SIGNALS FROM THE GOVERNMENT: POLICY UNCERTAINTY AND THE TRANSMISSION OF FISCAL SHOCKS

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In this paper, we investigate the influence of fiscal policy uncertainty in the propagation of government spending shocks in the US economy. We propose a new index to measure fiscal policy uncertainty which relies on the dispersion of government spending forecasts as presented in the Survey of Professional Forecasters (SPF). This new index is solely focused on the uncertainty surrounding federal spending and is immune from the influence of general macroeconomic uncertainty by as much as is possible. Our results indicate that, in times of elevated fiscal policy uncertainty, the output response to policy announcements about future government spending growth is muted. Instead, periods of low policy uncertainty are characterised by a positive and persistent output response to fiscal announcements. Our analysis also shows that the stronger effects of fiscal policy in less uncertain times is mainly the result of agents' tendency to increase investment decisions in these periods, in line with the prediction of the option value theory in Bernanke (1983).

1 Introduction

Policy communication in the public sector is a delicate task. When communicating their intentions, fiscal policy makers face political, institutional and regulatory constraints that significantly complicate their job. Moreover, fiscal policy ramifies into a multiplicity of instruments, which makes particularly difficult for the policy-makers to send unambiguous signals to the rest of the economy.

In such a complex environment, the decision-making process can easily generate an elevated degree of uncertainty among economic agents, with respect to both the main policy objectives and the specific measures that fiscal authorities intend to adopt to achieve them. Moreover, governments can engage in strategic uncertainty whenever their policy and political objectives are in conflict, and they are unwilling to commit to a specific course of action. In this context, signals about future fiscal policies can have different economic consequences depending on the level of signal precision and on the credibility of policymakers.[1]

Until the recent financial crisis, signalling and fiscal policy uncertainty were of limited relevance in policy discussions. Since the onset of the financial crisis in 2008, however, policy

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[1] The analysis of the relationship between signaling and uncertainty begins with Spence (1973). More recently, central banks have recognised the importance of the active managing of expectations on monetary policy in reducing uncertainty, and enhancing policy effectiveness (see, for example, the literature on forward guidance, e.g., Eggertsson and Woodford, 2003; Campbell *et al.*, 2012; Werning, 2011; Del Negro *et al.*, 2012). As noted also in Baeriswyl and Cornand (2010) and Bachmann and Sims (2012), for respectively monetary and fiscal interventions, policy signalling may change private sector views about future fundamentals or policies, providing more leeway to policy makers.

makers have faced a new and challenging economic context. This has re-launched fiscal policy as a stabilisation tool and, contemporaneously, highlighted the importance of policy communication for an effective transmission of the policy impulses.

The turbulent political environment has also contributed to increase policy uncertainty during the crisis. Notably, in the US, the emergence of a strong anti-governmental opposition within the Congress, the expiration of specific policy provisions, and a frequently revised debt limit have created an environment for protracted political conflicts that culminated with the "Fiscal Cliff" debate in 2012 (see, e.g., Ilzetzki and Pinder, 2012) and the Federal Shutdown in 2013. In Europe, the sovereign debt crisis and the subsequent strengthening of the consolidation plans were not always accompanied by a detailed definition of the required fiscal measures. Moreover, the enhanced role of the European Commission in the supervision of member states' budgetary policies introduced a new layer to the decision process that sometimes resulted in conflicting policy signals.

Despite the increased importance of fiscal policy communication in times of crisis, the literature on the role of fiscal policy uncertainty is still limited.[2] However, since the work of Baker *et al.* (2012), which proposed a new index of economic policy uncertainty for the US, the economic literature examining the empirical effects of policy uncertainty has rapidly expanded.[3]

In this paper, we make two main contributions to the existing literature. First, we construct a new index of fiscal policy uncertainty. This index is based on the dispersion of government spending forecasts as reported in the Survey of Professional Forecasters (SPF). The idea underpinning our policy index is that a precise signal on the outlook of federal spending can coalesce private sector expectations on the future realizations of this variable, hence reducing uncertainty and disagreement among forecasters. Symmetrically, higher than average disagreement about future government spending reveals poor signalling from the government about the future stance of fiscal policies. Compared to the index proposed by Baker *et al.* (2012), our index is more specific to the type of shock under analysis (the federal spending shock). It is also more clearly connected to changes in the variance of economic agents' due to policy signalling. Moreover, it explicitly removes any influence of general macroeconomic uncertainty, to which the Baker *et al.* (2012) is exposed because it is, by construction, (linearly) uncorrelated with macroeconomic uncertainty. This should help to provide a more precise quantification of the policy signal's precision from budgetary authorities.

Second, we explore how fiscal spending shocks propagate, conditional on the level of fiscal policy uncertainty. In particular, we test whether fiscal policy announcements are more effective in stimulating GDP in an environment characterised by low or high uncertainty about present and future public spending policies.

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2 The literature on the economic impact of uncertainty dates back to the early 1970s, with the analysis of the role of uncertainty on private savings and investment decisions (see Leland, 1968; Kimball, 1990; and Carroll, 1997). The study of investment decisions in uncertain times is centred on Bernanke (1983) which showed that during uncertain times, firms might have an incentive to wait until the uncertainty is resolved, even in presence of investment project with a positive net present value. In recent years, Bloom (2009) proposed a new modeling framework to analyse the impact of second-moment shocks in the presence of non-convex capital and labour adjustment costs, and showing that uncertainty shocks can generate short and sharp recessions, immediately followed by sudden recoveries.

3 Papers using the Baker *et al.* (2012) index, or alternative measures, generally find large adverse effects of policy uncertainty onto macroeconomic activity (see, among others, Bachmann *et al.*, 2013; Benati, 2013; Carriero *et al.*, 2013; Mumtaz and Surico, 2013; Caggiano *et al.*, 2013). Building on the SVAR methodology, Davig and Foerster (2013) find that increased policy uncertainty related to the US "Fiscal Cliff" tends to depress investment and employment. Fernandez-Villaverde *et al.* (2012) study the impact of fiscal policy uncertainty in a DSGE model with stochastic volatility. They show that an increases in volatility can have a sizeable adverse impact on the economy, especially when the volatility affects the capital tax process. Bi *et al.* (2013) explore the effects of uncertainty on the timing and composition of consolidation plans in a non-linear New-Keynesian model. They conclude that the uncertainty on the composition (tax- or spending-based) of a consolidation can significantly alter the response of economic agents and the success of the plan in eventually reducing debt. For additional references on policy uncertainty see www.policyuncertainty.com

Our paper is related to Bachmann and Sims (2012), although we focus on the signal sent by fiscal policy authorities (and thus on fiscal policy uncertainty) rather than on confidence, which is more a measure of the degree of agent optimism towards future economic developments.[4] Our empirical analysis is structured in two steps. First, following Ramey (2011), we identify fiscal spending shocks using an expectational time series derived from the US SPF's data. However, unlike Ramey (2011), we identify the spending shocks by looking at the individual revision of forecasts, as published in the SPF, that can be thought of as proxies for fiscal news shocks. In particular, we focus on the revisions in forecaster expectations at both one and three quarter horizons. This expectational identification of fiscal shocks helps to align the econometrician information set with the real-time information flow received by the agents, thus eliminating the problem of fiscal foresight as defined by Leeper *et al.* (2013) (see Ricco, 2013).[5]

Second, based on Bayesian techniques, we estimate an Expectational Threshold VAR (ETVAR) model in which the proxies for fiscal news shocks are included together with the fiscal policy uncertainty index, SPF expectations on GDP, GDP, federal spending and the Barro-Redlick marginal tax rate. The uncertainty index is the threshold variable, and the threshold level is estimated endogenously within the model. We also study the effects of fiscal shocks on the federal fund rates, private consumption and investment. The use of a TVAR model allows us to derive some stylized facts about the propagation of fiscal shocks, conditional on the level of uncertainty surrounding fiscal policy communication.

Our results suggest that, during periods of high fiscal policy uncertainty, fiscal interventions have only weak effects on the economy. In these phases, authorities tend to accompany announcements about increases in spending with a reduction in marginal tax rates. Despite this higher activism, however, output does not significantly respond to the policy news. In periods of low uncertainty, however, the output response to the spending news shock is positive and significantly different from zero, reaching a cumulative multiplier of about 2.45 after 8 quarters. Our analysis also shows that the stronger stimulative effects in less uncertain times are mainly the result of agents' tendency to increase investment decisions, in line with the predictions of the option value theory of Bernanke (1983). We also find that, in presence of clear policy signals (*i.e.*, in the low uncertainty regime), the Federal Reserve tends to be more reactive to spending increases than in periods of high uncertainty.[6]

Overall, our analysis indicates that policy signalling should be seen as a potentially additional policy tool which may enhance the effectiveness of fiscal stimulus. Policy authorities have several concrete options when using this tool. For example, they can accompany the announcement of fiscal targets with a clear indication of the measures that they intend to adopt to achieve them. This should reduce the risk of changes in the fiscal strategy in its implementation phase, thus decreasing uncertainty. In the same vein, a reduction in the level of fiscal policy uncertainty can also be achieved through enhanced credibility of the policy authorities which can be reinforced via a consistent record of fulfilment of the policy announcements with coherent actions. These policy considerations, however, cannot be symmetrically transposed to the opposite case of negative spending shocks (*i.e.*, to the case of fiscal consolidations). In fact, our generalized impulse response functions, which account for endogenous shifts across regimes, show a smaller

4 See also Aastveit *et al.* (2013) for a study on the effectiveness of monetary policy shocks under different levels of uncertainty.

5 The identification of structural fiscal shocks using news has also been proposed by Ben Zeev and Pappa (2014), Leeper *et al.* (2012) and Gambetti (2012). In the field of monetary policy analysis, similar approaches have been used by Altavilla and Giannone (2014) and Gertler and Karadi (2014).

6 Other works on state-dependent multipliers include Kirchner *et al.* (2010), Auerbach and Gorodnichenko (2012), Batini *et al.* (2012) and Cimadomo and D'Agostino (2014), which focus on business cycle phases; Afonso *et al.* (2011) and Caggiano *et al.* (2013), which investigate the implications of financial stress. These studies tend to point to higher multipliers during periods of recessions or high financial stress.

difference between the GDP effect of a negative spending shock under the two uncertainty regimes.[7]

Our paper is structured as follows. Section 2 is devoted to the construction of the Fiscal Policy Uncertainty Index used in the paper; Section 3 comments on the identification of fiscal shocks and we present the dataset. Section 4 illustrates our Bayesian Threshold VAR model; Section 5 is devoted to illustrate our main results on the transmission of fiscal policy shocks under uncertainty and Section 6 concludes.

2 A new measure of fiscal policy uncertainty

In this study, we interpret fiscal policy uncertainty as the dispersion of individual expectations on government spending dynamics that is not induced by macroeconomic uncertainty. In this context, fiscal policy uncertainty is thus due to the precision of signals sent by governments along with their credibility, the stability of the political environment and other exogenous factors such as, for example, the geopolitical situation.

From an empirical perspective, given the two-way interaction between macroeconomic uncertainty and policy uncertainty, measuring the effect of policy uncertainty is not a straightforward exercise. That is, an uncertain macroeconomic environment can make policies less predictable and vice versa. Further, uncertainty might not have a linear relation with output, as already highlighted by Bloom (2009).

To solve this problem, the empirical literature has taken three many approaches in computing measures of general policy uncertainty, based on: 1) *ex post* realised volatility in certain time series; 2) news-based word frequency counting for terms that can be thought of as related to policy uncertainty; 3) "disagreement" measures, computed as the cross-sectional variance of experts' point forecasts, as proxies for individual uncertainty.

With regard to fiscal policy uncertainty, the realised volatility of historical fiscal time series is not completely adequate for our purposes. This is because uncertainty is fundamentally an *ex ante* concept, related to the variance associated to a forecast before the actual outcome is known. Hence, measures of uncertainty should be constructed using data available in real time. Further, the relationship between *ex post* realised volatility and *ex ante* conditional variance of the forecasts for fiscal variables is likely to be unstable as policy uncertainty might not necessarily translate into an increase in the volatility of the fiscal variables. This was evident, for instance, by the uncertainty surrounding the extension of the Bush-era tax cuts, as also reflected in the "Fiscal Cliff" episode. Finally, an increase in the realised volatility of a fiscal variable might be purely due to a systematic relationship of the variable itself with macroeconomic conditions and their variability, especially in the presence of policy smoothing over the cycle, rather than to policy uncertainty.

The index proposed by Baker *et al.* (2012) follows mainly the second approach and is based on real-time data. In particular, their index is based on the weighted sum of three main components: (i) Google-based news searches for terms likely to be related to policy uncertainty; (ii) disagreement among economic forecasters about future spending growth and (iii) the number of provisions in the U.S. tax code set to expire in future years. The Baker *et al.* (2012) index is a

[7] Some papers find that, under specific circumstances and in particular when there are concerns regarding the sustainability of public finances, fiscal adjustments can be expansionary (see, e.g., Alesina and Ardagna, 2013). In these circumstances, a clearly signalled and front-loaded fiscal consolidation may induce expansionary effects, possibly through a confidence channel that reduces the default risk and reflects the government's commitment to fiscal target. However, this hypothesis is not investigated in this paper, given that we focus on the US, *i.e.*, on a country that did not experience a very severe fiscal crisis in the post-war period.

natural benchmark in the literature on policy uncertainty and it is now also widely used by policy institutions and market participants.

Despite its many advantages, the Baker *et al.* (2012) index is not suited for our analysis because it is more geared to measuring general policy uncertainty rather than uncertainty related to fiscal spending only. Indeed, the underlying components of the index are heterogeneous and indirectly related to the variability of economic agents' expectations. In fact, the intensity of news-search findings may be related to downside or tail risks rather than policy uncertainty as second moment of expectations. Another issue related to the Baker *et al.* (2012) index is that the first two components (news and disagreement) are not immune to the influence of general economic uncertainty. The third component (the number of expiring revenue measures), on the contrary, is completely policy-specific but being based on tax measures it is not directly relevant for our work, which is focused on federal spending shocks. Finally, the weights attributed to each component reflect the priors of the authors regarding the relative importance of each element of the index and are assigned in a discretionary way.

To address these issues, we focus on the component of the disagreement among forecasters about the future federal spending developments that is orthogonal to the disagreement about current macroeconomic conditions. This allows to tackle the issue of exogeneity (*i.e.*, with respect to macroeconomic uncertainty) and to develop a measure which is more likely to reflect fiscal policy uncertainty. The resulting index has three main features: (1) it relies on real time, *ex ante* data, but it also directly connects to a measure of agents' expectations (the SPF forecasts); (2) it is linearly uncorrelated with the macroeconomic uncertainty; (3) it is fully non-judgmental and could be potentially applied to a similar dataset. Moreover, it is consistent with our definition of fiscal shocks since they are extracted from the same dataset, thus referring to the same agents' information set. Also, because of this, it fully aligns the time horizon covered by our definition of our fiscal news shocks to the one over which policy uncertainty is measured.

To construct our index we follow a two-step procedure:

1) We compute the time-varying cross-sectional standard deviation of the SPF forecasts (disagreement), at different horizons, for real federal government spending and GDP. These, under reasonable assumptions, can be thought of as proxies for the time-varying overall fiscal and macroeconomic uncertainty of the agents;
2) We extract the policy uncertainty component, projecting the disagreement among forecasters about the future development of fiscal spending onto the disagreement about the current macroeconomic conditions.

We theoretically justify this procedure by discussing under which assumptions the index we obtain could be correctly thought of as an approximation of the policy uncertainty. In addition, we provide empirical support to this procedure by matching the index obtained with the historical narrative. We also compare our index with the fiscal component of the Baker *et al.* (2012) index.

2.1 Uncertainty and disagreement in a model of Bayesian learning

A standard model of Bayesian learning can help in more precisely defining the concepts we use and in clarifying the assumptions underlying our approach (see, in particular, Lahiri and Sheng, 2010). More specifically, we want to show that, in the case of fiscal spending, changes in the disagreement of forecasting are directly proportional to the changes of the square of uncertainty, up to some reasonable approximation.[8]

Let's assume that each forecaster *i*, at each quarter *t*, receives a public signal informative about the future fiscal spending growth at horizon h from the policy makers:

$$n_{t+h} = \Delta g_{t+h} + \eta_{t,h} \ , \qquad \eta_{t,h} \sim \mathcal{N}\left(0, \sigma^2_{(\eta)t,h}\right) . \tag{1}$$

The information carried by the public signal is complemented using other sources of information, e.g., a private signal or a signal obtained by random sampling from diffuse information publicly available:[9]

$$s^i_{t+h} = \Delta g_{t+h} + \zeta^i_{t,h} \ , \qquad \zeta^i_{t,h} \sim \mathcal{N}\left(0, \sigma^2_{(\zeta)i,t,h}\right) . \tag{2}$$

Without loss of generality, we can assume that the public and the private signals are independent. Each forecaster combines the two signals, via Bayesian updating, to form conditional expectations for g_{t+h}:

$$\Delta\widehat{g}_{i,t+h} = \mathbb{E}^i\left[\Delta g_{t+h} | n_{t+h}, s^i_{t+h}\right] = \frac{\sigma^2_{(\eta)t,h} s^i_{t+h} + \sigma^2_{(\zeta)i,t,h} n_{t+h}}{\sigma^2_{(\zeta)i,t,h} + \sigma^2_{(\eta)t,h}} \ , \tag{3}$$

With conditional variance:

$$U_{i,t,h} \equiv \mathbb{V}\mathrm{ar}^i\left[\Delta g_{t+h} | n_{t+h}, s^i_{t+h}\right] = \frac{\sigma^2_{(\eta)t,h}\sigma^2_{(\zeta)i,t,h}}{\sigma^2_{(\zeta)i,t,h} + \sigma^2_{(\eta)t,h}} \ . \tag{4}$$

The conditional variance of individual forecast is due to the precision of both the public signal and of the signal sent by private or diffuse sources. To obtain a measure of uncertainty in the aggregate economy we consider the average individual uncertainty:

$$U_{t,h} \equiv \frac{1}{N}\sum_{i=1}^{N} U_{i,t,h} = \frac{1}{N}\sum_{i=1}^{N} \frac{\sigma^2_{(\eta)t,h}\sigma^2_{(\zeta)i,t,h}}{\sigma^2_{(\zeta)i,t,h} + \sigma^2_{(\eta)t,h}} \ , \tag{5}$$

where N is the number of forecasters.

The disagreement amongst forecasters can be defined as:

$$\begin{aligned} D_{t,h} &\equiv \mathbb{E}\left[\tfrac{1}{N-1}\textstyle\sum_{i=1}^{N}\left(\Delta\widehat{g}_{i,t+h} - \tfrac{1}{N}\sum_{j=1}^{N}\Delta\widehat{g}_{j,t+h}\right)^2\right] \\ &= U_{t,h} - \tfrac{1}{N(N-1)}\mathbb{E}\left[\textstyle\sum_{i=1}^{N}\sum_{j\neq i}^{N}\Delta\widehat{g}_{i,t+h}\Delta\widehat{g}_{j,t+h}\right] \ , \end{aligned} \tag{6}$$

where $\Delta g_{i,t+h}$ is the individual forecast defined in equation 3.

The variance of the public signal may depend on the macroeconomic environment, as well as on the credibility of the policy maker and his or her willingness to clarify the policy indication.

On the other hand, the variance of the private signal – that we think of as extracted in a judgemental way from diffused information – may depend on several features of the social environment, viz., among others, the information system, the policy decision process and the institutional framework. Given the relative stability of the American institutional framework, we

8 It is possible to have forecast dispersion also when agents share the same information set but use different forecasting models or have different objective functions. However, these alternative hypotheses seem to find limited support in the data (see, for example, Coibion and Gorodnichenko, 2010).

9 In the case of fiscal policy, it is reasonable to assume that different forecasters attribute different weights to several diffuse sources of information.

can assume that the variance of the private information is nearly constant over the sample and equal across forecasters:

$$\sigma^2_{(\zeta)i,t,h} \approx \sigma^2_{(\zeta)h} + \mathcal{O}(2) \ . \tag{7}$$

Under this assumption, the expression for disagreement simplifies to:

$$D_{t,h} \approx \frac{\sigma^2_{(\eta)t,h}\sigma^2_{(\zeta)h}}{\sigma^2_{(\zeta)h} + \sigma^2_{(\eta)t,h}} - \frac{1}{\sigma^2_{(\eta)t,h}} \left(\frac{\sigma^2_{(\eta)t,h}\sigma^2_{(\zeta)h}}{\sigma^2_{(\zeta)h} + \sigma^2_{(\eta)t,h}} \right)^2 \ , \tag{8}$$

hence we find that the disagreement is approximately equal to the square of aggregate uncertainty times the average precision of the privately gathered information:

$$D_{t,h} \approx \frac{1}{\sigma^2_{(\zeta)h}} U^2_{t,h} \ . \tag{9}$$

The link between the dispersion of individual mean forecasts of inflation and the average dispersion of corresponding density forecast distributions has been extensively debated in the literature, mostly for the case of inflation (see, among many others, Lahiri and Sheng, 2010; Giordani and Soderlind, 2003; D'Amico and Orphanides, 2008; Rich and Tracy, 2010; and Lahiri and Sheng, 2010).[10] This issue is crucial in assessing the validity of using disagreement as a proxy for inflation uncertainty in empirical investigations. However results have so far been mixed.

For what concern fiscal spending, we believe our assumptions are plausible. As we will show in Section 2.3, the fact the our index matches a historical narrative provides support for our assumptions.

2.2 *The survey of professional forecasters' dataset*

In this section, we briefly describe the Philadelphia Fed Survey of Professional Forecasters (SPF) dataset, which underlines the construction of our index. In the SPF, professional forecasters are asked each quarter to provide forecasted values of a set 32 macroeconomic variables, for the present quarter and up to four quarters ahead. SPF forecasters do not know the current value of macroeconomic variables that have yet to be released, with a lag.[11]

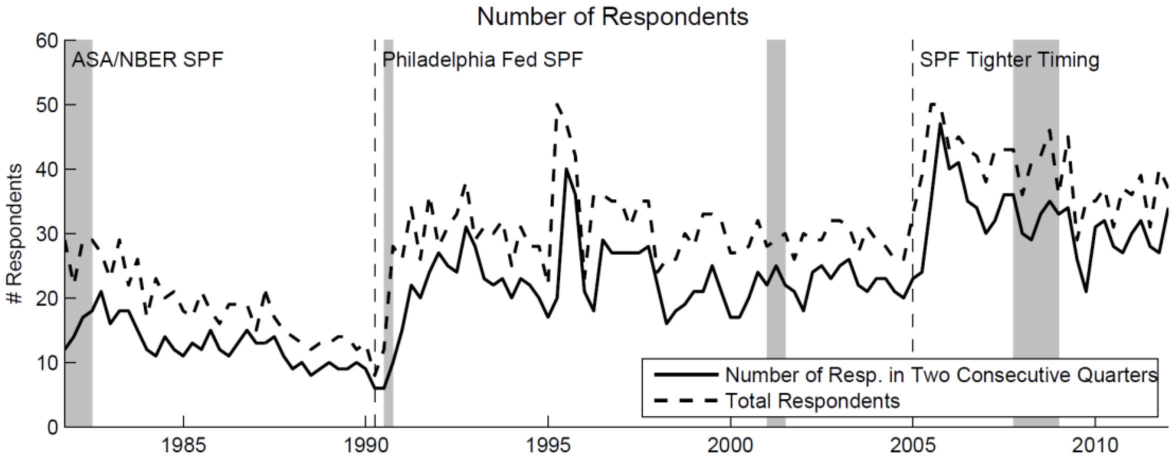
The Survey does not report the number of experts involved in each forecast or the forecasting method used. Professional forecasters are mostly private firms in the financial sector and, on average, there are 29 respondents per period in the sample, 22 of which appear in consecutive periods (see Figure 1). For *real federal government consumption expenditures and gross investment*, the main quantity of interest of this work, individual responses of professional

[10] For inflation forecasts, the SPF dataset contains both point and density forecasts. Using this data on inflation and a methodology based on entropy measures, Rich and Tracy (2010) conclude that there is little evidence that disagreement is a useful proxy for uncertainty. However, the SPF dataset is likely to contain a mixed of model based and judgmental forecasts. In this respect, the interpretation of density forecasts in terms of uncertainty is ambiguous and may not account for model uncertainty. However, unlike inflation, in the SPF real federal spending forecasts are reported in mean only.

[11] As reported in the SPF documentation notes: "The survey's timing is geared to the release of the Bureau of Economic Analysis' advance report of the national income and product accounts. This report is released at the end of the first month of each quarter. It contains the first estimate of GDP (and components) for the previous quarter. We send our survey questionnaires after this report is released to the public. Indeed, our survey questionnaires report recent historical values of the data from the BEA's advance report and the most recent reports of other government statistical agencies. Thus, in submitting their projections, our panelists' information sets include the data reported in the advance report. Our survey questionnaires are sent to the panelists on the day of the advance report. For the surveys we conducted after the 1990:Q2 survey, we have set the deadlines for responses at late in the second to third week of the middle month of each quarter".

Figure 1

Number of Professional Forecasters per Quarter



The figure plots the number of respondents in the Survey of Professional Forecasters (dashed line) and of respondents in two consecutive quarters (solid line). Vertical dashed lines indicate changes in the Survey of Professional Forecasters methodology. Prior to 1990:Q2 the Survey was conducted by the ASA/NBER, details of the timing of Survey in that period have not been reported. A minor change in the timing of the deadlines occurred beginning with the survey of 2005:Q1 when the schedule of the Survey was tightened. Grey shaded areas indicate the NBER business cycle contraction dates. On average, in the sample, there are 29 respondents per period, of which 22 appear in consecutive periods.

forecasters have been collected from 1981Q3 to 2012Q4.[12] As is customary, we convert level forecasts to forecasted growth rates because the base year changes several times within the sample. Figure 2 reports the median expected growth rate of federal spending for the current quarter and for the four quarters ahead, together with forecasters' disagreement up to one standard deviation. As a measure of disagreement, we use the dispersion of forecasts on real federal spending as reported by the SPF, measured as the cross-sectional variance of the point estimates of individual forecasters.

2.3 Accounting for the impact of general macroeconomic uncertainty

The uncertainty about fiscal variables can be thought of as a function of fiscal factors, macroeconomic uncertainty and other 'exogenous' components, e.g., the volatility of the geopolitical environment:

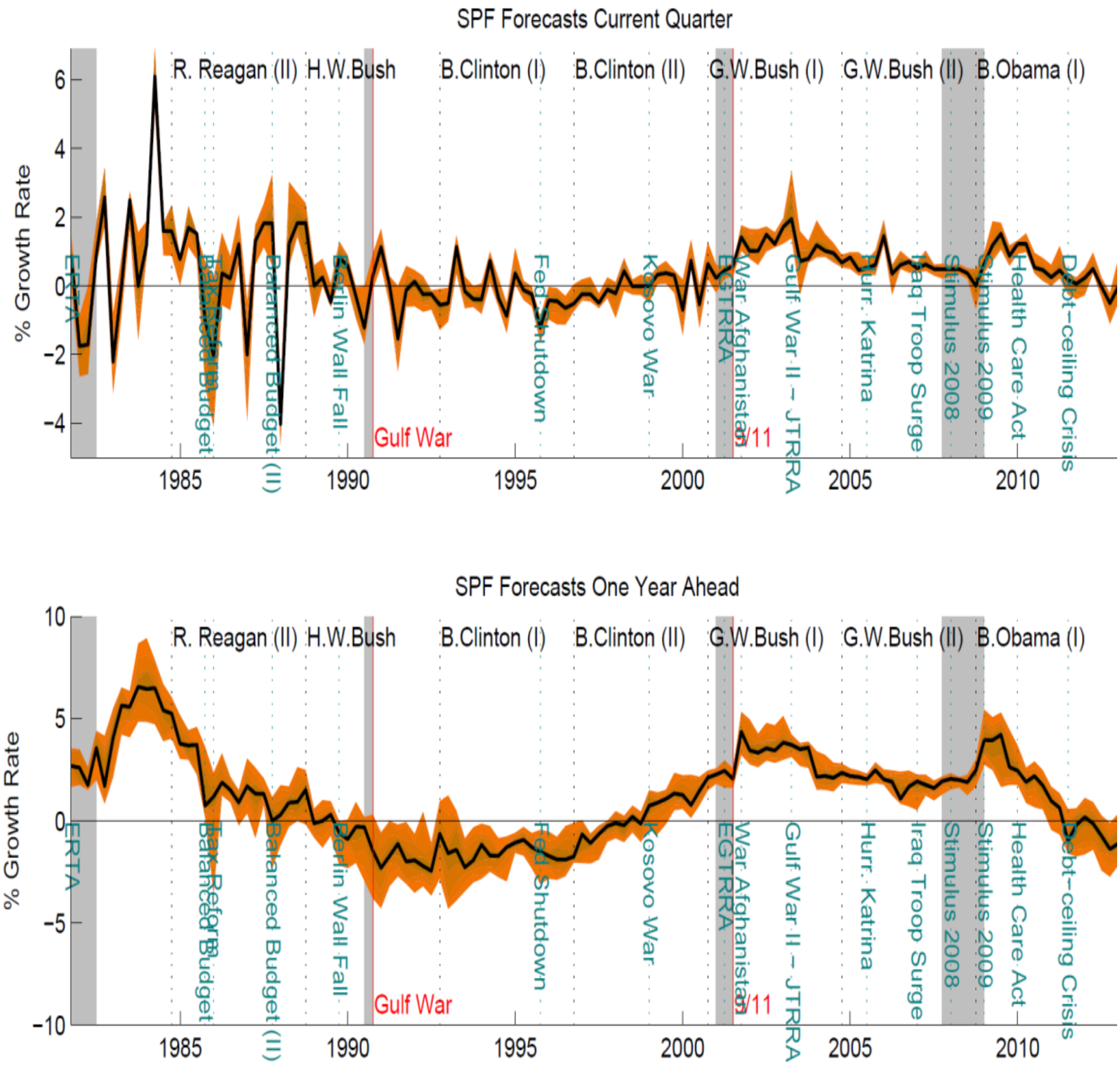
$$\begin{aligned} U_t &= f(\sigma_t^{\text{Macro}}, \sigma_t^{\text{Exogenous}}, \sigma_t^{\text{PolicyFactors}}) \simeq \\ &\simeq \alpha + \beta\sigma_t^{\text{Macro}} + \gamma\sigma_t^{\text{Exogenous}} + \delta\sigma_t^{\text{PolicyFactors}} + \mathcal{O}(2). \end{aligned} \tag{10}$$

In order to isolate the component of fiscal uncertainty due to policy factors, one cannot regress the proxy for uncertainty about fiscal variables (*i.e.*, the forecasters' disagreement of fiscal spending) onto a proxy for macroeconomic uncertainty and other factors. In fact, in doing this one would neglect the contemporaneous reverse causality between fiscal policy uncertainty and macroeconomic uncertainty.

[12] From 1969Q2 to 1981Q2, only forecasts of nominal federal defence spending were collected. This series has been discontinued thereafter.

Figure 2

Government Spending Expected Growth Rates – Fan Chart



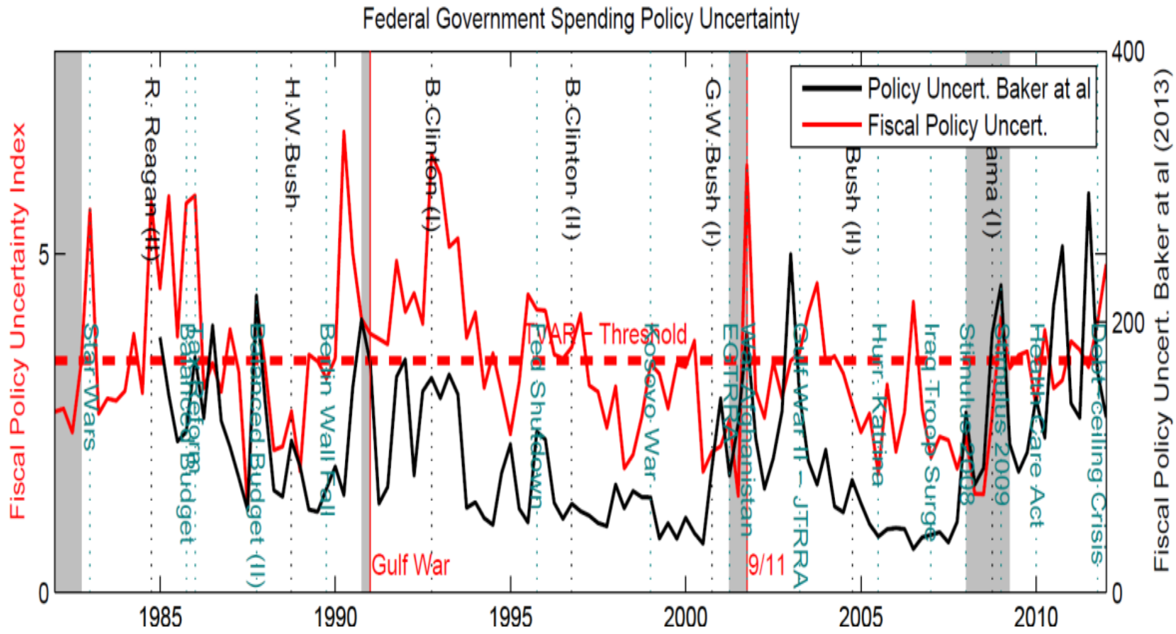
The figure plots the SPF median expected growth rate for the current quarter and for the four future quarters, together with forecasters' disagreement up to one standard deviation. Grey shaded areas indicate the NBER Business Cycle contraction dates. Vertical lines indicate the dates of the announcement of important fiscal and geopolitical events (teal), presidential elections (black), and the Ramey-Shapiro war dates (red).

We thus address this issue by assuming that uncertainty about future fiscal policies depends only on current macroeconomic uncertainty, and not on future macroeconomic conditions. Therefore, we regress the disagreement of the forecasts on real government spending for the four quarters ahead, measured as the log of the cross-sectional standard deviation, on the log-disagreement of the forecasts on current GDP, its lags, and a constant.

We also assume that the overall volatility of the other "exogenous" components has been

Figure 3

Policy Uncertainty Index



Time series of the fiscal policy uncertainty index based on the dispersion of SPF forecasts (red) and fiscal component of the policy uncertainty index of Baker *et al*. (2012) (black). Grey shaded areas indicate the NBER business cycle contraction dates. Vertical lines indicate the dates of the announcement of important fiscal and geopolitical events (teal), presidential elections (black), and the Ramey-Shapiro war dates (red). The thick red dashed line indicate the TVAR endogenous threshold.

roughly constant over the period of study.[13] Our fiscal policy uncertainty index is thus obtained by exponentiating and standardising the regression residuals. By construction, these residuals are linearly uncorrelated with the current macroeconomic uncertainty.[14]

Our policy uncertainty index is reported in Figure 3. It appears to well track the main events surrounding the management of fiscal policy in the US since the 1980s. The first peak coincides with the announcement of the "Star Wars" programme by President Reagan in 1983Q1. The index then rises in coincidence with the 1984 presidential elections and the following fiscal activism President Reagan's second term. The next spike in uncertainty is related to the fall of the Berlin wall. In the 1990s, the index reveals the uncertainty linked to the two presidential elections, the change from a Republican to a Democratic administration, the "federal shutdown" in 1995 and the war in Kosovo. In the 2000s, the first relevant moments of uncertainty are the war in Afghanistan and the Bush tax cuts of 2001 and 2003, followed by the Gulf war, Iraqi surge in the middle of the 2000s, the 2008 and 2009 stimulus acts and finally the "Debt Ceiling Crisis" in 2011.

Figure 3 plots on the right axis the fiscal component of the Baker *et al.* (2012) index. The linear correlation between the two indices is relatively low, *i.e.*, around 0.3. However the two indices seem generally to agree on the narrative of the main event generating policy uncertainty.

13 It might also be argued that a panel of professional forecasters is not representative of the economic agents. However, Carroll (2003) provides evidence that private agents, firms and households, update their forecast towards the views of professional forecasters.

14 As a robustness check, we have also added the dispersion of the forecasts on current unemployment to the regressors. Results (not shown, available upon request) are broadly unchanged.

3 Fiscal shocks identification

Following Perotti (2011) and Gambetti (2012), we identify fiscal shocks using SPF forecast revisions of federal government consumption and investment forecasts, which can be thought of as fiscal news, as in Ricco (2013). This procedure overcomes the problem of fiscal foresight (see Leeper *et al.*, 2013; Forni and Gambetti, 2010; Leeper *et al.*, 2012; Leeper *et al.*, 2013 and Ben Zeev and Pappa, 2014), because it aligns the economic agents' and the econometrician information sets. It also allows the analyst to associate the shock with the time of the announcement, rather than with the time of the actual implementation of the shock.

In particular, given that the SPF includes projections for the present quarter and up to four quarters ahead, we can actually examine the macroeconomic impact of policy news related to different time horizons. Formally, this can be seen through the following decomposition of the forecast error in a nowcast error and a flow of fiscal news, updating agents' information set I_t over time:

$$\underbrace{\Delta g_t - \mathbb{E}^*_{t-h}\Delta g_t}_{\substack{\text{forecast error} \\ h \text{ periods ahead}}} = \underbrace{(\Delta g_t - \mathbb{E}^*_t \Delta g_t)}_{\substack{\text{nowcast error} \\ \notin \mathcal{I}_t}} + \underbrace{(\mathbb{E}^*_t \Delta g_t - \mathbb{E}^*_{t-1}\Delta g_t)}_{\substack{\text{nowcast revision} \\ (\text{news at t}) \in \mathcal{I}_t}} + \dots$$
$$\dots + \underbrace{(\mathbb{E}^*_{t-h+1}\Delta g_t - \mathbb{E}^*_{t-h}\Delta g_t)}_{\substack{\text{forecast revision} \\ (\text{news at t-h+1}) \in \mathcal{I}_{t-h+1}}} . \tag{11}$$

The first term on the right-hand side corresponds to the nowcast errors, which can be thought of as proxies for agents' misexpectations (as in Ricco, 2013) that can only be revealed at a later date (a minimum of one quarter later). The other components, nowcast and forecast revisions, can be seen as proxies for the fiscal news shocks, related to current and future realisations of fiscal spending, received by the agents and incorporated in their expectations (see Gambetti, 2012; and Ricco, 2013).

Because of the different timing, the two news shocks are expected to generate a different economic impact and be subject to the influence of policy uncertainty to a different extent. Our main objects of interest are the news shocks related to future changes in government spending. In fact, given the more extended time lag between news and the actual implementation of the policy change, the macroeconomic effects of these shocks are likely to be more subject to the impact of policy uncertainty than the nowcast revision.

Using individual forecaster's expectation revisions as well as the procedure described in Ricco (2013), we define two measures of fiscal news shocks in the aggregate economy related to the revision of expectations of the growth rate of the government spending in the current quarter:

$$\mathcal{N}_t(0) \equiv \text{Mean}_i\left(\mathcal{N}^i_t(0)\right) = \text{Mean}_i\left(\mathbb{E}^{*i}_t \Delta g_t - \mathbb{E}^{*i}_{t-1}\Delta g_t\right) , \tag{12}$$

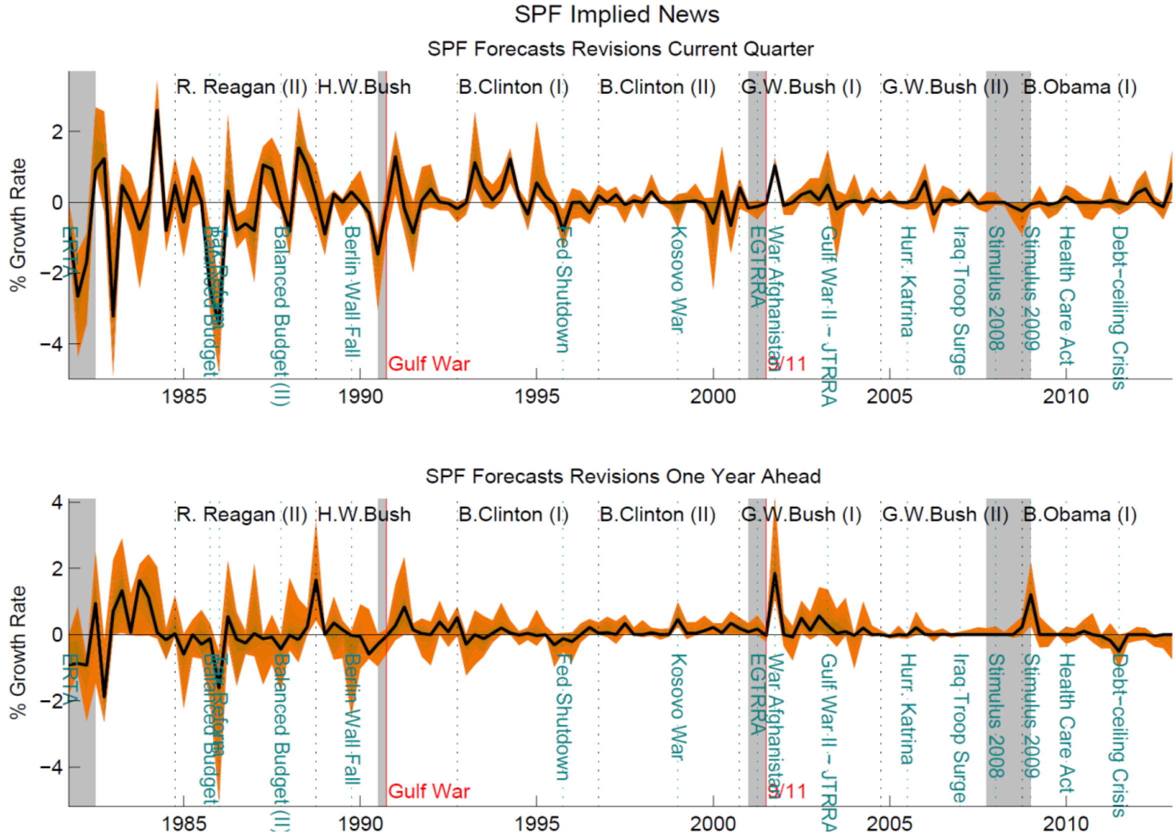
and in the future 3 quarters:

$$\mathcal{N}_t(1,3) \equiv \sum_{h=1}^{3} \mathcal{N}_t(h) = \sum_{h=1}^{3} \text{Mean}_i\left(\mathcal{N}^i_t(h)\right) = \sum_{h=1}^{q} \text{Mean}_i\left(\mathbb{E}^{*i}_t \Delta g_{t+h} - \mathbb{E}^{*i}_{t-1}\Delta g_{t+h}\right) , \tag{13}$$

where i is the index of individual forecasters. Figure 4 plots the mean implied SPF news on the current quarter and for future quarters, together with forecasters' disagreement up to one standard deviation. In the empirical analysis that follows, we use these two shocks, respectively labelled as *nowcast revision* (equation 12) and *forecast revision* (equation 13).

Figure 4

Government Spending News – Fan Chart



The figure plots the mean implied SPF news on the current quarter and for future quarters, together with forecast disagreement up to one standard deviation. Grey shaded areas indicate the NBER Business Cycle contraction dates. Vertical lines indicate the dates of the announcement of important fiscal and geopolitical events (teal), presidential elections (black), and the Ramey-Shapiro war dates (red)

In order to identify fiscal news shocks, we assume that discretionary fiscal policy does not respond to macroeconomic variables within one quarter and that the SPF time series for fiscal variables are meaningful proxy variables for the aggregate agents' expectations about government spending. As a consequence, innovations to SPF-implied fiscal news can be related to fiscal changes implemented on different horizons. We assume that the values of the main macroeconomic variables are fully revealed to the agents, but only with a lag. We also assume that forecasted future government spending incorporates the discretionary policy response to the expected values for output, as well as expectations about government spending in the present quarter. Finally, we assume that there are no shocks to future realisations of output not affecting its current realisation (e.g. technology or demand shocks) that are foreseen by the policymakers and to which the government can react.[15]

These assumptions allow for a recursive identification of the fiscal shocks in which the fiscal variables are ordered as follow:

[15] See Caldara and Kamps (2012) for a discussion of the identification of fiscal shocks in structural VAR models

$$\left(\mathcal{N}_t(0) \qquad \mathbb{E}_t^*\mathrm{GDP}_t \qquad \mathcal{N}_t(1,3) \qquad \mathbb{E}_t^*\mathrm{GDP}_{t+1year} \qquad Y_t'\right)' \tag{14}$$

and Y_t is a vector containing the macroeconomic variables of interest.

Our baseline model includes our SPF implied fiscal news, (median) SPF forecast of GDP growth for the current quarter and four quarters ahead, the policy uncertainty index, federal government spending, the Barro-Redlick marginal tax rate, and real GDP. Non-durable consumption, non-residential fixed investment and the Federal Funds rate are added using a marginal approach. We employ quarterly data from 1981Q3 to 2012Q4.

4 A Bayesian threshold VAR

The starting point of our analysis is a standard Vector-Autoregressive (VAR) model defined as:

$$y_t = C + A(L)y_{t-1} + \varepsilon_t \ , \tag{15}$$

where ε_t is a n-dimensional Gaussian white noise with covariance matrix Σ_ε, y_t is a $n \times 1$ vector of endogenous variable. The lag matrix polynomial $A(L)$ and the matrices C and are specified as matrices of suitable dimensions containing the model's unknown parameters. In the baseline model, y_t contains a measure of the fiscal news across different horizons, the fiscal policy uncertainty index, as well as government spending, GDP, nondurable consumption, non-residential fixed investment (all in real per capita log-levels) and the federal funds rate.

In order to study the effect of policy uncertainty in the transmission of fiscal shocks, we compare results from the VAR model with those obtained when specifying a Threshold Vector-Autoregressive (TVAR) model with two endogenous regimes.[16] In the TVAR model, regimes are defined with respect to the level of our fiscal policy uncertainty index (high and low uncertainty). A threshold VAR is well suited to provide stylised facts about the signalling effects of fiscal policy and to capture differences in regimes with high and low levels of uncertainty. Moreover, the explicit inclusion of regime shifts after the spending shock allows us to account for the possible dependency of the propagation mechanism to the size and the sign of the shock itself.

Following Tsay (1998), a two-regime TVAR model can be defined as:

$$y_t = \Theta(\gamma - \tau_{t-d})\left(C^l + A^l(L)y_{t-1} + \varepsilon_t^l\right) + \Theta(\tau_{t-d} - \gamma)\left(C^h + A^h(L)y_{t-1} + \varepsilon_t^h\right) \ , \tag{16}$$

where $\Theta(x)$ is an Heaviside step function, *i.e.*, a discontinuous function whose value is zero for negative argument and one for a positive argument. The TVAR model allows for the possibility of two regimes (high and low uncertainty), with different dynamic coefficients $\{C^i, A_j^i\}_{i=\{l,h\}}$ and variance of the shocks $\{\Sigma_\varepsilon^i\}_{i=\{l,h\}}$. Regimes are determined by the level of a threshold variable τ_t with respect to an unobserved threshold level γ. In our case, the delay parameter d is assumed to be known and equal to one. This in order to study the role of the uncertainty regime in place when the shock hit the economy.

The baseline VAR and the TVAR are estimated with 3 lags. However, results are virtually unchanged whether 2 or 4 lags are included. Longer lag polynomials are not advisable due to the relatively short length of the time series.

[16] It is possible to define TVAR models with an arbitrary number of regimes. However, for our study, a parsimonious specification guarantees a more precise estimation of the parameters and a clearer interpretation of results.

4.1 Bayesian priors

We adopt conjugate prior distributions for VAR coefficients belonging to the Normal-Inverse-Wishart family. This family of priors is commonly used in the BVAR literature due to the advantage that the posterior distribution can be analytically computed. For the conditional prior of the VAR coefficients, we adopt two prior densities commonly used in the macroeconomic literature for the estimation of BVARs in levels: the Minnesota prior, introduced in Litterman (1979) and the sum-of-coefficients prior proposed in Doan *et al.* (1983). The adoption of these two priors is based, respectively, on (i) the assumption that each variable follows either a random walk process, possibly with drift, or a white noise process, and (ii) on the assumption of the presence of a cointegration relationship between the macroeconomic variables.[17] The adoption of these priors has been shown to improve the forecasting performance of VAR models by effectively reducing the estimation error while introducing only relatively small biases in the parameters estimates (e.g., Sims and Zha, 1996; De Mol *et al.*, 2008; and Banbura *et al.*, 2010).

In selecting the value of the hyperparameters of our priors for our VAR model, we adopt the Bayesian method proposed in Giannone *et al.* (2012). From a purely Bayesian perspective, the informativeness of the prior distribution is one of the many unknown parameters of the model. Therefore, it can be inferred by maximising the conditional posterior distribution of the observed data. This method can be thought of as a procedure maximising the one-step-ahead out-of-sample forecasting ability of the model.

For the TVAR, we adopt natural conjugate priors parameters, generalising the priors for the VAR, and imposing identical priors in the two regimes. The prior tightness is set equal to the values selected for the VAR case for the sake of comparability. Details on the Bayesian priors adopted are provided in Appendix A.

4.2 Estimation of the model

The TVAR model specified in eq. (16) can be estimated by maximum likelihood. It is convenient to first concentrate on $\{C^i, A^i_j, \Sigma^i_\varepsilon\}_{i=\{l,h\}}$, *i.e.*, to hold γ (and d) fixed and estimate the constrained MLE for $\{C^i, A^i_j, \Sigma^i_\varepsilon\}_{i=\{l,h\}}$. Since $\{\varepsilon^i_t\}_{i=\{l,h\}}$ are assumed to be Gaussian, and the Bayesian priors are conjugate prior distributions, the Maximum Likelihood estimators can be obtained by using least squares. The threshold parameter can be estimated, using non-informative flat priors, as:

$$\hat{\gamma} = \arg\max \log \mathcal{L}(\gamma) = \arg\min \log |\widehat{\Sigma}_\varepsilon(\gamma)| \ , \tag{17}$$

where $\mathcal{L}$ is the Gaussian likelihood (see Hansen and Seo, 2002). The criterion function in equation 17, with flat priors, is not smooth and is not well suited for standard optimisation routines. However, given the low dimensionality of the problem, we can perform a grid search over a conveniently defined one dimensional space $\Gamma \equiv [\bar{\gamma}, \underline{\gamma}]$, covering the sample range of the threshold variable.[18]

The algorithm can be summarised as:

1) Form a conveniently defined grid $\Gamma \equiv [\bar{\gamma}, \underline{\gamma}]$.

[17] Loosely speaking, the objective of these additional priors is to reduce the importance of the deterministic component implied by VARs that are estimated conditional on the initial observations (see Sims, 1996).

[18] The grid is trimmed symmetrically in order to ensure a sufficient number of data points for the estimation in both regimes. Given the limited span of the time series, we adopt a 20 per cent trimming level.

2) For each value of $\gamma \in \Gamma$, estimate $\{\hat{C}^i(\gamma), \hat{A}^i_j(\gamma), \hat{\Sigma}^i_\varepsilon(\gamma)\}_{i=\{l,h\}}$, conditional on the Bayesian priors for the variance of the coefficients.
3) Find the value $\hat{\gamma}$ in Γ that minimizes $\log|\hat{\Sigma}_\varepsilon(\gamma)|$.
4) Set $\{\hat{C}^i, \hat{A}^i_j, \hat{\Sigma}^i_\varepsilon\}_{i=\{l,h\}} = \{\hat{C}^i(\hat{\gamma}), \hat{A}^i_j(\hat{\gamma}), \hat{\Sigma}^i_\varepsilon(\hat{\gamma})\}_{i=\{l,h\}}$ and $\{\hat{\varepsilon}^i_t\}_{i=\{l,h\}} = \{\hat{\varepsilon}^i_t(\hat{\gamma})\}_{i=\{l,h\}}$

4.3 Within-regime IRFs and inter-regimes GIRFs

In non-linear models the response of the system to disturbances depends on the initial state, size and sign of the shock. In our TVAR model, the shock can trigger switches between regimes thereby generating more complex dynamic responses to shocks than the linear mode. Because of this, the response of the model to exogenous shocks becomes dependent on the initial conditions and is no longer linear.

We study two sets of dynamic responses to disturbances: impulse responses when the economy is assumed to remain in one regime forever (within-regime IRFs), and impulse responses when the switching variable is allowed to respond to shocks (inter-regime IRFs). While the former set can be computed as standard IRFs by employing the estimated VAR coefficients for a given regime, the latter must be studied using generalised impulse response functions (GIRFs) as in Pesaran and Shin (1998).

For a TVAR(p), the GIRFs are defined as the change in conditional expectation of y_{t+i} for $i = 1,\dots,h$:

$$GIRF_y(h, \omega_{t-1}, \varepsilon_t) = \mathbb{E}\left[y_{t+h}|\omega_{t-1}, \varepsilon_t\right] - \mathbb{E}\left[y_{t+h}|\omega_{t-1}\right] \ , \tag{18}$$

Due an exogenous shock ε_t and given initial conditions $\omega^r_{t-1} = \{y_{t-1}, \dots, y_{t-1-p}\}$. Details on the GIRFs computation are provided in Appendix B.

4.4 Testing for non-linearities

In assessing the presence of non-linearities, we limit ourself to testing the hypothesis of a two-regime threshold VAR versus the null hypothesis of linear VAR model. These models are nested given that a linear VAR can be thought of as a two-regime TVAR satisfying the restrictions $\mathcal{H}_0: \{C^h, A^h_j, \Sigma^h_\varepsilon\} = \{C^l, A^l_j, \Sigma^l_\varepsilon\}$. We adopt the Lagrange Multiplier (LM) test proposed in Davies (1987) and generalised to a multivariate setting with heteroscedasticity in Hansen and Seo (2002). The test is constructed as follows:

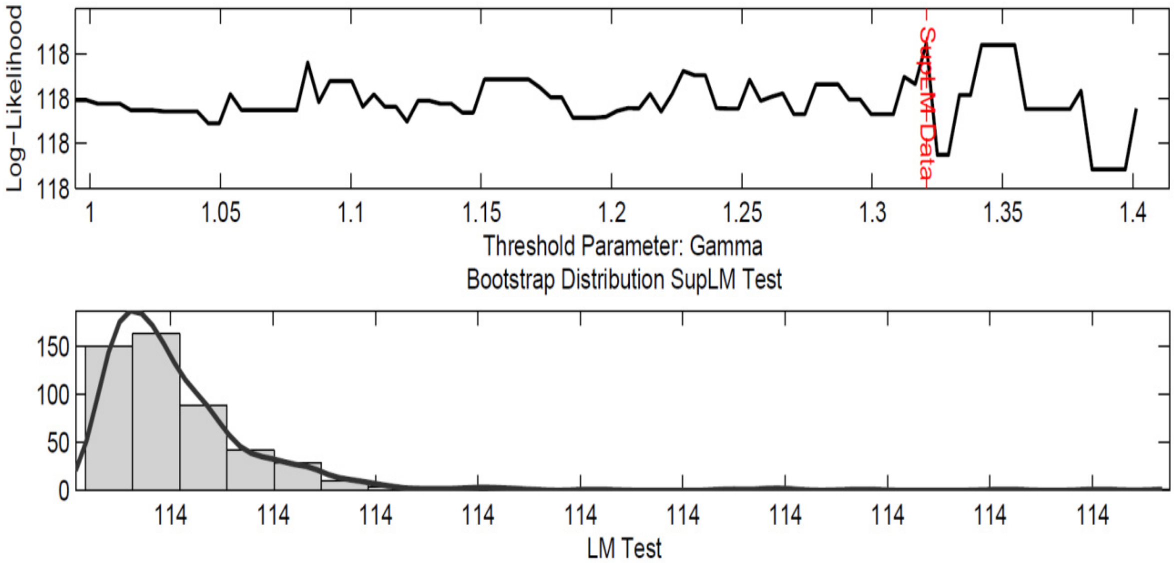
1) Estimate the model under the null hypothesis of linearity and compute the LM statistic (see Hansen and Seo, 2002).
2) Estimate the model under the alternative for each possible threshold value $\gamma \in \Gamma$, allowing for heteroscedasticity in the errors, and compute the LM statistic as function of γ.
3) Define the test statistic as:

$$\text{SupLM} = \sup_{\gamma\in\Gamma} \text{LM}(\gamma) \ . \tag{19}$$

4) The distribution of SupLM under the null hypothesis can be calculated using bootstrap simulation methods. The bootstrap calculates the sampling distribution of the test SupLM using the model, the residuals, and the parameter estimates obtained under the null.
   - Random draws are made from the residual vectors.
   - Given fixed initial conditions and the draws for the residuals, simulated time series are created by recursion, applying the linear model.

Figure 5

Hansen Test



- The SupLM is obtained for each simulated sample.

5) The bootstrap *p*-value is obtained as the percentage of simulated statistics which exceed the actual statistics.

Figure 5 shows the results of the Hansen SupLm test for our baseline model.[19] The reported p-values are essentially zero, confirming that our Bayesian-TVAR model performs better than the linear VAR benchmark based on the same specification.

5 Policy uncertainty and the transmission of fiscal shocks

Figure 6 reports the impulse responses generated by the TVAR described in equation 16. The responses in these two figures are calculated assuming that there is no-change in the uncertainty regime (as, for example, in Auerbach and Gorodnichenko, 2012), thus maintaining their linear nature and their independence from the specific initial conditions.

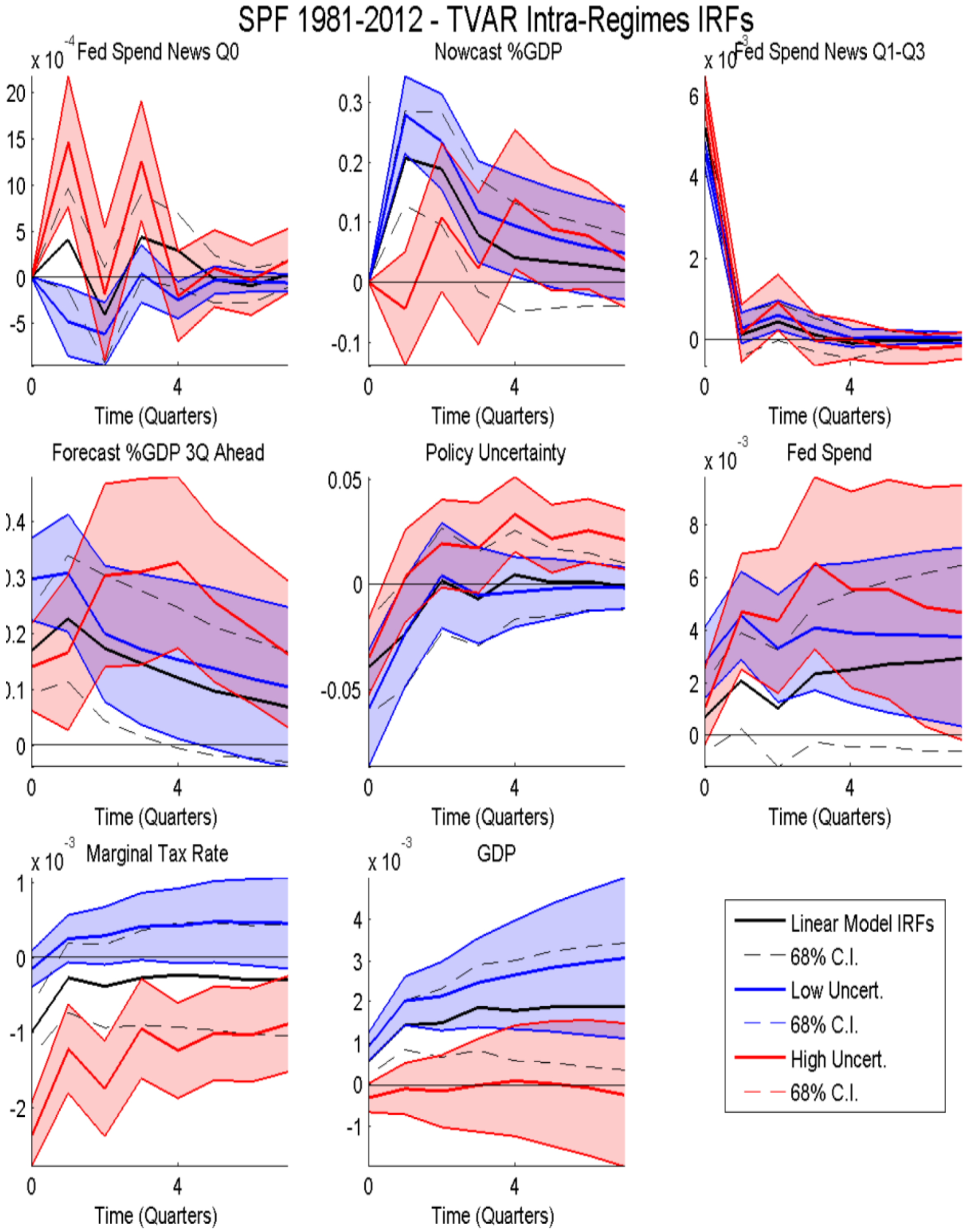
The blue line for the low-uncertainty (L-U) regime and red line for the high-uncertainty (H-U) regime indicate the responses of the endogenous variables to an innovation in the 3-quarter ahead forecast spending revisions, formalised in equation 13, with the fan describing the evolution of the 68 per cent confidence bands. As stated above, the innovations to the 3-quarter ahead forecast revisions are the main shock of interest. This is because the more extended time lag makes them more subject to the impact of uncertainty.[20] This set of results are relative to our baseline specification described in section 3, where the marginal tax rate is also included in order to provide a full picture of the behaviour of the main discretionary fiscal policy tools after the spending shock.

[19] Results are essentially equivalent for all the specifications adopted.

[20] This is especially due to what Leeper *et al.* (2013) define as "inside lag", *i.e.*, the time lag between the announcement and the passing of the law. The forecast revisions are also of particular interest because their time horizon is likely to include the shocks relative to budgetary news (usually impacting a period of one year, *i.e.*, 4 quarters).

Figure 6

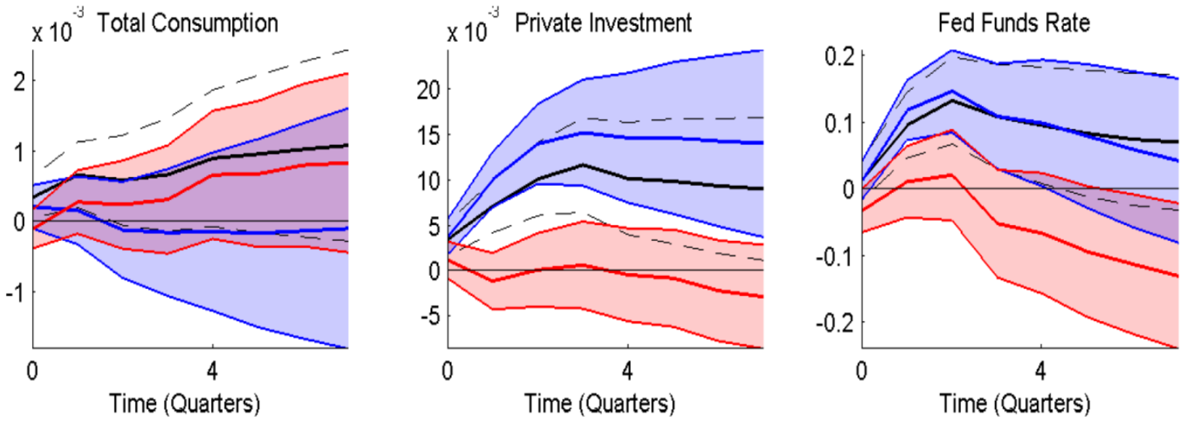
Within-regime Impulse Responses – Impact of Forecast Revisions



The shock corresponds to a one standard deviation change in the revision of the spending forecasts three quarters ahead. The responses are generated under the assumption of constant uncertainty regime. Blue line and fans are relative to the low-uncertainty regime, while the red lines and fans are relative to the high uncertainty regime. Black solid and dotted lines indicate the responses estimated in the linear VAR. Sample: 1981Q3-2012Q4.

Figure 7

Within-regime Impulse Responses – Impact of Forecast Revisions



The shock corresponds to one standard deviation change in the revision of the spending forecasts three quarters ahead. The responses of investments, total consumption and the federal funds rate are generated by adding the variables to our baseline specification. Black solid and dotted lines indicate the responses estimated in the linear VAR. Sample: 1981Q3-2012Q4.

In analysing the results of our Bayesian-TVAR, a useful benchmark is the set of IRFs from the linear VAR with no differentiations from the two uncertainty regimes, as reported by the black lines in Figure 6. The responses to a linear VAR are broadly in line with those of Gambetti (2012) and Ricco (2013). They show that a positive innovation to forecast revisions tends to have a positive and persistent effect on GDP, which can also be ascribed to the accompanying drop in marginal tax rates.

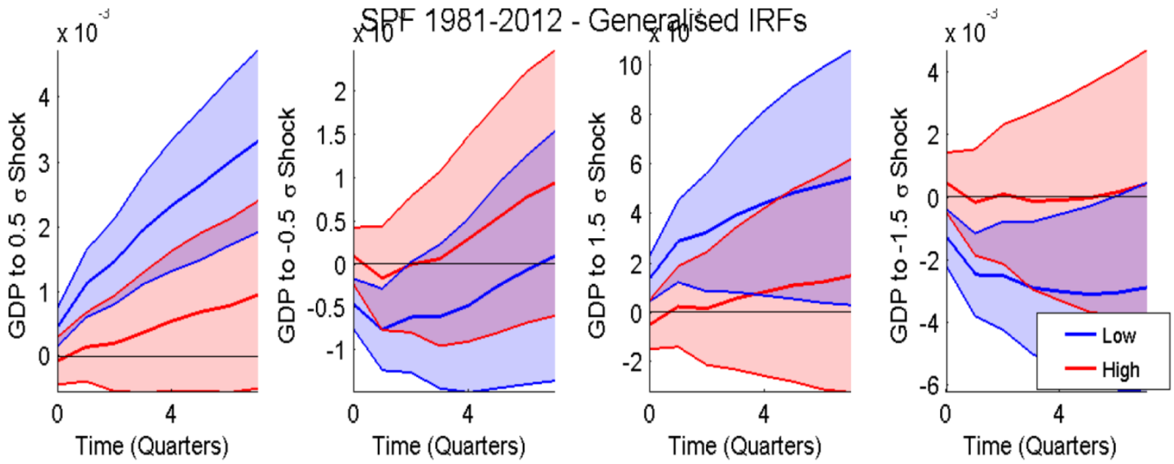
The analysis of the TVAR results, however, reveals two very different transmission mechanisms within the two regimes. While the response of spending to the policy announcement is very similar in the two regimes, in the L-U regime the marginal tax rate response is no longer significative. In the H-U regime, however, the fiscal expansion is also strengthened by a decisive reductions of the marginal tax rate. This additional policy action indicates a stronger activism of the fiscal authorities during period of L-U, as also confirmed by the relatively larger size of the spending news (right panel of the top row in Figure 6).

The GDP response reveals the full extent of the differing impact of the spending shock in the two regimes on the economy. Despite the smaller fiscal impulse generated in the L-U regime, the GDP response is always significant in the L-U regime and higher than in the H-U regime, for at least three quarters following the shock. We also compute the cumulative multipliers: as in the related literature, they are equal to the ratio between the sum of the GDP impulse responses up to the selected horizon (8th quarter in this paper), and the corresponding sum of the responses for federal spending (see also Ilzetzki *et al.*, 2013). The cumulative multiplier in the L-U regime is 2.45 whereas the one in the H-U regime is 0.49. The stronger GDP response in the L-U regime is also reflected in the impact response of 3-quarter ahead forecasted GDP, thus confirming that a fiscal shock is more able to affect economic expectations in the L-U than in the H-U regime.

Figure 7 provides some evidence of the channels through which the different uncertainty regime triggers a different propagation mechanism. While the response of consumption is essentially the same in the two regimes, the response of investment in the L-U regime is always significant and higher than the response in the H-U regime that, on the contrary, is never significantly different from zero. The higher effect on investment in less uncertain times can be

Figure 8

Inter-regime Impulse Responses – Impact of Forecast Revisions



The figure reports the GIRFs of a spending shock on GDP from four different shocks, detailed along the y-axis. These responses are estimated in the context of our baseline 8-variable TVAR. The other responses are not reported here to facilitate the reading, but are available on request. Sample: 1981Q3-2012Q4.

attributed to agents' tendency to increase investment decisions in these periods, in line with the prediction of the option value theory in Bernanke (1983).

Although not as decisively as in the case of investment, also the response of the Fed funds rate is also stronger in the L-U than in the H-U case, at least for the first three quarters.[21] This response, which tends to partially offset the impact of the spending shock on GDP, is consistent with the response on expected GDP and the higher ability of fiscal authorities to influence agents' expectation in periods of low policy uncertainty.

Finally, the analysis of the Generalized Impulse Response Functions (GIRFs) can help us understand how the impact on GDP changes with a different size and sign of the shocks, once we account for the possibility of endogenous regime shifts after the fiscal spending shock (which are neglected in the within-regime analysis presented in Figure 7). Figure 8 includes the GIRFs generated by four different shocks: a small positive fiscal shock of half standard deviation along with its symmetric negative shock (first two panels) and a large fiscal shock of 1.5 standard deviations along with its symmetric negative shock (last two panels). Unsurprisingly, the inclusion of possible regime shifts reduces the difference of the IRFs across the two regimes, though in a rather limited way, especially for small and positive shocks. In the case of negative spending shocks, however, the difference between the two IRFs is less significant, as confirmed by the largely overlapping impulse-response functions. In addition, the impulse responses in the case of negative shocks tends to revert to zero after an initial negative effect, thus revealing that fiscal retrenchments tend to have positive medium-run effects on output following an initial contraction. In summary, the evidence presented by the GIRFs suggests caution in transposing the conclusion inferred in the case of the spending stimulus to the case of spending consolidations given the non-linearities in the GDP effect. Finally, Table 1 reports the regime switching probabilities between the two regimes. It appears that – in the two years following the shock – there is a probability of around 70 per cent that the L-U regime switches to the H-U regime, and vice versa.

[21] See also Coenen *et al.* (2012) for a discussion of how the monetary policy stance may affect the size of fiscal multipliers.

Table 1

Regime Crossing Probabilities from GIRFs

Crossing Probabilities from GIRFs							
Low Uncertainty				**High Uncertainty**			
0.5 σ	–0.5 σ	1.5 σ	–1.5 σ	0.5 σ	–0.5 σ	1.5 σ	–1.5 σ
0.68	0.70	0.66	0.72	0.72	0.73	0.72	0.74

The probabilities of regime switching are computed using the GIRFs algorithm and evaluating the frequency of switching.

All in all, the evidence reported in Figures 6 and 7 highlights relevant differences between the responses under the two regimes and with the estimates produced by the linear VAR. This confirms the importance of taking the degree of policy uncertainty into account when analysing the transmission mechanism of spending shocks. In particular, despite a reduction in the marginal tax rates usually accompanying the spending shock in the L-U regime, the GDP response in the short-term is stronger than in the H-U regime. The stronger GDP response is mainly driven by an increase in investment and partially offset by the response of monetary authorities. These responses tend to align well with the option-value theory first proposed by Bernanke (1983), while providing further evidence that it is only in a low uncertainty regime that a fiscal announcement has the credibility required to influence agents' expectations.

5.1 *Additional results*

In order to give a complete overview of the results implied by our econometric model, Figure 9 shows the responses to a one standard deviation innovation on the nowcast revision, as defined in equation 11.

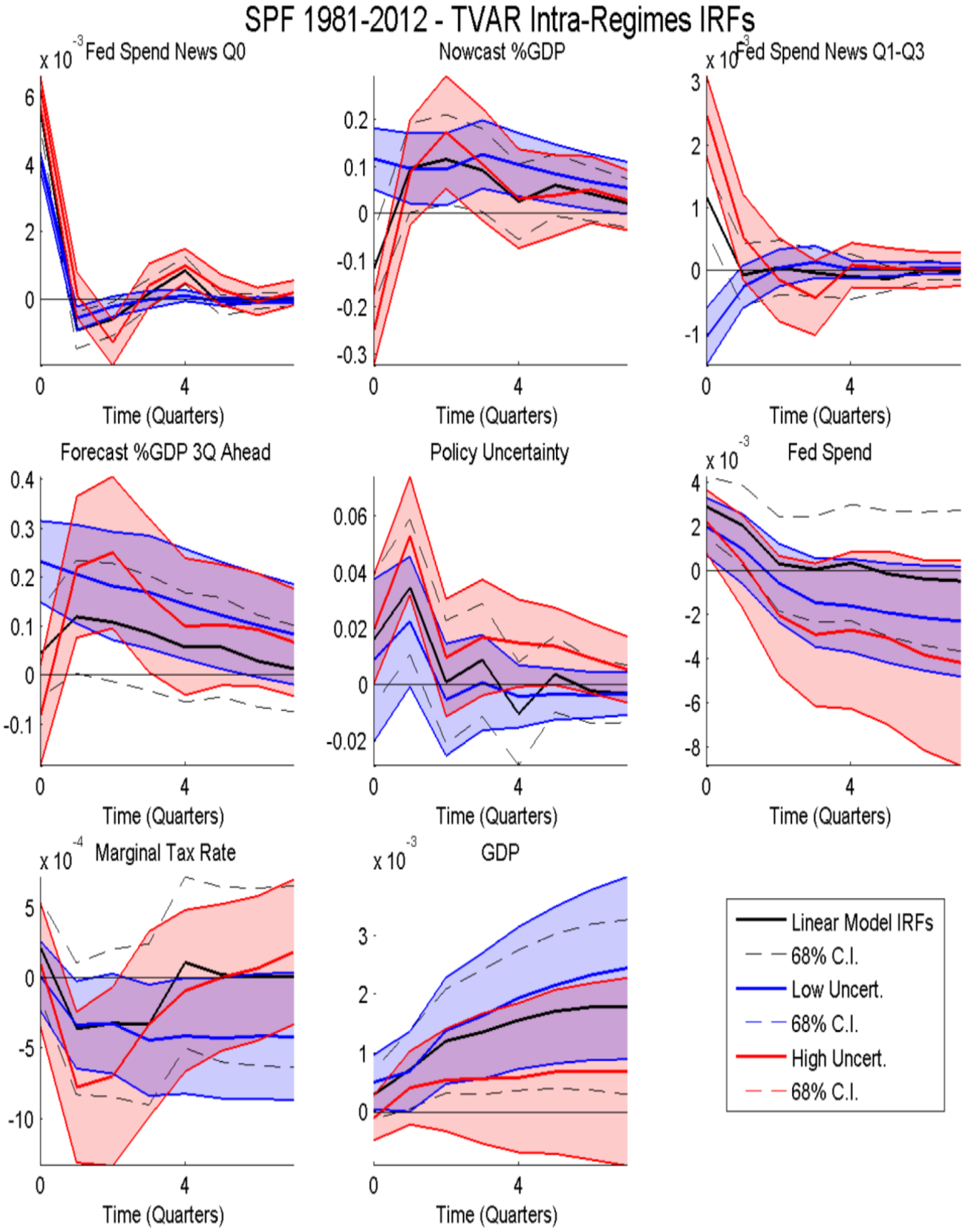
The pattern of the responses in the two regimes is consistent with what has been observed for news shocks relative to future changes in spending. Even though the point estimate of the L-U regime for GDP is generally outside the bands of the H-U regime, unsurprisingly, the responses do not show a strongly significant difference across regimes. The unresponsiveness of nowcast revision shocks to the uncertainty regimes can be rationalized by noting that uncertainty influences the propagation of fiscal shocks mainly through the investment channel (see Figure 7). The enacting of the measure inside the quarter provides little scope for reallocating productive investments in order to expand capacity and accommodate the fiscal expansion.

6 Conclusions

This paper offers new insights into the US economy's fiscal transmission mechanism. In particular, we study the role of fiscal policy uncertainty in the propagation of government spending shocks. We contribute to the existing literature in two main directions. First, we propose a new index focused solely on spending policy which is directly related to the dispersion of economic agents' expectations. Using the US Survey of Professional Forecasters (SPF) dataset, this new index is based on the dispersion of forecasts about future spending growth. The main idea is that disagreement about future government spending is indicative of poor signalling from the

Figure 9

Within-regime Impulse Responses – Impact of Nowcast Revisions



The shock corresponds to one standard deviation change in the revision of the spending forecasts for the current quarter. The responses are generated under the assumption of constant uncertainty regime. Blue line and fans are relative to the low-uncertainty regime, while the red line and fan are relative to the high uncertainty regime. Black solid and dotted lines indicate the responses estimated in the linear VAR. Sample: 1981Q3-2012Q4.

government about the future stance of fiscal policies. Our fiscal policy uncertainty index is as much as possible immune from general macroeconomic uncertainty influence. This has not been accounted for in previous attempts to measure policy uncertainty. Second, we provide stylized facts about the role of fiscal policy signalling and uncertainty in the propagation of government spending shocks on output and other macroeconomic variables.

Our results suggest that, during periods of high fiscal policy uncertainty, fiscal interventions are less stimulative. In these phases, fiscal authorities tend to accompany announcements about future spending growth with reductions in marginal tax rates. However, despite this higher activism, output does not respond to the policy news. At the same time, under low uncertainty, the output response to the spending news is positive and significantly different from zero, reaching a cumulative multiplier of about 2.45 after 8 quarters.

These results cannot be fully transposed to the case of negative fiscal shocks, *i.e.*, to fiscal consolidations. In fact, our Generalized Impulse Response analysis shows that, following a negative spending shocks, the difference between the two IRFs in the two regimes is less significant than in the case of a positive fiscal shock. In addition, the output response in the case of negative shocks tends to revert to zero, after an initial negative effect, thus revealing that fiscal retrenchments tend to have neutral medium-run effects on GDP, following an initial contraction.

With respect to positive fiscal shocks, we show that the strong stimulative effects in less uncertain times is essentially the result of agents' tendency to increase investment decisions, in line with the prediction of the option value theory of Bernanke (1983). We also find that, in presence of clear policy signals (*i.e.*, in the low uncertainty regime), the Federal Reserve tends to be more reactive to spending increases than in periods of high uncertainty.

Overall, these results indicate that fiscal communication can be used as a forward guidance tool. In other words, by committing to a future path of policies, fiscal authorities tend to generate stronger effects on the economy.

APPENDIX A
BAYESIAN PRIORS FOR VAR AND TVAR MODELS

In our empirical model, we adopt Bayesian conjugate prior distributions for VAR coefficients belonging to the Normal-Inverse-Wishart family:

$$\Sigma_\varepsilon \sim IW(\Psi, d) \ , \tag{20}$$

$$\beta|\Sigma_\varepsilon \sim N(b, \Sigma_\varepsilon \otimes \Omega) \ , \tag{21}$$

where $\beta \equiv \text{vec}([C, A_1, \ldots, A_4]')$ and the elements Ψ, d, b, and Ω embed prior assumptions on the variance and mean of the VAR parameters. These are typically functions of lower dimensional vectors of hyperparameters. This family of priors is commonly used in the BVAR literature because the posterior distribution can be analytically computed.

As for the conditional prior of β, we adopt two prior densities used in the existing literature for the estimation of BVARs in levels: the Minnesota prior, introduced in Litterman (1979), and the sum-of-coefficients prior proposed in Doan *et al.* (1983).

- **Minnesota prior**: This prior is based on the assumption that each variable follows a random walk process, possibly with drift. This is quite a parsimonious though reasonable approximation of the behaviour of economic variables. Following Kadiyala and Karlsson (1997), we set the degrees of freedom of the Inverse-Normal-Wishart distribution to $d = n + 2$ which is the minimum value that guarantees the existence of the prior mean of Σ_ε.[22] Moreover, we assume Ψ is a diagonal matrix with n × 1 elements ψ along the diagonal. The coefficients $A1, \ldots, A4$ are assumed to be a priori independent. Under these assumptions, the following first and second moments analytically characterise this prior:

$$E[(A_k)_{i,j}] = \begin{cases} \delta_i & j = i, \ k = 1 \\ 0 & \text{otherwise} \end{cases} \tag{22}$$

$$V[(A_k)_{i,j}] = \begin{cases} \frac{\lambda^2}{k^2} & j = i \\ \vartheta \frac{\lambda^2}{k^2} \frac{\psi_i}{\psi_j/(d-n-2)} & \text{otherwise.} \end{cases} \tag{23}$$

  These can be cast in the form of (21). The coefficients δ_i that were originally set by Litterman were $\delta_i = 1$ reflects the belief that all the variables of interest follow a random walk. However, it is possible to set the priors in a manner that incorporates the specific characteristics of the variables. We set $\delta_i = 0$ for variables that, in our prior beliefs, follow a white noise process and $\delta_i = 1$ for those variables that, in our prior beliefs, follow a random walk process. We assume a diffuse prior on the intercept. The factor $1/k^2$ is the rate at which prior variance decreases with increasing lag length. The coefficient ϑ weights the lags of the other variables with respect to the variable's own lags. We set $\vartheta = 1$. The hyperparameter λ controls the overall tightness of the prior distribution around the random walk or white noise process. A setting of $\lambda = \infty$ corresponds to the ordinary least squares estimates. For $\lambda = 0$, the posterior equals the prior and the data does not influence the estimates.

  The Minnesota prior can be implemented using Theil mixed estimations with a set of T_d artificial observations – *i.e.*, *dummy observations*:

[22] The prior mean of Σ_ε is equal to $\Psi/(d - n - 1)$.

$$y_d = \begin{pmatrix} \mathrm{diag}(\delta_1\psi_1, ..., \delta_n\psi_n)/\lambda \\ 0_{n(p-1)\times n} \\ .... \\ \mathrm{diag}(\psi_1, ..., \psi_n) \\ .... \\ 0_{1\times n} \end{pmatrix}, \quad x_d = \begin{pmatrix} J_p \otimes \mathrm{diag}(\psi_1, ..., \psi_n)/\lambda & 0_{np\times 1} \\ .... & .... \\ 0_{n\times np} & 0_{p\times 1} \\ .... & .... \\ 0_{1\times np} & \varepsilon \end{pmatrix},$$

where $J_p = diag(1, 2, ..., p)$.[23] In this setting, the first block of dummies in the matrices imposes priors on the autoregressive coefficients, the second block implements priors for the covariance matrix and the third block reflects the uninformative prior for the intercept (ε is a very small number).

- **Sum-of-coefficients prior**: To further favour unit roots and cointegration and to reduce the importance of the deterministic component implied by the estimation of the VAR conditioning on the first observations, we adopt a refinement of the Minnesota prior known as a sum-of-coefficients prior (Sims, 1980). Prior literature has suggested that with very large datasets, forecasting performance can be improved by imposing additional priors that constrain the sum of coefficients. To implement this procedure, we add the following dummy observations to the ones for the Normal-Inverse-Wishart prior:

$$\begin{aligned} y_d &= \mathrm{diag}(\delta_1\mu_1, ..., \delta_n\mu_n)/\tau \\ x_d &= \left((1_{1\times p}) \otimes \mathrm{diag}(\delta_1\mu_1, ..., \delta_n\mu_n)/\tau \quad 0_{n\times 1}\right). \end{aligned} \tag{24}$$

In this set-up, the set of parameters μ aims to capture the average level of each of the variables. The parameter τ controls for the degree of shrinkage and as τ goes to ∞, we approach the case of no shrinkage.

The joint setting of these priors depends on the set of hyperparameters $\gamma \equiv \{\lambda, \tau, \psi, \mu\}$ that control the tightness of the prior information and that are effectively additional parameters of the model.

The adoption of these priors has been shown to improve the forecasting performance of VAR models, effectively reducing the estimation error while introducing only relatively small biases in the estimates of the parameters (e.g., Sims and Zha, 1996; De Mol *et al.*, 2008; Banbura *et al.*, 2010). The regression model augmented with dummies can be written as a VAR(1) process:

$$y_* = x_* B + e_* , \tag{25}$$

where the starred variables are obtained by stacking $y = (y_1, ..., y_T)'$, $x = (x_1, ..., x_T)'$ for $x_t = (y'_{t-1}, \dots, y'_{t-4}, 1)'$, and $\varepsilon = (\varepsilon_1, \dots, \varepsilon_T)$ together with the corresponding dummy variables as $y_* = (y' y'_d)'$, $x_* = (x\, x'_d)'$, $e_* = (e\, e'_d)'$. The starred variables have length $T_* = T + T_d$ in the temporal dimension, and B is the matrix of regressors of suitable dimensions.

The resulting posteriors are:

$$\Sigma_\varepsilon | y \sim IW\left(\tilde{\Psi}, T_d + 2 + T - k\right) \tag{26}$$

$$\beta | \Sigma_\varepsilon, y \sim N\left(\hat{\beta}, \Sigma_\varepsilon \otimes \left(x_*' x_*\right)^{-1}\right) , \tag{27}$$

[23] This amounts to specifying the parameter of the Normal-Inverse-Wishart prior as:

$$b = (x'_d x_d)^{-1} x'_d y_d,\ \Omega_0 = (x'_d x_d)^{-1},\ \Psi = (y_d - x_d B_0)'(y_d - x_d B_0)$$

where $\hat{\beta} = \text{vec}(\hat{B}), \hat{B} = (x_*' x_*)^{-1} x_*' y_*$, and $\tilde{\Psi} = (y_* - x_*\hat{B})'(y_* - x_*\hat{B})$. It is worth noting that the posterior expectations of the coefficients coincide with the OLS estimates of a regression with variables y_* and x_*.

We adopt the pure Bayesian method proposed in Giannone *et al.* (2012) to select the value of the hyperparameters of our priors. However, we make additional assumptions to reduce the number of hyperparameters to be estimated and the uncertainty in the estimation of the VAR coefficients. Following the empirical BVAR literature we fix the diagonal elements ψ and μ using sample information. Although from a Bayesian perspective the parameters ψ should be set using only prior knowledge, it is common practice to pin down their value using the variance of the residuals from a univariate autoregressive model of order p for each of the variables. In the same way, the sample average of each variable is chosen to set the μ parameters.

Finally, we set a very loose sum-of-coefficients prior choosing $\tau = 50\lambda$. In this way, the determination of a rather large number of hyperparameters is reduced to selecting a unique scalar that controls for the tightness of the prior information.

Following Giannone *et al.* (2012), we adopt a Gamma distribution with mode equal to 0.2 (the value recommended by Sims and Zha, 1996) and standard deviation equal to 0.4 as hyperprior density for λ.

APPENDIX B
GENERALISED IMPULSE RESPONSE FUNCTIONS

Generalised impulse response functions are computed by simulating the model, using the following algorithm:

1) Random draws are made for the initial conditions (history) $\omega_{t-1}^{r} = \{y_{t-1}^{r}, \ldots, y_{t-1-p}^{r}\}$.
2) Random draws with replacement are made from the estimated residuals of the asymmetric model, $\{\varepsilon_{t-1}^{b}\}_{j=0}^{h}$. The shocks are assumed to be jointly distributed, so if date the *t* shock is drawn, the entire n-dimensional vector of residuals for date t is collected.
3) Given the draws for the history ω_{t-1}^{r} and the residuals $\{\varepsilon_{t-1}^{b}\}_{j=0}^{h}$, the evolution of y_t is simulated over $h + 1$ periods using the estimated parameter of the model and allowing for switches between regimes, obtaining a baseline path $y_{t+k}(\omega_{t-1}^{r}, \{\varepsilon_{t-1}^{b}\}_{j=0}^{h})$ for $k = 1, \ldots, h$.
4) Step three is repeated, substituting one of the residuals at time zero with an identified structural shock of size ι but leaving the remaining contemporaneous residual and the rest of the sequence of residuals unchanged. A new path for $y_{t+k}(\omega_{t-1}^{r}, \{\varepsilon_{t-1}^{*,b}\}_{j=0}^{h})$ for $k = 1, \ldots, h$ is generated.
5) Steps 2 to 4 are repeated R times, obtaining an empirical average over the sequence of shocks.
6) Steps 1 to 5 are repeated B times, obtaining an empirical average over the initial conditions.
7) The GIRF are computed as the median of the difference between the simulated shocked sequence $y_{t+k}(\omega_{t-1}^{r}, \{\varepsilon_{t-1}^{*,b}\}_{j=0}^{h})$ and the baseline path $y_{t+k}(\omega_{t-1}^{r}, \{\varepsilon_{t-1}^{b}\}_{j=0}^{h})$.

Coverage intervals for the TVAR parameters are computed as follow:

1) A draw for the TVAR parameters $\{C^{i}, A_{j}^{i}, \Sigma_{\varepsilon}^{i}\}_{i=\{l,h\}}$ is made from the estimated posterior distributions. New sequences of residuals are drawn.
2) Using the coefficients and errors from step 1 and initial conditions from the original dataset, GIRFs are computed.
3) Steps 1 to 3 are repeated Q times to generate an empirical distribution for the GIRFs, from which the coverage intervals are selected at the desired percentage level.

In our study, we set R = 200, B = 300 and Q = 1000.

REFERENCES

Aastveit, K.A., G.J. Natvik and S. Sola (2013), "Economic Uncertainty and the Effectiveness of Monetary Policy", Norges Bank, Working Paper, No. 2013/17, July.

Afonso, A., J. Baxa and M. Slavík (2011), "Fiscal Developments and Financial Stress: A Threshold VAR Analysis", European Central Bank, Working Paper, No. 1319, April.

Alesina, A. and S. Ardagna (2013), "The Design of Fiscal Adjustments", in National Bureau of Economic Research (ed.), *Tax Policy and the Economy*, Vol. 27, NBER Chapters, pp. 19-67, October.

Altavilla, C. and D. Giannone (2014), "Markets' Beliefs about the Effectiveness of Non-standard Monetary Policy Measures", mimeo.

Auerbach, A.J. and Y. Gorodnichenko (2012), "Measuring the Output Responses to Fiscal Policy", *American Economic Journal: Economic Policy*, Vol. 4, No. 2, pp. 1-27, May.

Bachmann, R., S. Elstner and E.R. Sims (2013), "Uncertainty and Economic Activity: Evidence from Business Survey Data", *American Economic Journal: Macroeconomics*, Vol. 5, No. 2, pp. 217-49, April.

Bachmann, R. and E.R. Sims (2012), "Confidence and the Transmission of Government Spending Shocks", *Journal of Monetary Economics*, Vol. 59, No. 3, pp. 235-49.

Baeriswyl, R. and C. Cornand (2010), "The Signaling Role of Policy Actions", *Journal of Monetary Economics*, Vol. 57, No. 6, pp. 682-95.

Baker, S.R., N. Bloom and S.J. Davis (2012), "Policy Uncertainty: a New Indicator", *CentrePiece – The Magazine for Economic Performance*, No. 362, Centre for Economic Performance, LSE.

Banbura, M., D. Giannone and L. Reichlin (2010), "Large Bayesian Vector Auto Regressions", *Journal of Applied Econometrics*, Vol. 25, No. 1, pp. 71-92.

Batini, N., G. Callegari and G. Melina (2012), "Successful Austerity in the United States, Europe and Japan", International Monetary Fund, Working Paper, No. 12/190, July.

Ben Zeev, N. and E. Pappa (2014), *Chronicle of a War Foretold: The Macroeconomic Effects of Anticipated Defense-spending Shocks*, Technical Report.

Benati, L. (2013), "Economic Policy Uncertainty and the Great Recession", mimeo.

Bernanke, B.S. (1983), "Irreversibility, Uncertainty, and Cyclical Investment", *The Quarterly Journal of Economics*, Vol. 98, No. 1, pp. 85-106, February.

Bi, H., E.M. Leeper and C. Leith (2013), "Uncertain Fiscal Consolidations", *Economic Journal*, Vol. 123, No. 566, pp. F31-F63, February.

Bloom, N. (2009), "The Impact of Uncertainty Shocks", *Econometrica*, Vol. 77, No. 3, pp. 623-85, May.

Caggiano, G., E. Castelnuovo and N. Groshenny (2013), "Uncertainty Shocks and Unemployment Dynamics: An Analysis of Post-WWII U.S. Recessions", Dipartimento di Scienze Economiche "Marco Fanno", Working Paper, No. 0166, June.

Caldara, D. and C. Kamps (2012), "The Analytics of SVARs: A Unified Framework to Measure Fiscal Multipliers", Federal Reserve Board, Divisions of Research and Statistics and Monetary Affairs, Finance and Economics Discussion Series, No. 2012-20, Washington (D.C.).

Campbell, J.R., C. Evans, J.D.M. Fisher and A. Justiniano (2012), "Macroeconomic Effects of Federal Reserve Forward Guidance", Federal Reserve Bank of Chicago, Working Paper, No. WP-2012-03.

Carriero, A., H. Mumtaz, K. Theodoridis and A. Theophilopoulou (2013), "The Impact of Uncertainty Shocks Under Measurement Error. A Proxy SVAR Approach", Queen Mary University of London, School of Economics and Finance, Working Paper, No. 707, August.

Carroll, C.D. (1997), "Buffer-stock Saving and the Life Cycle/Permanent Income Hypothesis", *The Quarterly Journal of Economics*, Vol. 112, No. 1, pp. 1-55, February.

————— (2003), "Macroeconomic Expectations of Households and Professional Forecasters", *The Quarterly Journal of Economics*, Vol. 118, No. 1, pp. 269-98, February.

Cimadomo, J. and A. D'Agostino (2014), "Combining Time-variation and Mixed-frequencies: An Analysis of Government Spending Multipliers in Italy", mimeo.

Coenen, G., C.J. Erceg, C. Freedman, D. Furceri, M. Kumhof, R. Lalonde, D. Laxton, J. Lindé, A. Mourougane, D. Muir, S. Mursula, C. De Resende, J. Roberts, W. Roeger, S. Snudden, M. Trabandt and J. in't Veld (2012), "Effects of Fiscal Stimulus in Structural Models", *American Economic Journal: Macroeconomics*, Vol. 4, No. 1, pp. 22-68, January.

Coibion, O. and Y. Gorodnichenko (2010), "Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts", National Bureau of Economic Research, Working Paper, No. 16537, November.

D'Amico, S. and A. Orphanides (2008), "Uncertainty and Disagreement in Economic Forecasting", Technical Report.

Davies, R.B. (1987), "Hypothesis Testing when a Nuisance Parameter is Present only Under the Alternatives", *Biometrika*, Vol. 74, No. 1, pp. 33-43.

Davig, T. and A.T. Foerster (2013), "Uncertainty and Fiscal Cliffs", Federal Reserve Bank of Kansas City, Technical Report, mimeo.

De Mol, C., D. Giannone and L. Reichlin (2008), "Forecasting Using a Large Number of Predictors: Is Bayesian Shrinkage a Valid Alternative to Principal Components?", *Journal of Econometrics*, Vol. 146, No. 2, pp. 318-28, October.

Del Negro, M., M. Giannoni and C. Patterson (2012), "The Forward Guidance Puzzle", Technical Report.

Doan, T., R.B. Litterman and C.A. Sims (1983), "Forecasting and Conditional Projection Using Realistic Prior Distributions", National Bureau of Economic Research, Working Paper, September.

Eggertsson, G.B. and M. Woodford (2003), The Zero Bound on Interest Rates and Optimal Monetary Policy", *Brookings Papers on Economic Activity*, Vol. 34, No. 1, pp. 139-235.

Fernandez-Villaverde, J., P.A. Guerrón-Quintana and J. Rubio-Ramírez (2012), "Estimating Dynamic Equilibrium Models with Stochastic Volatility", National Bureau of Economic Research, Working Paper, No. 18399, September.

Forni, M. and L. Gambetti (2010), "Fiscal Foresight and the Effects of Goverment Spending", CEPR, Discussion Paper, No. 7840.

Gambetti, L. (2012), "Government Spending News and Shocks", Universitat Autónoma de Barcelona and Barcelona GSE, mimeo.

Gertler, M. and P. Karadi (2014), "Monetary Policy Surprises, Credit Costs and Economic Activity", CEPR, Discussion Paper, No. 9824, February.

Giannone, D., M. Lenza and G.E. Primiceri (2012), "Prior Selection for Vector Autoregressions", ULB – Université Libre de Bruxelles, Working Paper, No. 1494, January.

Giordani, P. and P. Soderlind (2003), "Inflation Forecast Uncertainty", *European Economic Review*, Vol. 47, No. 6, pp. 1037-59, December.

Hansen, B.E. and B. Seo (2002), "Testing for Two-regime Threshold Cointegration in Vector Error-correction Models", *Journal of Econometrics*, Vol. 110, No. 2, pp. 293-318, October.

Ilzetzki, E., E.G. Mendoza and C.A. Végh (2013), "How Big (Small?) Are Fiscal Multipliers?", *Journal of Monetary Economics*, Vol. 60, No. 2, pp. 239-54.

Ilzetzki, E. and J. Pinder (2012), "Recession and Recovery: The US Policy Debate on Taxes, Spending and Public Debt", Centre for Economic Performance, LSE, US Election Analysis Paper, No. 001, October.

Kadiyala, K.R. and S. Karlsson (1997), "Numerical Methods for Estimation and Inference in Bayesian VAR-models", *Journal of Applied Econometrics*, Vol. 12, No. 2, pp. 99-132, March-April.

Kimball, M.S. (1990), "Precautionary Saving in the Small and in the Large", *Econometrica*, Vol. 58, No. 1, pp. 53-73, January.

Kirchner, M., J. Cimadomo and S. Hauptmeier (2010), "Transmission of Government Spending Shocks in the Euro Area: Time Variation and Driving Forces", European Central Bank, Working Paper, No. 1219, July.

Lahiri, K. and X. Sheng (2010), "Measuring Forecast Uncertainty by Disagreement: The Missing Link", *Journal of Applied Econometrics*, Vol. 25, No. 4, pp. 514-38.

Leeper, E.M., A.W. Richter and T.B. Walker (2012), "Quantitative Effects of Fiscal Foresight", *American Economic Journal: Economic Policy*, Vol. 4, No. 2, pp. 115-44, May.

Leeper, E.M., T.B. Walker and S.C.S. Yang (2013), "Fiscal Foresight and Information Flows", *Econometrica*, Vol. 81, No. 3, pp. 1115-45, May.

Leland, E.H. (1968), "Saving and Uncertainty: The Precautionary Demand for Savings", *The Quarterly Journal of Economics*, Vol. 82, No. 3, pp. 465-89, August.

Litterman, R.B. (1979), "Techniques of Forecasting Using Vector Autoregressions", Technical Report.

Mumtaz, H. and P. Surico (2013), "Policy Uncertainty and Aggregate Fluctuations", Queen Mary University of London, School of Economics and Finance, Working Paper, No. 708, September.

Perotti, R. (2011), "Expectations and Fiscal Policy: An Empirical Investigation", Technical Report.

Pesaran, H.H. and Y. Shin (1998), "Generalized Impulse Response Analysis in Linear Multivariate Models", *Economics Letters*, Vol. 58, No. 1, pp. 17-29, January.

Ramey, V.A. (2011), "Identifying Government Spending Shocks: It's All in the Timing", *The Quarterly Journal of Economics*, Vol. 126, No. 1, pp. 1-50.

Ricco, G. (2013), "A New Identification of Fiscal Shocks Based on the Information Flow", London Business School, mimeo.

Rich, R. and J. Tracy (2010), "The Relationships Among Expected Inflation, Disagreement, and Uncertainty: Evidence from Matched Point and Density Forecasts", *The Review of Economics and Statistics*, Vol. 92, No. 1, pp. 200-07, February.

Sims, C.A. (1980), "Macroeconomics and Reality", *Econometrica*, Vol. 48, No. 1, pp. 1-48, January.

—————(1996), "Inference for Multivariate Time Series Models with Trend", Technical Report.

Sims, C.A. and T. Zha (1996), "Bayesian Methods for Dynamic Multivariate Models", Technical Report.

Spence, A.M. (1973), "Job Market Signaling", *The Quarterly Journal of Economics*, Vol. 87, No. 3, pp. 355-74, August.

Tsay, R.S. (1998), "Testing and Modeling Multivariate Threshold Models", *Journal of the American Statistical Association*, No. 93, pp. 1188-202.

Werning, I. (2011), "Managing a Liquidity Trap: Monetary and Fiscal Policy", National Bureau of Economic Research, Working Paper, No. 17344, August.