Identifying U.S. Government Spending Shocks : It's all about the Information Flow

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First version: 1 September 2022
This version: 2 October 2023

Abstract

What is the economic effect of discretionary increases in government spending? We answer this question with a novel approach that accounts for the anticipation and imperfect information. Building on the class of imperfect information models, we provide a key decomposition of forecast errors into three orthogonal shocks: *expected*, *unexpected* and *misexpected* changes. A lack of distinction between anticipation and misperception blurs the impact of fiscal policy shocks: using a novel proxy of expectation based on the Greenbook forecasts and modern Bayesian techniques, we find that current and future news in the U.S. government spending stimulate economic activities. We also confirm these results in monthly analyses and explore the role of data revisions in agents' misperceptions. Our findings highlight the importance of imperfect information in reconciling previous results in the literature.

Keywords: Fiscal shocks, Large Bayesian VARs, Government spending, Fiscal foresight.
JEL Classification: C32, E32, E62.

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We are grateful to Luca Gambetti, Ivan Petrella, Fabrizio Venditti, Marija Vukotic, Sarah Zubairy, and participants of the Warwick macroeconomics workshop for insightful comments. We also thank Simon Van Norden and the Federal Reserve Bank of Philadelphia for giving us access to the dataset.

1 Introduction

After reaching the zero lower bound and breakout of COVID-19, there has been a revived interest in fiscal policy among policymakers worldwide. On September 17, 2020, amid the pandemic, an interesting debate about the impact of fiscal programs took place in the Congressional Oversight Commission hearing: Director Edwards of Cato Institute claimed that a dollar of Federal aid would result in less than a dollar of growth, citing Ramey (2019). Commissioner Ramamurti rebutted by pointing out that the same study suggests a fiscal multiplier of 1.5 when the monetary policy is very accommodative, which was the situation at that moment. In the end, the debate ended with an unbeatable statement from the commissioner: "Yesterday I called up Professor Ramey,..., and she said that conditional on the current economic and policy situation, the multiplier is likely to be between 1.2 and 1.5."[1]

While the hearing ended with deus ex machina, all of them are actually true: the empirical evidence on the effects of fiscal stimulus is still mixed. Ramey (2019) does mention that the US government spending multiplier is mostly around 0.6 to 1, though it varies with the state of the economy. Even without considering the state-dependency, however, there are still two main issues. First, results are sensitive to the sample: current estimates hold only if Korean war samples are included. An important concern in Ramey (2011) is that the 'military news' variable loses most of its explanatory power in post-Korean war samples. Moreover, the story becomes the complete opposite: when the government spending rises, GDP increases only at the impact and decreases afterwards: The estimated multiplier becomes negative.

A more critical issue is the problem of imperfect information, which affects agents' expectation formation process. The literature has mainly focused on the anticipation problem to explain the inconsistency across studies: for instance, Ramey (2011) argued that the inadequate control of anticipated future policy actions in structural VARs induced different results from the narrative approaches. So she suggested using SPF 1Q-ahead Forecast Errors on real federal spending as an alternative instrument in post-Korean war samples. This approach makes sense in the case of full information rational expectations models, where agents immediately process the new information. However, in the case

[1] Commission (2020). "The Fifth Report of the Congressional Oversight Commission" in *Congressional Oversight Commission Reports*, (October 15, 2020)

of imperfect information, such as Mankiw and Reis (2002) and Sims (2003), the new information is only partially absorbed over time, so average forecast errors are likely to be a combination of both current and past structural shocks, i.e. forecast errors are predictable. Then, forecast and nowcast errors are not suitable proxies for the structural innovations.

In this paper, we revisit this important but unresolved research question: what is the macroeconomic effect of government spending? Building on the class of imperfect information models, we propose a novel approach to study fiscal policy shocks that accounts for both *anticipation effects* and *imperfect information*. We make three observations from (Coibion and Gorodnichenko, 2015), that derives the relationship between forecast errors and revisions: first, conditional on the past information set, the revision of expectations are informative about policy innovations. Second, forecast errors do not contain additional information, conditional on past and current news. Finally, nowcast errors may contain additional information about government spending changes that agents cannot process in real-time. In sum, imperfect information models tell us that we should focus on forecast revisions, not forecast errors, to identify macroeconomic shocks.

We apply these ideas to the identifications of fiscal shocks. To assess the balance between misperception and foresight of fiscal changes, we decompose the forecast errors into three orthogonal fiscal shocks: *expected*, *unexpected* and *misexpected* fiscal changes, which we named from the psychology literature, Ekman and Friesen (1975). Specifically, we identify *expected* shocks using forecast revisions in future government spending. *Unexpected* changes are defined as the nowcast revisions in spending, as they correspond to changes in government spending that have not been anticipated by agents but are perceived upon their realisation. Finally, *misexpected* fiscal changes are identified using nowcast errors, as they represent fiscal changes that have not been anticipated and misperceived by agents when realised. Such a classification is consistent with Ricco (2015), on which this paper is built. Taking one step further from this paper, we shed more light on the source of misexpectation, by decomposing nowcast errors into three components: measurement error, re-definition and 'early' nowcast errors based on preliminary data releases.

To build expectational measures that account for the information flow on federal government spending, we utilise the Greenbook forecasts that have been hand-collected and cleaned, as in Croushore and van Norden (2018). Compared to the widely used Survey of Professional Forecasts (SPF), the new measure have a comparative advantage in at least three aspects. First, Greenbook forecasts are efficient, unbiased estimates constructed by the largest team of macroeconomic experts who possibly have informational superiority.[2] They take account of anticipated monetary reactions given the current and future the state of the economy, which might be confounding factors when identifying fiscal shocks. Second, they provide richer cross-sectional information: While the SPF data only offer forecasts on the aggregate government spending, the Greenbooks contain estimates on the sub-components and related items. Finally, they offer a more extended sample and forecast horizons at a higher frequency.[3] Since they are usually updated eight times per year, they are notably more helpful in capturing high-frequency variables' reactions, such as exchange rate movements.

We report three main findings using a large Bayesian VAR technique and recursive identification. First, an unexpected increase in government spending has expansionary effects on the economy. Real GDP responds positively up to 4 quarters: this contrasts with Ramey (2011), who finds the opposite effect with the same sample. Our result is more aligned with the Keynesian multiplier story, especially through consumption. Hours and real wages also increase, and the real exchange rate depreciates upon a surprise shock, consistently with the result from Forni and Gambetti (2016). We cross-check this result with expectational measures constructed from the SPF data.

Second, positive, expected changes in government spending also lead to an expansion, especially when the agents expect the news to take place within a year. The output significantly rises up to one year, driven by an increase in consumption and investment. The monetary policy attempts to prevent overheating from the fiscal stimulus in the short-run, and the real exchange rate slowly appreciates. Together with the response to unexpected changes, this finding confirms those of Forni and Gambetti (2016) – after separating fiscal news from surprises, the depreciation puzzle disappears in the case of the former. However, when the news is anticipated to occur after one year, effects tend to be recessionary: the economic growth slows down, possibly due to the agent expecting systematic spending reversals, with a simultaneous drop in consumption and investment.

[2]Croushore and van Norden (2019) report this by exploring the statistical properties of the Greenbook forecasts.

[3]Greenbook forecasts are available from August 1967 at the earliest, with forecast horizons up to 9 quarters and backcasts of past five quarters.

We do not observe a depreciation puzzle after this type of future news. For both one and two-year news, we find that expectational proxies based on Greenbooks more correctly captures the timing of policy implementations than the SPF data.

Finally, misexpected fiscal changes produce a transitory output increase on impact and a subsequent contraction. The overall response is more in line with the neoclassical mechanism: due to the crowding out of private consumption and investment, the GDP response quickly becomes negative. The labour market becomes loose, and hours fall. Interest rates, stock prices, and exchange rates experience a fall on impact but are not affected afterwards. Such results resemble those of Ramey (2011) for the post-Korean war samples, without delay in contractionary effects. To reconcile contrasting effects between misexpected and other fiscal surprises, we explore the role of data revisions as a source of misexpectation. Going above and beyond Ricco (2015), we further decompose the nowcast error into measurement errors, re-definitions (benchmark revisions), and the nowcast error based on earlier data releases. We find that once taking into account the re-definition component, most recessionary effects become short-lived and insignificant.

By fully utilising the Greenbook forecasts, we also study the monthly effect of discretionary fiscal spending to investigate high-frequency movements deeply. Identifying fiscal policy shocks with the Proxy SVAR approach á la Stock and Watson (2012) and Mertens and Ravn (2013), we find similar, if not reinforcing, results with the quarterly baseline. While unexpected and expected shocks lead to an economic boom, the effect of misexpected shock is contractionary. Interestingly, the depreciation puzzle seems to disappear in the monthly analysis even upon a surprise shock. The only difference is in responses to a one to two years ahead news, which weakly implies a boom rather than a recession: the output slightly rises with a simultaneous increase in new orders of durables and manufacturing sales, though almost no change in retail sales and consumer credit.

Our findings highlight the importance of considering both the anticipation effects and the information flow, in the reconciliation of previous results in the literature. Imperfect information models tell us that forecast errors mix past and current innovations when past news is not controlled. Once decomposing forecast errors into nowcast errors and revisions, we find that they induce the opposite effects. However, a larger variance of the former dominates empirical responses, so it dominates empirical responses and underestimates the impact of fiscal policy. This is a major limitation of Ramey (2011)'s

EVAR approach: a lack of distinction between anticipation and misperception blurs the impact of fiscal policy shocks. In the case of the structural VAR approaches, they seem to blend unexpected and expected fiscal changes. Based on these observations, we argue that forecast revisions, or news, should be studied to learn about policy effects.

The structure of this paper is the following. Section 2 provides the key idea behind our novel identification strategy based on imperfect information models. Section 3 introduces new empirical measures of agents' expectations based on the Greenbook forecasts. Section 4 describes the dataset and empirical framework to study the effect of government spending changes. The main results appear in Section 5. Section 6 explores the role of data revisions as a source of misexpectation. Section 7 concludes.

Related Literature. This paper is closely related to extensive literature on the effect of government spending shocks, and there are two main strands of papers. The first one is a narrative approach: based on the idea of Hall (1980) and Barro (1981) that focus on defence spending to identify exogenous government purchase shocks. Rotemberg and Woodford (1992) first estimated the VAR system with military spending, military employment, and a macroeconomic variable, such as hours worked, while restricting the feedback from economic indicators to military variables. Ramey and Shapiro (1998) employed a dummy variable approach representing major military build-ups from *Business Week*. While they estimated the effect of these "war dates" with a single regression, later studies, such as Edelberg et al. (1999) and Burnside et al. (2004), augmented this variable in VARs by ordering them first. Most of these papers found that increasing government spending raises GDP and hours but contracts consumption, investment, and the real wage.

The other strands of literature employ the structural VAR (SVAR) approach to identify government purchase shocks. Blanchard and Perotti (2002) apply a standard recursive identification strategy with the government spending ordered first, based on the assumption that government purchases do not respond to current economic conditions due to a delay in implementation. They observe that the shock raises consumption and real wages, on top of GDP and hours. This is more consistent with the prediction of new Keynesian models, such as Devereux et al. (1996) and Galí et al. (2007). The follow-up papers, e.g. Perotti (2004) and Pappa (2009), report similar results. Mountford and Uhlig (2009) employ sign restrictions approach. Ben Zeev and Pappa (2017) use a medium-horizon identification method by focusing on news orthogonal to the current defence spending and explaining the most spending variations over the next five years.

More recent studies attempt to reconcile different results from two methods with so-called the Expectational VAR (EVAR) approach– the term coined by perotti (2011). The main idea is that augmenting a proxy for agents' beliefs on top of the standard VAR alleviates a potential misalignment between the agents and the econometrician due to anticipation.Ramey (2011) argues that the SVAR approach fails to capture fiscal foresight by showing that this shock is Granger-caused by the War dates variable. She proposed to embed her military news series, which are estimates of changes in the expected present value of government purchases from *Business week*, in a standard VAR and order them first. As her news variable loses the instrumental relevance in post-Korean War samples, she proposes another proxy: the forecast error from Survey of Professional Forecasters. The results seem to be more consistent with those from the narrative approach, though only when the Korean War samples are included. Fisher and Peters (2010) use an alternative news series based on the excess stock returns of major defence contractors.

Later studies using the EVAR approach took one step further by separating surprises and the news components from the forecast error. perotti (2011) first decomposes the SPF one-quarter ahead forecast error into a time t surprise and a revision from *t-1* to *t*. Based on the observation that fiscal foresight is a medium-run phenomenon, Forni and Gambetti (2016) separate two shocks: the first "news" shock affects the spending with a delay but agents' expectations on impact. The second "surprise" shock is the residual from the EVAR, which affects the spending on impact but is observed by agents with a lag. Most closely related to our paper, Ricco (2015) decomposes the forecast error into three orthogonal components, which he named *expected*, *unexpected* and *misexpected* shocks, based on the information flow of the agents, while highlighting a potential aggregation bias in the aggregated SPF data. Compared to these papers, we propose a novel expectational measure based on the Greenbook forecasts. While Ricco (2015) provides only a descriptive explanation about the source of misexpectations, we further explore this issue by decomposing nowcast error into two components of data revisions, measurement error and re-definitions, and looking at their role in driving macroeconomic effects.

2 A Model based on the Information Rigidity

In this section, we present the key idea in identifying government spending shocks based on imperfect information models. First, we briefly review the vast literature on the class of these models and how they highlight important limitations in current empirical approaches. Second, we show that forecast errors cannot be good proxies for structural innovations when information rigidity is present, while forecast revisions could be good candidates conditional on past news. Finally, we distinguish three measures of surprises in fiscal spending by decomposing forecast errors.

Starting from the early literature such as Lucas (1972), it has been emphasised that agents encounter an imperfect information problem when forming expectations. Two classes of models have received wide attention so far: the sticky-information model by Mankiw and Reis (2002) and the noisy-information model such as Woodford (2001) and Sims (2003).[4] Deviating from the full rational expectation model, individuals need time and resources to absorb news even if the data becomes available. Hence, information spreads slowly and is not perfectly observable even in the near future.

In each model, agents realise fundamentals subject to lag and noise, respectively. Such a difference arises from seemingly analogous but disparate microfoundations: inattentiveness and rational inattention. In the sticky-information model, agents update their information sets infrequently due to fixed costs of acquiring, absorbing, and processing information (lag). If individuals prefer not to pay the costs, they continue to be "inattentive" and follow old information. While in the noisy-information model, agents continuously update their information sets, but they cannot fully observe the actual state (noise). Since observed fundamentals are contaminated by idiosyncratic noise, individuals build up expectations via solving a signal extraction problem. Agents cannot obtain complete information as in the sticky information model. Coibion and Gorodnichenko (2012) argued that agents might exhibit different speeds of information updating in response to a particular fundamental shock, unlike the sticky information model.[5]

What do these imperfect information models tell us about the effect of fiscal policy shocks? The presence of information rigidity modifies the agents' expectations and hence

[4] They are also referred to as Delayed information and Partial information models: see Mankiw and Reis (2010).

[5] Sims (2003) supports the idea that humans' processing abilities are bounded by fixed capacity for all information acquisition channels (Shannon's constraint).

their decisions – the *anticipation effect*. Ramey (2011) argued that a severe limitation in Blanchard and Perotti (2002)'s influential paper is that it suffers from anticipation by agents. As Leeper et al. (2013) pointed out, agents receive a continuous flow of information about future government spending.[6] Hence, while forward-looking agents take account of policy changes that are announced to occur in the future, the econometrician observes the state of the economy and the innovations in fiscal policy only with a lag. Such a misalignment between the agents' and econometrician's information set makes the vector autoregression (VAR) model misspecified, and the innovations to government spending mix the anticipated and unanticipated components: a phenomenon known as *fiscal foresight*. As a remedy to this issue, Ramey (2011) proposed the Expectational VAR (EVAR) approach. On top of the standard VAR specification, augmenting variables that can proxy for agents' beliefs – such as forecast errors on future government spending– helps the econometrician to align his information set to that of the agents.

However, with information rigidity, agents cannot fully process structural innovations in real-time. In reality, they observe past realisations of the economy and signals about the present and future realisation of macroeconomic variables. Agents need to solve a signal extraction problem using different sources, to infer the right content and timing of the policy to be implemented in the future. A common prediction of imperfect information models – regardless of assuming sticky or noisy information – is the partial absorption of information in the economy: agents' expectations respond only gradually to a shock to fundamentals, so the average forecast errors are the combination of current and past shocks. As Ramey (2011) highlighted, it is all about the timing, which is likely to be distorted when the informational problem has not been taken into account.

To highlight the limitation of the EVAR approach, we start with the observation made by Coibion and Gorodnichenko (2015). They found that in both class of imperfect information models, the average ex-post forecast errors across agents and the average ex-ante forecast revisions are related by the following expression:

$$\underbrace{x_t - E_{t-h}x_t}_{\text{Forecast Error}} = \frac{1-\kappa}{\kappa}\underbrace{(E_{t-h}x_t - E_{t-h-1}x_t)}_{\text{Forecast Revision}} + u_{t-h+1} + \cdots + u_t \tag{1}$$

[6] Due to the institutional process, changes in fiscal policy take place after two lags: (1) between the initial proposal of policy and its approval by the government (inside lag) and (2) between the enactment of the legislation and its actual implementation by the parliament (outside lag).

where x_t is the variable of interest, $E_{t-h}x_t$ is the average forecast across forecasters at the time t-h, and u_t is the rational expectation error. κ represents the degree of information rigidity: $\kappa = 1$ in full information rational expectation models, while $\kappa < 1$ under imperfect information, as the agents partially update their information sets. Hence, forecast and nowcast errors are predictable in this case. With little algebra, we can derive the following expression from Equation (1):

$$\underbrace{(E_{t-h}x_t - E_{t-h-1}x_t)}_{\text{Revision at t-h}} = (1-\kappa)\underbrace{(E_{t-h-1}x_t - E_{t-h-2}x_t)}_{\text{Revision at t-h-1}} + \kappa u_{t-h} \tag{2}$$

Appendix A describes the derivation in full detail. Considering equations (1) and (2), imperfect information models tell us that we should focus on forecast revisions, not forecast errors, to identify macroeconomic shocks. This claim is based on two observations. First, forecast revisions are informative about policy innovations. From equation (2), we can see that conditional on past forecast revisions (news), we can recover κu_{t-h}, the current innovation up to a scale.[7] However, this is not the case for forecast errors: as equation (1) suggests, one needs to control past news to recover shocks. Applying equation (2) to (1), one realises that the forecast error is a weighted sum of current and past shocks, with weights declining by $1/\kappa$. Hence, when the past revisions are not controlled for, forecast errors mix past and current innovations. This is a significant limitation in the current EVAR approach: forecast errors are unsuitable proxies for structural shocks, even after controlling their past values.[8]

The use of forecast errors comes with another caveat by their construction– data revisions. For instance, one can easily decompose the nowcast error into two components:

$$\underbrace{x_t^T - E_t x_t}_{\text{Nowcast Error}} = \underbrace{(x_t^T - x_t^{T-1} + \cdots + x_t^{t+1} - x_t^t)}_{\text{Data Revisions}} + \underbrace{(x_t^t - E_t x_t)}_{\text{1st Nowcast Error}} \tag{3}$$

where the superscript represents the vintage date for the data x_t. Hence, x_t^T is the most recent release, and the x_t^t is the first release of the data. While the idea of EVAR centres on using the last component, simply taking the current vintage of data results in

[7]For instance, let us take the case of nowcast revision, h=0. Then from equation (2), we can see that it is the weighted average of 1Q-ahead forecast revision made in the previous period and the current shock u_t, with the weight of (1-κ) and κ for each.

[8]For both equations (1) and (2), one should notice that the target date t remains the same. Hence, it is not about controlling for the usual serial correlation. Instead, it highlights the importance of accounting for forecasts made at all horizons.

mixing the data revisions component, which has nothing to do with policy innovations. This might not be problematic if revisions are just random noise, possibly due to the measurement error. However, as observed in Aruoba (2008), data revisions in the US are biased and not well-behaved: they are not mean zero, serially correlated, and predictable using the information set at the time of announcement. Hence, shocks are not well identified under the current practice. One can also further decompose the data revision components into re-definition and measurement errors, and we revisit this point in the Section 6.

Based on these insights from the models of imperfect information, we attempt to assess the balance between misperceptions and foresight of fiscal changes, as in Ricco (2015). The key idea is that we decompose the one-period ahead forecast error into two parts– nowcast error and nowcast revisions (contemporaneous news):

$$\underbrace{\Delta g_t - E_{t-1}\Delta g_t}_{\text{Forecast Error one ahead}} = (\underbrace{\Delta g_t - E_t\Delta g_t}_{\substack{\text{Nowcast Error} \\ \notin I_t}}) + (\underbrace{E_t\Delta g_t - E_{t-1}\Delta g_t}_{\substack{\text{Nowcast Revision} \\ \in I_t}}) \tag{4}$$

where Δg_t is the government spending in terms of growth, and I_t represents the information set of agents at the time t. Note that the nowcast error does not belong to the current information set: we leave the door open for the possibility that nowcast errors may contain additional information about government spending changes that agents may not process in real-time. By generalising this approach, we also decompose the h-period ahead forecast error into the nowcast error and the flow of news over time:

$$\begin{aligned}\underbrace{\Delta g_t - E_{t-h}\Delta g_t}_{\text{h-ahead Forecast Error}} &= (\underbrace{\Delta g_t - E_t\Delta g_t}_{\substack{\text{Nowcast Error} \\ \notin I_t}}) + (\underbrace{E_t\Delta g_t - E_{t-1}\Delta g_t}_{\substack{\text{Nowcast Revision (news at t)} \\ \in I_t}}) + \cdots \\ &+ (\underbrace{E_{t-h+1}\Delta g_t - E_{t-h}\Delta g_t}_{\substack{\text{Forecast Revision (news at t-h+1)} \\ \in I_{t-h+1}}})\end{aligned} \tag{5}$$

We think of these three components as proxies for different types of fiscal shocks and refer to them as *misexpected, unexpected, and expected fiscal changes*, respectively. This is because they have distinct properties concerning the information set of agents. Nowcast and forecast revisions contain news today and the future, so they modify the information set *before and upon* realisation. On the other hand, agents learn about errors in their forecasts only with a delay, by definition. Hence, they only enter the information set *after* the realisation and show up as the change in hindcast, if updated later.

Borrowing the concept from psychological research, Ekman and Friesen (1975), we distinguish three measures of surprises in fiscal spending: (1) expected fiscal changes (forecast revisions) that are anticipated by agents before occurence, (2) unexpected fiscal changes (nowcast revisions) that are unanticipated before but perceived upon at the time news take place, (3) misexpected changes (nowcast error) that are also unanticipated but realised only with the delay, possibly due to data revisions or deviations from full information rational expectations, for the rest of this paper. By exploring the macroeconomic effects from three types of fiscal shocks, we attempt to reconcile incongruent results across studies, particularly between the structural VAR and the EVAR approaches, where the former finds the effect of fiscal policy to be expansionary but the latter to be recessionary.

3 Greenbook Forecasts as Measures of Expectations

As highlighted in the last section, agents' expectations play a crucial role in measuring the effect of government spending shocks to account for both anticipation and information flow. Then, the key question is: which data shall we use as empirical measures of agents' expectation? This section discusses how we build these proxies before introducing our empirical strategy and the macroeconomic dataset.

In this paper, we construct empirical measures of agents' expectations of the macroeconomy and federal government spending based on the Greenbook forecasts published by the Federal Reserve before the FOMC meetings. As in Croushore and van Norden (2018), the Greenbook forecasts have been hand-collected and validated from two primary sources: page scans of each Greenbook made by the Federal Reserve and the Real-Time Data Research Center at the Federal Reserve Bank of Philadelphia.[9] Currently, our dataset includes the Greenbooks prepared for the March 1967 FOMC meeting and up to the December 2014, covering 454 meetings over the 47 years for macroeconomic variables, such as the real GDP, GDP deflator, and unemployment rate. In the case of

[9]While there is the third source – the ALFRED database – available, Croushore and van Norden (2018) its limitation compared to our two sources. The Greenbook estimated published in the ALFRED database at the Federal Reserve Bank of St.Louis only contains figures from the main volumes of the Greenbook. Therefore, it lacks late-breaking developments (such as statistical releases or revisions), which are collected and circulated as a supplement to the Greenbook.

fiscal variables, some are either missing or have very short time series in earlier records: while estimates of federal government purchases, defence, and non-defence spending are available from as early as August 1967, the fiscal impetus obtains reliability only from September 1988. They are primarily compiled from the Federal Sector Accounts and Main Economic Indicators tables in the Greenbooks.

To the best of our limited knowledge, this is the first paper to use the carefully validated Greenbook forecasts as empirical measures of agents' fiscal policy expectations.[10] So far, previous papers, such as Ramey (2011), Ricco (2015), and Forni and Gambetti (2016), focused on Survey of Professional Forecasters (SPF) data provided by the Federal Reserve Bank of Philadelphia. Using the Greenbook forecasts may provide comparative advantages to the SPF data in at least three aspects.

First, they offer estimates with extended samples, forecast horizons including hindcasts, and more frequency. The SPF forecasts for government spending are available quarterly, starting from 1981Q3.[11] The forecast horizon runs from h=0 to 4, so nowcasts up to one year ahead forecasts. On the other hand, the Greenbook forecasts are available from as early as August 1967, with the forecast horizons up to 9 quarters and backcasts of the past five quarters. So they allow us to examine the effect of policy changes that are anticipated to happen in more than one year. At the same time, with the SPF, the most extended horizon is limited to 4 or even three quarters when we explore the effect of forecast revisions (news). Moreover, the Greenbooks are usually updated eight times per year, allowing us to conduct monthly analyses, as done in the recent monetary policy literature such as Gürkaynak et al. (2005) and Gertler and Karadi (2015).[12][13]

Second, Greenbook forecasts are efficient, unbiased estimates (Croushore and van Norden, 2019). They are constructed by the largest team of macroeconomic experts, whose forecasts of inflation, GDP, and the unemployment compared to the very best

[10] Auerbach and Gorodnichenko (2012) also used the part of this dataset, but they only used it to cover the periods where the SPF data were unavailable. Moreover, they focus on the one-quarter ahead forecast error: not both forecast errors revisions in all available forecast horizons.

[11] Hence, for the periods before 1981, the literature either used the forecasts on the federal defence spending (Ramey, 2011) or the Greenbook forecasts on the federal government spendings (Forni and Gambetti, 2016).

[12] Since 1981, there have been precisely two FOMC meetings per quarter. Before that, there were usually 12 meetings per year (not necessarily one per month), but varying from 9 to 15 meetings per year.

[13] In the empirical literature on fiscal policy, Fisher and Peters (2010) are open to the possibility of conducting monthly analyses since their instrument, excess stock returns of the defence industry, is available in high-frequency. However, they only present results of the quarterly analyses.

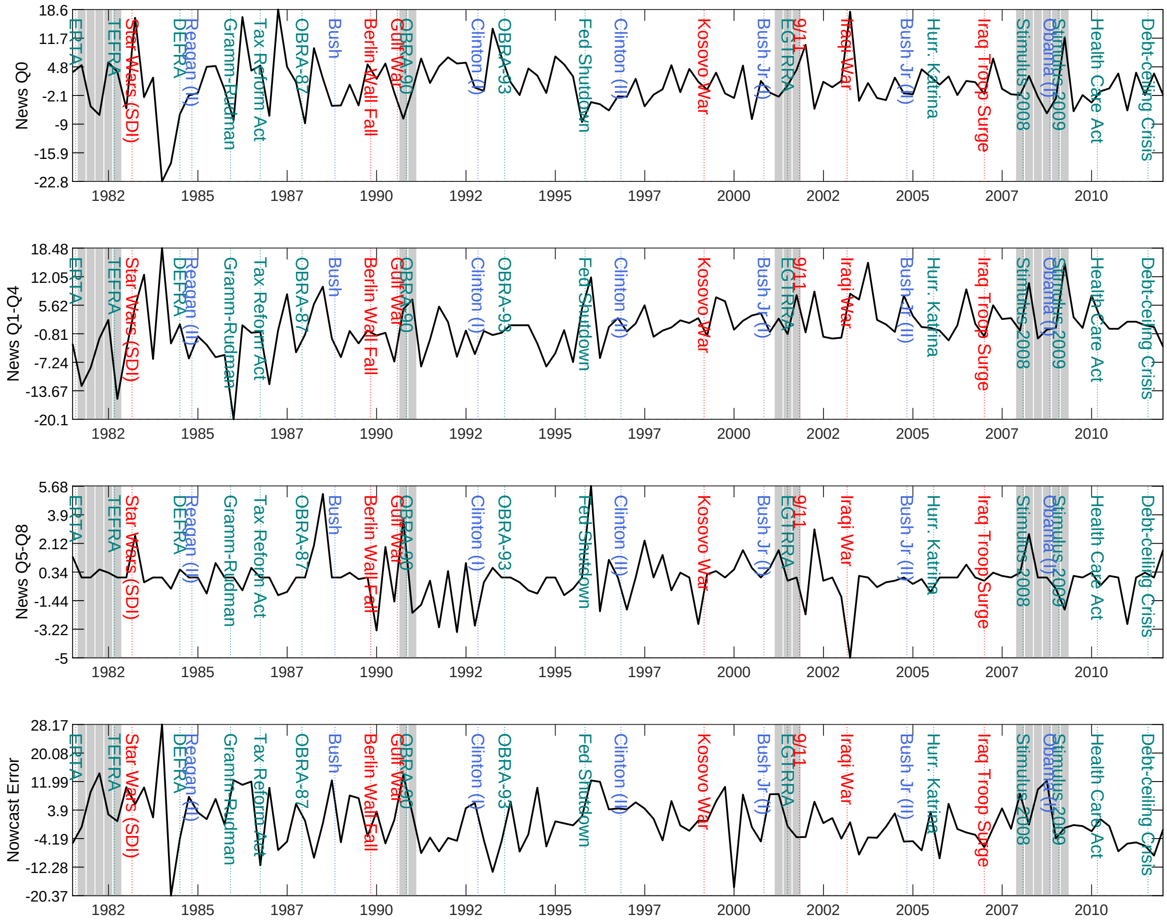
available. Romer and Romer (2000) showed that the Fed has considerable information beyond what is known to private forecasters, particularly in inflation. Moreover, since Greenbooks are precisely presented to monetary policymakers, they consider anticipated/recommended monetary policy decisions given the current and future state of the economy, which might be confounding factors when identifying fiscal shocks. Croushore and van Norden (2018) observed that these fiscal forecasts account for a significant fraction of exogenous changes in the federal funds target. This novel dataset allows us to explore the extent to which monetary policymakers identify current and future news on fiscal policy, while taking account of future development in the economy and the monetary reactions.

Finally, Greenbook forecasts provide more detailed estimates about future government spending. While the SPF data only offer forecasts on the aggregate federal government spending, the Greenbooks also make estimates on their sub-components: defence, non-defence, and other spending. Moreover, our dataset contains six other related items beyond the forecasts on real federal spending growth. In addition to the three sub-components, data on expenditures, borrowings, and fiscal impetus are also available. While they are not the focus of this paper, such details allow us to explore the effect of government spending changes by different types. Such details allow us to take on an important ongoing issue: a continuing decrease in the portion of defence spending in the U.S. since the 1990s.

Throughout this paper, we first focus on the forecasts about the aggregate, real federal government spending growth to ease the comparison with the literature. In the same vein, we focus on the sample from 1981Q3 to 2012Q1. Moreover, we use one observation per quarter – forecasts published in the middle month – to align the information set of the Fed with commercial forecasters. We use all observations in the monthly analyses, where the value is set to zero when no meeting is held that month.

Figure 1 shows the time series plot of forecast revisions and nowcast errors on the real government spending growth, based on the Greenbook forecasts. We also plot announcement dates of major fiscal events, presidential elections, and the war dates in vertical bars. Overall, peaks and troughs of our news series tend to match major fiscal events and wars coincidentally or with a short lag. For instance, large spikes take place around the announcement of Star Wars, Gramm-Rudman-Hollings Balanced Budget Act, Berlin

Figure 1: Government Spendings News and Nowcast Errors based on Greenbook Forecasts



Note: This plot shows Greenbook-implied new on the current, up to 1 year, 1 to 2 years, and the nowcast error. Grey areas represent NBER recession dates. Vertical lines are announcement dates of major fiscal events (green), presidential elections (blue), and the war dates (red). Forecasts are made at the middle of each quarter. Sample 1981Q3 – 2012Q1.

Wall Fall, Iraqi War, and the stimulus package of 2009.

By carefully inspecting this chart, it gives us the justification for separating different types of government spending shocks. The top plot represents revisions for the current quarter: they tend to increase around surprising events, such as the announcement of Star Wars, 9/11, Iraqi War, and the stimulus package of 2009. They also drop around events that reduce the spending in the short-term, such as the 1995-96 federal government shutdown in the US. The second plot, revisions up to a year, displays the largest swings when new fiscal policies are enacted: significant negative revisions are observed around the Economic Recovery Tax Act (ERTA), Tax Equity and Fiscal Responsibility Act (TEFRA), and Gramm-Rudman-Hollings Balanced Budget Act – all of them contain

Table 1: Explanatory power of fiscal news based on Greenbooks

Independent Variable	F-stat	Prob F	Coefficient	T-stat
Nowcast revisions	14.65	0.000	0.403	3.827
News (1,4)	1.451	0.232	0.544	1.204
News (1,8)	1.616	0.207	-0.519	-1.271
Nowcast Error	42.51	0.000	0.569	6.520

Note: this is the result of regressing real federal government spending growth on 4 current forecast variables and one to four lags of 8 macroeconomic indicators. Forecast variables are: nowcast revisions, the sum of 1-4 quarters ahead (News (1,4)), 1-8 quarters ahead forecast revisions (News (1,8)), and the nowcast error. Macroeconomic indicators are: GDP, the average marginal tax rate, real interest rate, nonresidential fixed investment, and durable/non-durable/services consumption. Sample 1981Q3 – 2012Q4.

tax cuts or reductions in federal deficits. Positive revisions take place for the stimulus packages of 2008 and 2009. Interestingly, while the 1995-96 federal government shutdown in the US is strongly positive news: our series correctly capture that since it freezes spending in short term, a large increase in spending happens afterwards. In the same vein, revisions from one to two years in the third plot hike during the same event, and they plummet around the Berlin Wall Fall and Iraqi War.

On the other hand, it seems like the nowcast errors have somewhat different properties. While they capture some of the important events, such as the drop around the Tax reform act of 1986, they also move in the opposite direction to the intention of the policy, e.g. the hike around Omnibus Budget Reconciliation Act of 1990 (OBRA-90) and fall with the stimulus act of 2009. There is also an unknown, sizeable negative shock around the first quarter of 2000. Compared to revisions, nowcast errors are not straightforwardly related to major events, so it is more difficult to interpret them. Later in Section 4, we also show only nowcast errors display serial correlation, possibly due to the property of data revisions, even after controlling the current news. Interestingly, given the scale, nowcast errors have larger variance than forecast revisions.

Before closing this section, we assess the explanatory power of fiscal news based on the Greenbooks by reporting F-statistics in Table 1. In order to test the relevance of these new measures, we regress real federal government spending growth on four forecasts revisions and errors and one to four lags of 8 macroeconomic variables: GDP, the average marginal tax rate, real interest rate, nonresidential fixed investment, and durable, nondurable, services consumption. Table 1 reveals that while the nowcast error displays the highest

F-statistics as Ramey (2011) pointed out, the F statistic of nowcast revision is also larger than 10. The 4 and 8 quarter ahead news are only weakly relevant, but this is not surprising as they relate to future government spending. In sum, our news measures based on the Greenbooks appear to be strong instruments and provide helpful information in terms of forecasting.

4 Data and Empirical Strategy

In this section, we introduce the information set of our model, the main empirical specification, and the identification strategy to measure the effect of government spending shocks. We adopt a large dataset consisting of 34 macroeconomic indicators to alleviate potential problems from the fiscal foresight. To efficiently handle such a large information set, we employ large Bayesian VAR techniques. Then, we identify three types of government spending shocks using the recursive and Proxy-SVAR approach, based on implications from the imperfect information models. Finally, we explore the properties of our shock series via statistical tests.

4.1 Data

Our benchmark model consists of a large econometric information set with 34 macroeconomic indicators. For the policy indicator, we use Real Government Consumption & Gross Investment: Federal (RGF) series from the Real-Time Dataset provided by the Federal Reserve Bank of Philadelphia. The rest of the data mostly came from the Federal Reserve Economic Data (FRED), which is publicly available on the website of St.Louis Fed. Our dataset contains 12 variables explored in the literature: GDP, the marginal tax rate, consumption of durables, nondurables, and services, residential and nonresidential fixed investment, consumer price index, real wages, total worked hours, real interest rate and the exchange rate.[14]

On top of these, we add 2 Fiscal variables: state and local government spending and net federal government deficit, 5 variables related to the labour market and productivity: civilian unemployment rate, civilian employment, output per hour, real disposable per-

[14]The marginal tax rate is from Barro and Redlick (2011). We measure the real interest rate by subtracting changes in the CPI from the 3-month US Treasury Bill rate.

sonal income, and TFP, 4 Financial and market sentiment variables: S&P 500, 10-year treasury rate, consumer sentiment index, and CEO confidence index, three indicators of the business activity: the ISM new orders index, inventories index and corporate profits after tax, 5 indicators related to the money and credit market: M2 money stock, Federal Funds rate, gross private savings, total consumer credit outstanding, and commercial & industrial loans. Finally, we also include the WTI spot oil price as a forward-looking price variable. We transform most variables in real log per capital level unless they are expressed in rates. Our sample covers the period from 1981Q4 to 2012Q1.[15]

We have a slightly smaller set of 25 variables in the monthly analysis, since most of the National Income and Product Accounts (NIPA) data are only available quarterly. Our monthly policy indicator is the Total Federal Outlays Series from the FRED database.[16] In addition, we include the Real Personal taxes, 4 measures of production: Industrial production, New Orders of durables, Business Inventories, and Capacity Utilization, 5 labor market variables: Unemployment rate, Civilian employment, Average weekly hours, Real Personal Income, and Average hourly earnings, three indicators related to the credit market: Total consumer credit, Commercial and Industrial loans, and Personal saving, three measures related to consumption: Retail sales, Real manufacturing sales, and Consumer sentiment, and two price measures: CPI and the WTI spot oil price. Finally, there are 6 variables related to the financial market and monetary policy: S&P 500, 10-Year treasury rate, Federal Funds rate, Real interest rates, real Exchange Rate, and VIX. Appendix B lists all variables used in our model and applied transformations.

In our benchmark model, Expectational VAR (EVAR), the above econometric information set is augmented by the set of proxies for the agents' expectations. This "expectational" block consists of 10 measures based on Greenbook forecasts, in the following order: forecast revisions (news) on government spending in the current quarter, the nowcast error, forecasts on the GDP and unemployment for the current quarter, 4-quarter ahead news, 8-quarter ahead news, and one and two-year ahead forecasts on the GDP and unemployment. We explain the ordering in more detail in Section 5.2.

Why do we construct such a large dataset? While it incurs more computational costs,

[15] To minimise the effect of benchmark revisions in the National Income and Product Accounts (NIPA) data, we use the historical vintage that became available in November 2012.

[16] Since this series is only available in unseasonalised nominal terms, we first apply the seasonal adjustment via the X-13 ARIMA-SEATS filter and then deflate the outcome by the CPI. The resulting series, when aggregated quarterly, shows a correlation of 0.9 with the RGF.

we believe it helps us to cope with fiscal foresight and possible non-fundamentalness. Due to the institutional implementation process in the fiscal policy, the econometrician cannot observe the flow of news about future policy changes that economic agents receive in real-time. The misalignment of respective information sets due to anticipation creates the informational insufficiency problem for standard SVAR models. One possible remedy to this issue is to include more information in the information set of econometricians so that it approximates that of the agents.[17] In particular, we include forecasts of GDP and unemployment, which are likely to enter the future policy function, in the expectational block and forward-looking variables such as the spot oil price, CEO confidence index, and the S&P500 index known to control agents' expectations.

4.2 The Empirical Model: Bayesian VAR

In order to efficiently extract the information from such a large dataset, we adopt the large Bayesian VAR approach proposed by Banbura et al. (2010). While large data alleviate the omitted variable bias, it also leads to the curse of dimensionality. The Bayesian approach allows us to deal with the latter, by consistently setting the informativeness of priors with the size of the cross-sectional dimension of the model. This is particularly useful when the variables in the set display strong collinearity, which is the characteristic of macroeconomic time series. Banbura et al. (2010) have shown that the large Bayesian VAR techniques result in better performance in terms of prediction than the small-scale VARs. Hence, this framework has been widely adopted in studies that explore macroeconomic shocks, especially in the case of monetary policy.[18]

We consider the following VAR(p) model:

$$Y_t = C + \sum_{\ell=1}^{p} A_\ell Y_{t-\ell} + \varepsilon_t \ , \quad \varepsilon_t \sim i.i.d.\mathcal{N}\left(0, \Sigma\right) \ , \tag{6}$$

where Y_t is the n-dimensional vector of endogenous variables, the series of n $\times$ n matrices A_1,...,A_p contain model parameters, and ε_t is n $\times$ 1 Gaussian errors with the covariance matrix Σ. In line with the standard macroeconometric practice, we consider VAR models that include 4 and 12 lags of endogenous variables for quarterly and monthly

[17]As Giannone and Reichlin (2006) observed, using larger datasets helps recover structural shocks correctly when fiscal foresight and non-fundamentalness are present.

[18]In the fiscal shock literature, Ellahie and Ricco (2017) also employs the Bayesian VAR approach.

analysis, respectively.

We impose two commonly used priors for the VAR coefficients: the Minnesota prior á la Litterman (1986) and the sum-of-coefficients prior proposed in Doan et al. (1986). These priors are based on common observations that each macroeconomic variable follows an independent random-walk model with a possible drift and the existence of cointegration among them.[19] Even though they are motivated by statistical properties rather than economic theory, these priors are not only computationally convenient but also known to improve the forecasting performance of VAR models – by significantly reducing the estimation error with only a small bias in parameter estimates.

Finally, to optimally control the informativeness of our priors, we select hyperparameters following the prior selection approach of Giannone et al. (2015) and construct the confidence bands using the Gibbs sampler algorithm with 1000 iterations.

4.3 Identification of Fiscal shocks

Based on our key decomposition in Section 2, we distinguish three types of government spending surprises: *unexpected*, *misexpected*, and *expected* changes. Fully exploiting longer forecast horizons given by the Greenbook forecasts, we distinguish two *expected* surprises – those up to one year and two years. We identify these four fiscal shocks using a recursive identification, with the following ordering:

$$\begin{bmatrix} N_t(0) & M_t(0) & E_tY_t & E_tU_t & N_t(1,4) & N_t(5,8) & F_{t+4,8} & Y_t' \end{bmatrix}' \tag{7}$$

where $N_t(0)$ and $M_t(0)$ represent nowcast revision and nowcast error, respectively. E_tY_t and E_tU_t are nowcasts on real GDP growth and unemployment rate. $N_t(1,4)$ and $N_t(5,8)$ correspond to forecast revisions (news) up to one year and between one to two years. $F_{t+4,8}$ include $[\ E_tY_{t+4} \quad E_tU_{t+4} \quad E_tY_{t+8} \quad E_tU_{t+8}\ ]$, one and two-year forecasts on real GDP growth and unemployment rate. The vector Y_t is the information set containing all the macroeconomic variables of interest.

This ordering implies the following five assumptions. First, discretionary fiscal policy responds to macroeconomic variables only with a lag. In reality, macroeconomic data are announced with a delay, e.g. in the next quarter. This is a standard assumption of

[19]In Bayesian analysis, priors usually reflect stylised facts about behaviours of the data rather than subjective belief of a researcher.

the SVAR approach, such as Blanchard and Perotti (2002). Second, we define *unexpected* fiscal shocks as innovations to nowcast revisions that are not predicted within the VAR. Third, *misexpected* fiscal shocks correspond to VAR innovations to nowcast errors that are orthogonal to unexpected changes. As shown in Section 2, while revisions are informative about policy innovations conditional on past news, forecast errors do not fully recover structural shocks even after controlling their past values. In the latter case, one must control past news to capture the shock correctly. These three assumptions tell us to order $N_t(0)$ first, $M_t(0)$ second, and then Y_t.

Identification of *expected* shocks requires us two more assumptions. Fourth, agents revise their forecasts by considering discretionary policy responses to the expected future state of the economy. Finally, *expected* fiscal shocks represent VAR innovations to forecast revisions, that are orthogonal to unexpected and misexpected fiscal changes and innovations to current expectations on the GDP and unemployment. These assumptions reflect the key idea of the EVAR approach and imperfect information models. While agents form expectations on the future policy before implementation, they do so based on past realisation and the (partial) signals about the present and future economic situation, due to informational limitation. In the end, they justify $N_t(1,4)$, $N_t(5,8)$, $F_{t+4,8}$ and at the end of the expectational block, plus E_tY_t and E_tU_t between $M_t(0)$ and the future news.

We also adopt the Proxy SVAR approach á la Stock and Watson (2012) and Mertens and Ravn (2013) to identify the four fiscal shocks, for our monthly analyses. Based on the same idea from the recursive identification, we construct the instruments in the following way:

$$N_t(0) = c + UFS_t \tag{8}$$

$$M_t(0) = c + N_t(0) + MFS_t \tag{9}$$

$$N_t(1,4) = c + N_t(0) + M_t(0) + E_tY_t + E_tU_t + EFS_{1,t} \tag{10}$$

$$N_t(5,8) = c + N_t(0) + M_t(0) + E_tY_t + E_tU_t + N_t(1,4) + EFS_{2,t} \tag{11}$$

where UFS_t, MFS_t $EFS_{1,t}$, and $EFS_{2,t}$ are our instruments of *unexpected*, *misexpected*, and *expected* fiscal policy surprises, which are the residuals obtained after running the series of regressions above. To explore the behaviour of our novel fiscal policy shocks, we first check the results from this regression and the serial correlation in our series in

Table 2 and Figure 2.

TABLE 2: Relationship between news and nowcast error

Dependent variable: Greenbook forecast & and revisions						
	Nowcast Error		News Q1-Q4		News Q5-Q8	
	β	t	β	t	β	t
Constant	0.605	(1.502)	1.651	(1.145)	-0.213	(-0.334)
News Q0	-0.371^{***}	(-3.385)	-0.320^{***}	(-3.214)	0.005	(0.208)
Nowcast Error			-0.046	(-0.099)	0.006	(0.605)
RGDP0 Forecast			0.036	(0.197)	0.045	(0.885)
Unemp0 Forecast			-0.208	(-1.022)	-0.360	(-0.886)
F	11.460		3.363		0.601	
R^2	0.073		0.111		0.020	

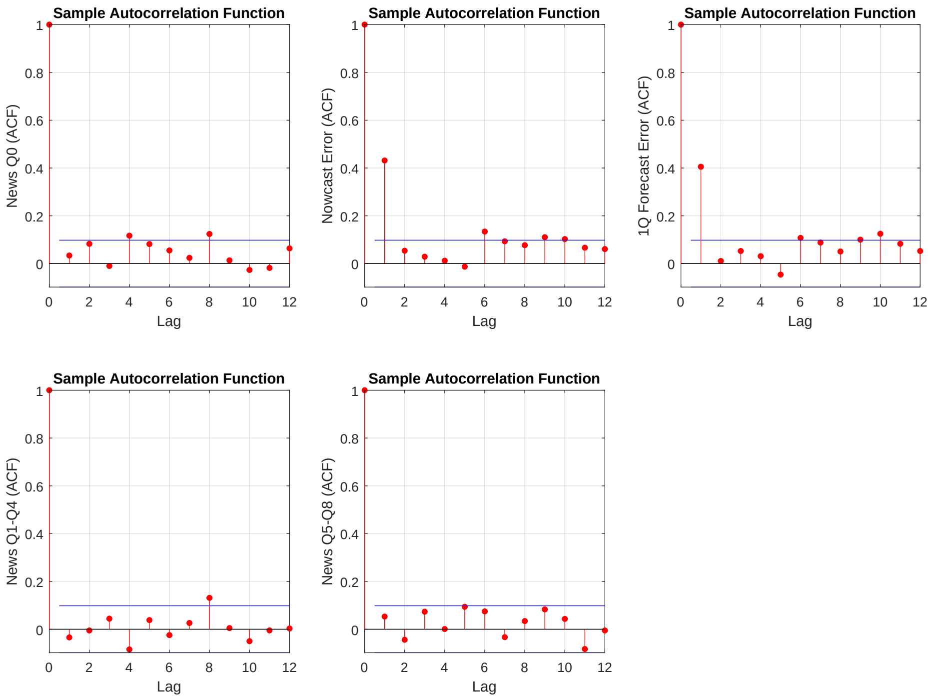
Note: This table reports the results from regressions (8)-(11). T-statistic in parentheses. *** is significant at the 1% level. Sample 1981Q3 – 2012Q4.

Table 2 confirms our key idea in identifying fiscal shocks based on imperfect information models. Due to information rigidity, the coefficient on nowcast revisions (news) is non-zero. It highlights the caveat that to fully recover structural shocks using forecast errors as proxies, news also needs to be controlled. Interestingly, as the size of news on fiscal policy increases, forecast error decreases. This is consistent with the observation from Coibion and Gorodnichenko (2015), that agents devote more resources to extract correct signals when facing large macroeconomic shocks, e.g. in recession.

Figure 2 reinforces our claim that with the presence of informational frictions, one should focus on forecast revisions, not forecast errors, to identify fiscal policy surprises. Since shocks are only supposed to capture unexpected movements in the policy stance, Ramey (2016) claims that they should be (1) mean-zero and (2) not serially correlated. However, Figure 2 shows that even after controlling the current news, nowcast and one-quarter ahead forecast errors display serial correlation, possibly due to the property of data revisions. On the other hand, this is not an issue for forecast revisions: our instruments of unexpected and expected are relatively well-behaved.

We close this section with the test for informational sufficiency proposed by Forni and Gambetti (2014). Using the EM algorithm, we extract five factors from 128 macroeconomic variables described in Appendix B. We assume that this dataset well describes the entire economy, so it is larger than our information set in the VAR model. If these factors provide useful information to forecast fiscal surprises, then agents utilise such

Figure 2: Autocorrelation in Fiscal Surprises



Note: This plot shows the autocorrelation function (ACF) for our four surprises: UFS_t, MFS_t $EFS_{1,t}$, $EFS_{2,t}$, plus the one-quarter ahead forecast error. They are collected in a monthly frequency. Lags = 12. Sample 1981.7 – 2012.3.

Table 3: Test of Informational Sufficiency

	Factor 1		Factor 2		Factor 3		Factor 4		Factor 5	
	F	p	F	p	F	p	F	p	F	p
Nowcast Error	5.177***	0.007	0.220	0.802	0.127	0.881	2.075*	0.130	0.480	0.620
Misexp Surprise	0.003	0.997	0.001	0.999	0.174	0.841	0.393	0.676	0.016	0.984
News Q0	0.831	0.438	0.888	0.414	0.007	0.993	0.090	0.914	0.180	0.836
Unexp Surprise	0.019	0.981	0.003	0.997	0.022	0.978	0.000	0.999	0.029	0.972
News Q1-Q4	6.382***	0.002	0.106	0.899	0.957	0.387	1.241	0.293	0.502	0.607
1Y Unexp	0.036	0.964	0.097	0.908	0.001	0.999	0.311	0.734	0.022	0.978
News Q5-Q8	0.526	0.593	0.216	0.806	1.103	0.335	1.336	0.267	0.060	0.942
2Y Unexp	0.001	0.999	0.005	0.995	0.065	0.937	0.024	0.976	0.001	0.999

Note: 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.

information to change their decisions before the change in policy takes place. Hence, to have a well-specified model, these factors should not predict our shocks.

Table 3 reports the results of this test. The first-factor Granger-causes nowcast errors and current fiscal news, and the fourth factor also weakly predicts nowcast errors. While it implies that even the Federal Reserve fails to aggregate all available information about the economy, this is not a surprise: imperfect information models imply the predictability of forecast errors and revisions, due to the slow absorption of information. Coibion and Gorodnichenko (2012) reported that information rigidity is also present in the Greenbook forecasts.

What really matters is the result of our EVAR-identified fiscal surprises. In table 3, none of the factors Granger-cause innovations to *unexpected*, *misexpected*, and *expected* fiscal shocks. After controlling past realisations and news, our shocks are unpredictable from the current market information. The informational sufficiency tests indicate that our model is well specified: the EVAR information set exceeds that of the agents.

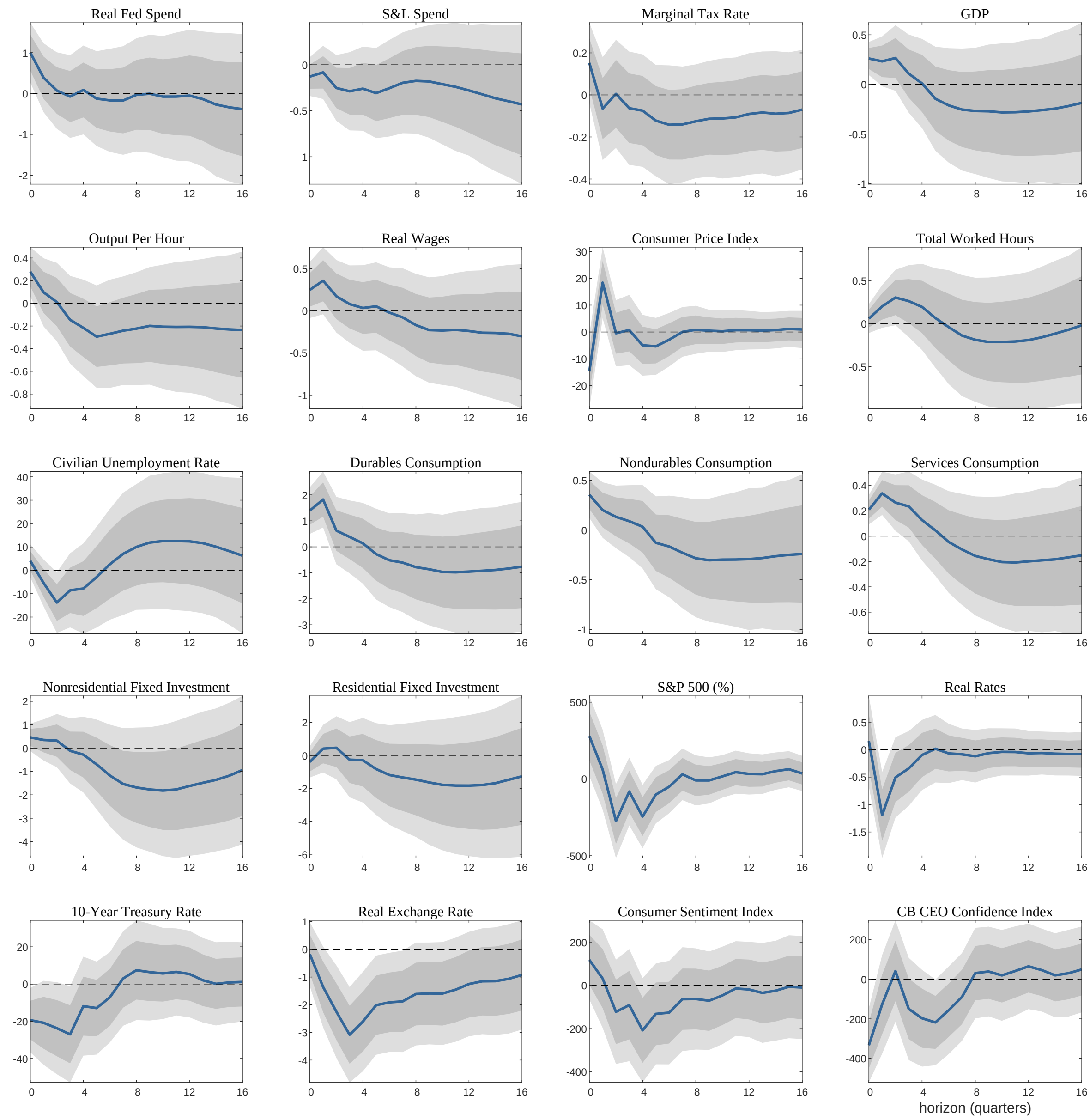
5 Results

We present empirical results based on our strategy in this section. First, we discuss the effects of three types of fiscal shocks: *unexpected*, *misexpected*, and *expected* changes from our baseline EVAR model. Then, we also explore the monthly effect of discretionary fiscal spending to provide a closer look at high-frequency movements. Overall, we find that while the misexpected shock is contractionary, unexpected and expected shock lead to an expansion: results previously reported for the post-Korean war samples are due to mixing two different structural shocks, where a *misexpected* dominated the estimated impulse responses.

5.1 Baseline results

Figure 3 shows impulse responses to an unexpected change in government spending. Upon a positive, unexpected fiscal shock, the response of GDP is positive on impact and up to four quarters. This is contrasts with previous studies, such as Ramey (2011), which finds the opposite effect with the same sample. It seems like the results are consistent with the Keynesian multiplier effect: any types of consumption – durable, non-durable, and services – increase on impact and revert to normal within a year. Nonresidential fixed investment also rises on impact, albeit not strongly significant. Hours and the real wage also increase up to 6 quarters, and the unemployment rate drops with a short lag. The productivity, measured by output per hour, also rises on impact and quickly reverts back. Responses of the S&P 500 and consumer sentiment spike on impact but quickly become negative, in line with the CEO confidence index.The real interest rate and the 10-year

Figure 3: Effects of Unexpected Fiscal Surprises

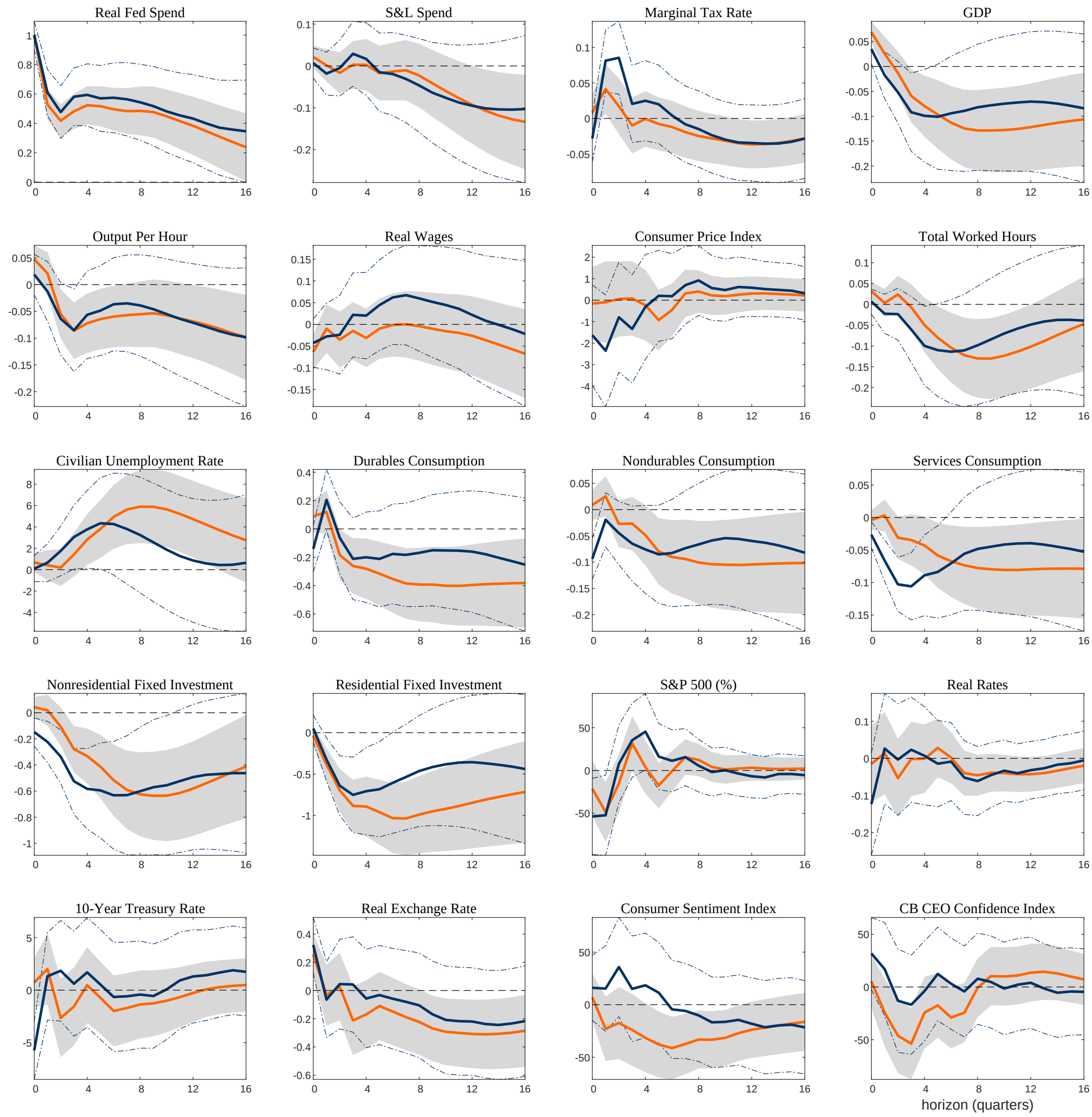


Note: This plot shows impulse responses to an unexpected federal government spending surprise from our large EVAR model. Shaded areas represent 90 and 68 percent confidence bands.Sample 1981.Q3 – 2012.Q1.

treasury rate fall to at least four quarters, so the monetary policy accommodates the fiscal shock in the short run. The real exchange rate depreciates upon a surprise shock, in line with Forni and Gambetti (2016). Overall, we find that an unexpected increase in government spending has expansionary effects on the economy in the short run.

Figure 4 compares responses to a misexpected federal government spending surprise versus the one-quarter ahead forecast errors from the SPF data, which is the proxy suggested by Ramey (2011). Upon a misexpected fiscal surprise, GDP and output per

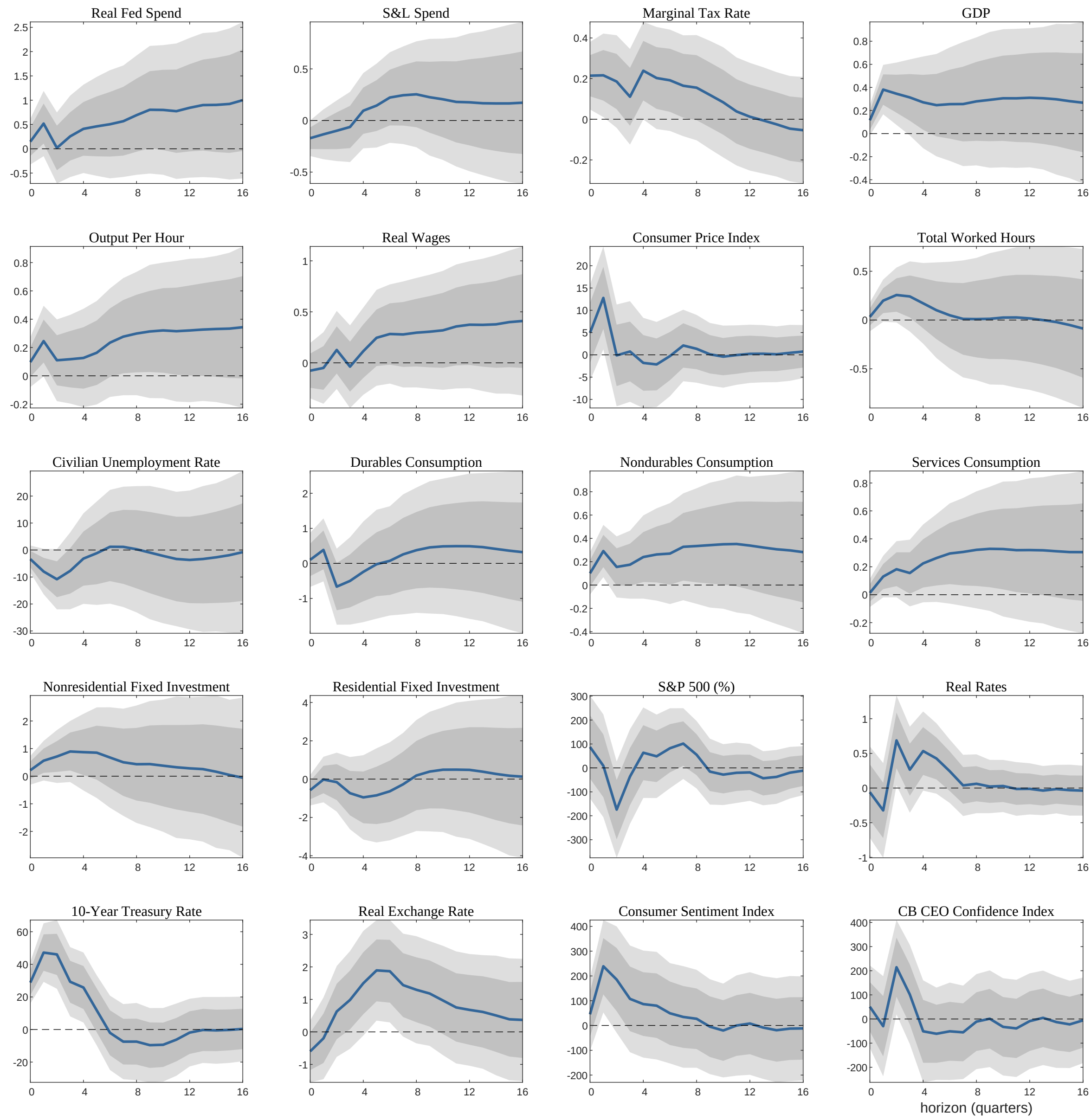
Figure 4: Effects of Misexpected Surprises v. SPF Forecast error



Note: This plot shows impulse responses to a misexpected federal government spending surprise from our large EVAR model. The *Orange line* corresponds to IRFs by using the SPF one-quarter ahead forecast errors as the proxy of fiscal shocks. The *Blue line* represent the IRFs constructed from the Greenbook nowcast errors. Shaded areas represent 90 percent confidence bands. Sample 1981.Q3 – 2012.Q1.

hour rise slightly on impact, but such responses quickly become negative. Components of consumption and investment behave in a similar way. Hours also drop, and unemployment rises. Interest rates and stock prices fall on impact, but they do not seem to be affected in general, and the same phenomenon takes place for the real exchange rate, with the opposite sign. Comparing the responses of misexpected surprises (nowcast errors from Greenbooks) and the SPF one-quarter ahead forecast errors á la Ramey, they are mostly

Figure 5: Effects of One-Year Expected Fiscal Surprises



Note: This plot shows impulse responses to an one-year expected federal government spending surprise from our large EVAR model. Shaded areas represent 90 and 68 percent confidence bands. Sample 1981.Q3 – 2012.Q1.

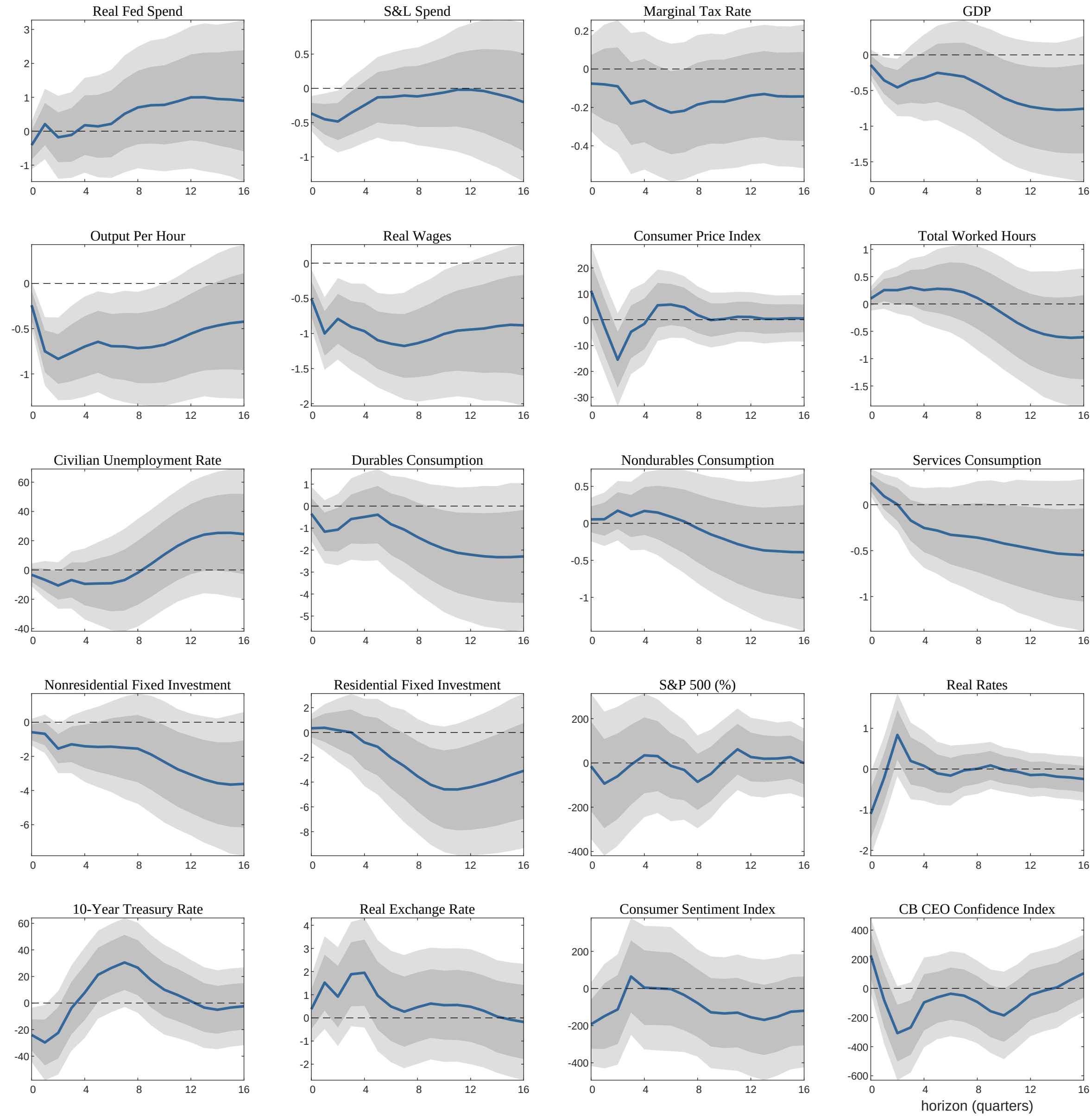
similar to each other: responses of the latter tend to follow those of the former with a delay, possibly reflecting superiority in terms of timing or information of the Fed.

Overall, a misexpected change in fiscal policy tends to generate recessionary effects, with the results echoing those of Ramey (2011) for the post-Korean war samples. Recall that we decompose the one-quarter ahead forecast errors into nowcast errors and revisions in Section 2. Together with the responses from unexpected surprises, these results point to the limitation of Ramey's approach: forecast errors are not the best proxy for structural shocks, since they mix the news about policy changes with misexpectations that agents cannot process in real-time. Since nowcast errors have a larger variance than the current news, as shown in Section 3, they dominate the estimated impulse response functions. This is why the expansionary effects have been overwhelmed by contractionary ones in previous studies.

Now we turn to the effects of expected fiscal policy changes. Figure 5 shows the responses to positive news on government spending expected to occur within a year. The real government spending begins to rise after 3-4 quarters: since this type of surprise represents future news, it reinforces the legitimacy of our identification strategy. The response of GDP is positive on impact and significant for up to a year. Hours increase while the unemployment rate falls up to 4 quarters. Response of non-durable, service consumption and non-residential fixed investment stays positive for all forecasting horizons, though weakly significant after a year. Output per hour behaves in a similar fashion, but durable consumption and residential fixed investment do not seem to change. The monetary policy attempts to counteract the fiscal stimulus in the short-run, with two quarters of delay. Consumer sentiment, CPI, and the CEO confidence index rise after the shock, albeit the latter reacts with a lag. The real exchange rate slowly appreciates: together with its response to unexpected changes, this finding echoes those of Forni and Gambetti (2016) – once we separate news and surprise fiscal shocks, there is no depreciation puzzle for the former.

Figure 6 presents responses to positive news expected to occur between one to two years ahead. Consistent with our definition, real government spending begins to rise after 5-8 quarters. Unlike the previous case, however, the effect of longer fiscal news turns out to be recessionary, possibly due to the agent anticipating systematic spending reversals. The response of real GDP is negative on impact and stays below zero for all horizons. Components of consumption and investment also fall continuously, though services rise slightly on impact and the nondurable consumption is mostly irresponsive. Output per hour and real wages drop significantly from the impact up to 10 quarters. The response of hours is slightly positive up to 8 quarters, but not significant. While the real rate peaks after two quarters, the 10-year treasury rate rises slowly and peaks at 7 quarters ahead, creating a hump-shaped response. Since this is also future news, we do not find a depreciation puzzle in this case as well.

Figure 6: Effects of Two-Year Expected Fiscal Surprises



Note: This plot shows impulse responses to a two-year expected federal government spending surprise from our large EVAR model. Shaded areas represent 90 and 68 percent confidence bands. Sample 1981.Q3 – 2012.Q1.

We also compare these results to those when the SPF data are used to construct shocks in Appendix C. Due to the shorter forecast horizon in the SPF data, we exclude the comparison of responses to two-year expected fiscal shocks.[20] Two observations follow. First, responses from the two sets of data are qualitatively similar when scale-adjusted, especially in the case of misexpected shocks. Second, using the Greenbook forecasts

[20] Also, for the one-year expected fiscal shock, the shock series constructed from the Greenbooks cover news up to 4 quarters ahead. However, the one based on the SPF data only contains information for up to three quarters due to the constraint in forecasting horizons.

seems to be more consistent with our classification of shocks: the response of government spending is short-lived upon an unexpected shock in the case of the Greenbooks, but it is too persistent when the SPF data are used – staying positive even four years later. Overall, responses from the Greenbooks and SPF deliver similar results, with a slight advantage over the former in identifying the current fiscal surprise.

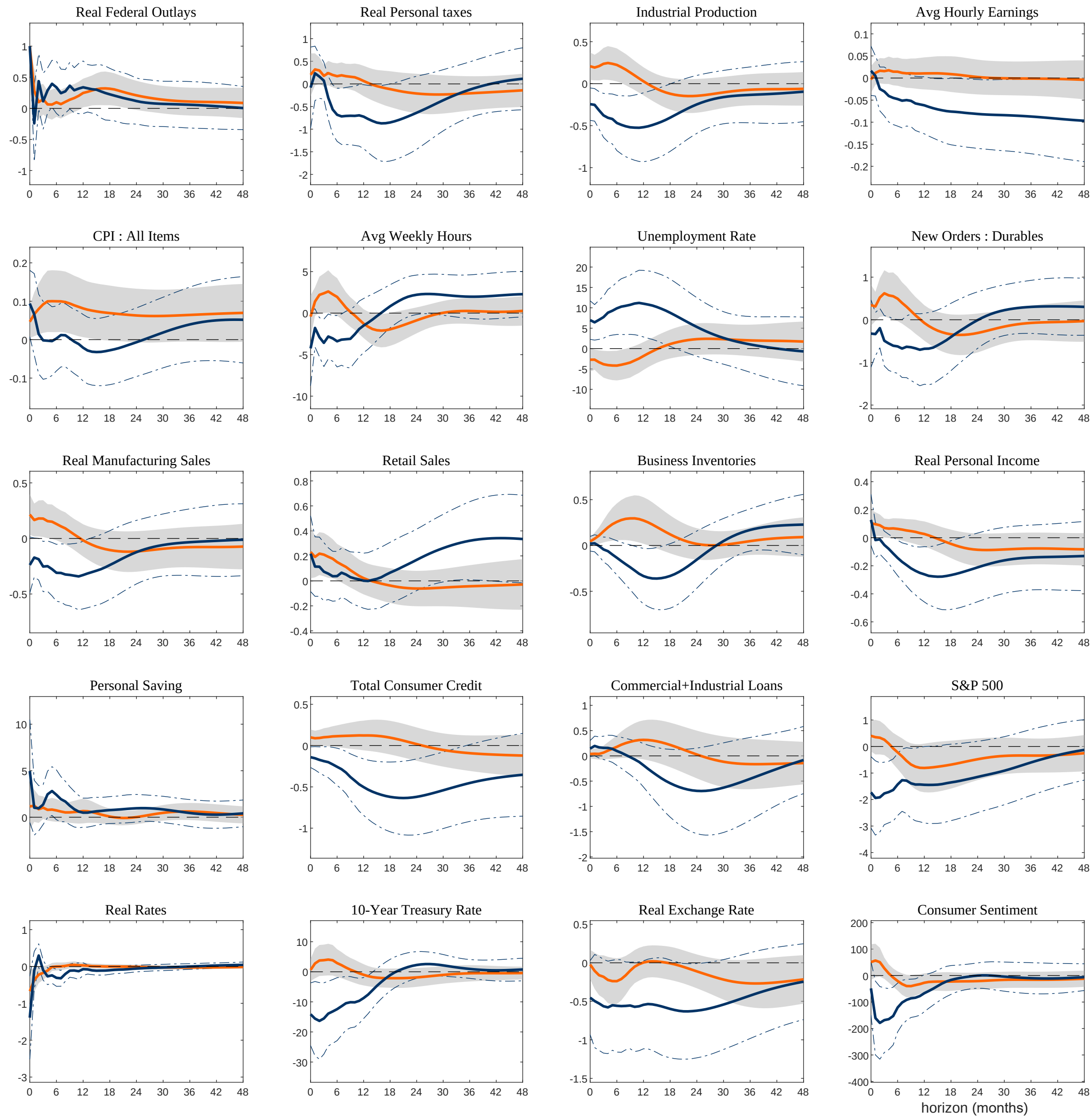
5.2 Monthly Proxy SVAR results

To fully utilise the advantage of Greenbook forecasts, we also explore the monthly effects of government spending surprises. Since the Greenbooks are updated at least 8 times per year, it allows us to conduct monthly analyses, similar to studies on the effect of monetary policy shocks. This is particularly useful to capture high-frequency phenomena, such as movements in exchange rates, that are likely to be missed in most empirical studies focusing on quarterly analyses. While we also report results based on the recursive identification method as in the baseline results in Appendix C, here we identify fiscal policy shocks by employing the Proxy SVAR approach á la Stock and Watson (2012) and Mertens and Ravn (2013), as described in Section .

We start with the effects of misexpected Fiscal Surprises in Figure 7. Here we compare two impulse responses: those using the Greenbook nowcast error and one-year forecast errors as proxies for shocks, respectively. We utilise the latter to imitate the approach á la Ramey (2011). Notice that the responses from forecast errors differ from the baseline results: their overall effects seem to be slightly expansionary, though mostly insignificant, especially after 6 months (in orange). While these contrast with Ramey (2011), they resemble the results from Fisher and Peters (2010), whose instruments are also in a monthly frequency.

On the other hand, responses constructed from the nowcast error proxies (in blue) tend to be more recessionary, consistent with the baseline. The output, measured by the industrial production index, falls significantly for at least 18 months. Consumption and investment contract, albeit with weak significance, as revealed by the decrease in new orders of durable goods, manufacturing and retail sales, and business inventories. Hours and earnings share a similar pattern, and the unemployment rate rises: consumer credit and loans decrease as there are more leverage-constrained agents. The stock market and consumer sentiment tumble on impact, and the monetary policy attempts to accommod-

Figure 7: Monthly Effects of Misexpected Fiscal Surprises

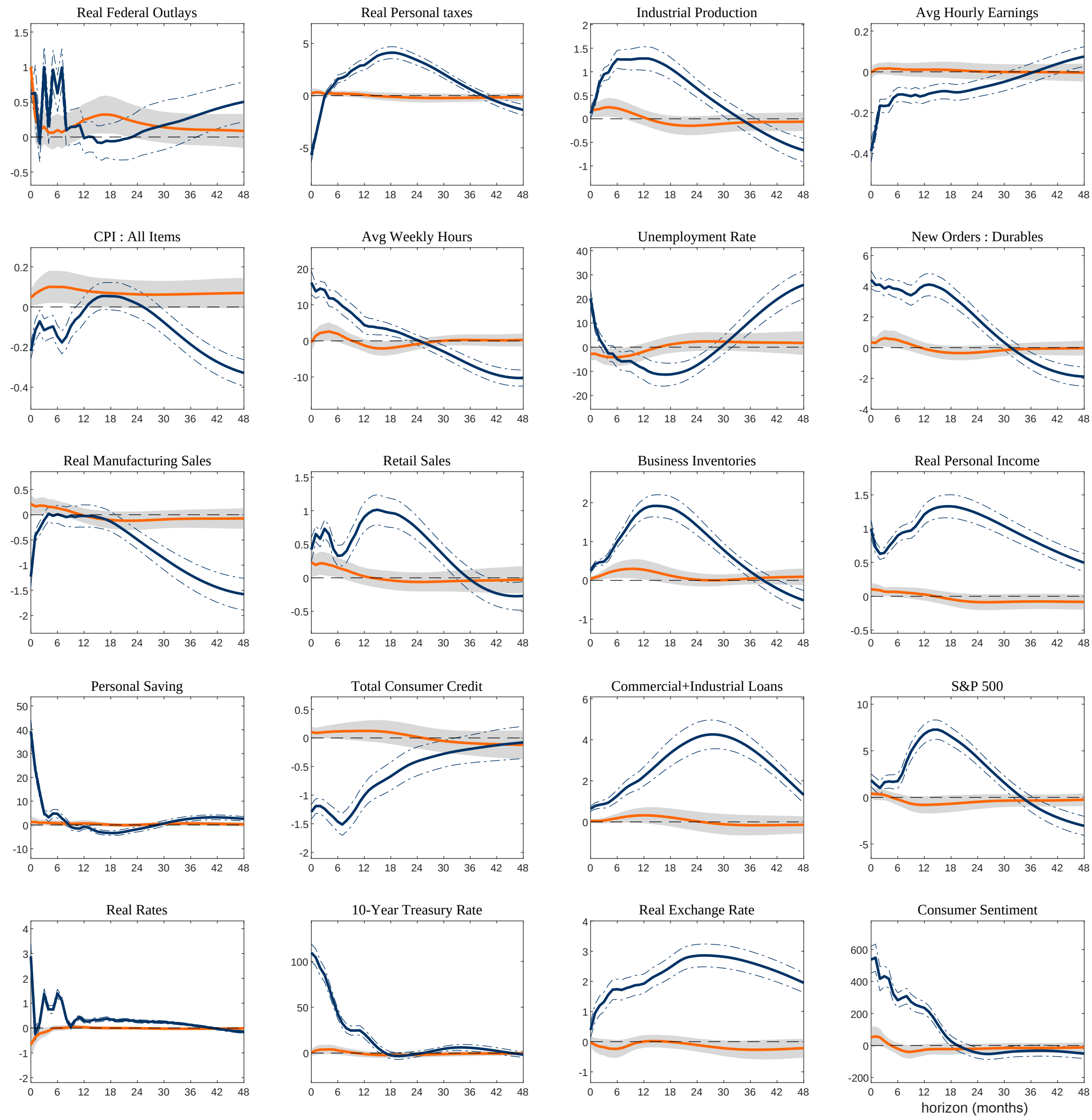


Note:This plot shows impulse responses to a misexpected federal government spending surprise from the large EVAR model. Shocks are identified via the Proxy-SVAR approach. The *Orange line* corresponds to IRFs by using the Greenbook one-year forecast error as the proxy of fiscal shocks. The *Blue line* represents the IRFs constructed from nowcast news. Shaded areas are 90 percent confidence bands. Sample 1981.7 – 2012.1.

ate the shock in short run. So the real exchange rate depreciates, though responses are insignificant.

Figure 8 shows the monthly effects of an unexpected change in government spending. In line with the baseline results in Figure 3, this type of fiscal shock induces expansionary effects overall. The output response is positive on impact and stays above zero for three years (in blue). New orders in durable goods, retail sales, and business inventories follow a

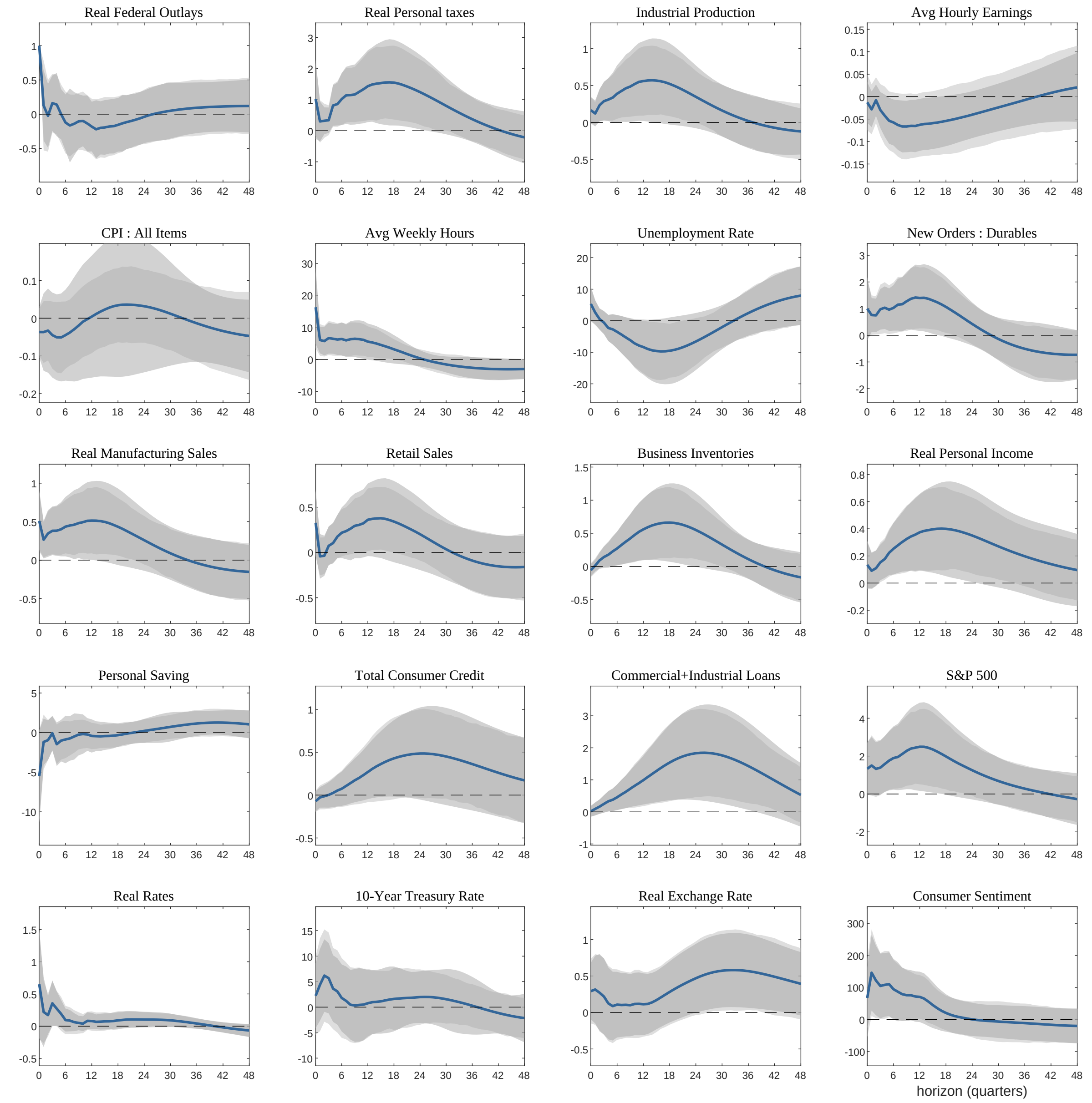
Figure 8: Monthly Effects of Unexpected Fiscal Surprises



Note:This plot shows impulse responses to an unexpected federal government spending surprise from the large EVAR model. Shocks are identified via the Proxy-SVAR approach. The *Orange line* corresponds to IRFs by using the Greenbook one-year forecast error as the proxy of fiscal shocks. The *Blue line* represents the IRFs constructed from nowcast news. Shaded areas are 90 percent confidence bands. Sample 1981.7 – 2012.1.

similar pattern, implying a significant rise in both consumption and investment. Looking at the labour market, hours and real personal income increase up to 30-48 months, and the unemployment rate falls with a slight delay. The S&P 500 and consumer sentiment also spike as the economy is booming, and agents reduce savings and take more loans. Concerned about overheating, the Fed becomes more hawkish: the real exchange rate appreciates as a result. Interestingly, in contrast to our baseline outcome, the depreciation

FIGURE 9: MONTHLY EFFECTS OF ONE-YEAR EXPECTED FISCAL SURPRISES

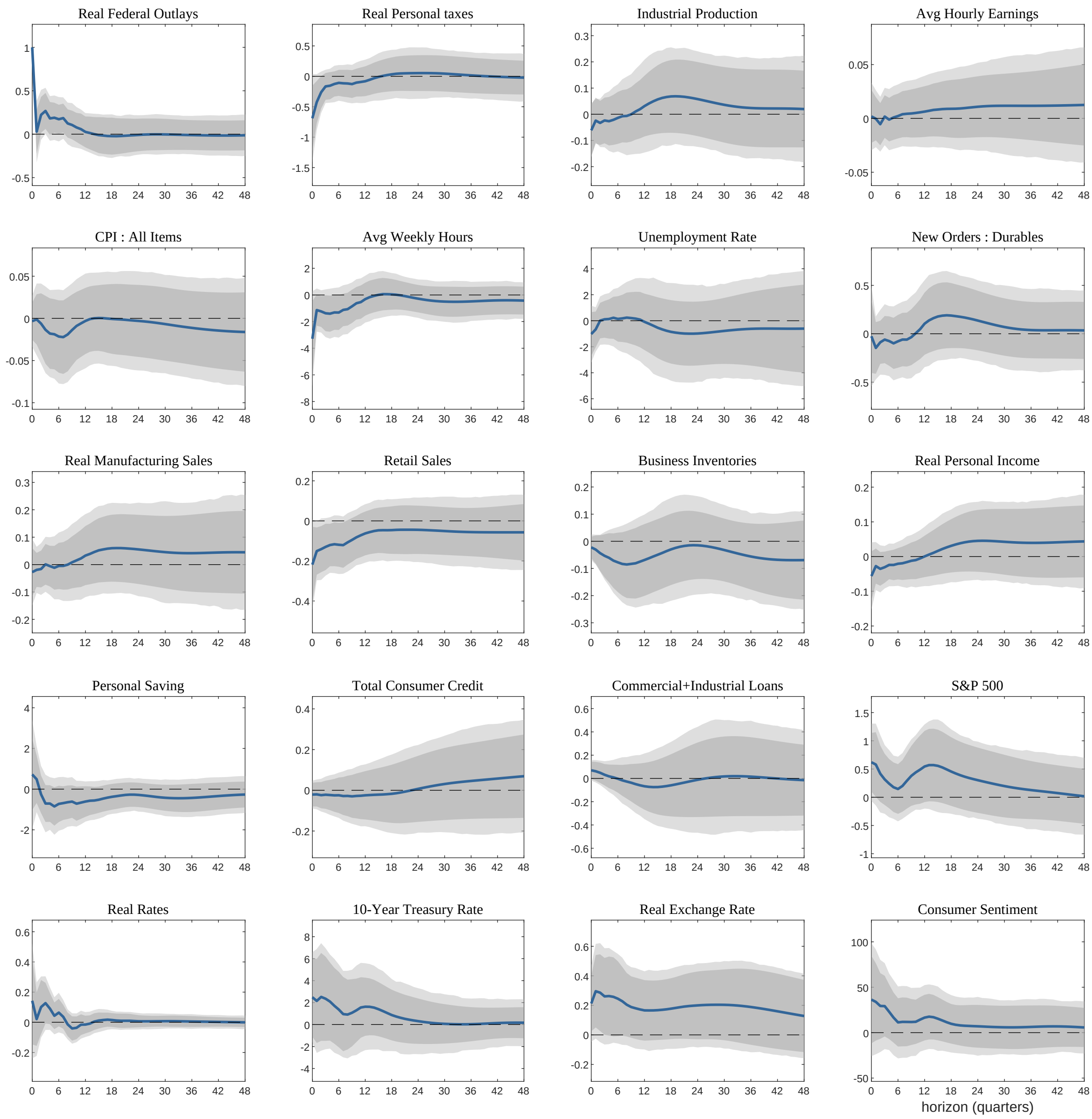


Note: This plot shows impulse responses to an one-year expected federal government spending surprise from our large EVAR model. Shocks are identified via the Proxy-SVAR approach. Shaded areas represent 90 and 68 percent confidence bands. Sample 1981.7 – 2012.1.

puzzle seems to disappear in the monthly analysis even upon a surprise shock.

Figures 9 and 10 present the effects of expected fiscal policy surprises up to one and two years ahead, respectively. The former responses are expansionary and mostly in line with the quarterly analyses, in Figure 5. The response of output stays positive for at least 24 months, and the indicators related to consumption and investment – e.g. new orders in durables, retail sales, and business inventories– display a similar pattern. With a boom in the economy, consumers gain more confidence, agents take more loans, and

Figure 10: Monthly Effects of Two-Year Expected Fiscal Surprises



Note: This plot shows impulse responses to a two-year expected federal government spending surprise from our large EVAR model. Shocks are identified via the Proxy-SVAR approach. Shaded areas represent 90 and 68 percent confidence bands. Sample 1981.7 – 2012.1.

the stock price surges. The monetary becomes more hawkish, and the real exchange rate appreciates. Responses to a two-year ahead news, however, are not so straightforward. Even though most IRFs are not significant, they seem to suggest a boom rather than recession between one to two years ahead: the output rises slightly, with a simultaneous increase in new orders of durables and manufacturing sales. Earnings and hours also show some modest increase. While consumer sentiment rises, there is not much reaction from retail sales and consumer credit. Overall, the effects of expected changes in government spending seem to be positive, with some inconsistency in the case of the two-year ahead news.

6 Data Revisions as a Source of Misexpectation

Our results in Section 5 showed that expected and unexpected fiscal changes are expansionary, and the effect of misexpected shocks is relatively in line with neoclassical crowding out. Why is the latter different from others? According to imperfect information models, nowcast errors occur due to partial absorption of information. Rewriting the equation (1) by setting h=0, we have:

$$\underbrace{x_t - E_t x_t}_{\text{Nowcast Error}} = \frac{1-\kappa}{\kappa} \underbrace{(E_t x_t - E_{t-1} x_t)}_{\text{Nowcast Revision}} \tag{12}$$

This equation shows that nowcast errors consist of incomplete updates of new information. Then, conditional on current and past news, the nowcast error does not contain additional information. From an empirical perspective, however, many other components can possibly create extra information content in nowcast errors beyond the deviations from rational expectations: data revisions, measurement errors, misspecification of the model, and the misalignment in timing between the forecast and data release.

In this section, we explore a potential source of misexpectations by particularly focusing on data revisions. This is because the Nowcast error can be decomposed into two components: a series of Data Revisions and the first Nowcast Error, which is the difference between the first release of the data and the nowcast, in equation (3) in Section 2. We can further decompose the data revision components into re-definition and measurement errors:

$$\begin{aligned}\underbrace{x_t^T - E_t x_t}_{\text{Nowcast Error}} &= \underbrace{(x_t^T - x_t^{T-1} + \cdots + x_t^{t+1} - x_t^t)}_{\text{Data Revisions}} + \underbrace{(x_t^t - E_t x_t)}_{\text{1st Nowcast Error}} \\ &= \underbrace{(x_t^T - x_t^{T-1} + \cdots - x_t^{t+2})}_{\text{Data Revisions}} + \underbrace{(x_t^{t+2} - x_t^{t+1} + x_t^{t+1} - x_t^t)}_{\text{Measurement Error}} + \underbrace{(x_t^t - E_t x_t)}_{\text{First Nowcast Error}}\end{aligned} \tag{13}$$

here we assume that the first few revisions, e.g. up to the third release of data, mainly represent measurement errors. Then the data revision components include annual and benchmark revisions, which also contain changes in the definitions of variables. For instance, our indicator of federal government spending underwent a re-definition in 1996: from "federal government purchases" to "federal government consumption expenditures and gross investment". All of the NIPA components experienced a similar process.

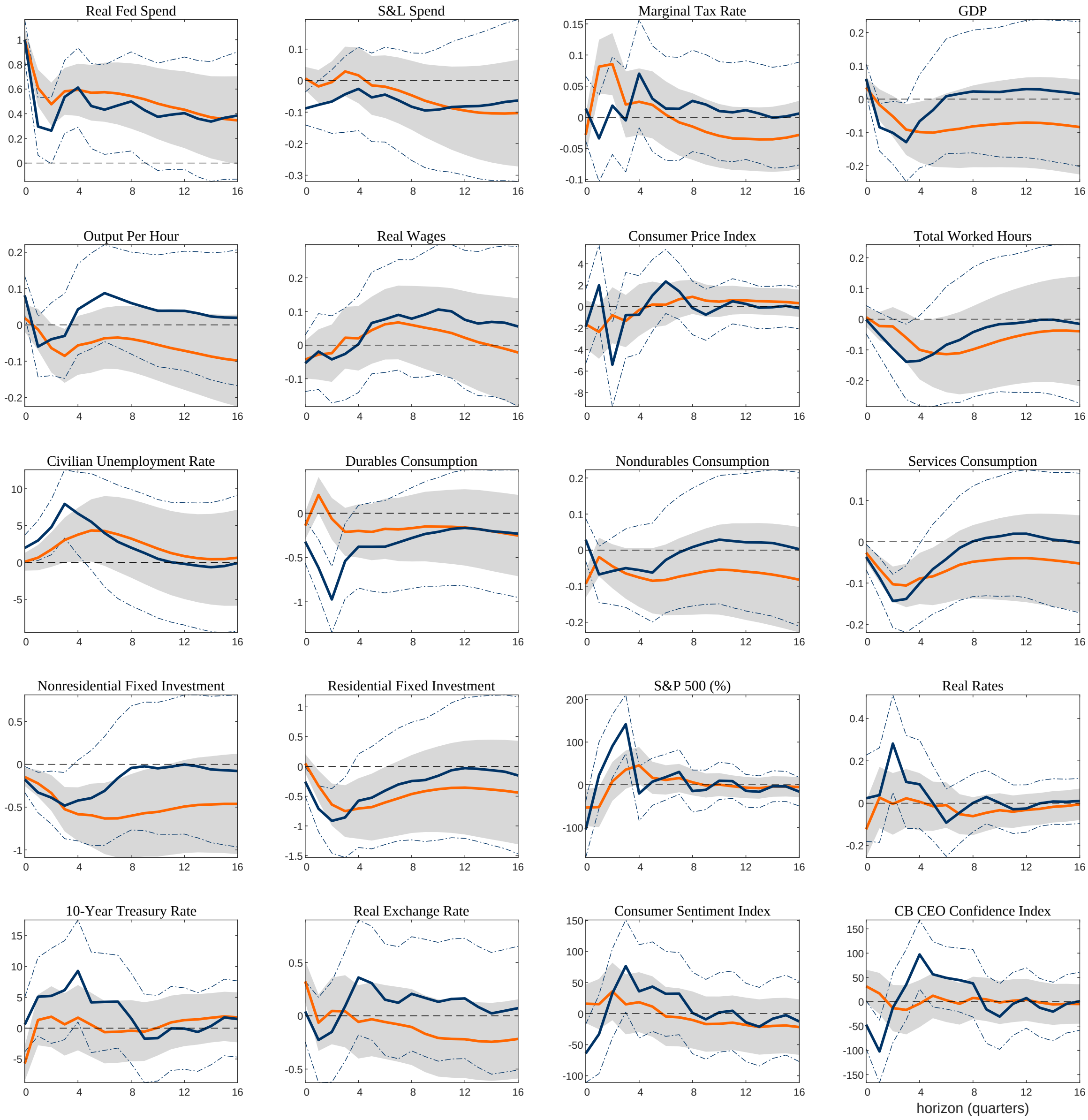
A rough way to gauge the role of data revisions is to compare the responses to two misexpectation shocks: one constructed as in our baseline, and the other that we re-define the nowcast error as the difference between the first release of the data and nowcast from the Greenbooks.[21] Since the latter does not contain data revisions component (measurement errors and re-definitions), any differences between the two are likely to be originated from the misalignment with the real-time information set of agents.

Figure shows the two impulse responses upon a misexpected policy change. While the overall effect is contractionary for both, they are also different in two aspects. First, the effect is more short-lived when we construct the nowcast error from the first release of the data: the output response quickly reverts to zero within 6 quarters (in blue). It seems like this change is primarily driven by non-durables, services consumption, and non-residential fixed investments, which display the same pattern. Second, most recessionary effects become insignificant, with broader confidence bands. Even though the median responses of output fall in the short-term, they are insignificant in all forecasting horizons: this is the case for most variables in our information set. We also compare the results of unexpected and expected changes in Appendix . While there are some differences in scale, mostly due to larger confidence bands, responses of unexpected and one-year expected shocks are qualitatively the same. Two impulse responses are identical in the case of two-year expected changes. To summarise, we find that data revisions do play some role: they reinforce the recessionary effects of misexpected changes, particularly in the medium-run.

As shown in equation (13), data revisions can be further decomposed into measurement errors and re-definitions. Which of these components matters more? A straightforward way to answer this question is to build the nowcast error from the third release of the data and compare the results with Figure 12. If responses remain the same regardless of using the first or third releases, then re-definitions from benchmark revisions are driving the results: measurement errors play only a minor role. In the opposite case, however, it

[21]We use the first, second, and third releases of Real Federal Government Consumption & Gross Investment, from the Real-Time dataset provided by the Philadelphia Fed.

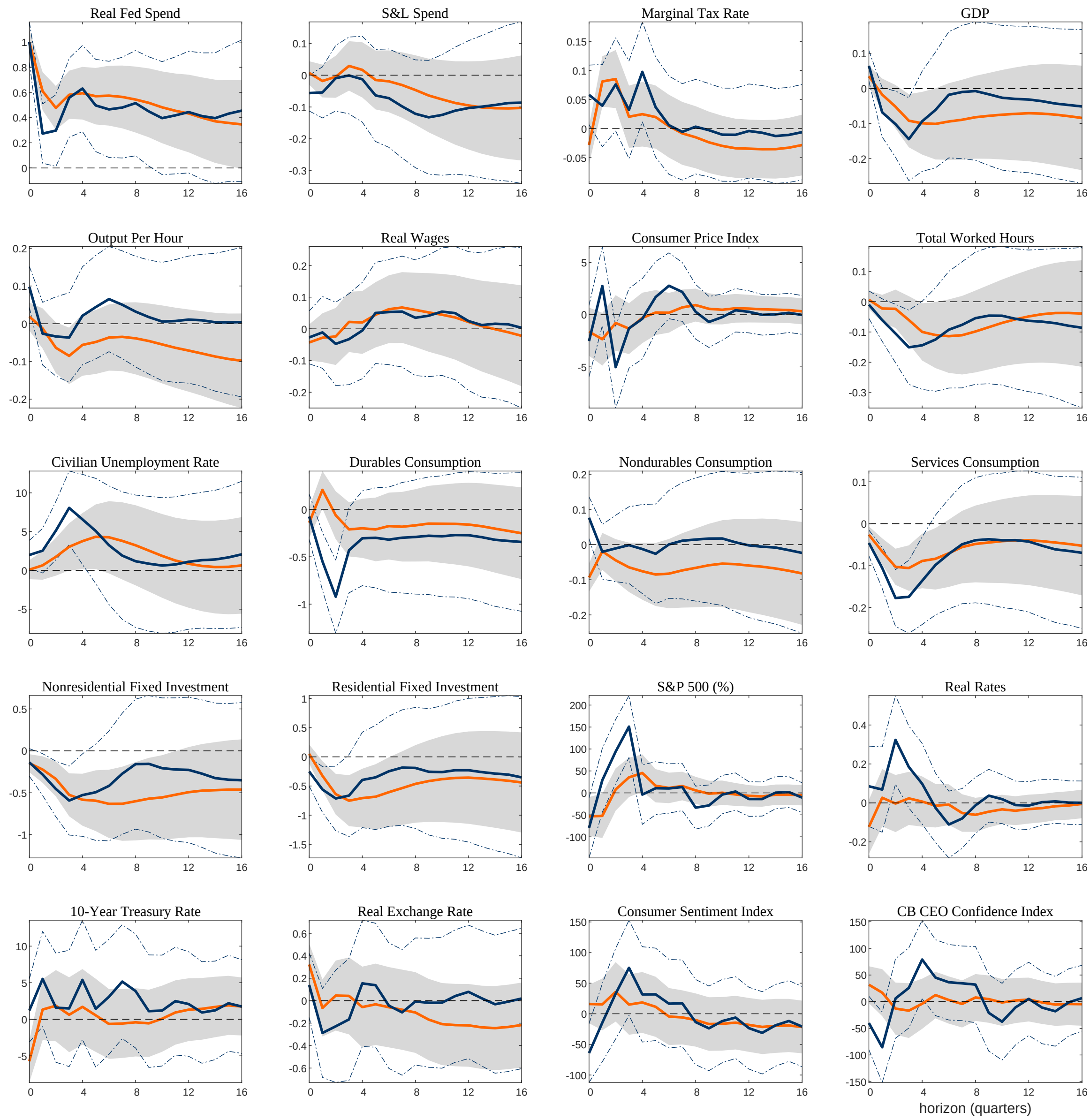
Figure 11: Effects of Misexpected, First v. Final Nowcast error



Note: This plot shows impulse responses to a misexpected federal government spending surprise from our large EVAR model. The *Orange line* corresponds to baseline IRFs using the Greenbook nowcast errors. The *Blue line* represents the IRFs constructed by replacing nowcast errors with the difference between the first release of the data and nowcast. Shaded areas are 90 percent confidence bands. Sample 1981.Q3 – 2012.Q1.

implies that a more random noise drives the difference. Figure 12 shows the results: they are qualitatively identical, with just a minor contraction in confidence bands, whether the first or third released values are used to construct nowcast errors. It implies that if data revisions take any parts in misexpectations, the key driver is likely to be benchmark revisions.

Figure 12: Effects of Misexpected, Third v. Final Nowcast error



Note: This plot shows impulse responses to a misexpected federal government spending surprise from our large EVAR model. The *Orange line* corresponds to baseline IRFs using the Greenbook nowcast errors. The *Blue line* represents the IRFs constructed by replacing nowcast errors with the difference between the third release of the data and nowcast. Shaded areas are 90 percent confidence bands. Sample 1981.Q3 – 2012.Q1.

7 Conclusion

This paper explores the macroeconomic effect of discretionary changes in government spending with a novel approach that accounts for both anticipation and imperfect information from economic agents. From the class of imperfect information models, we derive the decomposition of nowcast errors, nowcast revisions, and future news about the policy, which represent three orthogonal fiscal shocks we named as *expected*, *unexpected* and *misexpected* fiscal changes. We also built novel measures of expectations on the fiscal policy from the Greenbook forecasts, which have a comparative advantage over the SPF data in terms of statistical properties, richness, and frequency. The new measure comes without significant loss in terms of instrumental relevance while capturing the timing of policy implementation more correctly.

From a state-of-the-art Bayesian VAR technique, we report three main findings. First, a unexpected increase in government spending leads to an expansion via Keynesian multiplier mechanism. Second, the effect of positive, expected fiscal policy is also expansionary, though it is less clear for the news that are anticipated to occur after a year. The real exchange rate depreciates upon a current news, but the opposite happens for future changes in policy. Finally, misexpected changes in government spending induce an economic contraction, in line with the neoclassical point of view and previous empirical results for the post-Korean war samples. To further investigate a source of misexpectation, we also explore the role of data revisions, especially benchmark revisions, in driving recessionary effects. We also complement our findings with the monthly analysis via the Proxy-SVAR identification approach.

Our findings highlight the importance of imperfect information in reconciling previous results in the literature. In particular, current EVAR strategy might be misleading, as its proposed proxy of fiscal policy shock – the forecast error – blends current innovations with past news and data revisions. Imperfect information models tell us that in order to identify macroeconomic shocks, it is better to focus on forecast revisions, not forecast errors when informational frictions are present. Once information rigidities are accounted for, we demonstrate that expected fiscal changes stimulate economic activity and private investment.

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A Relationship between Forecast Revisions

Coibion and Gorodnichenko (2015) observed that in both classes of imperfect information models, the average ex-post forecast errors across agents and the average ex-ante forecast revisions are related by the following expression:

$$\underbrace{x_t - E_{t-h}x_t}_{\text{Forecast Error}} = \frac{1-\kappa}{\kappa}(\underbrace{E_{t-h}x_t - E_{t-h-1}x_t}_{\text{Forecast Revision}}) + u_{t-h+1} + \cdots + u_t$$

where x_t is the variable of interest, $E_{t-h}x_t$ is the average forecast across forecasters at the time t-h, and u_t is the rational expectation error. κ represents the degree of information rigidity: $\kappa = 1$ in full information rational expectation models, while $\kappa < 1$ under imperfect information, as the agents partially update their information sets. Hence, forecast and nowcast errors are predictable in this case. By increasing the forecast horizon by one period, we get:

$$\underbrace{x_t - E_{t-h-1}x_t}_{\text{Forecast Error}} = \frac{1-\kappa}{\kappa}(\underbrace{E_{t-h-1}x_t - E_{t-h-2}x_t}_{\text{Forecast Revision}}) + u_{t-h} + u_{t-h+1} + \cdots + u_t$$

By subtracting the first expression from the second, we get:

$$-E_{t-h}x_t + E_{t-h-1}x_t = \frac{1-\kappa}{\kappa}(E_{t-h}x_t - 2E_{t-h-1}x_t + E_{t-h-2}x_t) - u_{t-h}$$

Multiplying both sides by κ and re-arranging:

$$\begin{aligned}
-\kappa E_{t-h}x_t + \kappa E_{t-h-1}x_t &= (1-\kappa)(E_{t-h}x_t - 2E_{t-h-1}x_t + E_{t-h-2}x_t) - \kappa u_{t-h} \\
&= (1-\kappa)(E_{t-h}x_t) - 2(1-\kappa)(E_{t-h-1}x_t) + (1-\kappa)(E_{t-h-2}x_t) - \kappa u_{t-h} \\
&= E_{t-h}x_t - \kappa E_{t-h}x_t - (1-\kappa)(E_{t-h-1}x_t) + (\kappa-1)(E_{t-h-1}x_t) \\
&+ (1-\kappa)(E_{t-h-2}x_t) - \kappa u_{t-h}
\end{aligned}$$

After cleaning the terms, we get the following:

$$0 = E_{t-h}x_t - (1-\kappa)(E_{t-h-1}x_t) - E_{t-h-1}x_t + (1-\kappa)(E_{t-h-2}x_t) - \kappa u_{t-h}$$

With the final re-arrangement, we reach Equation (2) of this paper, which captures the relationship between forecast revisions (news). This expression tells us that conditional on the past information set, forecast revisions are informative about policy innovations.

$$\underbrace{E_{t-h}x_t - E_{t-h-1}x_t}_{\text{Forecast revision at t-h}} = (1-\kappa)\underbrace{E_{t-h-1}x_t - E_{t-h-2}x_t}_{\text{Forecast revision at t-h-1}} + \kappa u_{t-h}$$

B Data Sources and Transformations

All of the data used in our empirical models are from publicly available sources. Most of the series came from the Federal Reserve Economic Data (FRED) database, which is accessible from the website of St.Louis Fed. Variables that belong to the National Income and Product Accounts (NIPA) are also available from the Bureau of Economic Analysis website. We use the historical vintages rather than the current data release to minimise the effect of benchmark revisions in the NIPA data.

The following variables are from other sources. Our policy indicator in the baseline quarterly analysis, Real Government Consumption & Gross Investment: Federal (RGF), is from the Real-Time Dataset provided by the Federal Reserve Bank of Philadelphia. The marginal tax rate comes from Barro and Redlick (2011), and the real exchange rates are from the Bank of International Settlement (BIS)' effective exchange rate indices database. The total factor productivity (TFP) series is from Fernald (2014). Fiscal news and nowcast errors are from the Greenbooks. Finally, we construct the real interest rate by subtracting changes in the CPI from the 3-month US Treasury Bill rate, both of which are available from FRED.

Table 4: List of Variables

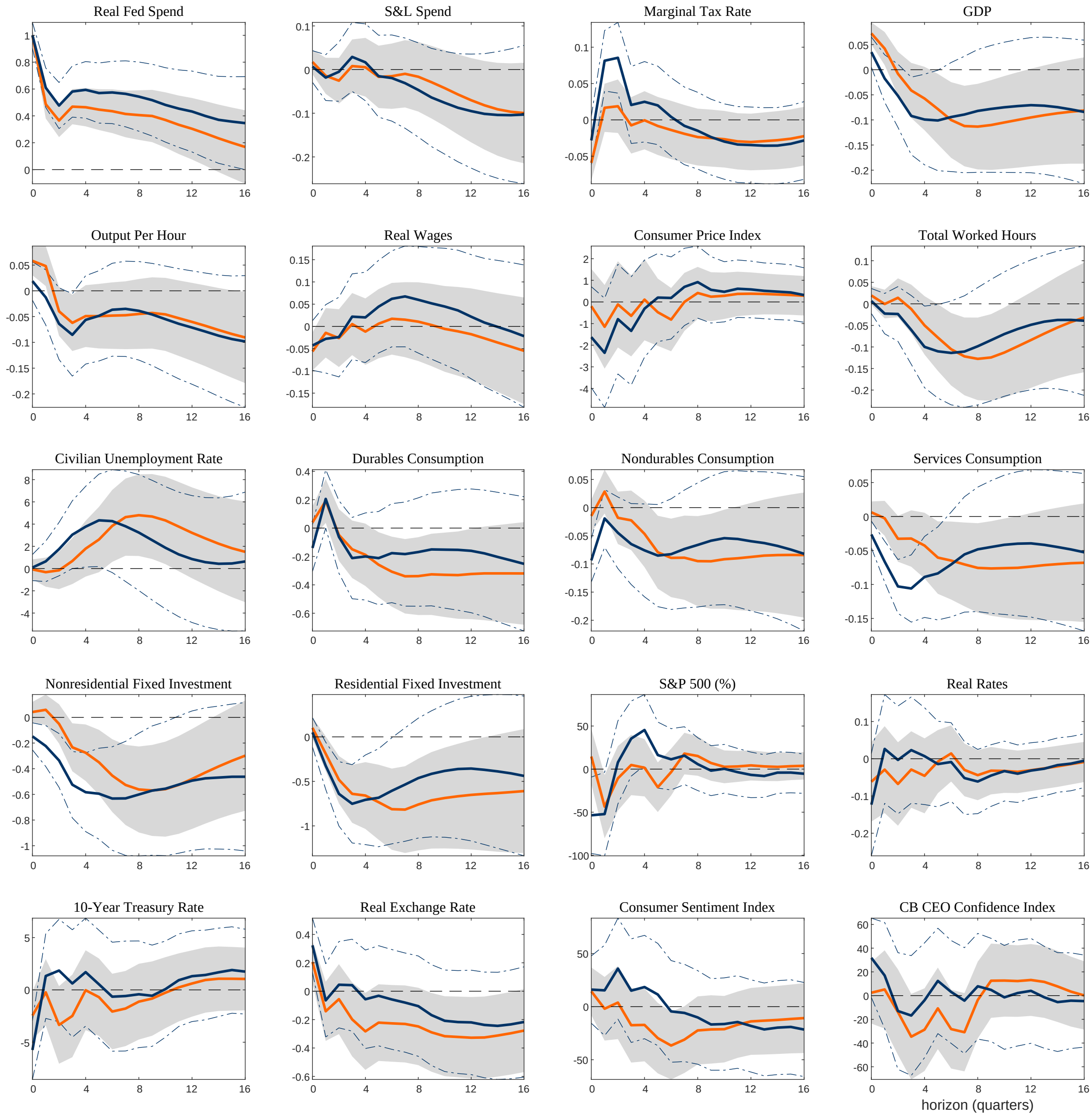
FRED Mnemonic	Variable	Baseline	Monthly	Factors	Logs	RW Prior	Per Capita
	Greenbook News & Nowcast Errors on Real Federal Govt Spending	•	•			•	
	Greenbook Forecasts on Real GDP Growth	•	•			•	
	Greenbook Forecasts on Unemployment Rate	•	•			•	
	Real Government Consumption & Gross Investment: Federal (RGF)	•		•	•	•	•
SLCE	State & Local Consumption Exp. & Gross Investment	•		•	•	•	•
	Barro-Redlick Income Weighted Avg. Marginal Tax Rate	•		•		•	
FGDEF	Net Federal Government Saving (Deficit)	•		•		•	
GDPC96	Real GDP	•		•	•	•	•
UNRATE	Civilian Unemployment Rate	•	•	•		•	
CE16OV	Civilian Employment	•	•	•	•	•	
HOABS	Business Sector: Hours of All Persons / Total Worked Hours	•		•	•	•	
RCPHBS	Business Sector: Real Hourly Compensation for All Employed Persons	•		•	•	•	•
DSPIC96	Real Disposable Personal Income	•		•	•	•	•
OPHPBS	Business Sector: Output Per Hour of All Persons / Output Per Hour	•		•	•	•	
	Utilization-adjusted Total Factor Productivity by Fernald (2014)	•				•	
PCDG	Personal Consumption Expenditures: Durable Goods	•		•	•	•	•
PCND	Personal Consumption Expenditures: Nondurable Goods	•		•	•	•	•
PCESV	Personal Consumption Expenditures: Services	•		•	•	•	•
PNFI	Private Nonresidential Fixed Investment	•		•	•	•	•
PRFI	Private Residential Fixed Investment	•		•	•	•	•
OILPRICE	Spot Oil Price: West Texas Intermediate (Dollar Per Barrel)	•	•	•	•	•	
CPIAUCSL	Consumer Price Index	•	•	•	•	•	
NAPMNOI	ISM Manufacturing: New Orders Index	•		•			
NAPMII	ISM Manufacturing: Inventories Index	•		•			
CPATAX	Corporate Profits After Tax with IVA and CCAdj	•		•	•	•	
UMCSENT	University of Michigan: Consumer Sentiment Index	•	•	•		•	
	Conference Board Measure of CEO Confidence	•		•		•	
SP500	S&P 500 Stock Market Index (Percent Change)	•	•	•		•	
	Real Interest Rate (3m T-Bill minus Inflation)	•	•	•		•	
FEDFUNDS	Federal Funds Rate	•	•	•		•	
GS10	10-Year Treasury Rate	•	•	•		•	
	Real Exchange Rate	•	•	•	•	•	
M2SL	M2 Money Stock (Growth Rate)	•		•		•	
GPSAVE	Gross Private Saving	•		•	•	•	•
TOTALSL	Total Consumer Credit Outstanding	•	•	•	•	•	•
BUSLOANS	Commercial & Industrial Loans at All Commercial Banks	•	•	•	•	•	
MTSR133FMSX	Total Federal Outlays		•		•	•	•
W055RC1	Personal Current Taxes		•		•	•	•
INDPRO	Industrial Production Index		•	•	•	•	
CUMFNS	Capacity Utilization		•				
AMDMNO	New Orders : Durable goods		•		•	•	
BUSINV	Business Inventories		•		•	•	
AWHMAN	Average Weekly Hours		•	•			
CES3000000008	Avg Hourly Earnings		•		•	•	
RPI	Real Personal Income		•		•	•	•
PMSAVE	Personal Saving		•		•	•	•
CMRMTSPL	Real Manufacturing Sales		•		•	•	
RETAIL	Retail Sales		•		•	•	
VXOCLS	VIX		•				
GCEC96	Real Govt. Consumption Exp.& Gross Invest.			•			
DEFCONS	Federal Defense Consumption Expenditures			•			
DGI	Federal Defense Gross Investment			•			
CIVCONS	Federal Nondefense Consumption Expenditures			•			
NDGI	Federal Nondefense Gross Investment			•			
SLCONS	State & Local Consumption Exp.			•			
SLINV	State & Local Gross Investment			•			
FGRECPT	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			•			
PPIACO	Producer Price Index: All Commodities			•			
HOUST	Housing Starts: Total: New Privately Owned Housing Units Started			•			
GPDIC96	Real Gross Private Domestic 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			•			
PCEPILFE	Personal Consumption Exp.: Chain-Type Price Index Less Food and Energy			•			
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			•			
CPILFENS	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			•			

List of Variables (cont.)

FRED Mnemonic	Variable	Baseline	Monthly	Factors	Logs	RW Prior	Per Capita
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			•			
CEU3100000008	Avg. Hourly Earnings of Prod. and Nonsupervisory Emp.: Durable Goods			•			
CES3200000008	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			•			
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			•			
PPIIDC	Producer Price Index: Industrial Commodities			•			
PPICRM	Producer Price Index: Crude Materials for Further Processing			•			
PPIITM	Producer Price Index: Intermediate Materials: Supplies & Components			•			
PPICPE	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			•			
EXCRESNS	Excess Reserves of Depository Institutions			•			

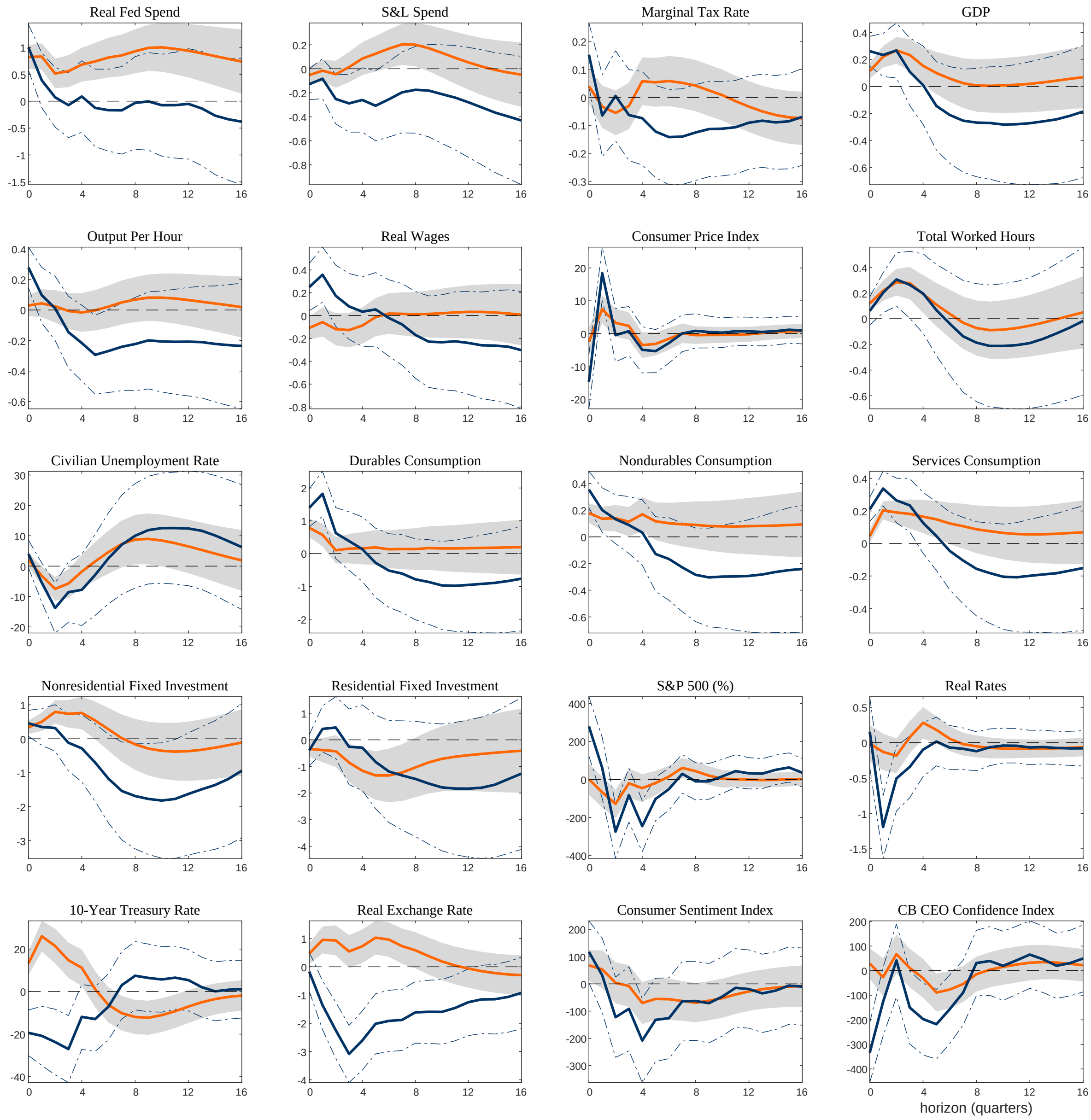
C Additional Results

Figure 13: Effects of Misexpected Surprises: Greenbooks v. SPF



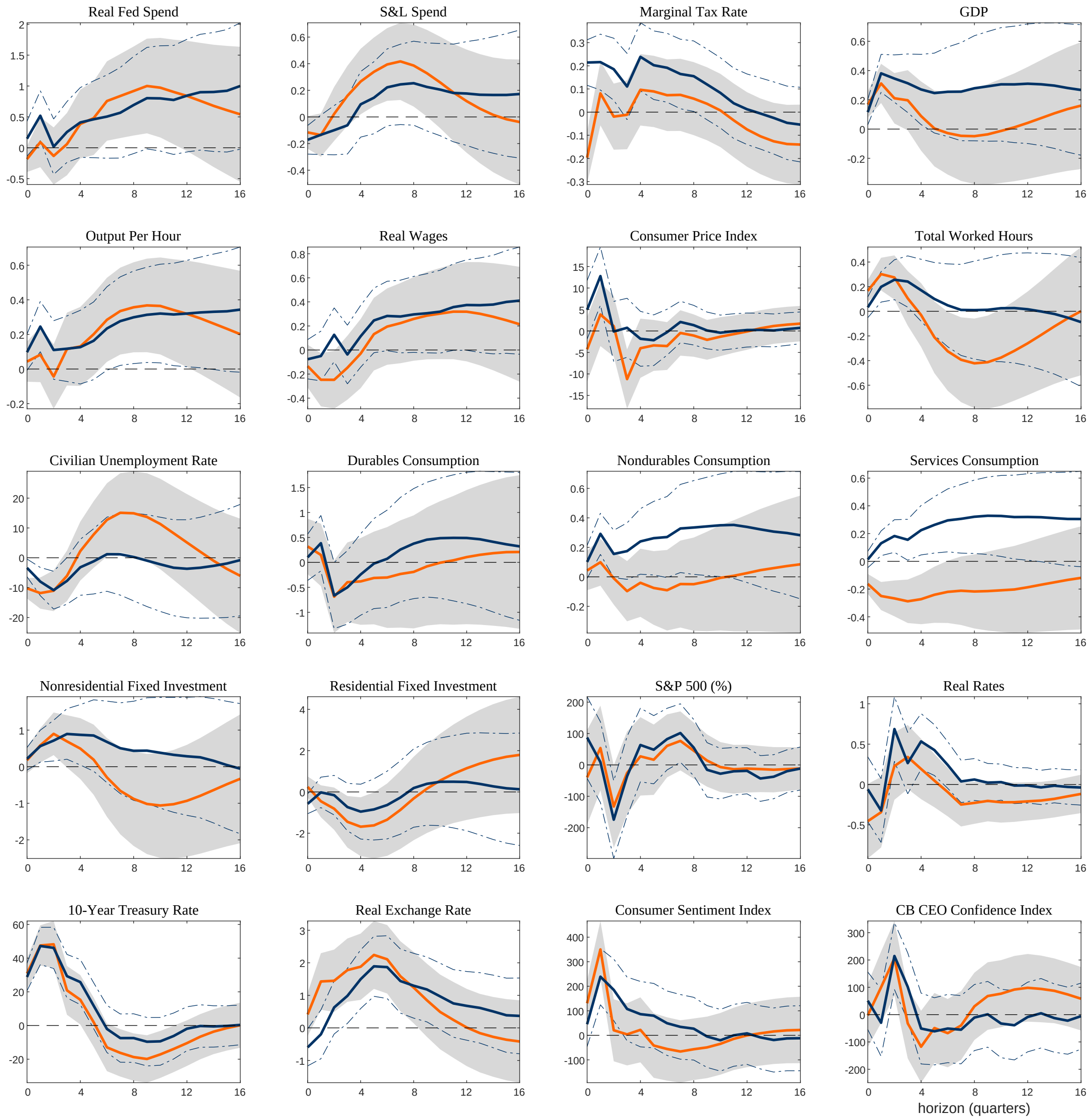
Note: This plot shows impulse responses to a misexpected federal government spending surprise from the large EVAR model. The *Orange line* corresponds to IRFs by using the SPF nowcast errors as the proxy of fiscal shocks. The *Blue line* represent the IRFs constructed from the Greenbook nowcast errors. Shaded areas represent 90 percent confidence bands. Sample 1981.Q3 – 2012.Q1.

Figure 14: Effects of Unexpected Surprises: Greenbooks v. SPF



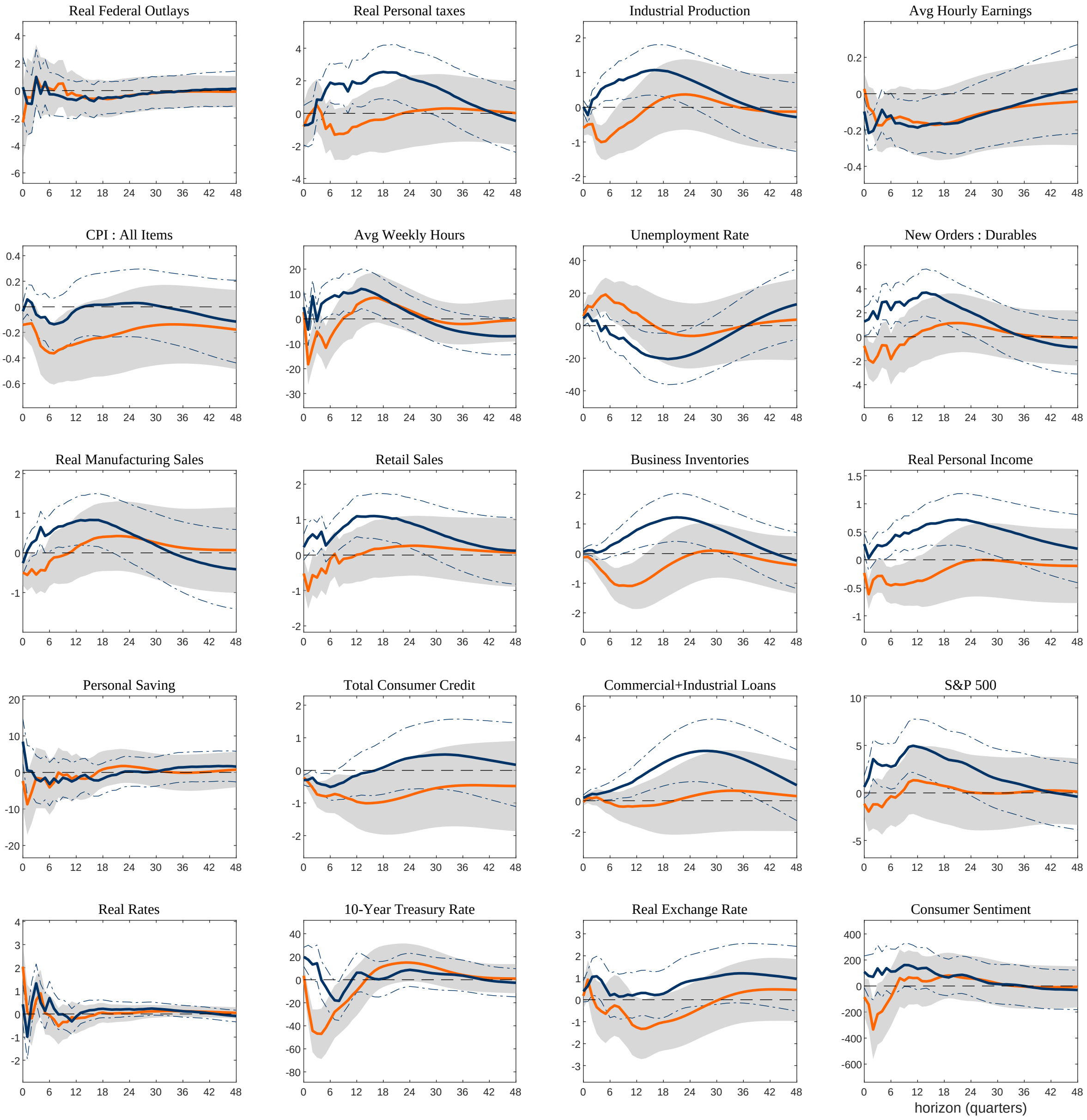
Note: This plot shows impulse responses to a unexpected federal government spending surprise from the large EVAR model. The *Orange line* corresponds to IRFs by using the SPF nowcast news as the proxy of fiscal shocks. The *Blue line* represent the IRFs constructed from the Greenbook nowcast news. Shaded areas represent 90 percent confidence bands. Sample 1981.Q3 – 2012.Q1.

Figure 15: Effects of 1Y Expected Surprises: Greenbooks v. SPF



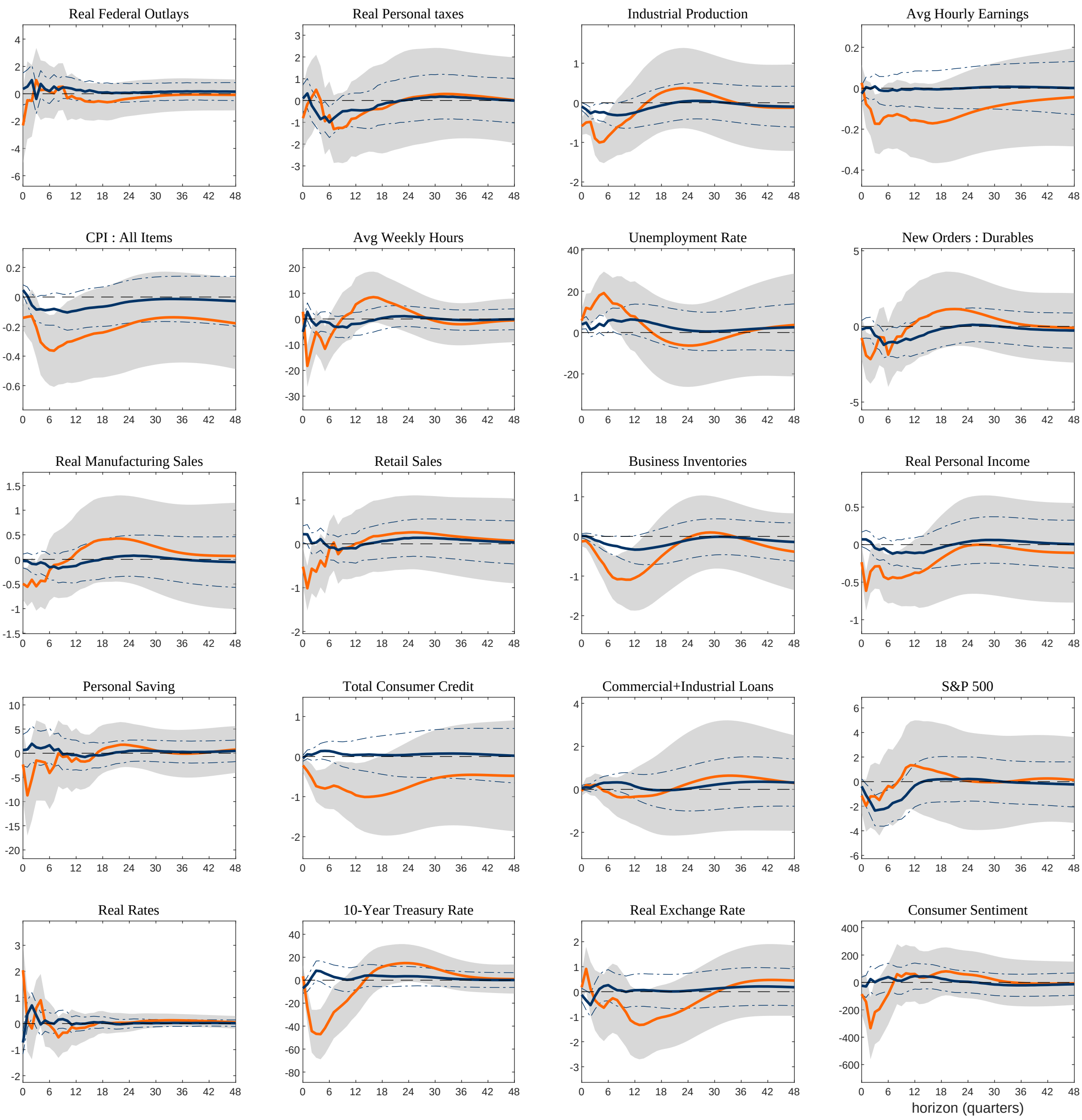
Note: This plot shows impulse responses to a one-year expected federal government spending surprise from the large EVAR model. The *Orange line* corresponds to IRFs by using the SPF forecast news up to 3 quarters as the proxy of fiscal shocks. The *Blue line* represent the IRFs constructed from the Greenbook forecast news up to a year. Shaded areas represent 90 percent confidence bands. Sample 1981.Q3 – 2012.Q1.

Figure 16: Monthly Unexpected Effects, Recursive ID



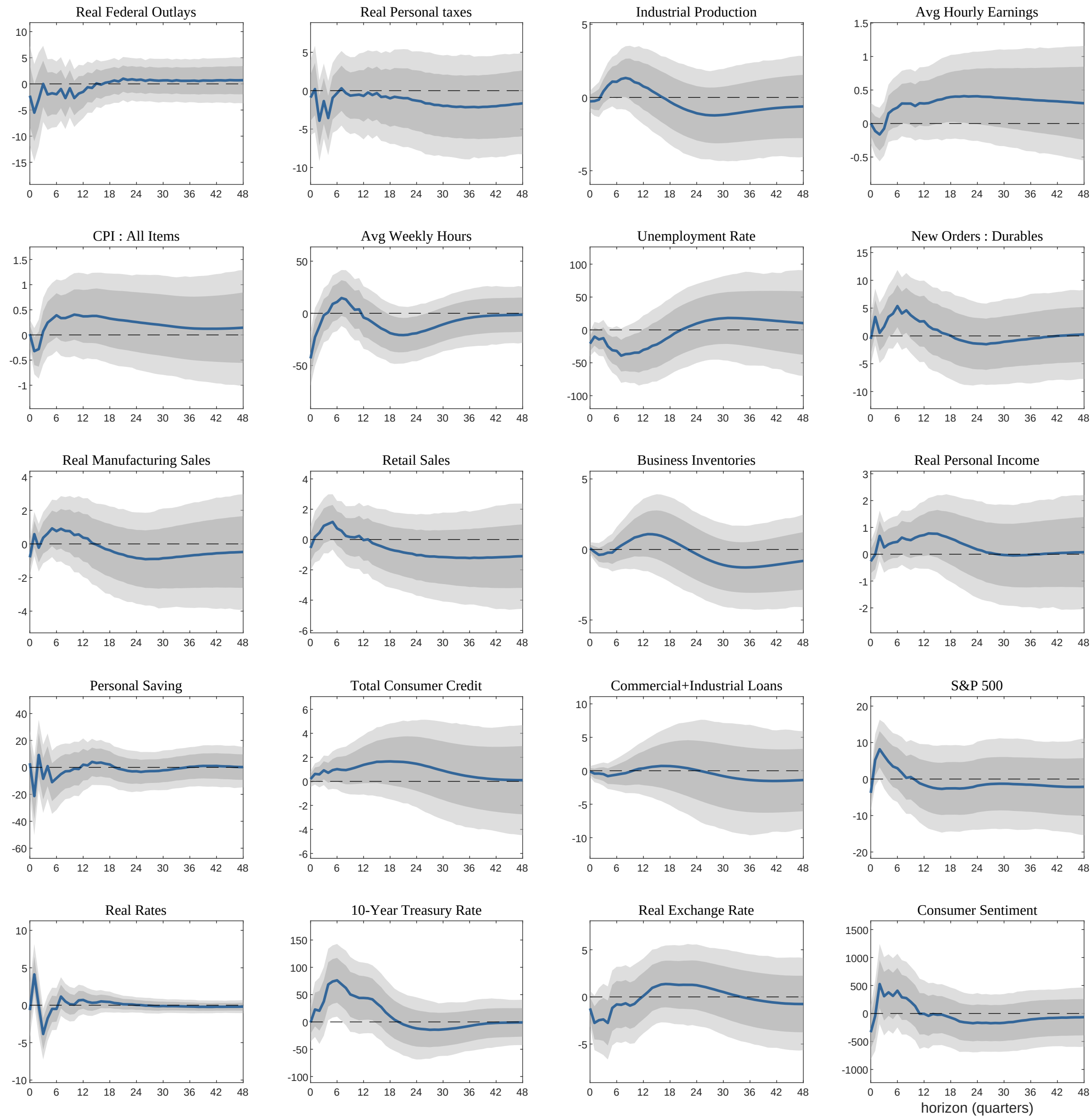
Note: This plot shows impulse responses to a unexpected federal government spending surprise from the large EVAR model. The *Orange line* corresponds to IRFs by using the Greenbook one-year forecast error as the proxy of fiscal shocks. The *Blue line* represent the IRFs constructed from nowcast news. Shaded areas represent 90 percent confidence bands. Sample 1981.7 – 2012.1.

Figure 17: Monthly Misexpected Effects, Recursive ID



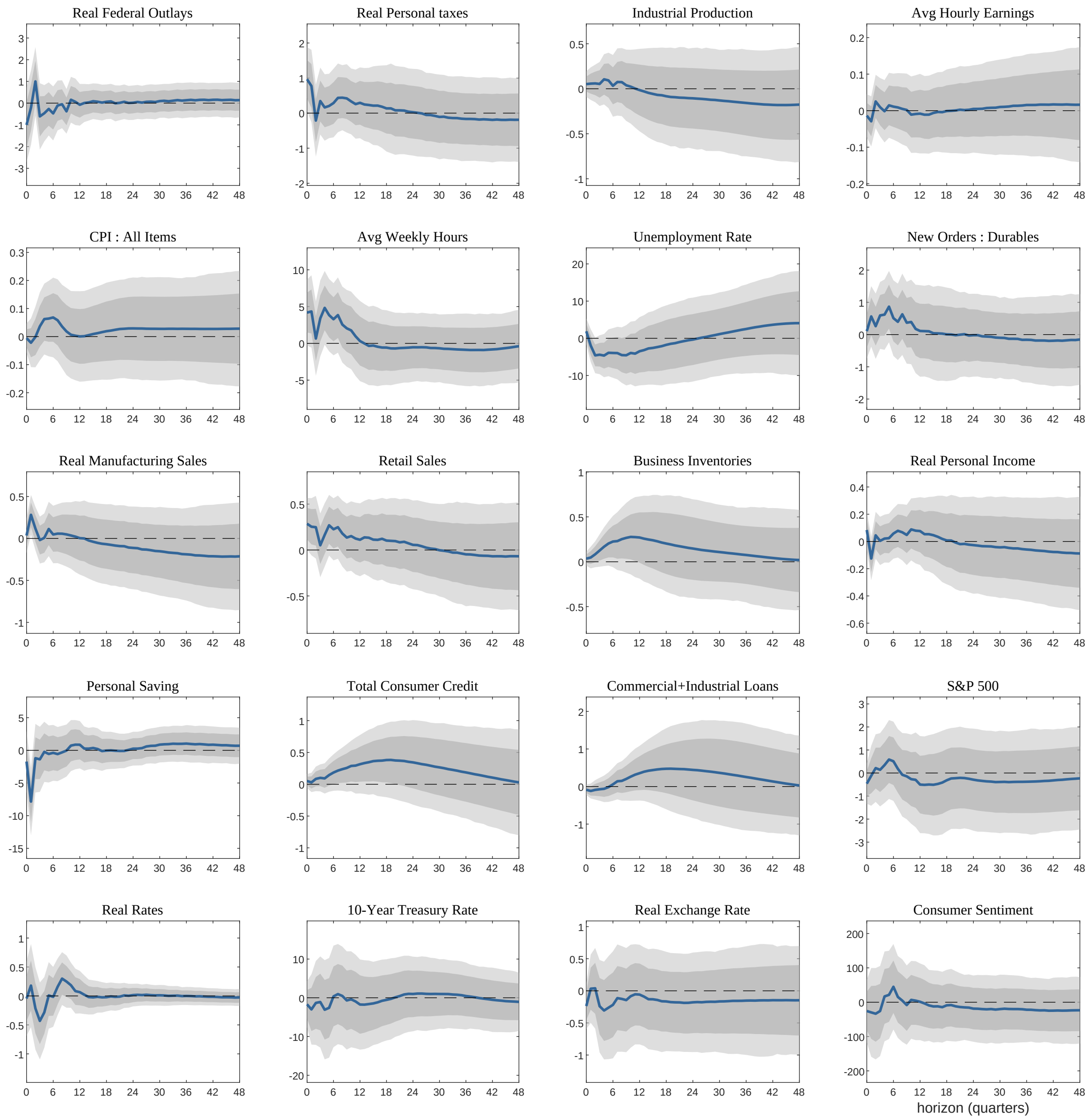
Note: This plot shows impulse responses to a misexpected federal government spending surprise from the large EVAR model. The *Orange line* corresponds to IRFs by using the Greenbook one-year forecast error as the proxy of fiscal shocks. The *Blue line* represent the IRFs constructed from nowcast news. Shaded areas represent 90 percent confidence bands. Sample 1981.7 – 2012.1.

Figure 18: Monthly Effects of One-Year Expected Fiscal Surprises



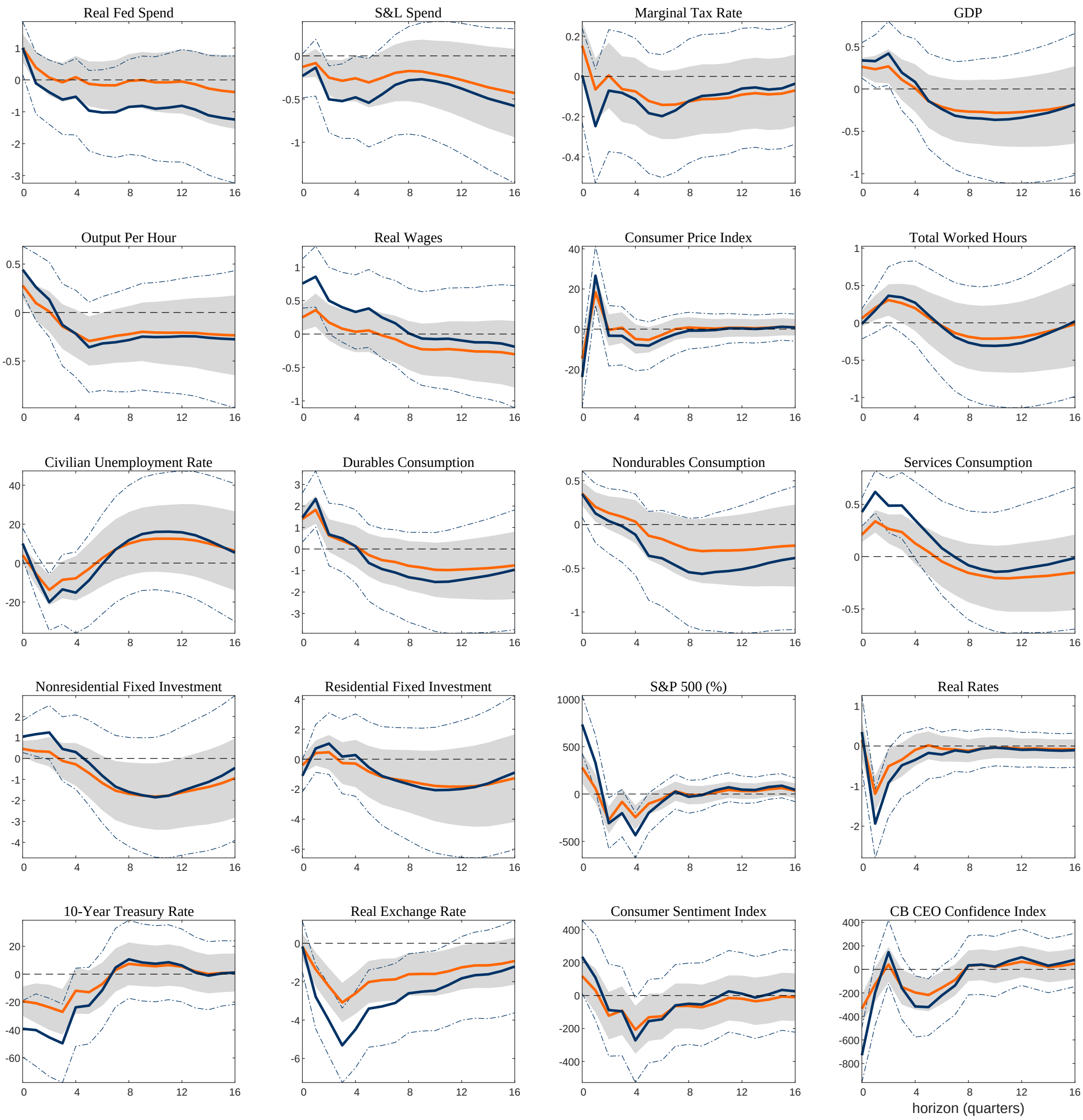
Note: This plot shows impulse responses to one-year expected federal government spending surprise from our large EVAR model. Shaded areas represent 90 and 68 percent confidence bands. Sample 1981.7 – 2012.1.

Figure 19: Monthly Effects of Two-Year Expected Fiscal Surprises



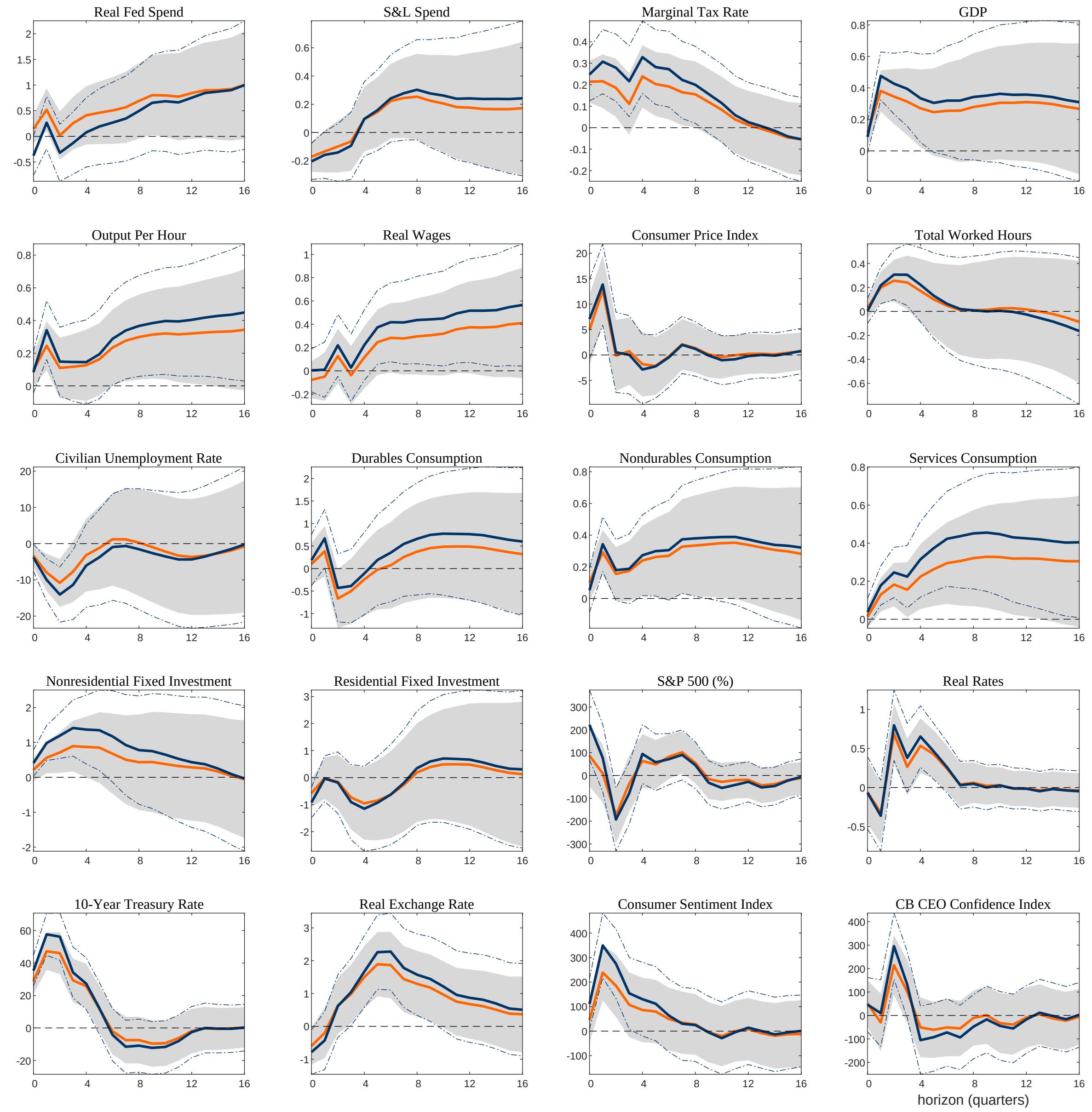
Note: This plot shows impulse responses to a two-year expected federal government spending surprise from our large EVAR model. Shaded areas represent 90 and 68 percent confidence bands. Sample 1981.7 – 2012.1.

Figure 20: Effects of Unexpected, First v. Final Nowcast error



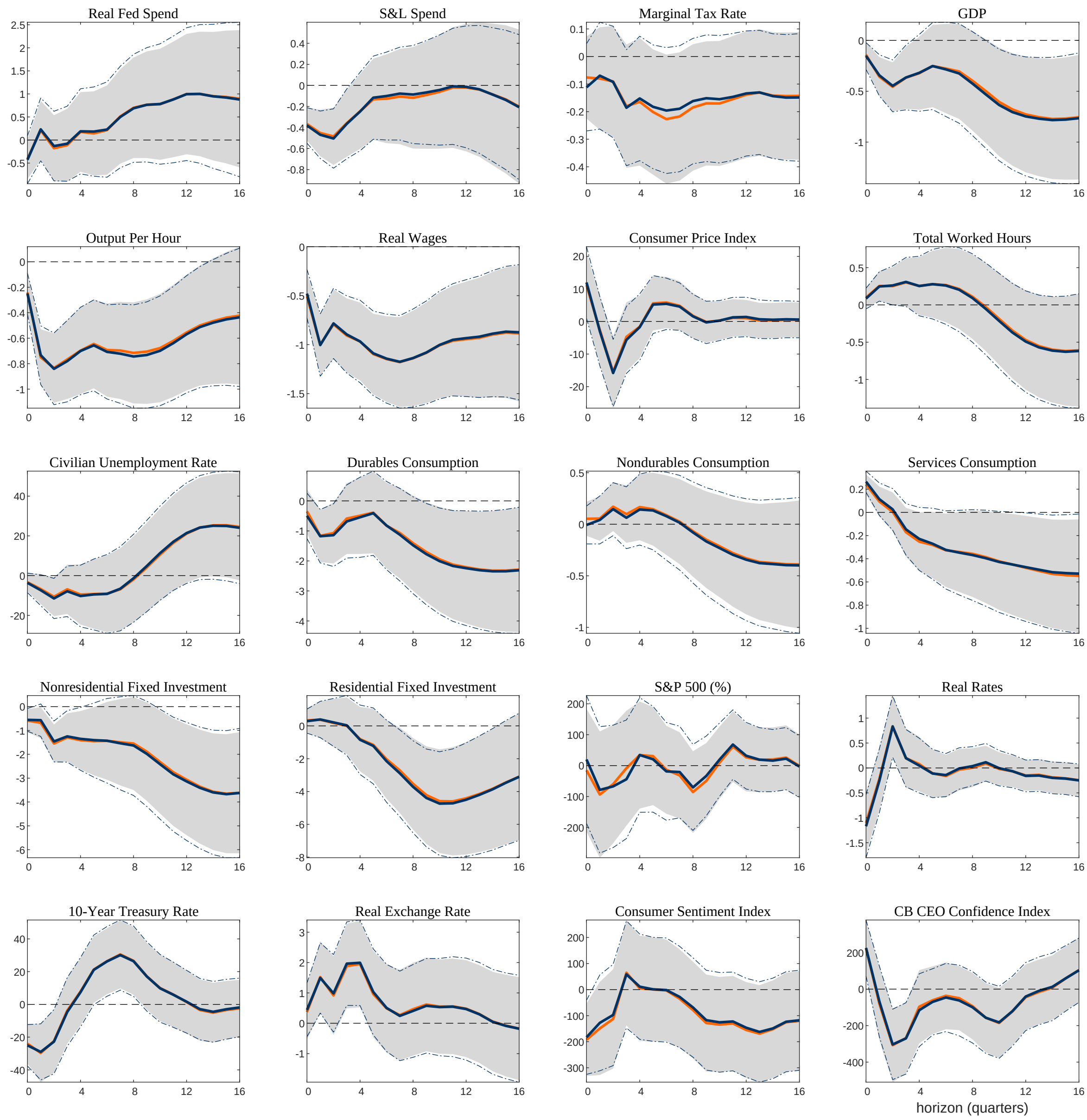
Note: This plot shows impulse responses to an unexpected federal government spending surprise from our large EVAR model. The *Orange line* corresponds to baseline IRFs using the Greenbook nowcast errors. The *Blue line* represent the IRFs constructed by replacing nowcast errors with the difference between the first release of the data and nowcast. Shaded areas represent 90 percent confidence bands. Sample 1981.Q3 – 2012.Q1.

Figure 21: Effects of 1Y Expected, First v. Final Nowcast error



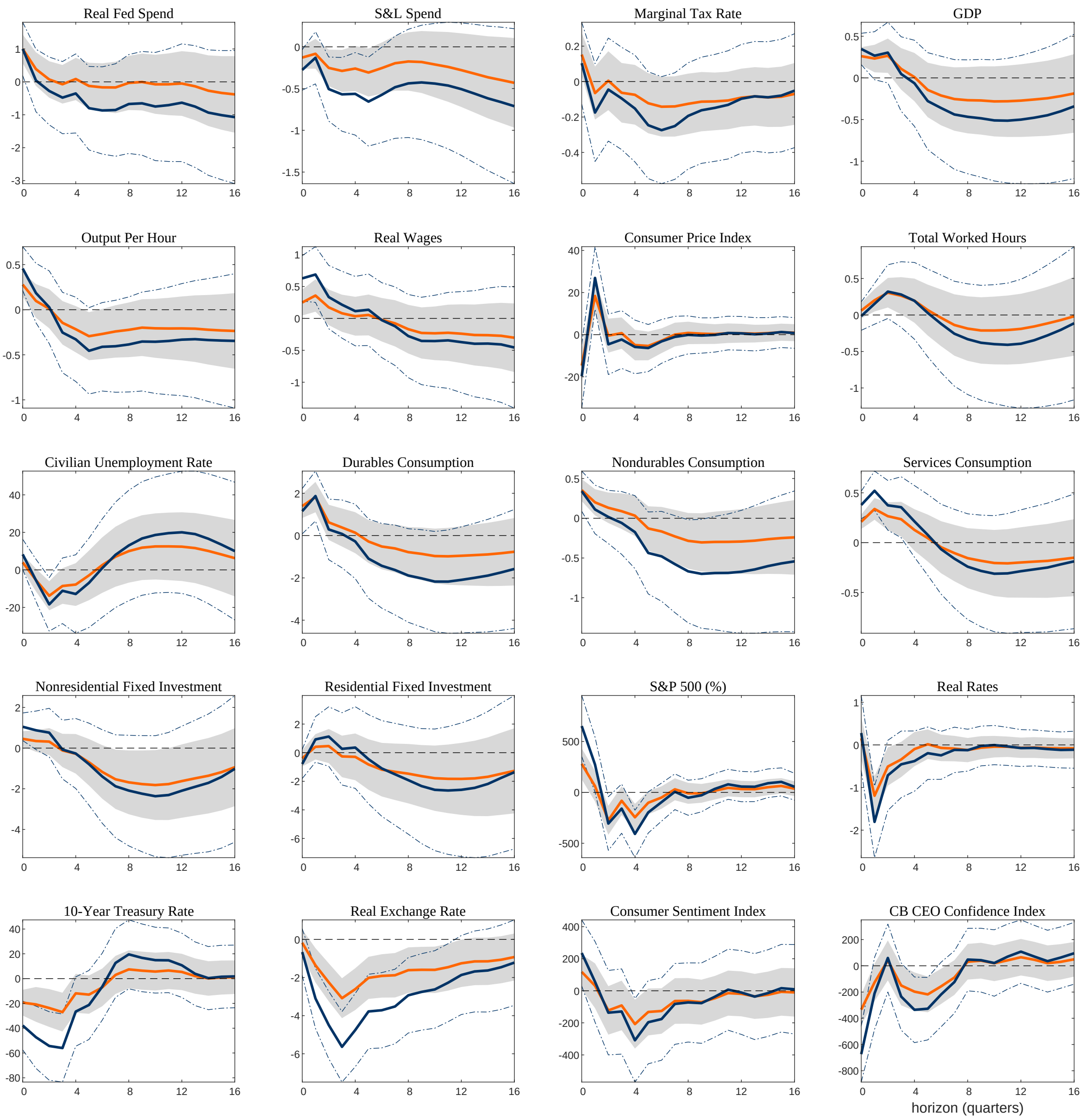
Note: This plot shows impulse responses to a one-year expected federal government spending surprise from our large EVAR model. The *Orange line* corresponds to baseline IRFs using the Greenbook nowcast errors. The *Blue line* represent the IRFs constructed by replacing nowcast errors with the difference between the first release of the data and nowcast. Shaded areas represent 90 percent confidence bands. Sample 1981.Q3 – 2012.Q1.

Figure 22: Effects of 2Y Expected, First v. Final Nowcast error



Note: This plot shows impulse responses to a two-year expected federal government spending surprise from our large EVAR model. The *Orange line* corresponds to baseline IRFs using the Greenbook nowcast errors. The *Blue line* represent the IRFs constructed by replacing nowcast errors with the difference between the first release of the data and nowcast. Shaded areas represent 90 percent confidence bands. Sample 1981.Q3 – 2012.Q1.

Figure 23: Effects of Unexpected, Third v. Final Nowcast error



Note: This plot shows impulse responses to an unexpected federal government spending surprise from our large EVAR model. The *Orange line* corresponds to baseline IRFs using the Greenbook nowcast errors. The *Blue line* represent the IRFs constructed by replacing nowcast errors with the difference between the third release of the data and nowcast. Shaded areas represent 90 percent confidence bands. Sample 1981.Q3 – 2012.Q1.