empirical analysis, this surge in policy uncertainty may have reduced real per capita GDP by around 0.7% on impact, which is not negligible. Furthermore, the negative effect is persistent. The responses of GDP remain negative at all reported horizons.

Second, the recursive VAR underestimates the adverse effects of government spending policy uncertainty. The response of GDP is small and is even positive at some horizons in the recursive VAR, and is not statistically significant across all reported horizons. These results are clearly the opposite of those in the proxy SVAR model. Moreover, the results are robust if I include macroeconomic uncertainty variables such as a GDP forecasting disagreement measure. The results are also robust when I exclude zero lower bound periods.[17]

What drives these differences? One potential candidate is the shortcomings of the identification strategy in the recursive VAR. Ludvigson et al. (2015) claim that the recursive VAR is a good starting point but that it is hard to justify the presumed variable

[17] See Appendices A.3 and A.4 for the results.

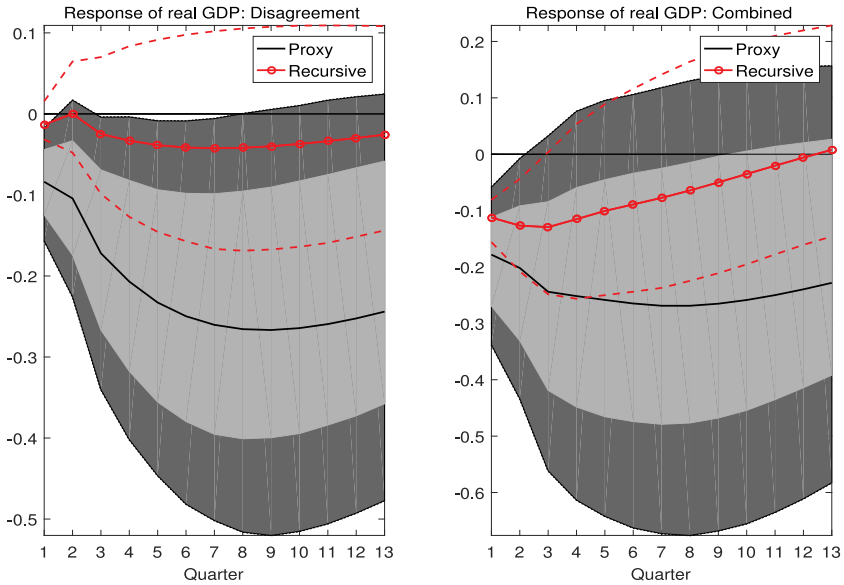


Fig. 3. Response of GDP to government spending uncertainty index: Extended VAR. Note: The black solid and red dotted lines indicate the impulse response of the log of real per capita GDP to a one-unit increase in government spending policy uncertainty in the proxy VAR and recursive VAR, respectively. The light gray and dark gray lines indicate 68% and 90% confidence bands for the response in the proxy VAR, and the dashed line indicates 90% confidence bands for the response in the recursive VAR. Confidence bands are constructed by the bootstrap method with 10,000 replications. The y-axis indicates the percentage change in the log of real per capita GDP, and the x-axis indicates quarters. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

ordering in the VAR system because contemporaneous changes in uncertainty can arise amid business cycle fluctuations; at the same time, contemporaneous changes can arise as a response to other shocks. Recursive structures explicitly rule out this possibility since they presume that some variables respond only with a lag to others. However, the proxy SVAR can mitigate this problem because it identifies exogenous uncertainty shocks using an instrument, not through the ordering assumption in the recursive VAR model. Since defense news is unlikely to be related to US business cycle fluctuations, the government spending uncertainty shock identified in the proxy SVAR will not be an endogenous response to other shocks. Furthermore, the proxy SVAR can allow contemporaneous changes in government spending uncertainty owing to other shocks because it does not rely on the ordering assumption to identify spending uncertainty shocks, as explained in Section 3.

Fig. 3 shows the response of GDP to policy uncertainty shocks in the extended model. I try to avoid including too many variables in the VAR to avoid an over-parameterization issue. I thus estimate the model following Burnside et al. (2004) and Gertler and Karadi (2015). I use a fixed set of variables and other rotating variables. The fixed set has five variables: uncertainty index, log of real per capita GDP, log of real per capita consumption, log of real per capita investment, and the shadow federal fund rate constructed by Wu and Xia (2016). The consumption and investment employed in the fixed set are useful for capturing the response of the private sector to government spending uncertainty. The shadow federal funds rate helps capture the effects of monetary policy, particularly in recent zero-lower bound episodes. There are five rotating variables: log of labor hours, log of real wage, log of markups, log of the GDP deflator, and GZ spread. Based on AIC criteria and an LR test of the model with the fixed set, the lag length for the extended model is set to two. For the recursive VAR with extended set-up, I order the uncertainty index first.[18]

Overall, the results of the extended model seem to be consistent with the results in the bivariate model. The GDP immediately drops by around 0.1% (disagreement index) - 0.2% (combined index). The GDP response is statistically significant on impact. The negative effects are persistent, as in the bivariate model. The GDP response stays negative across all reported horizons. Furthermore, the results of the extended recursive VAR do not significantly change. The extended recursive VAR with the disagreement index shows small and insignificant effects of spending policy uncertainty, contrary to the results in the proxy SVAR model. The recursive VAR with the combined index shows a negative response of GDP in the short run, but it still underestimates the adverse effects of government spending policy uncertainty.

Fig. 4 shows the responses of other variables in the extended system with the disagreement index. An increase in government spending policy uncertainty reduces output through a contraction of private consumption and investment. Private consumption decreases at most by around 0.2%. Moreover, this contraction continues for all reported horizons and is statistically significant in the short run. Private investment also drops by around 1% at most. Furthermore, the response of private investment remains negative for all reported horizons.

An increase in uncertainty increases price levels moderately except in the very short run, which implies that uncertainty shocks

[18] Here, the only shock that I identify is uncertainty shock. Therefore, an ordering of other variables is immaterial.

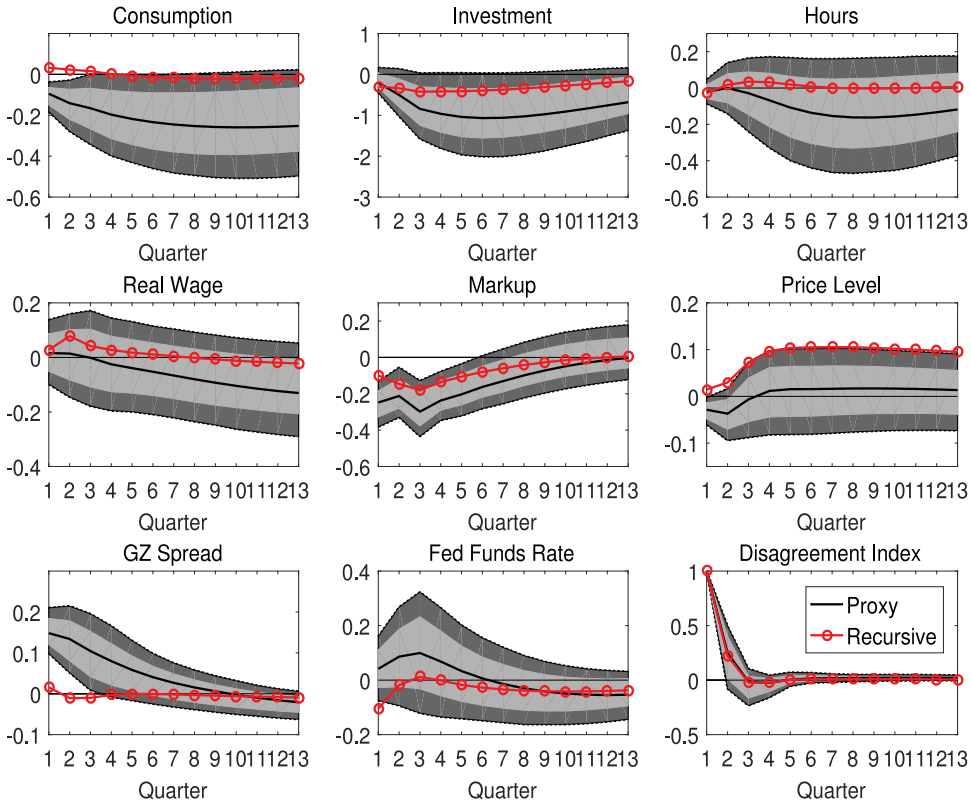


Fig. 4. Response of other variables: Extended VAR with disagreement index. Note: The black solid and red dotted lines indicate the impulse response of each variable to a one-unit increase in government spending policy uncertainty in the proxy SVAR and in the recursive VAR, respectively. Light gray and dark gray lines indicate 68% and 90% confidence bands for the response in the proxy VAR. Confidence bands are constructed by the bootstrap method with 10,000 replications. Changes are measured as percentage changes except the GZ spread and shadow rates, which are measured as percent point changes. The x-axis indicates quarters. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

generate future inflation.[19] This result is similar to the DSGE predictions in Fernández-Villaverde et al. (2015) and Born and Pfeifer (2014). The monetary authority conducts a contractionary monetary policy in response to this future inflation in the short run. Consequently, the response of the shadow federal funds rate is positive in the short run, though the price level and shadow rate responses are not statistically significant. However, output contraction becomes much larger at longer horizons, as shown in Figs. 2 and 3. Thus, the monetary authority will start to cut its policy rate to boost output; therefore, the response of shadow federal funds turns negative at some point. Labor hours and real wages are decreasing but are not statistically significant. Markups, measured by the inverse of the labor share in the business sector, drops on impact and stays negative for all reported horizons. The negative response of markups is statistically significant in the short run. An increase in government spending policy uncertainty increases firms' external financing costs as measured by the GZ spread.[20] In addition, the recursive VAR tends to underestimate private consumption and investment contraction, reductions in hours and real wages, and increases in the GZ spread. It overestimates an increase in price levels.

Fig. 5 shows the estimated impulse responses of variables in the extended model with the combined index. Overall, the implications of the results are consistent with those of the results in the model with the disagreement index. An increase in government spending uncertainty reduces consumption, investment, hours, and real wages. It also generates moderate inflation and decreases markups. Additionally, the recursive SVAR systematically underestimates the adverse effects of government spending uncertainty shocks.

In sum, the results imply that an increase in government spending policy uncertainty negatively affects private sector activity. Real wages and labor hours also decrease in response to government spending policy uncertainty shocks. Shocks generate moderate

[19] The model with inflation instead of price level shows the same result. See Appendix A.5 for these results.

[20] The response of markups and external financing costs are robust to the use of other proxies for markups and firms' external financing costs. I use two different markup series based on Nekarda and Ramey (2013) and two different external financing costs series (excess bond premium provided by Gilchrist and Zakrajšek (2012) and credit spreads (BAA bond rate less AAA bond rate)). The results are similar to those of the baseline estimation. See Appendices A.6 and A.7 for the results.

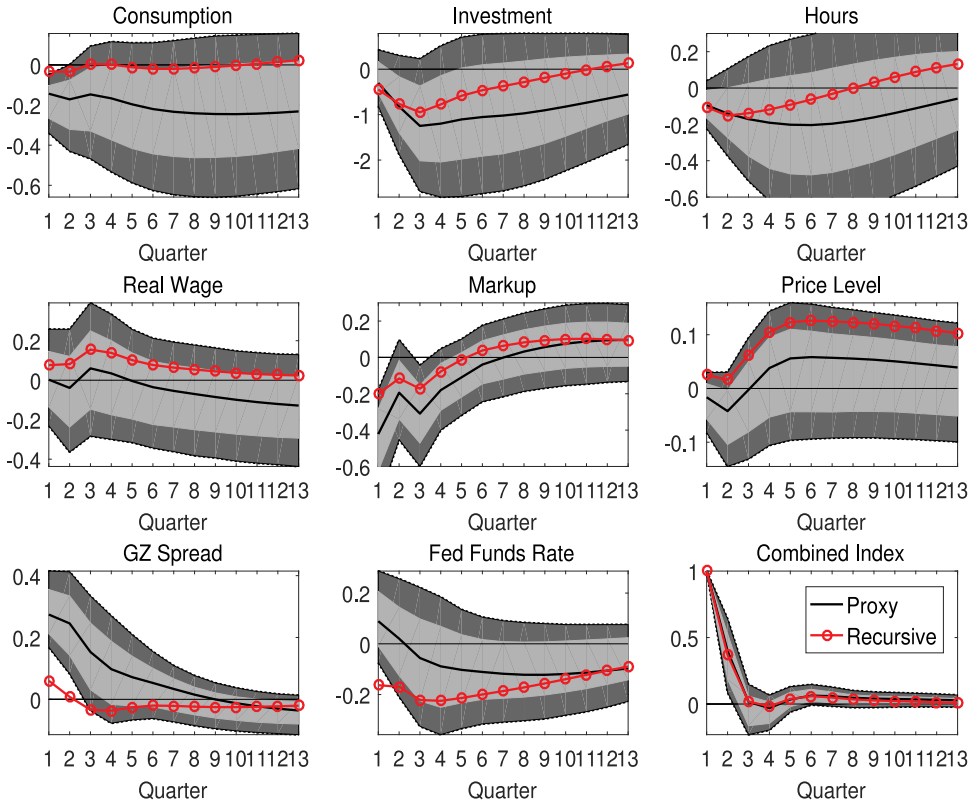


Fig. 5. Response of other variables: Extended VAR with combined index. Note: The black solid and red dotted lines indicate the impulse response of each variable to a one-unit increase in government spending policy uncertainty in the proxy SVAR and in the recursive VAR, respectively. Light gray and dark gray lines indicate 68% and 90% confidence bands for the response in the proxy VAR. Confidence bands are constructed by the bootstrap method with 10,000 replications. Changes are measured as percentage changes except the GZ spread and shadow rates, which are measured as percent point changes. The x-axis indicates quarters. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

future inflation. The monetary authority increases its policy rate in the short run in response to this future inflation but soon starts to cut its policy rate to boost the economy. Firms' external financing costs rise. Furthermore, the recursive VAR underestimates the negative effects of uncertainty, possibly owing to the identification problem.

4.2. Comparison with sign restriction VAR

This section discusses the advantages and disadvantages of the proxy VAR versus the sign restriction VAR. To this end, I estimate a sign restriction VAR and compare it with the proxy VAR. Sign restriction VAR models are popular because they are less restrictive and allow the imposition of response signs based on theoretical models.

To estimate a sign restriction VAR, I use the method proposed by Rubio-Ramirez et al. (2010) and a Bayesian method with Gibbs sampling. I use the disagreement index as the government spending uncertainty index.[21] I use a non-informative Normal–Wishart prior. To obtain the posterior distribution, I draw 10,000 and burn-in the first 9000. With the remaining 1000, I compute the median, 68%, and 90% credible sets.

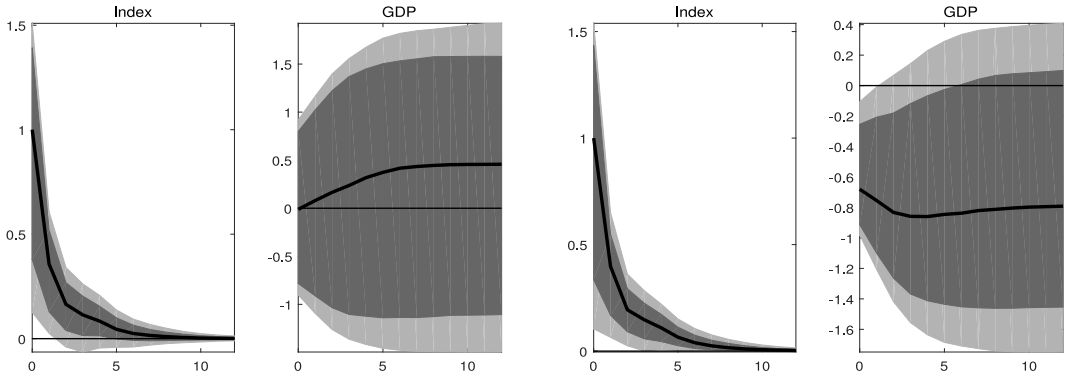
I start with the bivariate specification with sign restrictions in Table 2 as a benchmark. Shock1 means that uncertainty shocks increase the uncertainty index. Shock2 means that uncertainty shocks increase the uncertainty index but decrease GDP. The lag is set to 4.

A shock is defined as an increase in one unit of the uncertainty index. The results are shown in Fig. 6. The left panel shows the responses to Shock1. The response of real GDP is not statistically significant. The right panel shows the responses to Shock2. Though the results are qualitatively similar to those of the bivariate proxy VAR, this identification strategy does not seem to be appropriate for investigating the effects of government spending uncertainty on GDP, because the results may be driven by the restriction, rather than by the underlying data-generating process. Indeed, most studies using the sign restriction VAR do not directly impose signs on the responses of the variables of interest. Therefore, it is difficult to use a sign restriction approach in a parsimonious bivariate VAR.

[21] The results with the combined index are similar. See Appendix A.8 for the results.

Table 2
Sign restriction: Bivariate VAR. Note: the restrictions are imposed only on the contemporaneous responses.

	Shock1	Shock2
Index	+	+
Real GDP		−



(a) Shock1 (b) Shock2

Fig. 6. Responses to uncertainty shocks: bivariate VAR. Note: The black solid line indicates the median impulse response. Light gray and dark gray lines indicate 90% and 68% credible sets, respectively.

Table 3
Sign restriction: Extended model. Note: the restrictions are imposed only on the contemporaneous responses.

	Shock1	Shock2	Shock3
Index	+	+	+
RGDP		−	−
Consumption			−
investment	−		−
shadow rate			−
GDP deflator		−	+
markups	+		−
GZ spread	+		+

The proxy VAR enables me to economize the model and to investigate effects of government spending policy uncertainty on real GDP with a parsimonious specification.

Next, I estimate extended models with sign restrictions. In the extended models, I include eight variables: uncertainty index, real per capita GDP, real per capita private consumption, private per capita investment, shadow interest rate, the GDP deflator, markups, and the GZ spread. I use the sign restrictions shown in Table 3. The lag is set to 2.

In studying the effects of uncertainty on GDP and prices which are key macroeconomic variables, I try to avoid a direct imposition of signs on GDP and prices for Shock1. The negative signs on investment and GZ spread for Shock1 are in line with Redl (2017). Redl (2017), using a VAR model and various identification schemes such as sign restrictions, investigate the effects of macroeconomic and financial uncertainty in the UK. The restriction on markups is based on Fernández-Villaverde et al. (2015) and Born and Pfeifer (2014), who claim that fiscal policy uncertainty increases markups and that this countercyclical markup is essential for understanding the response of prices.[22]

Shock2 is based on the popular interpretation of uncertainty shocks as negative demand shocks. Leduc and Liu (2016) interpret macroeconomic uncertainty shocks as negative demand shocks that reduce GDP and prices. This identification strategy is more suitable for studying the effects of uncertainty shocks on the variables, except real GDP and prices. Shock3 is consistent with the proxy VAR results, which are used as a benchmark. The results are shown in Fig. 7.

Several notable results arise. First, most results with Shock1 and Shock2 are not statistically significant. For example, the responses of the key variables, GDP and price, are not significant in the model with Shock1. The responses of private investment, markups, and GZ spread are statistically significant but may be driven by the restrictions. In the results with Shock2, the responses of

[22] This assumption contradicts the results in Section 4.1. I discuss this in Section 5.

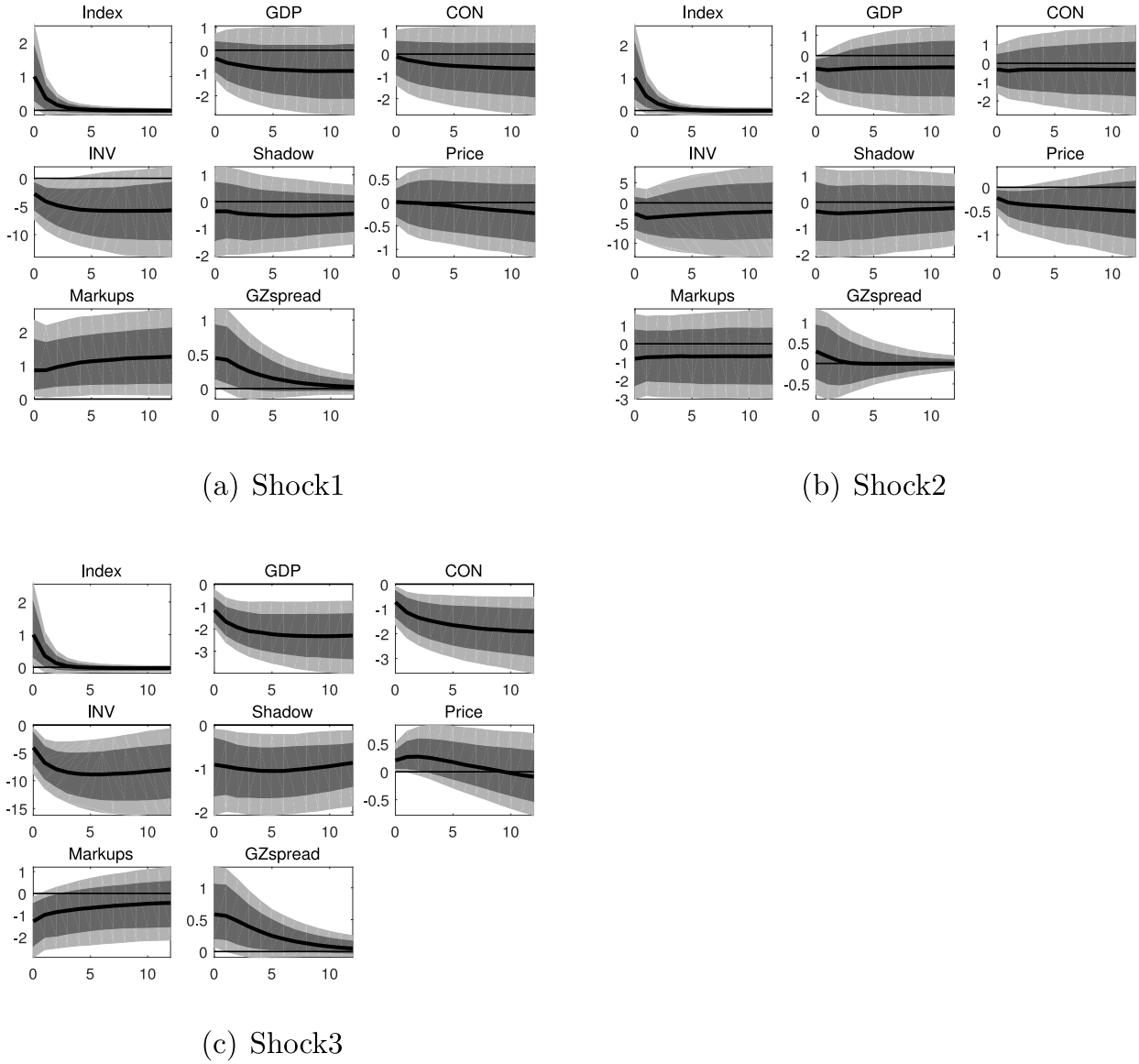


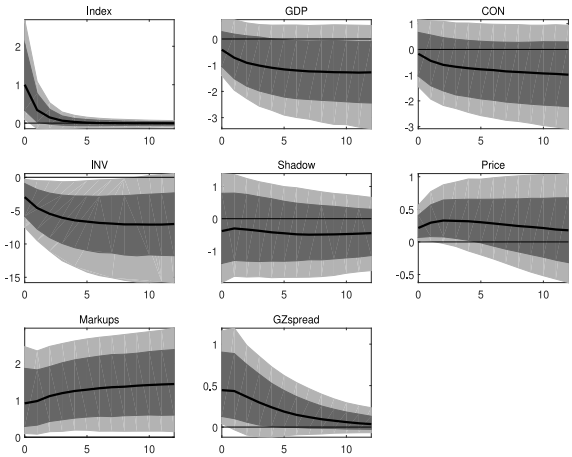
Fig. 7. Responses to uncertainty shocks: Extended model. Note: The black solid line indicates the median impulse response. Light gray and dark gray lines indicate 90% and 68% credible sets, respectively.

markups, GZ spread, private consumption, and investment are not statistically significant. In contrast to the results with Shock1 and Shock2, the results with Shock3 are statistically significant and are consistent with the results in the proxy VAR. This means that more sign restrictions can help sharpen the inferences taken from the results. In this case, however, it is not easy to determine whether the results are driven by the underlying process or by the direct restrictions.

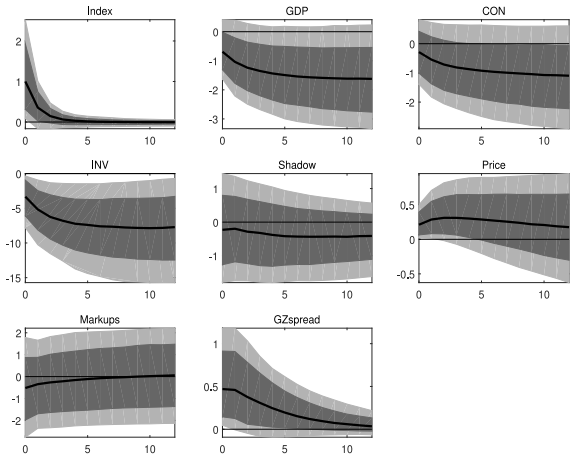
In contrast to the sign restriction approach, the proxy VAR can help sharpen the inferences taken from the results without requiring a large set of restrictions.[23] It requires only the exogeneity and relevance conditions. Moreover, depending on the research purpose, the sign restriction VAR requires several different assumptions because a direct imposition of signs on the variables of interest can generate artificial impulse responses. However, we can interpret all the responses in the proxy VAR without needing to address this concern.

This concern is stressed in Fig. 8. I estimate a sign restriction VAR with different assumptions for the response of markups in Table 4. Each shock has common restrictions on the index, private investment, price, and GZ spread but different assumptions for

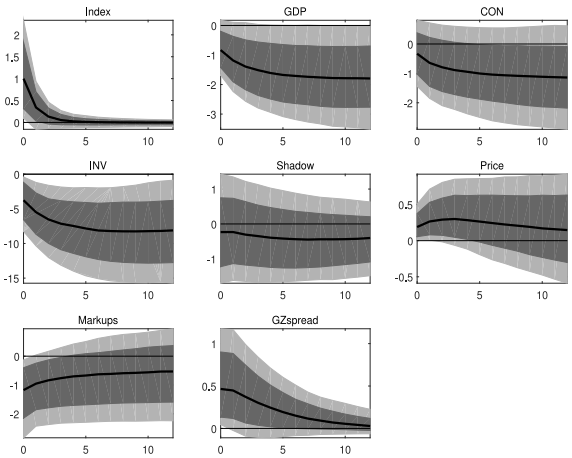
[23] The narrative sign restriction approach developed by Antolín-Díaz and Rubio-Ramírez (2018) is another option for sharpening the inferences from sign restriction VAR models.



(a) Shock1



(b) Shock2



(c) Shock3

Fig. 8. Responses to uncertainty shocks: Sensitivity. Note: The black solid indicates the median impulse response. Light gray and dark gray indicate 90% and 68% credible sets, respectively.

Table 4
Sign restriction: Different assumptions for markups. Note: The black solid line indicates the median impulse response. Light gray and dark gray lines indicate 90% and 68% credible sets, respectively.

	Shock1	Shock2	Shock3
Index	+	+	+
RGDP			
Consumption			
investment	−	−	−
shadow rate			
GDP deflator	+	+	+
markups	+		−
GZ spread	+	+	+

markups.[24] Shock1 assumes a positive response for markups, in line with the results in Fernández-Villaverde et al. (2015) and Born and Pfeifer (2014). Shock2 does not assume any sign for markups. Finally, Shock3 assumes a negative response for markups, in line with the proxy VAR results.

The results show that the responses of markups are sensitive to the assumptions, even when restrictions are imposed only on the contemporaneous responses. All other results are similar, but the statistical significance levels for GDP differ across the identifications. The response of GDP is not statistically significant in the result with Shock1. Thus, we should be careful when interpreting the impulse responses of variables on which we directly impose sign restrictions, particularly. I discuss the response of markups and the behavior of price in the next section.

Obviously, the proxy VAR has shortcomings. It needs proxy variables, which should be closely related to the shocks of interest but should not be related to others. Indeed, it is difficult to find proxy variables. Most proxy variables in the macroeconomics literature suffer from a weak IV problem caused by low relevance. For example, Hebous and Zimmermann (2018) point out that some of the results in Mertens and Ravn (2013) suffer from the weak IV problem. The results are thus sometimes not reliable, and we sometimes cannot use standard inference methods.

5. Discussion

The empirical results of the proxy VAR are clear: uncertainty about government spending policy reduces output, private consumption, and private investment. Those results are broadly in line with the results of previous DSGE studies such as Born and Pfeifer (2014) and Fernández-Villaverde et al. (2015). They show that uncertainty about fiscal policy, measured by time-varying volatility, hurts economic activity through the lens of the estimated DSGE model. The precautionary saving motive mainly reduces private consumption and investment in response to uncertainty shock in their DSGE. Moreover, the empirical results in this study support their DSGE predictions of a drop in real wages and labor hours. A decrease in real wages is caused by an increase in the household labor supply induced by the precautionary saving motive. However, firmsâ;; labor demands decrease because aggregate demand falls. Therefore, real wages and labor hours drop. Furthermore, their DSGE models show that fiscal uncertainty shocks generate inflation[25] The empirical result in Section 4 supports this view.[26]

However, the detailed mechanism for inflation is somewhat different. The main mechanism of inflation generation is the countercyclical markups in their DSGE models. In Born and Pfeifer (2014), firms' precautionary pricing behavior generates inflation. Firms want to increase their prices in response to fiscal uncertainty shocks because they do not want to be stuck with excessively low prices under the sticky price assumption and the convexity of marginal profit curve. To this end, firms increase their markups, which generates inflation, even though real wages and marginal costs decrease in response to uncertainty shocks. Fernández-Villaverde et al. (2015) suggest a similar channel. In their model, firms' upward pricing bias behavior causes inflation as a response to uncertainty shocks. In their model, it costs firms more to set excessively low prices relative to their competitors than to set excessively high prices because of the asymmetric profit function. Thus, firms want to increase their prices in response to uncertainty shocks. Therefore, markups and price levels increase. Fernández-Villaverde et al. (2015) claim that this countercyclical markup channel is a key transmission channel of capital tax policy uncertainty.[27]

In contrast to the DSGE studies, the empirical results in Section 4 show that markups decrease in response to government spending policy uncertainty shocks. This procyclical markups is matched to other empirical evidence. For example, the VAR results in Born and Pfeifer (2017) show that the price markups decrease in response to macroeconomic uncertainty shocks, similar to this study's results. Furthermore, Nekarda and Ramey (2013) claim that markups are procyclical or acyclical depending on demand shocks, though they do not directly consider uncertainty shocks. What, then, drives the difference between the results in the DSGE studies and the results in this study? One candidate is a source-dependent transmission mechanism. Fernández-Villaverde et al. (2015) focus on capital tax policy uncertainty, while I focus on government spending policy uncertainty. It is possible that the responses to uncertainty shocks vary depending on their sources.

The theory concerning external financing costs owing to financial frictions is an interesting way of understanding inflation. The empirical results show that the GZ spread, which is a proxy of firms' external financing costs, increases in response to government spending policy uncertainty shocks. This means that firms' external financing costs, which can be a component of marginal costs, increase. When this cost-push effect dominates a drop in markups, price levels may increase. Indeed, researchers have long discussed this cost-push channel caused by financial frictions.[28] In particular, Christiano et al. (2015) introduce the working capital channel in their DSGE model to explain the behavior of inflation during the Great Recession. In their model, the external financing premium increases in response to adverse shocks, which raises the cost of working capital and marginal costs. An increase in marginal costs

[24] The positive restriction on price is in line with Born and Pfeifer (2014) and the proxy VAR results.

[25] The VAR analysis in Fernández-Villaverde et al. (2015) shows that the response of price level is negative. They introduce the modified Taylor rule in their baseline DSGE to replicate this VAR result since their DSGE with the common Taylor rule fails to generate deflation. However, their modified Taylor rule is not conventional.

[26] The empirical evidence on the response of inflation to uncertainty shocks seems to be mixed. For example, Jones and Olson (2013) show that the time-varying correlation between inflation and uncertainty is positive after the late 1990s. The VAR result in Bordo et al. (2016) shows that the response of price level is positive, which is similar to the result in this study. In contrast to those studies, the VAR evidence in Carriero et al. (2015) and Leduc and Liu (2016) shows that macro uncertainty shocks lower inflation.

[27] Basu and Bundick (2012) also emphasize the role of countercyclical markups in an understanding of the effects of uncertainty shocks.

[28] See Marvin J. Barth and Ramey (2001); Chowdhury et al. (2006), and others.

owing to financial frictions is crucial to explaining the behavior of inflation during the Great Recession. However, the cost-push channel has received relatively little attention in the literature on uncertainty shocks. For example, Born and Pfeifer (2014) and Fernández-Villaverde et al. (2015) do not consider it. In most studies, moreover, uncertainty shocks are seen mainly as the adverse aggregate demand shocks that reduce output and lower inflation.[29] However, it is not easy to explain the evidence on inflation produced in this study using the standard adverse-demand-shock view. Moreover, the empirical evidence on procyclical markups and inflation seems to be incompatible with the standard DSGE model, which depends on the countercyclical markups to explain inflation. Thus, it is worth developing a theoretical model incorporating procyclical markups and inflation in response to government spending policy uncertainty shocks. The cost-push channel caused by financial frictions may be a fruitful direction.[30]

6. Concluding remarks

This study investigates the adverse effects of government spending policy uncertainty on economic activity using US time series data. I build government spending policy uncertainty indexes based on the SPF forecast disagreement measure and the government spending uncertainty measure provided by Baker et al. (2016). To isolate the exogenous variation of the uncertainty index, I use the proxy SVAR model developed by Stock and Watson (2012) and Mertens and Ravn (2013) and defense news constructed by Ramey and Zubairy (2014) as an instrument for the uncertainty index.

The results offer two main findings. First, an increase in government spending policy uncertainty has negative, sizable, and prolonged effects on GDP, private consumption, and private investment. Furthermore, it reduces real wages, labor hours, and markups, while it generates moderate inflation. An increase in external financing costs induced by financial frictions may explain the moderate inflation in response to government spending uncertainty shocks. Second, the recursive VAR tends to underestimate the adverse effects of government spending policy uncertainty on the economy, possibly owing to the weakness of the recursive VAR model.

One policy suggestion emanating from this study is that clear announcements of future spending paths can help enhance government spending policy effectiveness. The empirical work suggests that defense news, which can act as a guide to future paths of government spending, reduces uncertainty about government spending policy. This means that clear guidance about future government spending paths may reduce government spending policy uncertaintys adverse effects.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jmacro.2019.103124

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[29] See Leduc and Liu (2016).

[30] Another possible approach is the wage-markups channel suggested by Born and Pfeifer (2017). They find that price markups decrease in response to uncertainty shocks while wage markups increase in their VAR analysis. An increase in wage markups may raise wage inflation and price levels. This channel may also explain inflation in response to uncertainty shocks.

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