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Signals from the government: policy disagreement and the transmission of fiscal shocks

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Abstract

We investigate the effects of fiscal policy communication on the propagation of government spending shocks. To this aim, we propose a new index measuring the coordination effects of policy communication on private agents' expectations. This index is based on the disagreement amongst US professional forecasters about future government spending. The underlying intuition is that a clear fiscal policy communication can coalesce expectations, reducing disagreement. Results indicate that, in times of low disagreement, the output response to fiscal spending innovations is positive and large, mainly due to private investment response. Conversely, periods of elevated disagreement are characterised by muted output response.
JEL Classification: E60, D80.

Keywords: Disagreement, Government spending shock, Fiscal transmission mechanism.

Non-technical summary

Until the recent financial crisis, the role of signalling and fiscal policy management was of limited relevance in policy discussions in advanced economies. Since the outset of the financial crisis in 2008, however, budgetary authorities were faced with a relatively new - and certainly challenging - economic context. This re-launched fiscal policy as a stabilisation tool and, contemporaneously, highlighted the importance of policy communication for an effective transmission of the policy impulses.

Indeed, the signals sent by the fiscal authorities about future fiscal policies can have different economic consequences depending on the different level of the precision of the signal itself and on the credibility of fiscal policy-makers.

In this paper, we make two main contributions to the existing literature: first, we construct a new index for fiscal policy disagreement, 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 realisations of this variable, hence reducing disagreement among forecasters.

Second, we explore whether fiscal policy announcements are more effective in stimulating GDP in an environment characterised by low disagreement or if, instead, fiscal policy is more powerful in presence of higher disagreement about present and future public spending policies.

Our results provide evidence that, during periods of high disagreement on fiscal policy, spending shocks have weak effects on the economy. Conversely, in periods of low disagreement, the output response to the spending news shock is positive, strong and significantly different from zero, reaching a cumulative medium-term multiplier of about 2.7 after 16 quarters. Our analysis also shows that the stronger stimulative effects in times of low disagreement are mainly the result of an accelerator effect of planned fiscal spending on investment. During the low disagreement regime, the Federal Reserve tends to be more reactive to spending increases than in periods of high disagreement. Overall, our analysis highlights the case for policy signalling as a tool to reduce disagreement and enhance the impact of spending shocks.

Overall, our analysis indicates that policy signalling should be seen as a potentially additional policy tool, which may enhance the effectiveness of the fiscal stimulus. Policy authorities have several concrete options in using this tool: for example, they can accompany the announcements of fiscal targets with a clear indication of the measures that they intend to adopt to achieve them. This should reduce the risks of changes in the fiscal strategy in its implementation phase, thus decreasing disagreement. Otherwise stated, fiscal communication can be used a forward guidance tool, i.e., by committing to a future path of policy fiscal authorities tend to generate stronger effects on the economy.

1 Introduction

The impact of economic policy decisions depends, to a great extent, on how they are communicated and affect agents' expectations, and hence their actions. Indeed, private agents can form expectations about the future course of fiscal policy by combining information conveyed by government announcements and privately collected information. In an economic system with dispersed information where the government has potentially superior information on its procedures, forecasts and policy plans, policymakers can coordinate private agents' beliefs and reduce disagreement by releasing additional information about current and future policies.

This paper focuses on the expectation coordination effects of fiscal policy communication and provides an empirical assessment of the implications of disagreement amongst agents for the transmission of fiscal impulses in the United States. We develop an indirect measure of precision of fiscal policy communication derived from forecasters' disagreement on the future path of federal fiscal spending, based on the Survey of Professional Forecasters (SPF). The underlying intuition is that a clear fiscal policy communication can coalesce private sector expectations on future policy measures, which in turn reduces agents' disagreement. Based on this, we formulate our empirical strategy consistently with the implications of imperfect information models (see Mankiw and Reis, 2002, Woodford, 2002, Sims, 2003 and Reis, 2006a,b) by structuring it in the three following steps.

First, in order to pin down the fluctuations in disagreement that are due to policy communication and not to cyclical macroeconomic disturbances, we project the cross sectional dispersion of forecasts about future government spending onto the disagreement about current output. Second, following Ricco (2015), we identify fiscal spending shocks using individual revision of expectations at different horizons in US Survey of Professional Forecasters (SPF) data which we name 'fiscal news'. In doing this, we recognise that the presence of information frictions crucially modifies the econometric identification problem of fiscal shocks.[1] Third, we estimate an Expectational Threshold VAR (ETVAR) model using Bayesian techniques, where the proxies for fiscal news shocks are included together with a number of macroeconomic variables. The threshold variable is our disagreement index, and the threshold level is endogenously estimated.

Our results provide evidence that, during periods of high disagreement on fiscal policy, spending shocks have weak effects on the economy. Conversely, in periods of low disagreement, the output response to the spending news shock is positive, strong and significantly different from zero, reaching a cumulative medium-term multiplier of about 2.7 after 16 quarters. Our analysis also shows that the stronger stimulative effects in times of low disagreement are mainly the result of an accelerator effect of planned fiscal spending on investment. During the low disagreement regime, the Federal Reserve tends to be more reactive to spending increases than in periods of high disagreement. Overall, our analysis highlights the case for policy signalling as a tool to reduce disagreement and enhance the impact of spending shocks.

Our results speak to the literature on fiscal foresight (see Ramey, 2011a, Leeper et al., 2012 and Leeper et al., 2013), and on state-dependent effects of fiscal policy (see, for example, Auerbach and Gorodnichenko, 2012, Owyang et al., 2013 and Caggiano et al., 2014).

However, differently from these works, our paper connects to the recent literature on imperfect information and on the formation of economic expectations (see, amongst others, Mankiw et al., 2004, Dovern et al., 2012, Coibion and Gorodnichenko, 2010, 2012, Andrade

[1] In the presence of imperfect information, new information is only partially absorbed over time. Therefore, average forecast errors are likely to be a combination of both current and past structural shocks and cannot be thought of as being, *per se*, a good proxy for structural innovations (as, for example, proposed in Ramey, 2011a).

and Le Bihan, 2013 and Andrade et al., 2014). In fact, we employ an identification scheme of fiscal shocks that is coherent with the implications of imperfect information models and use expectational data in order to study the effects of disagreement amongst agents. Importantly, we focus on the role of public signals in reducing disagreement and in coordinating expectations. To the best of our knowledge, this is the first empirical attempt to study how different levels of precisions in fiscal policy communication affect the transmission mechanism of fiscal shocks, through disagreement.

In doing that we also relate to the literature on policy communication. The analysis of the trade-offs underlying the provision of public signals by policy-makers to an economy in which agents have dispersed information was pioneered by Morris and Shin (2003a,b) in the context of monetary policy.[2] Differently from this literature, our paper focuses on fiscal policy and provides stylised empirical facts on the implication of increased transparency, without studying the relation between public and private signal from a welfare perspective. In this respect, it is more closely related to Melosi (2012) that proposes an econometric study of a signalling channel of monetary policy.

This paper is structured as follows: Section 2 discusses the properties of expectational data on US fiscal spending. Section 3 is devoted to the construction of the fiscal policy disagreement index used in this paper. Section 4 comments on the identification of fiscal shocks. Section 5 illustrates our Bayesian Threshold VAR model. Section 6 presents our main results and provides insights on the transmission channels. Finally, Section 7 concludes.

[2]More recent theoretical contributions have been proposed, amongst others, by Angeletos et al. (2006), Baeriswyl and Cornand (2010), Hachem and Wu (2014), Frenkel and Kartik (2015).

2 Forecasting Fiscal Spending

In the Philadelphia Fed's quarterly SPF, professional forecasters are asked to provide expected values of a set of 32 macroeconomic variables for both the present quarter (nowcast) and up to four quarters ahead (forecast). SPF forecasters do not know the current value of these macroeconomic variables, which are only released with a lag. The panelists' information set includes the BEA's advance report data, which contains the first estimate of GDP (and its components) for the previous quarter. The deadline for responses is the second to third week of the middle month of each quarter.[3]

For 'real federal government consumption expenditures and gross investment', the main series of interest in this work, professional forecasters' individual responses have been collected from 1981Q3 to 2012Q4. Figure 1 reports the median expected growth rate of federal spending for the current quarter and for the four quarters ahead, together with forecasters' disagreement (the cross-sectional standard deviation of individual forecasts) and the historically realised growth rates.

Some features of the SPF's survey data on fiscal spending are noteworthy and common to the forecasts of other macroeconomic variables. As is evident in Figure 1, expectations about fiscal spending are more stable than the actual series. Expectations are sluggish in that they typically underestimate the movements of the forecast variable, despite being able to capture low frequency movements. Moreover, experts' forecasts exhibit predictable errors and can be Granger-predicted (see Ricco, 2015). Experts disagree as they report different predictions at different forecast horizons and when updating their forecasts. The extent of their disagreement evolves over time (see Figure 1 and discussion in Section 4). Finally,

[3] 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. On average, in the sample, there are 29 respondents per period of which 22 appear in consecutive periods.

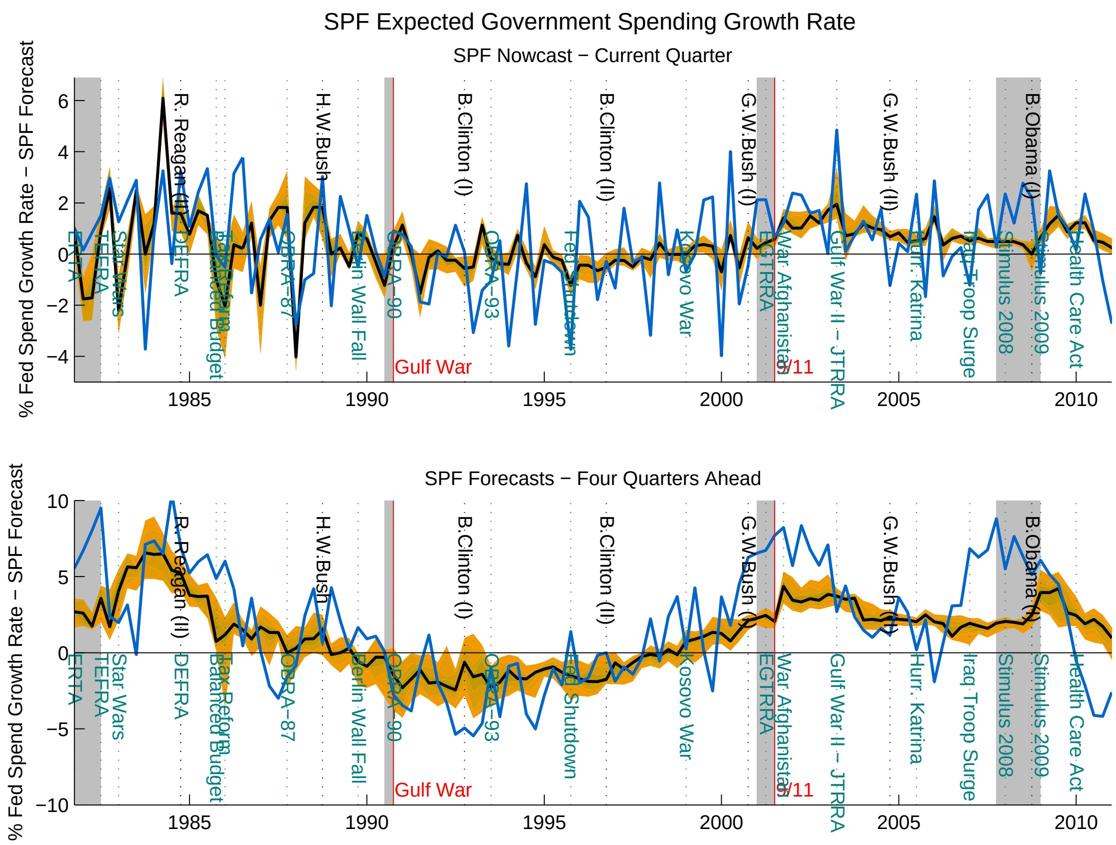

Figure 1: **Government Spending Expected Growth rates – Fan Chart**. The figure plots the SPF median expected growth rate for the current quarter and for the four future quarters, together with forecasters' disagreement up to one standard deviation (orange), and the realised growth reates (blue). Grey 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).

forecast revisions at different horizons for a given event in time are positively correlated.

The above facts are broadly consistent with professional forecasters' data being generated in a model of imperfect information rational expectations. In fact, imperfect information models in the form of delayed-information or noisy-information are able to account for at least three important features of expectational data: the presence of disagreement, the forecastability of errors, and the autocorrelation of expectation revisions. As shown by Coibion and Gorodnichenko (2010), the latter can be used to evaluate the implied degree of information rigidity.[4]

[4] In our sample, the serial correlation between forecast revisions is around 0.2, implying a degree of information rigidity of 0.8.

3 Disagreement over Fiscal Policy

We propose an index of precision of fiscal policy communication derived from the forecasters' disagreement on the future path of fiscal spending. The underlying intuition is that a clear fiscal policy communication can coalesce private sector expectations on future policy measures, which in turn reduces agents' disagreement. Conversely, higher than average disagreement about future government spending reveals poor communication from the government about the future stance of fiscal policies.

Developing this idea, 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. The resulting index has three main features: (1) it relies on expectational real time ex-ante data only; (2) it is linearly uncorrelated with the business cycle; (3) it is fully non-judgmental. Moreover, it is consistent with our definition of fiscal shocks that are extracted from the same expectational dataset, and on a similar time horizon.

To construct the index for fiscal policy disagreement, a two-step procedure is followed. First, the time-varying cross-sectional standard deviation of the SPF forecasts (disagreement) for real federal government spending is computed at the four-quarters horizon. Second, the component of disagreement related to discretionary policy is extracted by projecting the disagreement among forecasters about the future development of fiscal spending onto the disagreement about the current macroeconomic conditions. This is done in order to address the issue of exogeneity with respect to the macroeconomic cycle. We think of this component as affected by the policy communication regime.

We justify this procedure (i) theoretically, using a simple noisy-information model to discuss under which assumptions the index obtained could be correctly thought of as an approximation of the agents' disagreement about the discretionary fiscal spending and (ii) empirically, matching this index with a historical narrative.

3.1 Disagreement in a Stylised Noisy-information Model

A simple noisy-information model with Bayesian learning can help in more precisely defining the concepts used and in clarifying the assumptions underlying our approach. A stylised reduced form equation that decomposes government spending into a discretionary component and an automatic one can be written as

$$g_t = \mu_g + g_t^d + \kappa y_{t-1} \ , \tag{1}$$

where μ_g is a constant, g_t^d is the discretionary component of fiscal spending and the term κy_{t-1} represent the (lagged) systematic response of fiscal spending to business cycle fluctuations. Similarly to Lahiri and Sheng (2010), we assume that each agent i, at each quarter t, receives a public signal from the policymaker that is informative about the future growth of discretionary fiscal spending, g_{t+h}^d, at horizon h

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

Agents complement the information carried by the public signal using other sources of information. That is, they receive a private signal or a signal obtained by random sampling from diffuse information publicly available, i.e.,

$$s_{t+h}^i = g_{t+h}^d + \zeta_{t,h}^i \ , \qquad \zeta_{t,h}^i \sim \mathcal{N}\left(0, \sigma^2_{(\zeta)i,t,h}\right) . \tag{3}$$

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^d_{t+h}:

$$\widehat{g}^d_{i,t+h} = \mathbb{E}^i \left[g^d_{t+h} | n_{t+h}, s^i_{t+h} \right] = \frac{\sigma^2_{(\eta)t,h} s^i_{t+h} + \sigma^2_{(\zeta)i,t,h} n_{t+h}}{\sigma^2_{(\zeta)i,t,h} + \sigma^2_{(\eta)t,h}} \ . \tag{4}$$

The disagreement at time t amongst forecasters about discretionary fiscal spending at time $t+h$ can be defined as:

$$\begin{aligned} \mathcal{D}_t(g^d_{t+h}) &\equiv \mathbb{E}\left[\frac{1}{N-1} \sum_{i=1}^{N} \left(\widehat{g}^d_{i,t+h} - \frac{1}{N} \sum_{j=1}^{N} \widehat{g}^d_{j,t+h} \right)^2 \right] \\ &= \frac{\sigma^2_{(\eta)t,h}}{N} \sum_{i=1}^{N} \frac{\sigma^2_{(\zeta)i,t,h}}{\sigma^2_{(\zeta)i,t,h} + \sigma^2_{(\eta)t,h}} \left(1 - \frac{1}{N-1} \sum_{j \neq i}^{N} \frac{\sigma^2_{(\zeta)j,t,h}}{\sigma^2_{(\zeta)j,t,h} + \sigma^2_{(\eta)t,h}} \right) \ , \end{aligned} \tag{5}$$

where $\widehat{g}_{i,t+h}$ is the individual forecast defined in equation (4). From Eq. (5), it is clear that when the precision of the public signal (the inverse of its variance) goes to infinity, the disagreement amongst agents goes to zero. Therefore, variations in the precision of the public signal are reflected in the variations of agents' disagreement over time. We think of the variance of the public signal on discretionary spending as dependent on the willingness of the policymaker to blur or clarify the policy indication, as well as the policymaker's credibility.[5]

In our empirical analysis, we conceive the policy communication as roughly having two 'polar' regimes: high and low precision. While fluctuations of disagreement may be due to the endogenous dynamics of absorption of new information, as suggested by delayed-

[5]The precision of the privately extracted signal, possibly using diffused information, may depend on the information system, the policy decision process and institutional framework. We assume that, over the period of study, fluctuations in the precisions of the private signals are small compared to the variations in the variance of the public signal.

information models, we think of shifts in disagreement as a reflection of policy communication regimes.

3.2 Cyclical Variations in Disagreement

In order to pin down fluctuations in government spending disagreement that are due to policy communication and not due to cyclical macroeconomic disturbances, we need to control for variations of disagreement along the business cycle. In fact, it has been documented that disagreement about GDP growth strongly intensifies during recessions and reduces during expansions (see Dovern et al., 2012). For a linearised reduced form equation for output of the following form, which we might think as derived from a structural model

$$y_t = \mu_y + \sum_{i=1}^{n} c_n y_{t-i} + \sum_{j=0}^{m} d_j g^d_{t+j} + a_t \ , \tag{6}$$

where the first sum is an autoregressive component of output up to lag n, the second is the sum of the output responses to the path of fiscal spending up to horizon m (the maximum horizon on which the government is able to release information) and a_t is a combination of macroeconomic shocks. The disagreement about total government spending (the observed quantity) is

$$\mathcal{D}_t(g_{t+1}) = (1 + d_1\kappa)\mathcal{D}_t(g^d_{t+1}) + \kappa^2 \mathcal{D}_t(y_t) \ . \tag{7}$$

Hence, by regressing the disagreement amongst forecasters about the future development of fiscal spending onto the disagreement about current macroeconomic conditions, one can extract a measure of disagreement about discretionary policy measures.[6]

In light of the considerations made above, we regress the disagreement of the forecasts

[6]Regressing $\mathcal{D}_t(g_{t+1})$ onto $\mathcal{D}_t(y_t)$ can generate an endogeneity issue due to the fact that the residual in Eq. 7 may be correlated with the regressor. However, for our purpose, the bias introduced is likely to be small. A simple dimensional argument provides the intuition for this. Regressing $\log(\mathcal{D}_t(g_{t+1}))$ onto

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. In doing this, we assume that forecasts of future government spending do not incorporate information about other macroeconomic shocks affecting future but not current GDP. Our fiscal policy disagreement index is thus obtained by exponentiating and standardising the regression residuals. By construction, these residuals are linearly uncorrelated with the disagreement about current macroeconomic conditions.[7]

3.3 Policy Disagreement

Our fiscal policy disagreement index is reported in Figure 2. It appears to well track a narrative of 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 Reagan in 1983Q1. The index then rises with the 1984 presidential elections and following the fiscal activism of President Reagan's second term. The next spike in disagreement is related to the fall of the Berlin wall. In the 1990s, the index shows increases in disagreement generated by the 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 disagreement index spikes in relation to the war in Afghanistan and the 2001 and 2003 Bush tax cuts, followed by the Gulf War, Iraq War troop surge, the 2008 and 2009 stimulus acts

$\log(\mathcal{D}_t(y_t))$, one would find

$$\hat{\kappa}^2 = \frac{\mathbb{C}\mathrm{ov}(\log(\mathcal{D}_t(g_{t+1})), \log(\mathcal{D}_t(y_t)))}{\mathbb{V}\mathrm{ar}(\log(\mathcal{D}_t(y_t)))} = \kappa^2 + (1 + d_1\kappa) d_1^2 \frac{\mathbb{V}\mathrm{ar}(\log(\mathcal{D}_t(g^d_{t+1})))}{\mathbb{V}\mathrm{ar}(\log(\mathcal{D}_t(y_t)))} . \tag{8}$$

We can assess the order of magnitude of the second term observing that - based on SPF historical data - the ratio of disagreement on current output over disagreement on future government spending is around 10^{-1}, hence the constant d_1^2 (the output multiplier of a quarter ahead increase in fiscal spending) has to be of order 10^{-2}. Hence, we conclude that the bias is at most of order 10^{-2}, while κ^2 is likely to be of order one.

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

and, finally, the 'Debt Ceiling Crisis' of 2011.

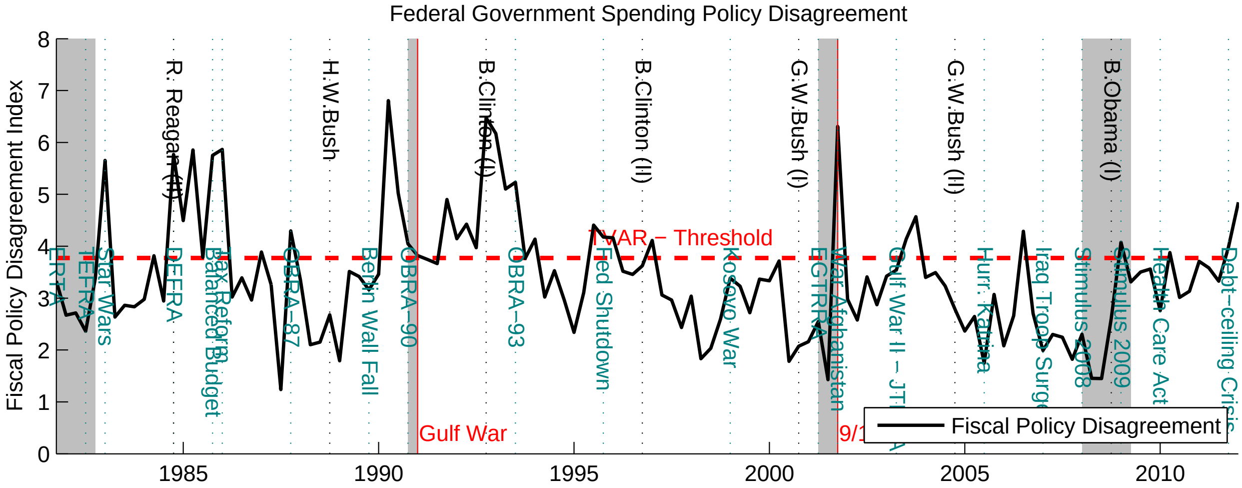

Figure 2: **Policy Disagreement Index** - Time series of the fiscal policy disagreement index based on the dispersion of SPF forecasts (black). Grey shaded areas indicate the NBER business cycle contraction dates. Vertical lines indicate the dates of the announcement of important fiscal and geopolitical events (teal), presidential elections (black), and the Ramey-Shapiro war dates (red). The thick red dashed line indicate the TVAR endogenous threshold.

4 Fiscal News

We identify fiscal shocks using SPF forecast revisions of federal government consumption and investment forecasts, which can be thought of as fiscal news. The h quarters ahead forecast error can be decomposed into the flow of fiscal news, which updates the agents' information set $\mathcal{I}_t$ over time:

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

$$\dots + \underbrace{(\mathbb{E}^*_{t-h+1} g_t - \mathbb{E}^*_{t-h} g_t)}_{\substack{\text{forecast revision} \\ \text{(news at t-h+1)} \in \mathcal{I}_{t-h+1}}} . \quad (9)$$

where $\mathbb{E}^*$ is the agents' expectation operator and g is government spending growth. The first term on the right-hand side corresponds to the *nowcast error*, which can be thought of as a proxy for agents' misexpectations which can be revealed only at a later date (at least after a quarter). The other components (nowcast and forecast revisions) can be seen as proxies for the *fiscal news*, which are related to current and future realisations of fiscal spending, and are received by the agents and incorporated into their expectations.

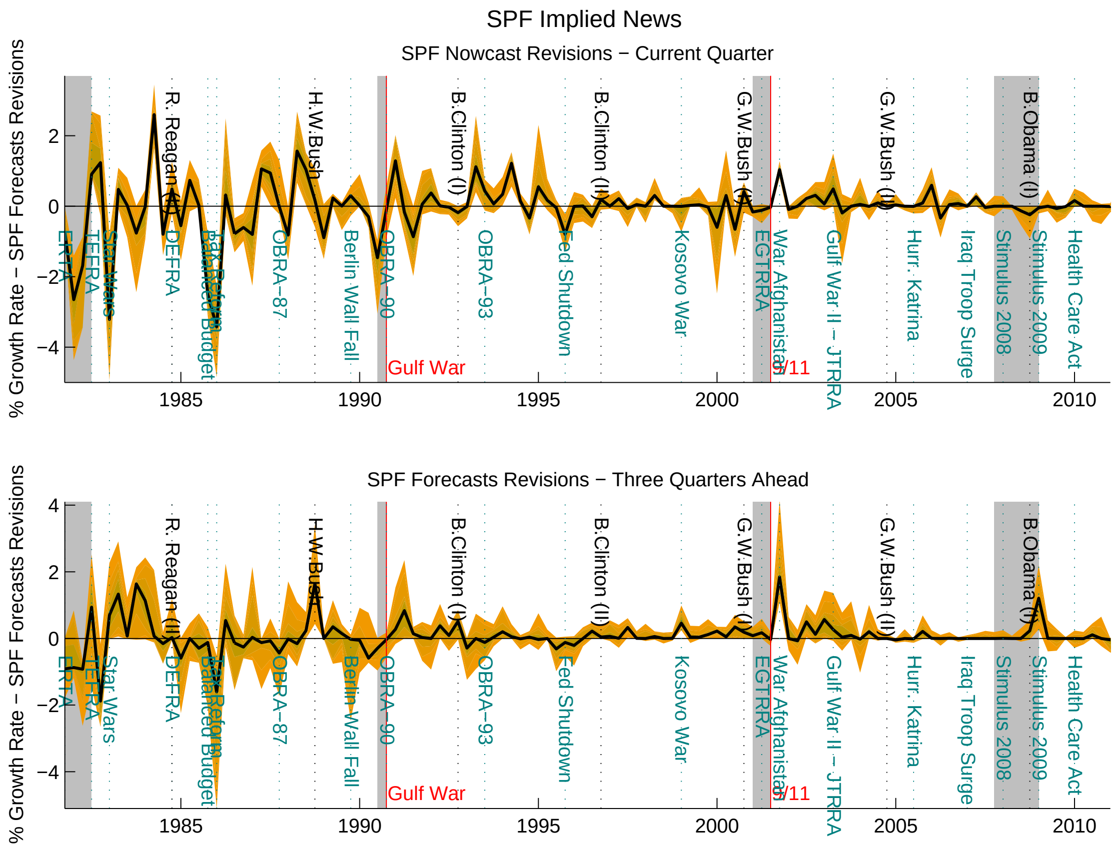

Figure 3: **Government Spending News – Fan Chart**. The figure plots the mean implied SPF news on the current quarter and for future quarters, together with forecast disagreement up to one standard deviation. Grey shaded areas indicate the NBER Business Cycle contraction dates. Vertical lines indicate the dates of the announcement of important fiscal and geopolitical events (teal), presidential elections (black), and the Ramey-Shapiro war dates (red).

We define two measures of fiscal news in the aggregate economy that are both related to the revision of expectations of the government spending growth rate in the current quarter and in the future 3 quarters (the maximum horizon available in the data):

$$\mathcal{N}_t(0) = \frac{1}{N}\sum_{i=1}^{N}\left(\mathbb{E}_t^{*i} g_t - \mathbb{E}_{t-1}^{*i} g_t\right) \ , \tag{10}$$

$$\mathcal{N}_t(1,3) = \frac{1}{N}\sum_{i=1}^{N}\sum_{h=1}^{3}\left(\mathbb{E}_t^{*i} g_{t+h} - \mathbb{E}_{t-1}^{*i} g_{t+h}\right) \ , \tag{11}$$

where i is the index of individual forecasters. Figure 3 plots the mean implied SPF news on the current quarter and for future quarters, together with forecaster disagreement up to one standard deviation. In the empirical analysis which follows, we use these two news measures, labelled as *nowcast revision* (equation 10) and *forecast revision* (equation 11), respectively.

The identification of fiscal shocks using expectation revisions is consistent with an imperfect information framework. As observed in Coibion and Gorodnichenko (2010), in more general models of imperfect information, the average *ex-post* forecast errors across agents and the average *ex-ante* forecast revisions are related by the following expression:

$$\underbrace{g_t - \mathbb{E}_{t-h}^{*} g_t}_{\text{forecast error}} = \frac{\lambda}{1-\lambda}\underbrace{\left(\mathbb{E}_{t-h}^{*} g_t - \mathbb{E}_{t-h-1}^{*} g_t\right)}_{\text{forecast revision (news)}} + u_{t-h+1,t} \ , \tag{12}$$

where λ is the parameter of information rigidity ($\lambda = 0$ in the case of full information), $\mathbb{E}_{t-h}^{*} x_t$ is the average forecast at time $t-h$, and $u_{t-h+1,t}$ is a linear combination of rational expectations errors from time $t-h$ to time t. Hence, conditional on the past information set, the revision of expectations is informative about structural innovations. In fact, from Equation (12) one readily obtains:

$$\underbrace{\left(\mathbb{E}_{t-h}^{*} g_t - \mathbb{E}_{t-h-1}^{*} g_t\right)}_{\text{news at t-h}} = \lambda\underbrace{\left(\mathbb{E}_{t-h-1}^{*} g_t - \mathbb{E}_{t-h-2}^{*} g_t\right)}_{\text{news at t-h-1}} + (1-\lambda) u_{t-h} \ . \tag{13}$$

In particular, we will think of the parameter of information rigidity related to fiscal spending as having two possible values, λ_L and λ_H, reflecting the policy communication regime.

5 A Bayesian Threshold VAR

In order to study the effects of policy communication in the transmission of fiscal shocks, we estimate a Threshold Vector-Autoregressive (TVAR) model with two endogenous regimes. In the TVAR model, regimes are defined with respect to the level of our fiscal spending disagreement index (high and low disagreement). A threshold VAR is well suited to provide stylised facts about the signalling effects of fiscal policy and to capture difference in regimes with high and low disagreement. Moreover, the possibility of regime shifts after the spending shock allow us to account for possible dependency of the propagation mechanism on the size and the sign of the shock itself. Following Tsay (1998), a two-regime TVAR model can be defined as

$$y_t = \Theta(\gamma - \tau_{t-d}) \left(C^l + A^l(L) y_{t-1} + \varepsilon_t^l \right) + \Theta(\tau_{t-d} - \gamma) \left(C^h + A^h(L) y_{t-1} + \varepsilon_t^h \right) \ , \qquad (14)$$

where $\Theta(x)$ is an Heaviside step function, i.e. a discontinuous function whose value is zero for a negative argument and one for a positive argument. The TVAR model allows for the possibility of two regimes (high and low disagreement), with different dynamic coefficients $\{C^i, A^i_j\}_{i=\{l,h\}}$ and variance of the shocks $\{\Sigma^i_\varepsilon\}_{i=\{l,h\}}$. 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 a known parameter and equal to one, in order to check for the role of the communication regime in place right before the shock hits the economy.[8]

[8] The baseline TVAR model is estimated with 3 lags. Results are, however, robust if 2 or 4 lags are included. Longer lag polynomial are not advisable due to the relatively short time series available.

We estimate the TVAR model using Bayesian technique and the standard Minnesota and sum-of-coefficients prior proposed in the macroeconomic literature. 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., Banbura et al., 2010).

The TVAR model specified in Eq. (14) can be estimated by maximum likelihood. It is convenient to first concentrate $\{C^i, A^i_j, \Sigma^i_\varepsilon\}_{i=\{l,h\}}$, i.e., to hold γ (and d) fixed and estimate the constrained MLE for $\{C^i, A^i_j, \Sigma^i_\varepsilon\}_{i=\{l,h\}}$. In fact, conditional on the threshold value γ, the model is linear in the parameters of the model $\{C^i, A^i_j, \Sigma^i_\varepsilon\}_{i=\{l,h\}}$. 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

$$\hat{\gamma} = \arg\max \log \mathcal{L}(\gamma) = \arg\min \log |\widehat{\Sigma}_\varepsilon(\gamma)| \ , \tag{15}$$

where $\mathcal{L}$ is the Gaussian likelihood (see Hansen and Seo, 2002). Details on the Bayesian priors adopted, on the criteria applied for the choice of the hyperparameters and on the estimation procedure are provided in the appendix.

Our baseline TVAR model includes the SPF implied fiscal news, the mean SPF forecast of GDP growth for the current quarter and four quarters ahead, the fiscal policy disagreement index, federal government spending, the Barro-Redlick marginal tax rate[9], total private consumption and investment, real GDP and the Federal Fund Rate. We use quarterly data

[9]The marginal tax rate is originally produced at the annual frequency by Barro and Redlick (2009), based on the NBER's TAXSIM model (see website). To generate data at the quarterly frequency we have applied the Litterman (1983)'s random walk Markov temporal disaggregation model - which is a refinement of Chow and Lin (1971) that allows to avoid step changes due to serial correlation in the regression's residuals - using as indicators quarterly data on GDP, prices and tax receipts.

from 1981Q3 to 2012Q4 in real log per capita levels for all variables except those expressed in rates (see appendix for data description).

In order to identify fiscal news shocks inside our model, we assume that discretionary fiscal policy does not respond to macroeconomic variables within a quarter. We also assume that agents observe only lagged values of macroeconomic variables and that, in forecasting future government spending, they incorporate the discretionary policy response to the expected output. 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. These assumptions allow for a recursive identification of the fiscal shocks in which the fiscal variables are ordered as follow

$$(\mathcal{N}_t(0) \qquad \mathbb{E}^*_t\Delta\mathrm{GDP}_t \qquad \mathcal{N}_t(1,3) \qquad \mathbb{E}^*_t\Delta\mathrm{GDP}_{t+4} \qquad Y_t')' \tag{16}$$

and Y_t is a vector containing the macroeconomic variables of interest. Results are robust to ordering expectations about future output before fiscal news related to future quarters.

It is worth stressing that this ordering is consistent with the structure of expectation revisions delivered by models of imperfect information (see equation 13). Indeed, the VAR structure controls for past expectations revisions for a given event in time, isolating the contemporaneous structural shocks from components due to the slow absorption of information.

6 Disagreement and the Transmission of Fiscal Shocks

Figure 10 reports the impulse responses to the 3-quarter ahead fiscal news shock, formalised in equation 11, and generated by the 11-variables TVAR described in equation 14.

Indeed, our main objects of interest are the news shocks related to future changes to government spending. In fact, given the more extended time lag between news and the actual implementation of the policy change, these shocks are more likely to be affected by policy communication than the nowcast revisions.[10] The responses are 'intra-regime' IRFs, i.e, computed assuming no transition between regimes.

In order to facilitate the comparison between the two regimes, the impulse responses have been normalised to have a unitary increase in federal spending at the 4-quarters horizon. Also, the IRFs of the variables in log-levels have been re-scaled by multiplying them by the average 'Variable-to-Federal Spending' ratio. In this way, the GDP, investment and consumption IRFs can be interpreted in 'dollar' terms. The impulse responses of the Federal Funds rate, of the marginal tax rate, and of the forecast and nowcast for GDP growth can be interpreted in terms of basis points change. The blue lines with crosses (for the low-disagreement regime, hereafter "L-D") and red lines with circle markers (for the high-disagreement regime, hereafter "H-D") indicate the reaction of the endogenous variables to an innovation in the forecast spending revision, with the shaded areas describing the evolution of the 68% coverage bands.

While the response of federal spending to the policy announcement is similar across the two regimes, the TVAR results reveal a very different transmission mechanism in the two regimes. The GDP response is always significant in the L-D regime and higher than in the H-D regime for at least three quarters after the shock. We also compute cumulative medium-run output multipliers, defined as the ratio between the sum of the GDP impulse responses up to the selected horizon (here, at horizon 16 quarters), and the corresponding sum of the responses for federal spending (see also Ilzetzki et al., 2013). The cumulative

[10]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., four quarters).

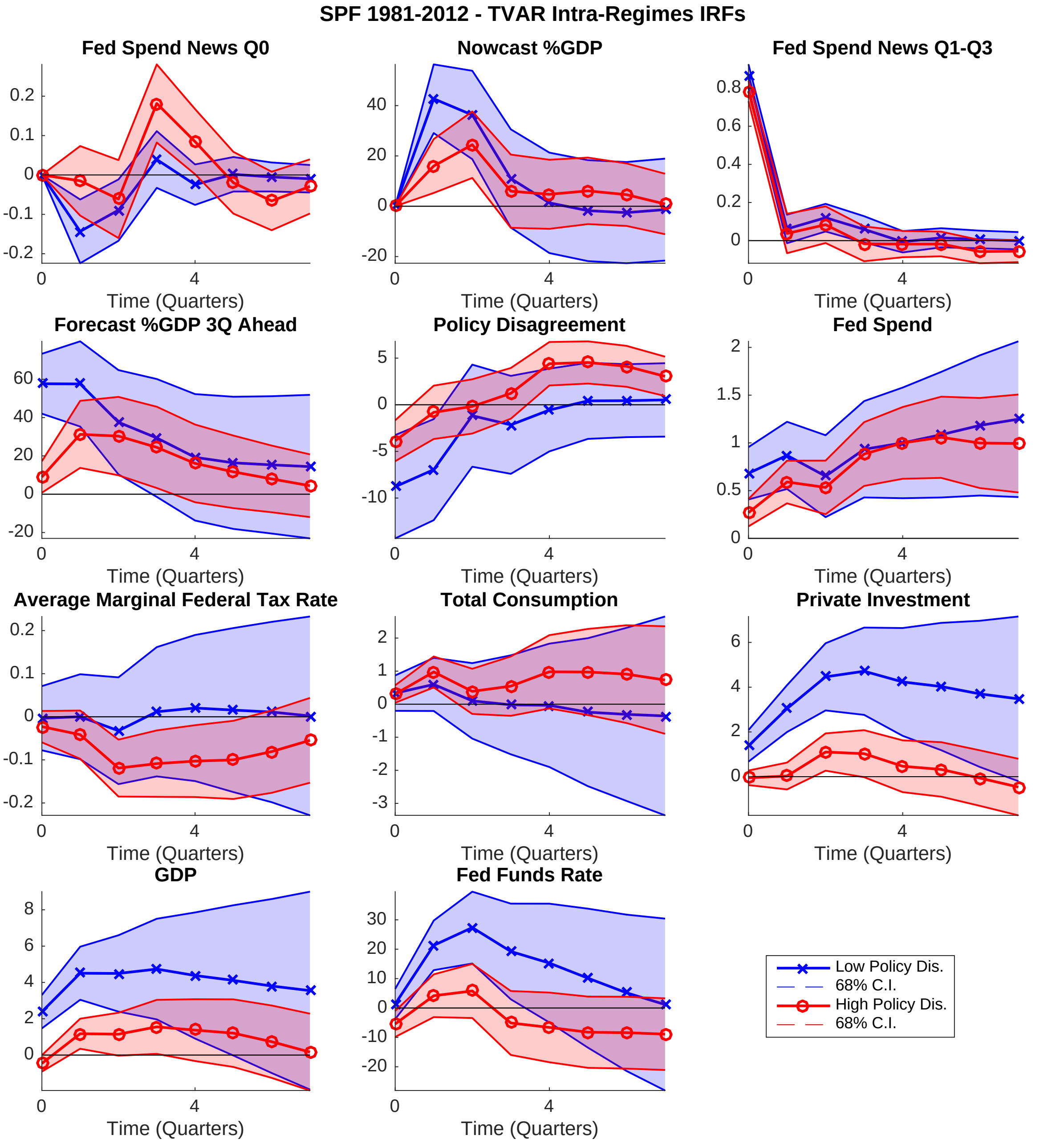

Figure 4: **Within-regime impulse responses - Impact of forecast revisions.** The shock corresponds to one standard deviation change in the revision of the spending forecasts three quarters ahead. The responses are generated under the assumption of constant disagreement regime. Impulse responses have been been normalised to have a unitary increase in Federal Spending at the 4-quarters horizon. Blue crossed line and fans (68% coverage bands) are relative to the low-disagreement regime, while the red lines with circle markers and fans (68% coverage bands) are relative to the high disagreement regime. Sample: 1981Q3-2012Q4.

multiplier in the L-D regime is around 2.7, whereas the one in the H-D regime is around 0.5. The output multiplier from the linear model, averaging the two regimes, is about 1.2. The stronger GDP response in the L-D regime is also reflected in the impact response of 3-

quarter ahead forecast GDP, thus confirming that a fiscal shock is more powerful in affecting economic expectations in the L-D than in the H-D regime.

The responses of the Federal Funds rate, and of total private consumption and investment, provide some evidence on the channels through which the two disagreement regimes are associated with a different propagation mechanism. While the response of private consumption is essentially the same in the two regimes (slightly positive on impact before becoming insignificantly different from zero), the response of private investment in the L-D regime is significant and higher than the response in the H-D regime which, on the contrary, is never significantly different from zero. The accelerator effect of planned fiscal spending on investment in times characterised by less disagreement may be attributed to the expectation coordination effects of policy communication. The average marginal tax rate declines slightly in the medium run in the high disagreement regime, albeit it is not significantly different from the low disagreement regime response. The monetary policy stance tightens in the low disagreement case, as reflected in the more pronounced increase of the Federal Funds Rate. This may be explained by the willingness of the Fed to react to the potential inflationary pressure to the announced extra spending. This seems to reflect a response to the boost in demand observed following the news shock. Finally, our index of policy disagreement tends to decrease in the short-run after the news shock, and especially so in the low disagreement regime. This may be due to the release of information about the fiscal measure, which help to coordinate expectations and has the effect of dissipating the disagreement built-up in the policy debate prior to the announcement (as can also be inferred from Figure 2).

The evidence reported in Figure 10 highlights relevant differences between the responses under the two regimes, thus confirming the importance of taking into account the degree of disagreement about future policies when analysing the transmission mechanism of spending shocks.[11]

6.1 Exploring the Transmission Channels

In this section, we further explore the transmission channels of the fiscal spending shocks in the two regimes. In particular, we complement the baseline model with additional variables that are added to the model following a 'marginal approach'.

The first chart of Figure 5 shows the response of the Michigan's Consumer Sentiment Index to the forecast revision. The responses in the two regimes are both positive on impact and in the short-run, but the response in the L-D regime (blue line) is somewhat higher and more persistent than that of the H-D regime (red line), revealing that a clearer policy communication tends to improve private sector confidence. This result provides evidence of an additional confidence channel to the transmission of fiscal shocks (see also Bachmann and Sims, 2012). The figure also highlights that the responses of both durable and non-durable consumption tend to be positive and significant in the L-D regime in the short-run, whereas the H-D regime is characterised by a negative durable consumption response in the short-run.

The responses of private investment's subcomponents help to shed more light on the main drivers of the GDP response in the L-D regime which, as highlighted in Figure 10, is mostly driven by the investment component of GDP. As shown in Figure 5, residential fixed investment and real inventories are important in explaining the strong total private investment response in the L-D regime. At the same time, the non-residential investment

[11] In the appendix, we also provide results for a robustness exercise carried out by varying the threshold level in an interval that excludes the higher and lower 30% observations of the threshold variable, i.e., the disagreement index. These exercise shows that the different effects stemming from the two communication regimes are confirmed when using alternative values for the disagreement threshold.

responses appear broadly similar, and not statistically different from zero, in the two regimes. These results provide additional evidence of the presence of an accelerator effect of planned fiscal spending on investment in times characterised by less disagreement. The private sector appears to be willing to scale up investment and inventories to accommodate the future increase in public demand. The observed persistent growth of federal spending is important in order to explain this behaviour.[12]

The response of prices, based on both CPI inflation and GDP deflator inflation, turns out to be similar between the two regimes: it is generally not significantly different from zero, except in the H-D regime where the effect is somewhat negative after one year. A weak response of prices to the government spending shock is in line with related research on the US.[13]

Figure 5 also shows that civilian employment tends to rise significantly in the L-D regime following the news shock compared to the H-D regime, which instead shows a drop. This is also mirrored in the unemployment response, which falls below zero in the low disagreement scenario. The additional demand on the labour market appears to be reflected in the upward movement of wages in the L-D regime. Indeed, real wages and total hours worked significantly rise in the short-run following the news shock in the L-D scenario, whereas in the H-D scenario the response of wages remains muted. This finding adds to the literature addressing the effects of government spending shocks on real wages (e.g., Perotti, 2008 and Ramey, 2011a). Our results shows that, in response to the identified news shock on government spending, real wages tend to rise in the short-run and especially so in the L-D regime.

[12]An average positive response of private investment to fiscal spending announcement is common to news-based identifications (e.g., Ricco, 2015, Forni and Gambetti, 2014 and Ben Zeev and Pappa, 2014).

[13]For example, Dupor and Li (2013) finds little evidence of a positive response of inflation to government expenditure shocks in the US since WWII, even during the Federal Reserve's passive period (1959-1979).

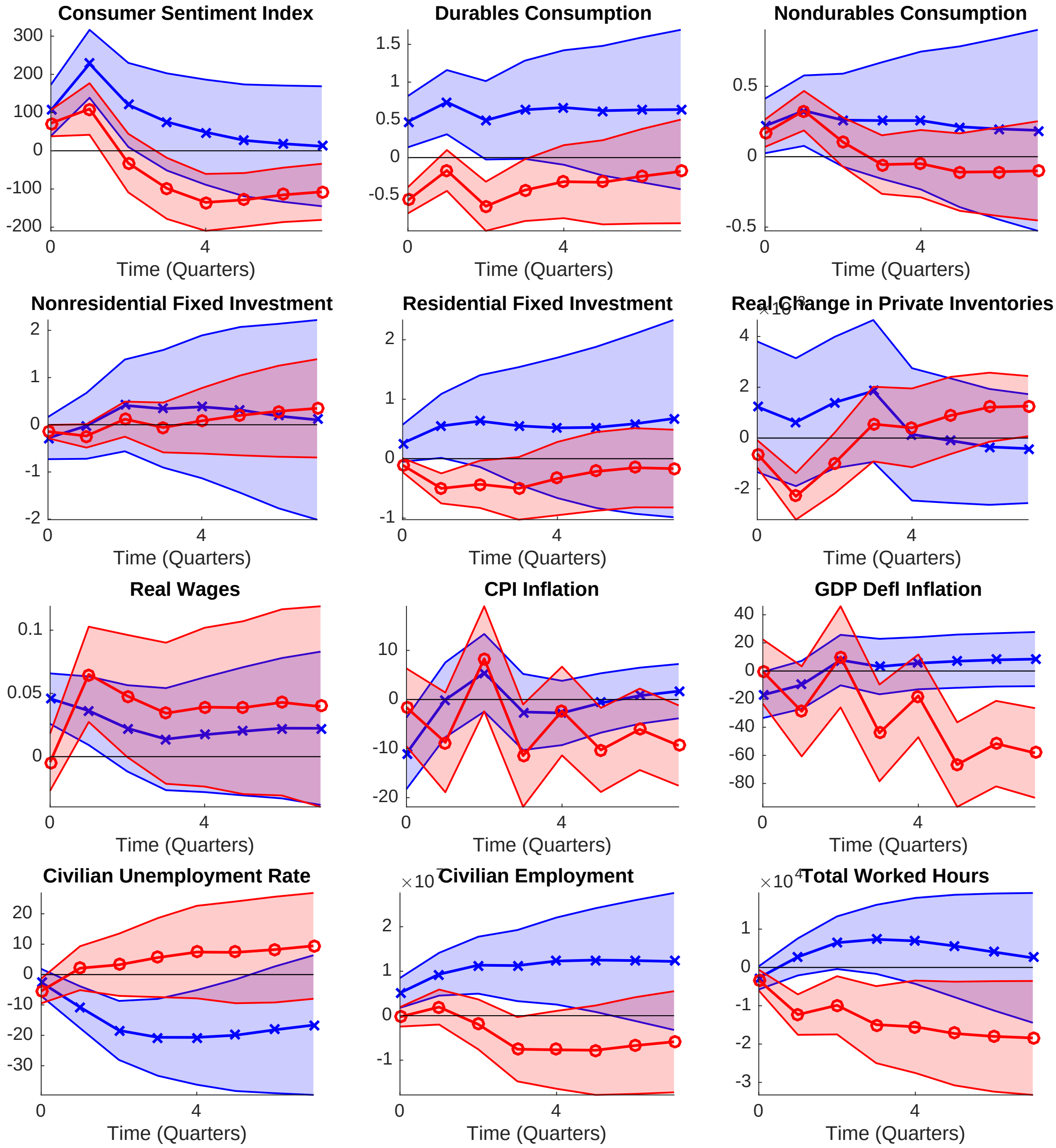

Figure 5: **Impact of forecast revisions on other variables.** Impulse responses of the Michigan's consumer sentiment index, civilian employment and unemployment, residential fixed investment, non-residential fixed investment and inventories, durable and non-durable consumption, real wages and hours worked, GDP deflator and CPI inflation. IRFs have been estimated resorting to a 'marginal approach'. For simplicity, we report here only the impulse response of the additional variable. The responses of the other variables are very similar to the baseline case, therefore we do not report them. Blue crossed line and fans are relative to the low-disagreement regime, while the red lines with circles and fans are relative to the high disagreement regime. Sample: 1981Q3-2012Q4.

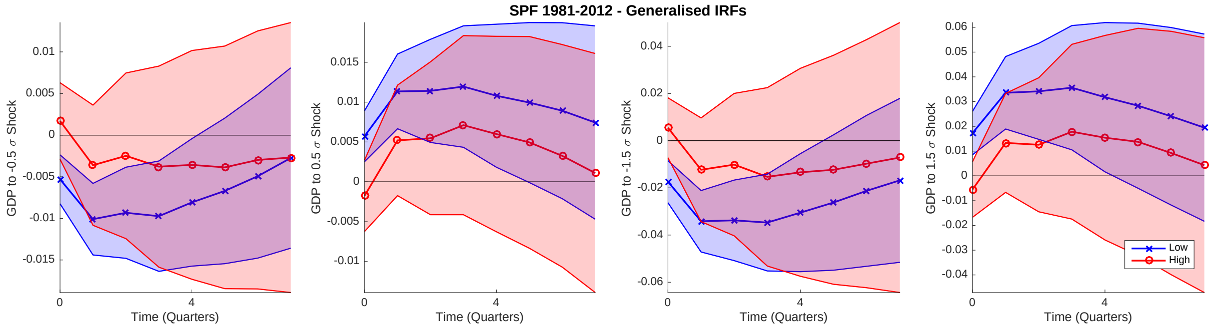

Figure 6: **Inter-regime impulse responses - Impact of forecast revisions.** The figure reports the GIRFs of a spending shock on GDP from four different shocks, detailed along the y-axis, generated from the baseline 11-variables TVAR. Blue crossed line and fans are relative to the low-disagreement regime, while the red lines with circles and fans are relative to the high disagreement regime. Sample: 1981Q3-2012Q4.

6.2 Nonlinear Effect of Fiscal News

Figure 6 presents the Generalised Impulse Response Functions (GIRFs) generated by four different shocks: a small positive fiscal shock of half standard deviation and its symmetric negative shock (first two panels), and a large fiscal shock of 1.5 standard deviation and its symmetric negative shock (last two panels). GIRFs can help to understand how the impact on GDP may change in relationship to the size and sign of the shock, accounting for the possibility of endogenous regime shifts triggered by the propagation of the fiscal spending shock (which are not taken into account in the within-regime analysis presented in Figure 10). Unsurprisingly, the inclusion of possible regime shifts reduces the difference of the IRFs across the two regimes. A less clear-cut distinction between the two regimes is consistent with an endogenous propagation of the information about the shock in the economy.[14] It also emerges that negative and positive shocks are characterised by responses that are broadly symmetric, thus highlighting that contractionary and expansionary fiscal news have quantitatively similar effects (though, with opposite sign).

[14]The regime switching probabilities between the two regimes suggest that - in the two years following the shock - there is a probability of around 70% to switch from the L-D regime to the H-D one, and vice versa.

7 Conclusions

This paper offers new insights into the fiscal transmission mechanism in the US economy by studying the role of disagreement about fiscal policy in the propagation of government spending shocks. The central idea is that disagreement about future government spending reveals poor signalling from the government about the future stance of fiscal policies. At the same time, clear fiscal policy communication can coalesce agents' expectations, thereby reducing disagreement.

Our results provide some evidence that, in times of low disagreement about future policies, the output response to news about future government spending growth is positive, strong and persistent. Conversely, periods of elevated disagreement are characterised by a muted output response to fiscal news. The stronger impact of fiscal policy when expectations are coordinated is mainly the result of the positive response of investment to news on fiscal spending. This channel is different from the more standard consumption accelerator effect proposed in New Keynesian models with rule of thumb consumers, and poses an interesting modelling challenge. Overall, our analysis indicates that fiscal communication can be used as a forward guidance tool to coordinate economic agents' expectations and thus consumption, investment and savings decisions.

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A Additional Charts and Tables

A.1 Impulse Responses Generated from the Linear VAR Model – Responses to the Forecast Revision Shock

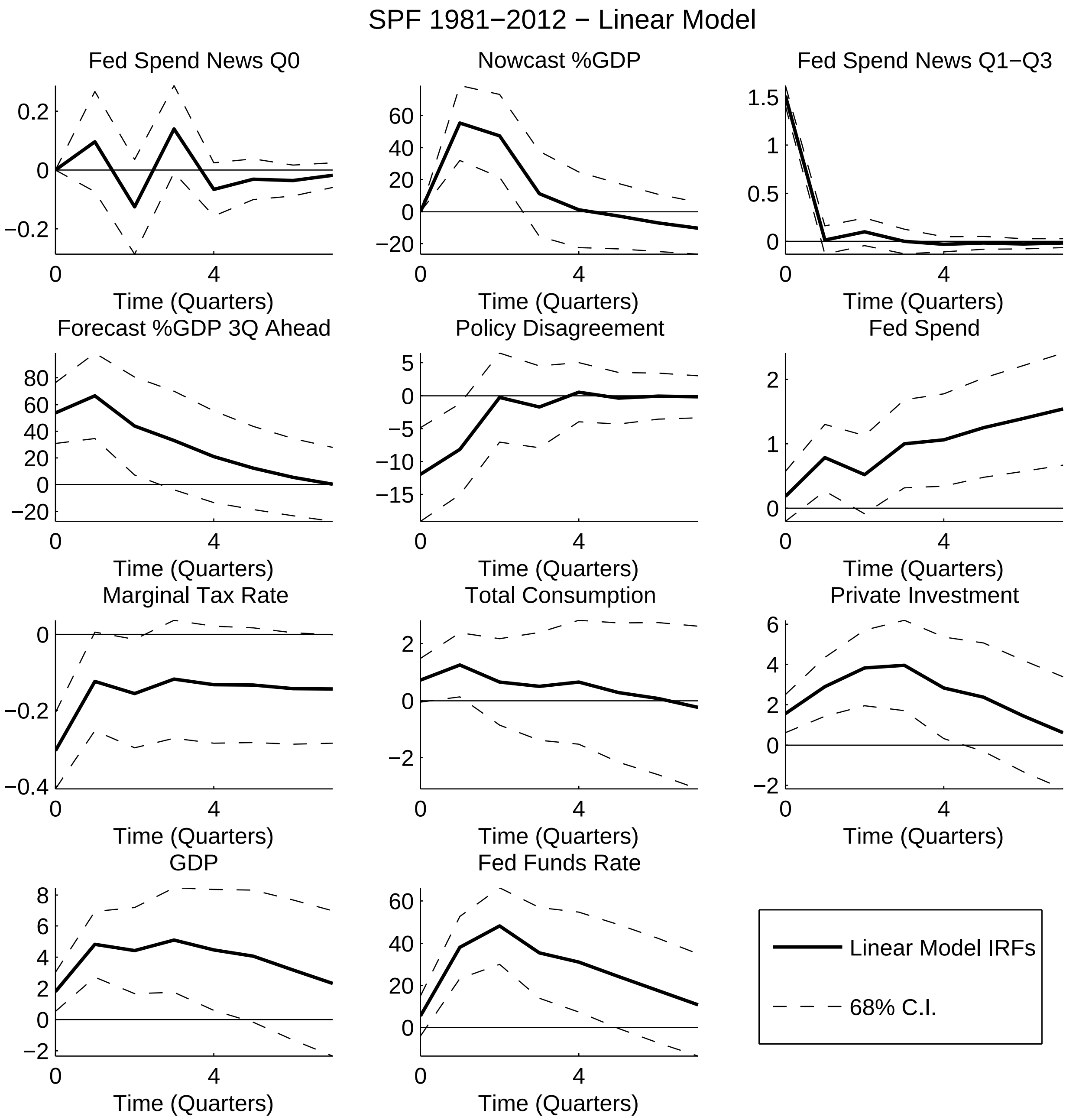

Figure 7: **Linear VAR model.** Impulse responses have been been normalised to have a unitary increase in federal spending at the 4-quarters horizon. Dotted lines are the 68% coverage bands. Sample: 1981Q3-2012Q4.

A.2 Robustness with respect to the Threshold Level

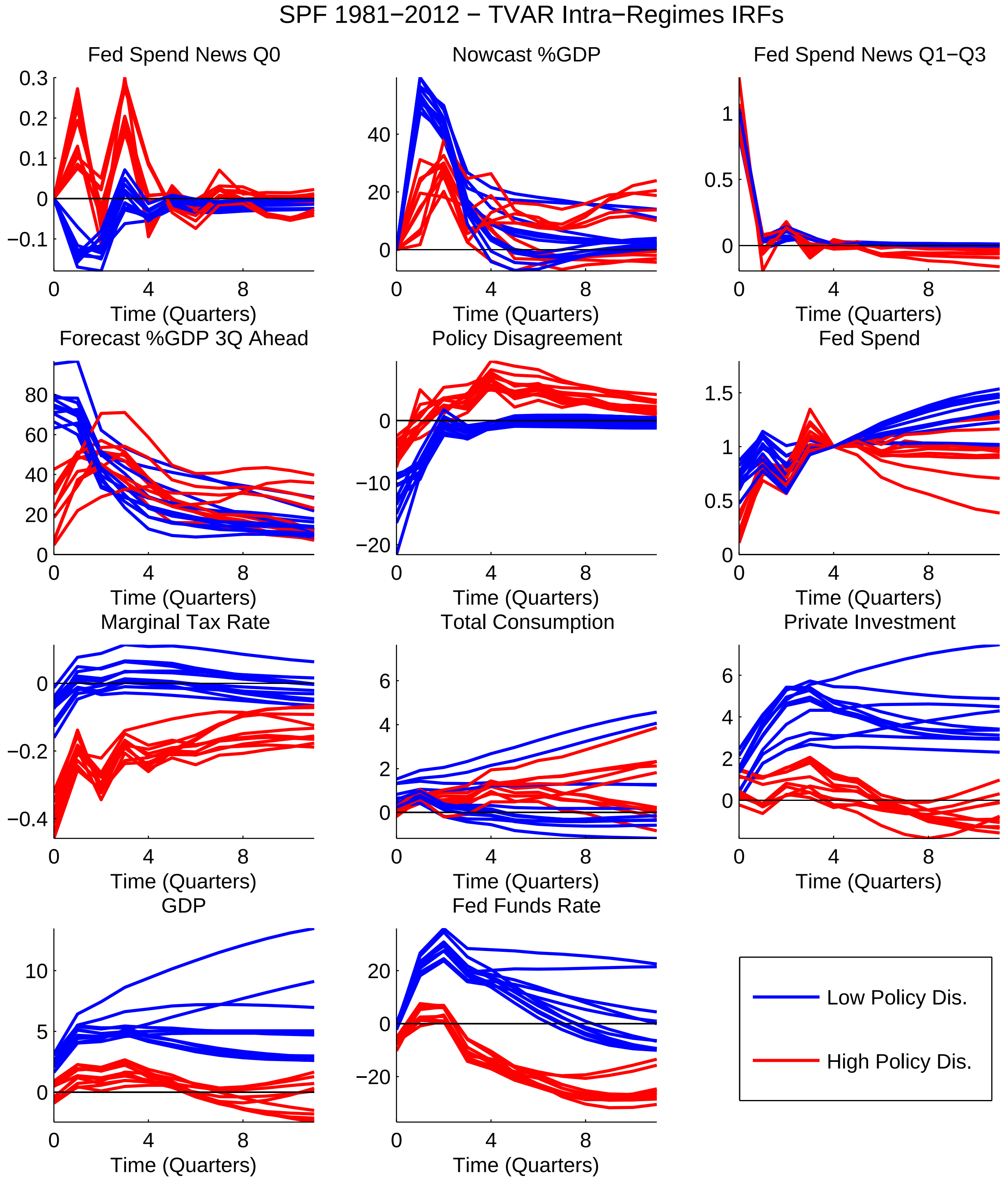

Figure 8: Robustness exercises carried out by varying the threshold level in an interval that excludes the higher and lower 30% observations of the threshold variable, i.e., the disagreement index. Impulse responses have been been normalised to have a unitary increase in federal spending at the 4-quarters horizon. The responses are generated under the assumption of constant disagreement regime. Blue lines are the baseline responses relative to the low-disagreement regime, while the red lines are the baseline responses relative to the high disagreement regime. Sample: 1981Q3-2012Q4.

A.3 Impulse Responses Generated from the Linear VAR Model – Responses to the Nowcast Revision

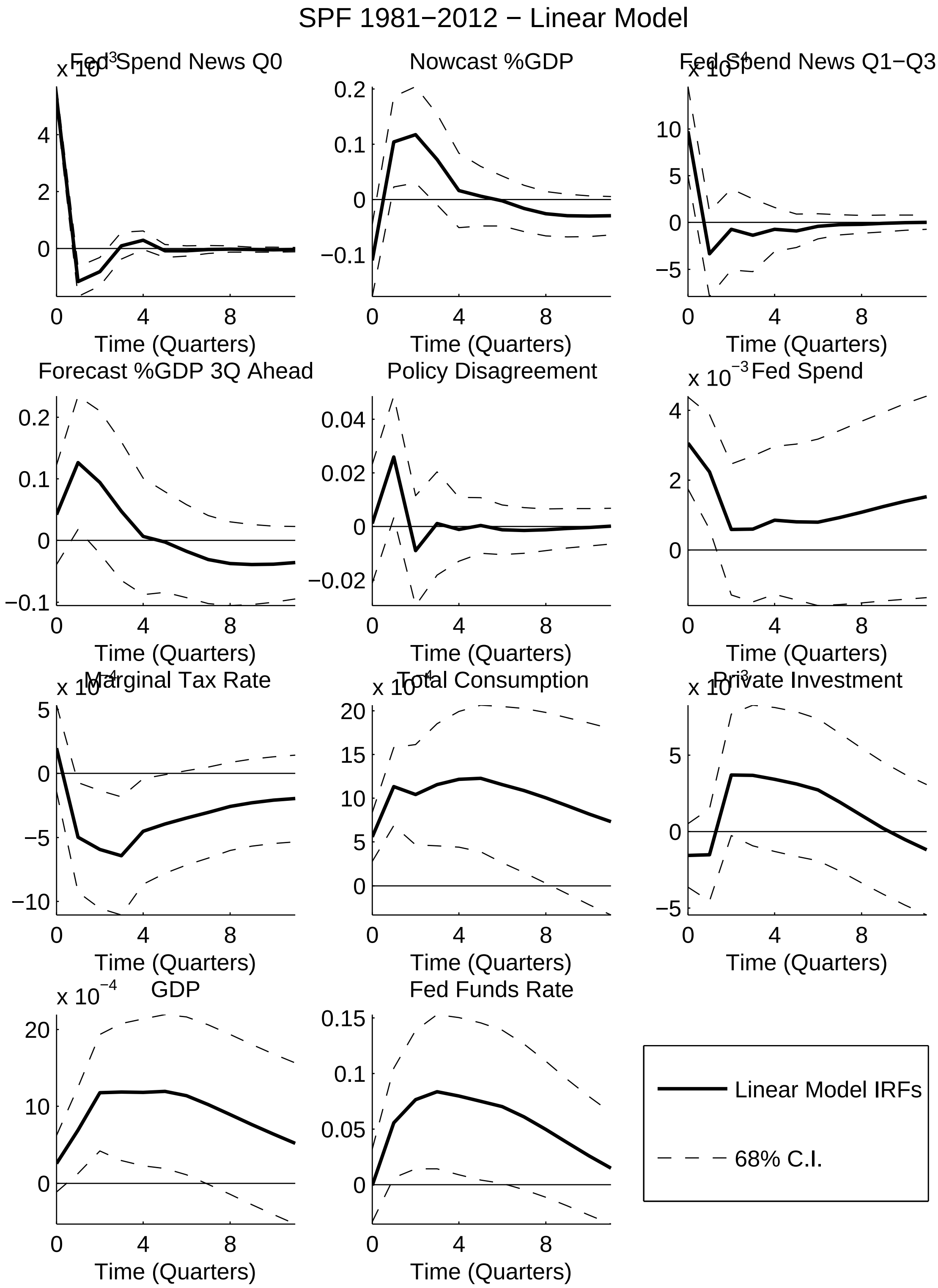

Figure 9: **Linear VAR model - nowcast revision.** Impulse responses have been been normalised to have a unitary increase in federal spending at the 4-quarters horizon. Dotted lines are the 68% coverage bands. Sample: 1981Q3-2012Q4.

A.4 Impulse Responses Generated from the Threshold VAR Model – Responses to the Nowcast Revision

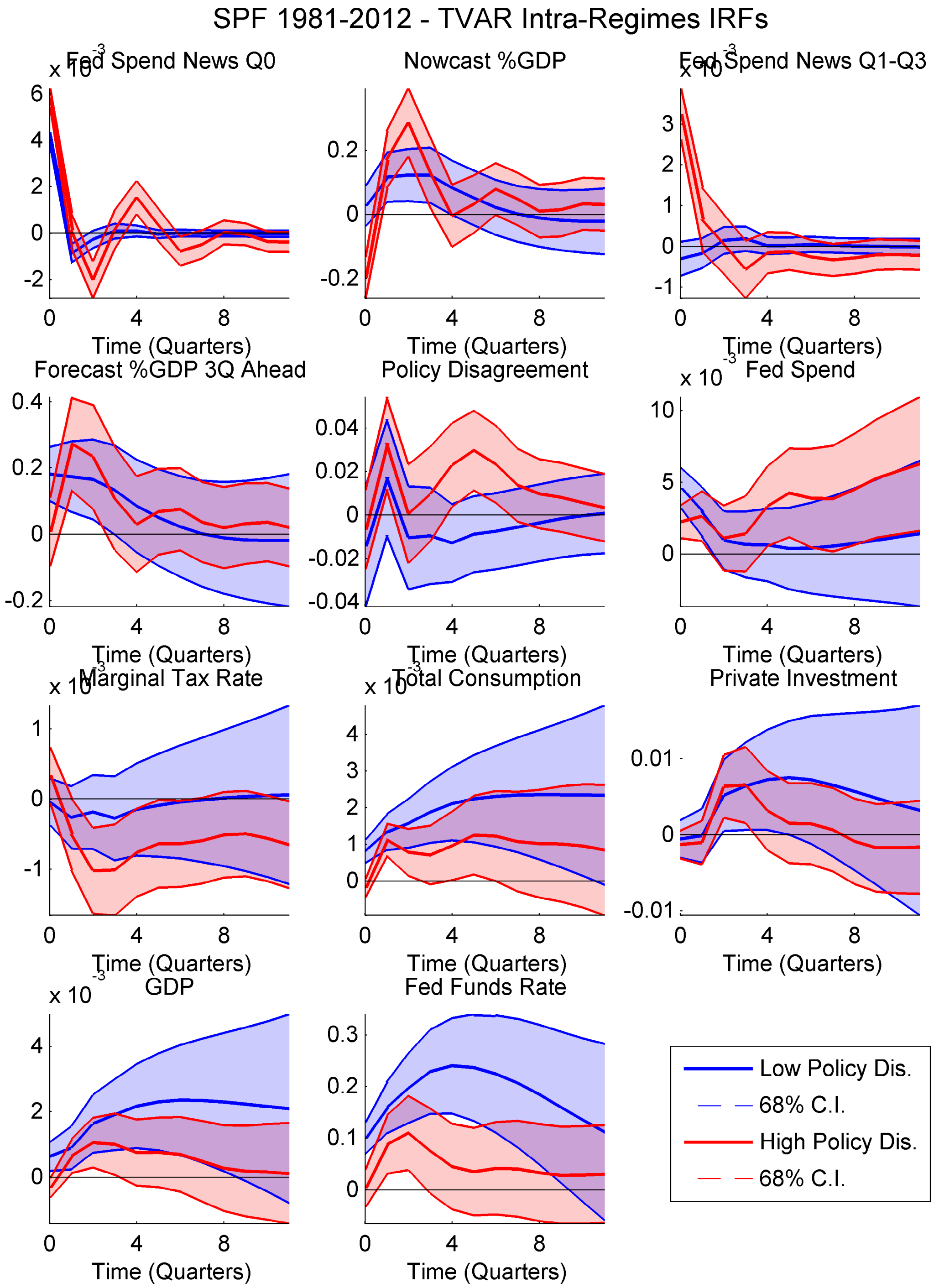

Figure 10: **Within-regime impulse responses - Impact of nowcast revisions.** The shock corresponds to one standard deviation change in the revision of the spending forecasts three quarters ahead. The responses are generated under the assumption of constant disagreement regime. Blue line and fans (68% coverage bands) are relative to the low-disagreement regime, while the red lines and fans (68% coverage bands) are relative to the high disagreement regime. Sample: 1981Q3-2012Q4.

Table 1: **Nowcast Errors and News.** The table presents descriptive statistics for the SPF real federal government spending Expected Growth (%) implied misexpectations and news.

	mean of individual forecasts		
	$\mathcal{M}_t$	$\mathcal{N}_t(0)$	$\mathcal{N}_t(1,3)$
mean	0.0005	-0.0003	0.0011
std	0.0161	0.0085	0.0069
	median of individual forecasts		
	$\mathcal{M}_t$	$\mathcal{N}_t(0)$	$\mathcal{N}_t(1,3)$
mean	0.0007	-0.0004	0.0007
std	0.0165	0.0080	0.0052
	std distribution forecasts		
	$\mathcal{M}_t$	$\mathcal{N}_t(0)$	$\mathcal{N}_t(1,3)$
mean	0.0126	0.0125	0.0154
std	0.0126	0.0075	0.0077

B Fiscal News

B.1 Summary Statistics and Tables for the Fiscal News

We report some summary statistics of the two news shocks used in the paper (nowcast and forecast revisions, defined $\mathcal{N}_t(0)$ and $\mathcal{N}_t(1,3)$ as in the paper). We also show some statistics of the nowcast errors defined as $(\Delta g_t - \mathbb{E}_t^* \Delta g_t)$ (we label this variable here as $\mathcal{M}_t$). The results reported below are largely drawn from Ricco (2015).

Table 1 reports some descriptive statistics for the the two news shocks and the nowcast error. Mean and median news and nowcast errors are reported as measures of the central tendency for the distribution of SPF individual forecasters data. We also present statistics for the second moments of the measures. From table 1 it emerges that: (i) nowcast errors have larger variance than the news variables; (iii) the mean of the news distribution is very close to zero; (ii) mean and median measures are very close, thus indicating that the distributions tend to be symmetric around zero.

Next, in Figure 11 we report the spectral densities for the government spending growth rate, and the SPF-implied measures of $\mathcal{M}_t$, $\mathcal{N}_t(0)$ and $\mathcal{N}_t(1,3)$. A few features of these charts are noteworthy: (i) the realised government spending growth rate has a concentrated mass at low frequencies (i.e., the so called "typical spectral shape" of macroeconomic variable, see e.g., Levy and Dezhbakhsh (2003)). This peak does not appear in the nowcast errors and news indicating that forecasters tend to correctly forecast slow moving components of spending while errors are concentrated at higher frequencies; (ii) SPF-implied nowcast errors and news have small peaks at business cycle frequencies, which are possibly related to difficulties in correctly anticipating discretionary countercyclical measures; (iii) All four variables show some mass concentrated at high frequencies, possibly due to observational noise.

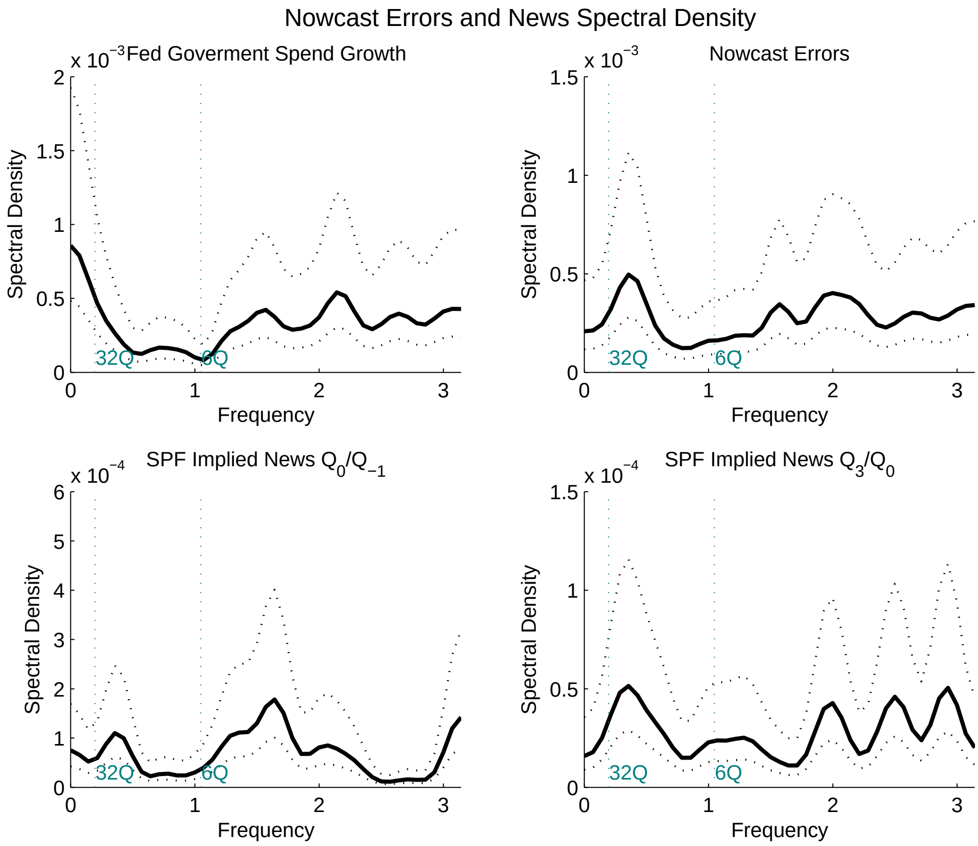

Figure 11: **Spectrum of Nowcast Errors and News (median).** The figure plots the spectral density, obtained with the method of averaged periodograms, for the real federal spending growth rate, the median implied nowcast errors and news (solid line) with confidence bands at the 95 percent confidence level (dashed line). The vertical dotted lines limit the business cycle frequency band.

To analyse the informational content of the news variable we (1) match peaks and through with a narrative of events, (2) perform an F-statistics to formally assess the explanatory power of SPF-implied fiscal news.

Figure 3 in the paper shows the time series plot of the two news shocks together with the Ramey-Shapiro war dates, presidential elections and some relevant fiscal and geopolitical events. It is apparent that peaks and troughs for the news series are related to important fiscal and geopolitical events. For example, large spikes are related to the Gramm-Rudman Acts and the Reagan Tax Reforms, the I and II Gulf War, the War in Afghanistan as well as the 1995-1996 Federal Government Shutdown and the 2009 Stimulus.

Table 2 reports F-statistics for the SPF-implied fiscal news. We regress the real federal government consumption growth rate on the first four lags of real federal government consumption, the average marginal tax rate, output, nonresidential fixed investment, nondurable consumption real rates and on the current $\mathcal{N}(0)$ or the 4th lag of $\mathcal{N}(1,3)$. The

Table 2: **Explanatory power of SPF-implied fiscal news.** The table reports marginal F-statistics, coefficients and t-statistics for the news variables. The real federal government consumption growth rate is regressed on lags 1 to 4 of real federal government consumption, the average marginal tax rate, output, nonresidential fixed investment, nondurable consumption real rates and on the lag 0 of $\mathcal{N}(0)$ or the lag 4 of $\mathcal{N}(1,3)$.

Independent Variable	**F-stat**	**Prob > F**	**reg. coeff.**	**t-stat**
$\mathcal{N}(0)$	7.54	0.007	0.620	2.75
$\mathcal{N}(1,3)$	6.76	0.011	0.783	2.60

news variables provide information which is helpful in forecasting future and current government spending, even though the F statistics is below 10 and the SPF-implied news does not appear to be strong instruments.

B.2 Comparison with other Shocks used in the Literature

We compare our shocks with other measures of news proposed in the related literature. Ramey (2011b) has proposed two proxy variables for aggregate expectations about government spending. The first is the *military news* variable, a judgemental estimate of changes in the expected present value of military spending, constructed ex-post using the Business Week and other newspaper sources. Future changes in military spending are discounted using the 3-year Treasury bond rate at the time of the news. This variable is assumed to proxy for the sum of expectations revision about government spending in the current quarter (unexpected changes) and the future quarters (expected changes). Figure 12 plots the Ramey military news variable against our SPF-implied news variables for the current quarter (top chart) and three quarters ahead (bottom chart). The correlation between the military news variable and our SPF-implied news on different horizons is virtually zero both with current and future quarter news (see also table 3). Also, it is interesting that the timing of recognisable increase in military spending (e.g., the Gulf War or the war in Afghanistan) is different. However, when comparing the series, it should be kept in mind that the forecast horizon of the Ramey military news variable is much longer than the one of the professional forecaster of the SPF dataset.

The second measure proposed in Ramey (2011b) is a measure of agents' forecast errors on government spending based on the median value of SPF forecasts of federal government spending. It is given by the difference between realised government spending growth and the median expected government spending growth, one lag ahead. Formally, the Ramey's shocks are identified filtering through a VAR SPF forecast errors made at time $t-1$ defined as: $(\Delta g_t - \mathbb{E}^*_{t-1}\Delta g_t)$.

Table 3 reports the correlations of our measures for fiscal news and nowcast errors with other proxy variables for fiscal, monetary and policy uncertainty shocks commonly used in literature. Nowcast errors and news on the current quarter are correlated to the SPF forecast

Table 3: **Correlations of News and Nowcast Errors with Other Proxy Variables**: (1) Ramey (2011b) Federal Spending SPF Forecast Errors, (2) Ramey (2011b) Present Discounted Value of Military Spending - PDVMIL, (3) Romer and Romer (2010) Endogenous Tax Changes, (4) Romer and Romer (2010) Exogenous Tax Changes, (5) Romer and Romer (2004) Monetary Policy Shocks, (6) Baker et al. (2012) Uncertainty Index, (7) Baker et al. (2012) Uncertainty Index - Monetary Policy, (8) Baker et al. (2012) Uncertainty Index - Taxes, (9) Baker et al. (2012) Uncertainty Index - Government Spending.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Nowcast Errors (median)	0.77	0.00	0.06	-0.10	-0.09	-0.04	0.11	-0.04	-0.07
News Q0 (median)	0.33	0.01	-0.01	0.15	0.03	-0.08	0.02	-0.06	-0.19
News Q1-Q3 (median)	-0.02	-0.01	0.02	-0.02	0.07	0.00	0.07	0.06	-0.16

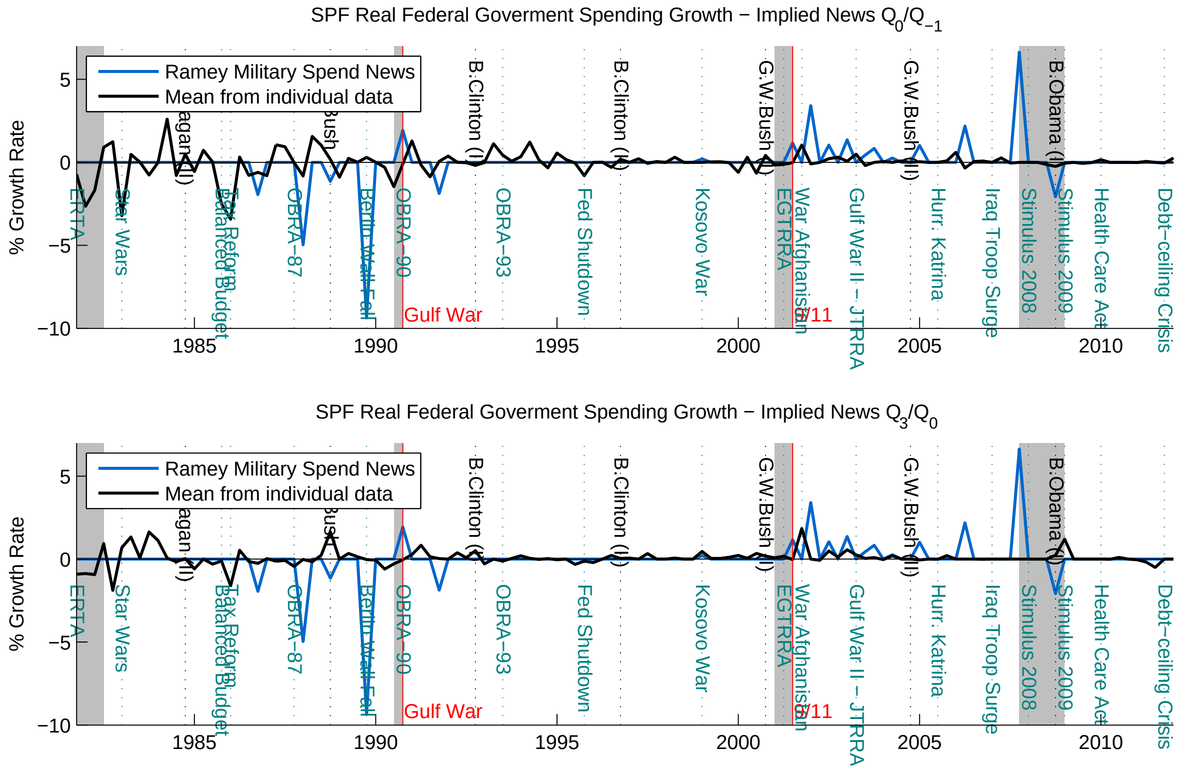

Figure 12: Government Spending News and Ramey's Military Spending News. The figure plots the time series for implied SPF news (black), as well as Ramey's military spending news (blue). Grey shaded areas indicate the NBER Business Cycle contraction dates. Vertical lines indicate the dates of the announcement of important fiscal and geopolitical events (teal), presidential elections (black), and the Ramey-Shapiro war dates (red).

errors defined in Ramey (2011b), with correlation 0.77, as expected given their definitions. Our news shocks also appear to be mildly correlated to tax changes as defined in Romer and Romer (2010). They also appear to be weakly correlated to the Policy Uncertainty Index defined in Baker et al. (2012), and with this Index's subcomponents.

B.3 List of Fiscal Events

Fiscal Events	
1981.Q4	ERTA – Economic Recovery Tax Act of 1981
1982.Q2	TEFRA – Tax Equity and Fiscal Responsibility Act of 1982
1983.Q1	Star Wars – Strategic Defense Initiative
1984.Q4	DEFRA – Deficit Reduction Act of 1984
1985.Q4	Balanced Budget Act – Gramm-Rudman-Hollings Balanced Budget Act
1986.Q1	Tax Reform – Tax Reform Act of 1986
1987.Q4	OBRA-87 – Omnibus Budget Reconciliation Act of 1987
1989.Q4	Berlin Wall Fall
1990.Q3	Gulf War
1990.Q4	OBRA-90 – Omnibus Budget Reconciliation Act of 1990
1993.Q3	OBRA-93 – Omnibus Budget Reconciliation Act of 1993
1995.Q4	Federal Shutdown 95-96
1999.Q1	Kosovo War
2001.Q2	EGTRRA – Economic Growth And Tax Relief Reconciliation Act of 2001
2001.Q4	9/11 – September 11 attacks
2001.Q4	War in Afghanistan
2003.Q2	Gulf War II
2003.Q2	JTRRA – Jobs and Growth Tax Relief Reconciliation Act of 2003
2005.Q3	Hurricane Katrina
2007.Q1	Iraq Troop Surge
2008.Q1	Stimulus 2008 – Economic Stimulus Act of 2008
2009.Q1	Stimulus 2009 – American Recovery and Reinvestment Act of 2009
2010.Q1	Health Care Reform – Health and Social Care Act 2012
2011.Q1	2011 Debt-ceiling Crisis

C Model Estimation

C.1 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

$$\Sigma_\varepsilon \sim IW(\Psi, d) \ , \tag{17}$$
$$\beta|\Sigma_\varepsilon \sim N(b, \Sigma_\varepsilon \otimes \Omega) \ , \tag{18}$$

where $\beta \equiv \mathrm{vec}([C, A_1, \ldots, A_4]')$, 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 due to the advantage that 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). The adoption of these two priors is based respectively on the assumption that each variable follows either a random walk process, possibly with drift, or a white noise process, and on the assumption of the presence of cointegration relationship among the macroeconomic variables.[15] 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)).

- **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-Wishart distribution to $d = n+2$ which is the minimum value that guarantees the existence of the prior mean of Σ_ε.[16] Moreover, we assume Ψ to be a diagonal matrix with $n\times 1$ elements ψ along the diagonal. The coefficients $A_1, \ldots, A_4$ are assumed to be *a priori* independent. Under these assumptions, the following first and second moments analytically characterise this prior:

$$E[(A_k)_{i,j}] = \begin{cases} \delta_i & j = i, \ k = 1 \\ 0 & \text{otherwise} \end{cases} \tag{19}$$

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

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

$$V[(A_k)_{i,j}] = \begin{cases} \frac{\lambda^2}{k^2} & j = i \\ \vartheta \frac{\lambda^2}{k^2} \frac{\psi_i}{\psi_j/(d-n-2)} & \text{otherwise.} \end{cases} \tag{20}$$

These can be cast in the form of (18). The coefficients δ_i that were originally set by Litterman were $\delta_i = 1$ reflecting 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*

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

where $J_p = diag(1, 2, ..., p)$.[17] 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 *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

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

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

.

we add the following dummy observations to the ones for the Normal-Inverse-Wishart prior:

$$\begin{aligned} y_d &= \mathrm{diag}(\delta_1\mu_1, ..., \delta_n\mu_n)/\tau \\ x_d &= ((1_{1\times p}) \otimes \mathrm{diag}(\delta_1\mu_1, ..., \delta_n\mu_n)/\tau \;\; 0_{n\times 1}) \, . \end{aligned} \tag{21}$$

In this set-up, the set of parameters μ aims to capture the average level of each of the variables, while 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 the dummies can be written as a VAR(1) process

$$y_* = x_* B + e_* \ , \tag{22}$$

where the starred variables are obtained by stacking $y = (y_1, \ldots, y_T)'$, $x = (x_1, \ldots, x_T)'$ for $x_t = (y'_{t-1}, \ldots, y'_{t-4}, 1)'$, and $\varepsilon = (\varepsilon_1, \ldots, \varepsilon_T)$ 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:

$$\Sigma_\varepsilon | y \sim IW\left(\tilde{\Psi}, T_d + 2 + T - k\right) \tag{23}$$

$$\beta | \Sigma_\varepsilon, y \sim N\left(\hat{\beta}, \Sigma_\varepsilon \otimes ({x_*}'x_*)^{-1}\right) \ , \tag{24}$$

where $\hat{\beta} = \mathrm{vec}(\hat{B})$, $\hat{B} = ({x_*}'x_*)^{-1}{x_*}'y_*$ 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_*.

C.2 Within-regime IRFs and Inter-regimes GIRFs

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

We study two sets of dynamic response 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, 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 $i = 1, \ldots, h$

$$GIRF_y(h, \omega_{t-1}, \varepsilon_t) = \mathbb{E}\left[y_{t+h}|\omega_{t-1}, \varepsilon_t\right] - \mathbb{E}\left[y_{t+h}|\omega_{t-1}\right] \ , \tag{25}$$

due an exogenous shock ε_t and given initial conditions $\omega^r_{t-1} = \{y_{t-1}, \ldots, y_{t-1-p}\}$. Details on the GIRFs computation are provided in Appendix C.3.

C.3 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) $\omega^r_{t-1} = \{y^r_{t-1}, \ldots, y^r_{t-1-p}\}$.

2. Random draws with replacement are made from the estimated residuals of the asymmetric model, $\{\varepsilon^b_{t+j}\}^h_{j=0}$. The shocks are assumed to be jointly distributed, so if date t shock is drawn, all the n-dimensional vector of residuals for date t is collected.

3. Given the draws for the history ω^r_{t-1} and the residuals $\{\varepsilon^b_{t+j}\}^h_{j=0}$, 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 $y_{t+k}(\omega^r_{t-1}, \{\varepsilon^b_{t+j}\}^h_{j=0})$ for $k = 1, \ldots, h$.

4. Step three is repeated substituting one of the residual at time zero with an identified structural shock of size ι and leaving the remaining contemporaneous residual and the rest of the sequence of residuals unchanged. A new path for $y_{t+k}(\omega^r_{t-1}, \{\varepsilon^{*,b}_{t+j}\}^h_{j=0})$ 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 the difference between the simulated shocked sequence $y_{t+k}(\omega^r_{t-1}, \{\varepsilon^{*,b}_{t+j}\}^h_{j=0})$ and the baseline path $y_{t+k}(\omega^r_{t-1}, \{\varepsilon^b_{t+j}\}^h_{j=0})$.

Coverage intervals for the GIRF are computed as follow:

1. A draw for the TVAR parameters $\{C^i, A^i_j, \Sigma^i_\varepsilon\}_{i=\{l,h\}}$ 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 $Q = 1000$.

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