Policy Uncertainty and Aggregate Fluctuations*

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Abstract

This paper estimates the impact on the US economy of four types of uncertainty about (i) government spending, (ii) tax changes, (iii) public debt and (iv) monetary policy. Uncertainty on the government debt has a large and persistent effect on output, consumption, investment, consumer confidence and business confidence. Uncertainty about tax changes also has detrimental consequences for real activity but the effect of spending and monetary policy uncertainty appears to be small. About 25% of output fluctuations are accounted for by policy uncertainty, with government debt making the largest contribution at longer horizons.

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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, several 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) back in 2009. 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 in place since 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

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* stance of economic policies) may *both* have a highly detrimental impact on the economic outlook, the empirical literature on policy uncertainty has, so far, mostly focused on current 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 government spending, tax changes, public debt and 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 government debt has a large and statistically important impact on real activity, with effects of about 0.5%, 0.3% and 1% 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 net taxes volatility appears to be more important than uncertainty about government spending and monetary policy, with the impact of the latter two shocks close to zero. Third, debt and net tax shock uncertainty appears to have a more detrimental impact

on consumer confidence than on business confidence. Fourth, the contribution of policy uncertainty to variations in output, consumption and investment is around 20% to 30%. Fifth, shocks to public debt volatility make the largest contributions to aggregate fluctuations in GDP, accounting for about one third 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 by Baker, Bloom and Davis (2016), Stock and Watson (2012) and Caggiano, Castelnuovo and Groshenny (2013), among others.

Our paper contributes to a growing literature on quantifying the effects of economic policy uncertainty on the real economy. On the macro side, Fernández-Villaverde, Guerrón-Quintana, Kuester and Rubio-Ramírez (2015) and Born and Pfeifer (2014) 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, Bloom and Davis (2016) find that uncertainty has detrimental effects on both the level and volatility of GDP growth. Brogaard and

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

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 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 most earlier contributions, our main focus is on uncertainty about fiscal sustainability and as such it seems closer in spirit to the quantitative models put forward by Bianchi and Melosi (2015a and 2015b) on the extent to which uncertainty about how rising public debt will be stabilized can account for the dynamics of U.S. inflation during the Great recession.

The paper is organized in five 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. 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.

2 Empirical Model

In this section, we use a simple generalization of structural VARs with stochastic volatility, which makes it suited to study the impact of economic policy uncertainty on macroeconomic variables. In particular, we refer to the following empirical model:

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

where

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

In equation (1), the vector Z_t denotes the $i = 1, .., N$ macroeconomic variables, I_N is a $N \times N$ identity matrix, 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 A matrix has ones on the main diagonal and the structure of the 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:

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

with the covariance matrix Q being diagonal.[2] 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.[3] 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 variables in Z_t.

Note that equation (3) makes the assumption that the shocks η_t to the volatility equation and the shocks e_t to the observation equation are uncorrelated. With this

[2] In the working paper version (Mumtaz and Surico, 2013), we show that the results below are robust to allowing for possible co-movements among volatility shocks. Under this scenario, however, the interpretation of the impulse response functions and variance decomposition becomes slightly more convoluted (and possibly less intuititve) relative to the case of a diagonal Q presented here.

[3] 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.

assumption in place, given an estimate of $Q^{1/2}$, one can interpret an innovation to the i^{th} element of η_t as a shock to the volatility of the i^{th} structural shock and then calculate the response of the volatility h_t and the endogenous variables Z_t. 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 and further identifying restrictions are required to separate the innovation to the volatility from the innovation to the level. In particular, there seems to be 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.

This framework builds upon and extends the empirical models in Mumtaz and Zanetti (2013) and Mumtaz and Theodoridis (2015), with the main departures being the identification of the policy uncertainty shocks, especially those related to fiscal policy, as well as the novel focus on government debt, which is discussed in the section on identification.[4] 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 (2009)). 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 (2002) and applied by Berument, Yalcin and Yildirim (2009) and Lemoine and Mougin (2010). Furthermore, our model shares similarities with the stochastic volatility

[4]Mumtaz and Theodoridis (2014) and Alessandri and Mumtaz (2014) use VARs with common stochastic volatility in mean as in Carriero et.al (2016) but do not identify any structural shocks.

specifications with leverage studied by Asai and McAleer (2009).

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: the log of real per-capita government spending, the log of real per-capita investment, the log of real per-capita consumption, the log of real per-capita GDP, annual consumer price inflation, the log of per-capita net taxes, federal government debt held by the public as a percentage of nominal GDP, a measure of the monetary policy instrument, business confidence and the University of Michigan consumer confidence index.[5]

The sample runs from 1970 Q1 to 2015 Q4. In order to proxy the stance of monetary policy we use the three-month Treasury Bill rate (3m TB rate) from 1970 Q1 to 2008 Q4. However over the 2009 Q1 to 2015 Q4 period we replace the 3m TB rate with the shadow interest rate estimated by Wu and Xia (2015) using a non-linear term structure model in order to proxy the monetary policy stance under the zero lower bound. The appendix provides details on the sources of the data and their construction.

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.[6] Finally, we use linear de-trending to account for low-frequency movements in the macroeconomic variables.

[5]Note that in our estimation we consider the face value of federal debt rather than the market value. This is mainly because data on the market value of debt consistent with NIPA based measures of taxes and spending include in our model are not readily available from official sources.

[6]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.

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 (1994).

2. Conditional on a draw for $\tilde{h}_t$ and Γ, the elements of the matrix A can be drawn 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 (1994) - see also Carlin, Polson and Stoffer (1992).

We use 500,000 replications in total discarding the first 50,000 as burn in. We base our inference on every 45th draw of the remaining replications giving us a set of 10,000 draws. The appendix presents the Raftery and Lewis (1992) diagnostic and inefficiency factors which suggest that the number of iterations used are sufficient to achieve convergence.

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 covariance matrix $\Omega_t = A'_{0,t}A_{0,t}$. 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 Sims, 1980, Primiceri, 2005, and Canova and Gambetti, 2009). The variables are ordered as follows: (1) government spending, (2) investment, (3) consumption, (4) GDP, (5) inflation, (6) net taxes, (7) government debt, (8) monetary policy instrument, (9) business confidence and (10) the University of Michigan consumer confidence index.

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 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.

As for net taxes, we follow Caldara and Kamps (2008) in assuming that these are

affected contemporaneously by GDP and prices but react only with a lag to the short-term rate and the consumer confidence index. The first assumption is based on the idea that shocks to output and inflation affect the tax base within the quarter and this leads to contemporaneous changes in tax revenues. However, as taxes are defined net of interest payments, it is likely that they are not affected immediately by changes in interest rates and financial variables. The main difference relative to the identification of net tax shocks in Perotti (2007) is that we estimate (rather than impose fixed values for) the contemporaneous elasticities of taxes to output and inflation.[7] 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. In the sensitivity analysis below, we show that using the scheme in Blanchard Perotti (2002) or the exogenous tax liability changes proposed by Romer and Romer (2010) as a measure of tax shocks produces similar results.

Interpreting public debt shocks. Previous VAR studies have typically abstracted from public debt in their empirical analysis with the notable exception of Cheng and Leeper (2007) and Favero and Giavazzi (2012), who however study only level shocks rather than modelling and focussing on the volatility shock considered in the empirical model proposed in this paper. One of the goals of our analysis is therefore to establish whether such an exclusion is warranted for the purpose of measuring the effects of

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

economic policy uncertainty. Because of the scarcity of empirical precedents, we take a relatively reduced-form approach rather than trying to identify the specific mechanism, among several theoretical alternatives, that may give rise to a public debt shock. Still, to develop intuition, in this part of the paper we discuss briefly some more structural interpretations for the deviations of the debt-to-GDP ratio from its expected path.

Following the empirical literature on fiscal SVARs, our model includes net taxes, namely government receipts net of transfer and interest payments.[8] But Figure 2 reveals that movements in transfer payments and movements in public debt are remarkably synchronized, consistent with a possible interpretation of our public debt shock as a temporary deviation from the expected path of future transfer payments. Indeed, the CBO projections in Figure 1 as well as the public and policy debates feature prominently this as a main source of uncertainty surrounding the expected level of future public debt.

Second, the theoretical framework developed by Leeper, Plante and Traum (2010), Bi (2012) and Bi and Leeper (2013) reveal that the 'residuals' of the equation determining the debt-to-gdp ratio (i.e. the government flow budget constraint) have a natural interpretation as a shock to fiscal sustainability. The latter two papers explicitly model this equation as a regime-switching process for transfer payments. While it would be computationally infeasible to build such a non-linear dynamics in our non-linear model, we note that –conceptually consistent with these theoretical studies– our debt shocks might also be interpreted as *temporary* deviations from a fiscal sustainable path.

Third, the intertemporal budget constraint relates current government purchases to the present value of future tax revenues through the accumulation of public debt. So, while shocks to net taxes and government spending are more likely to capture deviations

[8] See for instance Blanchard and Perotti (2002), Perotti (2007), Caldara and Kamps (2008), Mountford an Uhlig (2009), among many others.

from the current stance of fiscal policies, shocks to public debt might be interpreted as possible deviations from the stance of fiscal policy that will be adopted in the future. Finally, our debt shocks may also reflect time-variation in debt management, including changes in the maturity structure and interest payments, and any approximation error associated with the linearization of the intertemporal government budget constraint.

The considerations above further motivate the choice to include government debt in our empirical model, over and above government spending and net taxes. Still, additional restrictions are needed to identify a public debt shock. In analogy to any other fiscal shock, the complication comes from distinguishing among three main drivers: automatic stabilizers, discretionary responses to business cycle conditions and discretionary responses *unrelated* to the business cycle. Our identification strategy seek to isolate this third component. Following the literature, we normalize the level of nominal government debt by nominal GDP. To purge the residuals of the debt equation from the effects of the endogenous response of fiscal policy to the business cycle, we order the debt-to-gdp ratio after real GDP. Similarly, to account for the impact of the price level, inflation is ordered before the debt-to-gdp ratio.

3.3 Computing impulse responses to volatility shocks

To account for the non-linear interaction between stochastic volatility and the level shocks in equation (1), we use Monte Carlo integration to compute the Generalized Impulse Response Functions (GIRF) in the spirit of Koop, Pesaran and Potter (1996). The GIRF is defined as

$$GIRF = E\left(Z_{t+k} \mid \tilde{h}_t, \Psi, Z_t, \eta_{t,j} = \mu\right) - E\left(Z_{t+k} \mid \tilde{h}_t, \Psi, Z_t\right) \tag{4}$$

where Ψ denotes all parameters of the VAR model, k is the horizon under consideration and η denotes the shock to transition equation (3). Equation (4) states that the impulse response functions are calculated as the difference between two conditional expectations. The first term in equation (4) denotes the forecast of the endogenous variables conditioned on an innovation μ to the volatility shock of interest at horizon 0. The second term is the baseline forecast, namely a scenario conditioned on the shocks being integrated out. Koop, Pesaran and Potter (1996) describe how to approximate these conditional expectations via a stochastic simulation of the VAR model. Note that we calculate the impulse responses for all possible initial conditions $(Z_t, \tilde{h}_t)$ in the sample and report below the average impulse responses for each endogenous variables. Finally, equation (4) can also be used to compute the forecast error variance conditional on a particular shock. Given that, the resulting contribution of each shock to the total forecast error variance can easily be derived.

4 Empirical evidence

The model (1)-(3) is estimated on U.S. data over the period 1980q1-2015q4 using the identification scheme described in the previous section. Data between 1970q1 and 1979q4 are used to initialize the priors. We compare the fit of the benchmark VAR model with a linear homoskedastic VAR by using the deviance information criterion (DIC) proposed in Spiegelhalter et.al.(2002). As described in the on-line technical appendix, the DIC rewards fit while penalising model complexity. A model with a lower DIC is preferred. The estimated DIC for our benchmark model is 1795.6 while the estimate for the linear VAR is 2002.9, suggesting a better fit for the model used in the analysis below.

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 sensitivity of our findings to alternative identification schemes.

4.1 A novel measure of economic policy uncertainty

The measures of policy uncertainty produced by our empirical model are presented in Figure 3, together with the policy uncertainty index (dashed blue line) proposed by Baker, Bloom and Davis (2016).[9] 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.

Our measures of policy uncertainty share a significant number of turning points with the index compiled by Baker, Bloom and Davis (2016). Furthermore, the estimates in Figure 3 offer an interpretation of specific episodes of the recent U.S. economic policy history. For instance, the large swing in the measure of monetary policy uncertainty at the beginning of our sample coincides with the Volcker experiment of non-borrowed reserve targeting. The recession of 1991 and the 'Economic Growth and Tax Relief Reconciliation Act' of 2001 are associated with an increase in the volatility of both taxes and public debt shocks.

The Great Recession is characterized by the largest uncertainty on the U.S. public

[9] 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.

debt, which over the period 2007-09 appears to become the most prominent source of economic policy uncertainty. This is interesting because the policy interventions during the great recession were, at least partially, the endogenous response to macroeconomic conditions. Still, Figure 3 suggests that the long term finance, and possibly the scale, of these interventions (as captured by the unanticipated component of movements in the public debt) rather than the interventions per sè (as captured by the unanticipated component of movements in government spending) appear to be the most significant source of economic policy uncertainty.

From 2010-2014, policy uncertainty is largely reflected in the volatility of the net taxes shock which remains persistently high over this period. The end of the sample is characterised by a sharp rise in the uncertainty associated with government spending, monetary policy and public debt shocks with the latter showing the largest increase.

Overall, we regard the good match between swings in our uncertainty measures and the narrative records of fiscal and monetary interventions as sufficiently reassuring to proceed to the impulse response function analysis.[10]

4.2 Impulse response functions

In this section, we report the impact of shocks to the four policy uncertainty measures. The response to innovations in the level of fiscal variables and the short-term interest rate is presented in the technical appendix. The estimated responses are reasonable from an economic point of view and fairly close to those obtained from a linear BVAR. A positive spending shock raises GDP and consumption. In contrast, an innovation to

[10] More specifically, the correlation between the Baker, Bloom and Davis (2016) policy uncertainty index and our measures of tax, debt and monetary policy uncertainty is 0.6, 0.4 and 0.3 respectively. Our government spending uncertainty, however, has a negligible correlation with their policy uncertainty index.

taxes and debt results in a decline in real activity, with the estimates being larger in the latter case. The shock to the short-term interest rate leads to a decline in GDP, consumption and investment at the one year horizon with inflation displaying a modest price puzzle only in the short-run.

The responses to policy uncertainty shocks are the main focus of our analysis and are presented in Figure 4. We report the dynamic effects of the four policy uncertainty measures on real activity, namely output, consumption and investment, and confidence indicators, both for households and firms, following a one standard deviation shock. The red lines represent median estimates while the shaded areas are 68% and 90% highest posterior density intervals. Each column refers to a different economic policy uncertainty shock, from government spending and taxes on the left to public debt and monetary policy on the right.

Uncertainty about the debt to GDP ratio in the third column has the largest effect on output, with a peak around 0.5%.[11] The response of GDP is statistically different from zero and long-lasting, inheriting the persistence of the volatility process. The response of consumption is similar, both in shape and magnitude, to the response of output whereas the decline in investment appears sizably larger. As shown in the technical appendix, the level of debt also displays a persistent increase in response to this shock possibly contributing to the adverse impact on real activity. Interestingly, consumer confidence is more sensitive than business confidence to debt uncertainty.

The effects of volatility shocks to net taxes are similar to the impact of debt volatility. Note that debt volatility shocks have a marginally larger impact on GDP than tax

[11] This peak effect is about *three* times smaller than the peak effect estimated by Baker, Bloom and Davis (2016). 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 (2016), who consider a shock as large as the difference in their policy uncertainty index between 2006 and 2011.

volatility innovations and also appear to affect business confidence by a larger amount. In contrast to net tax and debt volatility shocks, innovations to spending and monetary policy volatility do not have an impact that is statistically different from zero.

In summary, the dynamic effects of economic policy uncertainty shocks, especially public debt and net taxes, on economic activity, consumer confidence and business confidence appears sizable and persistent. To give a metric 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 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 and business confidence. In Figure 5 of this section, we evaluate their contributions to aggregate 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 have verified that similar findings are obtained over different sub-periods.

Our estimates suggest that policy uncertainty shocks typically account for about 25% of fluctuations in real activity and confidence measures, with slightly higher shares for

consumption. The overall contribution is typically smaller on impact, tends to increase with the forecast horizon within the first year and then stabilize afterwards. While net taxes and monetary policy volatility make an important contribution to fluctuations in GDP, investment and business confidence, the lion's share of fluctuations appears accounted by uncertainty on the debt-to-GDP ratio, especially over the medium term.

5 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. In order to implement this scheme, we use the value of the output elasticity of government revenue (i.e. -2.08) estimated in Blanchard and Perotti (2002). We retain the assumption that the debt shock has a lagged impact on the remaining variables in the system. The second robustness check uses the measure of tax shocks proposed by Romer and Romer (2010) as an endogenous variable in the VAR model, replacing net taxes. In the third exercise, we focus on the identification of public debt shocks and add to the baseline specification a measure of the average cost of servicing the debt, which we order before the debt to GDP ratio. Furthermore, we order the measures of public debt and its average cost after the short-term interest rate but

we have verified that the results below are not overturned if we order it before the short rate. Finally, in order to account for the possible impact of anticipated fiscal shocks, we add the Ramey (2011) fiscal news shock to each equation of the benchmark VAR as an exogenous variable.

The results of these sensitivity analyses are presented in Figure 6, 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 (light blue solid line), taxes (red line with stars) and monetary policy (green crosses).

In all models, the shock to public debt uncertainty is associated with the largest effects on real activity, with peak values ranging from about -0.1% in the specification based on Romer and Romer's measure of exogenous tax changes to around -0.9% using Blanchard and Perotti's identification scheme. Adding the average cost of public debt to the endogenous variables of the VAR brings the peak effect into the neighborhood of -0.5%. It should be noted, however, that for virtually all measures of real activity and specifications only the impulse responses to a government debt uncertainty shock are systematically different from zero at most horizons, with the exception of the Romer and Romer identification under which the negative effects of public debt uncertainty on output are still the largest among the policy uncertainty shocks but become insignificant.[12]

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,

[12] In the on-line technical appendix we show that the benchmark results are preserved if a stock market index is added to the benchmark VAR model.

uncertainty about public debt tends to have the most detrimental effect.[13]

6 Conclusions

Uncertainty about government debt appears to have large and persistent negative effects on output, consumption and investment as well as on confidence indicators for households and firms. Uncertainty about the current stance of taxes also appears to have a detrimental impact. Policy uncertainty shocks appear to explain about 25% of fluctuations in real activity, with public debt uncertainty shocks making the largest contribution.

Our results are based on an empirical model in which the volatility of *identified* shocks is allowed, but not required, to have direct and dynamic effects on the endogenous variables of an otherwise standard structural VAR with stochastic volatility. The empirical framework used in this paper may prove useful to study in future research also the dynamic effects on the real economy of other sources of macroeconomic uncertainty stemming, for instance, from technological progress, labour market policies and exchange rate dynamics.

[13] The variance decomposition analysis confirms that public debt uncertainty accounts for the largest share of fluctuations explained by economic policy uncertainty shocks at horizons beyond two years.

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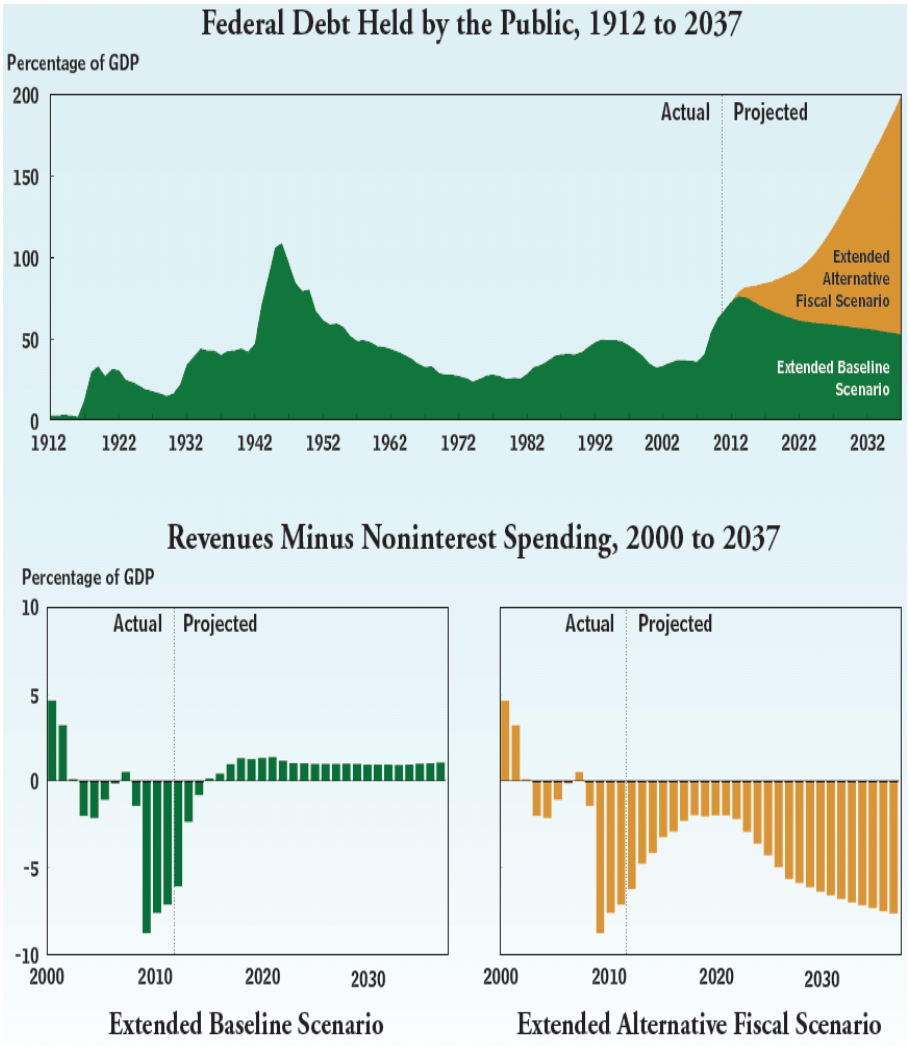

Figure 1: Source: CBO https://www.cbo.gov/

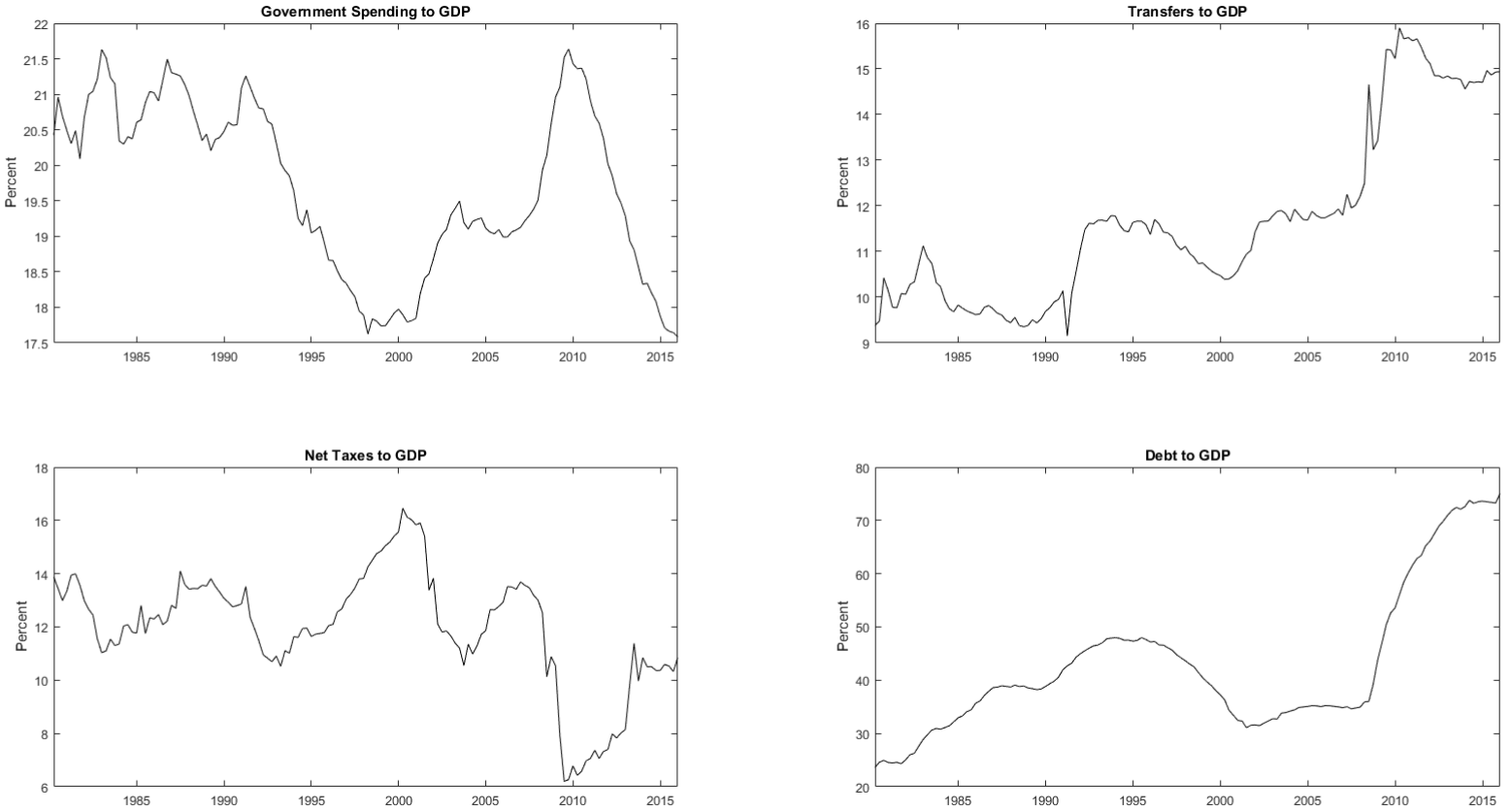

Figure 2: Government spending, net taxes, transfers and government debt as a share of GDP. Net taxes are defined as current government receipts minus current transfer payments minus interest rate payments. Sample: 1980q1-2015q4.

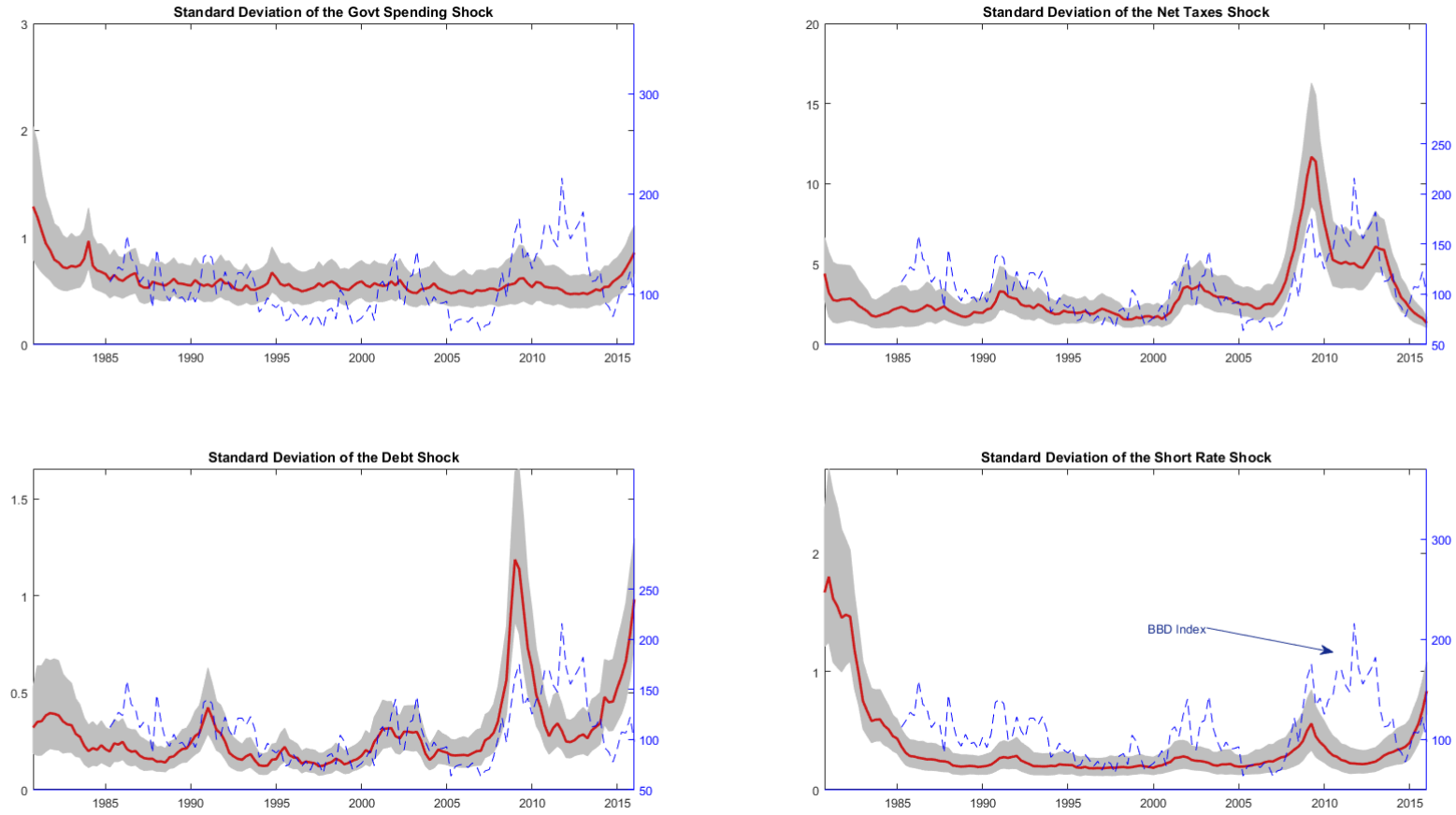

Figure 3: estimates of the policy uncertainty shocks based on the benchmark model. Shaded areas represent 68% credible sets. BBD index stands for the measure of economic policy uncertainty constructed by Baker, Bloom and Davis (2016).

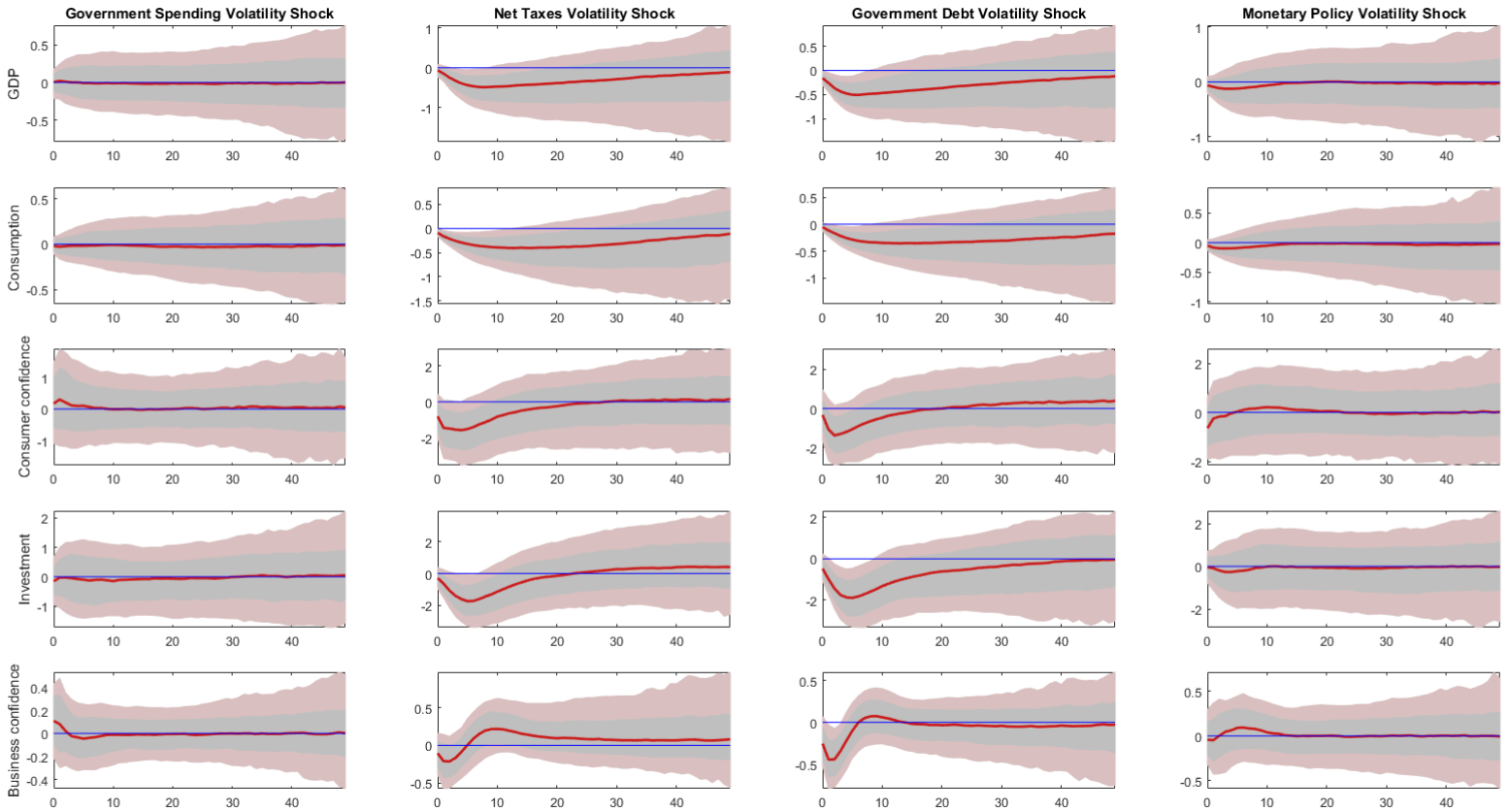

Figure 4: dynamic effects of 1 standard-deviation policy uncertainty shocks based on the benchmark model. The dark shaded areas represent the 68% highest posterior density interval, while the lighter shaded area is the 90% highest posterior density interval.

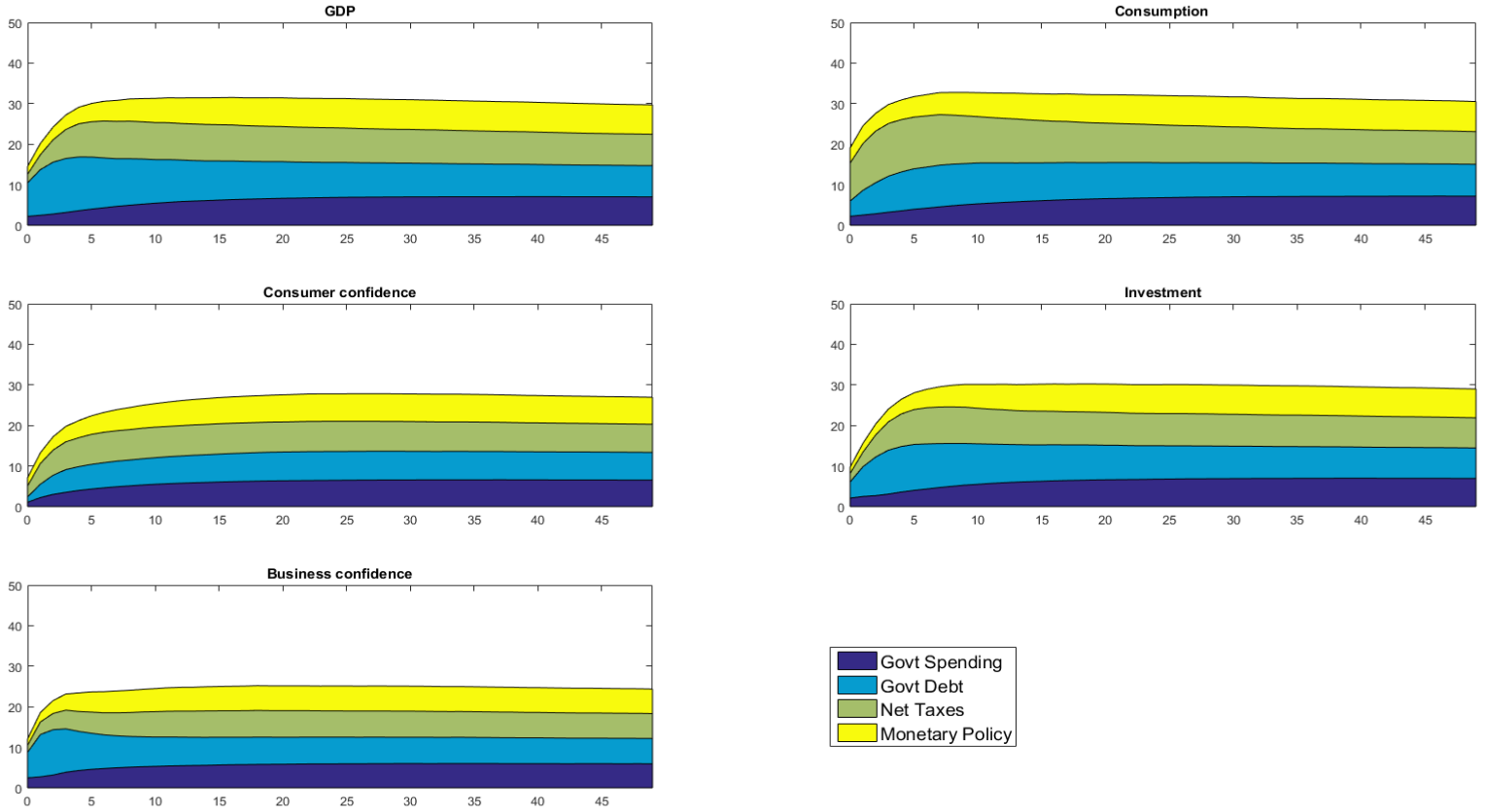

Figure 5: median estimates for the forecast error variance decomposition based on the benchmark model.

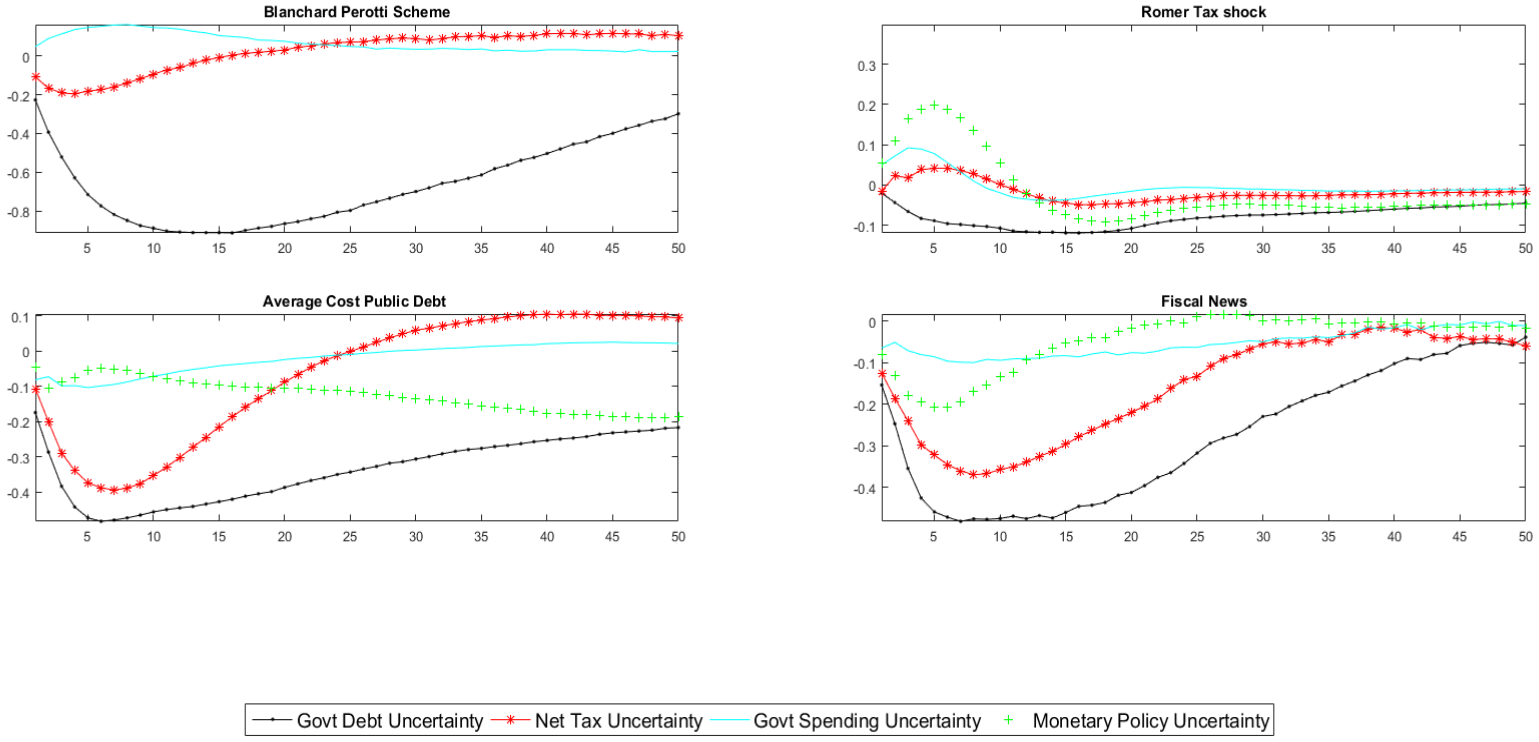

Figure 6: median estimates of the dynamic effects of policy uncertainty shocks on GDP under five alternative identifications of fiscal shocks based on four structural VARs estimated for the U.S. economy over the sample 1980q1-2015q4.

Appendix A: the Gibbs sampling algorithm

Prior Distributions and starting values

Consider the model to be estimated

$$Z_t = c + \sum_{j=1}^{P} \beta_j Z_{t-j} + \sum_{j=0}^{J} \gamma_j \tilde{h}_{t-j} + \Omega_t^{1/2} e_t, e_t \tilde{} N(0,1) \quad (5)$$

$$\Omega_t = A^{-1} H_t A^{-1'}, H_t = diag\left(\exp \tilde{h}_t\right) \quad (6)$$

$$\tilde{h}_t = \theta \tilde{h}_{t-1} + Q^{1/2} \eta_t \quad , \eta_t \tilde{} N(0,1), \quad E\left(e_t, \eta_{i,t}\right) = 0, \quad i = 1, 2..N \quad (7)$$

VAR coefficients

Let the vectorised coefficients of equation 5 be denoted by $\Gamma = vec\left(\beta_j, \gamma_j, c\right)$. 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 (5) 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 10.

The initial estimate of stochastic volatility 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 initialize 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 $A_0 \sim N\left(\hat{a}, V\left(\hat{a}\right)\right)$ where $\hat{a}$ are the elements of this matrix from the initial estimation described above. $V\left(\hat{a}\right)$ 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 (7). 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 (2010)) and the prior tightness is set to 0.1.

Simulating the Posterior Distributions

The joint posterior distribution $H(\Gamma, A, H_t, \theta, Q)$ is approximated via a Metropolis within Gibbs algorithm that samples from the following conditional posterior distributions:

VAR coefficients : $H(\Gamma|A, H_t, \theta, Q)$

The distribution of the VAR coefficients Γ conditional on all other parameters Ξ and the stochastic volatility $\tilde{h}_t$ is linear and Gaussian: $\Gamma|Z_t, \tilde{h}_t, \Xi \sim N\left(\Gamma_{T|T}, P_{T|T}\right)$ where $\Gamma_{T|T} = E\left(\Gamma_T|Z_t, \tilde{h}_t, \Xi\right), P_{T|T} = Cov\left(\Gamma_T|Z_t, \tilde{h}_t, \Xi\right)$. Following Carter and Kohn (1994), we use the Kalman filter to estimate $\Gamma_{T|T}$ and $P_{T|T}$ 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 $\Gamma_{T|T}$ and $P_{T|T}$. The Kalman filter is initialized 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 : $H(A|\Gamma, H_t, \theta, Q)$

Given a draw for Γ and $\tilde{h}_t$, the VAR model can be written as $A(v_t) = e_t$ where $v_t = Z_t - c + \sum_{j=1}^{P} \beta_j Z_{t-j} + \sum_{j=0}^{J} \gamma_j \tilde{h}_{t-j}$ and $VAR(e_t) = H_t$. 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 (see Cogley and Sargent (2005)). The ith equation of this system is given as $v_{it} = -\alpha v_{-it} + e_{it}$ where the subscript i denotes the ith column while $-i$ denotes columns 1 to $i-1$. Note that the variance of e_{it} is time-varying and given by $\exp\left(\tilde{h}_{it}\right)$. A GLS transformation involves dividing both

sides of the equation by $\sqrt{\exp\left(\tilde{h}_{it}\right)}$ to produce $v_{it}^{*} = -\alpha v_{-it}^{*} + e_{it}^{*}$ where * denotes the transformed variables and $var\left(e_{it}^{*}\right) = 1$. The conditional posterior for α is normal with mean and variance given by M^{*} and V^{*} :

$$\begin{aligned} M^{*} &= \left(V\left(\hat{a}^{ols}\right)^{-1} + v_{-it}^{*\prime} v_{-it}^{*}\right)^{-1}\left(V\left(\hat{a}^{ols}\right)^{-1}\hat{a}^{ols} + v_{-it}^{*\prime} v_{it}^{*}\right) \\ V^{*} &= \left(V\left(\hat{a}^{ols}\right)^{-1} + v_{-it}^{*\prime} v_{-it}^{*}\right)^{-1} \end{aligned}$$

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 (2014), 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 $H_t : H\left(H_t | A, \Gamma, \theta, Q\right)$

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:

$$\tilde{h}_t | Z_t, \Xi \propto f\left(\tilde{h}_t | \tilde{h}_{t-1}\right) \times f\left(\tilde{h}_{t+1} | \tilde{h}_t\right) \times f\left(Z_t | \tilde{h}_t, \Xi\right) \tag{8}$$

where Ξ denotes all other parameters. In the context of stochastic volatility models, Jacquier, Polson and Rossi (1994) 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 $f\left(\tilde{h}_t | \tilde{h}_{t-1}, \tilde{h}_{t+1}, \Xi\right) \propto f\left(\tilde{h}_t | \tilde{h}_{t-1}\right) \times f\left(\tilde{h}_{t+1} | \tilde{h}_t\right)$ and show that this is given by:

$$f\left(\tilde{h}_t | \tilde{h}_{t-1}, \tilde{h}_{t+1}, \Xi\right) \tilde{} N\left(B_{2t} b_{2t}, B_{2t}\right) \tag{9}$$

where $B_{2t}^{-1} = \tilde{Q}^{-1} + \tilde{F}' \tilde{Q}^{-1} \tilde{F}$ and $b_{2t} = \tilde{h}_{t-1} \tilde{F}' \tilde{Q}^{-1} + \tilde{h}_{t+1} \tilde{Q}^{-1} \tilde{F}$. Here $\tilde{F}$ and $\tilde{Q}$ denote the coefficients and the error variance of the transition equation, i.e. θ and Q in companion form. Note that, due to the non-linearity of the observation equation of the model, an

analytical expression for the complete conditional $\tilde{h}_t|Z_t, \Xi$ is unavailable and a Metropolis step is required.

Following Jacquier, Polson and Rossi (1994), we draw from (8) using a date by date independence Metropolis step with the density in (9) being the candidate generating density. This choice implies that the acceptance probability is given by the ratio of the conditional likelihood $f\left(Z_t|\tilde{h}_t, \Xi\right)$ 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 (1994).

Parameters of the transition equation : $H\left(\theta|\Gamma, A, H_t, Q\right)$ **and** $H\left(Q|\Gamma, A, H_t, \theta\right)$

Conditional on a draw for $\tilde{h}_t$, the transition equation (7) is a VAR(1) model with a diagonal covariance matrix. The conditional posterior for the coefficients θ is normal with mean and variance given respectively by:

$$\begin{aligned} \theta^* &= \left(x^{*\prime}x^*\right)^{-1}\left(x^{*\prime}y^*\right) \\ v^* &= Q \otimes \left(x^{*\prime}x^*\right)^{-1} \end{aligned}$$

where $y^* = [\tilde{h}_t; y_d]$ and $x^* = [\tilde{h}_{t-1}; x_d]$ with y_d and x_d denoting the dummy observations that implement the prior.

The conditional posterior for Q is inverse Wishart and is given by

$$H\left(Q|\Gamma, A, H_t, \theta\right) \tilde{} IW(S^*, T^*)$$

where T^* denote the number of actual observations plus the number of dummy observations and $S^* = \left(y^* - x^*b^*\right)'\left(y^* - x^*b^*\right)$

The on-line technical appendix to the paper presents a small Monte-Carlo experiment that shows that this algorithm displays a satisfactory performance.

Convergence

The MCMC algorithm is applied using 500,000 iterations discarding the first 50,000 as burn-in. We retain every 45th draw out of the remaining 450,000 iterations. In order to assess convergence, we compute the Raftery and Lewis (1992) diagnostic which indicates

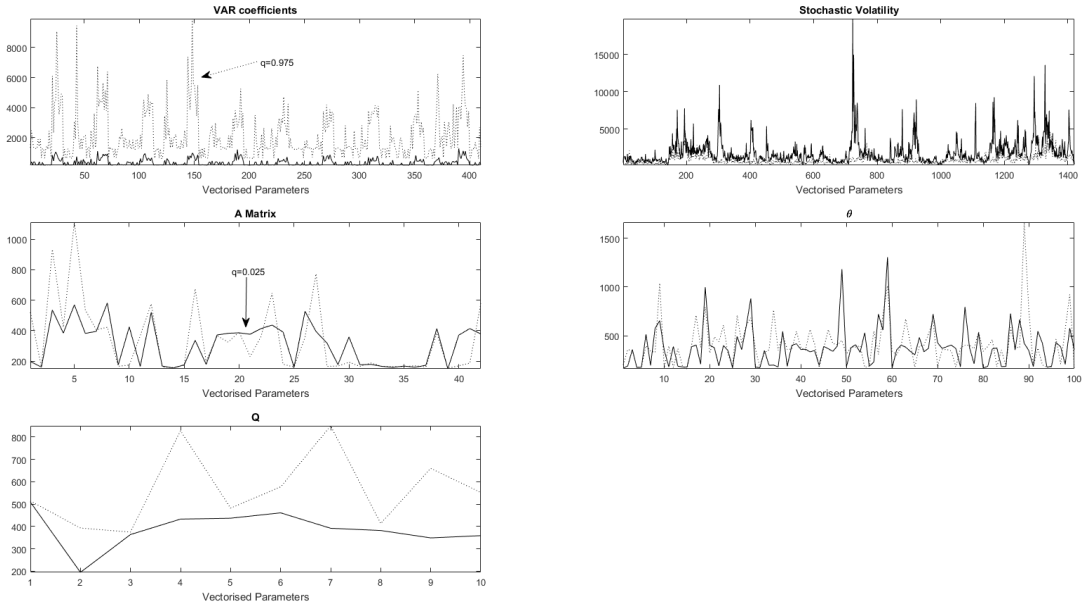

Figure 7: The Raftery and Lewis (1992) diagnostic.

the total length of the run required to generate a desired level of accuracy. We report the diagnostic for two quantiles 0.025 and 0.975. As in Primiceri (2005), the remaining parameters are: desired accuracy 0.025, probability of attaining desired accuracy 0.95. The results are presented in figure 7. The figure shows the estimated total length of the run across the elements of the different parameter block. Note that the suggested number of iterations are well below the 500,000 iterations employed in our algorithm. As a further check we calculate inefficiency factors (IF) and report them in figure 8. The IF are an estimate of $1 + 2\sum_{k=1}^{\infty} \rho_k$ where ρ_k is the autocorrelation of the chain and the infinite lag is approximated using a Parzen window. Values of IF around 20 are deemed acceptable. With the exception of some stochastic volatilities, this conditions seems to be satisfied for most parameters. For the stochastic volatilities the majority (greater than 70%) of IF are below 30. Given the large number of endogenous and state variables, in our view this is reasonable evidence for convergence.

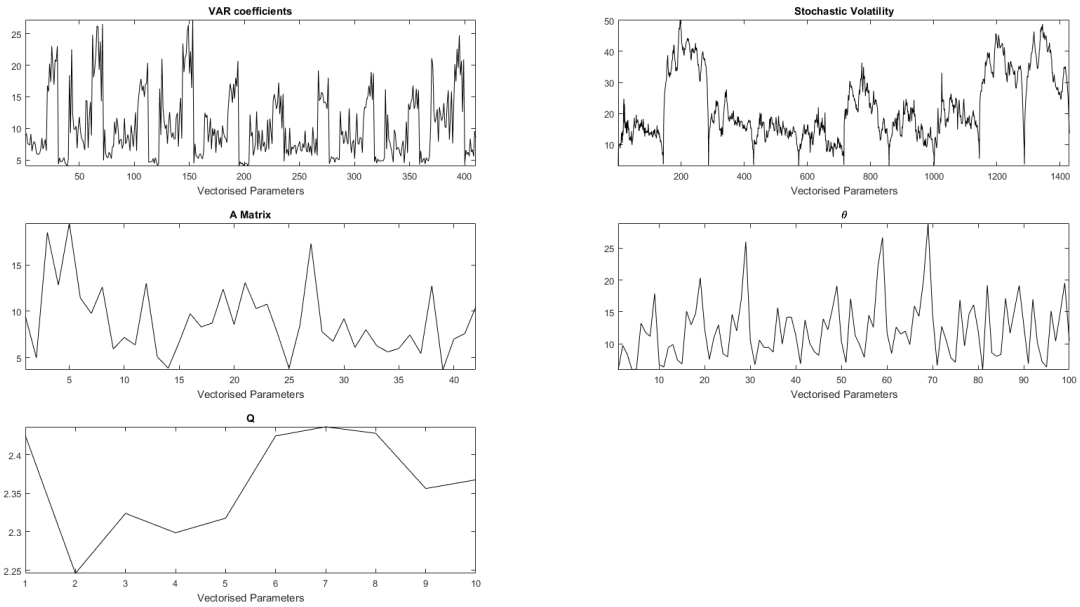

Figure 8: Inefficiency Factors

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/) and GFD refers to Global Financial Data. The data is available from 1970Q1 to 2015Q4. We employ the first 40 observations as a training sample, hence the effective sample runs from 1980Q1 to 2015Q4.

Fiscal data

- Government spending: Government consumption expenditures and gross investment (BEA Table 1.15 Line 22) divided by population and deflated by the GDP deflator.
- Net Taxes: Current Receipts (BEA Table 3.1 Line 1) minus current transfer payments (BEA Table 3.1 Line 22) and interest payments (BEA Table 3.1 Line 27) divided by population and deflated by the GDP deflator.
- Government Debt: Federal Debt Held by the Public (FRED series id FYGFDPUN) divided by nominal GDP.
- Average cost of debt servicing: Net interest payments divided by Federal Debt held by the public lagged one quarter. Net interest payments are obtained as interest payments (BEA Table 3.2 Line 32 minus interest receipts (BEA Table 3.2 Line 15).

Macroeconomic/Financial data

- Real GDP per capita: Real GDP (FRED series id GDPC96) divided by population.
- 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. This is then divided by population.

- CPI (FRED series id CPIAUCSL). We calculate inflation as the annual growth in CPI.
- 3 month Treasury Bill rate (FRED series id TB3MS). From 2009Q1 to 2015Q4, we use the shadow rate calculated by Wu and Xia (2015). This is obtained from the Federal Reserve Bank of Atlanta.
- Business Confidence Index: OECD business confidence indicator (GFD code: BCUSAM).
- Consumer Confidence index: University of Michigan Consumer sentiment (FRED id UMCSENT and UMCSENT1).
- Population (FRED series id POP)
- GDP deflator (FRED series id GDPDEF)