Signals from the Government: Policy Disagreement and the Transmission of Fiscal Shocks*

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Abstract

This paper investigates the influence of fiscal policy communication on the propagation of government spending shocks. We propose a new index to measure the coordination effects of policy communication on private agent expectations. This index relies on the disagreement amongst US professional forecasters about future government spending. The underlying intuition is that a clear fiscal policy communication can coalesce agents' expectations, reducing disagreement. Our results indicate that, in times of low disagreement about future policies, the output response to fiscal spending announcements is large and positive. Conversely, periods of elevated disagreement are characterised by muted responses. The stronger effects of fiscal policy when expectations are coordinated are due to the accelerator effect of planned fiscal spending on private investment.

JEL Classification: E60, D80.

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

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Introduction

The impact of economic policy decisions depends, to a great extent, on how these decisions are communicated to the public and on how they affect agents' expectations. Policymakers can guide private agent beliefs by providing information about their economic forecasts and the design of their current and future policies. In particular, a clear and precise policy communication can (1) coordinate expectations, as reflected in reduced disagreement amongst agents, and (2) limit economic uncertainty, thus reducing the ex-ante variance of individual forecasts. These two channels are intertwined. However, as the recent literature has pointed out, uncertainty and disagreement are distinct concepts and are generally weakly correlated.[1] This paper focuses on the expectation coordination effects of fiscal policy communication and studies the implications of disagreement amongst agents for the transmission of fiscal policy shocks.

The existing literature has investigated some of the implications of disagreement with respect to inflation and GDP (see, e.g., Mankiw et al. (2004)). However, to the best of our knowledge, this is the first attempt to study how disagreement about current and future fiscal policies may affect macroeconomic outcomes. In particular, this work contributes to the literature by empirically analysing the role of fiscal policy communication in the transmission of government spending shocks. In this framework, we develop an indirect measure of precision of fiscal policy communication derived from forecasters' disagreement on the future path of fiscal spending, based on the Survey of Professional Forecasters (SPF). The key idea underlying the proposed index is that a clear fiscal policy communication can coalesce private sector expectations of future policy measures, which in turn reduces agents' disagreement.

[1] The link between disagreement and uncertainty has been extensively investigated in the literature, mainly using survey data for inflation (see, among many others, Lahiri and Sheng (2010), D'Amico and Orphanides (2008), Rich and Tracy (2010)).

Conversely, higher than average disagreement about future government spending reveals poor communication from the government about the future stance of fiscal policies.

This intuition is based on the literature studying rational expectations in the presence of imperfect information. In a full information rational expectation model, communication has no independent role and any systematic pattern in the way policy is enacted is inferred by the agents. In such a world, agents' expectations reflect the structure of the economy and are perfectly anchored at all times. Thus, there is no scope for disagreement. However, unlike the case of perfect information, survey data suggest that real world agents disagree both on the current and projected state of the economy. Furthermore, the extent of their disagreement evolves over time.

Two general classes of imperfect information models have been offered to explain this empirical evidence at variance with the full information rational expectation frameworks: 'delayed-information' and 'noisy-information' models. In delayed-information models, as in Mankiw and Reis (2002) and Reis (2006a,b), agents update their information set infrequently but ultimately arrive at perfect information. In noisy-information models, as in Woodford (2002), Sims (2003) and Mackowiak and Wiederholt (2009), agents continuously update their information set but observe only noisy signals about the true state. In both classes of models, there is scope for disagreement amongst agents, which can be driven by exogenous or endogenous factors.[2,3]

Imperfect information in delayed-information and noisy-information models can be mi-

[2] While in noisy information models, the disagreement amongst agents is due to the variance of the exogenous noise, which can be time-varying, in delayed-information models, the disagreement evolves endogenously following a shock. In response to shocks, some people do update their information set and revise their forecasts, while others remain uninformed. The size of the shocks determines the magnitude of the disagreement. Over time, more people become informed, but new shocks hit the economy. Therefore, disagreement does not go to zero but fluctuates over time.

[3] Empirical evidence of informational rigidities that can be explained by these models of imperfect information has been reported in Coibion and Gorodnichenko (2010, 2012) and in Andrade and Le Bihan (2013).

crofounded and related to the inattention of agents to new information, a behaviour that can be rationalised by costly access to information (e.g., Reis (2006a,b) or limited processing capacities (e.g., Sims (2003)). Through the lenses of these models, policymaker communication could potentially alter the degree of information rigidity in the economy by affecting the signal-to-noise ratio or by modifying the costs of acquisition new information. This would create shifts in the level of disagreement that unrelated to macroeconomic disturbances. The intuition behind our index relies on these mechanisms.

Our empirical strategy is consistent with the implications of imperfect information models and is structured in three steps. First, we construct a fiscal policy disagreement index, based on the dispersion of government spending forecasts as reported in the Survey of Professional Forecasters (SPF). The index is constructed by projecting the cross sectional dispersion of forecasts about future government spending onto the disagreement about current output. This is in order to pin down the fluctuations in disagreement that are due to policy communication and not to cyclical macroeconomic disturbances.[4] Second, following Ricco (2014), 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.[5] 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. The TVAR model allows for the derivation of some stylised facts about the

[4]Indeed, it has been documented that disagreement about GDP growth intensifies strongly during recessions and reduces during expansions (see Dovern et al. (2012)).

[5]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 (2011)).

propagation of fiscal shocks, conditional on the level of disagreement about discretionary fiscal spending.

Our results provide evidence that, during periods of high disagreement on fiscal policy, spending shocks have 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 stronger fiscal activism, output does not significantly respond to policy news. 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. Also, 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 (e.g, Ramey (2011), Leeper et al. (2012) and Leeper et al. (2013)) and on state-dependent effects of fiscal policy (e.g., Auerbach and Gorodnichenko (2012), Owyang et al. (2013) and Caggiano et al. (2014)). Differently from these works, however, we look at communication effects in fiscal policy and in doing that we relate to the literature on policy communication (see surveys in Blinder et al. (2008) and Dincer and Eichengreen (2014)). Our paper is also linked to the literature using survey data to study expectation formation (see Pesaran and Weale (2006)). In particular, we connect the recent empirical literature on imperfect information (see, amongst others, Mankiw et al. (2004), Dovern et al. (2012), Coibion and Gorodnichenko (2010, 2012), Andrade and Le Bihan (2013) and Andrade et al. (2014)).

Our paper is structured as follows: Section 1 discusses properties of expectational data on US fiscal spending. Section 2 is devoted to the construction of the fiscal policy disagreement index used in this paper. Section 3 comments on the identification of fiscal shocks. Section 4 illustrates our Bayesian Threshold VAR model. Section 5 is devoted to illustrating our main results and provides insights on the transmission channels. Finally, Section 6 concludes.

1 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.[6]

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

[6]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.

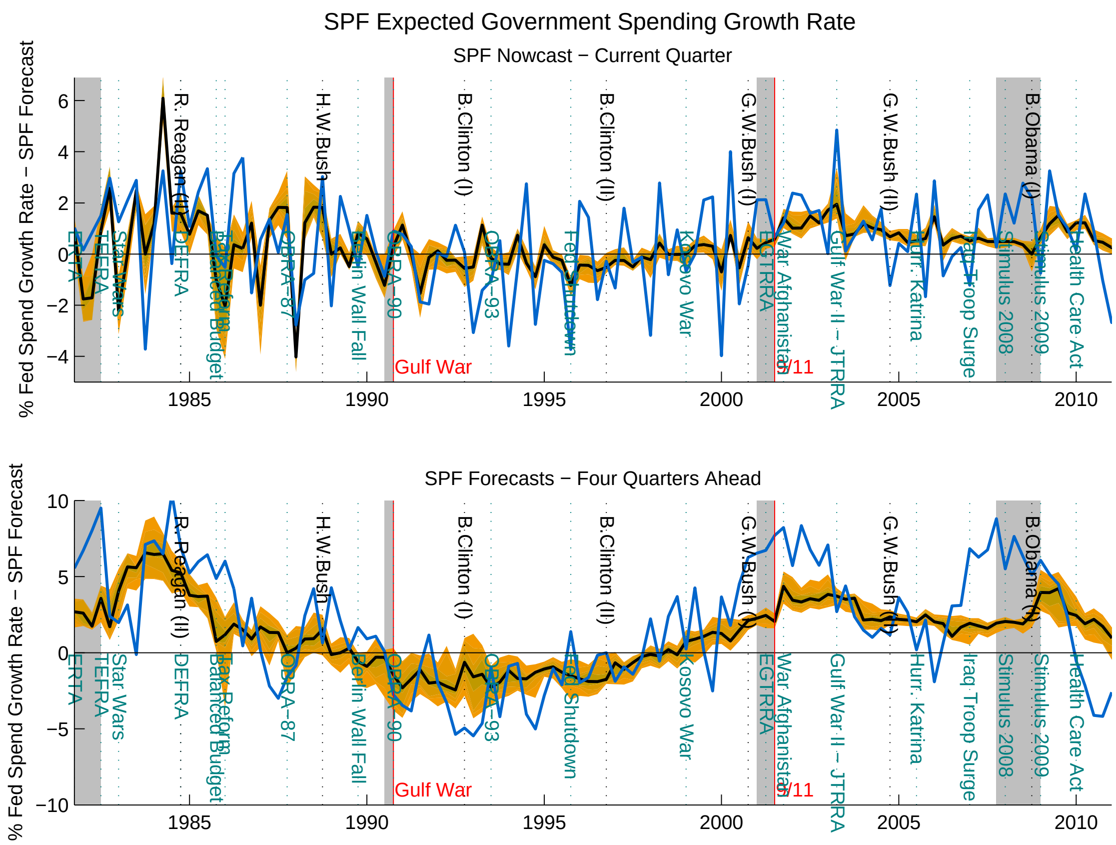

Figure 1: **Government Spending Expected Growth rates – Fan Chart**. The figure plots the SPF median expected growth rate for the current quarter and for the four future quarters, together with forecasters' disagreement up to one standard deviation (orange), and the realised growth reates (blue). Grey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

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 (for government spending, see Ricco (2014)). 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 3). Finally, 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.[7,8]

2 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.

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

[8] Coibion and Gorodnichenko (2012) find that consumers do not appear to have a slower rate of information acquisition and processing with respect to other agents as firms, professional forecasters, and central bankers. However, disagreement among consumers is much larger than for other agents.

To construct our index for fiscal policy disagreement, we follow a two-step procedure. First, we compute the time-varying cross-sectional standard deviation of the SPF forecasts (disagreement), at the four-quarters horizon, for real federal government spending.[9] Second, we extract the component of disagreement related to discretionary policy 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 toy 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.

2.1 Disagreement in a Stylised Noisy-information Model

A toy 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

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

[9]The horizon of one year is in our view reasonable, as reflected also in survey data. In fact, the investment horizon for firms has been found to be above one year only for around 33% of U.S. private firms, as shown by the Atlanta Fed's Business Inflation Expectation Survey (see July 2014 issue available on the website of Atlanta Fed). This suggests that private investors often look at a relatively short horizon when making their investment decisions.

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_{t+h}^d:

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

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

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

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.[10]

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-information models, we think of shifts in disagreement as a reflection of policy communication regimes.[11]

[10] 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.

[11] Through the lenses of microfounded models of imperfect information rationalising the agents' inattention to new information by costly access to information (e.g., Reis (2006a,b)) or limited processing capacities (e.g., Sims (2003)), we think of policymakers as able to alter the degree of information frictions affecting the signal-to-noise ratio or by modifying the costs of new information acquisition. This would create shifts in the level of disagreement that are not related to macroeconomic disturbances.

2.2 Cyclical Variations in Disagreement

Considering equation 1, it is evident that 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.[12]

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

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

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

2.3 Policy Disagreement

In light of the considerations made above, 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. 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.[13]

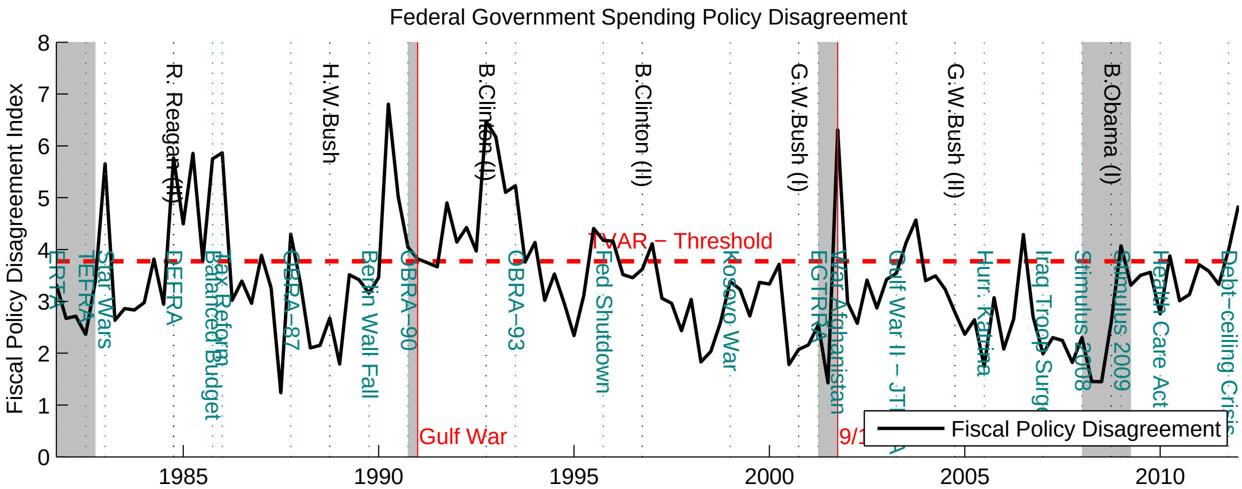

Figure 2: **Policy Disagreement Index** - Time series of the fiscal policy disagreement index based on the dispersion of SPF forecasts (black). Grey shaded areas indicate the NBER business cycle contraction dates. Vertical lines indicate the dates of the announcement of important fiscal and geopolitical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

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

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.

[13] 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.

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

3 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, as in Ricco (2014) and Forni and Gambetti (2014). 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:

$$\begin{aligned}
\underbrace{g_t - \mathbb{E}^*_{t-h} g_t}_{\substack{\text{forecast error} \\ \\ h \text{ periods ahead}}} \quad = \quad \underbrace{(g_t - \mathbb{E}^*_t g_t)}_{\substack{\text{nowcast error} \\ \\ \notin \mathcal{I}_t}} \quad + \quad \underbrace{(\mathbb{E}^*_t g_t - \mathbb{E}^*_{t-1} g_t)}_{\substack{\text{nowcast revision} \\ \\ (\text{news at t}) \in \mathcal{I}_t}} \quad + \dots \\
\dots + \quad \underbrace{(\mathbb{E}^*_{t-h+1} g_t - \mathbb{E}^*_{t-h} g_t)}_{\substack{\text{forecast revision} \\ \\ (\text{news at t-h+1}) \in \mathcal{I}_{t-h+1}}} \quad . \qquad (9)
\end{aligned}$$

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.

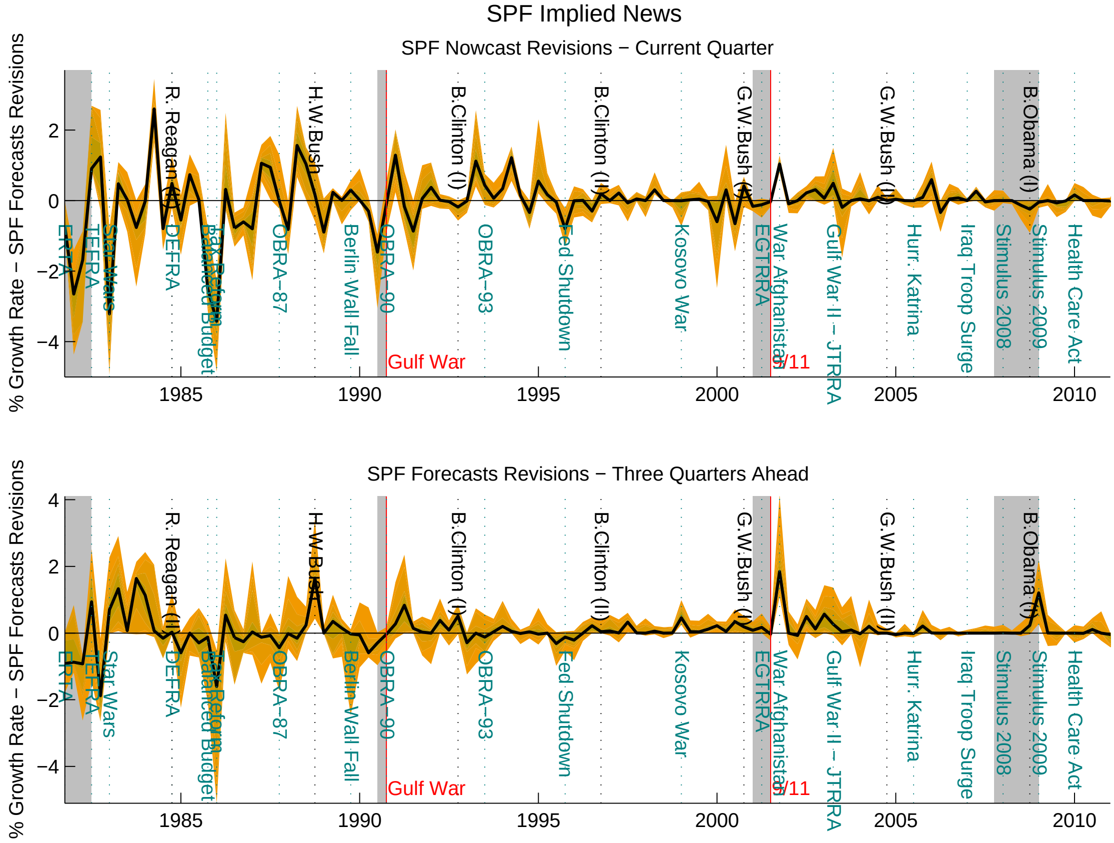

Figure 3: **Government Spending News – Fan Chart**. The figure plots the mean implied SPF news on the current quarter and for future quarters, together with forecast disagreement up to one standard deviation. Grey shaded areas indicate the NBER Business Cycle contraction dates. Vertical lines indicate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

Following Ricco (2014), 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 (see Ricco (2014)). 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:[14]

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

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.

[14]Conversely, forecast errors are not good proxies for structural shocks *per se*, and do not contain additional information, conditional on past and current news. In fact, substituting recursively Eq. (13) in (12) one obtains

$$\underbrace{g_t - \mathbb{E}^*_{t-1} g_t}_{\text{forecast error}} = \sum_{j=0}^{\infty} \lambda^j u_{t-j} \ ,$$

where u_{t-j} is a linear combination of rational expectations errors at time $t-j$.

4 A Bayesian Threshold VAR

In order to study the effect 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 explicit inclusion 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

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

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.[15]

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

[15]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.

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 Webappendix.

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, total private consumption and investment, real GDP and the Federal Fund Rate. We use quarterly data from 1981Q3 to 2012Q4 in real log per capita levels for all variables except those expressed in rates (see Webappendix 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 whcih the fiscal variables are ordered as follow

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

and Y_t is a vector containing the macroeconomic variables of interest.[16] 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.

5 Disagreement and the Transmission of Fiscal Shocks

Figure 4 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.[17] 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

[16]We also assume that the relation between professional forecasters' expectations and other agents (firms and consumers) expectations is stable. Under this assumption, in the veins of Carroll (2003), the VAR model would capture the endogenous dynamic of dispersion of the information in the economy, and the identification would be correct.

[17]In the Webappendix, we also report the impulse responses generated from a linear VAR. These are broadly in line with the results of Ricco (2014) and Forni and Gambetti (2014). They show that a positive innovation to forecast revisions tends to have a positive and persistent effect on GDP.

communication than the nowcast revisions.[18] 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, 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 (for the low-disagreement regime, hereafter "L-D") and red lines (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.

The TVAR results reveal a very different transmission mechanism in the two regimes. While the response of federal spending to the policy announcement is very similar in the two regimes, in the L-D regime, the response of the marginal tax rate is not significant while, in the H-D regime, the news shock is also strengthened by decisive reductions in the marginal tax rate. This additional policy action indicates a relative stronger activism of the fiscal authorities during period of H-D. The GDP response highlights the different impact of a spending shock in the two regimes. Despite the smaller overall fiscal impulse generated in the L-D regime, 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

[18] 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).

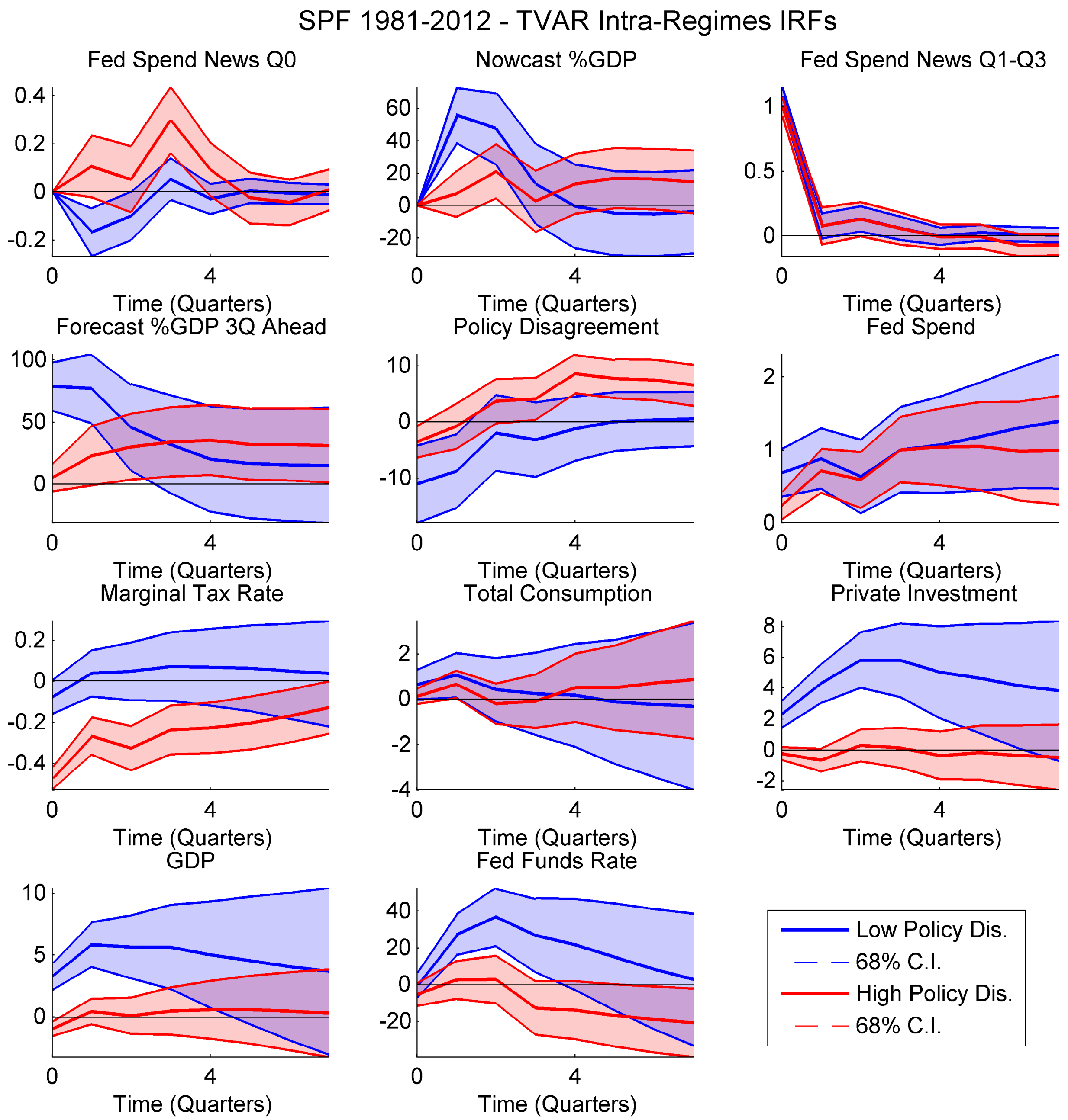

Figure 4: **Within-regime impulse responses - Impact of forecast revisions.** The shock corresponds to one standard deviation change in the revision of the spending forecasts three quarters ahead. The responses are generated under the assumption of constant disagreement regime. Impulse responses have been been normalised to have a unitary increase in Federal Spending at the 4-quarters horizon. Blue 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.

sum of the responses for federal spending (see also Ilzetzki et al. (2013)). The cumulative 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 monetary policy stance tightens in the low disagreement case, as reflected in the more pronounced increase of the Federal Funds Rate. This may reflect 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 4 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.

5.1 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 one at a time 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 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 following two charts of Figure 5 report the response of civilian employment and unemployment to the shock. It appears that 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., Ramey (2011) and Perotti (2008)). Our results shows that, in response to the identified news shock on government spending, real wages rise 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 4, 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. Also, the non-residential investment responses appear to diverge in the two regimes, though not significantly. 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.

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 positive non-durable consumption response and a negative durable consumption response in the short-run.

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 positive and significant in the short run. A weak response of prices to the government spending shock is in line with related research on the US.[19,20]

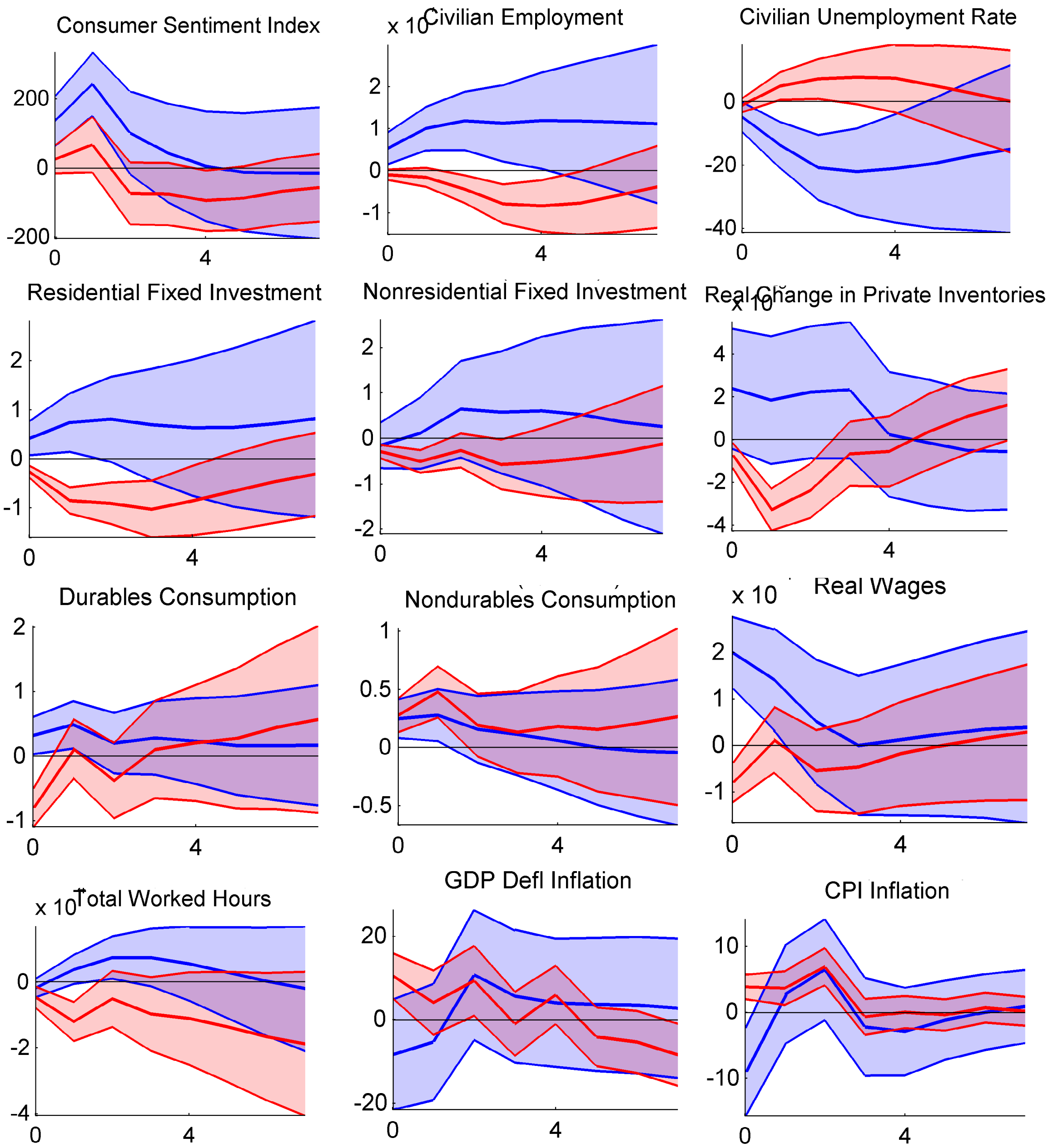

Figure 5: **Impact of forecast revisions on other variables.** Impulse responses of the Michigan's consumer sentiment index, civilian employment and unemployment, residential fixed investment, non-residential fixed investment and inventories, durable and non-durable consumption, real wages and hours 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 line and fans are relative to the low-disagreement regime, while the red lines and fans are relative to the high disagreement regime. Sample: 1981Q3-2012Q4.

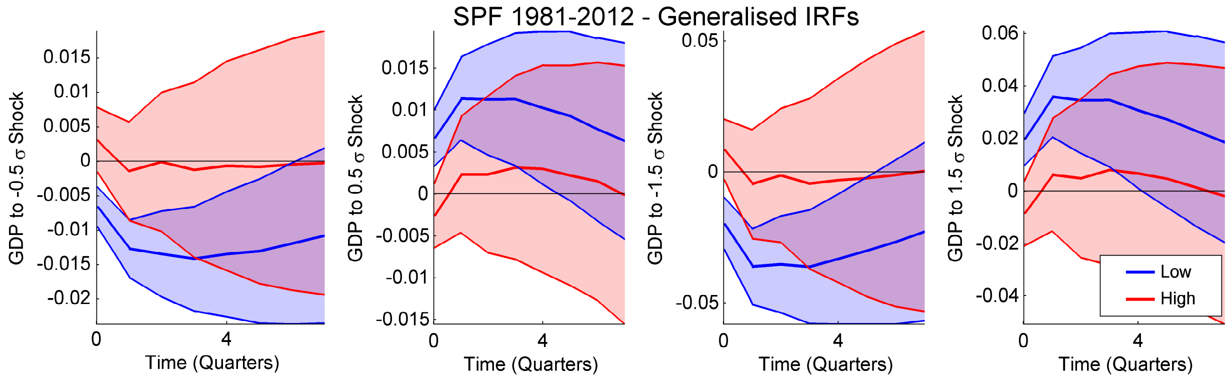

Figure 6: **Inter-regime impulse responses - Impact of forecast revisions.** The figure reports the GIRFs of a spending shock on GDP from four different shocks, detailed along the y-axis, generated from the baseline 11-variables TVAR. Sample: 1981Q3-2012Q4.

5.2 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 4). Unsurprisingly, the inclusion of possible regime shifts reduces the difference of the IRFs across the two regimes, although on impact and up to the first quarter after the shock the two set of IRFs appear to be statistically different from each other. A less clear-cut distinction between the two regimes is consistent with an endogenous propagation of the information about the shock in the economy.[21] It also emerges that negative and positive

[19]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).

[20]In the Webappendix, 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.

[21]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.

shocks are characterized by responses that are broadly symmetric, thus highlighting that contractionary and expansionary fiscal news have quantitatively similar effects (though, with opposite sign).

5.3 Moving forward

Our results pose some interesting challenges for the literature on both the effects of fiscal policy shocks and on imperfect information rational expectations. First, the positive response of investment, conditional on the communication regime, seems to be the main propagation channel of news shocks. 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.[22]

Second, our results highlights the policymakers's ability to alter the degree of information frictions in the economy. Depending on the model of reference, a clearer fiscal policy communication can alter the informational problem of economic agents by either increasing the signal-to-noise ratio or by reducing the costs of information acquisition. This opens a dynamic interaction between the agents' decisions in allocating economic resources or attention in acquiring new information, and the problem of fiscal authorities in deciding the precision of their policy communication. The interaction between agents' and policymakers' informational problems poses a challenge for benchmark sticky-information and noisy-information models, in which the choice of frequency of updates or allocation of attention is assumed to be based on 'average' economic conditions rather than being state-contingent. Further research is needed to understand how different institutional and political conditions can affect the management of fiscal policy communication and, through it, the way agents optimally

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

allocate attention and process information over time.[23]

6 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 suggestive evidence that, in times of low disagreement about future policies, the output response to policy announcements about future government spending growth is positive, strong and persistent. Conversely, periods of elevated disagreement are characterised by a muted output response to fiscal announcements. 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. 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.

[23] The state contingent frequency of updates or allocation of attention is also an interesting problem from an econometric point of view. In fact, the correlation of forecast revisions (news) and the structural shocks is governed by the information friction parameter. The fact that the information rigidities can be state dependent has important consequences for the identification problem using expectational time series. This paper is a first attempt to explore this econometric issue in the identification of fiscal shocks.

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Webappendix of the Paper
"Signals from the Government: Policy Disagreement and the Transmission of Fiscal Shocks"

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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

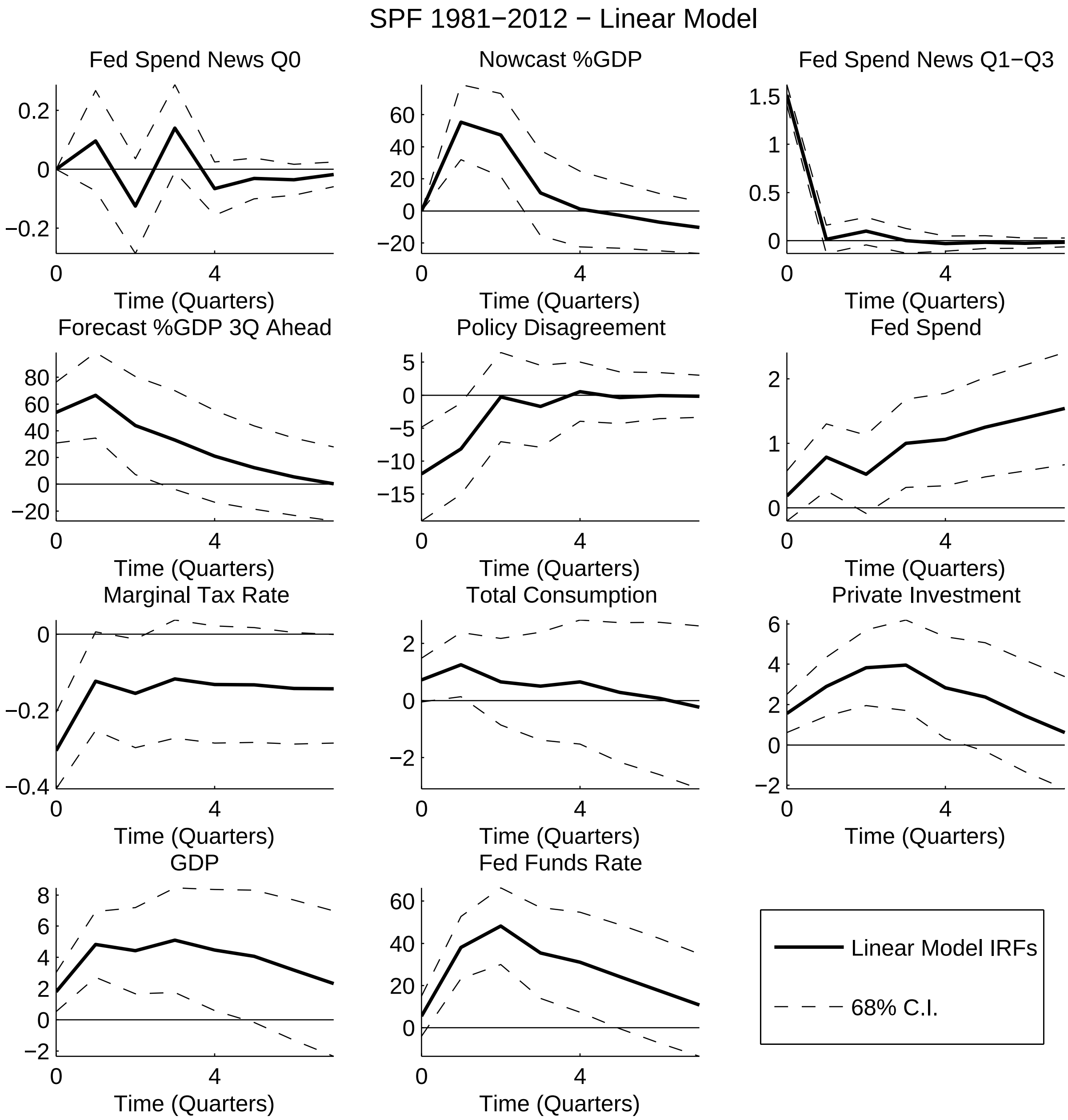

Figure 1: **Linear VAR model.** Impulse responses have been been normalised to have a unitary increase in federal spending at the 4-quarters horizon. Dotted lines are the 68% coverage bands. Sample: 1981Q3-2012Q4.

A.2 Robustness with respect to the Threshold Level

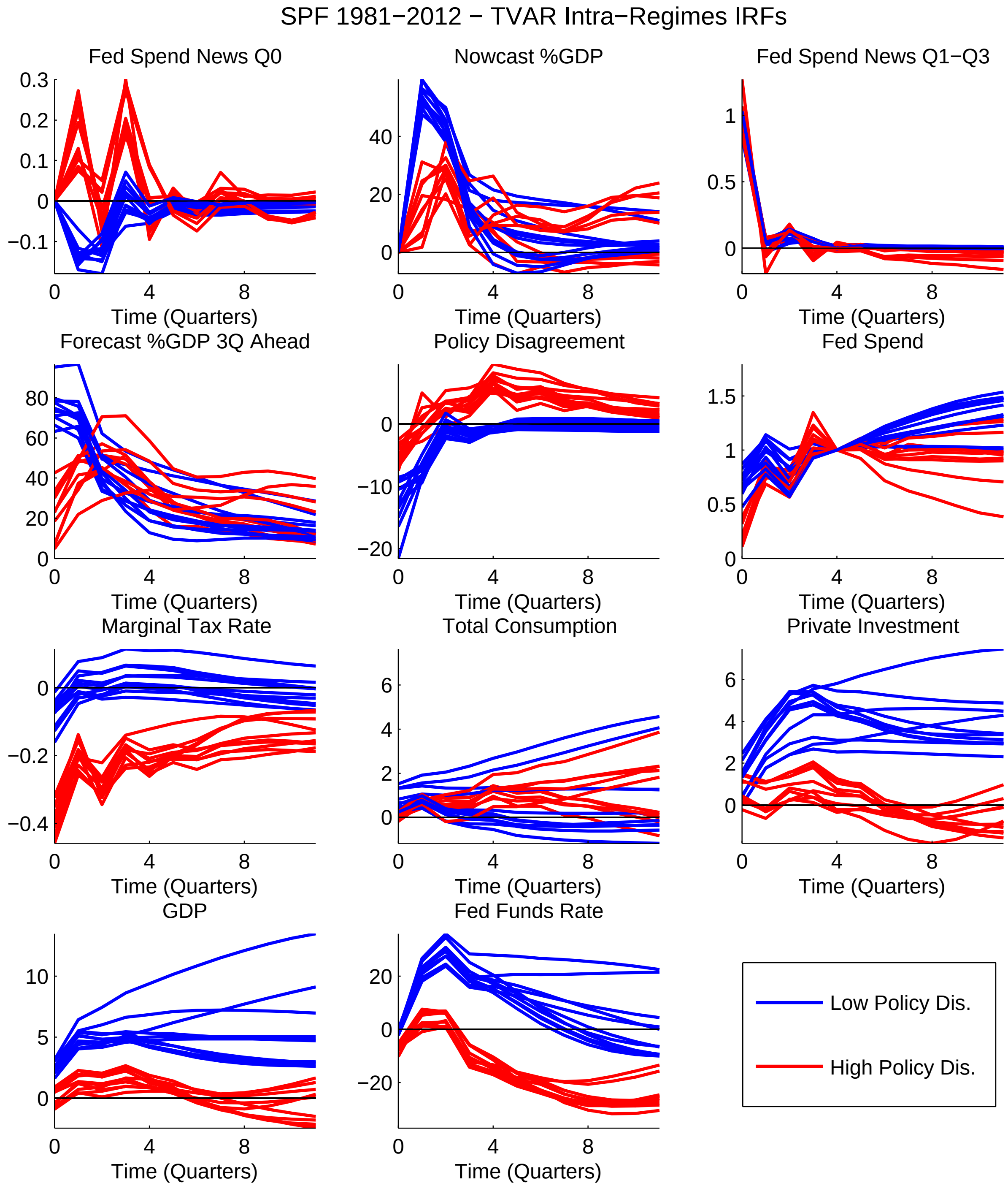

Figure 2: Robustness exercises carried out by varying the threshold level in an interval that excludes the higher and lower 30% observations of the threshold variable, i.e., the disagreement index. Impulse responses have been been normalised to have a unitary increase in federal spending at the 4-quarters 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

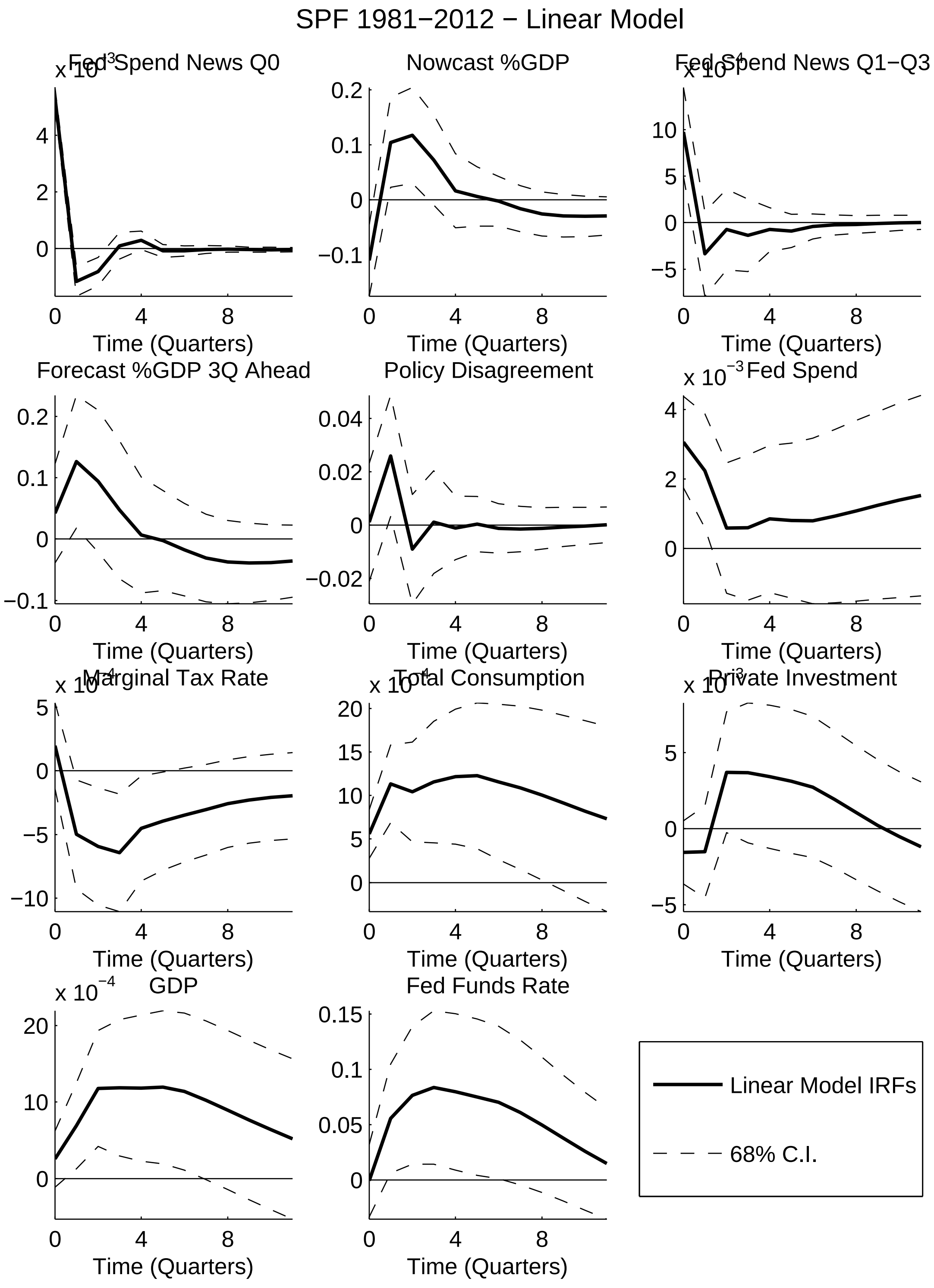

Figure 3: **Linear VAR model - nowcast revision.** Impulse responses have been been normalised to have a unitary increase in federal spending at the 4-quarters horizon. Dotted lines are the 68% coverage bands. Sample: 1981Q3-2012Q4.

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

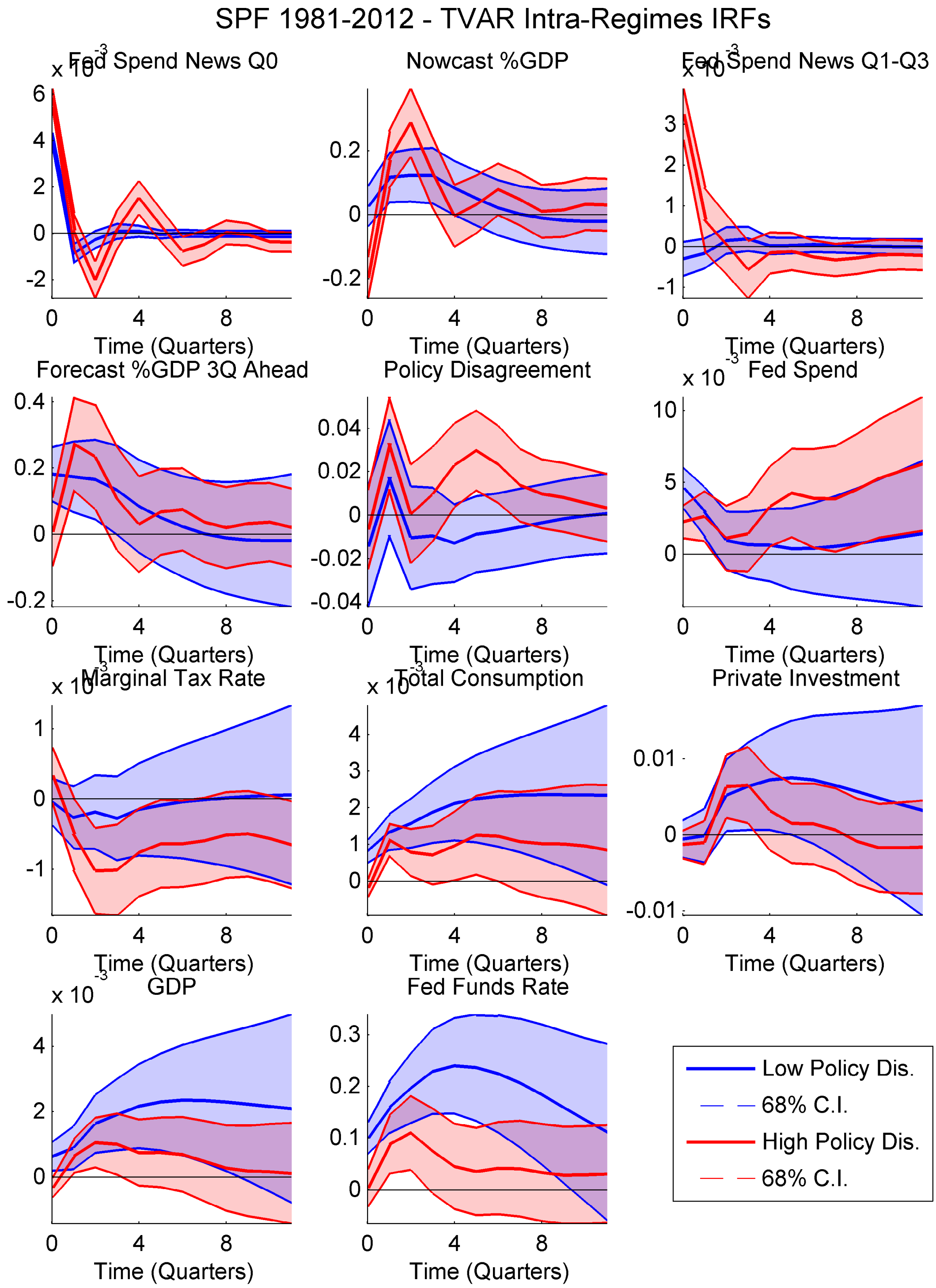

Figure 4: **Within-regime impulse responses - Impact of nowcast revisions.** The shock corresponds to one standard deviation change in the revision of the spending forecasts three quarters ahead. The responses are generated under the assumption of constant disagreement regime. Blue line and fans (68% 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 (2014).

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 5 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.

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.

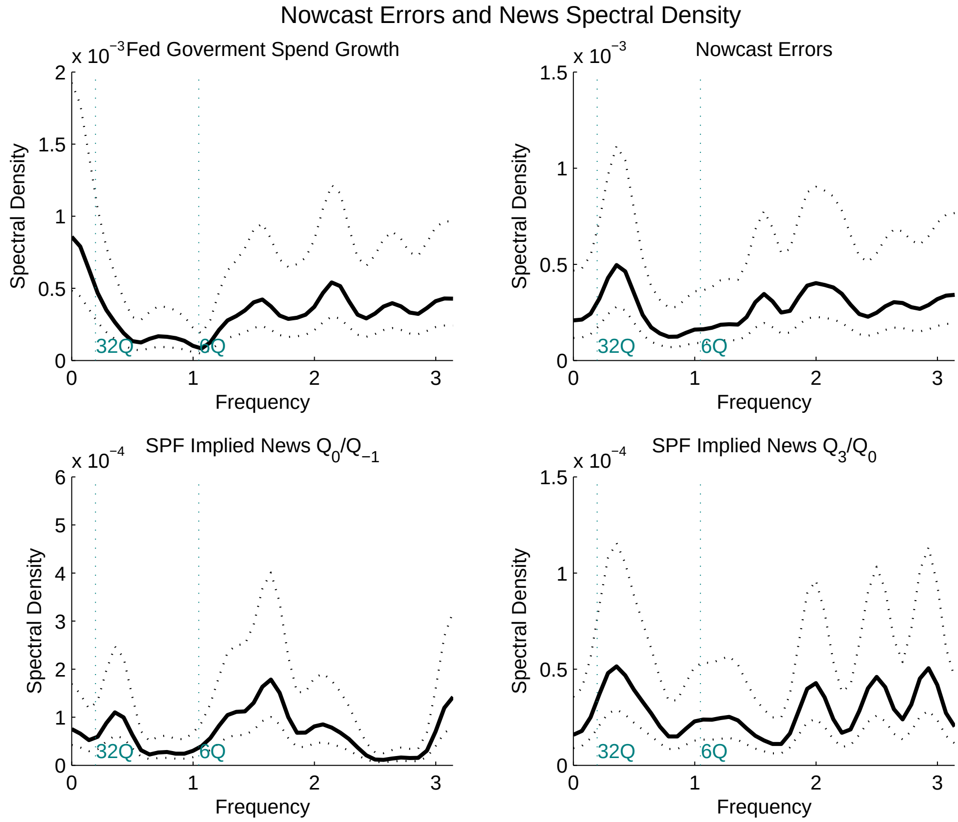

Figure 5: **Spectrum of Nowcast Errors and News (median).** The figure plots the spectral density, obtained with the method of averaged periodograms, for the real federal spending growth rate, the median implied nowcast errors and news (solid line) with confidence bands at the 95 percent confidence level (dashed line). The vertical dotted lines limit the business cycle frequency band.

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 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 (2011) 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

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

Table 3: **Correlations of News and Nowcast Errors with Other Proxy Variables**: (1) Ramey (2011) Federal Spending SPF Forecast Errors, (2) Ramey (2011) 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

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 6 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 (2011) 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 errors defined in Ramey (2011), 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.

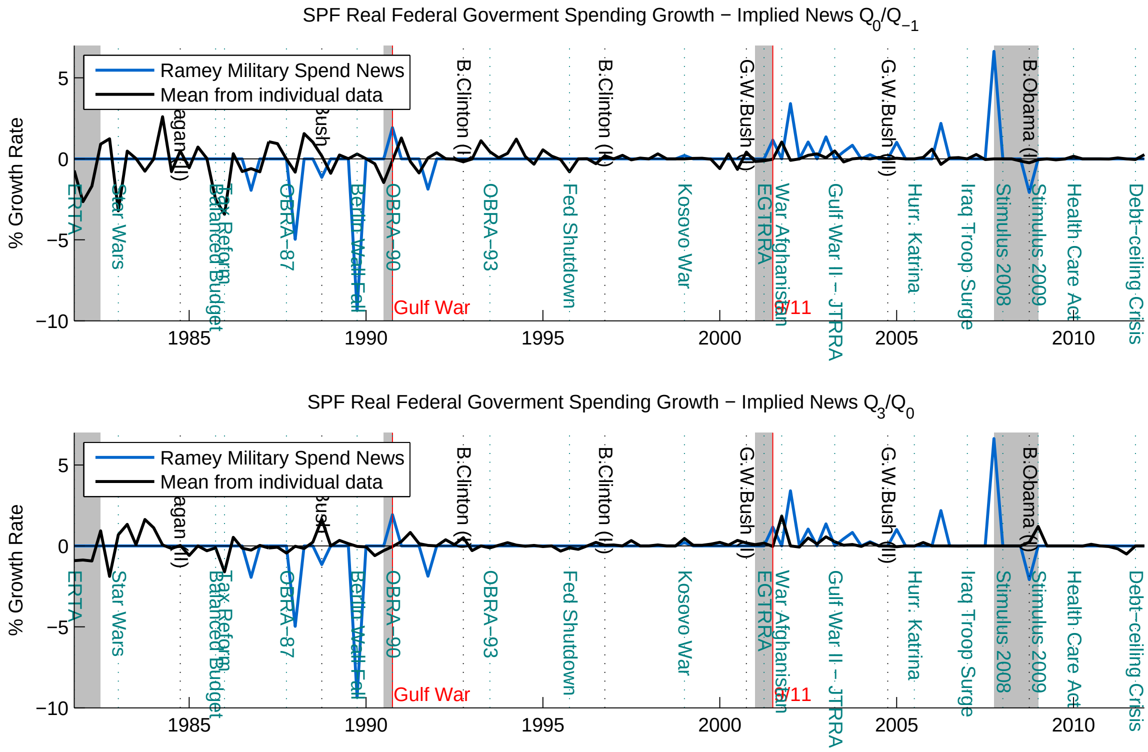

Figure 6: Government Spending News and Ramey's Military Spending News. The figure plots the time series for implied SPF news (black), as well as Ramey's military spending news (blue). Grey shaded areas indicate the NBER Business Cycle contraction dates. Vertical lines indicate the dates of the announcement of important fiscal and geopolitical events (teal), presidential elections (black), and the Ramey-Shapiro war dates (red).

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

$$\Sigma_\varepsilon \sim IW(\Psi, d) \;, \tag{1}$$
$$\beta|\Sigma_\varepsilon \sim N(b, \Sigma_\varepsilon \otimes \Omega) \;, \tag{2}$$

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 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.[1] 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.[2] 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:

$$E[(A_k)_{i,j}] = \begin{cases} \delta_i & j = i,\ k = 1 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

$$V[(A_k)_{i,j}] = \begin{cases} \frac{\lambda^2}{k^2} & j = i \\ \vartheta \frac{\lambda^2}{k^2} \frac{\psi_i}{\psi_j/(d-n-2)} & \text{otherwise.} \end{cases} \tag{4}$$

These can be cast in the form of (2). 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

[1] 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)).

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

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*

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

where $J_p = diag(1, 2, ..., p)$.[3] 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 we add the following dummy observations to the ones for the Normal-Inverse-Wishart prior:

$$\begin{aligned} y_d &= \text{diag}(\delta_1\mu_1, ..., \delta_n\mu_n)/\tau \\ x_d &= ((1_{1\times p}) \otimes \text{diag}(\delta_1\mu_1, ..., \delta_n\mu_n)/\tau \;\; 0_{n\times 1}) \,. \end{aligned} \tag{5}$$

  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

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

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

.

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

$$y_* = x_* B + e_* \ , \tag{6}$$

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:

$$\Sigma_\varepsilon | y \sim IW\left(\tilde{\Psi}, T_d + 2 + T - k\right) \tag{7}$$

$$\beta | \Sigma_\varepsilon, y \sim N\left(\hat{\beta}, \Sigma_\varepsilon \otimes \left({x_*}' x_*\right)^{-1}\right) \ , \tag{8}$$

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_*.

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 $i = 1, \ldots, h$

$$GIRF_y(h, \omega_{t-1}, \varepsilon_t) = \mathbb{E}\left[y_{t+h} | \omega_{t-1}, \varepsilon_t\right] - \mathbb{E}\left[y_{t+h} | \omega_{t-1}\right] \ , \tag{9}$$

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) $\omega_{t-1}^r = \{y_{t-1}^r, \ldots, y_{t-1-p}^r\}$.
2. Random draws with replacement are made from the estimated residuals of the asymmetric model, $\{\varepsilon_{t+j}^b\}_{j=0}^h$. 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_{t-1}^r and the residuals $\{\varepsilon_{t+j}^b\}_{j=0}^h$, 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 $y_{t+k}(\omega_{t-1}^r, \{\varepsilon_{t+j}^b\}_{j=0}^h)$ 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 $y_{t+k}(\omega_{t-1}^r, \{\varepsilon_{t+j}^{*,b}\}_{j=0}^h)$ 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 the difference between the simulated shocked sequence $y_{t+k}(\omega_{t-1}^r, \{\varepsilon_{t+j}^{*,b}\}_{j=0}^h)$ and the baseline path $y_{t+k}(\omega_{t-1}^r, \{\varepsilon_{t+j}^b\}_{j=0}^h)$.

Coverage intervals for the GIRF 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 $Q = 1000$.

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