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ABSTRACT

Policy Uncertainty and Aggregate Fluctuations*

This paper estimates the impact on the US economy of four types of uncertainty about (i) government spending, (ii) tax changes, (iii) public debt sustainability and (iv) monetary policy. Following a one standard deviation shock, uncertainty about debt sustainability has the largest and most significant impact on real activity, with negative effects on output, consumption and investment after two years around 0.5%, 0.3% and 1.5% respectively. Uncertainty on the other economic policies has also detrimental consequences but these tend to be smaller and short-lived, especially for taxes and monetary policy. About 30% of output fluctuations are explained by policy uncertainty at most frequencies, with the lion's share accounted for by debt sustainability. Our results are based on a new empirical framework that allows the volatility of identified shocks to have a direct impact on the endogenous variables of an otherwise standard structural VAR.

JEL Classification: D80, E32 and E63
Keywords: debt sustainability, economic policy uncertainty and long-run effects.

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*The views in this paper are those of the authors and do not necessarily reflect the views of the Bank of England or the Monetary Policy Committee. Surico gratefully acknowledges financial support from the European Research Council Starting Independent Grant (Agreement 263429). The graphs in this paper are best viewed in color.

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1 Introduction

In response to the great recession of 2007-2008, governments and central banks across the industrialized world have resorted to a wide set of *short-run* stabilization policies, ranging from boosts in public spending, labour tax refunds, consumption tax cuts, near zero short-term interest rates and nontraditional balance-sheet monetary tools. The breadth and depth of the economic conditions, however, have called into questions the effectiveness of conventional and unconventional short-run stabilization policies and, six years since the outbreak of the financial crisis, the uncertainty around the impact of existing fiscal and monetary interventions does not seem to have dissipated. Furthermore, the surge of public debt associated with the recent short-run stabilization policies has triggered a perhaps even more pervasive uncertainty about the *long-run* sustainability of existing fiscal positions.

The significance of long-run fiscal uncertainty is exemplified in Figure 1, which reports the debt-to-gdp ratio projections prepared by the Congressional Budget Office (CBO). The extended *baseline* scenario reflects the assumption that current laws generally remain unchanged, which is lawmakers will allow changes that are scheduled under current law to occur, forgoing adjustments routinely made in the past that have boosted deficits. The extended *alternative* fiscal scenario is constructed under the hypothesis that certain macroeconomic policies that have been in place for a number of years will be continued going forward and that some provisions of law which might be difficult to sustain for a long period will be modified, thus maintaining what some analysts might consider "current policies", as opposed to current laws.

Three points are worth emphasizing about the CBO projections. First, the two

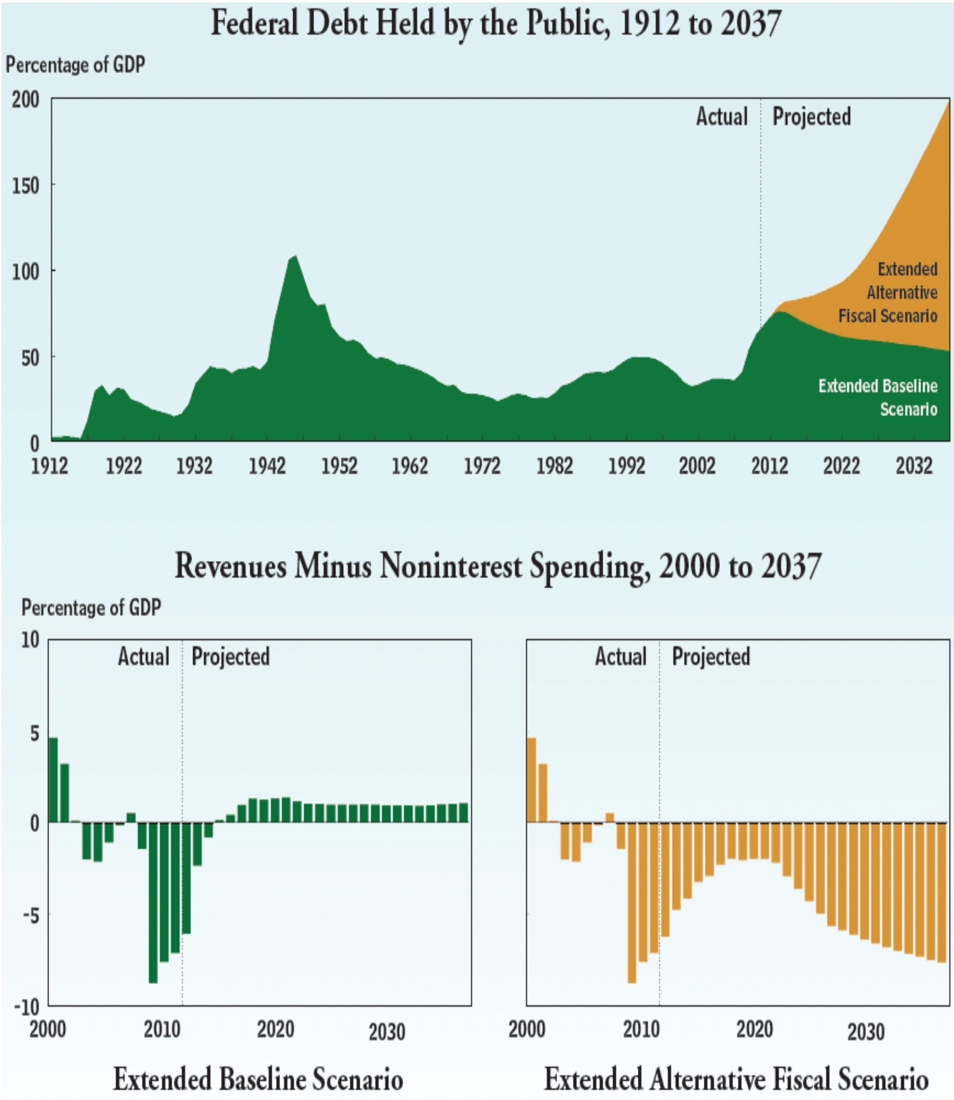

Figure 1: Federal Debt Held by the Public Under CBO's Long-Term Budget Scenarios. Source: CBO 2012 Long-Term Budget Outlook, available at http://www.cbo.gov/sites/default/files/cbofiles/attachments/06-05-Long-Term_Budget_Outlook.pdf

scenarios produce debt levels which are apart from one other by more than 150% of GDP by 2037. Second, the discrepancy increases with the forecast horizon. Third, the two scenarios are computed under maintained assumptions about the effectiveness of government and tax policies on real activity, and therefore they abstract implicitly from uncertainty about the effectiveness of short-run policies.

Despite the recognition in policy and academic circles that short-run uncertainty (about the *current* stance of fiscal and monetary policy) and long-run uncertainty (about the *future* sustainability of public debt) may *both* have a highly detrimental impact on the economic outlook, the empirical literature on policy uncertainty has, so far, mostly focused on government spending and tax policies.

In this paper, we complement existing contributions by estimating the impact on real activity of four types of policy uncertainty associated with *(i)* government spending, *(ii)* tax changes, *(iii)* public debt sustainability and *(iv)* monetary policy. While the focus on short-run stabilization policies is shared with earlier studies, the analysis of long-run fiscal uncertainty is –to the best of our knowledge– new.

Our main results can be summarized as follows. First, uncertainty about long-run fiscal sustainability has the largest and most significant impact on real activity, with effects of about 0.5%, 0.3% and 1.5% after two years on GDP, non-durable consumption and investment respectively. These estimates are sizable: on the basis of our empirical model, we calculate that to generate effects of similar magnitude a monetary policy shock would need to move the short-term nominal interest rate by about 60 basis points. Second, the impact of uncertainty on the other economic policies is typically smaller but still significant, with the impact of government spending volatility being typically larger and more persistent than those of tax changes and monetary policy volatility. Third, the contribution of economic policy uncertainty to fluctuations in output and consumption is around 30% while the contribution to variation in investment is about 25%. Fourth, shocks to public debt volatility make the largest contributions to fluctuations in real activity, accounting for about half of the total share explained by economic policy uncertainty shocks at horizons beyond the first year.

In our empirical model, the volatility of *identified* shocks is allowed to have a direct impact on the variables of a Structural Vector Autoregression (SVAR).[1] This is an advancement relative to existing SVAR studies with stochastic volatility which do not feature a direct link from second moments to first moments (see for instance Primiceri, 2005, Canova and Gambetti, 2010, and Gambetti, 2011). Furthermore, by modelling the dynamic relationship between the volatility of *identified* shocks and endogenous variables, our framework can shed light on the causality behind the dynamic correlations between the uncertainty measures and other macroeconomic variables reported, among others, by Leahy and Whited (1996), Baker, Bloom and Davis (2012), Stock and Watson (2012) and Caggiano, Castelnuovo and Groshenny (2013).

Our paper contributes to a growing literature on quantifying the effects of economic policy uncertainty on the real economy following the influential work by Baker, Bloom and Davis (2012). On the macro side, Fernández-Villaverde, Guerrón-Quintana, Kuester and Rubio-Ramírez (2011) and Bonn and Pfeifer (2012) use estimated volatility of government spending and tax policy shocks in calibrated general equilibrium models of the U.S. economy to study the real effects of short-run fiscal interventions. Exploiting cross-country variation in natural disasters, terroristic attacks and unexpected political events, Baker and Bloom (2012) find that uncertainty has detrimental effects on both

[1] Throughout the paper, we will refer to 'volatility of structurally identified shocks' as 'uncertainty'.

the level and volatility of GDP growth. Brogaard and Detzel (2012) quantify the impact of a search-based policy uncertainty measure on stock market returns. Using firm-level data, Julio and Yook (2010) report that government policy uncertainty, as measured by the timing of national elections, has a dampening effect on corporate investment while Handley and Limao (2012) assess the impact of uncertainty about trade policies on firms' investment and entry decisions. It is worth emphasizing that, unlike earlier contributions, our main focus is on uncertainty about fiscal sustainability.

The paper is organized in six parts. In section 2, we lay out the empirical method. In section 3, we present the estimation algorithm and the restrictions to isolate fiscal and monetary policy innovations. The main results are reported in section 4 before evidence from augmented specifications featuring either consumption or investment in section 5. In the last part, we assess the robustness of our findings to alternative identification schemes for the fiscal policy shocks as well as to including the average cost of public debt and consumer confidence.

2 Empirical Model

In this section, we lay out a simple generalization of structural VARs with stochastic volatility, which we show to be well-suited to study the impact of economic policy uncertainty on macroeconomic variables. In particular, we propose the following empirical model:

$$Z_t = c + \sum_{j=1}^{P} \beta_j Z_{t-j} + \sum_{j=0}^{J} \gamma_j \tilde{h}_{t-j} + \Omega_t^{1/2} e_t, e_t \tilde{\ } N(0,1) \tag{1}$$

where

$$\Omega_t = A^{-1} H_t A^{-1\prime} \tag{2}$$

In equation (1), the vector Z_t denotes the $i = 1, .., N$ macroeconomic variables while $\tilde{h}_t = [h_{1t}, h_{2t}...h_{Nt}]$ refers to the log volatility of the structural shocks in the VAR. The structure of the matrix H_t in equation (2) is given by $diag(\exp(h_{1t}), \exp(h_{2t})... \exp(h_{Nt}))$. The structure of the A matrix is chosen by the econometrician to model the contemporaneous relationship amongst the reduced form shocks. We discuss our choice for the structure of the A matrix in Section 3.

The transition equation for the stochastic volatility is given by:

$$\tilde{h}_t = \theta \tilde{h}_{t-1} + Q^{1/2}\eta_t, \eta_t \tilde{~} N(0,1), E\left(e_t, \eta_{i,t}\right) = 0, i = 1, 2..N \tag{3}$$

There are two noteworthy features about the complete system (1)-(3). First, equation (1) allows the volatility of the *structural* shocks $\tilde{h}_t$ to have a direct impact on the endogenous variables Z_t.[2] Second, the structure of the matrix A in equation (2) determines the interpretation of the structural shocks and hence their volatility H_t. As discussed below, these two features imply that, by imposing an appropriate set of restrictions on the A matrix, our framework is able not only to identify monetary and fiscal shocks but also to investigate the impact of innovations to the volatility of these structural shocks on the macroeconomic variables in the vector Z_t.

Note that equation (3) makes the assumptions that *(i)* the shocks to the volatility equation η_t and the observation equation e_t are uncorrelated and *(ii)* the reduced form residuals of equation (3) have a non-diagonal covariance matrix Q, thereby allowing for the possibility of co-movements in volatility. With assumption *(i)* in place and with an estimate of $Q^{1/2}$, one can interpret an innovation to the i^{th} element of η_t as a shock to

[2] In our specification it is the log volatility (rather than its level) to enter the VAR equations. This is primarily because the level specification proved to be far more computationally unstable. In particular, the level specification is sensitive to the scaling of the variables with the possibility of overflow whenever the scale of the variables is relatively large.

the volatility of the i^{th} structural shock and then calculate the response of h_t and Z_t. If assumption *(i)* is relaxed, further identifying restrictions are required to separate the innovation to the volatility from the innovation to the level.

Under the more general scenario of a full covariance matrix among the volatility and the level innovations, the identification of the volatility shocks is substantially more convoluted. In particular, there is no simple way to assign $h_{i,t}$ to a particular structural shock. In contrast, the assumptions in equation (3) allows us to use standard identification schemes.[3]

Finally, the model presented above is related to a number of recent empirical contributions. The structure of stochastic volatility, for instance, closely resembles the formulations used in time-varying VAR models (see for instance Cogley and Sargent, 2005, Primiceri, 2005, Canova and Gambetti, 2009 and 2010, and Canova, Gambetti and Pappa, 2008). Our model differs from these studies in that it allows a direct impact of the volatilities on the level of the endogenous variables.

The framework proposed in this paper can be thought of as a multivariate extension of the stochastic volatility in mean specification put forward by Koopman and Uspensky (2000) and applied by Berument, Yalcin and Yildirim (2009) and Lemoine and Mougin (2010). Furthermore, our model shares similarities with the stochastic volatility specifications with leverage studied by Asai and McAleer (2009).

In closing, it is worth emphasizing that, unlike earlier contributions, our empirical method is designed to quantify the dynamic effects of the volatility of *identified* shocks and therefore it can shed light on the causality behind the reduced-form correlations between uncertainty measures and macroeconomic variables available in the literature.

[3] Mumtaz and Zanetti (2013) employ a simplified version of the empirical model proposed here to examine the impact of monetary policy volatility shocks using data on output, inflation and short rate.

3 Estimation and identification

In this section, we present the Gibbs sampling algorithm to estimate the empirical model presented in the previous section and the identification strategy to isolate the dynamic effects of the policy volatility shocks. The vector of endogenous variables, Z_t, contains in order: government spending, real per-capita GDP, the Consumer Price Index (CPI), net taxes, federal government debt held by the public, the three-month Treasury Bill rate (3m TB rate) and the University of Michigan consumer confidence index.[4] The three fiscal variables are measured relative to nominal GDP. As the model contains a large number of endogenous variables, we keep the specification parsimonious and restrict the lag lengths P and J to 2 and 1 respectively.[5] We include a time-trend τ_t to account for possible trends in the macroeconomic variables.

3.1 The Gibbs sampling algorithm

The non-linear state space model (1)-(3) is estimated using a Gibbs sampling algorithm. The appendix presents details of the priors and the conditional posterior distributions while a summary of the algorithm is laid out below, proceeding in the following steps:

1. Conditional on a draw for the stochastic volatility $\tilde{h}_t$, and the matrix A, equation (1) represents a VAR model with heteroskedastic disturbances. We re-write the VAR as a state space model and draw from the conditional distribution of $\Gamma = [\beta, \gamma]$ using the algorithm in Carter and Kohn (2004).

2. Conditional on a draw for $\tilde{h}_t$ and Γ, the elements of the matrix A can be drawn

[4] The results below are robust to replacing consumer confidence with a stock price index such as Standard & Poors' 500.

[5] The results below are robust to setting either P or J to 4, though the estimates are less precise because of the considerably larger number of parameters.

using a series of linear regression models amongst the elements of the residual matrix $v_{it} = \Omega_t^{1/2} e_{it}$, as shown in Cogley and Sargent (2005). Conditional on $\tilde{h}_t$, the autoregressive parameters θ_i and variances Q_i can be drawn using standard results for linear regressions.

3. Conditional on Γ, A, θ_i and Q_i, the stochastic volatilities are simulated using a date by date independence Metropolis step as described in Jacquier, Polson and Rossi (2004) - see also Carlin, Polson and Stoffer (1992).

We use 200,000 replications and base our inference on the last 10,000 replications. The recursive means of the retained draws (see Appendix) show little fluctuations, thereby providing informal evidence for convergence of the algorithm.

3.2 Identification of the policy shocks

The statistical identification of the stochastic volatilities requires a normalization of the innovation covariance matrix Ω_t. This can be conveniently obtained by a Cholesky factorization of the matrices Ω_t and Q. While such a normalization has no specific economic content, an appropriate ordering of the endogenous variables in the vector Z_t can allow one to attach an economic interpretation to the orthogonalized shocks (see Primiceri, 2005, and Canova and Gambetti, 2009).

The specific ordering proposed above assumes that government spending (consumer confidence) is the most (least) exogenous variable in the system. The first assumption is justified by the lags of fiscal policy and follows the identification strategy for spending shocks in Blanchard and Perotti (2002) and Perotti (2007, p. 192), who argues that "by and large, [discretionary] government spending on goods and services does not respond to macro economic news within a quarter." Ordering consumer confidence last appeals to the same rationale used in the identification strategy by Bernanke, Boivin and Eliasz (2005), who note that fast moving variables -like financial and confidence variables- are the most likely to react within the quarter to macroeconomic news. The ordering of the remaining variables implies that the short-term nominal interest rate is allowed to react contemporaneously to the slower-moving variables while the latter can respond only with a quarter lag to unanticipated movements in the former. This is a rather standard identification for monetary shocks in the VAR literature.

Given the computational complexity of estimating our proposed model, in the baseline specification we try to keep the (perhaps more controversial) identification of the other fiscal shocks as simple as possible. In particular, we follow Caldara and Kamps (2008) in assuming that taxes are affected contemporaneously by GDP and prices but react only with a lag to the short-term rate and the consumer confidence index. Therefore, the main difference relative to the identification of tax shocks in Perotti (2007) is that we estimate (rather than impose fixed values for) the contemporaneous elasticities of taxes to output and inflation.[6] Perotti (2007) also sets to zero the contemporaneous elasticities of taxes and government spending to the interest rate as well as the contemporaneous elasticity of government spending to output. These identifying restrictions are consistent with ordering government spending before output and the interest rate as well as ordering taxes before the interest rate but after output and inflation, as we do here. We show in the sensitivity analysis below that using the scheme in Blanchard Perotti (2002) to identify net tax shocks produces similar results.

Finally, the debt-to-gdp ratio is contemporaneously affected by innovations to the government primary balance but spending, taxes, output and inflation adjust to in-

[6] Caldara and Kamps (2012) show that imposing fixed values for these elasticities may distort the inference on the dynamic effects of fiscal shocks.

novations to the public debt after at least one quarter. The reason for including the debt-to-gdp ratio in our empirical model is twofold. First, the transversality condition on the government intertemporal budget constraint implies that the current level of debt equals the net present value of *expected future* primary balances. As expectations of future economic growth as well as expectations of future discretionary fiscal measures are not directly observed, we interpret the shocks to public debt as temporary deviations from the fiscally sustainable equilibrium path, as due for instance to unanticipated deviations of *future* spending and tax policies from the projections of current ones (see Figure 1). Second, Favero and Giavazzi (2012) demonstrate that omitting debt dynamics has the potential to generate distorted inference on the impact of fiscal shocks on the real economy. In the sensitivity analysis below, we show that our results are robust to using the exogenous tax liability changes proposed by Romer and Romer (2010) as a measure of tax shocks as well as to adding the average cost of public debt and modifying the ordering of the debt-to-gdp ratio in the SVAR.

4 Empirical evidence

The model (1)-(3) is estimated on U.S. data over the period 1980q1-2011q4 using the identification scheme described in the previous section. Data between 1970q1 and 1979q4 are used to initialize the priors. We begin by reporting the estimated time series for the volatility of the fiscal and monetary shocks, which we interpret as measuring economic policy uncertainty. Then, we move to the impulse response function analysis and finally to the forecast error variance decomposition. In the next section, we will investigate the effects of policy uncertainty shocks onto two augmented systems which also include consumption and investment respectively.

4.1 Measuring economic policy uncertainty

The measures of policy uncertainty produced by our empirical model are presented in Figure 2, together with the policy uncertainty index (dashed blue line) proposed by Baker, Bloom and Davis (2012).[7] The approach proposed in this paper allows us to distinguish among uncertainty about the *current* stance of fiscal policy, as exemplified by the standard deviation of the shocks to *(i)* government spending and *(ii)* net taxes; uncertainty about the *future* stance of fiscal policy, as exemplified by the standard deviation of the shocks to *(iii)* the debt-to-GDP ratio, and uncertainty about *(iv)* monetary policy. As discussed above, the interpretation of the volatility of the public debt shock as a measure of uncertainty about future fiscal sustainability follows from the equilibrium condition implied by imposing the transversality condition on the government intertemporal budget constraint: innovations to public debt are interpreted as temporary deviations from this equilibrium path.

Our measures of policy uncertainty share a significant number of turning points with the index put forward by Baker, Bloom and Davis (2012). The correlation coefficients range from 0.79 for government spending to a value of 0.60 for net taxes. Furthermore, the peaks of the standard deviations in Figure 2 tend to coincide with the introduction of unprecedented policy measures as identified –for instance– by the narrative accounts of the U.S. economic history. This includes the Volcker experiment of non-borrowed reserve targeting in the early 1980s, the accumulation of public debt associated with the large budget deficits of the Reagan administration, the increases in spending triggered by the first Gulf war and by the 'War on Terror' campaign following the 9/11 attacks,

[7] The authors combine into a single index of economic policy uncertainty the frequency of news media references, the number of federal tax code provisions set to expire in future years and the extent of forecaster disagreement over future inflation and federal government purchases.

the changes in taxes and spending legislated in the 'Economic Growth and Tax Relief Reconciliation Act' of 2001 and the 'Economic Stimulus Act' of 2007 as well as the financial sector rescue plan of 2008.

Finally, the volatility of public debt shocks during the great recession is unprecedentedly large, both from the historical perspective of our sample period and in comparison to the time profile of the government spending uncertainty. This is worth noting because the policy interventions of 2007-2009 were, at least partially, the endogenous response to macroeconomic conditions. Still, Figure 2 suggests that the long term finance, and possibly the scale, of these interventions (as captured by public debt) rather than the interventions per sè (as captured by government spending) appear the most significant and unanticipated source of uncertainty.

Overall, we regard the good match between swings in our uncertainty measures and the timing of well-known episodes of unprecedented fiscal and monetary interventions as sufficiently reassuring to move to the impulse response and variance decomposition analyses of the macroeconomic variables to the economic policy uncertainty shocks.

4.2 Impulse response functions

In Figure 3, we report the dynamic effects of the four policy uncertainty measures on output, prices, the short-term rate and consumer confidence following a one standard deviation shock.[8] The red lines represent median estimates while the shaded areas are 68% central credible sets. Under a normal distribution, this corresponds to one standard error bands and is the same confidence level reported by Baker, Bloom and Davis (2012). Each column refers to a different economic policy uncertainty shock, from government

[8]The standard deviation of the four policy uncertainty shock are 0.56, 1.04, 0.89 and 0.71 for public debt, net taxes, government spending and monetary policy respectively.

spending and taxes on the left to public debt and monetary policy on the right.

The main results can be summarized as follows. First, uncertainty about fiscal sustainability -as measured by shocks to the volatility of the debt to GDP ratio in the third column- has the largest effect on real activity, with a peak around 0.5% after two years.[9] The response of GDP is significant and long-lasting, inheriting the persistence of the volatility process. Second, the impact of government spending volatility shocks on real activity tends to be smaller than the impact of fiscal sustainability, especially at shorter horizons, though the estimates are relatively less precise. Third, the effects of uncertainty shocks to net taxes and monetary policy are smaller and significantly shorter-lived. Fourth, CPI does not appear to be significantly altered by any policy volatility shock with the exception of innovations to the debt-GDP ratio. Furthermore, only uncertainty about fiscal sustainability has a significantly positive effect on the short-term nominal rate on impact. Finally, government spending and monetary policy volatilities have significantly negative consequences for consumer confidence during the first year after the shock.[10]

In summary, the peak effects on real activity of economic policy uncertainty shocks, especially debt sustainability, tend to be sizable. To give a sense for the magnitude presented in this section, we calculate that –according to the estimates of our empirical model– it would take a movement in the short-term rate of about 60 basis points for a

[9] This peak effect is about *three* times smaller than the peak effect estimated by Baker, Bloom and Davis (2012) using a monthly VAR, a Cholesky identification and industrial production as measure of real activity. On the other hand, the size of our shock is about *two* times smaller than the size that would have been implied by the metrics proposed by Baker, Bloom and Davis (2012), who consider a shock as large as the difference in their policy uncertainty index between 2006 and 2011.

[10] The negative (although insignificant) response of the short-term nominal rate to a debt sustainability uncertainty shock at horizons between two and five years can be rationalized by noting that *(i)* the 3 month maturity of the short rate is significantly shorter than the average maturity on US public debt, *(ii)* the output response is also significantly negative and the short-term rate reacts to that through the monetary policy rule.

monetary policy shock to generate an effect on output similar to the effect generated by a one standard deviation shock to the volatility of the debt to GDP ratio.

4.3 Variance decomposition

The impulse response function analysis of the previous section suggests that policy uncertainty shocks may have large effects on the real economy as well as on consumer confidence. In Figure 4 of this section, we evaluate their contributions to macroeconomic fluctuations by presenting median estimates for the forecast error variance decomposition of the endogenous variables of the VAR. It is worth noting that the presence of stochastic volatility in the VAR model makes the variance of the structural shocks time-varying. This implies that the contribution to the forecast error variance are also time-varying. In the results below, we report the average of the forecast error variance decomposition across the entire sample, but we emphasize here that similar findings are obtained over different sub-periods.[11]

Overall, policy uncertainty shocks account for about 30% of fluctuations in GDP (CPI) at most horizons (at horizons beyond five years) as well as about 25% variations in the 3m TB rate after two years and some 20% in consumer confidence. The contributions to short-run movements is typically smaller for CPI and the short-term rate. The largest variance share tends to be accounted for by fiscal sustainability followed, in order, by government spending, monetary policy and a small portion explained by net taxes. For virtually all variables, the contribution of the volatility shocks to both government spending and debt-GDP ratio tends to increase with the forecast horizon. Interestingly, also the variations in government spending and taxes feature prominently

[11] On the other hand, the impulse response functions to uncertainty shocks are fixed over time.

the uncertainty about fiscal sustainability. Finally, the relative contribution of monetary policy uncertainty is more pronounced for the short-term rate and consumer confidence.

5 The response of consumption and investment

In this section, we expand the vector of endogenous variables to explore the impact of the policy uncertainty shocks onto some of the components of GDP, namely consumption and investment. Preliminary attempts to estimate the model (1)-(3) using nine variables and the weakly informative priors described in the Appendix led to a significant increase in the computational burden as well as imprecise estimates. Hence, we report below results from two 8-variable specifications in which either real per-capita expenditure on non-durable goods and services or real gross private investment are used (before GDP) as an additional variable. As the impulse responses of GDP, CPI, 3m TB rate and consumer confidence appear similar to those from the 7-variable VAR of the previous section, we only report the dynamic effects of the uncertainty shock to fiscal and monetary policy on consumption and investment.

Each column of Figure 5 refers to a separately estimated model and provides important qualifications to the findings presented in the previous section. The largest impact occurs on investment in the right column, following a shock to the volatility of government debt. This impulse response peaks at 1.8% one year ahead, becomes insignificant after two years and then reverts slowly towards its average value. The investment responses to the government spending and monetary policy volatility shocks are always insignificant whereas taxes uncertainty exerts its maximum impact within the first year, at a peak around 1.3%. As for consumption, the magnitudes of the responses are uniformly smaller. In the left column of Figure 5, only the dynamic effects of debt sustainability and government spending volatility shocks appear significant, displaying both a similar magnitude and a similar degree of persistence.

As for the variance decomposition, Figure 6 reveals that policy uncertainty shocks account for around 30% and 25% of fluctuations in consumption and investment respectively, with portions that tend to increase with the forecast horizon. Uncertainty about fiscal sustainability confirms itself as the main driver of policy uncertainty, with shares up to 15% from the second year after the shock onwards. The relative contribution of government spending (net taxes) volatility appears larger for fluctuation in consumption (investment) whereas the fraction accounted by volatility shocks to monetary policy is below one tenth, at values similar to those reported for output.

6 Sensitivity analysis

In this section, we assess the robustness of our conclusions to four variants of the restrictions imposed onto the baseline specification of Section 4 to recover the fiscal shocks. The first sensitivity analysis is based on the identification of tax shocks proposed by Blanchard and Perotti (2002). In line with their baseline VAR, we only consider a specification with government spending, GDP and net taxes to which we add public debt. The reason for this choice is that in order to apply Blanchard and Perotti's scheme, we need to transform the model in a way that standard Bayesian methods for linear regressions are applicable. In the context of our framework, this is computationally feasible only using a reduced system. The second robustness check uses the measure of tax shocks proposed by Romer and Romer (2010). In the next two exercises, we focus on the identification of public debt shocks. In line with our desire to isolate temporary deviations from the fiscally sustainable path, we add to the baseline specification a measure of the average cost of serving the debt, which we order before the debt to GDP ratio. In the specification denoted by 'a' ('b'), we order the measures of public debt and its average cost before (after) the short-term interest rate.

The results of these sensitivity analyses are reported in Figure 7, which reports the median estimates for the dynamic effects of the shocks to our measures of policy uncertainty on GDP. Each chart presents the output response to a volatility shock to public debt (black line with dots), government spending (red line with asterisks), taxes (light blue solid line) and monetary policy (green line with crosses).

In all models, the shock to public debt uncertainty is associated with the largest negative peak effect on real activity, with values ranging from about -0.3% in the specification based on Romer and Romer's measure of exogenous tax changes to -1.1% using Blanchard and Perotti's identification scheme. Adding the average cost of public debt to the endogenous variables of the VAR brings the peak effects a touch below -0.8. It should be noted, however, that in virtually all specifications only the impulse responses to a government debt uncertainty shock are significantly different from zero at most horizons, with the output response to government spending uncertainty in the left bottom panel and to monetary policy uncertainty in the right bottom panel being the only exceptions on impact.

In summary, the results of these alternative identifying restrictions corroborate the findings of the previous section that *(i)* an increase in policy uncertainty appears to be associated with a significant output contraction and *(ii)* among the policy shocks, uncertainty about public debt tends to have the most detrimental effect.[12]

[12] The variance decomposition analysis across the different specifications confirms that fiscal sustainability accounts for the largest share of fluctuations explained by economic policy uncertainty shocks.

7 Conclusions

Uncertainty about future fiscal sustainability appears to have large and persistent negative effects on output, consumption and investment. Uncertainty about the current stance of government spending and taxes as well as about monetary policy tend to have a smaller but still significantly detrimental impact. Policy uncertainty shocks appear to explain some 30% of fluctuations in real activity, with government debt uncertainty shocks making the largest contribution.

Our results are based on an empirical method in which the volatility of identified shocks is allowed, but not required, to have direct and dynamic consequences on the vector of endogenous variables in an otherwise standard structural VAR with stochastic volatility. The empirical framework proposed in this paper may prove well-suited to study in future research the dynamic effects on the real economy of other sources of macroeconomic uncertainty stemming, for instance, from technological progress, the labour market or business and consumer confidence.

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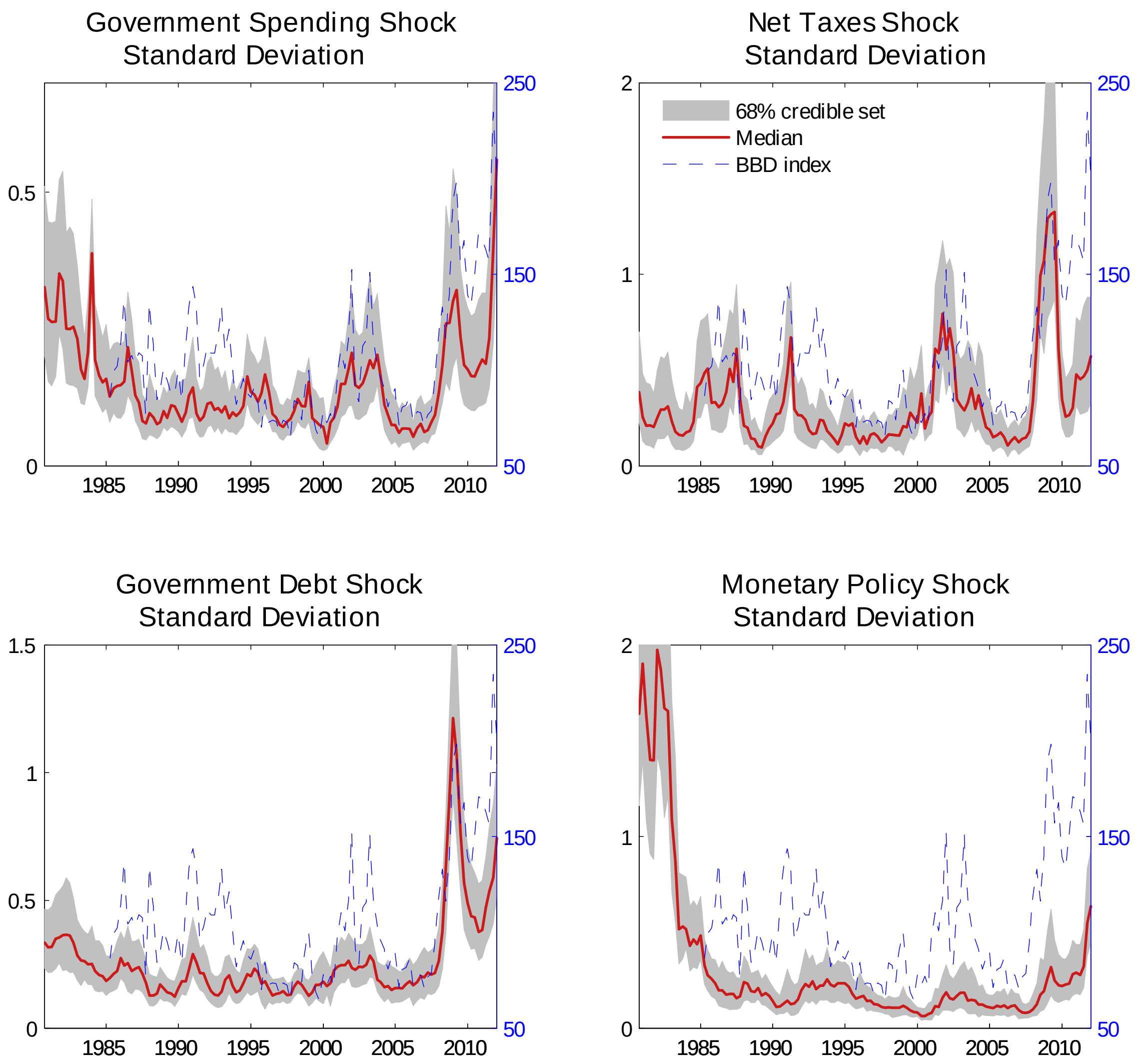

Figure 2: estimates of the policy uncertainty shocks based on a structural VAR in government spending, GDP, CPI, net taxes, public debt, short-term rate and consumer confidence for the U.S. economy over the sample 1980q1-2011q4. Shaded areas represent 68% credible sets. BBD index stands for the measure of economic policy uncertainty constructed by Baker, Bloom and Davis (2012).

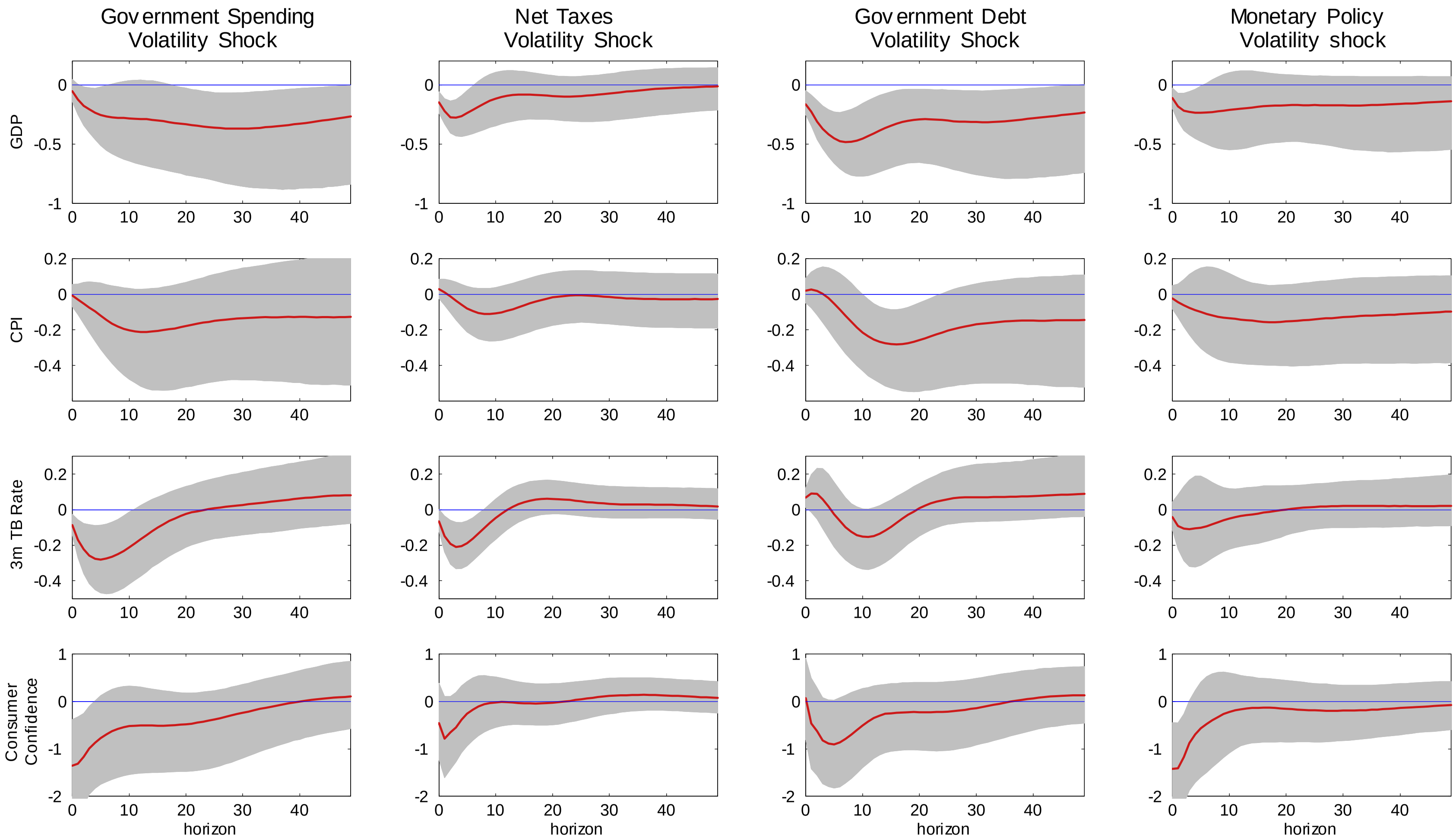

Figure 3: dynamic effects of policy uncertainty shocks based on a structural VAR in government spending, GDP, CPI, net taxes, public debt, short-term rate and consumer confidence estimated for the U.S. economy over the sample 1980q1-2011q4. Shaded areas represent 68% credible sets.

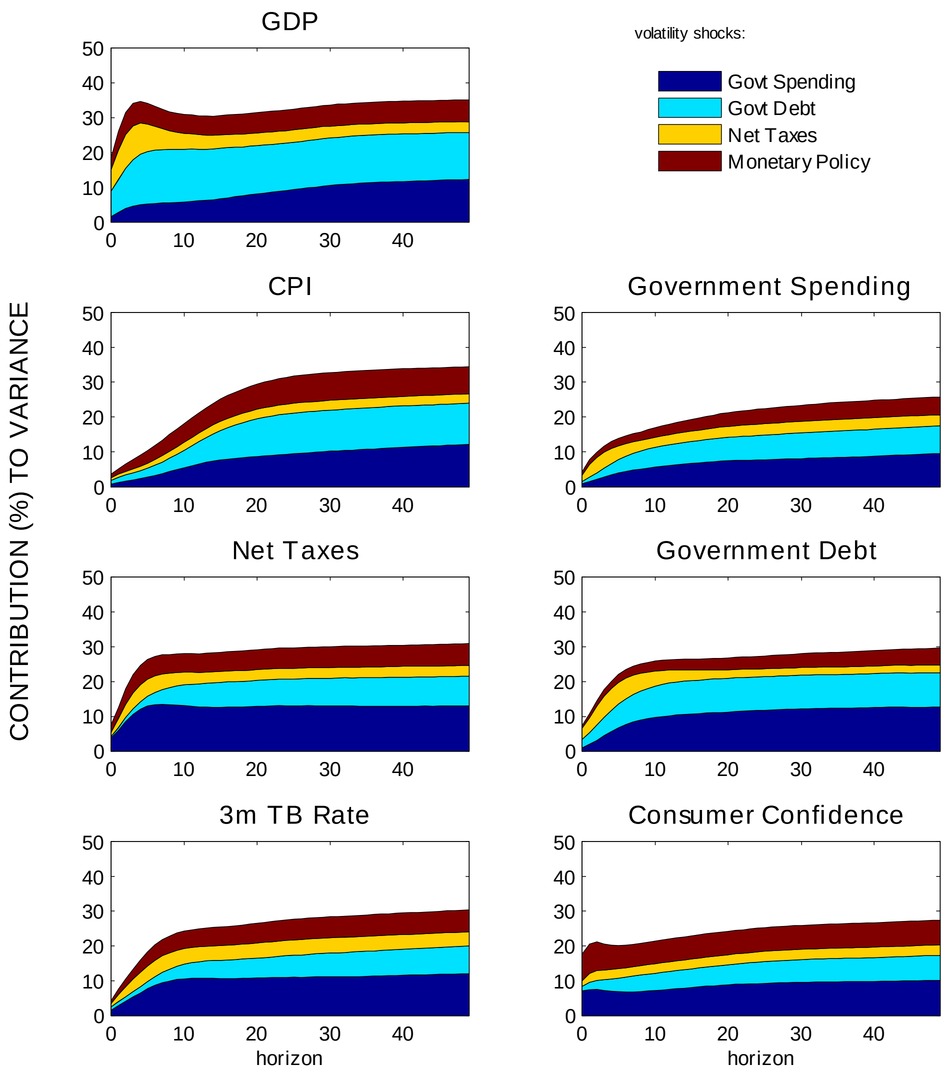

Figure 4: median estimates for the forecast error variance decomposition based on the 7-variable structural VAR. See notes to Figure 3.

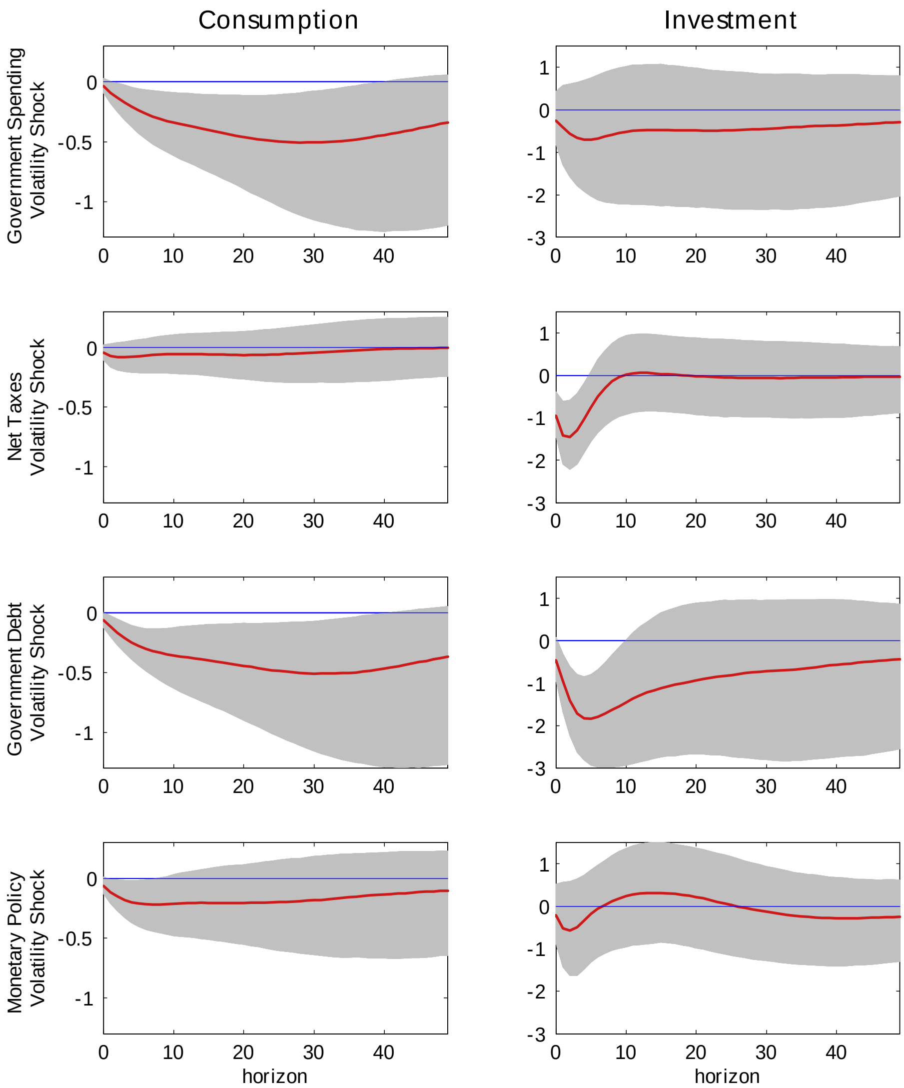

Figure 5: dynamic effects of policy uncertainty shocks on consumption (investment) in the first (second) column based on two separate 8-variable structural VARs in government spending, consumption (investment), GDP, CPI, net taxes, public debt, short-term rate and consumer confidence estimated for the U.S. economy over the sample 1980q1-2011q4. Shaded areas represent 68% credible sets.

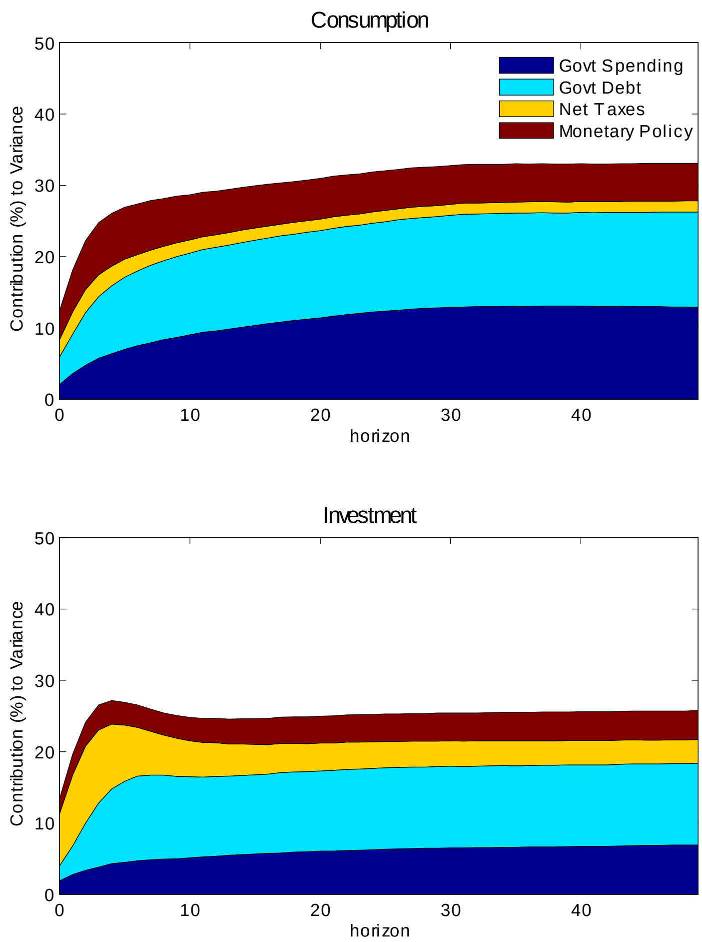

Figure 6: median estimates of the forecast error variance decomposition based on the two 8-variable structural VARs. See notes to Figure 5.

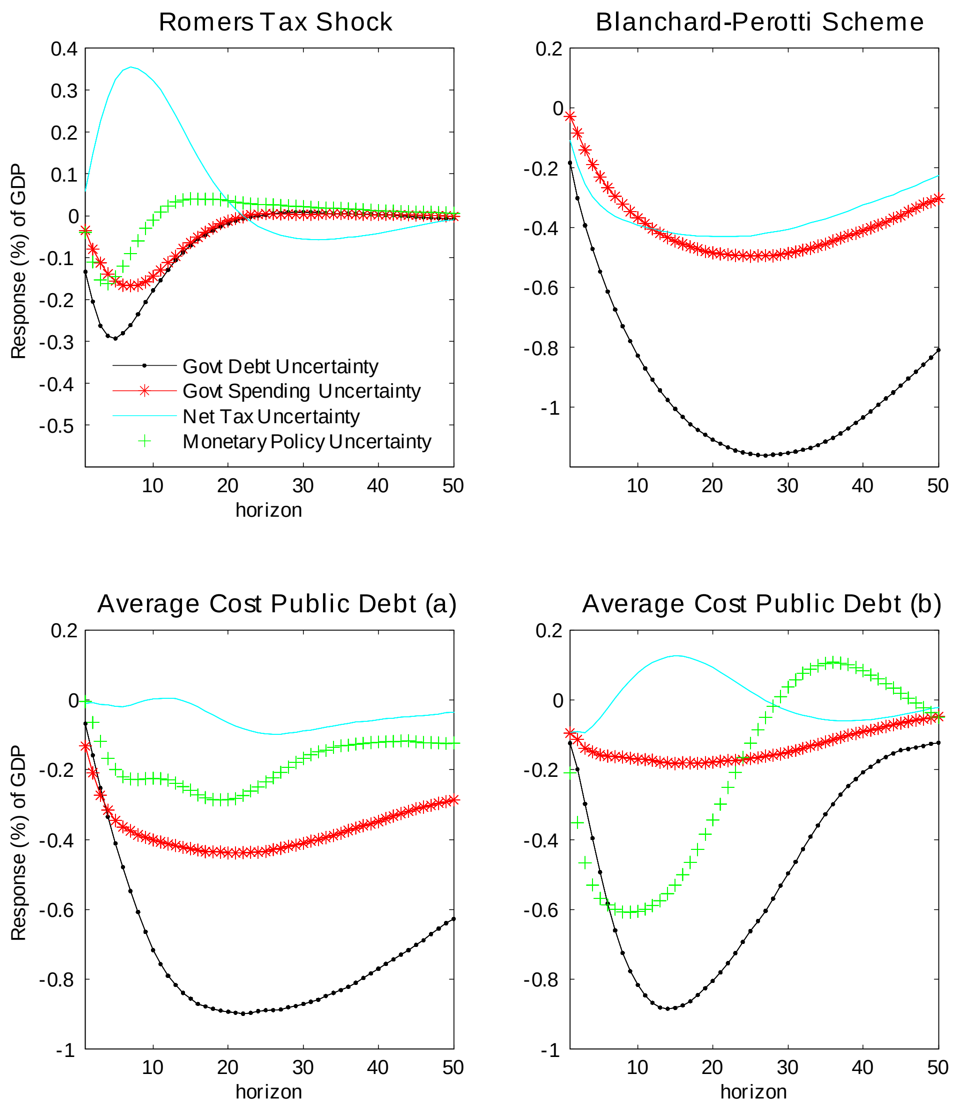

Figure 7: median estimates of the dynamic effects of policy uncertainty shocks on GDP under five alternative identifications of fiscal shocks based on four structural VARs estimated for the U.S. economy over the sample 1980q1-2011q4.

Appendix A: the Gibbs sampling algorithm

Prior Distributions and starting values

VAR coefficients

The initial conditions for the VAR coefficients Γ_0 (to be used in the Kalman filter as described below) are obtained via an OLS estimate of equation (1) using an initial estimate of the stochastic volatility. The covariance around these initial conditions P_0 is set to a diagonal matrix with diagonal elements equal to 100.

The initial estimate of stochastic volatility estimate is obtained via a simpler version of the benchmark model where the stochastic volatility does not enter the mean equations. We use a training sample of 40 observations to initialise the estimation of this simpler model. The Gibbs algorithm for this model is a simplified version of the algorithm described in Cogley and Sargent (2005), employing uninformative priors. The estimated volatility from this model is added as exogenous regressors to a VAR using the data described in the text in order to provide a rough guess for initial conditions for the VAR coefficients.

Elements of H_t

The prior for $\tilde{h}_t$ at $t = 0$ is defined as $\tilde{h}_0 \sim N(\ln \mu_0, I_N)$ where μ_0 are the first elements of the initial estimate of the stochastic volatility described above.

Elements of A

The prior for the off-diagonal elements A is $A_0 \sim N(\hat{a}, V(\hat{a}))$ where $\hat{a}$ are the elements of this matrix from the initial estimation described above. $V(\hat{a})$ is assumed to be diagonal with the elements set equal to the absolute value of the corresponding element of $\hat{a}$.

Parameters of the transition equation

We postulate a Normal, inverse-Wishart prior distribution for the coefficients and the covariance matrix of the transition equation (3). Under the prior mean, each stochastic volatility follows an AR(1) process with an AR(1) coefficient equal to the estimated value over the training sample. The prior is implemented via dummy observations (see Banbura et al 2009) and the prior tightness is set to 0.1.

Simulating the Posterior Distributions

VAR coefficients

The distribution of the VAR coefficients Γ conditional on all other parameters Ξ and the stochastic volatility $\tilde{h}_t$ is linear and Gaussian: $\Gamma \backslash Z_t, \tilde{h}_t, \Xi \sim N\left(\Gamma_{T\backslash T}, P_{T\backslash T}\right)$ where $\Gamma_{T\backslash T} = E\left(\Gamma_T \backslash Z_t, \tilde{h}_t, \Xi\right), P_{T\backslash T} = Cov\left(\Gamma_T \backslash Z_t, \tilde{h}_t, \Xi\right)$. Following Carter and Kohn (2004), we use the Kalman filter to estimate $\Gamma_{T\backslash T}$ and $P_{T\backslash T}$ where we account for the fact that the covariance matrix of the VAR residuals changes through time. The final iteration of the Kalman filter at time T delivers $\Gamma_{T\backslash T}$ and $P_{T\backslash T}$. The Kalman filter is initialised using the initial conditions (Γ_0, P_0) described above. This application of Carter and Kohn's algorithm to our heteroskedastic VAR model is equivalent to a GLS transformation of the model.

Element of A_t

Given a draw for Γ and $\tilde{h}_t$, the VAR model can be written as $A\left(\tilde{Z}_t\right) = e_t$ where $\tilde{Z}_t = Z_t - c + \sum_{j=1}^{P} \beta_j Z_{it-j} + \sum_{j=0}^{J} \gamma_j \tilde{h}_{it-j} = v_t$ and $VAR\left(e_t\right) = H_t$. For a triangular A matrix, this is a system of linear equations with known form of heteroskedasticity. The conditional distributions for a linear regression apply to this system after a simple GLS transformation to make the errors homoskedastic. More details on this step can be found in Cogley and Sargent (2005). The identification scheme in Blanchard and Perotti (2002) involves a non-triangular A matrix and can be written as $Cv_t = Fe_t$. However, as shown in Pereira and Lopes (2010), the C and the F matrices can be transformed such that each implied equation only contains exogenous shocks on the right hand side. Given this transformation, Cogley and Sargent's equation by equation algorithm becomes applicable again.

Elements of H_t

Conditional on the VAR coefficients and the parameters of the transition equation, the model has a multivariate non-linear state-space representation. Carlin, Polson and Stoffer (1992) show that the conditional distribution of the state variables in a general state space model can be written as the product of three terms:

$$\tilde{h}_t \backslash Z_t, \Xi \propto f\left(\tilde{h}_t \backslash \tilde{h}_{t-1}\right) \times f\left(\tilde{h}_{t+1} \backslash \tilde{h}_t\right) \times f\left(Z_t \backslash \tilde{h}_t, \Xi\right) \tag{4}$$

where Ξ denotes all other parameters. In the context of stochastic volatility models, Jacquier, Polson and Rossi (2004) show that this density is a product of log normal densities for $\bar{h}_t$ and $\bar{h}_{t+1}$ and a normal density for Z_t where $\bar{h}_t = \exp\left(\tilde{h}_t\right)$. Carlin, Polson and Stoffer (1992) derive the general form of the mean and variance of the underlying normal density for $f\left(\tilde{h}_t \backslash \tilde{h}_{t-1}, \tilde{h}_{t+1}, \Xi\right) \propto f\left(\tilde{h}_t \backslash \tilde{h}_{t-1}\right) \times f\left(\tilde{h}_{t+1} \backslash \tilde{h}_t\right)$ and show that this is given by:

$$f\left(\tilde{h}_t \backslash \tilde{h}_{t-1}, \tilde{h}_{t+1}, \Xi\right) \tilde{\ } N\left(B_{2t} b_{2t}, B_{2t}\right) \tag{5}$$

where $B_{2t}^{-1} = Q^{-1} + F'Q^{-1}F$ and $b_{2t} = \tilde{h}_{t-1}F'Q^{-1} + \tilde{h}_{t+1}Q^{-1}F$. Note that, due to the non-linearity of the observation equation of the model, an analytical expression for the complete conditional $\tilde{h}_t \backslash Z_t, \Xi$ is unavailable and a metropolis step is required.

Following Jacquier, Polson and Rossi (2004), we draw from (4) using a date by date independence metropolis step using the density in (5) as the candidate generating density. This choice implies that the acceptance probability is given by the ratio of the conditional likelihood $f\left(Z_t \backslash \tilde{h}_t, \Xi\right)$ at the old and the new draw. In order to take endpoints into account, the algorithm is modified slightly for the initial condition and the last observation. Details of these changes can be found in Jacquier, Polson and Rossi (2004).

Parameters of the transition equation

Conditional on a draw for $\tilde{h}_t$, the transition equation (3) is a VAR model and the standard normal and inverse Wishart conditional posteriors apply.

Convergence

The MCMC algorithm is applied using 200,000 iterations discarding the first 190,000 as burn-in. The figure below plots recursive means calculated using intervals of 20 draws for the retained draws of the main VAR parameters. The figure shows little fluctuations providing evidence for convergence of the algorithm.

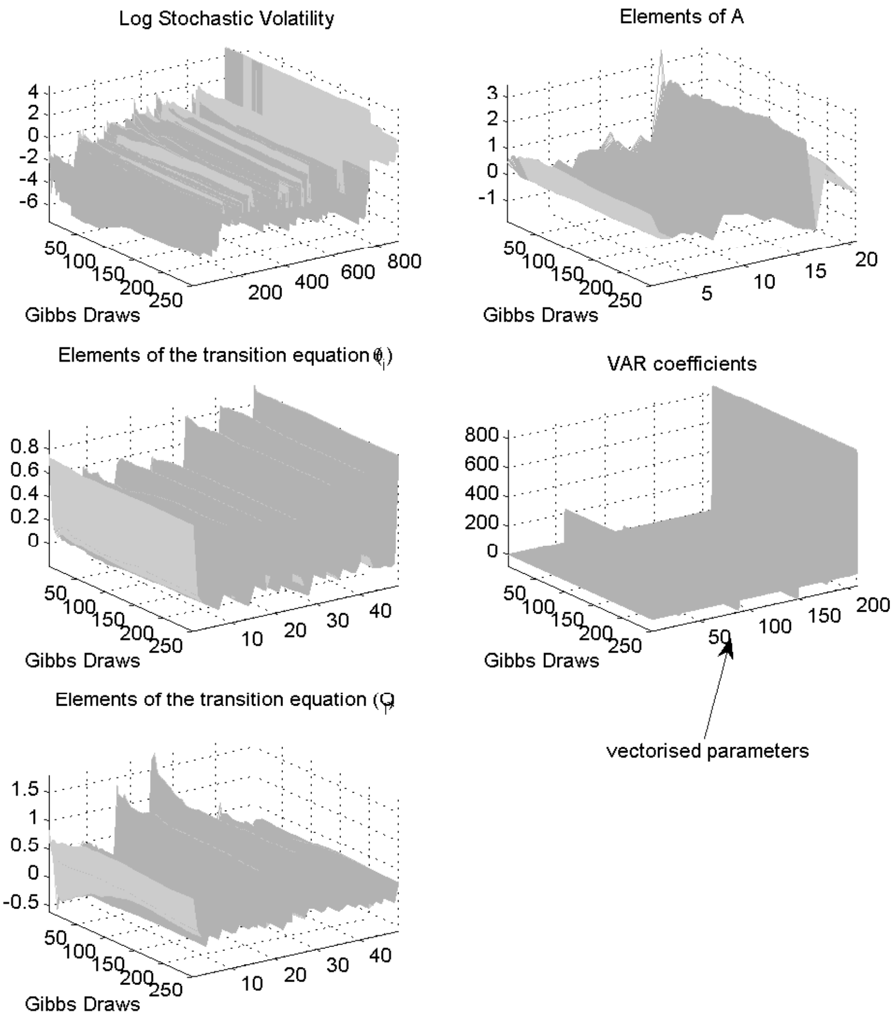

Figure 8: recursive means of hidden states.

Appendix B: data

BEA refers to Bureau of Economic Analysis (http://www.bea.gov/), FRED is Federal reserve economic data (http://research.stlouisfed.org/fred2/). The data is available from 1970Q1 to 2011Q4. We employ the first 40 observations as a training sample, hence the effective sample runs from 1980Q1 to 2011Q4.

Fiscal data

- Government spending: Government consumption expenditures and gross investment (BEA Table 1.15 Line 21) divided by nominal GDP (FRED series id GDP)
- Net Taxes: Current Receipts (BEA Table 3.1 Line 1) minus current transfer payments (BEA Table 3.1 Line 17) and interest payments (BEA Table 3.1 Line 22) divided by nominal GDP.
- Government Debt: Federal Debt Held by the Public (FRED series id FYGFDPUN) divided by nominal GDP.

Macroeconomic/Financial data

- Real GDP per capita: Real GDP (FRED series id GDPC96) divided by population (FRED series id POP).
- Consumption of non durable goods and services: (FRED series PCND plus FRED series PCESV) deflated by the personal consumption expenditures deflator (FRED series id PCECTPI) and divided by population.
- Investment: Gross Private domestic investment (FRED series id GPDI) deflated by the GDP deflator (FRED series id GDPDEF)
- CPI (FRED series id CPIAUCSL).
- 3 month treasury bill rate (FRED series id TB3MS) .
- Consumer Confidence: University of Michigan Consumer sentiment (FRED id UMCSENT and UMCSENT1).