UNIVERSITÀ DEGLI STUDI DI PADOVA

Dipartimento di Scienze Economiche ed Aziendali "Marco Fanno"

ESTIMATING FISCAL MULTIPLIERS:
NEWS FROM A NONLINEAR WORLD

GIOVANNI CAGGIANO
University of Padova

EFREM CASTELNUOVO
University of Padova

VALENTINA COLOMBO
University of Padova

GABRIELA NODARI
University of Verona

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Estimating Fiscal Multipliers: News From a Nonlinear World*

Giovanni Caggiano
University of Padova

Efrem Castelnuovo
University of Melbourne
University of Padova

Valentina Colombo
University of Padova

Gabriela Nodari
University of Verona

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Abstract

We estimate nonlinear VARs to assess to what extent fiscal spending multipliers are countercyclical in the United States. We deal with the issue of nonfundamentalness due to fiscal foresight by appealing to sums of revisions of expectations of fiscal expenditures. This measure of anticipated fiscal shocks is shown to carry valuable information of future dynamics of public spending. Results based on generalized impulse responses suggest that fiscal spending multipliers in recessions are greater than one, but not statistically larger than in expansions. However, nonlinearities arise when focusing on deep recessions vs. strong expansionary periods.

Keywords: Fiscal news, Fiscal foresight, Fiscal spending multipliers, Smooth Transition Vector-AutoRegressions.

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1 Introduction

How large is the fiscal spending multiplier? When it comes to take policy decisions, the answer to this question is key. Suppose the multiplier of public expenditure is large. Then, if there is slack in the economy, an expansionary fiscal stance can help the economy out of a recession. Differently, if the multiplier is small, an expansionary fiscal stance would end up worsening public debt and, via an increase in expected future tax rates, have a contractionary effect.

Following the lead of Blanchard and Perotti (2002), several VAR models featuring fiscal aggregates have been estimated to compute fiscal multipliers. Such multipliers are often found to be of modest amount, typically lower than one (Barro and Redlick (2011), Ramey (2011a)). However, the quantification of fiscal multipliers with standard VARs is controversial for two reasons. First, as stressed by Parker (2011), fiscal spending multipliers may very well be countercyclical. Theoretical support for a larger multiplier in periods of slack comes from the textbook IS-LM-AD-AS model, in which a flatter AS curve in recessions implies a milder crowding out of private consumption and investments; from microfounded DSGE models dealing with the zero-lower bound, in which expansionary fiscal shocks are not immediately followed by an increase in nominal and real interest rates that would otherwise chock off expansions (Eggertsson (2009), Christiano, Eichenbaum, and Rebelo (2011), Woodford (2011), Fernández-Villaverde, Gordon, Guerrón-Quintana, and Rubio-Ramírez (2012)); by DSGE models dealing with financial frictions, in which countercyclical financial spreads imply a large effect of government spending shocks on the consumption of credit constraint agents and, therefore, on aggregate consumption and output (Canzoneri, Collard, Dellas, and Diba (2011)); and by search-and-matching frameworks with procyclical crowding out determined by state-dependent labor market tightness (Michaillat (2014)). Empirical evidence in favor of state-dependent fiscal multipliers is provided by, among others, Tagkalakis (2008), Auerbach and Gorodnichenko (2012, 2013a, 2013b), Bachmann and Sims (2012), Batini, Callegari, and Melina (2012), Mittnik and Semmler (2012), Baum, Poplawski-Ribeiro, and Weber (2012), Fazzari, Morley, and Panovska (2013).[1] Second, anticipation effects

[1] Other forms of state-dependence have been identified in the literature. Corsetti, Meier, and Müller (2012) investigates the sensitivity of government spending multipliers to different economic scenarios. They find fiscal multipliers to be particularly high during times of financial crisis. Rossi and Zubairy (2011) and Canova and Pappa (2011) show that fiscal multipliers tend to be larger when positive spending shocks are accompanied by a decline in the real interest rate. Perotti (1999) shows that fiscal multipliers may depend on the debt-to-GDP ratio in place when fiscal shocks occur. For a DSGE-based quantification of fiscal multipliers in presence of normal vs. abnormal debt-to-GDP ratios, see Cantore,

are likely to be of great relevance in the transmission of fiscal policy shocks, a phenomenon often referred to as "fiscal foresight" (see, among others, Yang (2005), Fisher and Peters (2010), Mertens and Ravn (2011), Ramey (2011b), Gambetti (2012a, 2012b), Kriwoluzky (2012), Leeper, Walker, and Yang (2013)). Modeling a standard set of U.S. variables with a medium-scale structural model that allows for foresight up to eight quarters, Schmitt-Grohe and Uribe (2012) find that about sixty percent of the variance of government spending is due to anticipated shocks.

Fiscal foresight makes the identification of fiscal shocks complicated. If agents in the economy adjust their expectations on the basis of anticipated, future shocks, the information set available to agents in the economy is larger than that of the VAR econometrician. Unfortunately, standard VARs, which rely on current and past shocks to interpret the dynamics of the modeled variables, are ill-suited to capture the effects of future, anticipated shocks that affect agents' expectations and, consequently, current realizations of the variables embedded in the VAR. Therefore, VARs estimated with variables subject to anticipations (i.e., affected by anticipated, "news" shocks) are "non-fundamental".[2] Leeper, Walker, and Yang (2013) work with a variety of fiscal models and show that the anticipation of tax policy shocks severely affects VAR exercises aiming at identifying fiscal shocks. Forni and Gambetti (2011) and Ramey (2011b) show that government spending shocks estimated with standard fiscal VARs are predictable, i.e., they are non-fundamental. Ellahie and Ricco (2013) show that informational insufficiency is likely to be a driver of the discrepancy among estimates of the fiscal multipliers in the literature.

This paper estimates *state-dependent fiscal multipliers* by explicitly addressing the issue of *fiscal foresight*. State-dependent fiscal multipliers are allowed (but not forced) to arise via a nonlinear Smooth Transition Vector AutoRegressive (STVAR) model, which we use to discriminate dynamic responses to fiscal shocks in bad and good times (i.e., recessions vs. expansions). We tackle the issue of non-fundamentalness by jointly modeling a measure of *anticipated ("news") fiscal spending shocks* along with a set of standard macro-fiscal variables. Such a measure of fiscal news is the *sum of revisions of expectations about future government spending* collected by the Survey of Professional Forecasters. As shown by Gambetti (2012a, 2012b), this measure of fiscal shocks contains valuable information about the future evolution of fiscal expenditure and has

Levine, Melina, and Pearlman (2013).

[2]Early analysis on non-fundamentalness in a macroeconomic context with rational expectations are Hansen and Sargent (1980, 1991), and Lippi and Reichlin (1993). A presentation on issues related to VAR analysis and non-fundamentalness is provided by Lütkepohl (2012).

the potential to isolate exogenous, anticipated variations of public expenditure more precisely relative to some alternatives recently proposed in the literature. Importantly, sums of revisions allow us to capture the effects of fiscal spending shocks when the implementation lag of fiscal policy is larger than one quarter, a very plausible assumption as for U.S. fiscal policy decisions.[3]

The inclusion of this measure of fiscal news in our STVAR allows us to compute dynamic responses to an anticipated fiscal spending shock occurring in recessions vs. expansions. To assess the effects of public spending shocks on output and compute the fiscal multipliers in recessions and expansions, we compute Generalized Impulse Response Functions (GIRFs). This enables us to model a switch from a regime to another conditional on the evolution of the economic conditions. In this way, we complement some recent contributions by Bachmann and Sims (2012) and Auerbach and Gorodnichenko (2012, 2013a), who perform their investigations by assuming conditionally-linear IRFs. Moreover, this gives us the chance of opening the recessions and expansions "boxes". As explained by Koop, Pesaran, and Potter (1996), the computation of GIRFs depends upon initial conditions. For instance, the very same fiscal shock (say, a positive fiscal shock amounting to a standard deviation-increase of our measure of news) in the very same state same (say, a recession) may trigger different economic responses if initial conditions are different (say, in presence of a deep recession vs. a mild downturn). We then scrutinize the role played by different initial conditions by isolating "extreme events", i.e., deep recessions and strong expansions, and compare the corresponding GIRFs to those computed in presence of mild business cycle conditions.

Our results are the following: i) anticipated fiscal expenditure shocks trigger a significant reaction of output; ii) such a reaction is not statistically different across different phases (recessions/expansions) of the U.S. business cycle; iii) the reaction becomes statistically different for extreme phases of the business cycle, i.e., deep recessions vs. strong expansions; iv) fiscal multipliers in recessions are statistically larger than one; v) spending shocks in recessions have a noticeable stabilization effect and substantially reduce the probability that the economy will remain slack. A battery of robustness checks, dealing with potential misspecification of our baseline VAR, inclusion of expectations about the future evolution of output, and different specifications of our news variables confirm these findings.

[3]Yang (2005) shows that the average implementation lag for major postwar U.S. income tax legislation is about seven months. Mertens and Ravn (2011) find that the median implementation lag is six quarters.

One limit of our analysis is the relatively short sample we use, i.e., 1981Q3-2013Q1. This is due to data availability: the information required to construct our measure of anticipated fiscal shocks, which is based on expectations revisions over future government spending, is available via the Survey of Professional Forecasters starting from 1981Q3. Hence, our sample does not embed the spectacular variations in fiscal spending due to World War II and the Korean War exploited in other studies to isolate fiscal spending shocks via a narrative approach (Ramey and Shapiro (1998), Barro and Redlick (2011), Ramey (2011b), Owyang, Ramey, and Zubairy (2013)). As pointed out by Christiano (2013), however, such exogenous increases in fiscal spending were i) accompanied by strong increases in taxes, and ii) likely to be perceived as quite persistent by the private sector (the last point being mainly related to the Korean War episode). Moreover, rationing was in place during World War II, a phenomenon that refrained public spending from increasing further. All these elements are likely to contaminate the computation of the fiscal spending multiplier when including the two War episodes, therefore reducing the cost of not having such episodes in our sample.[4]

The structure of the paper is the following. Section 2 deals with the issue of non-fundamentalness in the macro-fiscal context due to the presence of fiscal foresight, and explains why the sums of revisions of fiscal expectations variable employed in our analysis helps solving the issue. Section 3 offers statistical support to the role of non-linearities in this context and presents the Smooth Transition VAR model employed in our analysis. Our main results are shown in Section 4. Section 5 documents a battery of robustness checks. Section 6 relates our work to the literature. Concluding remarks are provided in Section 7.

2 Non-fundamentalness and the role of expectations revisions

Structural VARs have been extensively employed to recover the impulse responses of key macroeconomic variables to fiscal shocks. The implicit assumption when working with SVARs is that their VMA representations are invertible in the past, or in other words that they are fundamental Wold representations of the vector of interest. When such conditions are met, the econometrician has the same information set as the economic

[4] Gordon and Krenn (2010) argue that the 1939-1941 recovery from the Great Depression was largely due to fiscal spending. In such a period, there was a considerable slack in the economy, spending increased (about 18 months before Pearl Harbor) while the interest rate remained roughly constant, and no rationing was in place. They estimate the fiscal spending multiplier to be as high as 2.5.

agents and can recover the structural shocks by conditioning the VAR estimates on past and current observables.

Fiscal foresight and non-fundamentalness. It is well known, however, that in presence of fiscal foresight (and news shocks in general), this assumption may not hold and fundamental shocks to fiscal policy cannot be recovered from past and current observations. The non-fundamentalness is due to the different discount patterns employed by agents and the econometrician: while the agents attach a larger weight to realizations of the shock occurring in the past, the econometrician discounts in the usual way, and attach lower weights to past observations compared to more recent ones, the reason being that the econometrician's information set lags that of the agents (Leeper, Walker, and Yang (2013)). Hence, in presence of a non-fundamental process, an econometrician not endowed with a large enough information set will not be able to correctly recover the impulse response function of a variable of interest to the structural shock.

How severe is the non-fundamentalness problem? As pointed out by Sims (2012) and Beaudry and Portier (2013), the answer to this question depends on the very same process(es) one wants to model. In terms of fiscal shocks, Leeper, Walker, and Yang (2013) convincingly show that when non-fundamentalness holds the magnitude of the error is quite severe. They employ two DSGE models of the business cycle - a calibrated RBC model and an estimated DSGE model with a number of nominal and real frictions à la Smets and Wouters (2007) - to quantify the mistake an econometrician makes when failing to model fiscal foresight. They show that fiscal multipliers may turn out to be off by hundreds of percent, and can even get the wrong sign.[5] Moreover, Forni and Gambetti (2011) and Ramey (2011b) show that government spending shocks estimated with standard fiscal VARs can be predicted, evidence supporting the case for non-fundamentalness.

VAR analysis in presence of anticipated shocks. In this section, we propose a framework to fix ideas about the relationship between fiscal foresight and non-fundamentalness and to discuss how the problem can be tackled. To this aim, consider the model

$$y_t = \delta E_t y_{t+1} + g_t + \omega_t \tag{1}$$

$$g_t = \varepsilon_{t-h} + \phi_1 \varepsilon_{t-h-1} + \ldots + \phi_q \varepsilon_{t-q} = \Phi(L)\boldsymbol{\varepsilon}_t \tag{2}$$

[5] Leeper, Walker, and Yang (2013) model fiscal foresight associated to tax policies. As already pointed out, Schmitt-Grohe and Uribe (2012) find government spending shocks anticipated up to eight quarters to be responsible of about 60% of the overall variability of government spending.

where $|\delta| < 1, \phi_i > 0\ \forall i, h \geq 0, q \geq h$. The forward-looking process y_t - say, output measured as log-deviations from its trend - is affected by the exogenous stationary process g_t - say, a fiscal shock - plus a random shock ω_t, which is assumed to capture non-fiscal spending shocks affecting output and which is assumed to be *i.i.d.* with zero mean and unit variance. The process (2) features an unanticipated contemporaneous shock ε_t as well as anticipated shocks ε_{t-h} for $h > 0$, where h is the number of foresight periods. The latter are known in advance by rational agents, i.e., agents foresee fiscal moves occurring h-periods ahead. The process g_t is a news-rich process if $\left|\phi_q\right| > 1$ for at least one $q > 0$ (Beaudry and Portier (2013)). In all cases, $\{\varepsilon_{t-j}\}_{j=h}^{q}$ is said to be fundamental for g_t if the roots of the polynomial $\Phi(L)$ lie outside the unit circle (Hansen and Sargent (1991)). Importantly, if the g_t process is non-fundamental, its structural shock is not recoverable by employing current and past realizations of g_t only. Consequently, its impulse response to an anticipated shock as well as the dynamic responses of other variables – in this example, y_t – will not be correctly recovered by estimating a VAR in y_t and g_t.

For simplicity, and without loss of generality, consider the case in which the unanticipated component is zero, i.e., $h > 0$. We assume that agents have rational expectations and observe news shocks without noise.[6] To begin with, consider the case $h = q = 1$, so that[7]

$$g_t = \varepsilon_{t-1}.$$

Under rational expectations, the solution for the process y_t reads

$$y_t = \delta\varepsilon_t + \varepsilon_{t-1} + \omega_t. \tag{3}$$

The VMA representation of the vector (y_t, g_t) is:

$$\begin{bmatrix} y_t \\ g_t \end{bmatrix} = \underbrace{\begin{bmatrix} \delta & 1 \\ 0 & 0 \end{bmatrix}}_{A_0} \begin{bmatrix} \varepsilon_t \\ \omega_t \end{bmatrix} + \underbrace{\begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix}}_{A_1} \begin{bmatrix} \varepsilon_{t-1} \\ \omega_{t-1} \end{bmatrix}. \tag{4}$$

The VMA representation (4) is fundamental if all the roots of $|\sum_{i=0}^{q} A_i z^i|$ in absolute value lie outside the unit circle. It is easy to verify that in this case the condition is

[6] Forni, Gambetti, Lippi, and Sala (2013) investigate the case in which economic agents deal with noisy news. Agents are assumed to receive signals regarding the future realization of TFP shocks. Since such signals are noisy, agents react not only to genuinely informative news, but also to noise shocks that are unrelated to economic fundamentals. They find that such noise shocks explain about a third of the variance of output, consumption, and investment. We leave the quantification of the role of noise shocks in the fiscal context to future research.

[7] This process is termed "degenerated news-rich process" by Beaudry and Portier (2013). For an application, see Fève, Matheron, and Sahuc (2009).

not met, since one gets $|z| = 0$. Hence, in this economic system, inference based on an estimated VAR which includes y_t and g_t only would be incorrect.

Importantly, if a variable η_t added to the econometrician's information set contains "enough" information about the structural shock ε_t, then the VMA representation becomes invertible and the non-fundamentalness issue is circumvented (Giannone and Reichlin (2006), Sims (2012), Beaudry and Portier (2013), and Forni and Gambetti (2014)). Based on this argument, a way to tackle the issue of non-fundamentalness is to include in the VAR a variable which is informative about the effects that news shocks exert on the endogenous variables of interest.[8] In the case of fiscal foresight, then, one has to find a measure of anticipated fiscal spending shocks to correctly gauge the reaction of output to such shocks. It is easy to show that, in the context of model (4), replacing g_t with its one-step-ahead forecast, i.e. $E_t g_{t+1}$, leads to a fundamental VMA representation for the vector $(y_t, E_t g_{t+1})$:

$$\begin{bmatrix} y_t \\ E_t g_{t+1} \end{bmatrix} = \underbrace{\begin{bmatrix} \delta & 1 \\ 1 & 0 \end{bmatrix}}_{A_0} \begin{bmatrix} \varepsilon_t \\ \omega_t \end{bmatrix} + \underbrace{\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}}_{A_1} \begin{bmatrix} \varepsilon_{t-1} \\ \omega_{t-1} \end{bmatrix}.$$

This can be seen by verifying that $|A_0 + A_1 z| \neq 0, \forall z$.

It is important to notice that expectations *per se* do not necessarily provide a correct measure of fiscal shocks. Consider the case $h = 1$ and $q = 2$, so that

$$g_t = \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2}. \tag{5}$$

The VMA representation for (y_t, g_t) is:

$$\begin{bmatrix} y_t \\ g_t \end{bmatrix} = \underbrace{\begin{bmatrix} \delta(1+\delta\phi_2) & 1 \\ 0 & 0 \end{bmatrix}}_{A_0} \begin{bmatrix} \varepsilon_t \\ \omega_t \end{bmatrix} + \underbrace{\begin{bmatrix} 1+\delta\phi_2 & 0 \\ 1 & 0 \end{bmatrix}}_{A_1} \begin{bmatrix} \varepsilon_{t-1} \\ \omega_{t-1} \end{bmatrix} + \underbrace{\begin{bmatrix} \phi_2 & 0 \\ \phi_2 & 0 \end{bmatrix}}_{A_2} \begin{bmatrix} \varepsilon_{t-2} \\ \omega_{t-2} \end{bmatrix}, \tag{6}$$

which is non-fundamental since the roots of $|A_0 + A_1 z + A_2 z^2|$ are $z_1 = 0$ and $|z_2| = \phi_2^{-1}$. In this case, adding the one-step-ahead forecast of g_t does not solve the problem. The

[8] Alternative ways of dealing with this issue have been proposed in the literature. Lippi and Reichlin (1993) propose to use Blaschke matrices to "flip" the roots that are outside the unit circle in order to recover the fundamental representation of the process of interest. Alessi, Barigozzi, and Capasso (2011) and Forni and Gambetti (2014) propose to augment the VAR with information coming from factors extracted from large datasets. However, in the context of fiscal foresight, non-fundamentalness has a clearly detectable cause, i.e., omitted information due to the absence in the VAR of an informative measure regarding (variations concerning) future fiscal spending moves (Leeper, Walker, and Yang (2013), Beaudry and Portier (2013)). Hence, a direct, fiscal-related way of tackling the presence of foresight appears to be desirable.

VMA representation for the vector $(y_t, E_t g_{t+1})$ is given by:

$$\begin{bmatrix} y_t \\ E_t g_{t+1} \end{bmatrix} = \underbrace{\begin{bmatrix} \delta(1+\delta\phi_2) & 1 \\ 1 & 0 \end{bmatrix}}_{A_0} \begin{bmatrix} \varepsilon_t \\ \omega_t \end{bmatrix} + \underbrace{\begin{bmatrix} 1+\delta\phi_2 & 0 \\ \phi_2 & 0 \end{bmatrix}}_{A_1} \begin{bmatrix} \varepsilon_{t-1} \\ \omega_{t-1} \end{bmatrix} + \underbrace{\begin{bmatrix} \phi_2 & 0 \\ 0 & 0 \end{bmatrix}}_{A_2} \begin{bmatrix} \varepsilon_{t-2} \\ \omega_{t-2} \end{bmatrix},$$

which is non-fundamental if $|\phi_2| > 1$.

The role of forecast revisions. Expectation *revisions* help solving the problem. Consider the variable $\eta_t = E_t g_{t+1} - E_{t-1} g_{t+1}$. The VMA representation for the vector (y_t, η_t) is given by:

$$\begin{bmatrix} y_t \\ \eta_t \end{bmatrix} = \underbrace{\begin{bmatrix} \delta(1+\delta\phi_2) & 1 \\ 1 & 0 \end{bmatrix}}_{A_0} \begin{bmatrix} \varepsilon_t \\ \omega_t \end{bmatrix} + \underbrace{\begin{bmatrix} 1+\delta\phi_2 & 0 \\ 0 & 0 \end{bmatrix}}_{A_1} \begin{bmatrix} \varepsilon_{t-1} \\ \omega_{t-1} \end{bmatrix} + \underbrace{\begin{bmatrix} \phi_2 & 0 \\ 0 & 0 \end{bmatrix}}_{A_2} \begin{bmatrix} \varepsilon_{t-2} \\ \omega_{t-2} \end{bmatrix},$$

which is fundamental, since $|A_0 + A_1 z + A_2 z^2| \neq 0$, $\forall z$. It can recursively be shown that expectations revisions of the form $E_t g_{t+1} - E_{t-1} g_{t+1}$ help tackling the issue of non-fundamentalness for any $q > h = 1$.

However, when $h > 1$ is unknown, even expectation revisions are not of help. Consider for example the process:

$$g_t = \varepsilon_{t-2} + \phi_3 \varepsilon_{t-3}.$$

This is not an unlikely case, given that typically the implementation lag for fiscal policy decisions is longer than one quarter. The VMA representation for the vector (y_t, g_t) is:

$$\begin{aligned} \begin{bmatrix} y_t \\ g_t \end{bmatrix} &= \underbrace{\begin{bmatrix} \delta^2(1+\delta\phi_3) & 1 \\ 0 & 0 \end{bmatrix}}_{A_0} \begin{bmatrix} \varepsilon_t \\ \omega_t \end{bmatrix} + \underbrace{\begin{bmatrix} \delta(1+\delta\phi_3) & 0 \\ 0 & 0 \end{bmatrix}}_{A_1} \begin{bmatrix} \varepsilon_{t-1} \\ \omega_{t-1} \end{bmatrix} \\ &+ \underbrace{\begin{bmatrix} 1+\delta\phi_3 & 0 \\ 1 & 0 \end{bmatrix}}_{A_2} \begin{bmatrix} \varepsilon_{t-2} \\ \omega_{t-2} \end{bmatrix} + \underbrace{\begin{bmatrix} \phi_3 & 0 \\ \phi_3 & 0 \end{bmatrix}}_{A_3} \begin{bmatrix} \varepsilon_{t-3} \\ \omega_{t-3} \end{bmatrix}, \end{aligned}$$

and the roots of $|A_0 + A_1 z + A_2 z^2 + A_3 z^3|$ are $z_{1,2} = 0, |z_3| = \phi_3^{-1}$. Using expectations revisions as before is in this case uninformative, since $E_t g_{t+1} - E_{t-1} g_{t+1} = 0$.

Knowing exactly the number of anticipation periods h would solve the problem, since $E_t g_{t+2} - E_{t-1} g_{t+2} = \varepsilon_t$. However, h is typically unknown. To solve this issue, Gambetti (2012a) proposes to use an alternative, more general measure of expectations revisions, i.e., the news variable defined as:

$$\eta_{1J}^g = \sum_{j=1}^{J} \left(E_t g_{t+j} - E_{t-1} g_{t+j} \right),$$

with J large enough to ensure that $J \geq h$. It can be shown that setting $J \geq 2$ leads to a fundamental representation associated with the vector (y_t, η^g_{1J}), since $\eta^g_{12} = \varepsilon_t$, $\eta^g_{13} = (1+\phi_3)\,\varepsilon_t$ and so on. In our example, if $J = 2$, the VMA representation for (y_t, η^g_{12}) is:

$$\begin{bmatrix} y_t \\ \eta^g_{12} \end{bmatrix} = \underbrace{\begin{bmatrix} \delta^2(1+\delta\phi_3) & 1 \\ 1 & 0 \end{bmatrix}}_{A_0} \begin{bmatrix} \varepsilon_t \\ \omega_t \end{bmatrix} + \underbrace{\begin{bmatrix} \delta(1+\delta\phi_3) & 0 \\ 0 & 0 \end{bmatrix}}_{A_1} \begin{bmatrix} \varepsilon_{t-1} \\ \omega_{t-1} \end{bmatrix}$$
$$+ \underbrace{\begin{bmatrix} 1+\delta\phi_3 & 0 \\ 0 & 0 \end{bmatrix}}_{A_2} \begin{bmatrix} \varepsilon_{t-2} \\ \omega_{t-2} \end{bmatrix} + \underbrace{\begin{bmatrix} \phi_3 & 0 \\ 0 & 0 \end{bmatrix}}_{A_3} \begin{bmatrix} \varepsilon_{t-3} \\ \omega_{t-3} \end{bmatrix},$$

where the determinant of $|A_0 + A_1 z + A_2 z^2 + A_3 z^3| \neq 0$, $\forall z$.[9]

In general, when the period of foresight h is unknown or uncertain, the solution would be to include in the VAR a measure of expectations revisions taken over a long enough horizon:

$$\sum_{j=1}^{J} (E_t g_{t+j} - E_{t-1} g_{t+j}) = (\phi_1 + \phi_2 + \ldots + \phi_J)\,\varepsilon_t. \tag{7}$$

with J large enough.

The cumulated news variable. Following Gambetti (2012a,b), we will then consider a fiscal VAR augmented with a measure of news constructed by summing up revisions of expectations as follows:

$$\eta^g_{13} = \sum\nolimits_{j=1}^{J} (E_t g_{t+j} - E_{t-1} g_{t+j}) \tag{8}$$

where $E_t g_{t+j}$ is the forecast of the growth rate of real government spending from period $t+j-1$ to period $t+j$ based on the information available at time t. Hence, $E_t g_{t+j} - E_{t-1} g_{t+j}$ represents the "news" that becomes available to private agents between time $t-1$ and t about the growth rate of government spending j periods ahead.[10] The optimal strategy here is to construct a measure based on the sum of the largest available number of news. The Survey of Professional Forecasters collects forecasts conditional on time

[9] It is important to notice that, though related in spirit, Perotti's (2011) variable $(E_t g_t - E_{t-1} g_t) + (E_t g_{t+1} - E_{t-1} g_{t+1})$ is uninformative in a case like this, because it does not contain any valuable information about ε_t, i.e., it is equal to zero. The reason is that the forecast horizon covered by such a variable is too short.

[10] SPF data are affected by frequent changes in the base years. Forecast errors on the growth rates are not affected by these changes. Hence, they are preferable to forecast errors computed with SPF levels. About this point, see also Perotti (2011).

$t-1$ of variables up to time $t+3$. Hence, our baseline analysis will be conducted by considering the variable η_{13}^{g}.

Information content of expectations revisions. To assess the statistical relevance of anticipated shocks for the dynamics of public expenditure, we regress public spending on a constant and three lags of the dependent variable, public receipts, real GDP, and one lag of the measure of news η_{13}^{g} (a detailed description of the data is provided in Section 3). This regression augments the public spending equation of a trivariate VAR system modeling the "usual suspects" (public spending, tax receipts, output) with our news variable lagged one period. Public spending shocks are often identified in the trivariate VAR described above with a Cholesky decomposition of the covariance matrix of the VAR residuals. Hence, the (orthogonalized) residuals of the public spending equation are interpreted as public spending shocks. The regression is intended to investigate if such residuals are partly predictable by employing lagged values of the forecast revisions. If so, this might be taken as evidence that the VAR is non-fundamental, since it would not embed enough information to correctly identify the effects of a public spending shock.

Table 1 collects the p-values for our η_{13}^{g} variable in the equation described above.[11] News shocks are found to carry significant information to predict the future evolution of public expenditure. Digging deeper, we find that all the three components (forecast revisions) included in η_{13}^{g} have predictive power about the future evolution of public spending. Overall, this empirical exercise highlights the significant contribution given by news revisions regarding *future* realizations of public expenditure. Differently, revisions of expectations based on nowcasting, i.e. $E_t g_t - E_{t-1} g_t$, turn out to be insignificant at the 90% confidence level (see Table 1, last column). In line with Ricco (2014), this result suggests that revisions based on "nowcasts" (revision of expectations at time t of contemporaneous public expenditures) are possibly of help in identifying truly *unanticipated* fiscal shocks, rather than *anticipated, news* shocks.[12]

Overall, our results i) show that, from a statistical standpoint, residuals typically employed in a standard trivariate fiscal VAR cannot be interpreted as fiscal shocks; ii) suggest that the components of the variable η_{13}^{g}, which we interpret as a measure

[11] The regression includes variables in (log-)levels and the news η_{13}^{g} variable in cumulated sums to preserve the same order of integration. This is consistent with the modeling choices of our baseline VAR analysis (specified in the next Section).

[12] These results are conditional on news variables constructed as revisions of the mean predicted values of the levels of future government spending as collected by the Survey of Professional Forecasters. Similar results were obtained by employing median values of such forecasts, as well as variables expressed in growth rates.

of anticipated fiscal shocks, can augment the information content of our VAR system. These results are consistent with the outcome of the Granger-causality tests conducted by Gambetti (2012b), who shows that η_{13}^{g} Granger-causes fiscal spending at different horizons.[13]

Comparison with Ramey's (2011b) news variable. Figure 1 plots our news variable (an updated version of Gambetti's 2012b), along with the military spending news variable constructed by Ramey (2011b), and extended up to 2010Q4 by Owyang, Ramey, and Zubairy (2013).[14] A first inspection of the series suggests that the variable η_{13}^{g} conveys useful information about fiscal policy shocks in the United States. For example, the negative spike in 1989Q4 is associated with the fall of the Berlin Wall. The positive spike in 2001Q4 is associated with the second Gulf War. The last spike we observe is positive and is dated 2009Q1, associated with the fiscal stimulus package approved by the Obama administration. The two measures tend to move together with a few exceptions, e.g., the positive spikes in Ramey's news dated 2004Q2 and 2007Q4. In general, it appears that the η_{13}^{g} variable anticipates changes in Ramey's, or at least it is not anticipated by the latter.

We further corroborate the predictive power of our news shocks by running Granger-causality tests based on an estimated bivariate VAR with one lag involving the military spending news proposed by Ramey (2011) (as well as its updated version by Owyang, Ramey, and Zubairy, 2013) and the η_{13}^{g} variable. Table 2 collects the outcome (p-values associated to testing the null hypothesis that the column variable does not Granger-cause the alternative news measure) of this exercise for our benchmark sample and a shorter sample to account for the fact that, for the first five years in the benchmark sample, Ramey's (2011) variable is equal to zero. While the contribution of our news shock variable finds large statistical support, Granger-causality running from Ramey's shock to ours is clearly rejected by the data. This is driven by the fact that the largest spikes in η_{13}^{g} tend to anticipate (or, at least, are not anticipated by) those in Ramey's variable. The same evidence emerges when employing the news variable by Owyang,

[13] In a recent paper, Perotti (2011) questions the use of the SPF forecast errors employed by Ramey (2011) to isolate fiscal spending anticipated shocks. In particular, he shows that the one-step-ahead predictive power of the forecast revisions as for federal spending is quite modest, since such revisions are shown to be noisy. Our results are fully consistent with Perotti's (2011) analysis, in that we also reject the relevance of very short-term SPF forecast revisions on future fiscal spending. This evidence suggests the need of searching for anticipation effects beyond one-quarter relative to the moment in which predictions are formulated, and supports the construction of the variable η_{13}^{g}.

[14] Ramey (2011b) employs *Business Week* and other newspaper sources to construct an estimate of changes in the expected present value of goverment spending (nominal spending divided by nominal GDP one period before).

Ramey, and Zubairy (2013), whose last observations are related to 2007-2009 recession. Again, these results are in line with those reported in Gambetti (2012b), who also finds Ramey's news shock to be predicted by forecast revisions over one quarter.[15]

3 Econometric approach: A STVAR macro-fiscal model

Modeling choices. We assess the state-dependence of fiscal spending multipliers to news shocks by estimating a Smooth-Transition VAR model (for an extensive presentation, see Teräsvirta, Tjøstheim, and Granger (2010)). Our STVAR framework reads as follows:

$$
\begin{aligned}
\boldsymbol{X}_t &= F(z_{t-1})\boldsymbol{\Pi}_R(L)\boldsymbol{X}_t + (1 - F(z_{t-1}))\boldsymbol{\Pi}_E(L)\boldsymbol{X}_t + \boldsymbol{\varepsilon}_t, && (9)\\
\boldsymbol{\varepsilon}_t &\sim N(0, \boldsymbol{\Omega}_t), && (10)\\
\boldsymbol{\Omega}_t &= F(z_{t-1})\boldsymbol{\Omega}_R + (1 - F(z_{t-1}))\boldsymbol{\Omega}_E, && (11)\\
F(z_t) &= \exp(-\gamma z_t)/(1 + \exp(-\gamma z_t)), \gamma > 0, z_t \sim N(0, 1). && (12)
\end{aligned}
$$

where $\boldsymbol{X}_t$ is a set of endogenous variables which we aim to model, $F(z_{t-1})$ is a transition function which captures the probability of being in a recession, γ regulates the smoothness of the transition between states, z_t is a transition indicator, $\boldsymbol{\Pi}_R$ and $\boldsymbol{\Pi}_E$ are the VAR coefficients capturing the dynamics of the system during recessions and expansions (respectively), $\boldsymbol{\varepsilon}_t$ is the vector of reduced-form residuals having zero-mean and whose time-varying, state-contingent variance-covariance matrix is $\boldsymbol{\Omega}_t$, and $\boldsymbol{\Omega}_R$ and $\boldsymbol{\Omega}_E$ stand for the covariance structure of the residuals in recessions and expansions, respectively.

The modeling assumption is that the variables can be described with a combination of two linear VARs, one suited to describe the economy during recessions and the other during expansions. The transition from a state to another is regulated by the standardized transition variable z_t. The smoothness parameter γ affects the probability of being in a recession $F(z_t)$, i.e., the larger the value of γ, the faster the transition from

[15] A second news variable constructed by Ramey (2011) relies on SPF predictions of public spending formulated at time t-1 and confronted with realized expenditures. Unfortunately, as already commented, this very short-run revisions have low predictive power as for future public spending and low ability to isolate anticipated shocks.

a state to another. Notably, the model (9)-(12) allows for nonlinearities to arise both from the contemporaneous relationships and the dynamics of the economic system.

Our baseline analysis refers to the vector $\boldsymbol{X}_t = [G_t, T_t, Y_t, \eta^g_{13,t}]'$, where G is the log of real government (federal, state, and local) purchases (consumption and investment), T is the log of real government receipts of direct and indirect taxes net of transfers to business and individuals, and Y is the log of real GDP.[16] The construction of G and T closely follows Auerbach and Gorodnichenko (2013a).[17] The variable η^g_{13} is the public expenditure news variable (8). The variables are expressed in levels because of possible cointegration relationships. Consistently, the variable η^g_{13} is considered in cumulated sums to preserve the same order of integration as the other variables included in the vector. Our sample spans the period 1981Q3-2013Q1, 1981Q3 being the first available quarter to construct the news variable.

The choice of the transition variable z_t and the calibration of the smoothing parameter γ are justified as follows. As in Auerbach and Gorodnichenko (2012), Bachmann and Sims (2012), Caggiano, Castelnuovo, and Groshenny (2013), and Berger and Vavra (2014), we employ a standardized moving average of the real GDP quarter-on-quarter percentage growth rate.[18] We calibrate the smoothness parameter γ to match the observed frequencies of the U.S. recessions as dated by the NBER business cycle dates, i.e. 15% in our sample. Then, we define as "recession" a period in which $F(z_t) \geqslant 0.85$, and calibrate γ to obtain $\Pr(F(z_t) \geqslant 0.85) \approx 15\%$. This metric implies a calibration $\gamma = 2.3$.[19] The choice is consistent with the threshold value $\overline{z} = -0.75\%$ discriminating recessions and expansions, i.e., realizations of the standardized transition variable z lower (higher) than the treshold will be associated to recessions (expansions).[20] Figure

[16] Our fiscal aggregates are constructed using the Bureau of Economic Analysis' NIPA Table 3.1. Current tax receipts are constructed as the difference between current receipts and government social benefits. Fiscal expenditure is the sum of consumption expenditure and gross government investment from which we subtract the consumption of fixed capital. Data on real GDP and the implicit GDP deflator (which we use to deflate all nominal series) are provided by the Federal Reserve Bank of St. Louis.

[17] Auerbach and Gorodnichenko (2013a) check and verify the robustness of the results in Auerbach and Gorodnichenko (2012) to the employment of a different definition of the net tax series that avoids the double-counting of mandatory Social Security contributions.

[18] The transition variable z_t is standardized to render our calibration of γ comparable to those employed in the literature. We employ a backward-looking moving average involving four realizations of the real GDP growth rate.

[19] Our calibrated γ is different from the 1.5 value employed by Auerbach and Gorodnichenko (2012). This is due to the different sample considered in our paper, which is shorter than the post-WWII period employed in those papers. However, the degree of correlation between their $F(z)$ and ours is equal to 0.84.

[20] The corresponding threshold value for the non-standardized moving average real GDP growth rate

2 plots the transition function $F(z_t)$. Clearly, high realizations of $F(z_t)$ tend to be associated with NBER recessions. Importantly, our results are robust to the employment of alternative calibrations of the slope parameter γ that imply a number of recessions in our sample ranging from 10% to 20%, where the lower bound is determined by the minimum amount of observations each regime should contain according to Hansen (1999) (checks not shown here for the sake of brevity, but available upon request).

Identification of the anticipated fiscal shock. The construction of the variable η_{13}^g is performed to isolate exogenous variations in fiscal spending.[21] However, shocks other than the fiscal spending one may very well contribute to the revisions of agents' expectations. To purge the η_{13}^g variable from other macroeconomic shocks hitting the economic system, we order it as last in our vector and orthogonalize the reduced-form residuals of the VAR via a Cholesky-decomposition of the variance-covariance matrix. This modeling choice lines up with that of Fisher and Peters (2010), who also identify anticipated fiscal shocks with the Cholesky innovation to their measure of anticipated fiscal shocks (i.e., excess returns of large U.S. military contractors) ordered last in their VAR.[22]

Statistical evidence in favor of nonlinearity. Before estimating the STVAR model, we formally test for the presence of nonlinearities in the relationship among the variables included in the VAR. To this end, we consider the multivariate test proposed by Teräsvirta and Yang (2013). In particular, for our vector of endogenous variables $\mathbf{X}_t$, we test the null hypothesis of linearity versus a specific nonlinear alternative, that of a (Logistic) Smooth Transition Vector AutoRegression with a single transition variable. The test suggests a clear rejection of the null hypothesis of linearity. Details on this test and its implementation are available upon request.

Given the high nonlinearity of the model, we estimate it via the Monte-Carlo Markov-Chain algorithm developed by(Chernozhukov and Hong (2003).[23] It is worth

is equal to 0.34%. The sample mean of the non-standardized real GDP growth rate in moving average terms is equal to 0.71, while its standard deviation is 0.50. Then, its corresponding threshold value is obtained by "inverting" the formula we employed to obtain the standardized transition indicator z, i.e., $\overline{z}^{nonstd} = -0.75 \times 0.50 + 0.71 = 0.34$.

[21] The null hypothesis of no-serial correlation of our variable η_{13}^g cannot be rejected at standard confidence levels according to standard tests for dynamic correlation.

[22] Given the ordering of the variables in our VAR, our identification strategy implies that η_{13}^g exerts, by construction, no on-impact effect on the remaining variables of the vector. This may be seen as inconsistent with the idea of anticipated shocks being able to influence output contemporaneously through adjustments of agents' expectations. As shown in Section 5, our main results are qualitatively robust to ordering the η_{13}^g variable first in the vector, a choice consistent with expectational effects being at work.

[23] Our Appendix reports details on the estimation methodology. In principle, one could estimate

stressing that our STVAR framework exploits information coming from all the observations in the dataset, which are "indexed" by the transition function $F(z_t)$. Differently, the estimation of two different VAR models (one for each given regime) would imply more imprecise estimates due to the smaller number of observations, especially for recessionary periods. The (linear/nonlinear) VARs include three lags. This choice is based on the Akaike criterion applied to a linear model estimated on the full-sample 1981Q3-2013Q1.

4 Generalized impulse responses and fiscal multipliers

This Section reports the impulse responses to an anticipated fiscal spending shock. Following Koop, Pesaran, and Potter (1996), we compute generalized impulse responses to take into account the interaction between the evolution of the variables in the vector $\mathbf{X}_t$ and the transition variable, the latter being directly influenced by the evolution of output. This is important in our context, given that a positive fiscal shock is possibly expansionary. Hence, while the assumption of starting the system in expansion and remaining there for a large number of horizons is perhaps not too problematic, that of starting the system in a recession and remaining there in spite of a positive fiscal shock is unpalatable. The GIRFs are computed by accounting for the evolution of the probability of being in a recessionary state, which is allowed to evolve period-by-period. In other words, we model the feedback from the evolution of output in the vector $\mathbf{X}_t$ to the transition indicator z_t and, consequently, the probability $F(z_{t-1})$. Hence, in computing our GIRFs, the probability $F(z)$ is endogenized.[24] Koop, Pesaran, and Potter (1996) and Ehrmann, Ellison, and Valla (2003) show that initial conditions affect the computation of the GIRFs. In our benchmark exercise, we randomize over all possible histories within each state, so to control for the role of initial conditions.

the STVAR model via maximum likelihood. However, since the model is highly nonlinear and has many parameters, using standard optimization routines is problematic. Under standard conditions, the algorithm put forth by Chernozhukov and Hong (2003) finds a global optimum in terms of fit as well as distributions of parameter estimates.

[24]Recall that our transition indicator $z_t \equiv \frac{1}{4}(\Delta Y_t + \Delta Y_{t-1} + \Delta Y_{t-2} + \Delta Y_{t-3})$, i.e., the relationship between z_t and $\Delta Y_{t-i}, i = 0, 1, 2, 3$ features no stochastic elements. Hence, stochastic singularity prevents us from estimating our model jointly with the evolution of z_t. Following Koop, Pesaran, and Potter (1996), our GIRFs are based on simulations that take into account the link between $\mathbf{X}_t$ and z_t after the estimation of our econometric framework.

We compute the GIRFs by normalizing the news shocks to one.[25] The Appendix offers details of the algorithm we employed to compute the GIRFs.

GIRFs. Figure 3 reports the impact of an expenditure news shock computed with our linear and nonlinear VARs. The responses obtained with our linear model point to a delayed short-run increase in government expenditure and output, and a decrease in government receipts. Public spending reaches its peak value after about three years. Differently, output increases for the first three quarters after the shock, then gradually goes back to zero, and crosses the zero line about 10 quarters after the shock.

Next, we look at the evidence coming from the nonlinear VAR. Interestingly, the estimated response of output is persistently stronger under recessions. Output increases in expansions in the short-run, but the increase is much milder compared to recessions, and vanishes after about four quarters. Another difference between the two states is the reaction of government spending itself, which is always positive but stronger in recessions. Tax receipts react asymmetrically in the very short run, but then after three quarters their pattern becomes virtually identical.

Are the reactions of output in recessions vs. expansions different from a statistical standpoint? Figure 4 plots the GIRFs and the associated 90% confidence intervals estimated for both states. Focusing on output, we see that the confidence bands overlap substantially. This result suggests that the reaction of output to a fiscal shock is not necessarily stronger if the economy is slack. This finding is in line with some recent results put forth by Valerie Ramey and coauthors (see Ramey (2011b), Owyang, Ramey, and Zubairy (2013) and Ramey and Zubairy (2013)), which are obtained with a different identification strategy (fiscal spending news shocks constructed following Ramey's (2011) approach) and methodology (local projections à la Jordà (2005)). At a first glance, the evidence seems to be at odds with the impulse response analysis proposed by Auerbach and Gorodnichenko (2012, 2013a), who find a statistically significant difference between the response of output conditional on different states. However, a subtle difference in the construction of the dynamic responses must be considered. Auerbach and Gorodnichenko (2012, 2013a) assume the economy hit by the fiscal shock to start and remain in a recession/expansion for twenty quarters. Differently, here we allow the economic system to switch from a state to another according to the endogenous evolution of the transition indicator. Moreover, the GIRFs plotted in Figure 4 are

[25] The standard deviation of the news variable employed in the sample is 0.19 according to our linear model, 0.21 conditional on our framework under recessions, and 0.18 under expansions. While being theoretically size-dependent, we verified that the sensitivity of our impulse responses to reasonable changes in the size of the shock is negligible.

constructed by randomizing over the possible histories belonging to a state (recessions, expansions). Hence, impulse responses in recessions and expansions are computed by integrating the effect of different initial conditions including deep vs. mild recessions and strong vs. weak expansions. We scrutinize the role played by initial conditions in a following part of the paper.

Quantifying the multipliers. We now turn to the key issue of computing the multipliers and the associated 90% confidence intervals. Following most of the literature, we measure fiscal multipliers in two ways. First, the fiscal multiplier is calculated as the peak response of output divided by the peak response of fiscal expenditure. This strategy, popularized by Blanchard and Perotti (2002), has been widely adopted in recent investigations on the fiscal multipliers. Second, the multiplier is calculated as the integral of the response of output divided by the integral of the response of fiscal expenditure. This latter measure is designed to account for the persistence of fiscal shocks (Woodford (2011)). Given that output and public expenditure enter the VARs in log-terms, we scale such ratio by the sample average value of the Y/G ratio (taken in levels) to convert percent changes into dollar changes.[26] Results are reported in Table 3, where multipliers have been computed considering horizons from one to five years. The evidence clearly speaks in favor of larger (short-run) fiscal spending multipliers in recessions, with values between 3.32 after 8 quarters and 2.58 after 20 quarters when we look at the "peak" measure, and between 3.05 after 8 quarters and 1.00 after 20 quarters according to the "sum" measure. The point-estimates of our multipliers in expansions are substantially lower (from 1.24 to 1.09, and from 0.33 to -2.27 after 8 and 20 quarters, respectively, calculated according to the two measures). The multipliers under recession are statistically larger than one at all horizons when assessed according to the "peak" measure. This result is confirmed, conditional on the short run (i.e., for the first four quarters) by the "peak" measure.

Are our multipliers statistically bigger in recessions? We answer this question by constructing a test based on the difference between the multiplier estimated under recessions and that estimated under expansions. Such a test is constructed to account

[26] Ramey and Zubairy (2013) warn against this practice by noticing that, in a long U.S. data sample spanning the 1889-2011 period, the Y/G ratio varies from 2 to 24 with a mean of 8. Hence, the choice of a constant value for the ratio Y/G may importantly bias the estimation of the multipliers. In our sample, the mean value of such a ratio is 6, and it varies from 5.39 to 6.76. Hence, the commonly adopted *ex-post* conversion from the estimated elasticities to dollar increases does not appear to be an issue for our exercise. Moreover, the average value of the Y/G ratio in our sample in 5.81 in NBER recessions, and 6.02 in NBER expansions. Hence, if anything, this difference is working against finding different multipliers across the business cycle.

for the correlation between the estimated state-dependent multipliers.[27] Figure 5 plots the distribution of the difference for both measures of multipliers (peak, sum) and for a range of horizons of our impulse responses along with 90% confidence bands. Evidence in favor of state-dependent multipliers would be gained if zero were not included in the confidence bands. In all cases, although marginally, the difference turns out to be not different from a statistical standpoint.

The stabilizing effects of anticipated fiscal shocks. Our STVAR allows also to estimate the impact of government spending shock on the probability of being in a recession for each given horizon of interest after the shock. Figure 6 plots the estimated transition function implied by our model, $\widehat{F(z)}$, along with the 90% confidence bands. The Figure gives interesting information about the estimated impact of a positive government spending shock on the likelihood of remaining in the same phase of the business cycle. Looking at the behavior of the $\widehat{F(z)}$ under recession, we notice that the fiscal shock leads to a clear drop in the probability of remaining in recession. Given the large uncertainty surrounding the response of output to a fiscal shock, different paths of $\widehat{F(z)}$ are admittedly possible. However, the median indication clearly suggests a quick fall of such a probability under the threshold value $\overline{F} = 0.85$ just after five quarters, which is exactly the average duration of a NBER recession in the sample. In terms of the econometric methodology employed to estimate the state-dependent effect of government spending shocks on output, this evidence shows the importance of allowing for the possibility of switching from one phase of the business cycle to another. Unsurprisingly, given its expansionary effect, the probability of falling into a recession after the news shock when starting from an expansions is basically zero.

These results have two important implications. First, government spending shocks are quite effective under recessions: regardless of the measure we adopt to calculate it, the fiscal multiplier is statistically larger than one when there is slack in the economy in the short run, i.e., within four quarters. Consistently, the estimated probability of remaining in a recession after an expansionary fiscal shocks substantially decreases. Second, the results suggest that linear models, which do not discriminate between the two states, may be misleading if nonlinearities are actually present in the economic system, since they much likely will underestimate the true value of fiscal multipliers in recessions, when a stabilizing fiscal policy may be powerful.

[27] In short, we compute differences of our multipliers in recessions vs. expansions conditional on the same set of draws of the stochastic elements of our model as well as the same realizations of the coefficients of the vector. The empirical density of the difference between our multipliers is based on 500 realizations of such differences for each horizon of interest.

Fiscal multipliers in presence of "extreme events". So far, our analysis has focused on the possible state-dependence of output reactions to fiscal news shocks and fiscal multipliers, finding weak evidence in favor of countercyclical spending multipliers. The next question we address is whether evidence of nonlinearities might arise when recessions and expansions are "extreme events". We then re-compute the GIRFs by randomizing over different subsets of histories associated to recessions and expansions. We label "deep" recessions/"strong" expansions the histories associated to realizations of the transition variable which are below/above two standard deviations. Given that our transition variable is standardized, this amounts to saying that all historical realizations of z above two are associated to a strong expansion, while all realizations below minus two are associated to a deep recession. This criterion leads us to isolate two deep recessions, i.e., in the early 1980s (1982Q1, 1982Q3) and the recent great recession (2008Q3-2009Q3), as well as one strong expansion (1983Q4-1984Q2). In a complementary fashion, mild recessions/weak expansions are associated to histories consistent with realizations of the transition variable below/above the threshold value $\overline{z} = -0.75$ but within the range $[-2, 2]$. Hence, once created these four sub-categories of initial conditions, we re-compute the GIRFs by randomizing over histories within each subcategory.

Figure 7 shows the GIRFs obtained by distinguishing between "deep" and "mild" recessions and "strong" and "weak" expansions. The estimated GIRFs show that the response of output is roughly proportional to the strength of the recession (expansion). Although in the short-run the response of output in the case of a "mild recession" is very similar to the response of output in the "deep" recessions, the response of output is much more persistent at longer horizons when conditioning on the latter case. This, however, cannot be immediately turned into evidence about multipliers, since the persistence in output response might be driven by the persistence of government spending in recession. Table 4 reports the fiscal multipliers estimated in the four different cases under scrutiny. Interestingly, multipliers are still larger in recessions relative to expansions, regardless of the strength of the recession (expansion). Moreover, a comparison between the multipliers in the case of "deep" recessions and those conditional on "strong" expansions suggests that the confidence bands do not overlap, and point to a strong evidence in terms of nonlinear responses of the economy to an expansionary fiscal shock. Our result corroborates the finding by Auerbach and Gorodnichenko (2012, 2013a), who suggest that recessions are associated with larger fiscal spending multipliers. As already pointed out, their general conclusion might be driven by the implicit assumption that all recessions are treated like "extreme events" when conducting their impulse response analysis. Our analysis suggests that this may very well be the case. This finding has important implications from a policy perspective too, given that a fiscal stimulus may be needed exactly in correspondence to deep recessions.

Our findings are confirmed also by an analysis looking at the distribution of the difference between the estimated state-dependent multipliers. As shown in Figure 8, the countercylicality of fiscal multipliers conditional on extreme realizations of the business cycle is supported regardless of the way in which we calculate the multipliers and regardless of the horizon.[28]

In our context, however, it might be more appropriate to test for the null hypothesis of equal multipliers versus the one-sided alternative of multipliers larger in recessions relative to expansions. To provide an answer to this question, Table 6 collects the fraction of multipliers that are larger in recessions for both "Normal" (recessions/expansions) and "Extreme" (deep recessions/strong expansions) phases of the business cycle. As before, these numbers are estimated by referring to different initial conditions, all else being equal. Hence, any entry greater than or equal to 90 might be interpreted as evidence in favor of larger multipliers in recessions at a 90% confidence level in the context of a one-sided test. The figures corresponding to the exercises conducted so far refer to the "Baseline" scenario. Under the "Normal" scenario, evidence in favor of countercyclical multipliers is borderline, and it depends on the way in which the multiplier is constructed. Differently, the analysis conducted on extreme events robustly points towards larger multipliers during recessions. We postpone the analysis of the robustness of this result to a number of perturbations of the baseline framework to the next Section.

How does the economic system evolve after a fiscal shock hitting during an extreme event? Figure 9 plots the estimated value of the $\widehat{F(z)}$ conditional on the four scenarios. When referring to deep recessions, a sizeable decrease of the probability of remaining in such a state occurs as a consequence of the government spending shock: after about five quarters, the value of $\widehat{F(z)}$ decreases from 1 (the economy is in a recession with

[28]Berger and Vavra (2012) show that, in presence of transaction costs that make adjustments to durable consumption and housing investment infrequent and lumpy, macroeconomic shocks occurring during recessions may exert a weaker influence on durable consumption than in expansions. According to their theoretical framework, the procyclicality of the response of durable expenditures is due to variations in the distribution of households' desired durable holdings over the cycle. Berger and Vavra (2014) show that this prediction is supported by a nonlinear VAR model like the one used in this paper. Importantly, they also show that the output fiscal spending multiplier is larger during recessions. We leave the analysis of the effects of anticipated fiscal spending shocks on the various components of the U.S. aggregate demand to future research.

probability one) to about 0.5 (the economy is unlikely to be in a recession). This drop is quicker and more substantial than the one estimated in presence of mild recessions, and it is also more precisely estimated. Somewhat symmetrically, the probability of moving away from a strong expansion is low, and more precisely estimated than the one of drifting away from a weak expansion. However, none of the two suggests a high likelihood of falling into a recession.

Overall, our analysis based on "disaggregated" recessions and expansions shows that nonlinearities are likely to arise when we look *within* each of the two states typically investigated in a business cycle context, i.e., recession and expansion. In particular, we find support in favor of a larger fiscal multipliers when deep recessions are considered.

5 Robustness checks

Our baseline analysis suggests that evidence in favor of countercyclical fiscal multipliers is borderline when we condition upon recessions vs. expansions, while it becomes much clearer and solid when conditioning upon extreme events. We then conduct a variety of robustness checks to verify the solidity of our results. We present the robustness checks below and discuss our results by referring to Table 6, which summarizes the outcome.

FAVAR. Our baseline VAR is meant to parsimoniously model a set of key macroeconomic indicators crucial to quantify fiscal spending multipliers. A further reason to prefer a parsimonious VAR is the somewhat limited number of observations available to construct the measures of forecast revisions we deal with, as well as the nonlinearity of our framework, in which a large number of VAR coefficients is estimated. Despite its advantages, a parsimonious model might suffer from an omitted-variable problem, which may bias the results of our baseline scenario. In particular, reactions of variables like the real interest rate and the real exchange rate may be important for the computation of the fiscal spending multipliers. Interactions between financial variables and real aggregates may also be at work conditional on our fiscal news shock. We tackle this informational insufficiency issue by adding to our VAR a factor extracted from a large dataset, so to purge the (possibly bias-contaminated) estimated shocks. This strategy leads us to deal with a nonlinear version of the Factor-Augmented VAR (FAVAR) model popularized, in the monetary policy context, by Bernanke, Boivin, and Eliasz (2005). In particular, we consider a large dataset composed of 150 time-series, and extract the common factors which maximize the explained variance of such series (a description of the series included in our dataset, their transformations, and the computation of the factors is provided in the Appendix). Following Stock and Watson (2012) in their recent analysis on the drivers of the post-WWII U.S. economy, we extract six common factors and then focus on the fiscal FAVAR $\boldsymbol{X}_t^{favar} = [f_t^1, G_t, T_t, Y_t, \eta_{13,t}^g]'$, where "$f_t^1$" is the factor explaining the largest share of variance of the series in our enlarged database. Due to the limited number of degrees of freedom, we focus on a VAR model with two lags, a choice that we will keep for all the five-variate VAR we estimate to check the robustness of our baseline results.[29] Results on the difference of the fiscal multiplier in different states of the economy are collected in Table 6 under the label "FAVAR".

Expectation revisions of output. Our baseline results rests on the identifying assumption that our fiscal news variable carries valuable information regarding fiscal shocks which may have led economic agents to revise their expectations of future public spending. However, such revisions may have been undertaken because of "news" about some other shocks. Suppose news about the future evolution of technology become part of agents' information sets between time $t-1$ and t. This might induce agents to revise their expectations regarding future realizations of output. Given the link between output and public spending (due to, e.g., automatic stabilizers), such revisions may induce agents to further revise their expectations of future fiscal spending as well. Hence, revisions of future fiscal spending may be triggered not only by anticipated fiscal shocks, but also by anticipated shocks of a different nature (say, news concerning technology).

We tackle this issue by modeling the five-variate VAR $\boldsymbol{X}_t^Y = [\eta_{13,t}^Y, G_t, T_t, Y_t, \eta_{13,t}^g]'$, where η_{13}^Y stands for the sum of forecast revisions regarding future real GDP. The construction of this variable replicates the construction of η_{13}^g explained in Section 2. We put η_{13}^Y before η_{13}^g in the vector to control for the effects exerted by contemporaneous movements in η_{13}^Y on η_{13}^g.[30] Notice that one can interpret this robustness check as pointing to the role of an identified factor omitted in the baseline analysis, i.e., the role of expectation revisions on output. Table 6 collects our results under the label "η_{13}^Y".

Contemporaneous effects of η_{13}^g shocks. Our approach features a recursive identification scheme. Our choice aims at purging the movements of the η_{13}^g fiscal variable by accounting for its systematic response to government spending, tax revenues, and output. However, such a choice has an obvious limitation, i.e., output is not allowed to move immediately after the realization of the news shock. We then perform

[29] The entire set of results regarding our robustness checks is not documented in this paper to save space, but it is available upon request.

[30] Given the choice of a Cholesky-identification scheme, the ordering of the variables before η_{13}^g is irrelevant for the computation of our impulse responses to a fiscal news shock.

a robustness check by focusing on the five-variate VAR $\boldsymbol{X}_t^{\eta^g} = [\eta^g_{13,t}, \eta^Y_{13,t}, G_t, T_t, Y_t,]'$, which enables fiscal news shocks to move output immediately. We keep the measure of news on output to control for the systematic movements of fiscal news due to output news. Notice that this VAR allows for (without forcing) an immediate response of fiscal spending G, which would however be inconsistent with the idea of a news shock. Interestingly, a look at our GIRFs (available upon request) suggest that public spending moves in neither of the two states. This result confirms the potential of the measure of fiscal news shocks employed in this paper to capture anticipated fiscal shocks, i.e., shocks which do not exert an immediate impact on public spending but, possibly, trigger an immediate reaction of output.[31] As for the difference in fiscal multipliers, the results are presented in Table 6 under "η^g_{13} first".

Expectation revisions of total government spending. Our baseline analysis hinges upon a η^g_{13}, which is based on revisions of forecasts over the growth rates of federal spending only. However, expectations concerning levels of future fiscal spending regarding state and local expenditures are also available. We then construct levels of expected total spending and compute the growth rates of such expected realizations. We use this variable as a proxy of the expected growth rates of total fiscal spending that are not readily available in the SPF dataset. We then use this proxy as an alternative to our η^g_{13} variable in our vector. Our results are collected in Table 6 under the label "η^g_{13} total".

Ricco's news indicator. In a recent paper, Ricco (2014) shows that the news variable we employ in our study to account for fiscal foresight may be affected by aggregation bias. Our measure is based on forecast revisions constructed by appealing to location measures (e.g., mean, median) of the distribution of the forecasts (across forecasters). However, since the composition of the pool of respondents to the SPF changes over time, one problem related with our measure is that use of measures of central tendency might induce a non negligible bias if the distribution of forecast revisions is skewed. The resulting aggregation bias may in principle imply important quantitative effects for the computation of fiscal multipliers. Ricco (2014) circumvents this problem by constructing a measure of news based on the revisions of expectations of each individual forecaster in the pool, whose forecast is available for at least two consecutive

[31] Interestingly, our impulse responses suggest that output moves immediately in recessions, while its contemporaneous response is not significant when expansions are considered (IRFs not shown for the sake of brevity, but available upon request). The contemporaneous zero reaction of public spending to changes in output is consistent with the evidence on the zero contemporaneous output elasticity of government spending in the U.S. surveyed by Caldara and Kamps (2012).

quarters. Ex-post aggregation of such revisions gives rise to a "microfounded" measure of aggregate news. Even though the correlation between the two measures of fiscal anticipation in our sample is quite high (it reads 0.84), it is of interest to repeat our exercise by employing Ricco's news measure as an alternative to our η_{13}^{g}.[32] Results are documented in Table 6 under "η_{13}^{g} à la Ricco".

Table 6 collects the figures related to the robustness checks discussed above. Two main messages arise. First, the "Normal" scenarios generally points to a rather fragile evidence of countercyclical fiscal multipliers. The most evident exception is the case of the news variable *à la* Ricco, which leads to larger multipliers in recessions. This is in line with the fact that, in presence of a skewed distribution of forecast revisions, our measure of news would downward-bias the estimated fiscal multipliers (see Ricco (2014) for a detailed explanation of the sources of this bias). Second, our extreme events analysis robustly supports larger multipliers in recessions. Hence, our results corroborate a recent statement by Blanchard and Leigh (2013) on the magnitude of fiscal multipliers and the effectiveness of fiscal stabilization policies in periods of substantial economic slack. These results lend support also to Parker's (2011) call for empirical models able to capture the possible countercyclicality of fiscal multipliers.

6 Relation to the literature

Our investigation and results are related to Auerbach and Gorodnichenko's (2012, 2013a), who find evidence in favor of larger multipliers in recessions. As already pointed out, Auerbach and Gorodnichenko estimate responses to fiscal shocks by assuming that the economy starts in a state of the business cycle (recession, expansion), and remains in that state with probability one after the shock has hit the economy. This assumption provides an "upper bound" for the estimate of the fiscal multiplier in recessions. Our findings suggest that their results may be recovered by appealing to "extreme events", i.e., deep recessions and strong expansions, even when the probability of getting out of a recession after an expansionary fiscal shock is endogenously determined. In other words, part of our analysis is conducted by working with initial conditions associated to severe recessions or quite strong economic booms. Although we do not force the economy to remain in any of such states with probability one after the positive fiscal shock has hit the economic system, we also find evidence of countercyclical fiscal multipliers over the business cycle. Importantly, such scenarios are not empirically unrealistic. Focusing on

[32] We thank Giovanni Ricco for providing us with his measure of fiscal news.

recessions, our deep recessions are the deep downturns occurred in the early 1980s and the 2007-09 great crisis. Our results suggest that fiscal multipliers may indeed be quite large when the economy is in a phase of serious slack. Differently, our multipliers are estimated not to be statistically different when we randomize over all recessions and expansions to select initial conditions to estimate the GIRFs. In this case, the GIRFs "average up" the effect of different initial conditions, and imply multipliers that are more similar between states. From a policy standpoint, our results therefore suggest that an expansionary fiscal stance would be quite effective when implemented in periods of deep recessions.

Our paper joins the group of contributions dealing with expectations revisions to isolate fiscal shocks. Perotti (2007) employs revisions of the CBO public spending forecasts to assess the predictability of fiscal spending shocks coming from a standard fiscal SVAR. He finds such revisions to carry no valuable information to anticipate fiscal news shocks. Due to data availability, his sample starts from 1984 and features bi-annual data. Differently, Ramey (2011b) computes revisions of the one step-ahead public spending forecasts collected by the Survey of Professional Forecasters to produce a quarterly series of news shocks beginning in 1981Q3. Perotti (2011) shows that the one step-ahead forecast revisions of the SPF forecasts have low power in predicting the future evolution of public spending due to a noisy expectational component. Our contribution differs from these approaches since we employ h-steps-ahead forecast revisions (with h larger than one) as a measure of public spending news. As stressed in Section 2, moving beyond one-quarter-ahead expectations revisions is crucial for a correct identification of fiscal shocks. In line with Gambetti (2012b), we find that these longer horizon-revisions carry valuable information about the future evolution of public expenditure. We provide evidence based on single equation-estimations as well as on multivariate VAR model-estimations. Ricco (2014) employes an expectation-augmented VAR to identify shocks coming from unexpected, misexpected, and anticipated fiscal changes. He also finds expected fiscal changes to have expansionary effects and induce a cumulative multiplier larger than one. Our paper complements the studies conducted by Blanchard and Leigh (2013) and Alesina, Favero, and Giavazzi (2013), who employ revisions of expectations over fiscal consolidation plans to assess the role of fiscal policy changes in affecting the business cycle of a number of European countries and at an international level, respectively.

Two related strands of the literature have dealt with fiscal foresight and anticipated fiscal spending shocks in VARs by following different strategies. The first has focused on the estimation of VARMA models to solve the problem of non-invertibility. Mertens and Ravn (2010) exploit restrictions coming from economic theory to gauge information about economic agents' anticipation rate, i.e., the rate at which they discount fiscal "news". The anticipation rate is then used as input in the Blaschke matrices, which flip the roots that cause non-invertibility of the VMA representation of fiscal spending and output. In doing so, they are able to recover the non-fundamental responses to an anticipated fiscal policy shock. Kriwoluzky (2012) recovers reduced-form innovations by estimating a VARMA model using the Kalman filter. Then, he identifies anticipated fiscal shocks via sign restrictions coming from a structural DSGE framework à la Galí, López-Salido, and Vallés (2007). A second approach, starting with the seminal contribution by Ramey and Shapiro (1998), has resorted to the so-called narrative approach. The basic idea in Ramey and Shapiro (1998) is to identify truly exogenous changes in fiscal spending as military spending shocks. The identification is achieved by isolating "war dates" for the U.S.. One problem with the original Ramey-Shapiro war dates variable is the limited number of identified shocks. To circumvent this problem, Ramey (2011b) constructs a measure of changes in the expected present value of government spending. A related contribution is that by Fisher and Peters (2010), who construct a measure of excess returns of large U.S. military contractors. This measure anticipates future military spending. Similarly, Ben Zeev and Pappa (2014) identify U.S. defense news shocks as the shocks that best explain future movements in defense spending over a five year horizon and are orthogonal to current defense spending. All these contributions show that, at least qualitatively, anticipated fiscal shocks induce a significant increase in output.

With respect to the above mentioned contributions, this paper is novel in two important respects. First, we estimate the impact of fiscal shocks using a nonlinear model, which allows to differentiate the impact of fiscal shocks over the business cycle, by endogenously determining the probability of switching from one business cycle regime to the other. Second, we tackle explicitly the issue of non-fundamentalness of VAR models in presence of fiscal foresight by using a measure of fiscal news that exploits expectation revisions over a horizon greater than one quarter. So far, the two aspects, both crucial for a correct understanding of the transmission mechanism of fiscal policy, had been treated in isolation. To the best of our knowledge, this paper is the first attempt to jointly address both issues in the context of a VAR analysis.

It is important to notice that a different approach to deal with fiscal foresight in a nonlinear framework has been proposed by Owyang, Ramey, and Zubairy (2013) and Ramey and Zubairy (2013). They employ local-projection methods à la Jordà (2005) to investigate the nonlinearity of fiscal multipliers. The local-projection approach allows them to circumvent the "absorbing state" assumption made by Auerbach and Gorodnichenko (2012, 2013a), i.e., the assumption that the economy will never switch from a recession to an expansion after the fiscal shock has occurred. Owyang, Ramey, and Zubairy (2013) and Ramey and Zubairy (2013) find no evidence of larger fiscal multipliers during downturns as for the United States. The comparability between our exercises and theirs is not immediate due to a number of different modeling choices (construction of the news shocks, sample dates, construction of the impulse responses).[33] We note here that our exercises computed with Generalized Impulse Response Functions take into account the feedback linking the evolution of the business cycle due to news fiscal shocks to the probability of being in a recessionary phase. Hence, here we relax the assumption of being in an "absorbing state" made by Auerbach and Gorodnichenko (2012, 2013a), who do not allow for any transition from a state to another after the fiscal shock has hit the economic system. Our GIRFs, when computed by integrating over all possible initial conditions in either of the two states, deliver conclusions similar to Owyang, Ramey, and Zubairy (2013) and Ramey and Zubairy (2013). An advantage of using the GIRFs over the local projection method is that we are not forced to stick to average responses of output to news shocks in recessions vs. expansions. Differently, we employ the flexibility of GIRFs to conduct our "extreme events" analysis, which is constructed by conditioning on a subset of initial conditions while considering several different histories of the shocks as well as parameter uncertainty. As pointed out above, this last empirical exercise reveals that fiscal multipliers may very well be nonlinear and larger in recessions.

[33] One intriguing difference regards the use of post-WWII data for conducting analysis regarding the effects of news spending shocks. Ramey and Zubairy (2013) find that, when using the sample 1948-2011, integral multipliers in recessions are quite unstable, and can also be negative (-2 after two years vs. 18 (!) after four years). Moreover, the impulse responses are very imprecisely estimated. Finally, output reacts negatively to a news shock in recessions, and government spending also becomes negative after 2-3 years. Our GIRFs analysis returns quite stable integral multipliers across different horizons, quite precisely estimated responses, and positive responses of output and fiscal spending. An investigation on the drivers of the differences between our results and Ramey and Zubairy's is in our agenda.

7 Conclusions

This paper quantifies the fiscal spending multiplier in the U.S. and tests the theoretical prediction of a larger reaction of output to fiscal shocks in economic downturns. Following Gambetti (2012a,b), we tackle the issue of non-fundamentalness due to fiscal foresight by identifying anticipated government spending shocks via sums of forecast revisions collected by the Survey of Professional Forecasters. We show that such a measure of fiscal spending news carries relevant information to predict the future evolution of fiscal expenditures and Granger-causes other measures of fiscal news recently proposed in the literature. Then, we augment a macro-fiscal nonlinear VAR with this measure of fiscal news and estimate the size of fiscal spending multipliers across different phases of the business cycle.

Our empirical investigation points to fiscal multipliers larger than one in recessionary periods. However, conditional on a standard "recession vs. expansion" classification of the phases of the U.S. business cycle, our results do not support the idea of a countercylical fiscal multiplier. Differently, when we condition the estimates of the fiscal multipliers on the *strength* of the business cycle (namely, when we distinguish between deep and mild recessions, and weak and strong expansions), we find that fiscal multipliers are actually larger in recessions.

The results of our paper highlight the relevance of the initial economic conditions *within* each of the two states typically considered for classifying the U.S. business cycle. Fiscal multipliers may very well be larger when a fiscal shock occurs in presence of a deep recession like the 2007-09 one than when a fiscal shock occurs in presence of milder downturns of the business cycle. Hence, our results imply that a correct measurement of the fiscal multipliers can be performed just if flexible-enough econometric models are put at work.

As stressed in the paper, fiscal multipliers in presence of recessions are larger than one. While being somewhat higher than those found by most of the literature, our multipliers appear to be in line with those found in presence of financial frictions by Canzoneri, Collard, Dellas, and Diba (2011) and Corsetti, Meier, and Müller (2012). Given the likely interactions between the financial and the real side of the economy, the "Wall Street goes to Main Street" link appears worth investigating if one is willing to assess the power of fiscal shocks. An analysis jointly involving macro, fiscal, and financial variables is already in our agenda.

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$News$	$(1,3)$	$(1,1)$	$(2,2)$	$(3,3)$	$(0,0)$
$p-value$	**0.00**	**0.00**	**0.00**	**0.00**	0.11

Table 1: **Anticipated fiscal spending shocks: Statistical relevance.** P-values related to the exclusion Wald-test of one period-lagged News variables entering (one at a time) a regression involving Federal government spending (dependent variable), a constant, three lags of federal government spending, three lags of fiscal receipts, and three three lags of real GDP. Figures in bold are associated to a predictive power of news found to be significant at a 10 percent confidence level. News are expressed in cumulated terms to have an order of integration comparable to that of the other variables. Estimation conducted by considering Newey-West standard errors robust to heteroskedasticity and serial correlation.)

$Sample$	$Ramey$	η_{13}^{g}	ORZ	η_{13}^{g}
1981:III-2008:IV	0.44	**0.06**		
1986:IV-2008:IV	0.28	**0.02**		
1981:III-2010:IV			0.71	**0.06**
1986:IV-2010:IV			0.59	**0.02**

Table 2: **News à la Ramey vs. forecast revisions: Granger-causality tests.** 'Ramey' stands for the news variable employed by Ramey (2011), 'ORZ' stands for its updated version employed by Owyang, Ramey, and Zubairy (2013). P-values related to the exclusion Wald-test of one period-lagged covariate of interest. Figures in bold are associated to a predictive power of news found to be significant at a 10 percent confidence level. Results based on a bivariate VAR(1) with one lag. Null hypothesis: Column variable does not Granger cause the alternative news measure.

	$Peak$		Sum	
$Horizon/State$	$Expansion$	$Recession$	$Expansion$	$Recession$
4	1.68 [1.12,3.49]	3.38 [1.77,4.70]	1.73 [0.52,3.50]	3.15 [1.71,4.27]
8	1.24 [0.80,3.19]	3.32 [1.55,4.91]	0.33 [−1.05,2.77]	3.05 [0.68,4.70]
12	1.11 [0.74,2.69]	2.77 [1.40,4.28]	−0.57 [−2.24,1.54]	2.13 [0.13,3.82]
16	1.09 [0.71,2.43]	2.60 [1.38,3.96]	−1.41 [−3.96,0.74]	1.54 [−0.42,2.95]
20	1.09 [0.71,2.41]	2.58 [1.38,3.90]	−2.27 [−6.23,−0.01]	1.00 [−0.94,2.47]

Table 3: **Fiscal spending multipliers.** Figures conditional on our baseline VAR analysis. Log-values of the government spending and output of our impulse responses scaled by the sample average values of Y/G to move from elasticities to dollar changes.

	Peak			
Hor./State	*Strong exp.*	*Deep rec.*	*Weak exp.*	*Mild rec.*
4	1.24 [0.78,1.88]	3.57 [2.14,4.73]	1.68 [1.15,3.44]	3.23 [1.74,4.69]
8	0.86 [0.53,1.25]	3.58 [1.94,4.75]	1.24 [0.82,3.16]	3.24 [1.56,4.72]
12	0.79 [0.48,1.10]	2.39 [1.48,3.30]	1.11 [0.75,2.56]	2.88 [1.32,4.20]
16	0.79 [0.45,1.09]	2.27 [1.45,2.93]	1.09 [0.72,2.31]	2.72 [1.32,3.96]
20	0.79 [0.43,1.08]	2.24 [1.44,2.90]	1.09 [0.72,2.29]	2.71 [1.31,3.94]

	Sum			
Hor./State	*Strong exp.*	*Deep rec.*	*Weak exp.*	*Mild rec.*
4	1.03 [−0.51,2.03]	3.42 [2.05,4.35]	1.69 [0.64,3.40]	3.09 [1.71,4.14]
8	−0.26 [−2.01,0.84]	3.42 [1.22,5.14]	0.30 [−0.87,2.83]	2.94 [0.56,4.46]
12	−1.32 [−3.68,−0.03]	2.21 [0.61,3.54]	−0.62 [−2.15,1.48]	2.06 [0.03,3.78]
16	−2.26 [−5.63,−0.78]	1.60 [0.18,2.63]	−1.40 [−3.91,0.65]	1.38 [−0.48,3.02]
20	−3.28 [−7.00,−1.56]	1.09 [−0.31,2.07]	−2.37 [−6.08,0.01]	0.83 [−0.97,2.54]

Table 4: **Fiscal spending multipliers: Extreme events.** Figures conditional on our VAR analysis with GIRFs conditional on four different sets of initial conditions. Log-values of the government spending and output of our impulse responses scaled by the sample average values of Y/G to move from elasticities to dollar changes.

		Peak				
Scenario/Horizon	*Cycle*	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
Baseline	*Normal*	87.80	90.80	90.00	90.60	90.20
	Extreme	99.60	100.00	100.00	100.00	100.00
FAVAR	*Normal*	87.40	91.00	93.20	93.40	93.40
	Extreme	100.00	99.80	99.60	99.60	99.60
η_{13}^{Y}	*Normal*	62.60	80.60	82.20	84.00	84.80
	Extreme	93.00	99.20	99.40	99.20	99.20
η_{13}^{g} *first*	*Normal*	81.00	86.80	88.60	90.00	90.00
	Extreme	97.60	99.20	99.40	99.60	99.60
η_{13}^{g} *total*	*Normal*	94.60	92.60	92.60	93.20	93.40
	Extreme	100.00	100.00	100.00	100.00	100.00
η_{13}^{g} *à la Ricco*	*Normal*	95.00	94.00	94.00	94.20	94.40
	Extreme	100.00	100.00	100.0	100.00	100.00
		Sum				
Scenario/Horizon	*Cycle*	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
Baseline	*Normal*	84.80	91.60	93.60	95.40	96.60
	Extreme	100.00	100.00	100.00	100.00	100.00
FAVAR	*Normal*	89.80	85.20	85.60	88.20	89.80
	Extreme	100.00	100.00	100.00	100.00	100.00
η_{13}^{Y}	*Normal*	36.80	73.00	79.80	83.00	86.40
	Extreme	86.20	100.00	100.00	100.00	100.00
η_{13}^{g} *first*	*Normal*	74.20	84.60	88.20	90.40	91.40
	Extreme	96.20	99.80	100.00	100.00	100.0
η_{13}^{g} *total*	*Normal*	89.80	86.60	85.40	85.80	87.00
	Extreme	98.60	95.20	99.00	100.00	100.00
η_{13}^{g} *à la Ricco*	*Normal*	93.00	90.80	90.60	90.20	90.40
	Extreme	99.80	99.80	99.80	99.80	99.80

Table 5: **Fiscal spending multipliers: Shares of multipliers larger in recessions.** Figures conditional on our VAR analysis with GIRFs conditional on four different sets of initial conditions. Log-values of the government spending and output of our impulse responses scaled by the sample average values of Y/G to move from elasticities to dollar changes.

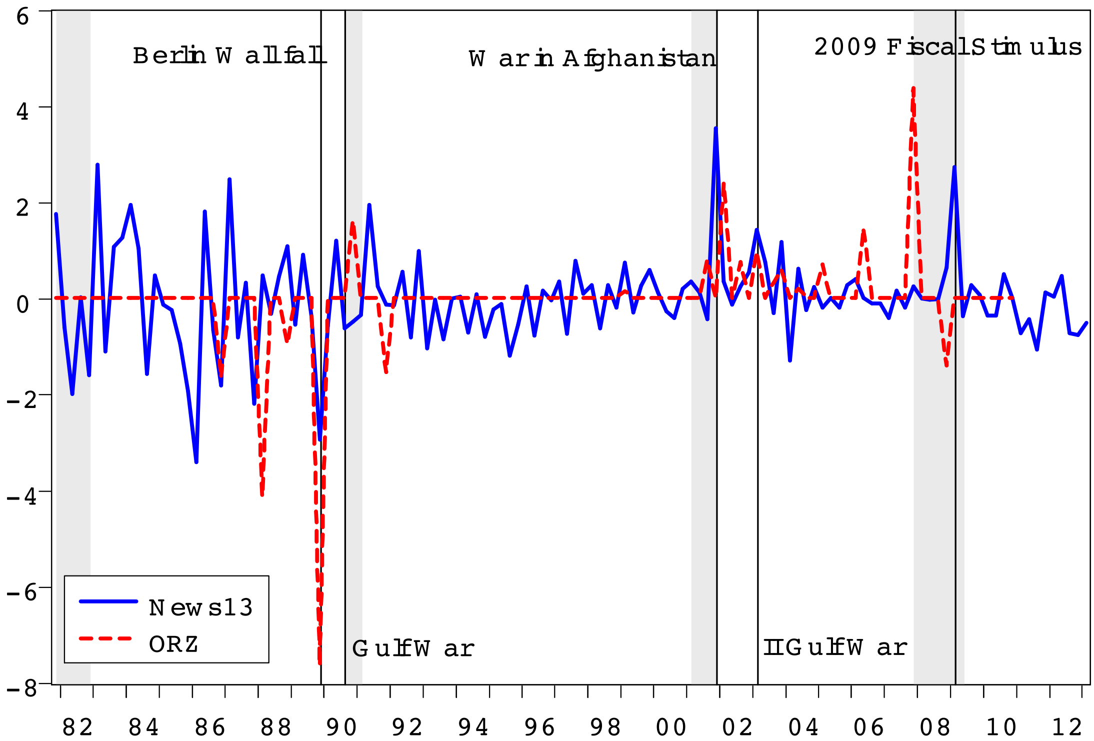

Figure 1: **News13 (this paper) vs. Owyang, Ramey, and Zubairy's (2013) news variable**. Blue, solid line: News variable constructed by considering the cumulated sum of Survey of Professional Forecasters' forecast revisions regarding future public spending from one to three period-ahead. Red, dashed line: News variable constructed by Owyang, Ramey, and Zubairy (2013), who extended Ramey's (2011) news variable up to 2010Q4. Ramey's (2011) variable is constructed by considering the present discounted value of expected changes in defense spending (nominal spending divided by nominal GDP one period before). Both news measures in this Figure are standardized.

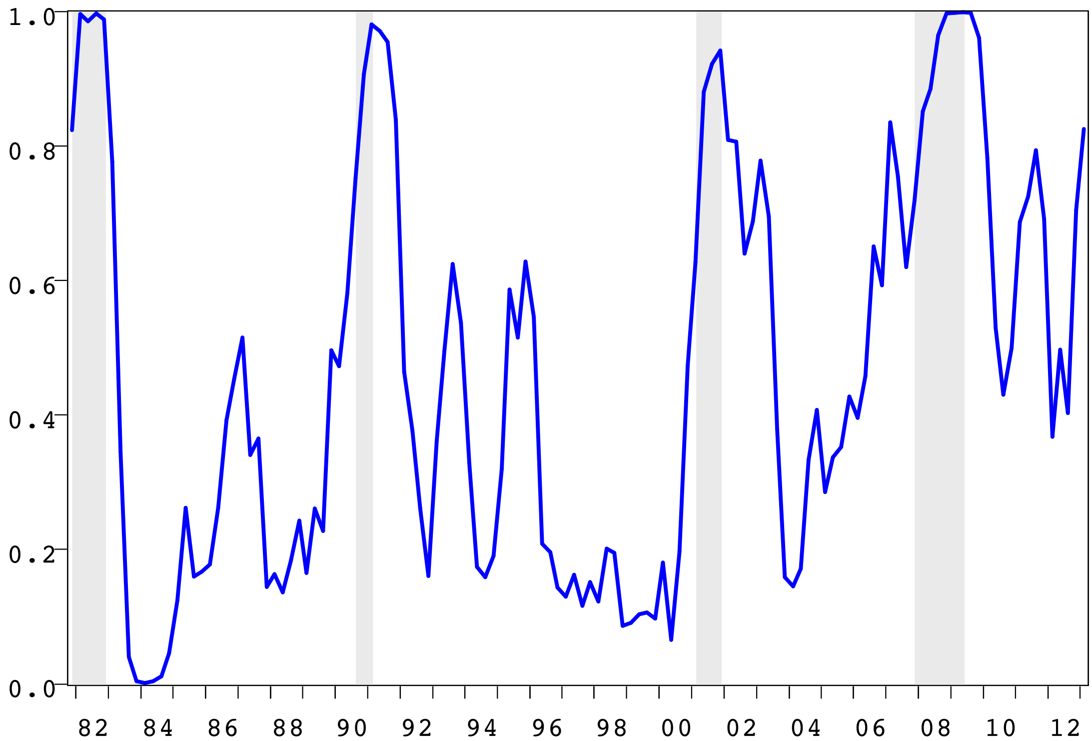

Figure 2: **Probability of being in a recessionary phase F(z).** Probability computed according to the logistic function presented in the text. Transition variable: Standardized backward-looking moving average constructed with four realizations of the quarter-on-quarter real GDP growth rate. Value of the slope parameter: 2.3.

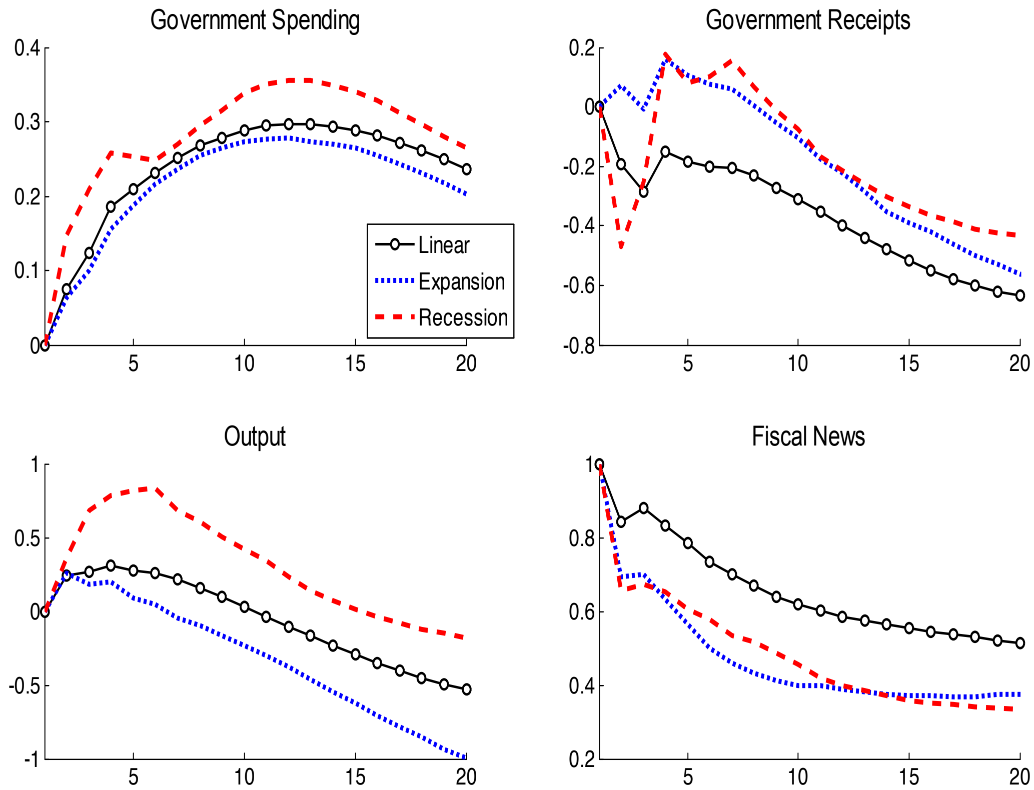

Figure 3: **Generalized impulse responses to a fiscal news (anticipated) spending shock: Linear model, recessions, expansions.** Median responses to a fiscal news shock normalized to one. News variable constructed as the sum of the revisions of the one, two, and three step-ahead expectation values over future fiscal spending growth. News variable expressed in cumulated terms to have the same order of integration as the one of the log-real variables in the vector. Output reaction scaled by the sample average of the ratio of Y/G to be consistent with the computation of the fiscal multipliers. Sample 1981Q3-2013Q1. VAR models estimated with a constant and three lags.

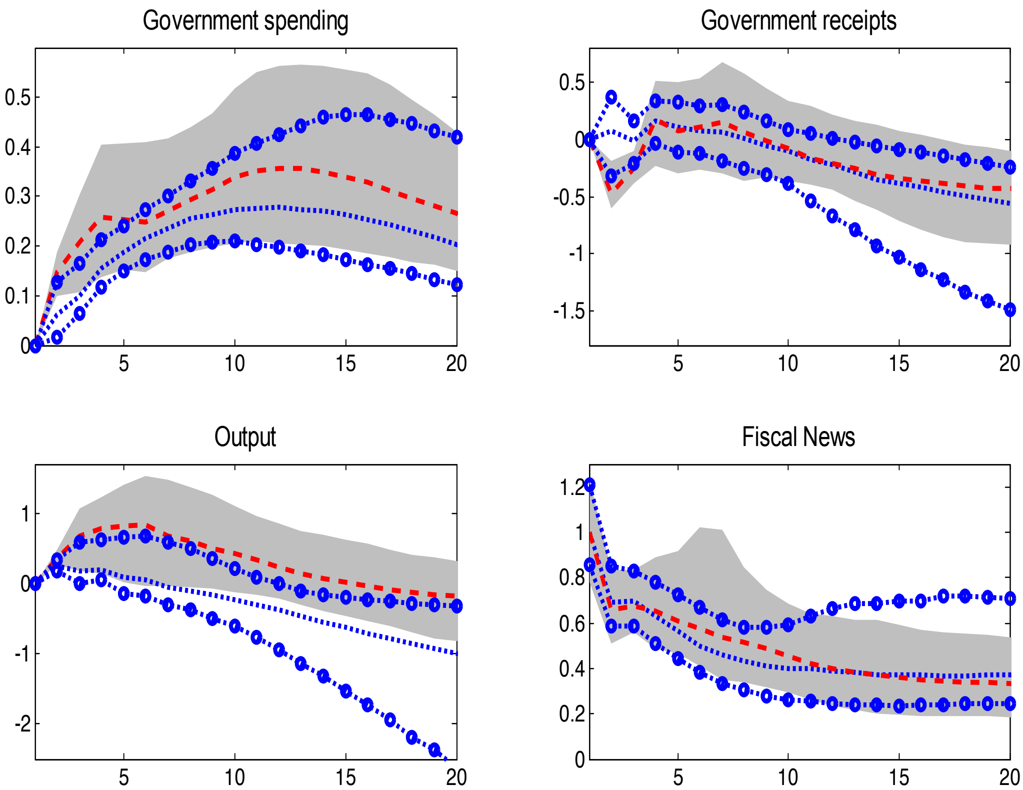

Figure 4: **Generalized impulse responses to a fiscal news (anticipated) spending shock: Recessions vs. expansions.** Median responses to a fiscal news shock normalized to one. 90 percent confidence intervals identified with gray areas (recessions) and circled lines (expansions). Black solid lines with circles: Linear model. Red dashed lines: Recessions. Dotted blue lines: Expansions. News variable constructed as the sum of the revisions of the one, two, and three step-ahead expectation values over future fiscal spending growth. News variable expressed in cumulated terms to have the same order of integration as the one of the log-real variables in the vector. Output reaction scaled by the sample average of the ratio of Y/G to be consistent with the computation of the fiscal multipliers. Sample 1981Q3-2013Q1. VAR models estimated with a constant and three lags.

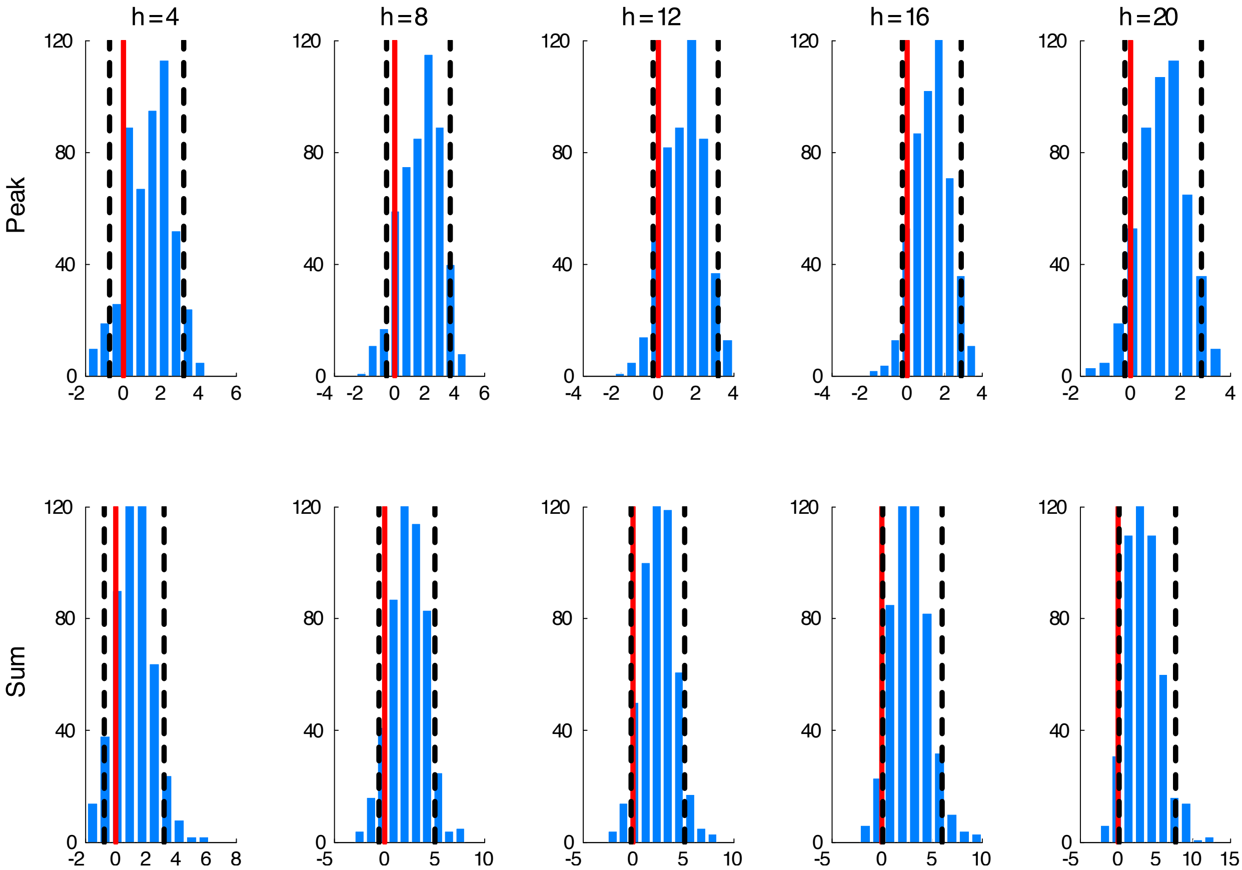

Figure 5: **Difference in multipliers between recessions and expansions: All histories.** Empirical densities of the differences computed as multipliers in recessions minus multipliers in expansions. Densities constructed by considering all recessions and expansions (initial conditions) present in the sample. Multipliers conditional on the same set of draws of the stochastic elements of our STVAR model as well as the same realizations of the coefficients of the vector. Densities based on 500 realizations of such differences per each horizon of interest.

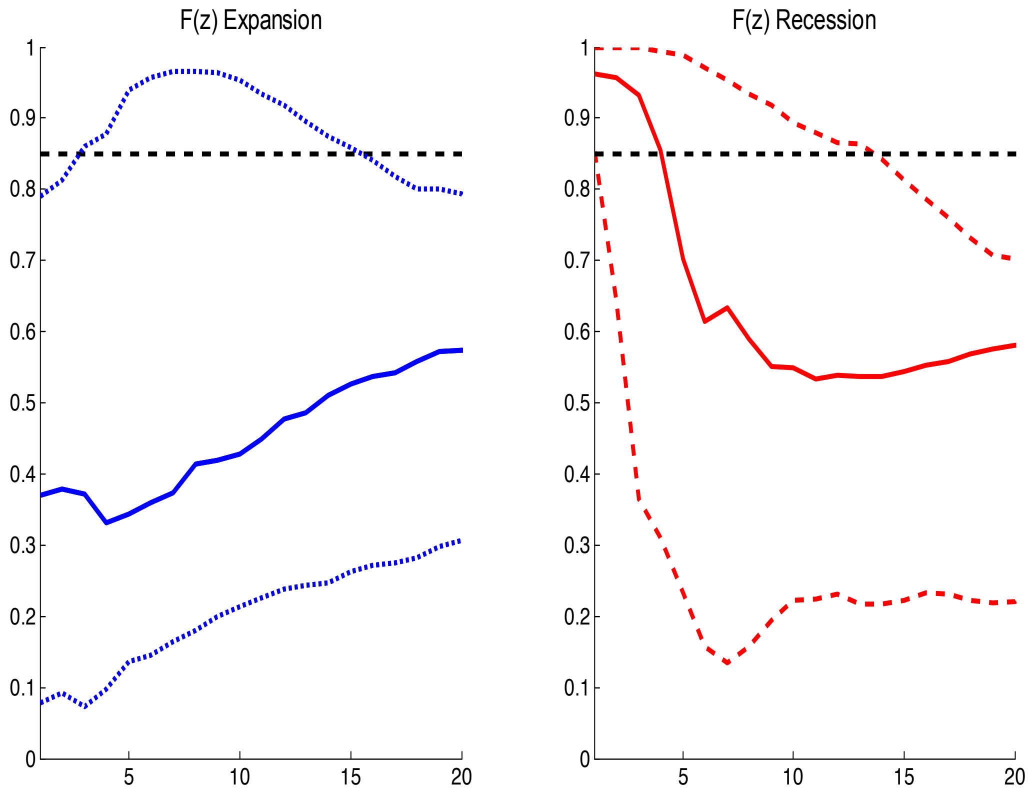

Figure 6: **Evolution of the probability of being in a recessionary phase F(z) consistent with our GIRFs.** Solid lines: Median reactions. Blude dotted/ red dashed lines: 90 percent confidence intervals. Black dashes horizonal line: Threshold value to switch from a regime to another. Probability computed according to the logistic function presented in the text and the evolution of output conditional on a fiscal news shock. Transition variable: Standardized backward-looking moving average constructed with four realizations of the quarter-on-quarter real GDP growth rate. Value of the slope parameter: 2.3.

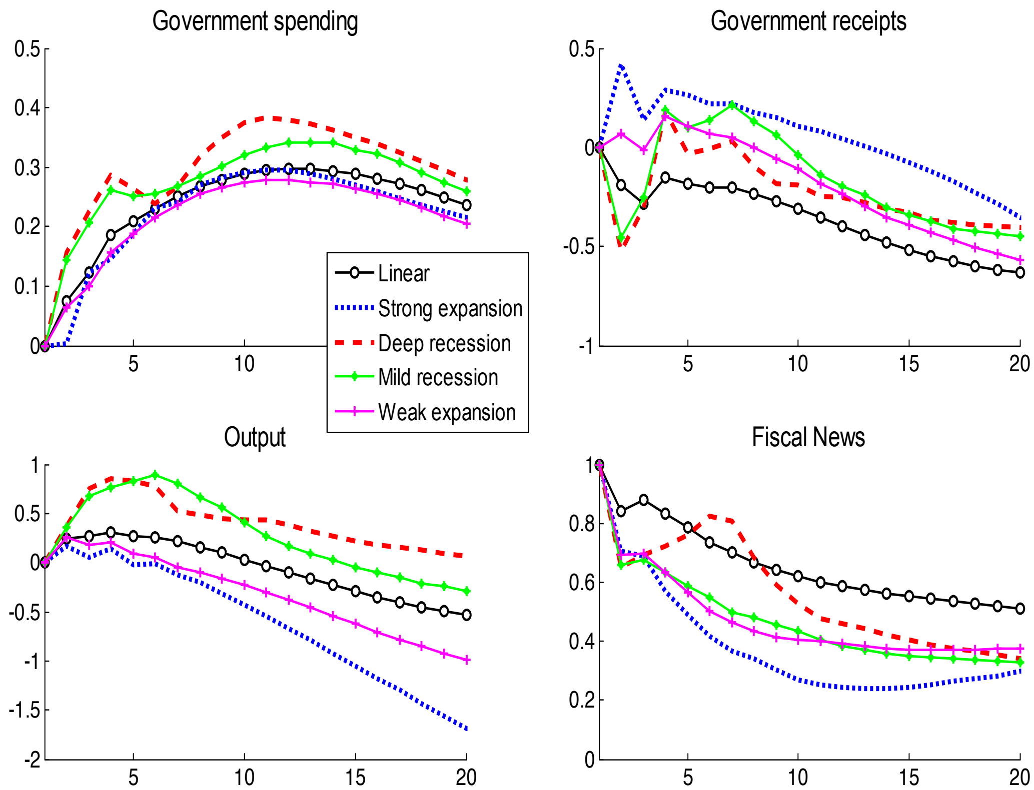

Figure 7: **Generalized impulse responses to a fiscal news (anticipated) spending shock: Linear model, deep vs. mild recessions, strong vs. weak expansions.** Deep recessions/strong expansions associated to histories consistent with realizations of our transition variable which are below/above two standard deviations. Mild recessions/weak expansions associated to histories consistent with realizations of our transition variable below/above -0.75 but within the range [-2,2]. Median responses to a fiscal news shock normalized to one. News variable constructed as the sum of the revisions of the one, two, and three step-ahead expectation values over future fiscal spending growth. News variable expressed in cumulated terms to have the same order of integration as the one of the log-real variables in the vector. Output reaction scaled by the sample average of the ratio of Y/G to be consistent with the computation of the fiscal multipliers. Sample 1981Q3-2013Q1. VAR models estimated with a constant and three lags.

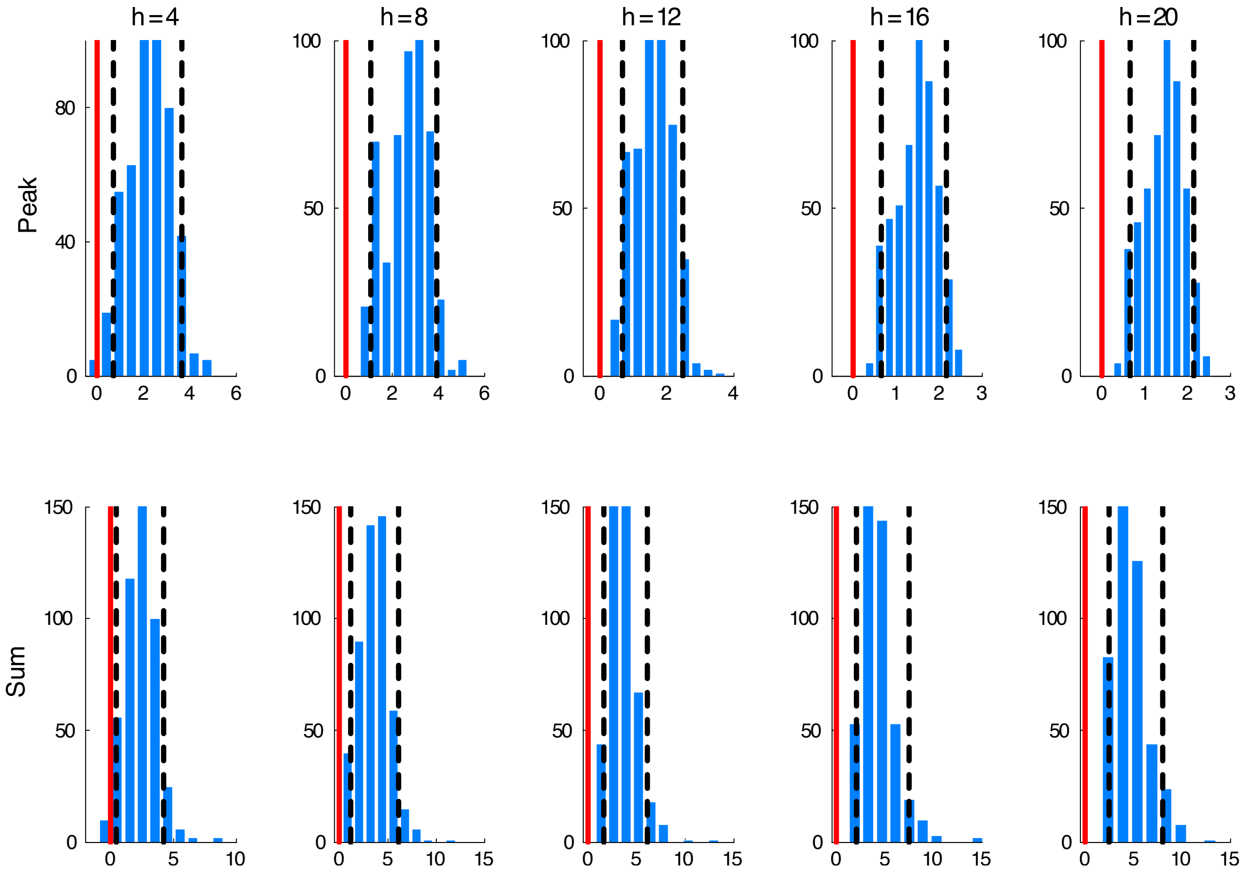

Figure 8: **Difference in multipliers between recessions and expansions: Extreme events.** Empirical densities of the differences computed as multipliers in recessions minus multipliers in expansions. Densities constructed by considering just extreme realizations of recessions and expansions (initial conditions) present in the sample. Multipliers conditional on the same set of draws of the stochastic elements of our STVAR model as well as the same realizations of the coefficients of the vector. Densities based on 500 realizations of such differences per each horizon of interest.

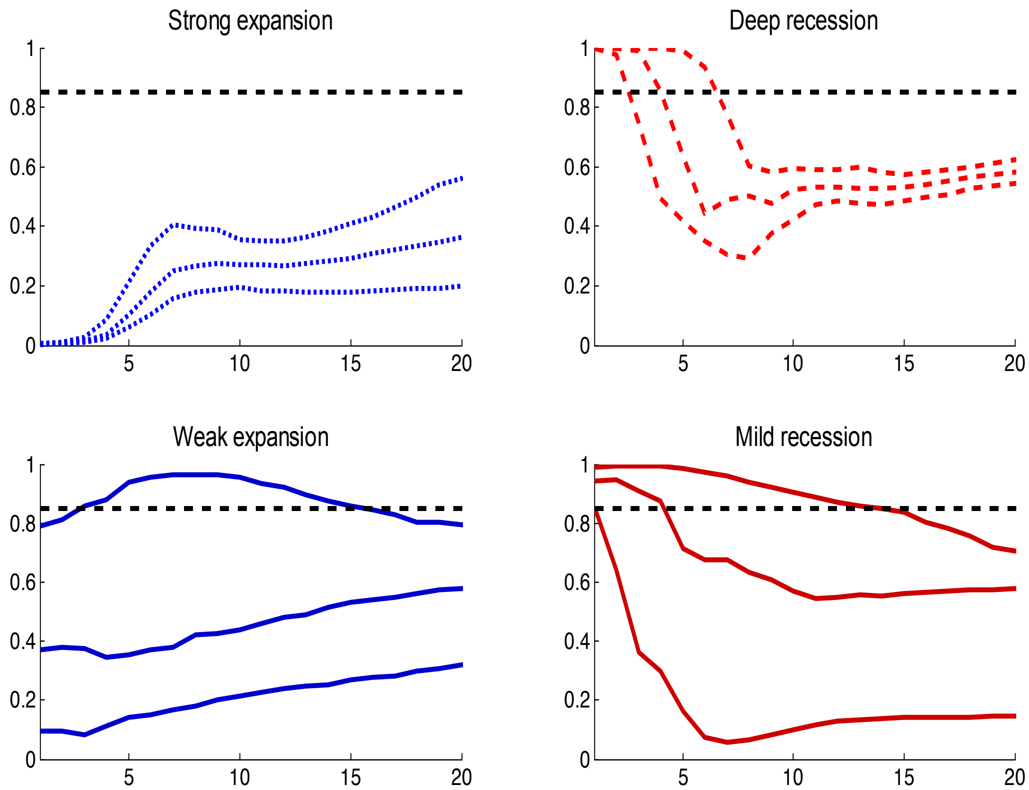

Figure 9: **Evolution of the probability of being in a recessionary phase F(z) consistent with our GIRFs: Extreme events.** Median reactions and 90 percent confidence intervals. Black dashes horizonal line: Threshold value to switch from a regime to another. Deep recessions/strong expansions associated to histories consistent with realizations of our transition variable which are below/above two standard deviations. Mild recessions/weak expansions associated to histories consistent with realizations of our transition variable below/above -0.75 but within the range [-2,2]. Probability computed according to the logistic function presented in the text and the evolution of output conditional on a fiscal news shock. Transition variable: Standardized backward-looking moving average constructed with four realizations of the quarter-on-quarter real GDP growth rate. Value of the slope parameter: 2.3.

Appendix of "Estimating Fiscal Multipliers: News From a Nonlinear World" by Giovanni Caggiano, Efrem Castelnuovo, Valentina Colombo, Gabriela Nodari

This Appendix reports some details on the estimation of our nonlinear VARs, as well as on the computation of the Generalized Impulse Responses.

Estimation of the nonlinear VARs

Consider the model (9)-(12). Its log-likelihood reads as follows:[1]

$$\log L = const + \frac{1}{2}\sum\nolimits_{t=1}^{T} \log|\boldsymbol{\Omega}_t| - \frac{1}{2}\sum\nolimits_{t=1}^{T} \boldsymbol{u}_t'\boldsymbol{\Omega}_t^{-1}\boldsymbol{u}_t \tag{A1}$$

where the vector of residuals $\boldsymbol{u}_t = \boldsymbol{X}_t - (1 - F(z_{t-1})\boldsymbol{\Pi}_E\boldsymbol{X}_{t-1} - F(z_{t-1})\boldsymbol{\Pi}_R\boldsymbol{X}_{t-1}$. Our goal is to estimate the parameters $\boldsymbol{\Psi} = \{\gamma, \boldsymbol{\Omega}_R, \boldsymbol{\Omega}_E, \boldsymbol{\Pi}_R(L), \boldsymbol{\Pi}_E(L)\}$, where $\boldsymbol{\Pi}_j(L) = \left[\begin{array}{ccc} \boldsymbol{\Pi}_{j,1} & \dots & \boldsymbol{\Pi}_{j,p} \end{array}\right]$, $j \in \{R, E\}$. The high-non linearity of the model and its many parameters render its estimation with standard optimization routines problematic. Following Auerbach and Gorodnichenko (2012), we employ the procedure described below.

Conditional on $\{\gamma, \boldsymbol{\Omega}_R, \boldsymbol{\Omega}_E\}$, the model is linear in $\{\boldsymbol{\Pi}_R(L), \boldsymbol{\Pi}_E(L)\}$. Then, for a given guess on $\{\gamma, \boldsymbol{\Omega}_R, \boldsymbol{\Omega}_E\}$, the coefficients $\{\boldsymbol{\Pi}_R(L), \boldsymbol{\Pi}_E(L)\}$ can be estimated by minimizing $\frac{1}{2}\sum\nolimits_{t=1}^{T} \boldsymbol{u}_t'\boldsymbol{\Omega}_t^{-1}\boldsymbol{u}_t$. This can be seen by re-writing the regressors as follows. Let $\boldsymbol{W}_t = \left[\begin{array}{cccccc} F(z_{t-1})\boldsymbol{X}_{t-1} & (1 - F(z_{t-1})\boldsymbol{X}_{t-1} & \dots & F(z_{t-1})\boldsymbol{X}_{t-p} & 1 - F(z_{t-1})\boldsymbol{X}_{t-p} \end{array}\right]$ be the extended vector of regressors, and $\boldsymbol{\Pi} = \left[\begin{array}{cc} \boldsymbol{\Pi}_R(L) & \boldsymbol{\Pi}_E(L) \end{array}\right]$. Then, we can write $\boldsymbol{u}_t = \boldsymbol{X}_t - \boldsymbol{\Pi}\boldsymbol{W}_t'$. Consequently, the objective function becomes

$$\frac{1}{2}\sum\nolimits_{t=1}^{T} (\boldsymbol{X}_t - \boldsymbol{\Pi}\boldsymbol{W}_t')'\boldsymbol{\Omega}_t^{-1}(\boldsymbol{X}_t - \boldsymbol{\Pi}\boldsymbol{W}_t').$$

It can be shown that the first order condition with respect to $\boldsymbol{\Pi}$ is

$$vec\boldsymbol{\Pi}' = \left(\sum\nolimits_{t=1}^{T} \left[\boldsymbol{\Omega}_t^{-1} \otimes \boldsymbol{W}_t'\boldsymbol{W}_t\right]\right)^{-1} vec\left(\sum\nolimits_{t=1}^{T} \boldsymbol{W}_t'\boldsymbol{X}_t\boldsymbol{\Omega}_t^{-1}\right). \tag{A2}$$

This procedure iterates over different sets of values for $\{\gamma, \boldsymbol{\Omega}_R, \boldsymbol{\Omega}_E\}$. For each set of values, $\boldsymbol{\Pi}$ is obtained and the $logL$ (A1) computed.

Given that the model is highly nonlinear in its parameters, several local optima might be present. Hence, it is recommended to try different starting values for $\{\gamma, \boldsymbol{\Omega}_R, \boldsymbol{\Omega}_E\}$. To ensure positive definiteness of the matrices $\boldsymbol{\Omega}_R$ and $\boldsymbol{\Omega}_E$, we focus on the alternative

[1] This Section heavily draws on Auerbach and Gorodnichenko's (2012) "Appendix: Estimation Procedure".

vector of parameters $\boldsymbol{\Psi} = \{\gamma, chol(\boldsymbol{\Omega}_R), chol(\boldsymbol{\Omega}_E), \boldsymbol{\Pi}_R(L), \boldsymbol{\Pi}_E(L)\}$, where $chol$ implements a Cholesky decomposition.

We estimate our nonlinear model by employing the Monte-Carlo Markov-Chain Metropolis-Hastings algorithm proposed by Chernozhukov and Hong (2003). Given a starting value $\boldsymbol{\Psi}^{(0)}$, the procedure constructs chains of length N of the parameters of our model following these steps:

Step 1. Draw a candidate vector of parameter values $\boldsymbol{\Theta}^{(n)} = \boldsymbol{\Psi}^{(n)} + \boldsymbol{\psi}^{(n)}$ for the chain's $n+1$ state, where $\boldsymbol{\Psi}^{(n)}$ is the current state and $\boldsymbol{\psi}^{(n)}$ is a vector of i.i.d. shocks drawn from $N(0, \boldsymbol{\Omega}_\Psi)$, and $\boldsymbol{\Omega}_\Psi$ is a diagonal matrix.

Step 2. Set the $n+1$ state of the chain $\boldsymbol{\Psi}^{(n+1)} = \boldsymbol{\Theta}^{(n)}$ with probability $min\left\{1, L(\boldsymbol{\Theta}^{(n)})/L(\boldsymbol{\Psi}^{(n)})\right\}$, where $L(\boldsymbol{\Theta}^{(n)})$ is the value of the likelihood function conditional on the candidate vector of parameter values, and $L(\boldsymbol{\Psi}^{(n)})$ the value of the likelihood function conditional on the current state of the chain. Otherwise, set $\boldsymbol{\Psi}^{(n+1)} = \boldsymbol{\Psi}^{(n)}$.

The starting value $\boldsymbol{\Theta}^{(0)}$ is computed by working with a second-order Taylor approximation of the model (8)-(11), so that the model can be written as regressing $\boldsymbol{X}_t$ on lags of $\boldsymbol{X}_t$, $\boldsymbol{X}_t z_t$, and $\boldsymbol{X}_t z_t^2$. The residuals from this regression are employed to fit the expression for the reduced-form time-varying variance-covariance matrix of the VAR (see our paper) using maximum likelihood to estimate $\boldsymbol{\Omega}_R$ and $\boldsymbol{\Omega}_E$. Conditional on these estimates and given a calibration for γ, we can construct $\boldsymbol{\Omega}_t$. Conditional on $\boldsymbol{\Omega}_t$, we can get starting values for $\boldsymbol{\Pi}_R(L)$ and $\boldsymbol{\Pi}_E(L)$ via equation (A2).

The initial (diagonal matrix) $\boldsymbol{\Omega}_\Psi$ is calibrated to one percent of the parameter values. It is then adjusted "on the fly" for the first 20,000 draws to generate an acceptance rate close to 0.3, a typical choice for this kind of simulations (Canova (2007)). We employ $N = 50,000$ draws for our estimates, and retain the last 20% for inference.

As shown by CH, $\overline{\boldsymbol{\Psi}} = \frac{1}{N}\sum_{n=1}^{N} \boldsymbol{\Psi}^{(n)}$ is a consistent estimate of $\boldsymbol{\Psi}$ under standard regularity assumptions on maximum likelihood estimators. Moreover, the covariance matrix of $\boldsymbol{\Psi}$ is given by $\boldsymbol{V} = \frac{1}{N}\sum_{n=1}^{N}(\boldsymbol{\Psi}^{(n)} - \overline{\boldsymbol{\Psi}})^2 = var(\boldsymbol{\Psi}^{(n)})$, that is the variance of the estimates in the generated chain.

Generalized Impulse Response Functions

Once calibrated our VAR with the point estimates obtained via the procedure presented in the previous sub-Section, we compute the Generalized Impulse Response Functions from our STVAR model by following the approach proposed by Koop, Pesaran, and Potter (1996). The algorithm features the following steps.

1. Consider the entire available observations, with sample size $t = 1981Q3,\ldots,2013Q1$, with $T = 123$, and construct the set of all possible histories $\boldsymbol{\Lambda}$ of length $p = 6$:[2] $\{\boldsymbol{\lambda}_i \in \boldsymbol{\Lambda}\}$. $\boldsymbol{\Lambda}$ will contain $T - p + 1$ histories $\boldsymbol{\lambda}_i$.

2. Separate the set of all recessionary histories from that of all expansionary histories. For each $\boldsymbol{\lambda}_i$ calculate the transition variable z_{λ_i}. If $z_{\lambda_i} \leq \overline{z} = -0.75\%$, then $\boldsymbol{\lambda}_i \in \boldsymbol{\Lambda}^R$, where $\boldsymbol{\Lambda}^R$ is the set of all recessionary histories; if $z_{\lambda_i} > -\overline{z} = -0.75\%$, then $\boldsymbol{\lambda}_i \in \boldsymbol{\Lambda}^E$, where $\boldsymbol{\Lambda}^E$ is the set of all expansionary histories.

3. Select at random one history $\boldsymbol{\lambda}_i$ from the set $\boldsymbol{\Lambda}^R$. For the selected history $\boldsymbol{\lambda}_i$, take $\widehat{\boldsymbol{\Omega}}_{\lambda_i}$ obtained as:
$$\widehat{\boldsymbol{\Omega}}_{\lambda_i} = F\left(z_{\lambda i}\right)\widehat{\boldsymbol{\Omega}}_R + \left(1 - F\left(z_{\lambda_i}\right)\right)\widehat{\boldsymbol{\Omega}}_E, \tag{A3}$$
where $\widehat{\boldsymbol{\Omega}}_R$ and $\widehat{\boldsymbol{\Omega}}_E$ are derived from model (8)-(11) estimated over the entire sample. z_{λ_i} is the transition variable calculated for the selected history $\boldsymbol{\lambda}_i$.

4. Cholesky-decompose the estimated variance-covariance matrix $\widehat{\boldsymbol{\Omega}}_{\lambda_i}$:
$$\widehat{\boldsymbol{\Omega}}_{\lambda_i} = \widehat{\mathbf{C}}_{\lambda_i}\widehat{\mathbf{C}}'_{\lambda_i} \tag{A4}$$
and orthogonalize the residuals to get the structural shocks:
$$\mathbf{e}^{(j)}_{\lambda_i} = \widehat{\mathbf{C}}^{-1}_{\lambda_i}\widehat{\boldsymbol{\varepsilon}}. \tag{A5}$$

5. From $\mathbf{e}_{\lambda_i}$ draw with replacement h four-dimensional shocks and get the vector of bootstrapped shocks
$$\mathbf{e}^{(j)*}_{\lambda_i} = \left\{\mathbf{e}^*_{\lambda_i,t}, \mathbf{e}^*_{\lambda_i,t+1}, \ldots, \mathbf{e}^*_{\lambda_i,t+h}\right\}, \tag{A6}$$
where h is the horizon for the IRFs we are interested in.

6. Form another set of bootstrapped shocks which will be equal to (A6) except for the k_{th} shock in $\mathbf{e}^{(j)*}_{\lambda_i,t}$ which is the shock we want to perturbate (news in our model) by an amount equal to δ. Denote the vector of bootstrapped perturbated shocks by $\mathbf{e}^{(j)\delta}_{\lambda_i}$.

[2] The choice $p = 6$ is due to the number of moving average terms (four) of our transition variable z_t, which is constructed by considering five realization of the levels of the (log-)real GDP, i.e., four realizations of the growth rates. Moreover, such transition variable enters our STVAR model via the transition probability $F(z_{t-1})$ with one lag.

7. Transform back $\mathbf{e}_{\lambda_i}^{(j)*}$ and $\mathbf{e}_{\lambda_i}^{(j)\delta}$ as follows:

$$\widehat{\boldsymbol{\varepsilon}}_{\lambda_i}^{(j)*} = \widehat{\mathbf{C}}_{\lambda_i}\mathbf{e}_{\lambda_i}^{(j)*} \tag{A7}$$

and

$$\widehat{\boldsymbol{\varepsilon}}_{\lambda_i}^{(j)\delta} = \widehat{\mathbf{C}}_{\lambda_i}\mathbf{e}_{\lambda_i}^{(j)\delta}. \tag{A8}$$

8. Use (A7) and (A8) to generate two sequences $\mathbf{X}_{\lambda_i}^{(j)*}$ and $\mathbf{X}_{\lambda_i}^{(j)\delta}$ and get the $GIRF^{(j)}\left(h, \delta, \lambda_i\right)$.

9. Conditional on history λ_i, repeat for $j = 1, \dots, B$ vectors of bootstrapped residuals and get $GIRF^{(1)}\left(h, \delta, \lambda_i\right), GIRF^{(2)}\left(h, \delta, \lambda_i\right), \dots, GIRF^{(B)}\left(h, \delta, \lambda_i\right)$. Set $B = 500$.

10. Calculate the GIRF conditional on history λ_i as

$$\widehat{GIRF}^{(i)}\left(h, \delta, \lambda_i\right) = B^{-1}\sum_{j=1}^{B} GIRF^{(i,j)}\left(h, \delta, \lambda_i\right). \tag{A9}$$

11. Repeat all previous steps for $i = 1, \dots, 500$ randomly drawn histories belonging to the set of recessionary histories, $\boldsymbol{\lambda}_i \in \boldsymbol{\Lambda}^R$, and get $\widehat{GIRF}^{(1,R)}\left(h, \delta, \lambda_{1,R}\right), \widehat{GIRF}^{(2,R)}\left(h, \delta, \lambda_{2,R}\right)$, ... , $\widehat{GIRF}^{(500,R)}\left(h, \delta, \lambda_{500,R}\right)$, where now the subscript R denotes explicitly that we are *conditioning upon recessionary histories.*

12. Take the average and get $\widehat{GIRF}^{(R)}\left(h, \delta, \boldsymbol{\Lambda}^R\right)$, which is the average GIRF under recessions.

13. Repeat all previous steps - 3 to 12 - for 500 histories belonging to the set of all expansions and get $\widehat{GIRF}^{(E)}\left(h, \delta, \boldsymbol{\Lambda}^E\right)$.

14. The computation of the 90% confidence bands for our impulse responses is undertaken by picking up, per each horizon of each state, the 5th and 95th percentile of the densities $\widehat{GIRF}^{([1:500],R)}$ and $\widehat{GIRF}^{([1:500],E)}$.

Computation of the factors for the FAVAR approach

We follow Stock and Watson (2012) to estimate the factors from a large unbalanced data set of US variables. Let $\boldsymbol{X}_t = (X_{1t}, \dots, X_{nt})'$ denote a vector of n macroeconomic time series, with $t = 1, \dots, T$. X_{it} is a single time series transformed to be stationary and to have mean zero. The dynamic factor model expresses each of the n time series as the sum of a common component driven by r unobserved factors $\boldsymbol{F}_t$ plus an idiosyncratic disturbance term e_{it}:

$$\mathbf{X}_t = \mathbf{\Lambda} \mathbf{F}_t + \mathbf{e}_t \tag{A10}$$

where $\boldsymbol{e}_t = (e_{1t}, \ldots, e_{nt})'$ and $\mathbf{\Lambda}$ is the $n \times r$ matrix of factor loadings.

The factors are assumed to follow a linear and stationary vector autoregression:

$$\mathbf{\Phi}\left(L\right) \boldsymbol{F}_t = \boldsymbol{\eta}_t \tag{A11}$$

where $\mathbf{\Phi}\left(L\right)$ is a $r \times r$ matrix of lag polynomials with the vector of r innovations $\boldsymbol{\eta}_t$. Stationarity implies that $\mathbf{\Phi}\left(L\right)$ can be inverted and $\boldsymbol{F}_t$ has the moving average representation:

$$\boldsymbol{F}_t = \mathbf{\Phi}\left(L\right)^{-1} \boldsymbol{\eta}_t. \tag{A12}$$

With n large, under the assumption that there is a single-factor structure, simple cross-sectional averaging provides an estimate of $\boldsymbol{F}_t$ good enough to treat $\widehat{\boldsymbol{F}}_t$ as data in a regression without a generated regressor problem. With multiple factors, Stock and Watson (2002) show that a consistent estimate of $\boldsymbol{F}_t$ is obtained using principal components.

Our data set is standard in the recent literature on factor models (see Stock and Watson, 2012, and Forni and Gambetti, 2014). It contains an unbalanced panel of 150 quarterly series, with starting date 1947Q1 and end date 2012Q3. The data are grouped into 12 categories: NIPA variables (31); industrial production (16); employment and unemployment (14); housing starts (6); inventories, orders and sales (12); prices (15); earnings and productivity (13); interest rates (10); money and credit (12); stock prices (5); exchange rates (7); and other (9). Earnings and productivity data include TFP-adjusted measures of capacity utilization introduced by Basu, Fernald, and Kimball (2006). The category labeled "other" includes expectations variables.

The transformation implemented for the series to be stationary with zero mean are reported in Table A1. The factors were estimated using principal components as in Stock and Watson (2012). The assumption that the factors can be estimated with no breaks over the period 1947Q2-2012Q3 is motivated by the findings of Stock and Watson (2002), who show that the space spanned by the factors can be estimated consistently even if there is instability in $\mathbf{\Lambda}$.

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N	Series	Mnemonic	Tr.	Start	End
1	Real Gross Domestic Product, 1 Decimal	GDPC1	5	1947Q1	2012Q3
2	Real Gross National Product	GNPC96	5	1947Q1	2012Q3
3	Real National Income	NICUR/GDPDEF	5	1947Q1	2012Q3
4	Real Disposable Income	DPIC96	5	1947Q1	2012Q3
5	Real Personal Income	RPI	6	1959Q1	2012Q3
6	Nonfarm Business Sector: Output	OUTNFB	5	1947Q1	2012Q3
7	Real Final Sales of Domestic Product, 1 Decimal	FINSLC1	5	1947Q1	2012Q3
8	Real Private Fixed Investment, 1 Decimal	FPIC1	5	1995Q1	2012Q3
9	Real Private Residential Fixed Investment, 1 Decimal	PRFIC1	5	1995Q1	2012Q3
10	Real Private Nonresidential Fixed Investment, 1 Decimal	PNFIC1	5	1995Q1	2012Q3
11	Real Gross Private Domestic Investment, 1 Decimal	GPDIC1	5	1947Q1	2012Q3
12	Real Personal Consumption Expenditure	PCECC96	5	1947Q1	2012Q3
13	Real Personal Consumption Expenditure: Nondurable Goods	PCNDGC96	5	1995Q1	2012Q3
14	Real Personal Consumption Expenditure: Durable Goods	PCDGCC96	5	1995Q1	2012Q3
15	Real Personal Consumption Expenditure: Services	PCESVC96	5	1995Q1	2012Q3
16	Real Gross Private Saving	GPSAVE/GDPDEF	5	1947Q1	2012Q3
17	Real Federal Consumption Expenditures, Gross Investment, 1 Decimal	FGCEC1	5	1995Q1	2012Q3
18	Federal Goverment: Current Expenditures, Real	FGEXPND/GDPDEF	5	1947Q1	2012Q3
19	Federal Goverment: Current Receipts, Real	FGRECPT/GDPDEF	5	1947Q1	2012Q3
20	Net Federal Government Saving	FGDEF	2	1947Q1	2012Q3
21	Government Current Expenditures/GDP Deflator	GEXPND/GDPDEF	5	1947Q1	2012Q3
22	Government Current Receipts/GDP Deflator	GRECPT/GDPDEF	5	1947Q1	2012Q3
23	Government Real Expenditures minus Real Receipts	GDEF	2	1947Q1	2012Q3
24	Real Government Consumption Expenditures, Gross Investment, 1 Decimal	GCEC1	5	1947Q1	2012Q3
25	Real Change in Private Inventories, 1 Decimal	CBIC1	1	1947Q1	2012Q3
26	Real Exports of Goods and Services, 1 Decimal	EXPGSC1	5	1947Q1	2012Q3
27	Real Imports of Goods and Services, 1 Decimal	IMPGSC1	5	1947Q1	2012Q3
28	Corporate Profits After Tax, Real	CP/GDPDEF	5	1947Q1	2012Q3
29	Nonfinancial Corporate Business: Profits After Tax, Real	NFCPATAX/GDPDEF	5	1947Q1	2012Q3
30	Corporate Net Cash Flow, Real	CNCF/GDPDEF	5	1947Q1	2012Q3
31	Net Corporate Dividends, Real	DIVIDEND/GDPDEF	5	1947Q1	2012Q3
32	Industrial Production Index	INDPRO	5	1947Q1	2012Q3
33	Industrial Production: Business Equipment	IPBUSEQ	5	1947Q1	2012Q3
34	Industrial Production: Consumer Goods	IPCONGD	5	1947Q1	2012Q3
35	Industrial Production: Durable Consumer Goods	IPDCONGD	5	1947Q1	2012Q3
36	Industrial Production: Final Products (Market Group)	IPFINAL	5	1947Q1	2012Q3
37	Industrial Production: Materials	IPMAT	5	1947Q1	2012Q3
38	Industrial Production: Nondurable Consumer Goods	IPNCONGD	5	1947Q1	2012Q3
39	Capacity Utilization: Manufacturing	MCUMFN	4	1972Q1	2012Q3
40	Industrial Production: Manufacturing	IPMAN	5	1972Q1	2012Q3
41	Industrial Production: Durable Manufacturing	IPDMAN	5	1972Q1	2012Q3
42	Industrial Production: Mining	IPMINE	5	1972Q1	2012Q3
43	Industrial Production: Nondurable Manufacturing	IPNMAN	5	1972Q1	2012Q3
44	Industrial Production: Durable Materials	IPDMAT	5	1947Q1	2012Q3
45	Industrial Production: Electric and Gas Utilities	IPUTIL	5	1972Q1	2012Q3
46	ISM Manufacturing: PMI Composite Index	NAPM	1	1948Q1	2012Q3
47	ISM Manufacturing: Production Index	NAPMPI	1	1948Q1	2012Q3
48	Average Weekly Hours of Production and Nonsupervisory Employees: Manuf.	AWHMAN	1	1948Q1	2012Q3
49	Average Weekly Overtime Hours of Prod. and Nonsupervisory Employees: Manuf.	AWOTMAN	2	1948Q1	2012Q3
50	Civilian Labor Force Participation Rate	CIVPART	2	1948Q1	2012Q3

Table A1. Time series employed for the computation of the factors. Description of the Table in two pages.

N	Series	Mnemonic	Tr.	Start	End
51	Civilian Labor Force	CLF160V	5	1948Q1	2012Q3
52	Civilian Employment	CE160V	5	1948Q1	2012Q3
53	All Employees: Total Private Industries	USPRIV	5	1947Q1	2012Q3
54	All Employees: Goods-Producing Industries	USGOOD	5	1947Q1	2012Q3
55	All Employees: Service-Providing Industries	SRVPRD	5	1947Q1	2012Q3
56	Unemployed	UNEMPLOY	5	1948Q1	2012Q3
57	Average (Mean) Duration of Unemployment	UEMPMEAN	2	1948Q1	2012Q3
58	Civilian Unemployment Rate	UNRATE	2	1948Q1	2012Q3
59	Index of Help-Wanted Advertising in Newspapers	A0M046	1	1959Q1	2012Q3
60	HOANBS/CNP160V	HOANBS/CNP160V	4	1948Q1	2012Q3
61	Initial Claims	ICSA	5	1967Q3	2012Q3
62	Housing Starts: Total: New Privately Owned Units Started	HOUST	5	1959Q1	2012Q3
63	Housing Starts in Northeast Census Region	HOUSTNE	5	1959Q1	2012Q3
64	Housing Starts in Midwest Census Region	HOUSTMW	5	1959Q1	2012Q3
65	Housing Starts in South Census Region	HOUSTS	5	1959Q1	2012Q3
66	Housing Starts in West Census Region	HOUSTW	5	1959Q1	2012Q3
67	New Private Housing Units Authorized by Building Permits	PERMIT	5	1960Q1	2012Q3
68	US Manufacturers New Orders for Non Defense Capital Goods	USNOIDN.D	5	1959Q2	2012Q3
69	US New Orders of Consumer Goods and Materials	USCNORCGD	5	1959Q2	2012Q3
70	US ISM Manufacturers Survey: New Orders Index SADJ	USNAPMNO	1	1950Q2	2012Q3
71	Retail Sales: Total (Excluding Food Services)	RSXFS	5	1992Q1	2012Q3
72	Value of Manufacturers' Total Inventories for All Manufacturing Industries	UMTMTI	5	1992Q1	2012Q3
73	Value of Manufacturers' Total Inventories for Durable Goods	AMDMTI	5	1992Q1	2012Q3
74	Value of Manufacturers' Total Inventories for Nondurable Goods Industries	AMNMTI	5	1992Q1	2012Q3
75	ISM Manufacturing: Inventories Index	NAPMII	1	1948Q1	2012Q3
76	ISM Manufacturing: New Orders Index	NAPMNOI	1	1948Q1	2012Q3
77	Value of Manufacturers' New Orders for Cons. Goods: Cons. Dur. Goods Ind.s	ACDGNO	5	1992Q1	2012Q3
78	Manuf.s' New Orders: Durable Goods	DGORDER	5	1992Q1	2012Q3
79	Value of Manuf.s' New Orders for Dur. Goods Ind.: Transp. Equipment	ANAPNO	5	1992Q1	2012Q3
80	Gross Domestic Product: Chain-type Price Index	GDPCTPI	5	1947Q1	2012Q3
81	Gross National Product: Chain-type Price Index	GNPCTPI	5	1947Q1	2012Q3
82	Gross Domestic Product: Implicit Price Deflator	GDPDEF	5	1947Q1	2012Q3
83	Gross National Product: Implicit Price Deflator	GNPDEF	5	1947Q1	2012Q3
84	Consumer Price Index for All Urban Consumers: All Items	CPIAUCSL	6	1947Q1	2012Q3
85	Consumer Price Index for All Urban Consumers: All Items Less Food	CPIULFSL	6	1947Q1	2012Q3
86	Consumer Price Index for All Urban Consumers: All Items Less Energy	CPILEGSL	6	1957Q1	2012Q3
87	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy	CPILFESL	6	1957Q1	2012Q3
88	Consumer Price Index for All Urban Consumers: Energy	CPIENGSL	6	1947Q1	2012Q3
89	Consumer Price Index for All Urban Consumers: Food	CPIUFDSL	6	1947Q1	2012Q3
90	Producer Price Index: Finished Goods: Capital Equipment	PPICPE	6	1947Q1	2012Q3
91	Producer Price Index: Crude Materials for Further Processing	PPICRM	6	1947Q1	2012Q3
92	Producer Price Index: Finished Consumer Goods	PPIFCG	6	1947Q1	2012Q3
93	Producer Price Index: Finished Goods	PPIFGS	6	1947Q1	2012Q3
94	Spot Oil Price: West Texas Intermediate	OILPRICE	6	1947Q1	2012Q3
95	Nonfarm Business Sector: Hours of All Persons	HOANBS	5	1947Q1	2012Q3
96	Nonfarm Business Secotr: Output Per Hour of All Persons	OPHNFB	5	1947Q1	2012Q3
97	Nonfarm Business Sector: Unit Nonlabor Payments	UNLPNBS	5	1947Q1	2012Q3
98	Nonfarm Business Sector: Unit Labor Cost	ULCNFB	5	1947Q1	2012Q3
99	Compensation of Employees: Wages and Salary Accruals, Real	WASCUR/CPI	5	1947Q1	2012Q3
100	Nonfarm Business Sector: Compensation Per Hour	COMPNFB	5	1947Q1	2012Q3

Table A1 (continued). Time series employed for the computation of the factors. Description of the Table in the following page.

N	Series	Mnemonic	Tr.	Start	End
101	Nonfarm Business Sector: Real Compensation Per Hour	COMPRNFB	5	1947Q1	2012Q3
102	Growth in utilization-adjusted TFP	dtfp_util	1	1947Q2	2012Q3
103	Growth in business sector TFP	dtfp	1	1947Q2	2012Q3
104	Utilization in producing investment	du_invest	1	1947Q2	2012Q3
105	Utilization in producing non-investment business output	du_consumption	1	1947Q2	2012Q3
106	Utilization-adjusted TFP in producing equipment and consumer durables	dtfp_I_util	1	1947Q2	2012Q3
107	Utilization-adjusted TFP in producing non-equipment output	dtfp_C_util	1	1947Q2	2012Q3
108	Effective Federal Funds Rate	FEDFUNDS	2	1954Q3	2012Q3
109	3-Month Treasury Bill: Secondary Market Rate	TB3MS	2	1947Q1	2012Q3
110	1-Year Treasury Constant Maturity Rate	GS1	2	1953Q2	2012Q3
111	10-Year Treasury Constant Maturity Rate	GS10	2	1953Q2	2012Q3
112	Moody's Seasoned Aaa Corporate Bond Yield	AAA	2	1947Q1	2012Q3
113	Moody's Seasoned Baa Corporate Bond Yield	BAA	2	1947Q1	2012Q3
114	Bank Prime Loan Rate	MPRIME	2	1949Q1	2012Q3
115	GS10-FEDFUNDS Spread	GS10-FEDFUNDS	1	1954Q3	2012Q3
116	GS1-FEDFUNDS Spread	GS1-FEDFUNDS	1	1954Q3	2012Q3
117	BAA-FEDFUNDS Spread	BAA-FEDFUNDS	1	1954Q3	2012Q3
118	Non-Borrowed Reserves of Depository Institutions	BOGNONBR	5	1959Q1	2012Q3
119	Board of Gov. Total Reserves, Adjusted for Changes in Reserve Requirements	TRARR	5	1959Q1	2012Q3
120	Board of Gov. Monetary Base, Adjusted for Changes in Reserve Requirements	BOGAMBSL	5	1959Q1	2012Q3
121	M1 Money Stock	M1SL	5	1959Q1	2012Q3
122	M2 Less Small Time Deposits	M2MSL	5	1959Q1	2012Q3
123	M2 Money Stock	M2SL	5	1959Q1	2012Q3
124	Commercial and Industrial Loans at All Commercial Banks	BUSLOANS	5	1947Q1	2012Q3
125	Consumer Loans at All Commercial Banks	CONSUMER	5	1947Q1	2012Q3
126	Bank Credit at All Commercial Banks	LOANINV	5	1947Q1	2012Q3
127	Real Estate Loans at All Commercial Banks	REALLN	5	1947Q1	2012Q3
128	Total Consumer Credit Owned and Securitized, Outstanding	TOTALSL	5	1947Q1	2012Q3
129	St. Louis Adjusted Monetary Base	AMBSL (CHNG)	5	1947Q1	2012Q3
130	US Dow Jones Industrials Share Price Index (EP)	USSHRPRCF	5	1950Q2	2012Q3
131	US Standard & Poor's Index of 500 Common Stocks	US500STK	5	1950Q2	2012Q3
132	US Share Price Index NADJ	USI62...F	5	1957Q2	2012Q3
133	Dow Jones/GDP Deflator	DOW Jones/GDPDEF	5	1950Q2	2012Q3
134	S&P/GDP Deflator	S&P/GDPDEF	5	1950Q2	2012Q3
135	Trade Weighted U.S. Dollar Index: Major Currencies	TWEXMMTH	2	1973Q1	2012Q3
136	Euro/U.S. Foreign Exchange Rate	EXUSEU(-1)	5	1999Q1	2012Q3
137	Germany/U.S. Foreign Exchange Rate	EXGEUS	5	1971Q1	2001Q4
138	Switzerland/U.S. Foreign Exchange Rate	EXSZUS	5	1971Q1	2012Q3
139	Japan/U.S. Foreign Exchange Rate	EXJPUS	5	1971Q1	2012Q3
140	U.K./U.S. Foreign Exchange Rate	EXUSUK(-1)	5	1971Q1	2012Q3
141	Canada/U.S. Foreign Exchange Rate	EXCAUS	5	1971Q1	2012Q3
142	US The Conference Board Leading Economic Indicators Index SADJ	USCYLEADQ	5	1959Q1	2012Q3
143	US Economic Cycle Research Institute Weekly Leading Index	USECRIWLH	5	1950Q2	2012Q3
144	University of Michigan Consumer Sentiment: Personal Finances, Current	USUMPFNCH	2	1978Q1	2012Q3
145	University of Michigan Consumer Sentiment: Personal Finances, Expected	USUMPFNEH	2	1978Q1	2012Q3
146	University of Michigan Consumer Sentiment: Economic Outlook, 12 Months	USUMECO1H	2	1978Q1	2012Q3
147	University of Michigan Consumer Sentiment: Economic Outlook, 5 Years	USUMECO5H	2	1978Q1	2012Q3
148	University of Michigan Consumer Sentiment: Buying Conditions, Durables	USUMBUYDH	2	1978Q1	2012Q3
149	University of Michigan Consumer Sentiment Index	USUMCONSH	2	1991Q1	2012Q3
150	University of Michigan Consumer Sentiment - Current Conditions	USUMCNSUR	2	1991Q1	2012Q3

Table A1 (continued). **Time series employed for the computation of the factors**. Classification of the series: 1-31: "NIPA"; 32-47: "Industrial Production"; 48-61: "Employment and Unemployment"; 62-67: "Housing Starts"; 68-79: "Inventories", "Orders and Sales"; 80-94: "Prices"; 95-107: "Earnings and Productivity"; 108-117: "Interest Rates"; 118-129: "Money and Credit"; 130-134: "Stock Prices"; 135-141: "Exchange Rates"; 142-150: "Others". The column labeled "Tr." indicates the transformation applied to the series (1 = level, 2 = first difference, 3 = logarithm, 4 = second difference, 5 = first difference of logarithm, 6 = second difference of logarithm). Data source: Federal Reserve Bank of St. Louis' website.