

A New Identification of Fiscal Shocks Based on the Information Flow

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Abstract

Can discretionary increases in government spending stimulate the economy? We answer this question by taking into account both the information flow on fiscal measures and the role played by information frictions. Using a novel set of empirical proxies for fiscal news and agents' misperceptions, our approach identifies three types of innovations to government spending that modify the agents' information set at different horizons: *before*, *upon* and *after* the actual change materialises. Borrowing from the psychological literature, we name them *expected*, *unexpected* and *misexpected* fiscal changes. By missing this important distinction, we show that standard identification strategies blend unexpected and misexpected changes in a way that leads to significant underestimation of the effects of fiscal policy. An application to US data reveals that once information rigidities are fully accounted for, *expected* fiscal changes stimulate economic activity and private investments with a cumulative output multiplier around 1.5.

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If you have time to anticipate an event and do so correctly, then you cannot be surprised. [...] Surprise is triggered both by the unexpected and by what might be called the “misexpected” event. An unusual event which was unanticipated [...] is called unexpected rather than misexpected because at that moment the surprised person was not expecting anything in particular to happen. [...] The event is a misexpected surprise [if] there was an aroused specific anticipation for something different to happen at that moment.

“Unmasking the Face” – Ekman and Friesen (1975)

Introduction

This paper argues that the macroeconomic effects of discretionary changes to fiscal spending can be successfully studied by correctly accounting for both the *anticipation effects* elicited by fiscal announcement of future policy changes, and the *imperfect information* on which agents base their decisions in the setup of the econometric model of choice. While the anticipation issue has been correctly recognised in the macroeconomic fiscal literature, the informational problem has been largely overlooked.

The distinctive feature of our empirical approach is to recognise that the presence of information frictions crucially modify the agents’ decision problem. This has relevant consequences for the econometric identification problem of fiscal shocks. Building on ideas generated from models incorporating deviations from full information rational expectations (e.g., Woodford (2001), Mankiw and Reis (2002), and Sims (2003)), we propose a novel empirical methodology to study the effect of fiscal announcements and fiscal shocks that accounts for both *anticipation effects* and *imperfect information*.¹

In doing this, we shed light on a more general identification problem by making a methodological observation and arguing that econometric approaches that do not account for information frictions and are based on intuitions stemming from models of *perfect information rational expectations* may fail to correctly identify fiscal shocks. In fact, the presence imperfect information can modify the identification problem along four interrelated dimensions.

First, in full information rational expectations models agents immediately process the new information. On the contrary, in the case of imperfect information, the new information is only partially absorbed over time and, therefore, average forecast errors are likely to be a combination of both current and past structural shocks. This implies that forecast errors cannot be thought of as being *per se* a good proxy for structural innovations. On the other hand, conditional on the past information set, the revision of expectations are informative about structural innovations.

¹In delayed-information models as in Mankiw and Reis (2002) and Reis (2006a,b), agents update their information set infrequently but arrive at perfect information once they do. In noisy-information models, as in Woodford (2001), Sims (2003) and Mackowiak and Wiederholt (2009), agents continuously update their information but observe only noisy signals about the true state. These models have been successful towards explaining empirical regularities that are challenging for the standard framework. Empirical evidence of informational rigidities that can be explained by these models of imperfect information has been reported in Coibion and Gorodnichenko (2010, 2012) and in Andrade and Le Bihan (2013).

Second, with full information, agents can make forecast errors but are aware of shocks when realised. In other words, their expectations about the current state of the economy (their *nowcasts*) are correct. On the contrary, in the presence of information frictions, agents do not know the current state of the economy and can make nowcast errors. These *misperceptions* – i.e., the differences between the agents’ expectations about the current state of the economy and the ex-post revealed value of macroeconomic variables - may contain information about structural shocks that are not correctly identified by the agents on impact.

Third, in the presence of informational frictions and heterogeneous beliefs, in order to correctly identify innovations, *the econometric information set has to exceed* the information set of the agents. This is in contrast with the standard tenet of rational expectation econometrics that *the econometric information set has to be aligned* with that of the representative agent. The intuition for this is twofold. Firstly, when agents are unable to correctly identify structural shocks in real time, then the econometrician, faced with the same data as the agents, may not be able to correctly identify shocks either (see also Blanchard et al. (2013)).² Secondly, crucially, when agents have different information sets, the notion of the representative agent may be misleading.

Finally, the presence of *heterogeneous expectations* is a challenge to the necessary aggregation that is performed in reduced form models. In fact, when the agents entertain different beliefs due to differences in their information sets, subtle issues of aggregation may arise and caution is necessary in order to avoid *aggregation bias*.

We apply these ideas to the identifications of fiscal shocks. Carefully avoiding aggregation bias using *individual* US Survey of Professional Forecasters (SPF) data, we disentangle the expectation revisions (*news*) on spending in current and future quarters, as perceived by agents, from the nowcast errors, a reduced form measure of agents’ *misperceptions* about fiscal changes.³ We employ our observables proxying for news and misperceptions with large information techniques and apply a recursive identification that generalises the methodology proposed in Ramey (2011), in line with the lessons drawn from models of imperfect information.

Our novel method identifies three orthogonal fiscal shocks that, borrowing from the psychological literature, we name *expected*, *unexpected* and *misperceived fiscal changes* (see the above quotation from Ekman and Friesen (1975)). More specifically, we label changes that are anticipated to happen by agents as *expected fiscal changes*. We identify these shocks using news on spending in future quarters. We label changes to government spending that have not been anticipated but that are perceived as changes to fiscal spending upon their realisation as *unexpected fiscal changes*. We identify these shocks using news on spending in the current quarter. Finally, we label fiscal changes that have not been anticipated and that are misperceived by agents when realised as *misperceived fiscal changes*, and identify these shocks using nowcast errors.

²In light of this observation, the idea of using real-time data to approximate the information flow received by the agents in studying fiscal shocks may be a fallacy.

³It seems important to notice that changes in expectations may not be necessarily related to changes in the realised time series. Indeed, we show that the proposed expectational measures match narrative records of the contemporaneous and foreseen fiscal events and are valid statistical instruments for fiscal changes.

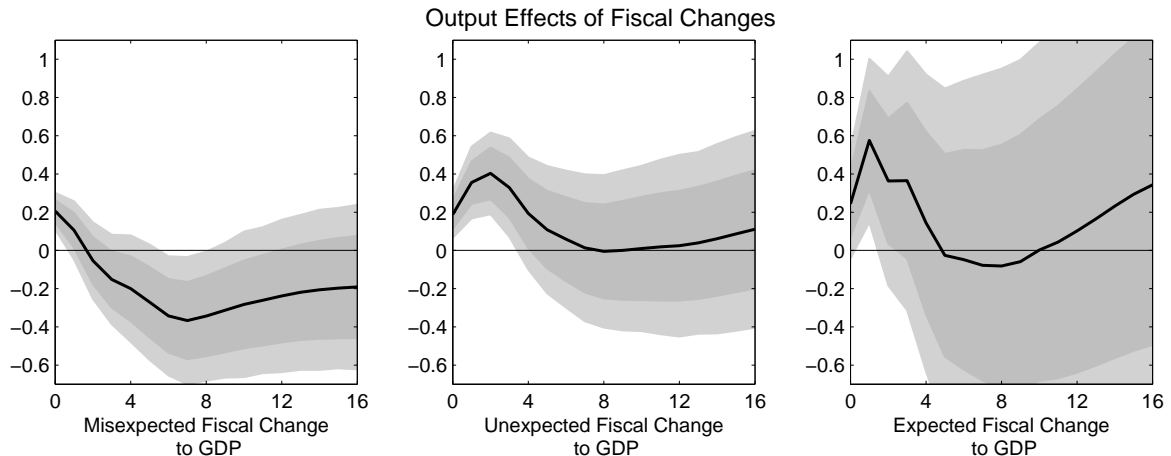


Figure 1: **Output Effects of Fiscal Shocks.** Shocks are normalised to produce a unitary cumulated increase in Federal Spending. Each chart shows shaded posterior coverage bands at the 90 and 68 percent level. The axes are equally scaled for comparison.

Empirical results indicate that the identification problems related to the presence of information frictions are of first order economic relevance. Unexpected and expected fiscal changes elicit large expansionary effects and increase prices (see Figure 1). These effects are driven by a rise in private investment and consumption, and are supported by optimism in consumer and CEO confidence. On the other hand, misexpected fiscal changes produce a transitory increase of output on impact and a subsequent contraction due to the crowding out of private consumption and investment. However, we argue that expected fiscal changes should be studied in order to learn about the effects of policy changes. In fact, fiscal measures – both stimulus and adjustment measures – are legislated measures enacted through fiscal plans that provide guidance to agents in forming expectations (as also observed in Alesina et al. (2012)). In this respect, empirical evidence based on the study of fiscal surprises may be misleading from a policy perspective.

This paper relates to the literature on foresight, news and anticipation in fiscal policy.⁴ However, in contrast to the existing literature, this paper emphasises the role of information frictions. We argue that the bulk of literature has identified combinations of the three shocks we identify, possibly misrepresenting their effects. In particular, we show that standard structural vector autoregressions (SVARs) do not distinguish between the three shocks (see, for example, Blanchard and Perotti (2002)). We also show that Expectational VARs (EVARs) employing identifications based on forecast errors are unable to separate unexpected and misexpected fiscal changes and miss the large effects of expected one (see, for example, Ramey (2011)). Finally, our study of news about future fiscal changes is related in spirit to Perotti (2011) and Forni and Gambetti (2014). Perotti (2011) was the first to propose the decomposition of the SPF one-step-

⁴Amongst others, important contributions are in Ramey (2011), Leeper et al. (2013), Leeper et al. (2012), Mertens and Ravn (2010), Mertens and Ravn (2012), Perotti (2011), Forni and Gambetti (2014) and Zeev and Pappa (2014).

ahead forecast error of government spending growth rate, used in Ramey (2011), into what he calls *time t surprise* (the nowcast error) and a *revision of expectations* from time $t - 1$ to time t . However, using aggregated SPF data, he concludes that “*government spending forecasts convey little information on future government spending, and so does their revision.*” In this paper, using individual SPF data, we overturn the conclusions in Perotti (2011) by showing that (1) forecast revisions are informative, can be interpreted as fiscal news, and are meaningful proxies for fiscal innovations; and (2) nowcast errors are difficult to interpret and produce puzzling responses. With respect to Forni and Gambetti (2014), we show that their measure of news, ignoring the heterogenous beliefs of the agents, contains aggregation bias. We also use a different identification based on ideas coming from models of imperfect information and argue that to correctly identify the effects of expected fiscal changes it is necessary to control for the other two types of fiscal changes.

The paper is organised as follow. Section 1 lays out the basic intuition underpinning our empirical identification of fiscal shocks. Section 2 introduces new measures of the information flow on federal government spending received by the agents, based on SPF data and discusses their properties. Section 3 presents the large information econometric model. Results appear in Sections 4. Section 5 discusses the findings and Section 6 concludes.

1 The Fiscal Policy Information Flow

In order to identify fiscal shocks, the econometrician has to empirically distinguish movements in the policy variables generated by deliberate policy measures from both (i) endogenous responses to development in the economy, and (ii) from random fluctuations in the timing of budgeted expenditures across the fiscal year. Furthermore, an additional challenge is to isolate the components of fiscal policy intervention that are not anticipated by the agents (Sims (1988)).

A set of assumptions supports the classical identification of fiscal shocks. The most crucial one, underlying Blanchard and Perotti (2002)’s influential paper, and common to a large number of studies in the structural vector autoregression literature, is that the innovations recovered by a vector autoregression with fiscal variables can be interpreted in terms of random shocks to the agents’ information set due to unexpected fiscal policy innovations and other structural shocks. This assumption can be justified either in a classic Keynesian setting in which agents are backward-looking or by postulating that little information on future fiscal spending is available.

By supplementing this assumption with some identifying restrictions, for example, that discretionary policy does not respond to output within the quarter, it is possible to make structural inferences about the causal effects of unexpected increases in government spending on the economy. From a policy perspective, these causal links are informative under the conditions that the economy responds in the same way to unexpected and announced policy changes and that fiscal multipliers are relatively constant over the

business cycle.⁵

Against these assumptions, and moving from a full information rational expectations framework, Ramey (2011) has argued that the government spending innovations recovered by a vector autoregression are likely to have been anticipated by agents. Economic agents receive a constant flow of information about future changes in fiscal policy, informed by the institutional process through which they are implemented (see Leeper et al. (2013)). In particular, changes in fiscal policy occur after two lags: the first between the initial proposal of a new fiscal measure and its approval (inside lag), and the second between the enactment of the legislation and its actual implementation (outside lag).

In a full information rational expectation world, forward-looking economic agents react to announcements of policy changes occurring in future periods, while standard macroeconomic time series, used in econometric analysis, record the innovation produced in fiscal variables by the lagged implementation of the new policy. The potential misalignment between the agents' and the econometrician's information set makes structural inference problematic. This phenomenon, known as *fiscal foresight*, implies that innovations to fiscal variables recovered by a vector autoregression (VAR) are combinations of anticipated and unanticipated changes (see Leeper et al. (2011)).

Therefore, empirical models that do not account for agents' expectations are severely misspecified. In fact, the true shock – the news related to announced fiscal changes entering the agents' information set – cannot be easily related to the current realisations of the economic variables.⁶ In order to draw correct inference, the econometrician has to align her/his information set to the agents', augmenting the econometric model with expectational series proxying for representative agents' beliefs. As a solution, Ramey (2011) proposes augmenting the VAR specification with variables that can proxy for agents' forecast errors or for expectations about the present value of future government spending. These models are known as Expectational VAR (EVAR).

However, differently from what is assumed in standard macroeconomic models, agents in the economy do not directly observe structural shocks and may have information limitations. What real world agents may observe – when attentive – are past realisations, subject to measurement errors, and signals about the present and future realisations of macroeconomic variables that can be conveyed either by prices or by the

⁵Given the extraordinary relevance of the fiscal policy debate in economic downturns, the key question is whether fiscal spending can provide effective stimulus to the economy in a recession. Despite the strong demand by policy makers, there is still only a handful of papers trying to assess how the effects of fiscal shocks vary in recession (i.e., Auerbach and Gorodnichenko (2012b,a), Fazzari et al. (2012), Owyang et al. (2013) and Gordon and Krenn (2010)). This work is not contributing to this important debate, however an application of the news variables proposed in this paper to the study cyclical variations in fiscal spending multipliers is in Caggiano (2014).

⁶In a dynamic stochastic general equilibrium (DSGE) model, fiscal foresight can produce a non-invertible moving-average (MA) component into the equilibrium process. If this is the case, there cannot be a standard VAR representation of the stochastic process, that is, a representation of the economic variables in terms of their current and past values. Structural shocks are said to be *non-fundamental* for the VAR specification (Hansen and Sargent (1980), Lippi and Reichlin (1993)). Blaschke transformations are needed to map recovered innovations into linear combinations of past and future structural shocks, allowing a non-fundamental MA representation to be mapped into a fundamental one, as discussed in Lippi and Reichlin (1994).

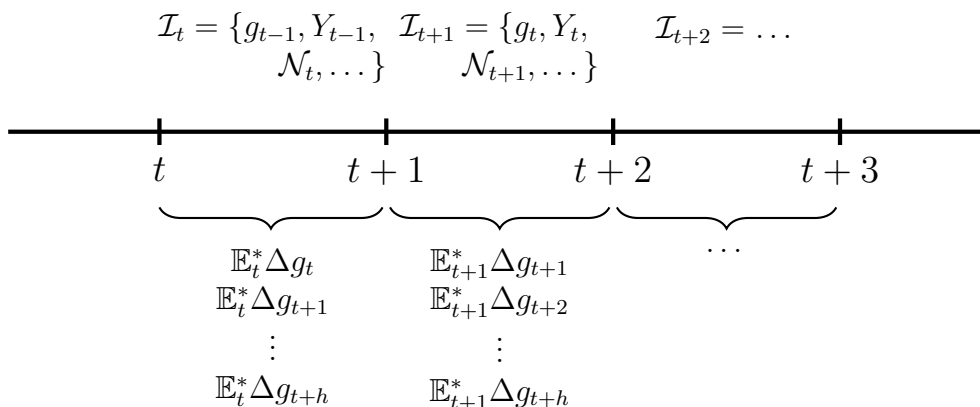


Figure 2: The information flow. At time t , agents in the economy form expectations about government spending in future periods possibly after observing past realisations of government spending g_{t-1} , past realisations of macroeconomic variables Y_{t-1} , as well as fiscal news \mathcal{N}_t , and signals about the present and future realisations of macroeconomic variables. More precisely, agents observe the most recent vintage of the real time data on past government spending $\{\dots, g_{t-2}^t, g_{t-1}^t\}$, and macroeconomic variables $\{\dots, Y_{t-2}^t, Y_{t-1}^t\}$. We drop this real-time notation for sake of simplicity.

flow of news and information in the economy. Also, as discussed in the political economy literature, the presence of bias and strategic behaviour by policy makers may distort the information content of fiscal plans (e.g., Beetsma et al. (2009), Frankel (2011), Frankel and Schreger (2012), Merola and Pèrez (2012)).⁷

Hence, agents may have to solve a complex problem of *optimal information acquisition/signal extraction* by combining different sources of signals and using tentative economic models. This is in order to infer the correct timing and fiscal weight of legislated measures and other exogenous shocks affecting the economy and the government budget. The large number of fiscal instruments and their potentially heterogenous effects on the economy make the forecasting problem a challenging task for the agents. While the fiscal foresight issue has been correctly recognised in the macroeconomic fiscal literature, both in the theoretical models and in the empirical analysis, the informational problem has been largely overlooked.

Theories incorporating deviations from perfect information have provided frameworks to understand empirical regularities that are challenging for the perfect information framework as sluggish price adjustment (Mankiw and Reis (2002), Mackowiak and Wiederholt (2009)), non-fundamental driven business cycle fluctuations (Barsky and Sims (2012), Blanchard et al. (2013), Lorenzoni (2009), Leduc and Sill (2010), Schmitt-Grohe and Uribe (2008), Jaimovich and Rebelo (2009))), booms and busts in asset

⁷Highlighting the difficulty of the signal extraction problem, Ramey (2011), in discussing the construction of the narrative military news variable, observes that ‘[...] For the most part, government sources could not be used because they were either not released in a timely manner or were known to underestimate the costs of certain actions. However, when periodical sources were ambiguous, I consulted official sources, such as the budget.’

prices (Scheinkman and Xiong (2003), Burnside et al. (2011)). However, how to model the process of expectation formation is still an open problem.

Two general classes of models have proven to be successful in accounting for a vast range of stylised facts: the delayed-information models as in Mankiw and Reis (2002), and the noisy-information models such as in Woodford (2001), Sims (2003), and Mackowiak and Wiederholt (2009). In the delayed-information model agents update their information sets infrequently, possibly as a result of fixed costs to the acquisition of information (see Reis (2006a,b)). The degree of information rigidity is given by the probability of not acquiring new information in each period. On the other hand, in the noisy-information models, agents continuously update their information sets but, because they can never fully observe the true state, they form and update beliefs about the underlying fundamentals via a signal extraction problem. Forecasts are a weighted average of agents' prior beliefs and the new information received. The weight on prior beliefs can be interpreted as the degree of information rigidity.

As observed in Coibion and Gorodnichenko (2010), a common prediction of these models is that average expectations respond more gradually to a shock to fundamentals than the variable being forecasted. The average forecast errors are therefore combinations of current and past shocks, due to the partial absorption of the information in the economy. This is in direct contrast to the prediction of full information rational expectations models in which agents would immediately process the new information. In these models of imperfect information, the average *ex-post* forecast errors across agents and the average *ex-ante* forecast revisions are related by the following expression:

$$\underbrace{x_t - \mathbb{E}_{t-h}^* x_t}_{\text{forecast error}} = \frac{1 - \kappa}{\kappa} \underbrace{(\mathbb{E}_{t-h}^* x_t - \mathbb{E}_{t-h-1}^* x_t)}_{\text{forecast revision (news)}} + u_{t-h+1} + \dots + u_t, \quad (1)$$

where x_t is the forecast variable, κ is the parameter of information rigidity ($\kappa = 1$ in the case of full information), $\mathbb{E}_{t-h}^* x_t$ is the average forecast at time $t-h$, and $u_{t-h+1} + \dots + u_t$ is the sum of rational expectations errors from time $t-h$ to time t . In these models, forecast and nowcast errors are predictable and are due to both the imperfectly updated agent's information sets and the shocks hitting the economy after the forecast has been made. Through the lenses of imperfect information models, conditional on the past information set, the revision of expectations are informative about policy innovations – i.e. can be thought of as news –, while the nowcast errors can be thought of as proxies for misexpectations. In fact, from Equation (1) one readily obtains:

$$\underbrace{(\mathbb{E}_{t-h}^* x_t - \mathbb{E}_{t-h-1}^* x_t)}_{\text{news at t-h}} = (1 - \kappa) \underbrace{(\mathbb{E}_{t-h-1}^* x_t - \mathbb{E}_{t-h-2}^* x_t)}_{\text{news at t-h-1}} + \kappa u_{t-h}. \quad (2)$$

Furthermore, the forecast and the nowcast errors are not good proxies for structural shocks *per se*, and do not contain additional information, conditional on past and current news. Lastly, in a yet more realistic scenario, misexpectations can also contain additional information about changes to government spending that agents are not able to process in real time.

Building on these ideas, coming from models of imperfect information, this paper is an attempt to quantitatively and qualitatively assess the balance between misperceptions

Table 1: Schematic representation of news and misexpectations to the agents' information set, \mathcal{I}_t .

	Unanticipated	Anticipated
Misperceived on impact	<i>Misexpected Fiscal Changes</i> $\notin \mathcal{I}_t$ \sim <i>proxy:</i> <i>nowcast error</i> $\Delta g_t - \mathbb{E}_t^* \Delta g_t$	
Perceived on impact	<i>Unexpected Fiscal Changes</i> $\in \mathcal{I}_t$ \sim <i>proxy:</i> <i>nowcast revision</i> $\mathbb{E}_t^* \Delta g_t - \mathbb{E}_{t-1}^* \Delta g_t$	<i>Expected Fiscal Changes</i> $\in \mathcal{I}_t$ \sim <i>proxy:</i> <i>forecast revision</i> $\mathbb{E}_t^* \Delta g_{t+h} - \mathbb{E}_{t-1}^* \Delta g_{t+h}$

and foresight of fiscal changes. In particular, we extract the from expectational series of the Survey of Professional Forecasters measures of news on spending in current and future quarters, as perceived by agents, and of nowcast errors.

The key observation is that the error in forecasting the government spending growth rate one period ahead can be decomposed as

$$\underbrace{\Delta g_t - \mathbb{E}_{t-1}^* \Delta g_t}_{\text{forecast error}} = \underbrace{(\Delta g_t - \mathbb{E}_t^* \Delta g_t)}_{\text{nowcast error}} + \underbrace{(\mathbb{E}_t^* \Delta g_t - \mathbb{E}_{t-1}^* \Delta g_t)}_{\text{nowcast revision (news)}}, \quad (3)$$

where Δg_t is the realised growth rate of government spending at t , and $\mathbb{E}_{t-h}^* \Delta g_t$ is the agent forecast at $t-h$, constructed under non necessarily rational expectations \mathbb{E}^* .⁸

More generally, following the flow of news updating the agents' information set \mathcal{I}_t over time (see Figure 2), we can decompose the forecast errors h periods ahead into the nowcast error and the flow of news (revisions) over time:

$$\underbrace{\Delta g_t - \mathbb{E}_{t-h}^* \Delta g_t}_{\substack{\text{forecast error} \\ h \text{ periods ahead}}} = \underbrace{(\Delta g_t - \mathbb{E}_t^* \Delta g_t)}_{\substack{\text{nowcast error} \\ \notin \mathcal{I}_t}} + \underbrace{(\mathbb{E}_t^* \Delta g_t - \mathbb{E}_{t-1}^* \Delta g_t)}_{\substack{\text{nowcast revision} \\ \text{(news at } t) \in \mathcal{I}_t}} + \dots \\ \dots + \underbrace{(\mathbb{E}_{t-h+1}^* \Delta g_t - \mathbb{E}_{t-h}^* \Delta g_t)}_{\substack{\text{forecast revision} \\ \text{(news at } t-h+1) \in \mathcal{I}_{t-h+1}}}. \quad (4)$$

We use these measures of news and nowcast errors as proxies for three types of fiscal shocks with different properties with respect to the information set of the agents (see Table 1). Paraphrasing the psychological research on emotions – see Ekman and Friesen

⁸A survey of the literature on the rationality of economic forecasters is in Pesaran and Weale (2006). Convincing empirical evidence of deviations from the full information rational expectations paradigm in the formation of expectations has been reported, among others, by Coibion and Gorodnichenko (2010, 2012) and Andrade and Le Bihan (2013).

(1975) – we may say that a realisation of an economic variable is a misexpected change for an economic agent if it mismatches a pre-existing, specific explicit belief of the agent, i.e., the *nowcast*. In contrast, the realisation is an unexpected change for the agent if it is detected by the agent to be inconsistent with his background beliefs and it triggers a revision of the agents’ expectations, i.e., the *forecasts*.

Hence, we call innovations in government spending (i) *expected fiscal changes* when anticipated by the economic agents, (ii) *unexpected fiscal changes* when unanticipated but perceived by the economic agents as changes to fiscal spending on impact, and (iii) *misexpected fiscal changes* when unanticipated and misperceived on their realisation.

With respect to the agents’ information set, the three shocks have very different properties. Expected and unexpected fiscal changes are related to news on current and future quarters that modify the agents’ information set *before* and *upon* their realisation, respectively. More precisely, while the unexpected fiscal changes trigger revisions of the expectations about the current quarter, i.e., of the *nowcast*, the expected fiscal changes are related to revisions of expectations about the future quarters, i.e., the *forecasts*. On the contrary, misexpected changes do not enter the information set of the agents upon their realisation but may be detected only *afterwards*, i.e., eventually modifying the *hindcast*.

While agents may learn about the realisation of misexpected changes only with delay, the news related to expected and unexpected changes modify the information set of the agents at the present. From a modelling perspective, expected and unexpected changes have properties that may recall innovations in a full information rational expectations model. In this framework, an increase in government spending lowers the present value of after-tax income, generating a negative wealth effect on labour supply and consumption. While unexpected fiscal changes can activate this channel on impact, misexpected ones cannot since they are unknown to the private sector upon realisation. Misexpectations can also only be generated in the presence of deviations from full information rational expectations that may influence the transmission channels of the shocks.

In light of the proposed classification, innovations recovered by the standard SVAR model are likely to be combinations of the three type of shocks. Further, as we will show in the next section, existing applications of Expectational VARs (EVARs) in the literature are likely to have identified combinations of either misexpected and unexpected surprise changes.

2 Empirical Measures of Expectations

In this section we build expectational measures that account for the information flow on federal government spending in the aggregate economy, using individual Survey of Professional Forecasters (SPF) data provided by the Federal Reserve Bank of Philadelphia. In particular, we propose new measures of the fiscal news and misexpectations that, by using individual forecasters’ data, have enhanced informational content. Ramey (2011), Perotti (2011) and Forni and Gambetti (2014) provide relevant contributions to the methodology used.

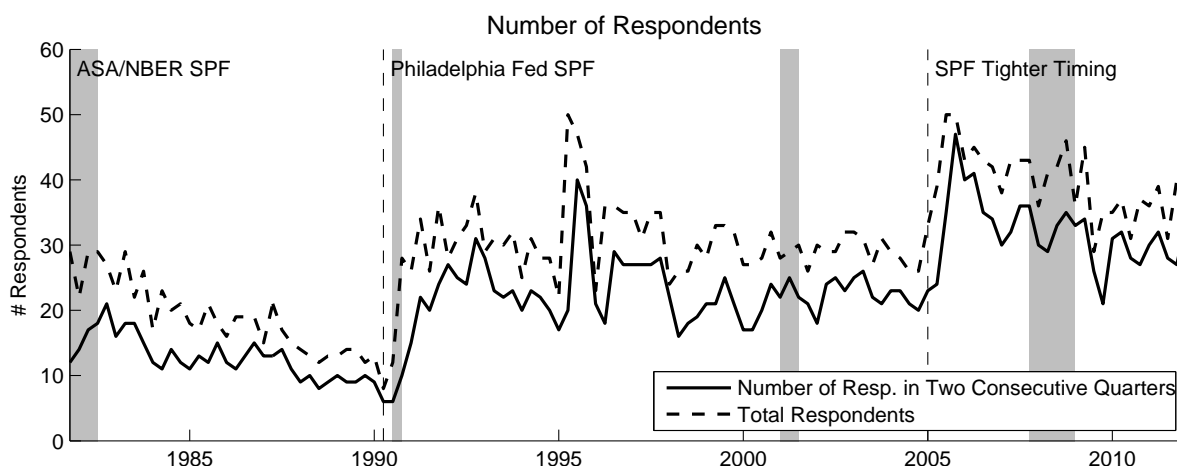


Figure 3: Number of Professional Forecasters per Quarter. The figure plots the number of respondents in the Survey of Professional Forecasters (dashed line) and of respondents in two consecutive quarters (solid line). Vertical dashed lines indicate changes in the Survey of Professional Forecasters methodology. Prior to 1990:Q2, the Survey was conducted by the ASA/NBER. Details of the timing of Survey in that period have not been reported. A minor change in the timing of the deadlines occurred as the survey of 2005:Q1, when the schedule of the survey was tightened. Grey shaded areas indicate the NBER business cycle contraction dates.

2.1 The Survey of Professional Forecasters

In the Philadelphia Fed survey, professional forecasters are asked to provide forecast values of a set of relevant macroeconomic variables for the present quarter and up to four quarters ahead. Because macroeconomic variables are released with a lag, SPF forecasters do not know the current value of macroeconomic variables.⁹ There are, on average, 29 professional forecast survey respondents per period – generally private firms –, 22 of which appear in consecutive periods (see Figure 3 for details). The Survey does not consistently report the number of experts involved in each forecast or the forecasting

⁹As reported in the SPF documentation notes: *The survey's timing is geared to the release of the Bureau of Economic Analysis' advance report of the national income and product accounts. This report is released at the end of the first month of each quarter. It contains the first estimate of GDP (and components) for the previous quarter. We send our survey questionnaires after this report is released to the public. Indeed, our survey questionnaires report recent historical values of the data from the BEA's advance report and the most recent reports of other government statistical agencies. Thus, in submitting their projections, our panelists' information sets include the data reported in the advance report. Our survey questionnaires are sent to the panelists on the day of the advance report. For the surveys we conducted after the 1990:Q2 survey, we have set the deadlines for responses at late in the second to third week of the middle month of each quarter.*

method used.¹⁰

For *real federal government consumption expenditures and gross investment*, the variable of interest for this work, individual responses have been collected from 1981Q3 to 2012Q4. As is customary, we convert level forecasts to forecast growth rates, due to the base year changing several times within the sample.

2.2 Misexpectations and News

Professional forecasters in the Survey disagree both in formulating and in updating baseline forecasts, possibly due to the use of different information sets and forecasting models.¹¹ Let $\mathbb{E}_t^{*i} \Delta g_{t+h}$ be the forecast value of real government spending growth from quarter $t+h-1$ to $t+h$, produced by the forecaster i , provided at time t . We define a measure of fiscal misexpectations at time t , for each forecaster, as the difference between Δg_t , the realised government spending growth rate from period $t-1$ to t , and her/his nowcast, $\mathbb{E}_t^{*i} \Delta g_t$ – i.e., the individual nowcast error.

A proxy for the misexpected changes in the aggregate economy is provided by a measure of the central tendency of the distribution of individual nowcast errors, e.g. the mean,

$$\mathcal{M}_t = \Delta g_t - \frac{1}{N_i} \sum_i \mathbb{E}_t^{*i} \Delta g_t, \quad (5)$$

or the median.

At each period t and for each forecast horizon h , the i -th individual forecaster's *forecast revision* is

$$\mathcal{N}^i(h) = \mathbb{E}_t^{*i} \Delta g_{t+h} - \mathbb{E}_{t-1}^{*i} \Delta g_{t+h}. \quad (6)$$

Employing individual forecaster's expectations revisions, we also define two measures of fiscal news in the aggregate economy related to the revision of expectations of the growth rate of the government spending in the current quarter:

$$\mathcal{N}_t(0) = \frac{1}{N_i} \sum_i \mathcal{N}_t^i(0) = \frac{1}{N_i} \sum_i (\mathbb{E}_t^{*i} \Delta g_t - \mathbb{E}_{t-1}^{*i} \Delta g_t), \quad (7)$$

and in the future q quarters:

$$\mathcal{N}_t(1, q) = \sum_{h=1}^q \mathcal{N}_t(h) = \sum_{h=1}^q \frac{1}{N_i} \sum_i \mathcal{N}_t^i(h) = \sum_{h=1}^q \frac{1}{N_i} \sum_i (\mathbb{E}_t^{*i} \Delta g_{t+h} - \mathbb{E}_{t-1}^{*i} \Delta g_{t+h}). \quad (8)$$

¹⁰In November 2009, the Real-Time Data Research Center of Philadelphia Fed conducted a special survey amongst forecasters to improve the quality and usefulness of the SPF. The survey revealed that almost all respondents in 2009 used a combination approach to forecasting: 20 of 25 respondents said they used a mathematical/computer model plus subjective adjustments to that model in reporting their projections. One respondent reported using pure model-generated forecasts, and four respondents said they used only their experience and intuition.

¹¹The disagreement can be rationalised by both delayed-information or noisy-information models of expectations, as discussed in Coibion and Gorodnichenko (2012) and in Andrade and Le Bihan (2013).

Table 2: **Nowcast Errors and News.** The table presents descriptive statistics for the SPF Real Federal Government Spending Expected Growth (%) implied misexpectations and news.

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

2.3 Empirical Measures of Misperceptions and News

Using the definitions proposed in equations (5), (7) and (8) with SPF data, we can compute empirical observables for \mathcal{M}_t , $\mathcal{N}_t(0)$ and $\mathcal{N}_t(1, 3)$.

Table 2 reports descriptive statistics for the SPF-implied fiscal misexpectations and news. Mean and median news and nowcast errors are reported as measures of the central tendency for the distribution of SPF individual forecasters data.¹² Table 2 also presents statistics for the second moments of the measures.

Figures 4 and 5 show the time series plot of these measures together with the Ramey-Shapiro war dates, presidential elections and some relevant fiscal and geopolitical events. Visually inspecting the charts and the statistics, it emerges that: (i) nowcast errors have larger variance than the news variables and seem to account for most of the movements in the government spending growth rate; (ii) mean and median measures are very closely related and show only minimal differences;¹³ (iii) while the movements of the nowcast errors are not always clearly related to fiscal events, peaks and troughs for the news series are related to important fiscal and geopolitical events, either coincidentally or lagging. For example, large spikes are related to the Gramm-Rudman Acts and the Reagan Tax Reforms, the I and II Gulf War, the War in Afghanistan as well as the 1995-1996 Federal Government Shutdown and the 2009 Stimulus.

Figure 6 displays the spectral densities for the government spending growth rate, and the SPF-implied measures of \mathcal{M}_t , $\mathcal{N}_t(0)$ and $\mathcal{N}_t(1, 3)$. A few features of these charts are noteworthy: (i) the realised government spending growth rate has a concentrated mass at low frequencies (i.e., the so called “typical spectral shape” of macroeconomic

¹²The statistics for these variables in periods of recession are in line with the full sample values.

¹³In all the subsequent analysis, charts and tables, we employ the median measures. The median is a robust statistic for the central tendency, while the mean is not.

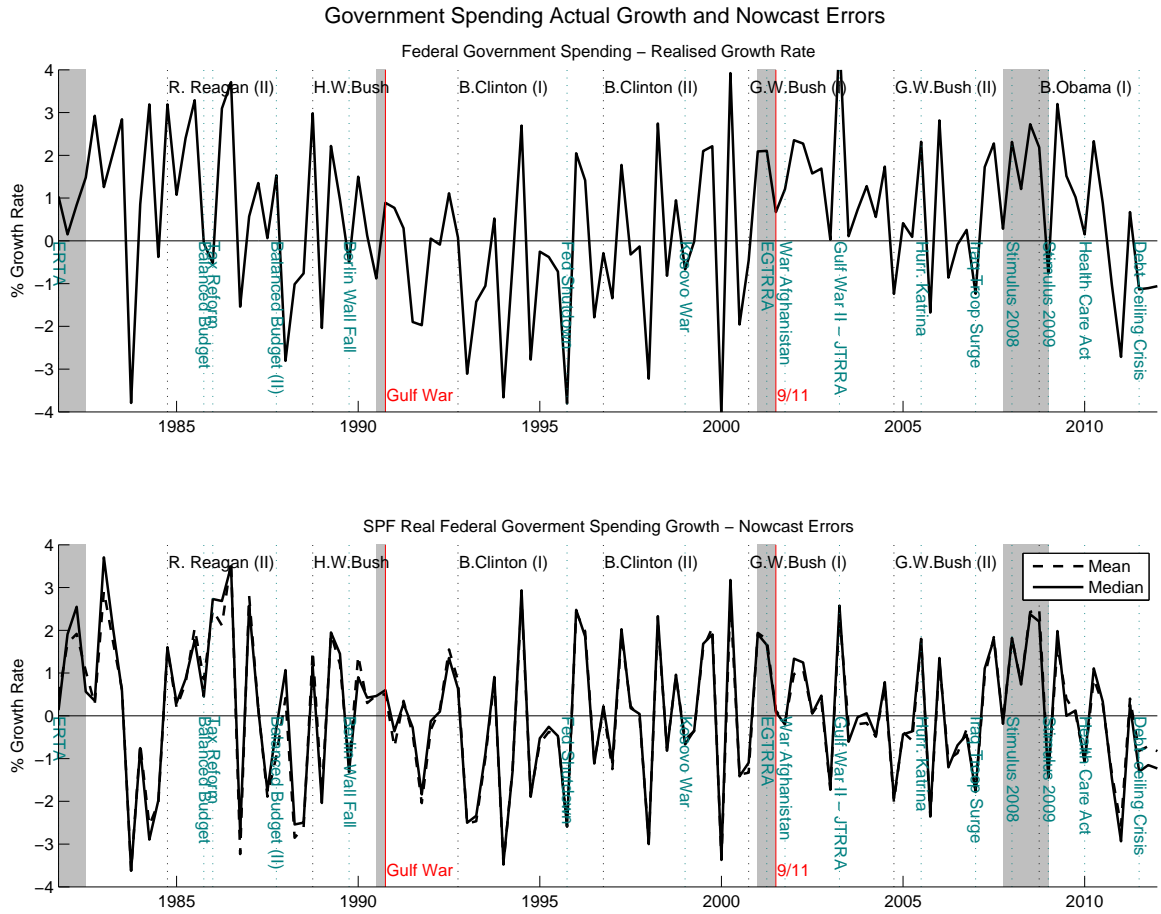


Figure 4: **Federal Government Spending – Realised Spending Growth and SPF-implied Nowcast Errors.** The figure plots the time series for real federal government spending growth and SPF-implied government spending nowcast errors. Grey shaded areas indicate the NBER business cycle contraction dates. Vertical lines indicate the dates of the announcement of important fiscal and geopolitical events (teal), presidential elections (black), and the Ramey-Shapiro war dates (red).

variable – e.g., Levy and Dezhbakhsh (2003)). This peak does not appear in the nowcast errors and news indicating that forecasters are able to correctly forecast slow moving components of spending. (ii) SPF-implied nowcast errors and news have small peaks at business cycle frequencies – possibly related to discretionary countercyclical measures. The news variable for the current quarter also peaks at yearly (seasonal) frequency. (iii) All four variables show some mass concentrated at high frequencies, possibly due to observational noise.

We formally assess the informational content of our variables by reporting F-statistics for the explanatory power of SPF-implied fiscal news in Table 3. To test the informativeness of our news measures, we regress the real federal government consumption growth rate on the first four lags of real federal government consumption, the average marginal tax rate, output, nonresidential fixed investment, nondurable consumption real

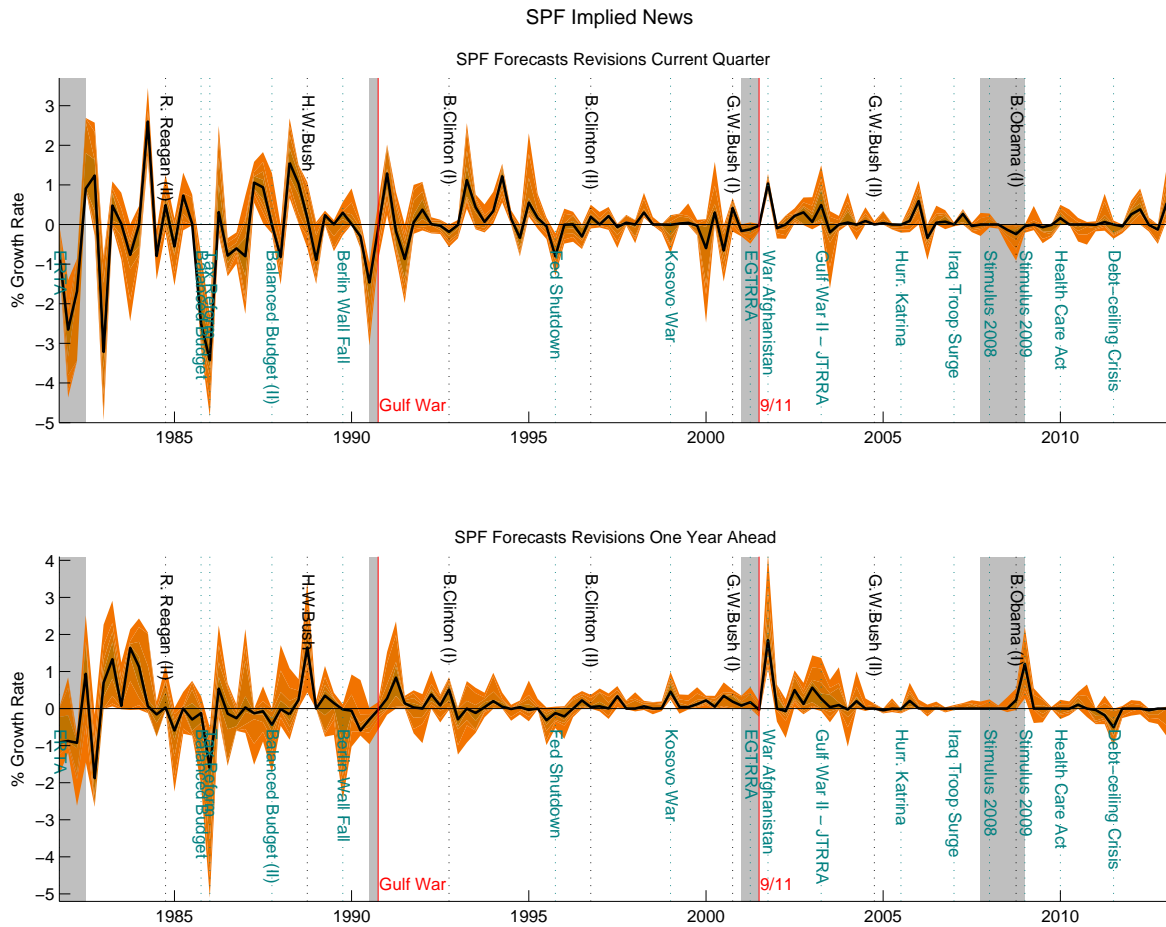


Figure 5: Government Spending News – Fan Chart. The figure plots the median implied SPF news on the current quarter and for future quarters, together with forecast disagreement up to one standard deviation. Grey shaded areas indicate the NBER Business Cycle contraction dates. Vertical lines indicate the dates of the announcement of important fiscal and geopolitical events (teal), presidential elections (black), and the Ramey-Shapiro war dates (red).

rates and on the current $\mathcal{N}(0)$ or the 4th lag of $\mathcal{N}(1, 3)$. The news variables provide information which is helpful in forecasting future and current government spending, even though the F statistics is below 10 and the SPF-implied news does not appear to be strong instruments.

The above results indicate that agents in the economy are able to predict slow moving components of government spending and are also able to incorporate in their forecasts announcements on the present and future realisations of fiscal spending. However, the magnitude of the nowcast errors points to the limitation of the agents' fiscal foresight given the possibly erratic behaviour of fiscal spending, and the noisy signalling by policy makers. The inspection of the fan charts in Figure 5, where we report the first quantiles up to a standard deviation of the distribution of the individual SPF-implied news, provides additional qualitative evidence of this remark. Forecasters coalesce in relation to the larger spikes related to large fiscal measures such as, for example, wars or fiscal

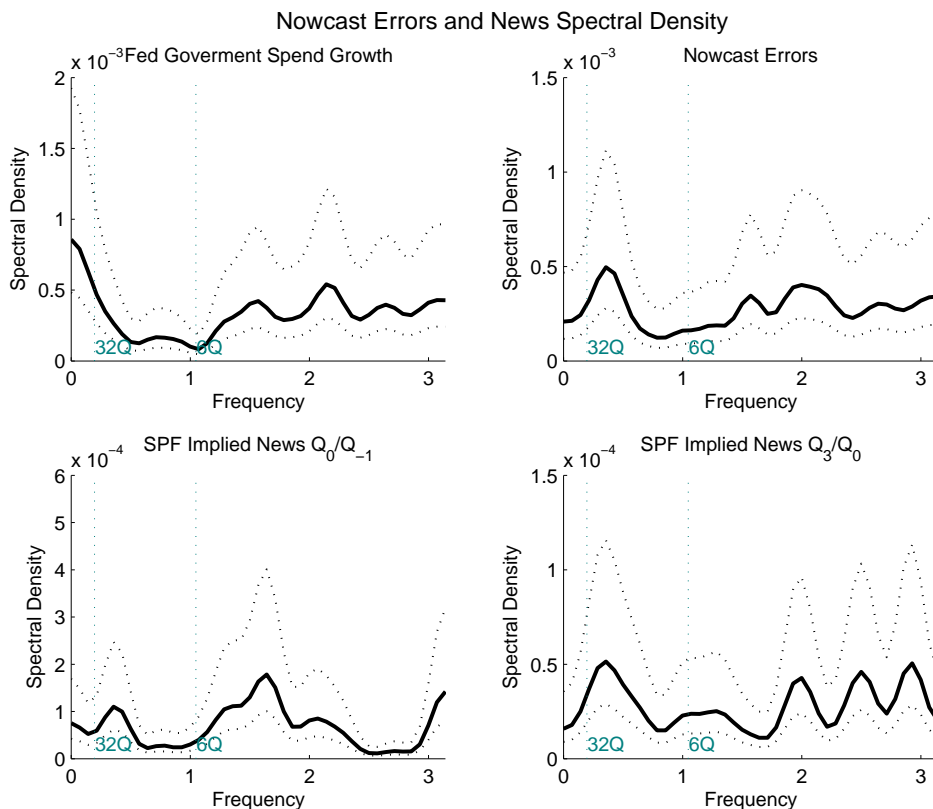


Figure 6: **Spectrum of Nowcast Errors and News (median)**. The figure plots the spectral density, obtained with the method of averaged periodograms, for the real federal spending growth rate, the median implied nowcast errors and news (solid line) with confidence bands at the 95 percent confidence level (dashed line). The vertical dotted lines limit the business cycle frequency band.

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

Independent Variable	F-stat	Prob > F	reg. coeff.	t-stat
$\mathcal{N}(0)$	7.54	0.007	0.620	2.75
$\mathcal{N}(0)$ (aggr. data)	3.50	0.064	0.448	1.87
$\mathcal{N}(1, 3)$	6.76	0.011	0.783	2.60
$\mathcal{N}(1, 3)$ (aggr. data)	3.57	0.062	0.457	1.89

stimulus measures.

Table 4: **Statistics of SPF and MC Simulated Forecast Data on Future Quarters.**

The table reports statistics on the median news from individual and aggregated SPF data and from SPF Monte Carlo simulated data ($n_{sim} = 10,000$). Column (1) reports statistics for Monte Carlo simulated data with news sampled from a Pearson distribution with skewness equal to zero and the time-varying kurtosis implied by SPF data. Column (2) reports statistics for Monte Carlo simulated data from an unbalanced panel in which 6 out of the 29 simulated forecasters are dropped from one period to the following. The news is sampled from a Pearson distribution with skewness equal to zero and the time-varying kurtosis implied by SPF data. Column (3) reports statistics for Monte Carlo simulated data with news sampled from a Pearson distribution with the time-varying skewness and kurtosis implied by SPF data. Column (4) adds an unbalanced panel composition as specified for column (2) to the specification in column (3).

	(1)	(2)	(3)	(4)	SPF data
Correlation Ind.–Aggr. Data Median News	1.000	1.00	0.87	0.86	0.82
Mean Abs Dist. Ind.–Aggr. Data Median News	0.00	0.01	0.21	0.20	0.36
Corr. of Av. Dist. Ind.–Aggr. News w/ Dist. Mean	-0.04	0.09	0.52	0.51	0.37
Corr. of Av. Dist. Ind.–Aggr. News w/ Dist. Std	0.02	-0.12	0.14	0.15	0.31
Corr. of Av. Dist. Ind.–Aggr. News w/ Dist. Skew.	0.04	-0.07	0.77	0.77	0.41
Corr. of Av. Dist. Ind.–Aggr. News w/ Dist. Kurt.	0.04	0.04	0.01	0.01	0.13

2.4 Heterogeneous Beliefs and Aggregation Issues

Forecasters disagree both in formulating their predictions and in updating them when new information is released (see, for example, Andrade and Le Bihan (2013)). Since the empirical distributions of forecasts and updates are usually not gaussian, subtle issues of aggregation can arise. Perotti (2011) and Forni and Gambetti (2014) have proposed proxies for fiscal news shocks using SPF mean or median aggregated forecasts data. In this section, we argue that this procedure may induce aggregation bias due to the properties of the empirical distribution of forecasts. In turn, this could explain why Perotti (2011) fails to find significant effects of expectation revisions in the current quarter.

In Figure 8, we compare our measure of news on future fiscal changes, $\mathcal{N}_t(1, 3)$, with the one proposed in Forni and Gambetti (2014), using the median aggregated value of SPF forecasts of federal government spending. The correlation of the two SPF-implied news measure is 0.8149 (a similar value is found for the news on the current quarter).

In the case of both normally distributed forecasts and news, and a large sample, median level aggregated measures would be equivalent to those obtained from individual forecasts data. However, in general,

$$\frac{1}{N_i} \sum_i \mathbb{E}_t^{*i} \Delta g_{t+h} - \frac{1}{N_j} \sum_j \mathbb{E}_{t-1}^{*j} \Delta g_{t+h} \neq \frac{1}{N_k} \sum_k (\mathbb{E}_t^{*k} \Delta g_{t+h} - \mathbb{E}_{t-1}^{*k} \Delta g_{t+h}) ,$$

for $N_k = N_i \cap N_j$. This may be due to (i) a skewed distributions of news and forecast and (ii) a relatively small sample with unbalanced composition of the panel of forecasters, especially in the presence of fat tails (high kurtosis). While the second case would introduce classical measurement noise, the first case may induce systematic errors in

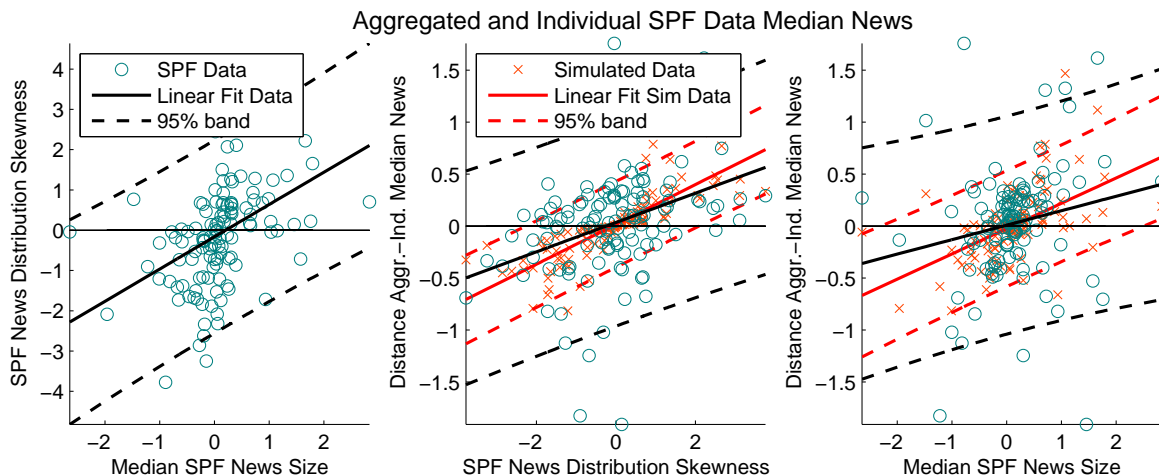


Figure 7: **SPF and MC Simulated Forecast Data on Future Quarters.** The plots above show scatter plots and respective linear fits with 95% confidence bands for: (1) the skewness of the distribution of the SPF-implied news against the size of the SPF-implied news; (2) the absolute distance between median news from individual and aggregated SPF data and SPF Monte Carlo simulated data, where the news have been sampled from a Pearson distribution with the skewness and kurtosis implied by SPF data, against the skewness of the distribution of the SPF-implied news; (3) the absolute distance between median news from individual and aggregated SPF data and SPF Monte Carlo simulated data against the size of the SPF-implied news.

the extraction of the fiscal news (non-classical measurement noise). This would happen in the presence of an empirical correlation between the size of the news and the skewness in the distribution of the updates to the forecasts (implied news).

The first chart in Figure 7 shows the empirical correlation in the SPF data between the skewness of the distribution of the implied news and the size of the median news. This correlation is also apparent in the top chart of Figure 8, where the time series of the median news from individual and aggregated SPF data and the skewness of the news distributions are plotted. Due to this empirical correlation, the correlation between the skewness of the news distribution and the distance between median news from individual and aggregated SPF data can introduce an *aggregation bias* in the median news obtained from aggregated data (see, for example Attanasio and Weber (1993), Imbs et al. (2005)).

To better understand the extent to which the time-varying skewness of the distribution of the implied news introduces bias in the median news measure from aggregated data, we perform Monte Carlo simulations. In particular, for each observed quarter, we fit (i) a normal distribution to the empirical distribution of the growth forecasts three quarters ahead, using the first two moments, and (ii) a Pearson distribution to the implied news distribution, using the first four moments. Varying one parameter at a time – skewness, kurtosis or unbalancedness of the panel – we run several simulations: (1) for each period, we randomly sample 29 baseline forecasts and news from the fitted distributions, as on average in the data; (2) when required, we randomly drop some of

Table 5: **Measurement Error in Individual and Median Aggregated News – MC Simulations.** The table reports average measurement errors for the median news from individual and median aggregated Monte Carlo simulated data ($n_{sim} = 10,000$). News are sampled from a Pearson distribution with the time-varying skewness and kurtosis implied by SPF data, taking into account the average unbalanced panel composition from a quarter to the next.

	MC Sim. Data
Std Measurement Error Individual News	0.25
Std Measurement Error Mean Aggregated News	0.55
Ratio Variance Errors Ind./Aggr. News	0.22

the simulated forecasters to reproduce the unbalancedness of the panel; (3) we compute the absolute distance between the median of the news distribution and the median news from median aggregated forecasts, at each period; (4) we repeat the draws 10,000 times and compute expected values. Finally, we compare the properties of the simulated data with those of the SPF data.

Results reported in Table 4 and Figure 7 indicate that the correlation in the data between size and skewness of the news introduces an aggregation bias in the median news obtained from aggregated data. In particular, there is a positive correlation between the size of the median news and the error made using median news from median aggregated forecasts.

On the other hand, the intuition that fiscal news measures obtained from individual forecasters data are possibly undistorted and contain less noise is confirmed by the analysis of the spectra at high frequencies (not shown), and by the F-statistics on the information content of the news variables, that is shown in Table 3.

To gain some intuition on the sign of the aggregation bias, we observe that, in a simplified model where

$$GDP_t = \alpha \mathcal{N}_t + u_t,$$

the estimated coefficient $\hat{\alpha}$, obtained using a measure of the news $\tilde{\mathcal{N}}_t = \mathcal{N}_t + \nu_t$ affected by non-classical measurement error ν_t – i.e., $\mathbb{E}[\mathcal{N}_t \nu_t] \neq 0$ – is biased. In particular, if the correlation between the measurement error and the news variable is positive, as it is the case in the data, the estimated coefficient $\hat{\alpha}$ will be biased downward, beyond the classical *attenuation bias*. In fact:

$$plim \hat{\alpha} = \left(1 - \frac{\sigma_\nu^2 + \sigma_{\mathcal{N}\nu}}{\sigma_{\mathcal{N}}^2 + \sigma_\nu^2 + 2\sigma_{\mathcal{N}\nu}} \right) \alpha,$$

where the term in parenthesis would be positive, less than one, and decreasing in the correlation $\sigma_{\mathcal{N}\nu}$ between the news and the error ν_t , for $\sigma_\nu < \sigma_{\mathcal{N}}$. Whether or not this intuition would remain valid in a VAR model, containing lags of many endogenous variables, remains an empirical problem.

Finally, we address a possible concern related to the unbalanced composition of the panel of forecasters. In extracting individual news, we track the individual forecast updates from one quarter to the next. We therefore limit the analysis to those respondents

that appear in two consecutive quarters, at each point in time. As shown in Figure 3, in the SPF dataset there are on average 29 respondents, 22 of which appear in consecutive quarters. This may induce measurement error in the proposed measure of news. To provide an assessment of the potential issue we perform Monte Carlo simulations, sampling news from a Pearson distribution with the time-varying skewness and kurtosis implied by SPF data forecast revisions, and taking into account the average unbalanced panel composition from a quarter to the next. Table 5 reports the simulation results. Reassuringly, the variance of the measurement error in the median news from individual data is about one fifth of the the variance of the measurement error in median news from aggregated data.

2.5 Other Measures in Literature

We complete the assessment of the variables by comparing them with other measures of news in previous literature. Ramey (2011) has proposed two proxy variables for aggregate expectations about government spending. The first is the *military news variable*, an estimate of changes in the expected present value of government spending due to unexpected exogenous geopolitical events, constructed using the Business Week and other newspaper sources. Future changes in military spending are discounted using the 3-year Treasury bond rate at the time of the news. This variable is assumed to proxy for the sum of expectations revision about government spending in the current quarter (unexpected changes) and the future quarters (expected changes).

Figure 8 plots the Ramey military news variable against our SPF-implied news variables three quarters ahead. The correlation between the military news variable and our SPF-implied news on different horizons is quite low: 0.01 with current quarter news, and -0.01 with news on future quarters. Also, it is interesting that the timing of recognisable increase in military spending (e.g., the Gulf War or the war in Afghanistan) is different. However, when comparing the series, it should be kept in mind that the forecast horizon of the Ramey military news variable is much longer than the one of the professional forecaster of the SPF dataset.¹⁴

The second measure proposed in Ramey (2011) is a measure of agents' forecast errors on government spending based on the median value of SPF forecasts of federal government spending. It is given by the difference between realised government spending growth and the median expected government spending growth, one lag ahead. This variable is thus the sum of nowcast errors and revisions of expectations about fiscal spending for the present quarter, two objects with potentially distinct macroeconomic properties (see Perotti (2011)). In particular, given the higher variance of nowcast errors, these are likely to dominate both the estimated impulse response functions and

¹⁴Quite interestingly, the measure of SPF-implied news from individual forecast data does not show a trough in correspondence to the Berlin Wall fall. SPF data show sign of skewness in that quarter with some outliers (see Figure 5).

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

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

the multipliers.¹⁵

Finally, Table 6 reports the correlations of our measures for fiscal news and nowcast errors with other proxy variables for fiscal, monetary and policy uncertainty shocks commonly used in literature. Nowcast errors and news on the current quarter are correlated to the SPF forecast errors defined in Ramey (2011), as expected. They also appear to be mildly correlated to tax changes as defined in Romer and Romer (2010). Nowcast errors and news also appear to be weakly correlated to the Policy Uncertainty Index defined in Baker et al. (2012), and with the Index’s subcomponents.

3 A Large Information Fiscal Expectational VAR

In the presence of forward looking behaviour and fiscal foresight, standard SVAR models generally suffer from *informational insufficiency*, originated from the misalignment of the respective information sets of the econometrician and economic agents (see Leeper et al. (2013)). This misalignment is due to the news flow about future policy changes conveyed by the institutional implementation process that is observed by economic agents in real time but not observed by the econometrician.

The natural solution to cope with fiscal foresight is to include more information in the econometrician’s information set in order to approximate the information flow on the future path of fiscal and macroeconomic variables.¹⁶

¹⁵Using an expanded information set and large Bayesian VAR techniques, Ellahie and Ricco (2012) have shown that fiscal shocks identified using a large SVAR with recursive identification and a large EVAR supplemented with the SPF Ramey measure of the forecast errors are virtually identical. In light of the previous observations, this can be understood by noting that both empirical models are likely to identify combinations of misexpected and unexpected fiscal changes.

¹⁶Theoretical foundations for this approach to deal with fiscal foresight and non-fundamentalness have been proposed in Giannone and Reichlin (2006). The key idea is to use larger datasets to address non-fundamentalness and to detect informational insufficiency with Granger causality tests. As proved in Giannone and Reichlin (2006), structural shocks are correctly recovered using large information under the assumptions that the shocks of interest are pervasive throughout the cross-section and that they generate heterogeneous dynamics. The remaining shocks must not propagate too widely and, therefore, can meaningfully be considered idiosyncratic.

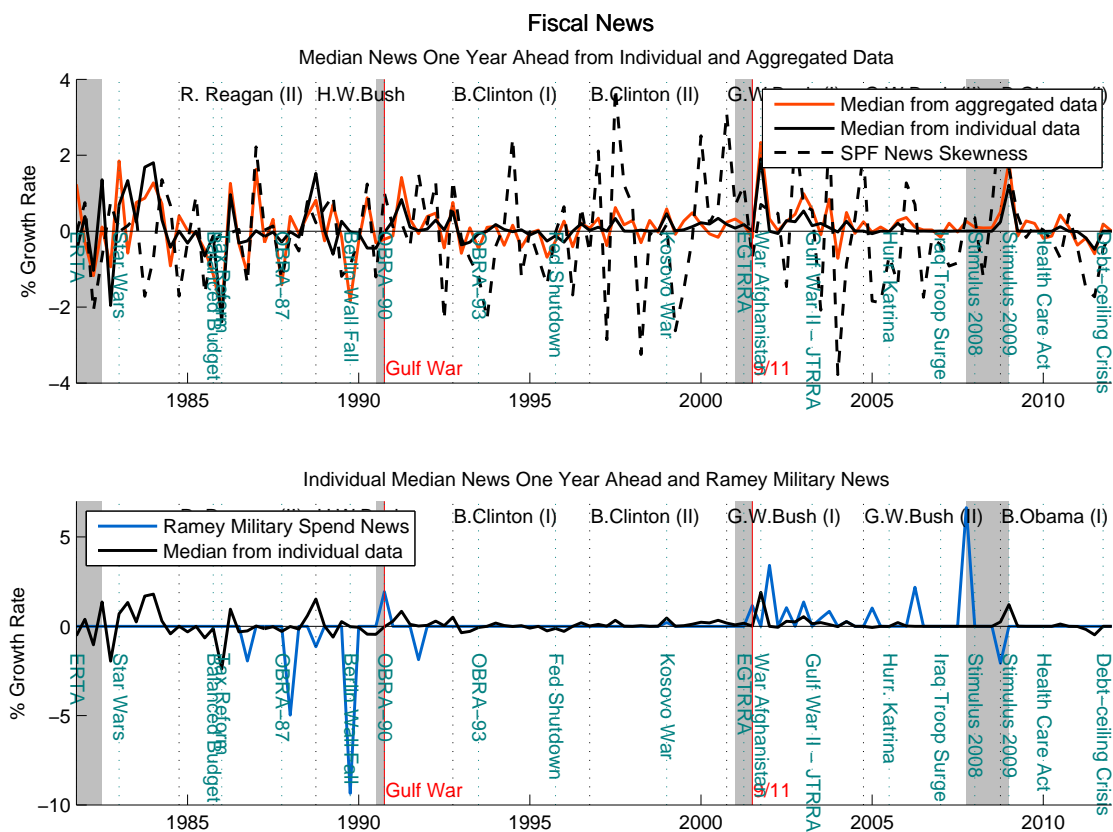


Figure 8: **Government Spending News from Individual Data, News from Aggregated Data, and Ramey’s Military Spending News.** The figure plots the time series for implied SPF news for future quarters obtained from individual data (black) and from (median) aggregated data (orange), as well as Ramey’s military spending news (blue). The dashed line in the top panel is the time series for the skewness of the distribution of SPF-implied individual updates (news). Grey shaded areas indicate the NBER Business Cycle contraction dates. Vertical lines indicate the dates of the announcement of important fiscal and geopolitical events (teal), presidential elections (black), and the Ramey-Shapiro war dates (red).

In the presence of fiscal foresight and imperfect information, ideally, one would like to incorporate in the econometric model an information set exceeding that of economic agents. This in order to control for misexpectations and changes to expectations not warranted by changes to fundamentals.

Following this intuition, we build a Large Expectational VAR (EVAR) model that includes several variables that proxy for agents’ expectations.¹⁷ In particular, to fully capture the real-time information flow in the economy, we enlarge the information set of the econometric model including: (i) our SPF measures of fiscal nowcast errors and fiscal news (medians); (ii) variables proxying for the future path of variables that may enter

¹⁷EVARs have been proposed by Ramey (2011) as a generalisation of SVAR in order to deal with agents’ forward looking behaviour. Proxy measures of agents’ expectations about the relevant macroeconomic variables are added to a standard VAR model.

into the Government policy response function (forecasts of both GDP and Unemployment); (iii) a large set of forward-looking variables including, among others, inventories, new orders, consumer sentiment index, CEO confidence index, the S&P500 index, rates and prices.¹⁸

3.1 The Econometric Model

We consider the following VAR(4) model:

$$y_t = C + A_1 y_{t-1} + A_2 y_{t-2} + A_3 y_{t-3} + A_4 y_{t-4} + \varepsilon_t \quad (9)$$

where ε_t is an n -dimensional Gaussian white noise with covariance matrix Σ_ε , y_t is a $n \times 1$ vector of endogenous variables and C , A_1, \dots, A_4 and Σ_ε are matrices of suitable dimensions containing the model's unknown parameters.

In order to deal with a large information set, we employ the Large VAR approach proposed in Banbura et al. (2010). In Banbura et al. (2010) and in De Mol et al. (2008), it has been shown that by applying Bayesian techniques, it is possible to handle large unrestricted VARs for structural estimation. In particular, De Mol et al. (2008) prove that, for the analysis of data sets that are characterised by strong collinearity, which is typically the case for macroeconomic time series, it is possible to increase the cross-sectional dimension of the information set by consistently setting the informativeness of the Bayesian priors in relation to the size of the model. This allows the VAR framework to be applied to empirical problems that require large data sets, potentially solving the issue of omitted variable bias. Large Bayesian SVARs have been used in Banbura et al. (2010) to identify monetary shocks and in Ellahie and Ricco (2012) to study fiscal shocks.

We adopt conjugate prior distributions for VAR coefficients belonging to the Normal-Inverse-Wishart family. This family of priors is commonly used in the BVAR literature due to the advantage that the posterior distribution can be analytically computed. For the conditional prior of the VAR coefficients, we adopt two prior densities commonly used in the macroeconomic literature for the estimation of BVARs in levels: the *Minnesota prior*, introduced in Litterman (1979), and the *sum-of-coefficients* prior proposed in Doan et al. (1983). The adoption of these two priors is based, respectively, on the assumption that each variable follows either a random walk process, possibly with drift or a white noise process, and on the assumption of the presence of a cointegration relationship among the macroeconomic variables.¹⁹ The adoption of these priors has been shown to improve the forecasting performance of VAR models, effectively reducing the estimation error while introducing only relatively small biases in the estimates of the parameters (e.g., Sims and Zha (1996), De Mol et al. (2008), Banbura et al. (2010)).

¹⁸The inclusion of forward looking variables, such as commodity prices, helps in correctly identifying structural shocks in VAR models, controlling for agents' expectations, as discussed in Sims (1992).

¹⁹Loosely speaking, the objective of these additional priors is to reduce the importance of the deterministic component implied by VARs estimated conditioning on the initial observations (see Sims (1996)).

In selecting the informativeness of our priors, we adopt the Bayesian method proposed in Giannone et al. (2012). Details on the estimation of the empirical model are provided in Appendices A and B.

3.2 The Identification of Fiscal Shocks

In order to identify misexpected and unexpected fiscal changes, we make the following assumptions: (i) discretionary fiscal policy does not respond to macroeconomic variables within a quarter; (ii) SPF time series for fiscal variables are meaningful proxy variables for the aggregate agents' expectations about government spending;²⁰ (iii) innovations to SPF-implied fiscal news on the current quarter not predicted within the VAR are *unexpected fiscal changes*; (iv) VAR innovations to SPF-implied nowcast errors, orthogonal to unexpected fiscal changes, are *misexpected fiscal changes*.

To identify expected fiscal changes, we also assume that (v) the values of the main macroeconomic variables are only fully revealed to the agents with a lag; (vi) forecast future government spending incorporate the discretionary policy response to expected values for output and unemployment; (vii) there are no shocks to future realisations of unemployment and output (e.g. technology or demand shocks) that are foreseen by the policy makers and to which the government can react; (viii) VAR innovations to implied SPF fiscal news on the future quarters, orthogonal to fiscal unexpected and misexpected changes, and to innovation to expected GDP and unemployment for the current quarter are *expected fiscal changes*.

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

$$(\mathcal{N}_t(0) \quad \mathcal{M}_t \quad \mathbb{E}_t^* \text{GDP}_t \quad \mathbb{E}_t^* U_t \quad \mathcal{N}_t(1, 3) \quad Y_t')' \quad (10)$$

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

This set of assumptions can be seen as a natural generalisation of the assumptions proposed in Ramey (2011), in line with the core intuition underlying the EVAR approach. However, differently from Ramey (2011), our identification accounts for imperfect information and respects the relationship between news and nowcast errors suggested by Equations (1) and (2). Moreover, the ordering of the variables is coherent with the factual informational limitation of the agents. Indeed, agents do not observe the state vector of the economy and may form expectations about current and future values of macroeconomic variables using their past realisations and signals about their present and future realisations.

²⁰We need to assume that the panel of professional forecasters in the Philadelphia SPF is representative of the economic agents. In making this assumption, we rely on Carroll (2003), which provides evidence that private agents, firms and households, update their forecast towards the views of professional forecasters. Differently from Carroll (2003), Coibion and Gorodnichenko (2012) find that consumers do not appear to have a slower rate of information acquisition and processing with respect to other agents as firms, professional forecasters, and central bankers. However, disagreement among consumers is much larger than for other agents.

3.3 The Econometric Information Set

The econometric information set of our benchmark Expectational VAR model contains a large set of macroeconomic variables supplemented by a set of “expectational” variables. The “expectational” block is ordered first and contains, in the following order, SPF-implied fiscal news on the current quarter, SPF-implied misexpectations (nowcast errors), GDP forecasts for the current quarter, the unemployment rate forecast for the current quarter and SPF-implied fiscal news for the three quarters ahead.²¹

The main macroeconomic variables of interest are federal government spending, state and local government spending, GDP, the Barro-Redlick marginal tax rate (see Barro and Redlick (2011)), real wages, total worked hours, output per hour, civilian unemployment rate, civilian employment, personal consumption of durables, nondurables, and services, nonresidential fixed investment, residential fixed investment, consumer price index, S&P 500, consumer sentiment index, CEO confidence index, 10-year treasury rate, real rates, and the real exchange rate.^{22,23} Real rates are measured using the three-month US Treasury Bill rate, adjusted for changes in the consumer price index.

We use US quarterly data for the period 1981Q2 to 2012Q1 in real log per capita levels for all the variables except those expressed in rates. A brief description of the sources of all the variables used in our study is in Appendix D. In Table 9, we summarise the data used in different analyses and transformation applied.

3.4 Forecastability and Informational Sufficiency

Before showing results from our Large EVAR, we assess whether the model is well specified by using the test for informational sufficiency proposed in Forni and Gambetti (2011). First, we extract factors from a large dataset assumed to be a good proxy for the whole economy – larger than the information set incorporated in the VAR model –. Then, we test whether the identified fiscal shocks are Granger caused by the factors. The intuition supporting this test is that, if the factors contain relevant information useful to forecast fiscal innovations, then economic agents could have used this information to alter their behaviour prior to the realisation of the forecast spending shock.

Using an EM algorithm, we extract five factors from a rich dataset of 128 macroeconomic variables, explaining about 99 percent of the variance in the data.²⁴ We use

²¹We also add as controls GDP forecast at one year, unemployment rate forecast at one year, forecast disagreement on fiscal news on the current quarter and for the three quarters ahead (standard deviation). Results shown in the paper are obtained using median measures of nowcast errors and news. However, results obtained with mean measures are largely identical.

²²The Barro-Redlick marginal tax rate is the income weighted average marginal tax rate available on the website of the National Bureau of Economic Research.

²³We expand the set of variables also to include other potentially relevant variables related to monetary policy (M2 money stock), government fiscal position (net federal government deficit), the credit market (gross private savings, total consumer credit outstanding, commercial and industrial loans), and the business activity (new orders index, inventories index and corporate profits after tax), as well as spot oil price and real disposable personal income. Following the conjecture in Banbura et al. (2010), we exclude from the EVAR model regional and sectoral components of macroeconomic variables as they appear not to be relevant in order to capture economy-wide structural shocks.

²⁴The dataset is described in Table 9 and in Appendix D.

Table 7: Informational Sufficiency Tests. The table reports F-statistics and p-values for Granger causality tests. The asterisks *, **, *** denote statistical significance at 20 percent, 10 percent and 5 percent level, respectively.

	Factor 1		Factor 2		Factor 3		Factor 4		Factor 5	
	<i>F</i>	<i>p</i>	<i>F</i>	<i>p</i>	<i>F</i>	<i>p</i>	<i>F</i>	<i>p</i>	<i>F</i>	<i>p</i>
Nowcast Err.	1.07	(0.35)	0.00	(1.00)	6.21***	(0.00)	1.24	(0.29)	0.05	(0.95)
<i>Misexp. Surp.</i>	0.00	(1.00)	0.00	(1.00)	0.01	(0.99)	0.31	(0.73)	0.04	(0.96)
News Q0	2.85**	(0.06)	1.04	(0.36)	1.77*	(0.17)	0.02	(0.98)	0.15	(0.86)
<i>Unexp. Surp.</i>	0.03	(0.97)	0.03	(0.97)	0.10	(0.90)	0.02	(0.98)	0.03	(0.97)
News Q1-Q3	0.01	(0.99)	0.04	(0.96)	0.08	(0.92)	2.55**	(0.08)	0.25	(0.78)
<i>Exp. Changes</i>	0.17	(0.85)	0.17	(0.84)	0.09	(0.92)	0.01	(0.99)	0.10	(0.90)

these five factors to assess the predictability of our news variables and the informational sufficiency of our EVAR model.

Table 7 reports the results of the tests. SPF-implied nowcast errors are Granger-caused by Factor 3, while SPF-implied fiscal news are Granger-caused, respectively, by Factors 1 and 3, and by Factor 4. These results seem to indicate that SPF forecasters do not efficiently aggregate all the available information.²⁵ This may be due to misspecifications of the model used or to the difficulties fronted by the forecasters in extracting signals on the future path of fiscal variables in real time. In fact, both delayed-information and noisy-information models can rationalise the predictability of forecast errors and revisions (see, for example the discussion in Andrade and Le Bihan (2013)).

The results of this test indicate that our proxy variables for news and misexpectations cannot be thought of as exogenous external instruments. To correctly identify fiscal shocks, we need to further expand the information set of the econometric model.

On the other hand, tests on the EVAR identified fiscal shocks in Table 7, indicate that factors fail to Granger-cause identified innovations to misexpectations and news. The informational sufficiency tests seem to indicate that our Large EVAR information set exceeds that of economic agents, as desired.

4 Expected, Unexpected and Misexpected Changes

In this section, we report the empirical results of our model. We begin by considering the effects of a fiscal misexpected change. Figure 10 shows the dynamic responses of macroeconomic variables to this shock, where IRFs have been normalised to have a unitary increase of federal spending on impact. In the figure, both the 90% and 68%

²⁵These results are in line with findings in Ellahie and Ricco (2012) for informational sufficiency tests on the ‘‘Ramey’’ military spending news variable, forecast errors and VAR residuals.

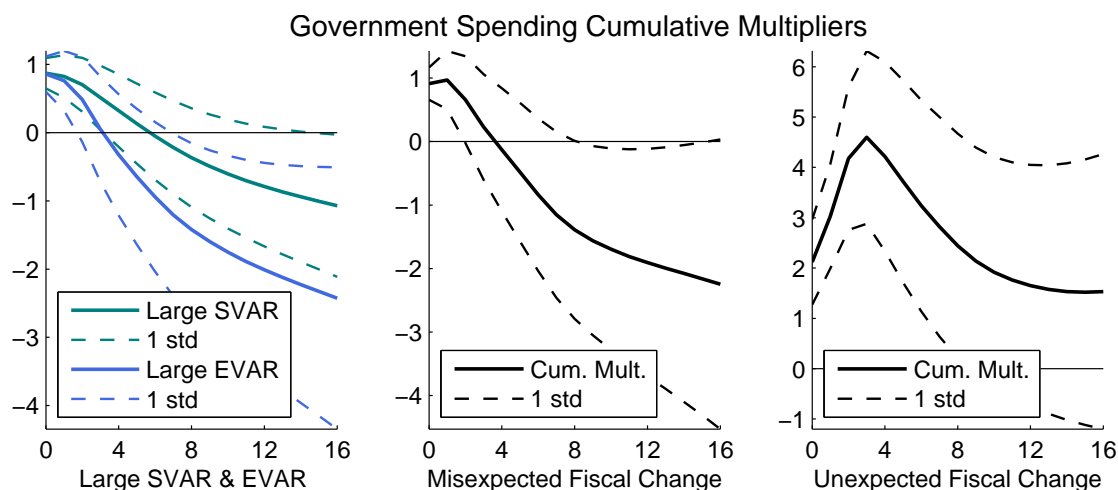


Figure 9: **Cumulative multipliers.** These figures plot the ratios of the cumulative increase in the net present value of GDP and the cumulative increase in the net present value of government spending induced by the indicated shock. Cumulative multipliers for expected fiscal changes are distorted by the increase in GDP that anticipates the actual increase in government spending and have not been plotted.

coverage bands are reported.²⁶ Cumulative multipliers are shown in Figure 9.²⁷ Also, peak/impact multipliers adjusted to account for the increase in state and local spending are shown in Table 8.²⁸

The misexpected change causes government spending to spike temporarily and then to fall back to normal values slowly. State and local spending decreases. GDP and output per hour rise slightly on impact, but then turn negative. The GDP peak response to a misexpected change is around 1. However, the cumulative multiplier after 16 quarters is quite large and negative. The GDP components of consumption and investment behave alike. Consistently, unemployment rate increases slowly to peak only after eight quarters. Prices do not appear to change; interest rates drop, both at short and long

²⁶These error bands do not include the additional uncertainty resulting from possible measurement errors in the news variable. In Ramey (2011), using simulations it was shown that measurement errors may induce little additional uncertainty.

²⁷Cumulative multipliers are defined as

$$\text{cumulative multiplier}(T) = \frac{\sum_{t=0}^T (1+i)^{-t} \Delta GDP_t}{\sum_{t=0}^T (1+i)^{-t} \Delta G_t}, \quad (11)$$

where i is the mean real interest rate in the sample (see Ilzetki et al. (2013)).

²⁸Government Spending peak multipliers are customarily computed as the effect on log GDP at various lags divided by the maximal effect on log spending times the average share of government spending over GDP. We compute adjusted government spending peak multipliers, defined in Appendix C, to account only for the direct effect on the output of the increase of federal government spending, modding out the indirect effect due to a possible increase in state and local government spending. However, it should be remembered that multipliers provide only a rough measure of the effects of fiscal policy and their meaning should not be overestimated.

Table 8: **Fiscal Multipliers** The table reports Government Spending Impact or Peak Multipliers, adjusted to take into account the increase in state and local government spending subsequent to the shock to federal spending (see Appendix C for details). Standard deviations in parentheses.

Fiscal Multipliers						
	Unexpected (imp.)		Misexpected (imp.)		Expected (peak)	
GDP	1.28	(0.63)	1.05	(0.29)	3.06	(1.24)
D. Cons.	0.54	(0.20)	0.17	(0.13)	0.21	(0.31)
N.D. Cons.	0.28	(0.12)	0.07	(0.08)	0.19	(0.21)
S. Cons.	0.21	(0.18)	0.04	(0.09)	-0.28	(1.44)
N.Res. Inv.	0.34	(0.19)	0.12	(0.14)	0.89	(0.49)
Res. Inv.	-0.15	(0.15)	0.08	(0.07)	0.90	(1.12)

horizon; the real exchange rate depreciates. Response of consumers sentiment, CEO confidence and markets are negative. Overall, the effects of a misexpected change appear to be contractionary.

Figure 10 also compares the dynamic responses of macroeconomic variables to a misexpected change with the effects of fiscal shocks identified (i) in a Large VAR with SPF forecast errors à la Ramey, and (ii) in a Large SVAR à la Perotti with recursive identification. As Figure 10 shows, the three identified innovations produce nearly identical responses (a similar result was shown in Ellahie and Ricco (2012)). This result can be understood by observing that nowcast errors have a higher variance than the revision of expectation and, therefore, dominate the estimated impulse response functions and multipliers.

Figure 11 shows the impulse response functions to an unexpected fiscal change. The responses are normalised so that the federal government spending response to the news shock is equal to unity on impact. After a positive unexpected fiscal shock, federal government spending persistently increases. GDP increases significantly, peaking three quarters after the shock and returning to normal after about two years. The peak GDP multiplier is around 1.3, while the cumulative multiplier after 16 quarters is around 1. Durables, non durables and services consumption significantly increase on impact but fall back to normal after six to eight quarters. Nonresidential fixed investment rises on impact but then turns negative after six quarters, while residential investment reduces after the shock. Unemployment reduces on impact but increases after one year. Consumer prices spike after one quarter and then revert to their equilibrium level. Real rates accommodate the fiscal shock in the short run, increase after three quarters, and return to normal values after six quarters; the 10-year treasury rate increases significantly; the real exchange rate appreciates persistently. Consumer sentiment reacts positively on impact, while CEO confidence and the S&P index are negative.

Impulse response functions to expected fiscal changes are reported in Figure 12. Federal government spending rises slowly after a couple of quarters and peaks after two years. State and local spending also increases. GDP and non residential investment

increase significantly, peaking two quarters after the shock. The peak GDP multiplier is high, around 3.1, significantly above unity. However, an estimate of the cumulative multiplier after 16 quarters delivers the more reasonable value of 1.5. Output per hour and real wages increase slowly and persistently. Consumption components and residential fixed investment decrease in the short run and then return to normal levels. The consumer price index adjusts upward soon after the shock and then reverts to normal. Real rates appreciate with two quarters of delay; the 10-year treasury rates increases significantly on impact and remains above equilibrium level for one year and half; the real exchange rate slowly appreciates after the shock, producing a hump-shaped response function. Consumer and CEO confidence indices increase significantly for three quarters and then revert to normal.

5 Discussion of Results and Possible Issues

The Macroeconomic Effects of Fiscal Shocks. The three shocks appear to have surprisingly different macroeconomic effects. While misexpected shocks produce rather contractionary effects due to the crowding out of private investment and consumption (reminiscent of neoclassical effects), expected and unexpected fiscal changes elicit expansionary responses due to the stimulation of private investment and consumption. However, in the latter cases, unlike classic Keynesian models, agents seem to react to the announcement of the fiscal measure. In fact, the stimulative effects appear to be due to the forward looking increase in private investment to accommodate the expansion in demand rather than simply to hand-to-mouth consumer responses.²⁹ Indeed, nonresidential fixed private investment either co-moves with the fiscal expansion or anticipates it. A possible interpretation of this relationship is that the private sector reacts to a well signalled fiscal expansion accommodating the increase (or the expected increase) in demand with an expansion in capacity. This possibly temporary expansion in potential output may enable a fiscal expansion to have multiplicative effects, undoing the potential “neo-classical” crowding-out of private demand. Supply-side factors which explain demand-side effects and positive responses of output to unexpected fiscal shocks are also found by Zeev and Pappa (2014).³⁰ These empirical stylised facts might be used to assess and to discriminate amongst theoretical models.

Misexpected Fiscal Changes. Estimated dynamic responses and multipliers to misexpected changes are very similar to the ones estimated in Ramey (2011) and almost identical to the one estimated in Ellahie and Ricco (2012) for a large SVAR and EVAR. This offers a partial reconciliation of previous results in the literature. As observed, this is due to the higher variance of the misexpected component *vis-à-vis* the unexpected one. Nowcast errors dominate the estimates of the dynamic responses in econometric

²⁹Results reported are robust under a number of different specifications: (i) with Minnesota priors only, (ii) within a large range of values of the informativeness of priors, (iii) using the mean measure for nowcast errors and news.

³⁰Murphy (2013) proposed a model of imperfect information in which only owners of firms targeted by an increase in government spending perceive an increase in their permanent income relative to their future tax liabilities, causing aggregate consumption and investment to increase.

Large SVAR, Ramey Large EVAR, and Misexpected Fiscal Changes

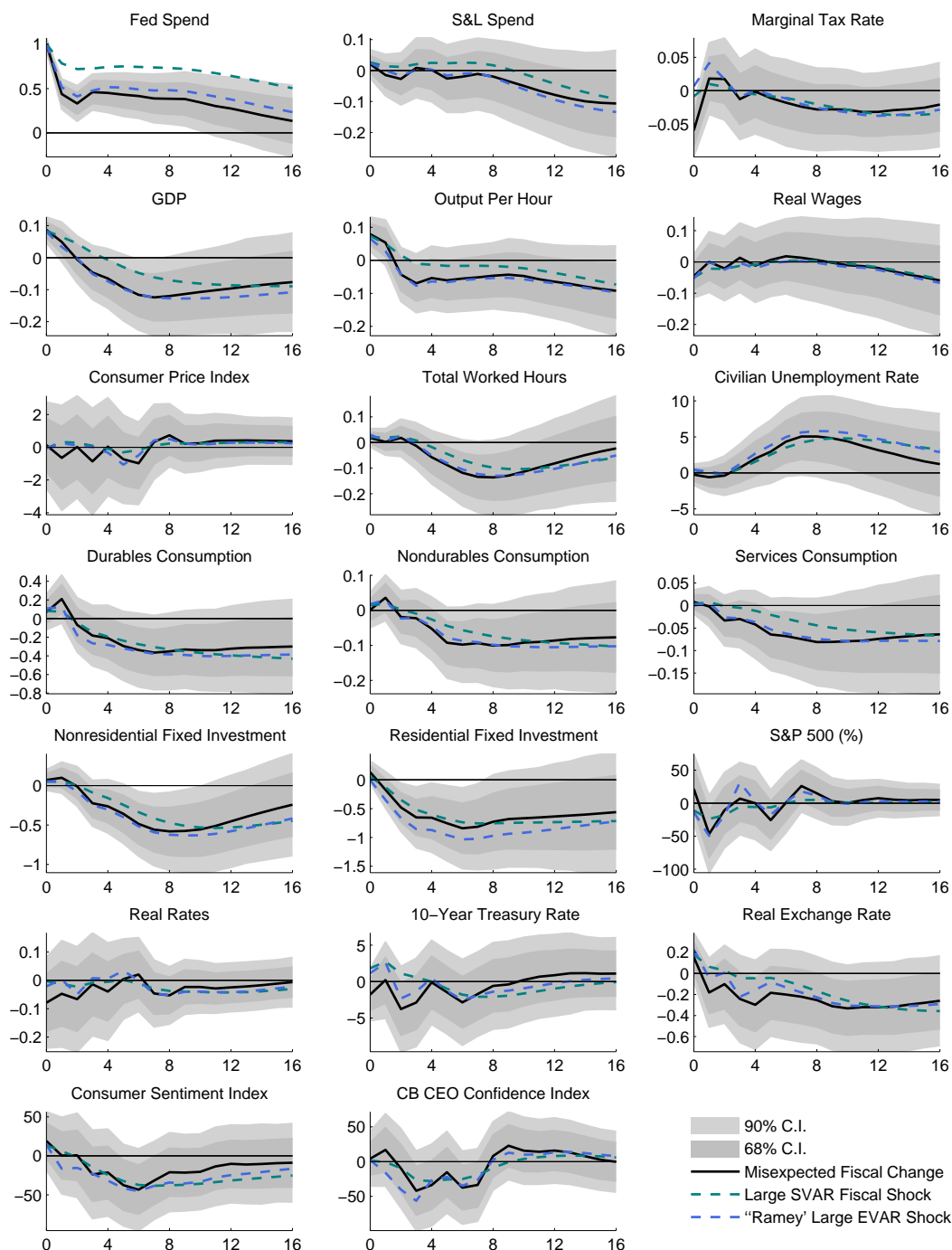


Figure 10: **Misexpected Fiscal Change, comparisons with Large SPF EVAR à la Ramey and Large SVAR Shocks.** This figure compares the impulse response functions to a misexpected federal government spending change (black), with a fiscal shock à la Ramey for a Large SPF EVAR, and with Large SVAR recursively identified fiscal shock (dashed teal). Each chart shows shaded posterior coverage bands for the Misexpected Fiscal Change at the 90 and 68 percent level.

Unexpected Federal Fiscal Change

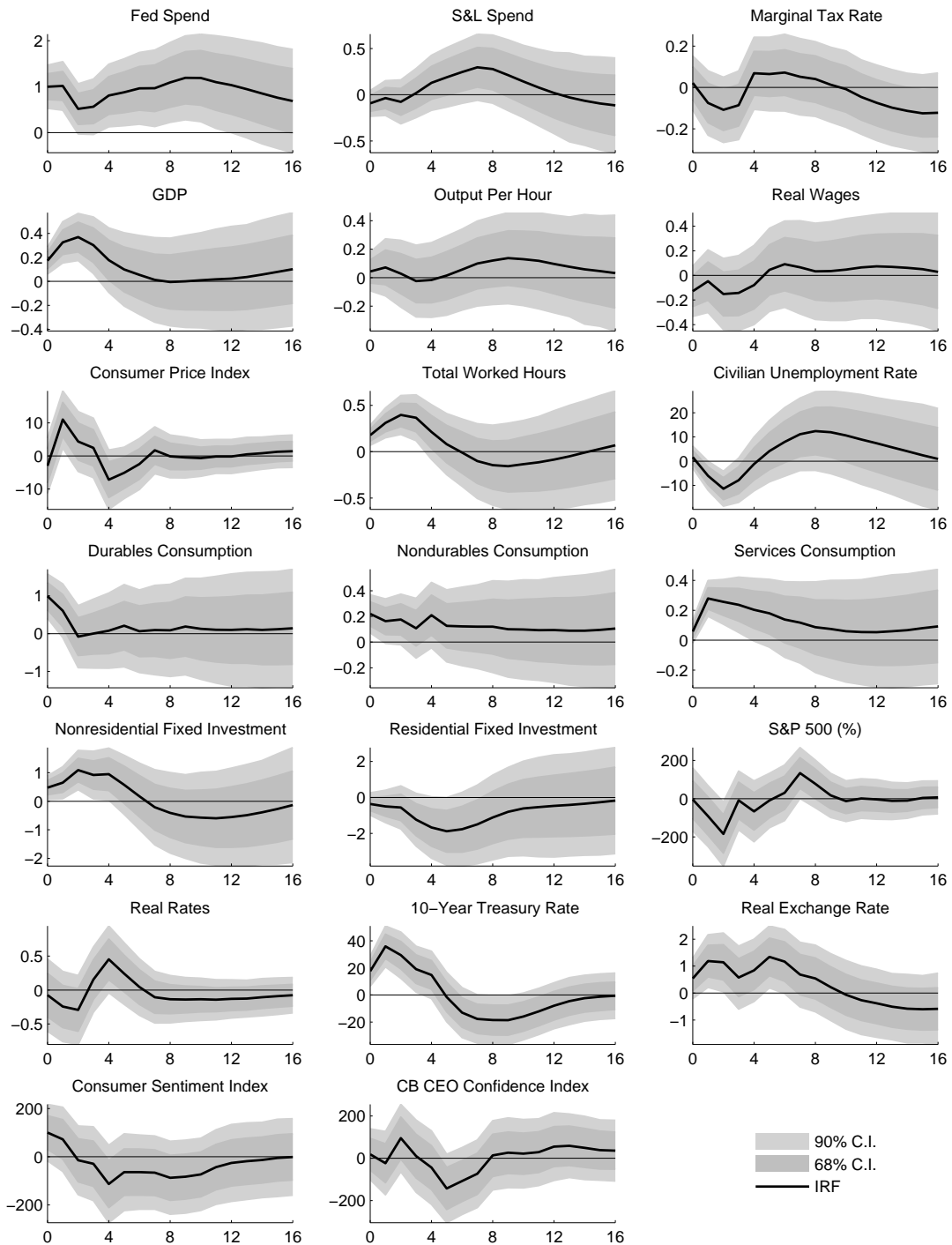


Figure 11: Unexpected Fiscal Change. This figure reports the impulse response functions to an unexpected federal government spending change. Each chart shows the Large EVAR response for the period 1981Q2 to 2012Q1 as a solid line with shaded posterior coverage bands at the 90 and 68 percent level.

Expected Federal Fiscal Change

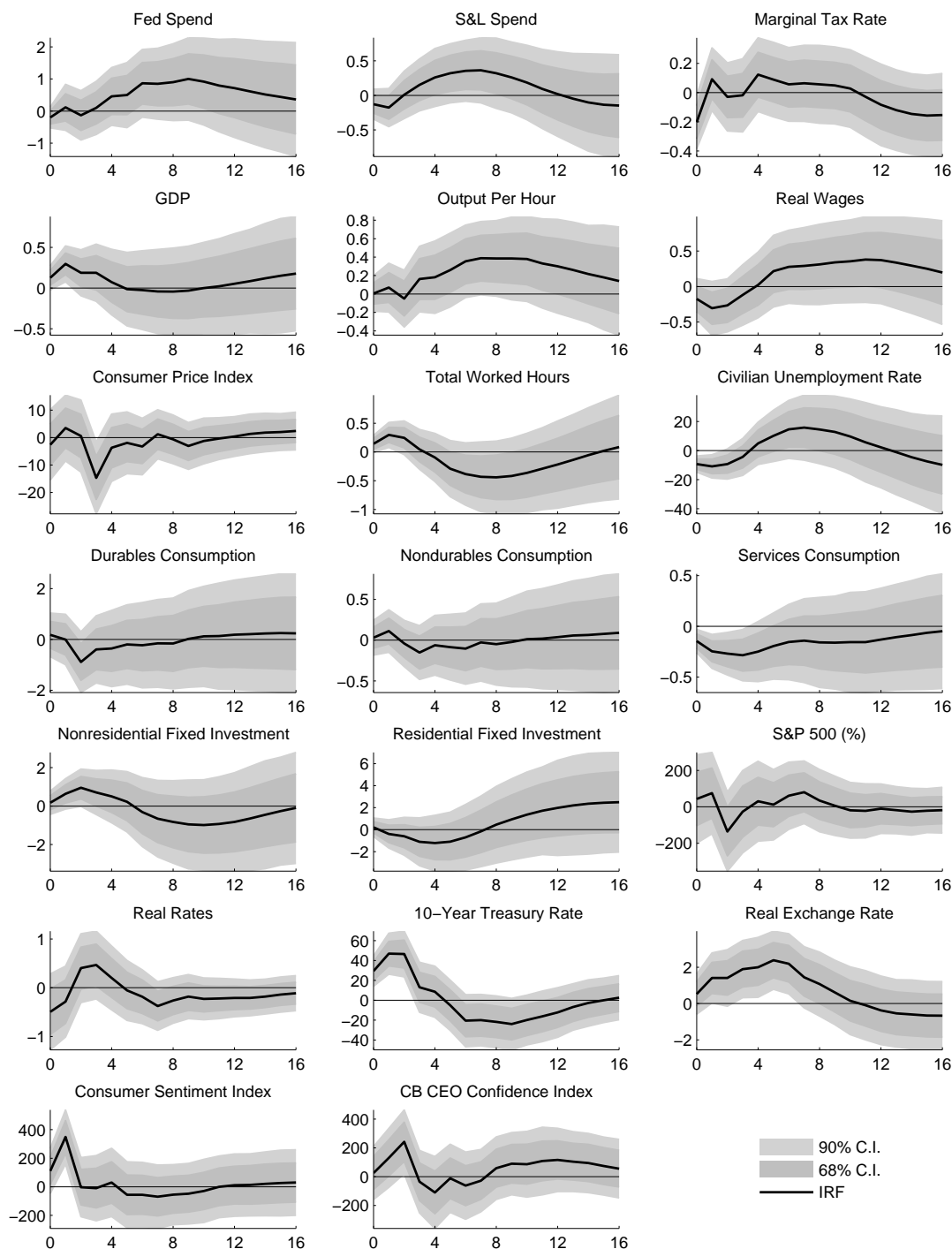


Figure 12: **Expected Fiscal Change.** This figure reports the impulse response functions to an expected federal government spending change. Each chart shows the Large EVAR response for the period 1981Q2 to 2012Q1 as a solid line with shaded posterior coverage bands at the 90 and 68 percent level.

models that do not discriminate between unexpected and misexpected components (e.g., existing EVARs and Large SVARs applications).

On the one hand, our analysis indicates that small information SVARs are likely to estimate innovations that are combinations of anticipated and unanticipated fiscal changes, when applying the so-called marginal SVAR approach. On the other hand, SPF EVARs *à la* Ramey and Large SVARs that control for anticipation are likely not to discriminate between unexpected and misexpected changes.

Misexpectations and Their Sources. The effect of misexpected fiscal changes are relatively in line with neoclassical predictions. However, they do not have the informational properties of fiscal shocks in a full information rational expectation model. These shocks may appear to the agents as demand shocks on impact. In fact, agents are not able to back out their fiscal nature from movements of prices in the aggregate economy. However, their weak impact on prices and rates is quite puzzling.

The nature of misexpected changes is an interesting open problem. As discussed, in models of imperfect information rational expectations, in the aggregate, nowcast errors are due to the incomplete updates of the forecasts over time:

$$\underbrace{g_t - \mathbb{E}_t^* g_t}_{\text{nowcast error}} = \frac{1 - \kappa}{\kappa} \underbrace{(\mathbb{E}_t^* g_t - \mathbb{E}_{t-1}^* g_t)}_{\text{nowcast revision (news)}}, \quad (12)$$

where κ is the parameter of informational rigidity and \mathbb{E}^* indicate the average expectations. Hence, conditional on past updates, the nowcast error should not contain additional information. Results reported seem to indicate that, on the contrary, the information content of nowcast errors may exceed the one conveyed by forecast revisions.

From an empirical perspective, many different components may contribute to misexpectations, including non-signalled fiscal changes, data revisions, measurement errors, random fluctuations in the timing of budgeted expenditures across the fiscal year, accounting issues, deviations from rational expectations, forecasting model misspecifications, partial misalignment of the forecast and of the data release horizons, along with several others. As observed in Enders et al. (2013), nowcast errors can also be the result of optimism/pessimism shocks, i.e., autonomous but fundamentally unwarranted changes in the agents' perceptions.^{31,32}

Overall, informational frictions seem to have an important role in explaining the different macroeconomic effects of fiscal misexpected changes and fiscal news. The relevance of informational frictions is not fully understood in the existing theoretical fiscal models and is an interesting research problem.

It is also worth stressing that fiscal policy, in particular counter-cyclical stimulative actions, is enacted through plans and is not intended to surprise agents (as also observed

³¹In order to identify optimism shocks, Enders et al. (2013) assume that GDP nowcast errors may emerge only as a result of optimism or productivity shocks, excluding the possibility that they might also be due to structural innovations. They find that optimism shocks induce a negative nowcast error and boost economic activity.

³²Rodríguez Mora and Schulstad (2007) study the effects of the announcements that the government makes on GNP growth, and of its final revised value. They find that the variable that determines future growth is the unexpected part of the announcement, while the "true" value of GNP growth at time t has no predictive power in determining growth at future times.

in Alesina et al. (2012)). Hence, to learn about the effects of discretionary fiscal policy, it is necessary to study expected fiscal changes. In this respect, empirical evidence based on the study of fiscal surprises (or misexpected fiscal changes) may be misleading from a policy perspective.

Open Economy Effects of Fiscal Shocks. Results reported in this paper on the real exchange rate may help to understand the “exchange rate puzzle” in the previous literature. Recent empirical research has provided mixed evidence. For example, Monacelli and Perotti (2010) and Ravn et al. (2012) find that a shock to government consumption produces real depreciation. However, Beetsma et al. (2006) report that a shock to government spending is associated with real appreciation.³³ Our results indicate that fiscal shocks that are correctly identified by agents elicit real appreciation. However, misexpected changes that are likely to dominate previous empirical analysis induce mildly significant depreciation. This relevant issue is explored further in Ricco (2014).

Fiscal Forward Guidance. The indication that fiscal shocks that are correctly identified by agents have strong expansionary effects may induce the belief that a better communicated and signalled path of fiscal policy can produce stronger effects. This may also be related to the recent finding of the adverse effect of fiscal policy uncertainty (e.g., Bloom (2009), Baker et al. (2012)). This observation may suggest the case for stronger *fiscal forward guidance*. In broad terms, forward guidance can be described as explicit statements by a policy maker about the likely path of future policy instruments, conditional on the evolution of certain key macroeconomic aggregates. For what concerns fiscal policy, the government constantly provides agents with institutional and political signals about the forward path of fiscal variables. The policy maker can choose to endow agents with public signals on fiscal spending which may be more or less informative. Our results provide suggestive evidence that effective policy signalling may enhance the effects of fiscal measures, possibly reducing policy uncertainty or increasing coordination amongst the agents. In this respect, the transparency in communicating (the precision of the signals on) the forward path of fiscal instruments can be seen as an additional policy tool (see also Ricco et al. (2014)).

Real Time Data. A possible concern regarding the econometric specification employed in this work relates to the use of real-time data. One may be tempted to believe that the use of revised data may cause misspecification to the model since SPF respondents were using real-time data when formulating their forecasts. This intuition stems directly from a full information rational expectation paradigm and follows the tenet of the rational expectations econometrics that requires the econometrician to align her/his information set to the representative agent’s one. However, in a context of imperfect information and, possibly, in the presence of heterogenous information amongst the agents, this may be a fallacy.

To better understand the issue, it is necessary to notice that there are two information sets the econometrician can consider: (i) the information set from which the correlation

³³Open-economy macroeconomic models with nominal rigidities generally imply that an expansion in government spending should be associated with real appreciation (Corsetti and Pesenti (2001)). However, it is also possible to construct models in which a fiscal expansion is associated with real depreciation, as in Monacelli and Perotti (2010), and Ravn et al. (2012).

amongst the variables of interest and the shocks are extracted, and (ii) the information set onto which the relevant variables are projected to identify the structural shocks. In a VAR, the two sets coincide but this would not be necessarily the case, for example, in a local projection model. For what concerns the first information set, it is obvious that one has to consider revised data in order to extract correlations least affected by measurement errors. The use of real-time data would provide dynamic responses to shocks that blend the impact of fiscal policy shock on the economy and data revisions (viz., the impact of fiscal policy shock on the statistical office). For what concerns the second information set, one may be induced to believe that, in order to correctly identify structural shocks, the variables of interest - news and nowcast errors, in our case - are to be projected onto the information set available to the agents in real time. However, this intuition seems also to be inaccurate. Indeed, the scope of our exercise is to identify structural shocks and not the sources of expectational errors. In other terms, what is to be identified is the change to expectations in real-time that *is due to the fiscal shock* and not the change to expectations that could have been perceived in real-time *as due to a fiscal shock*.³⁴

The Variance Issue. A general problem in the time series literature on fiscal shocks is that there is relatively low historical variation in post-Korea War US government spending, i.e., what Perotti (2011) calls the “variance problem” (see the discussion in Hall (2009) and Barro and Redlick (2009)). This lack of variation is often believed to be the source of the instability in the estimated multipliers in the SVAR literature.³⁵ The stronger version of this argument would posit that “there is not enough variation in government spending to identify with confidence meaningful responses to government spending shocks” (Perotti (2011)). However, the precision of the estimates should be assessed using posterior coverage sets that rely on the likelihood principle: conditional on the acceptance of the model, the evidence about the parameters of the model is contained in the p.d.f. for the sample with the data held fixed and the parameters allowed to vary. In this respect, this paper shares a common weakness with other paper in the related literature: the relatively large coverage bands for longer horizons. Indeed, the main aim of this paper is not to provide an exact measure of the fiscal spending multipliers but rather to help clarifying the average dynamic response of macroeconomic variables to fiscal shocks and whether those responses may be compatible with stimulative effects on the economy.³⁶ For this reason, results from this paper and the related literature should be complemented with evidence from natural experiments that aim to bridge the gap between microeconomic and macroeconomic approaches, and from a variety of other

³⁴Real-time revisions may be due to: (1) arrival of additional data and (2) to changes of the variables’ definitions. To better understand why the latter can be a serious issue, it is worth remembering that, for example, in 1996 there was a redefinition of the variable “federal government purchases” to “federal government consumption expenditures and gross investment”, the variable used in this paper. While SPF forecasts are consistent in forecasting “real federal government consumption expenditures & gross investment”, and the last-vintage time series has been consistently revised, the real-time data would bring in terrible misspecification into the model.

³⁵Ellahie and Ricco (2012) show that informational insufficiency, rather than the variance problem, is likely to be a major source of the discrepancy among estimated fiscal multipliers in the literature.

³⁶It is worth stressing that multipliers are not structural parameters and therefore their size is inherently not constant.

possible approaches (e.g., in Acconcia et al. (2011), Nakamura and Steinsson (2011), Wilson (2010)).

6 Conclusions

This paper is an empirical attempt to answer key questions about the effects of discretionary fiscal measures on the economy. We argued that a potentially major source of uncertainty in the literature on fiscal shocks is the difficulty of econometric models in dealing with both anticipation and imperfect information in the economy. Moving from ideas stemming from models of imperfect information rational expectations, we propose a novel approach to the study of fiscal shocks.

Our methodology identifies three types of government spending shocks that modify the agents' information set at different horizons: before, upon and after their realisation. Borrowing from the psychological literature, we name these innovations expected, unexpected and misexpected fiscal changes. We investigate the impact of these different fiscal shocks using a large information EVAR model supplemented with new measures of the real-time information flow received by agents, taking into account fiscal news and agents' misexpectations.

Results indicate that: (1) neglecting the difference between unexpected and misexpected changes blurs the effects of fiscal policy shocks; and (2) expected fiscal changes have expansionary effects with a cumulative output multiplier around 1.5. Our findings also provide some reconciliation of previous results and seem to suggest that a clearer forward guidance about the fiscal measures can enhance the effect of the policies.

Finally, our novel empirical methodology which accounts for both *anticipation effects* and *imperfect information* has different relevant applications to the study of several types of policy and structural shocks, as for example, monetary policy shocks.

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A Estimation of the Large Bayesian VAR

Let us consider the following VAR(4) model:

$$y_t = C + A_1 y_{t-1} + A_2 y_{t-2} + A_3 y_{t-3} + A_4 y_{t-4} + \varepsilon_t \quad (13)$$

where ε_t is an n -dimensional Gaussian white noise, with covariance matrix Σ_ε , y_t is a $n \times 1$ vector of endogenous variable and C , A_1, \dots, A_4 and Σ_ε are matrices of suitable dimensions containing the model's unknown parameters.

We adopt conjugate prior distributions for VAR coefficients belonging to the Normal-Inverse-Wishart family

$$\Sigma \sim IW(\Psi, d) \quad (14)$$

$$\beta | \Sigma \sim N(b, \Sigma \otimes \Omega) \quad (15)$$

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

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

- **Minnesota prior:** This prior is based on the assumption that each variable follows a random walk process, possibly with drift. This is quite a parsimonious, though reasonable approximation of the behaviour of economic variables. Following Kadiyala and Karlsson (1997), we set the degrees of freedom of the Inverse-Wishart distribution to $d = n + 2$ which is the minimum value that guarantees the existence of the prior mean of Σ .³⁷ Moreover, we assume Ψ to be a diagonal matrix with $n \times 1$ elements ψ along the diagonal. The coefficients A_1, \dots, A_4 are assumed to be *a priori* independent. Under these assumptions, the following first and second moments analytically characterise this prior:

$$E[(A_k)_{i,j}] = \begin{cases} \delta_i & j = i, k = 1 \\ 0 & \text{otherwise} \end{cases} \quad (16)$$

$$V[(A_k)_{i,j}] = \begin{cases} \frac{\lambda^2}{k^2} & j = i \\ \vartheta \frac{\lambda^2}{k^2} \frac{\psi_i}{\psi_j / (d-n-2)} & \text{otherwise.} \end{cases} \quad (17)$$

These can be cast in the form of (15). The coefficients δ_i that were originally set by Litterman were $\delta_i = 1$ reflecting the belief that all the variables of interest follow a random walk. However, it is possible to set the priors in a manner that incorporates the specific characteristics of the variables. We set $\delta_i = 0$ for variables

³⁷The prior mean of Σ is equal to $\Psi / (d - n - 1)$

that in our prior beliefs follow a white noise process and $\delta_i = 1$ for those variables that in our prior beliefs follow a random walk process. We assume a diffuse prior on the intercept. The factor $1/k^2$ is the rate at which prior variance decreases with increasing lag length. The coefficient ϑ weights the lags of the other variables with respect to the variable's own lags. We set $\vartheta = 1$. The hyperparameter λ controls the overall tightness of the prior distribution around the random walk or white noise process. A setting of $\lambda = \infty$ corresponds to the ordinary least squares (OLS) estimates. For $\lambda = 0$, the posterior equals the prior and the data does not influence the estimates.

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

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

where $J_p = \text{diag}(1, 2, \dots, p)$.³⁸ In this setting, the first block of dummies in the matrices imposes priors on the autoregressive coefficients, the second block implements priors for the covariance matrix and the third block reflects the uninformative prior for the intercept (ε is a very small number).

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

$$\begin{aligned} y_d &= \text{diag}(\delta_1\mu_1, \dots, \delta_n\mu_n)/\tau \\ x_d &= ((1_{1\times p}) \otimes \text{diag}(\delta_1\mu_1, \dots, \delta_n\mu_n)/\tau \quad 0_{n\times 1}). \end{aligned} \quad (18)$$

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

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

³⁸This amounts to specifying the parameter of the Normal-Inverse-Wishart prior as

$$b = (x_d'x_d)^{-1}x_d'y_d, \Omega_0 = (x_d'x_d)^{-1}, \Psi = (y_d - x_dB_0)'(y_d - x_dB_0)$$

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

$$y_* = x_*B + e_* \quad (19)$$

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

The resulting posteriors are:

$$\Sigma|y \sim IW\left(\tilde{\Psi}, T_d + 2 + T - k\right) \quad (20)$$

$$\beta|\Sigma, y \sim N\left(\hat{\beta}, \Sigma \otimes (x_*'x_*)^{-1}\right) \quad (21)$$

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

B Prior Selection

We adopt the pure Bayesian method proposed in Giannone et al. (2012) to select the value of the hyperparameters of our priors.³⁹

From a purely Bayesian perspective, the informativeness of the prior distribution is one of the many unknown parameters of the model that can be inferred given the conditional posterior distribution of the observed data. Consider a model described by a likelihood function $p(y|\theta)$ and a prior distribution $p_\gamma(\theta)$, where θ is the set of the model's parameters and γ corresponds to the hyperparameters. The hyperparameters are coefficients that parameterise the prior distribution, without directly affecting the likelihood.

Following Giannone et al. (2012), we choose these hyperparameters by interpreting the model as a hierarchical model, i.e. replacing $p_\gamma(\theta)$ with $p(\theta|\gamma)$, and evaluating their posterior. The posterior can be written as:

$$p(\gamma|y) \propto p(y|\gamma) \cdot p(\gamma) , \quad (22)$$

where $p(\gamma)$ is the prior density of the hyperparameters – the hyperprior –, and $p(y|\gamma)$ is the marginal likelihood (ML), that can be expressed as

$$p(y|\gamma) = \int p(y|\theta, \gamma)p(\theta|\gamma)d\theta . \quad (23)$$

³⁹In prior literature, a number of heuristic methodologies have been proposed to set the hyperpriors either by maximising the out-of-sample forecasting performance of the model (see Doan et al. (1983)) or by controlling for over-fitting by choosing the shrinkage parameters that yield a desired in-sample fit (see Banbura et al. (2010)).

This formulation makes evident that the ML is the density of the data as a function of the hyperparameters, obtained by integrating over the model's parameters θ . In our model, the choice of conjugate priors provides us with a closed-form ML.

As discussed in Giannone et al. (2012), this procedure has several appealing interpretations. In the limit case of a flat hyperprior, the shape of the posterior of the hyperparameters coincides with the ML, which is a measure of out-of-sample forecasting performance of a model. Hence the choice of the hyperparameters can be thought of as maximising the one-step-ahead out-of-sample forecasting ability of the model. This strategy can also be thought of as an Empirical Bayes method, which has a well-defined frequentist interpretation. Conversely, the full posterior evaluation of the hyperparameters can be thought of as conducting Bayesian inference on the population parameters of a random effects model or, more generally, of a hierarchical model.

Given the very large dimension of our information set, we make additional assumptions to reduce the number of hyperparameters to be estimated and the uncertainty in the estimation of the VAR coefficients.⁴⁰

Following the empirical BVAR literature we fix the diagonal elements ψ and μ using sample information. Although from a Bayesian perspective the parameters ψ should be set using only prior knowledge, it is common practice to pin down their value using the variance of the residuals from a univariate autoregressive model of order p for each of the variables. In the same way, the sample average of each variable is chosen to set the μ parameters.

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

Following Giannone et al. (2012), we adopt a Gamma distribution with mode equal to 0.2 (the value recommended by Sims and Zha (1996)) and standard deviation equal to 0.4 as hyperprior density for λ .⁴¹

C Adjusted Multipliers

To take into account the increase in state and local government spending in the computation of the fiscal spending multipliers we define adjusted fiscal multipliers.

The impulse response function of a variable, e.g. output, to the news shock \mathcal{N}_t can be expressed as follows

$$\begin{aligned} \frac{d \log Y_{t+h}}{d \mathcal{N}_t} &= \frac{\partial \log Y_{t+h}}{\partial \log G_{t+h}^{Fed}} \frac{d \log G_{t+h}^{Fed}}{d \mathcal{N}_t} + \frac{\partial \log Y_{t+h}}{\partial \log G_{t+h}^{S\&L}} \frac{\partial \log G_{t+h}^{S\&L}}{\partial \log G_{t+h}^{Fed}} \frac{d \log G_{t+h}^{Fed}}{d \mathcal{N}_t} \\ &= \frac{G_{t+h}^{Fed}}{Y_{t+h}} \left[\frac{\partial Y_{t+h}}{\partial G_{t+h}^{Fed}} + \frac{\partial Y_{t+h}}{\partial G_{t+h}^{S\&L}} \frac{\partial G_{t+h}^{S\&L}}{\partial G_{t+h}^{Fed}} \right] \frac{d \log G_{t+h}^{Fed}}{d \mathcal{N}_t}, \end{aligned} \quad (24)$$

⁴⁰In the our EVAR we would have about 50 scalar hyperparameters controlling the tightness of the priors.

⁴¹Using a flat hyperprior for λ , as well as an in-sample methodology to fixing λ as discussed in Banbura et al. (2010), we obtain similar numerical results. Moreover the results are similar over a wide range of values for τ and λ .

where the impact of the shock on G_t^{Fed} , can be normalised to one

$$\frac{d \log G_t^{Fed}}{d \mathcal{N}_t} = 1 . \quad (25)$$

The government spending fiscal multiplier at horizon $t + h$ is

$$m_{t+h} \simeq \frac{\partial Y_{t+h}}{\partial G_t^{Fed}} . \quad (26)$$

Using eq. (24), and assuming that fiscal multipliers for federal and state and local government spending have the same value, we obtain the expression

$$m_{t+h} \simeq \frac{\frac{Y_{t+h}}{G_{t+h}^{Fed}} \frac{d \log Y_{t+h}}{d \mathcal{N}_t}}{1 + \frac{G_{t+h}^{S\&L}}{G_{t+h}^{Fed}} \frac{\partial \log G_{t+h}^{S\&L}}{\partial \log G_{t+h}^{Fed}}} , \quad (27)$$

Substituting time $t + h$ ratios with historical averages of the variables and taking peak values, we get our expression for the adjusted peak multipliers

$$m^{peak} \equiv \frac{\frac{\bar{Y}}{\bar{G}^{Fed}} \text{IRF}^{peak}(Y)}{1 + \frac{\bar{G}^{S\&L}}{\bar{G}^{Fed}} \text{IRF}^{peak}(G^{S\&L})} , \quad (28)$$

where $\text{IRF}^{peak}(\cdot)$ is the normalised IRF of the variable in the argument at the peak.

D Data Sources

We identify the relevant components of US national income for our study using the National Income and Product Accounts (NIPA) which are made available by the Bureau of Economic Analysis of the US Department of Commerce on their website.⁴²

All data for the macroeconomic variables used in our model specifications are from publicly available sources. The primary source for the macroeconomic series is FRED Economic Data available from the website of the Federal Reserve Board of St. Louis (FRED).⁴³ Where available we use the real economic series from FRED, all of which are chained to 2005 dollars. Where the length of the real series is shorter than our sample period, we collect the nominal series and deflate it using the relevant chained-type price deflators which are all indexed at 100 in 2005. These various deflators are available on the website of the Bureau of Economic Analysis.⁴⁴

The total public debt series (PUBDEBT) is collected from the website of the US Department of Treasury.⁴⁵

⁴²www.bea.gov/national/index.htm. A guide to the description and calculation methodology of the main economic accounts is available at http://www.bea.gov/scb/pdf/national/nipa/methpap/mpi1_0907.pdf

⁴³research.stlouisfed.org/fred2/

⁴⁴<http://www.bea.gov/itable/index.cfm>

⁴⁵<http://www.treasury.gov/resource-center/data-chart-center/Pages/index.aspx>

We use the consumer sentiment index developed by the University of Michigan available on their website.⁴⁶ The survey data are also available as part of the FRED Economic Data.

We collect time series of federal government and state and local government spending individual forecasts published in the Survey of Professional Forecasters available on the website of the Federal Reserve Bank of Philadelphia.⁴⁷

The Barro-Redlick marginal tax rate is the income weighted average marginal tax rate from the website of the National Bureau of Economic Research.⁴⁸

The Real Exchange Rate is the average of the prior 3 month real effective exchange rate index for US Dollars calculated by the Bank for International Settlements (BIS) and made available on the BIS website.⁴⁹ BIS calculates the real effective exchange rate as geometric weighted averages of bilateral exchange rates adjusted by relative consumer prices. The weighting pattern is time-varying, and is based on bilateral trade data.

⁴⁶<http://www.sca.isr.umich.edu/>

⁴⁷<http://www.phil.frb.org/research-and-data/real-time-center/>

⁴⁸<http://users.nber.org/~taxsim/barro-redlick/currentp1.html>

⁴⁹<http://www.bis.org/statistics/eer/index.htm>

Table 9: List of Variables

Mnemonic	Variable Description / Short Label	EVAR	Factors	Log	RW Prior
RFEDGOV	SPF Real Federal Govt Spend Implied Nowcast Errors & News	•			•
RGDP	SPF Real Gross National Product/Gross Domestic Product Growth (median)	•			•
UNEMP	SPF Civilian Unemployment Rate (median)	•			
FEDSPEND	Federal Defense and Nondefense Consumption Exp. & Gross Investment	•	•		•
SLCE	State & Local Consumption Exp. & Gross Investment	•	•	•	•
MTR	Barro-Redlick Income Weighted Avg. Marginal Tax Rate / Marginal Tax Rate	•	•		•
FGDEF	Net Federal Government Saving (Deficit)	•	•		•
GDPC96	Real Gross Domestic Product / GDP	•	•		•
UNRATE	Civilian Unemployment Rate	•	•		•
CE16OV	Civilian Employment	•	•		•
HOABS	Business Sector: Hours of All Persons / Total Worked Hours	•	•		•
TOTALSL	Total Consumer Credit Outstanding	•	•		•
BUSLOANS	Commercial and Industrial Loans at All Commercial Banks	•	•		•
OILPRICE	Spot Oil Price: West Texas Intermediate (Dollar Per Barrel)	•	•		•
UMCSENT	University of Michigan: Consumer Sentiment Index	•	•		•
CBCEOCON	Conference Board Measure of CEO Confidence	•	•		•
GPSAVE	Gross Private Saving	•	•		•
DSPIC96	Real Disposable Personal Income	•	•		•
RCPHBS	Business Sector: Real Compensation Per Hour / Real Wages	•	•		•
PCECTPI	Personal Consumption Expenditures: Chain-type Price Index (Percent Change)	•	•		•
PGDG	Personal Consumption Expenditures: Durable Goods / Durables Consumption	•	•		•
PCND	Personal Consumption Expenditures: Nondurable Goods / Nondurables Consumption	•	•		•
PCESV	Personal Consumption Expenditures: Services / Services Consumption	•	•		•
NAPMNOI	ISM Manufacturing: New Orders Index	•	•		•
NAPMII	ISM Manufacturing: Inventories Index	•	•		•
GPATAX	Corporate Profits After Tax with IVA and CCAAdj	•	•		•
OPHPBS	Business Sector: Output Per Hour of All Persons / Output Per Hour	•	•		•
PNFI	Private Nonresidential Fixed Investment	•	•		•
PRFI	Private Residential Fixed Investment	•	•		•
SP500	S&P 500 Stock Market Index (Percent Change)	•	•		•
M2SL	M2 Money Stock (Growth Rate)	•	•		•
REALRATES	Real Interest Rates (3m T-Bill minus Inflation) / Real Rates	•	•		•
GS10	10-Year Treasury Constant Maturity Rate	•	•		•
RER	Real Exchange Rate USD (3 month average closing) / Real Exchange Rate	•	•		•
GCEC96	Real Govt. Consumption Exp.& Gross Invest. / Govt Consumption and Investment	•	•		•
DEFCONS	Federal Defense Consumption Expenditures / Fed Defense Consumption	•	•		•
DGI	Federal Defense Gross Investment / Fed Defense Investment	•	•		•
CIVCONS	Federal Nondefense Consumption Expenditures / Fed Civil Consumption	•	•		•
NDGI	Federal Nondefense Gross Investment / Fed Civil Investment	•	•		•
SLCONS	State & Local Consumption Exp. / State & Local Consumption	•	•		•
SLINV	State & Local Gross Investment / State & Local Investment	•	•		•
FGRECTPT	Federal Government Tax Receipts	•	•		•
PERSTAX	Personal Current Taxes	•	•		•
PUBDEBT	US Total Treasury Securities Outstanding (Public Debt)	•	•		•
UEMPMEAN	Average (Mean) Duration of Unemployment	•	•		•
REALLN	Real Estate Loans at All Commercial Banks	•	•		•

List of Variables (Continued)

Mnemonic	Variable Description / Short Label	EVAR	Factors	Log	RW	Prior
INDPRO	Industrial Production Index		•			
PPIACO	Producer Price Index: All Commodities		•			
HOUST	Housing Starts: Total: New Privately Owned Housing Units Started		•			
GPDI096	Real Gross Private Domestic Investment / Real Private Investment		•			
EXPGSC96	Real Exports of Goods & Services		•			
IMPGSC96	Real Imports of Goods & Services		•			
DJIA	Dow Jones Industrial Average Stock Price Index (Percent Change)		•			
AAA	Moody's Seasoned Aaa Corporate Bond Yield		•			
FEDFUNDS	Effective Federal Funds Rate		•			
GNPC96	Real Gross National Product		•			
PCEPILFE	Personal Consumption Exp.: Chain-Type Price Index Less Food and Energy		•			
CPIAUCSL	CPI for All Urban Consumers: All Items		•			
CPIUFDSL	CPI for All Urban Consumers: Food		•			
CPIMEDSL	CPI for All Urban Consumers: Medical Care		•			
CPIAPPNS	CPI for All Urban Consumers: Apparel		•			
CPIENGNS	CPI for All Urban Consumers: Energy		•			
CUUR0000SEHA	CPI for All Urban Consumers: Rent of primary residence		•			
CPITRNSL	CPI for All Urban Consumers: Transportation		•			
CUSR0000SAD	CPI for All Urban Consumers: Durables		•			
CPILPFNS	CPI for All Urban Consumers: All Items Less Food & Energy		•			
CUUR0000SETA01	Consumer Price Index for All Urban Consumers: New vehicles		•			
CUUR0000SETD	CPI for All Urban Consumers: Motor vehicle maint. and repair		•			
CUSR0000SAS	CPI for All Urban Consumers: Services		•			
CUUR0000SAN	CPI for All Urban Consumers: Nondurables		•			
LNS14000024	Unemployment Rate - 20 years and over		•			
PAYEMS	All Employees: Total nonfarm		•			
USPRIV	All Employees: Total Private Industries		•			
MANEMP	All Employees: Manufacturing		•			
USGOVT	All Employees: Government		•			
USCONS	All Employees: Construction		•			
USFIRE	All Employees: Financial Activities		•			
USGOOD	All Employees: Goods-Producing Industries		•			
SRVPRD	All Employees: Service-Providing Industries		•			
USTRADE	All Employees: Retail Trade		•			
USEHS	All Employees: Education & Health Services		•			
USPBS	All Employees: Professional & Business Services		•			
USINFO	All Employees: Information Services		•			
USLAH	All Employees: Leisure & Hospitality		•			
USTPU	All Employees: Trade, Transportation & Utilities		•			
USWTRADE	All Employees: Wholesale Trade		•			
PCTR	Personal Current Transfer Receipts		•			
AHEMAN	Avg. Hourly Earnings of Prod. and Nonsupervisory Emp.: Manufacturing		•			
AHECONS	Avg. Hourly Earnings of Prod. and Nonsupervisory Emp.: Construction		•			

List of Variables (Continued)

Mnemonic	Variable Description / Short Label	EVAR	Factors	Log	RW Prior
CEU3100000008	Avg. Hourly Earnings of Prod. and Nonsupervisory Emp.: Durable Goods	•			
CEU3200000008	Avg. Hourly Earnings of Prod. and Nonsupervisory Emp.: Nondurable Goods	•			
CEU0600000008	Avg. Hourly Earnings of Prod. and Nonsupervisory Emp.: Goods-Producing	•			
CEU1000000008	Avg. Hourly Earnings of Prod. and Nonsupervisory Emp.: Mining and Logging	•			
WASCUR	Compensation of Employees: Wages & Salary Accruals	•			
FINSLC96	Real Final Sales of Domestic Product	•			
CBIC96	Real Change in Private Inventories	•			
GPDICTPI	Gross Private Domestic Investment: Chain-type Price Index	•			
ULCBS	Business Sector: Unit Labor Cost	•			
HOABS	Business Sector: Hours of All Persons	•			
IPDCONGD	Industrial Production: Durable Consumer Goods	•			
IPBUSEQ	Industrial Production: Business Equipment	•			
IPCONGD	Industrial Production: Consumer Goods	•			
IPNCONGD	Industrial Production: Nondurable Consumer Goods	•			
IPDMAT	Industrial Production: Durable Materials	•			
IPNMAT	Industrial Production: Nondurable Materials	•			
NAPM	ISM Manufacturing: PMI Composite Index	•			
NAPMSDI	ISM Manufacturing: Supplier Deliveries Index	•			
NAPMEI	ISM Manufacturing: Employment Index	•			
NAPMPI	ISM Manufacturing: Production Index	•			
NAPMPRI	ISM Manufacturing: Prices Index	•			
PPIFGS	Producer Price Index: Finished Goods	•			
PPIHDC	Producer Price Index: Industrial Commodities	•			
PPICRM	Producer Price Index: Crude Materials for Further Processing	•			
PPIITM	Producer Price Index: Intermediate Materials: Supplies & Components	•			
PPICFE	Producer Price Index: Finished Goods: Capital Equipment	•			
PPIFCF	Producer Price Index: Finished Consumer Foods	•			
PERMITNSA	New Privately-Owned Housing Units Authorized by Building Permits: Total	•			
HOUSTMW	Housing Starts in Midwest Census Region	•			
HOUSTS	Housing Starts in South Census Region	•			
HOUSTW	Housing Starts in West Census Region	•			
HOUSTNE	Housing Starts in Northeast Census Region	•			
TB3MS	3-Month Treasury Bill: Secondary Market Rate	•			
TB6MS	6-Month Treasury Bill: Secondary Market Rate	•			
GS1	1-Year Treasury Constant Maturity Rate	•			
GS5	5-Year Treasury Constant Maturity Rate	•			
BAA	Moody's Seasoned Baa Corporate Bond Yield	•			
M1SL	M1 Money Stock	•			
MZMSL	MZM Money Stock	•			
MZMV	Velocity of MZM Money Stock	•			
M1V	Velocity of M1 Money Stock	•			
M2V	Velocity of M2 Money Stock	•			
AMBSL	St. Louis Adjusted Monetary Base	•			
EXCRESENS	Excess Reserves of Depository Institutions	•			