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

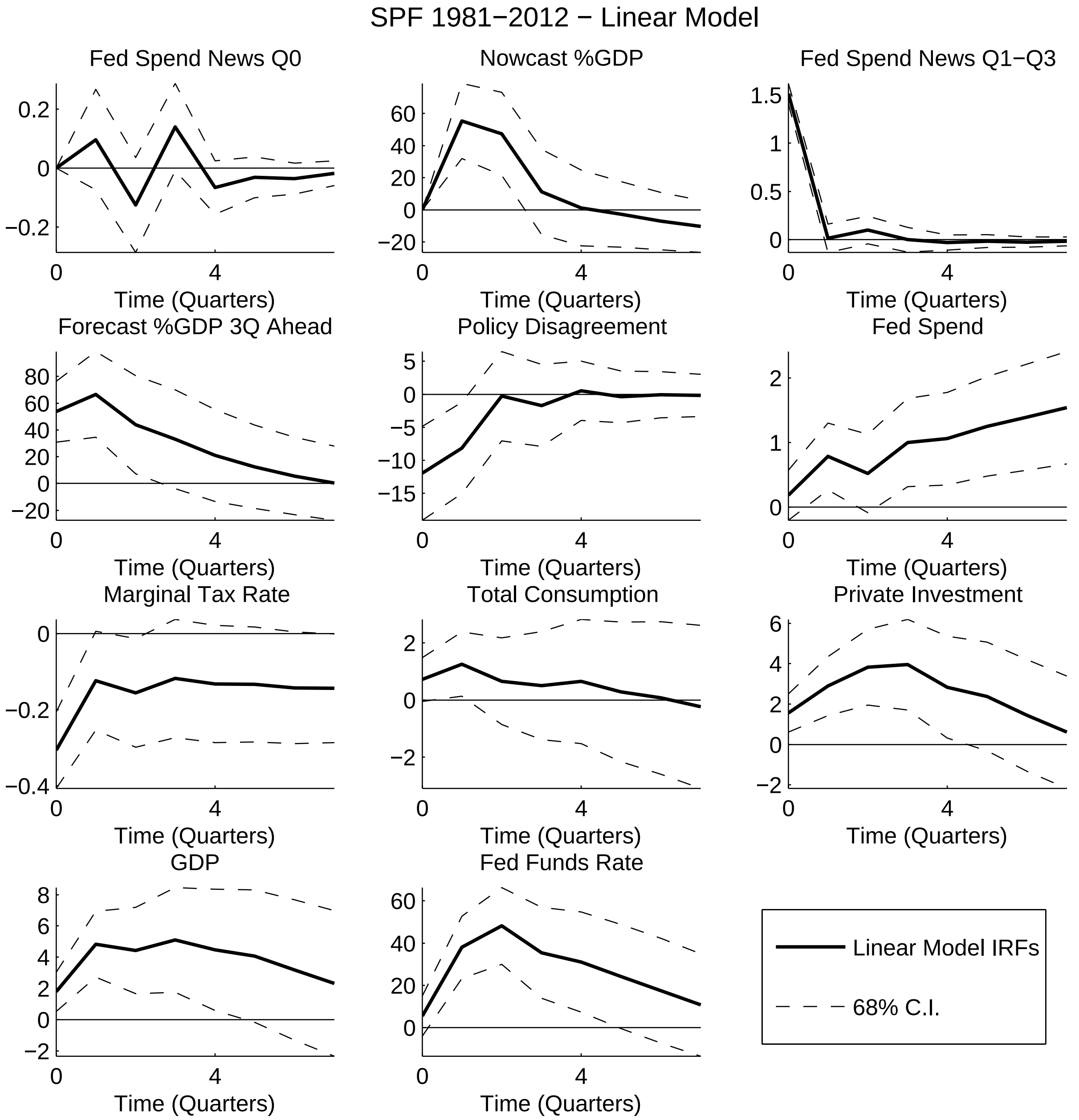

Figure 1: **Linear VAR model.** Impulse responses have been been normalised to have a unitary increase in federal spending at the 4-quarters horizon. Dotted lines are the 68% coverage bands. Sample: 1981Q3-2012Q4.

A.2 Robustness with respect to the Threshold Level

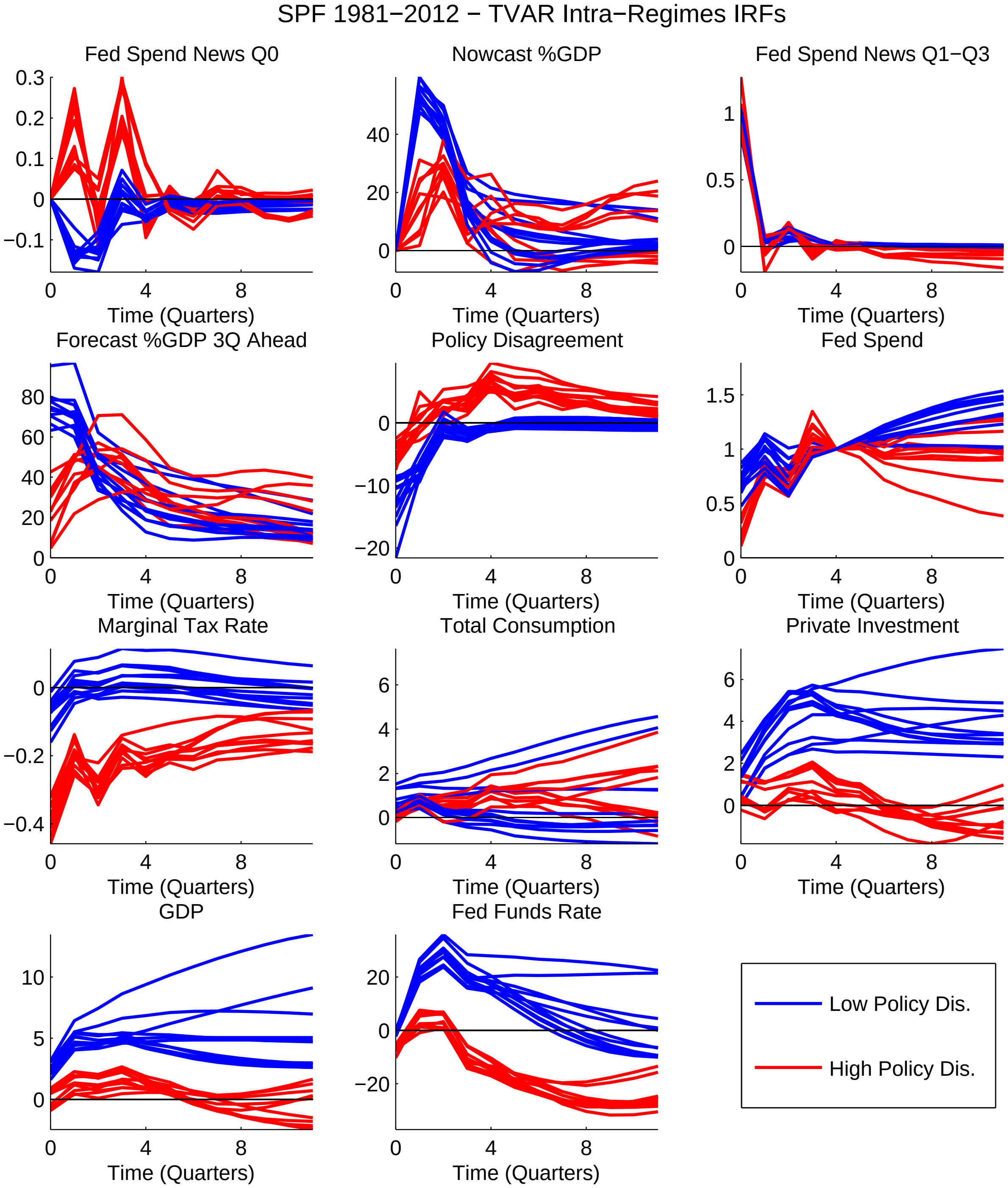

Figure 2: Robustness exercises carried out by varying the threshold level in an interval that excludes the higher and lower 30% observations of the threshold variable, i.e., the disagreement index. Impulse responses have been been normalised to have a unitary increase in federal spending at the 4-quarters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

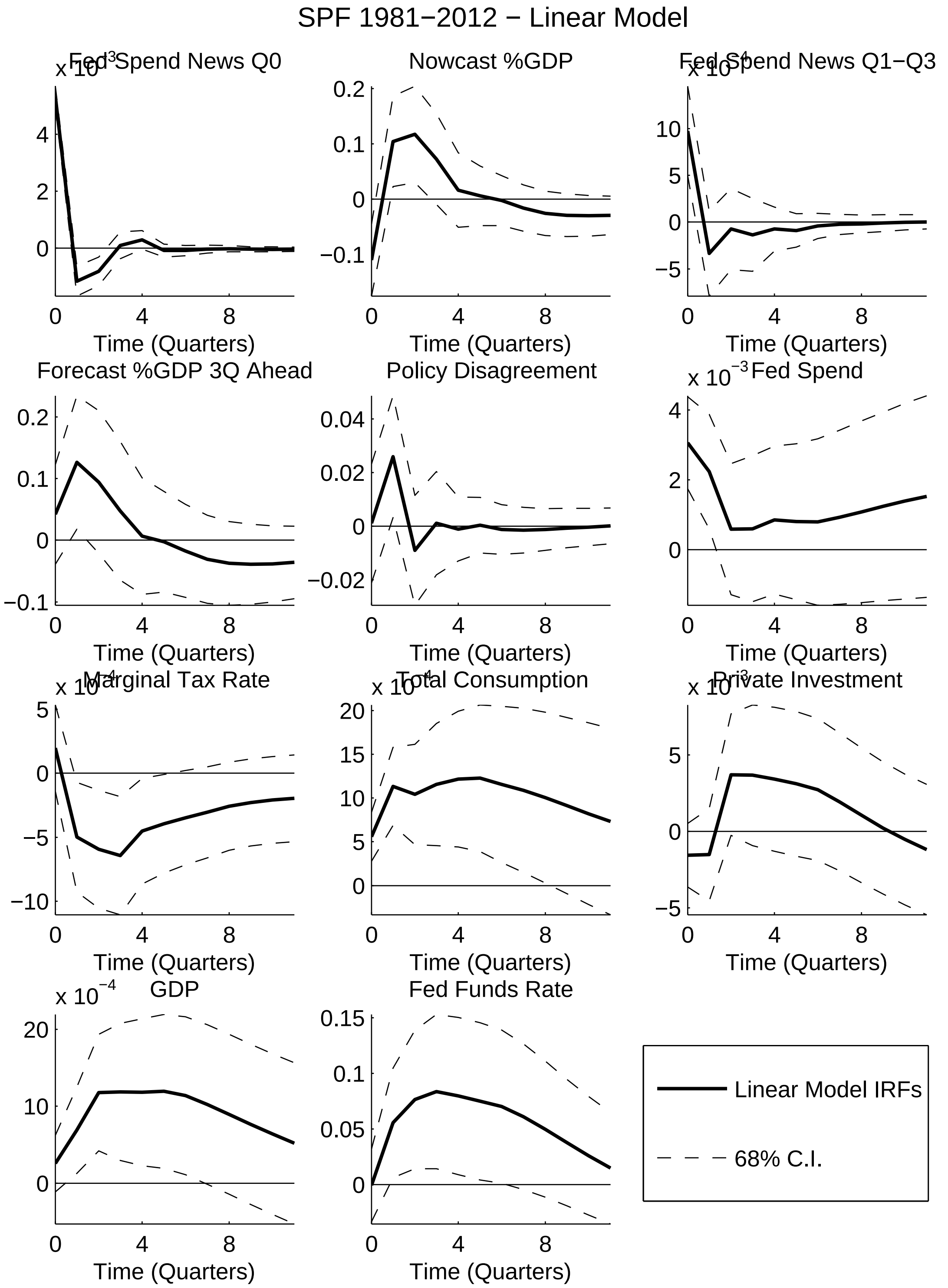

Figure 3: **Linear VAR model - nowcast revision.** Impulse responses have been been normalised to have a unitary increase in federal spending at the 4-quarters horizon. Dotted lines are the 68% coverage bands. Sample: 1981Q3-2012Q4.

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

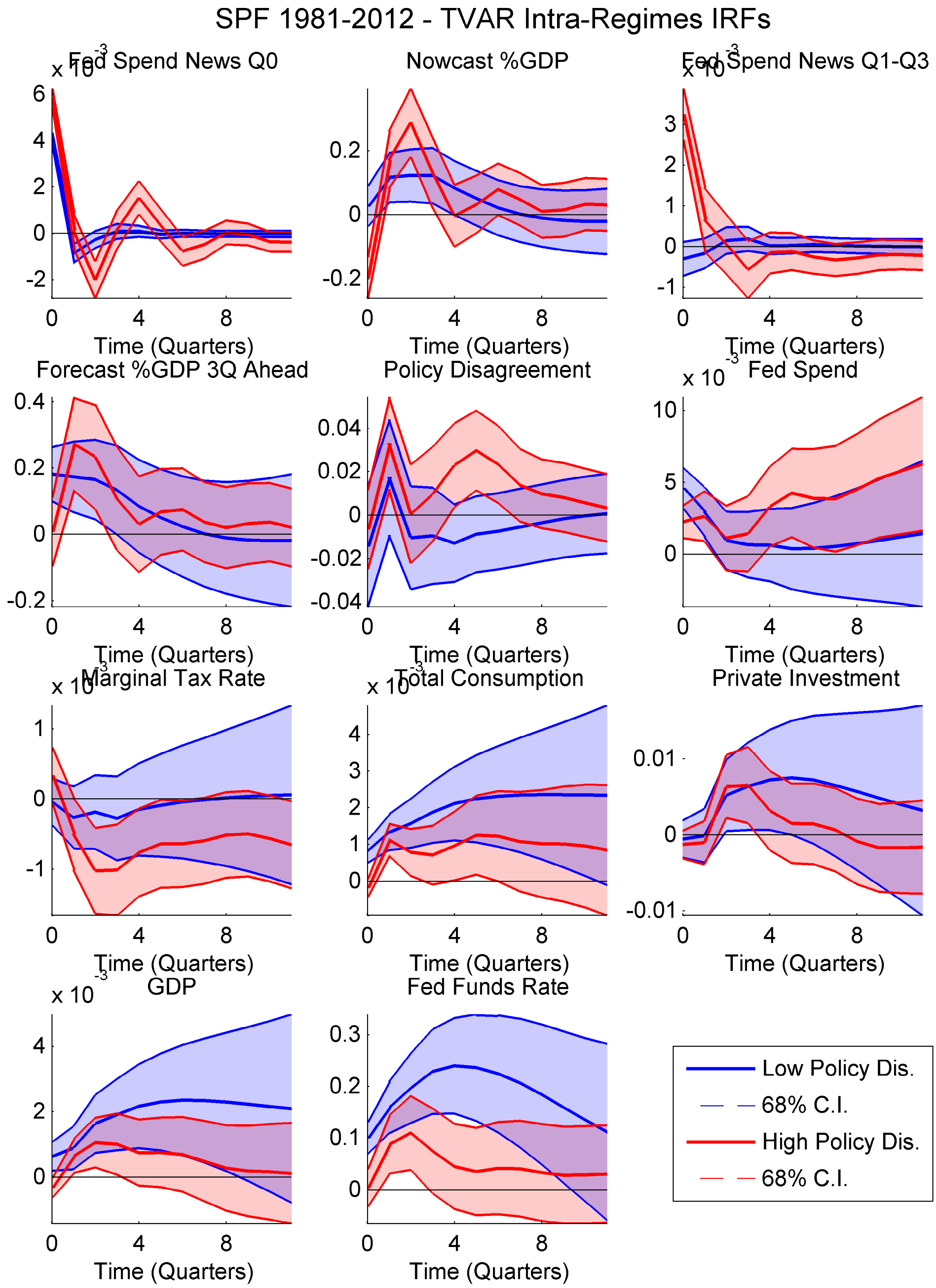

Figure 4: **Within-regime impulse responses - Impact of nowcast revisions.** The shock corresponds to one standard deviation change in the revision of the spending forecasts three quarters ahead. The responses are generated under the assumption of constant disagreement regime. Blue line and fans (68%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

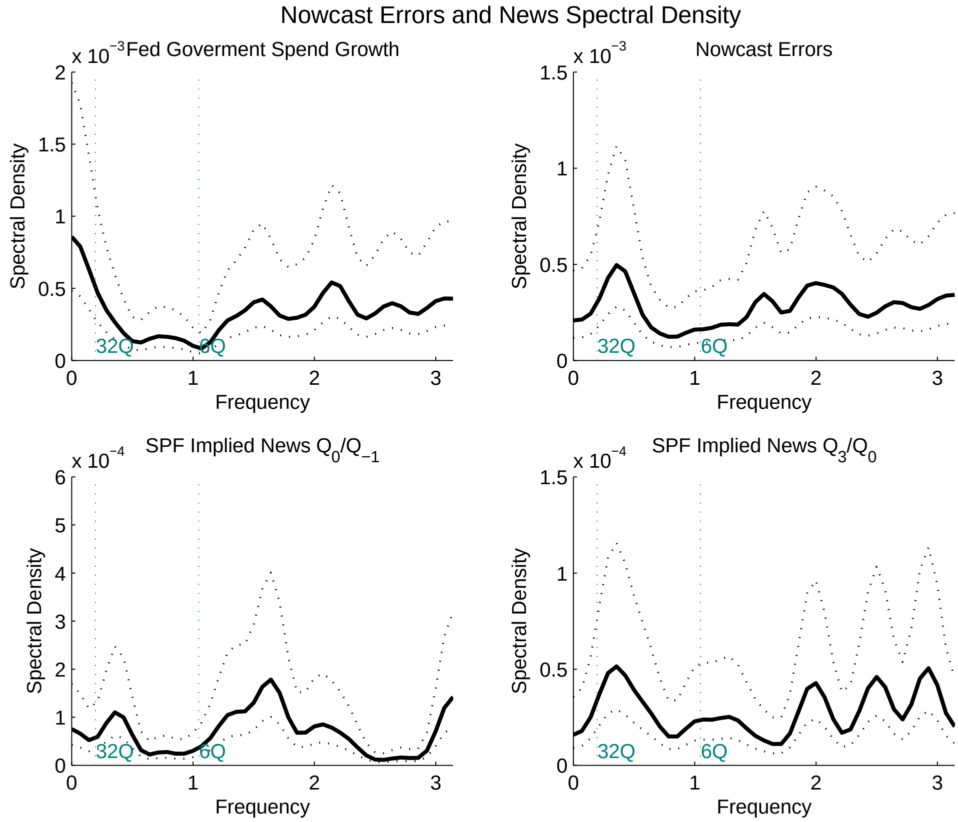

Figure 5: **Spectrum of Nowcast Errors and News (median).** The figure plots the spectral density, obtained with the method of averaged periodograms, for the real federal spending growth rate, the median implied nowcast errors and news (solid line) with confidence bands at the 95 percent confidence level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

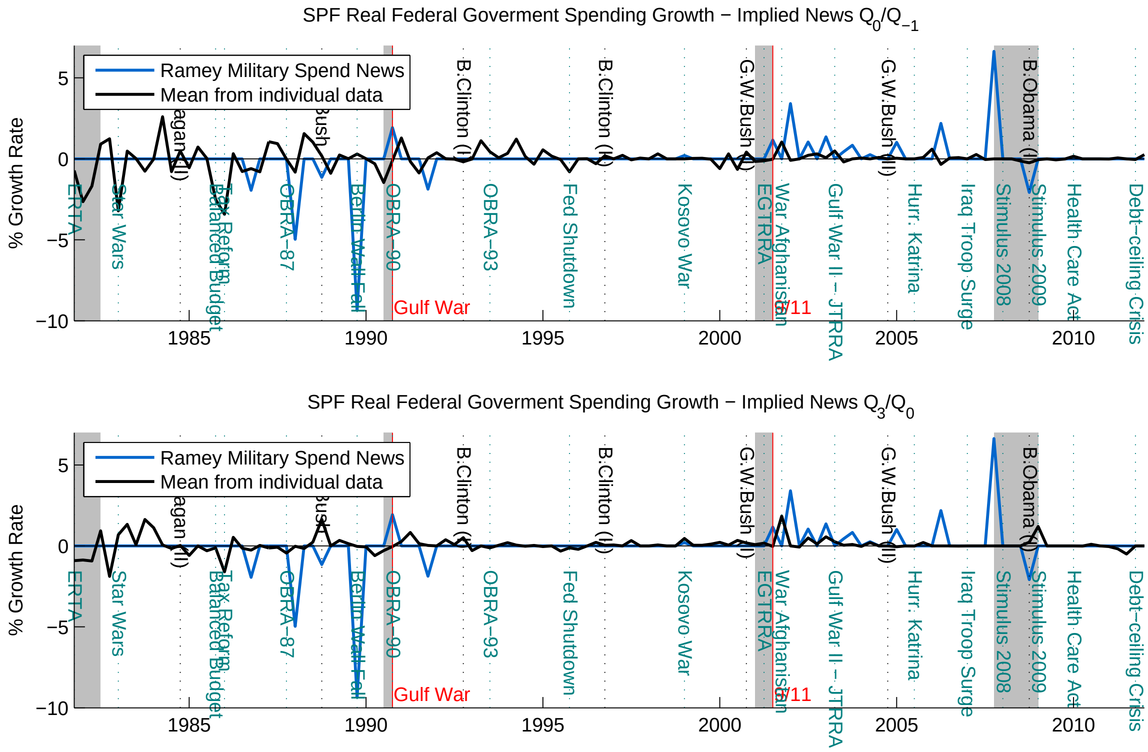

Figure 6: Government Spending News and Ramey's Military Spending News. The figure plots the time series for implied SPF news (black), as well as Ramey's military spending news (blue). Grey shaded areas indicate the NBER Business Cycle contraction dates. Vertical lines indicate the dates of the announcement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

$$\Sigma_\varepsilon \sim IW(\Psi, d) \ , \quad (1)$$

$$\beta|\Sigma_\varepsilon \sim N(b, \Sigma_\varepsilon \otimes \Omega) \ , \quad (2)$$

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:

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

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

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*

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

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 $\hat{\beta} = \mathrm{vec}(\hat{B})$, $\hat{B} = ({x_*}' x_*)^{-1} {x_*}' y_*$ 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 $i = 1, \ldots, h$

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

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