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Fiscal Foresight, Limited Information and the Effects of Government Spending Shocks[☆]

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Abstract

We quantify the impact of government spending shocks on the US economy. Thereby, we address the identification problem in structural vector autoregressions (SVARs) related to fiscal foresight by utilizing the narrative approach. Moreover, we surmount the generic limited information problem inherent in VARs by a factor-augmented VAR (FAVAR) approach. Overall, a positive deficit-financed defense shock raises output by more than what is found in a VAR. Furthermore, our evidence suggests that consumption is crowded in. These results are robust to different variants of controlling for fiscal foresight and reveal the crucial role of the limited information problem in fiscal VARs.

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1. Motivation

Differing empirical findings on the effect of government spending shocks on key variables such as consumption and real wage amongst others depend ultimately on the empirical approach employed. One consequence of different empirical findings is a controversy about the most suitable model to analyse fiscal policy in theory. Perotti (2007, p.1) gets to the point:

> "... perfectly reasonable economists can and do disagree on the basic theoretical effects of fiscal policy, and on the interpretation of the existing empirical evidence."

With regard to empirical findings, there exists the classic *SVAR approach* employed in Fatás and Mihov (2001), Blanchard and Perotti (2002), Perotti (2007) and Fragetta and Melina (2011) amongst others. These papers find an increase of consumption and real wage in response to a government spending shock in the US, which supports *(New-)Keynesian* theories.

An alternative is the *Narrative approach* followed by Ramey and Shapiro (1998), Edelberg et al. (1999), Burnside et al. (2004) and Ramey (2011b) which finds that consumption and real wage decrease in response to a government spending shock in the US. These results back *Neoclassical* theories. The virtue of these papers is that they overcome the *fiscal foresight* problem related to anticipation effects by economic agents that cause a misalignment of information sets.[2]

Basically the macroeconometric literature on quantifying the effects of fiscal policy has identified at least two distinct sources that might misaling the infor-

[2]Ramey (2011a) highlights the key differences in Neoclassical and (New-)Keynesian theories and surveys recent empirical findings based on the SVAR and Narrative approach in the light of these theories.

mation set of an econometrician on the one side and the economy he aims to analyse on the other side. One source is fiscal foresight and the other one is *limited information*.

The term fiscal foresight captures the fact that a preannounced fiscal policy change leads agents in the actual economy to revise their plans even before the policy change becomes effective. In consequence, the information set of the agents in the actual economy is larger than the information set of the econometrician that aims to analyse the dataset generated by the actual economy. In case the econometrician makes use of a classic SVAR approach, the differing information sets might flaw statistical inferences. What the econometrician beliefs to be a fiscal innovation is actually a discounted sum of current and past fiscal news observed by agents.[3]. Thus, one could argue that conclusions drawn from analyses following the SVAR approach must be viewed cautiously.

In contrast, the Narrative approach pioneered by Hamilton (1985) involves an identification strategy that adequately accounts for fiscal foresight and helps to align the information set of the agents in the actual economy and the econometrician. The basic idea of this approach nowadays is to build time series that contain the net present value of announced government spending or tax code changes that are going to be effective at a later date and that are not related to the state of the economy.[4] Such a time series is unmistakably fiscal news to

[3]Leeper et al. (2009), Mertens and Ravn (2010) or Favero and Giavazzi (2010) illustrate the fiscal foresight problem in more detail.

[4]Originally the idea was to conduct an event-study, where the events are not related to the state of the economy. Ramey and Shapiro (1998) have initiated a different, narrative, dummy variable approach to identify shocks to government spending focusing only on episodes where sudden forecasts of large rises in de-

both, the agents in the actual economy and the econometrician. We regard the Narrative approach as a consistent and convincing identification strategy in order to properly account for fiscal foresight. Thus, we simply follow this approach in our analysis below. Nevertheless, fiscal foresight is not the only source that can misalign the information set of the econometrician and the actual economy.

Our main goal is to highlight a second source of misalignment in information sets that may lead to biased estimates or *non-fundamentalness*. Typically an econometrician faces a limited information problem, i.e. she can only include a limited amount of variables in any VAR due to degrees of freedom. Therefore she ignores the information of a large number of economic indicators that might affect the decisions of agents. Undeniably this misaligns the information set of the econometrician on the one side and the agents in the actual economy on the other side. Compared to the econometrician's small VAR, it seems natural to assume that the latter may take into account a larger number of economic indicators when making their decisions. Hence this misalignment inherent in any VAR may lead to biased coefficient estimates. Bernanke et al. (2005) put forward this argument in a monetary policy context.

With regard to the empirical literature on fiscal multipliers, we think that all the aforementioned studies based on a fiscal VAR may suffer from this short-

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fense spending where announced by the Business Week magazine. More recently Ramey (2011b), in order to get more information, has quantified the military news, building a continuous variable which contains the discounted value of the resulting change in government spending forecasted by the Business Week. With this "defense news" measure, Ramey (2011b) overall confirms the previous finding arguing that SVAR analysis reach different conclusion because they miss the right timing.

coming and may lead to spurious conclusions about the effects of fiscal policy. Thus, our first key contribution is to demonstrate the consequences of the limited information problem in fiscal VARs with regard to the interpretation of empirical evidence.

One way of surmounting the limited information problem is to extract the information of a large informational dataset by the method of principal components in a first step. In a subsequent step, one incorporates the extracted information of the large informational dataset represented by factors into a VAR estimation. This is called the FAVAR approach. Note that different approaches to include factors in a VAR analysis are surveyed in Stock and Watson (2005), and a widely-cited application of the FAVAR approach in empirical monetary economics is Bernanke et al. (2005).

It is somewhat surprising that so far the merits of incorporating factors into VAR analysis have not been often utilized in the quantification of the effects of fiscal policy to date. We are only aware of the paper by Forni and Gambetti (2011), who assume a dynamic factor model and utilize sign restrictions à la Uhlig (2005) to identify the fiscal shock. However our FAVAR approach is different and likewise we use timing restrictions to identify the structural shock by explicitly considering a time series, which takes into account anticipation effects. Therefore outlining our application of the FAVAR approach to fiscal policy is our second key contribution in this paper.

As is well known, in the FAVAR approach, the vector of explicit variables can be specified almost as parsimonious as in a VAR analysis, but in contrast to a conventional VAR, one is able to remedy the limited information problem.

Given the FAVAR specification, we estimate the effect of an exogenous shock in government expenditures on various key macroeconomic variables such as output and its components in the US. Hence, our third key contribution is related to the realm of the empirical literature that aims to quantify fiscal multipliers. In particular, we take the VAR specification of Ramey (2011b) including her narrative measure of defense news and augment the VAR by factors.

We find that incorporating the information of a large dataset via factors makes a substantial difference for the US. A positive deficit-financed shock to government spending raises output by more than what is found in a VAR. Moreover, our evidence suggests that consumption is crowded in, which is consistent with the results of Forni and Gambetti (2011).

Finally, we control for robustness of our results by employing an alternative instrument proposed in the literature by Auerbach and Gorodnichenko (2010) as well as an alternative identification strategy proposed by Auerbach and Gorodnichenko (2010). It turns out that FAVAR estimates imply output multipliers in the range of 0.77 to 4.25, which is larger than what we find in corresponding VARs. Moreover crowding-in of consumption is a quite robust result.

The paper is organized as follows. In Section 2, we detail an econometric framework that has the potential to account for both the fiscal foresight and the limited information problem. Within Section 3 we discuss our basic specification, identification issues and alternatives to control for fiscal foresight, the dataset in use and the calculation of different types of output multipliers. Next, in Section 4 we compare impulse responses to a defense news shock based on a VAR to their counterparts in a FAVAR and illustrate the potential consequences of the limited information problem. Thereafter, we consider robustness of our results in Section 5. We conduct specification and fundamentalness tests. It turns out that the FAVAR is the favourable specification from a statistical point of view and that the defense news shocks suffer from a non-fundamentalness problem. In consequence, we derive results based on alternative specifications and demonstrate that our main findings remain robust. Section 6 discusses to what extent our evidence can be reconciled with contemporary leading theoretical views and Section 7 concludes.

2. Econometric Framework

The incorporation of factors in a multivariate time-series analysis comes along with additional identification issues compared to a standard VAR. In particular, the relationship between a large informational dataset and unobserved factors expressed in a measurement equation involves an idiosyncratic component, see for example Stock and Watson (2005). As a result, one cannot simply estimate a dynamic factor model and base structural inference on a vector moving average representation of the associated state equation that involves the unobserved factors. This would be misleading, as the errors in this representation are a combination of the idiosyncratic component in the measurement and the state equation, see Koop and Korobilis (2009) for an illustration.

Compared to a standard VAR, it requires further restrictions to achieve identification. As highlighted in Koop and Korobilis (2009), there exists no such thing as a mutually agreed identification strategy. On way is to impose further restrictions within the dynamic factor model. See for example Forni and Gambetti (2011), who take appropriate averages of the variables constituting the large informational dataset in order to eliminate the idiosyncratic component of the measurement equation.

In contrast, we opt for a FAVAR approach similar to Bernanke et al. (2005). The latter approach refines the dynamic factor model to the extent that explicit variables are part of the measurement equation, see Koop and Korobilis (2009, p.51).

In particular, there is a *VAR / state / transition equation*

$$\begin{bmatrix} Y_t \\ F_t \end{bmatrix} = \mathbf{\Phi}_0 + \alpha_1 t + \alpha_2 t^2 + \sum_{j=1}^{p} \mathbf{\Phi}_j \begin{bmatrix} Y_{t-j} \\ F_{t-j} \end{bmatrix} + \mathbf{U}_t,$$

or

$$\begin{bmatrix} Y_t \\ F_t \end{bmatrix} = \mathbf{\Phi}_0 + \alpha_1 t + \alpha_2 t^2 + \mathbf{\Phi}(L) \begin{bmatrix} Y_{t-1} \\ F_{t-1} \end{bmatrix} + \mathbf{U}_t, \tag{1}$$

where Y_t is the small $M \times 1$ vector of observables or explicit variables. In addition, we have the unobserved factors in the $K \times 1$ vector F_t and the $(M+K) \times 1$ error $\mathbf{U}_t$ which is i.i.d. $N(0, \mathbf{\Sigma}^f)$, where $\mathbf{\Sigma}^f$ is the variance-covariance matrix. $\mathbf{\Phi}_0$ is a $(M+K) \times 1$ vector of constants and α_1, α_2 are $(M+K) \times 1$ coefficient matrices for deterministic time trends.[5] $\mathbf{\Phi}(L)$ is a matrix polynomial of order p in the lag operator L with non-negative powers, where each matrix $\mathbf{\Phi}_1, ..., \mathbf{\Phi}_p$ is a matrix of dimension $(M+K) \times (M+K)$.

In particular, equation (1) is usually denoted a *factor-augmented vector-autoregression*. As we ultimately follow the narrative approach to identify the fiscal shock, there is no need to make any further identification assumption at this stage.

In order to be clear, we derive impulse-response analysis with respect to the explicit variables Y_t, by following a block-recursive strategy based on timing restrictions. Such restrictions typically state, which variables in Y_t a structural

[5]Be aware that we use a similar set-up as Ramey (2011b), who includes a constant as well as a linear and quadratic trend.

shock affects contemporaneously and which of the variables in Y_t respond with a lag to the structural shock. In a FAVAR framework, such a statement must be extended towards the vector of informational time series X_t, represented by the unobserved factors F_t in (1).

For this reason, the FAVAR framework involves also a *factor / observation / measurement equation*

$$X_{it} = \mathbf{\Lambda}_{0i} + \mathbf{\Lambda}_i^f F_t + \mathbf{\Lambda}_i^y Y_t + \mathbf{e}_{it}, \tag{2}$$

for $i = 1, ..., N$ or more compact

$$X_t = \mathbf{\Lambda}_0 + \mathbf{\Lambda}^f F_t + \mathbf{\Lambda}^y Y_t + \mathbf{e}_t, \tag{3}$$

which we can write as

$$\begin{bmatrix} Y_t \\ X_t \end{bmatrix} = \begin{bmatrix} \mathbf{0}_{M\times 1} \\ \mathbf{\Lambda}_0 \end{bmatrix} + \underbrace{\begin{bmatrix} \mathbf{I}_M & \mathbf{0}_{M\times K} \\ \mathbf{\Lambda}^y & \mathbf{\Lambda}^f \end{bmatrix}}_{\equiv\tilde{\mathbf{\Lambda}}} \begin{bmatrix} Y_t \\ F_t \end{bmatrix} + \underbrace{\begin{bmatrix} \mathbf{0}_{M\times N} \\ \mathbf{I}_N \end{bmatrix} \mathbf{e}_t}_{\equiv\tilde{\mathbf{e}}_t}. \tag{4}$$

X_t is a $N \times 1$ vector including *informational time series*, which are observables that are not part of the VAR specification. Naturally, the exclusion of the information in X_t may cause a bias to the VAR coefficient estimates. The $N \times 1$ error $\mathbf{e}_t$ is i.i.d. $N(0, \mathbf{\Sigma})$ with $\mathbf{\Sigma} = diag(\sigma_1^2, ..., \sigma_N^2)$, which allows us to treat these equations as N independent regressions given we know F_t. $\mathbf{\Lambda}_0$ is a $N \times 1$ vector of constants. $\mathbf{\Lambda}^f$ is the $N \times K$ matrix usually denoted as *factor loadings* and $\mathbf{\Lambda}^y$ is a $N \times M$ coefficient matrix. Therefore matrix $\tilde{\mathbf{\Lambda}}$ is of dimension $(M+N)\times(M+K)$.

By substituting the vector moving average representation of (1) into (4) it can be shown that the errors of the resulting vector moving average representation are solely associated with Y_t. In fact, the first $M \times 1$ idiosyncratic errors in the resulting vector moving average representation of (4) associated with the explicit variables are all equal to zero.

We opt for a two-step estimation procedure, where in a first step we extract unobserved factors via principal components as outlined in Stock and Watson (2002), Stock and Watson (2005), Bernanke et al. (2005) or Koop and Korobilis (2009). In order to econometrically identify the model, we need to impose some normalization restrictions as outlined in Bernanke et al. (2005, p.400) or Stock and Watson (2005, p.7). In the second step, the VAR is augmented by the extracted factors and estimated with standard methods.

Finally, the estimation and inference is accompanied by a two-step bootstrap procedure à la Hall (1992) with the intention to assess the significance of results.

3. Basic Specification, Identification, Data and Multiplier Calculation

This section is a briefing on the particular specification that we estimate in our analysis.

3.1. Basic Specification: Ramey (2011b)'s Explicit Variables

Ramey (2011b)'s basic specification of the vector Y_t is

$$Y_t' = [D_t \; g_t \; y_t \; i_t \; \tau_t \; \bullet_t],$$

where D_t is the "new measure of defense news" detailed in Ramey (2009). The advantage of using defense news is that one can account for fiscal foresight as outlined in Section 3.2 below. Intuitively, this measure contains data on government expenditures that are not related to US economic conditions but to defense spending related to events abroad. Note that the observations are not actual data but present values of preannounced defense spending and "should be viewed as an approximation to the changes in expectations at the time."[6]

Moreover, the other variables are the log levels of per capita government spending g_t, output y_t as well as the levels of the 3-month Treasury bill rate i_t and the Barro and Redlick (2009) tax rate τ_t. $\bullet_t$ represents a stand-in for different variables of interest that Ramey (2011b) rotates into Y_t, one at a time. This "intermediate strategy" has been suggested by Burnside et al. (2004, p.94) amongst others.[7] Similar to Ramey (2011b), we will consider such a VAR specification with four lags, but compare the results for our sample to a corresponding FAVAR specification in Section 4 below.

3.2. Identification: Fiscal Foresight and Implications for Identifying a (FA-)VAR

Consider any specification of the vector Y_t

$$Y_t' = [g_t \; ...]. \tag{5}$$

One can estimate such a VAR and, for example utilize a Choleski decomposition as illustrated in Sims (1980) to identify the structural shock. Thus, one shocks the first variable and derives the impulse responses. Such timing restrictions on g_t are at the heart of the classical SVAR literature (see for example, Fatás and Mihov (2001) and Blanchard and Perotti (2002)). The restrictions are motivated by legislation and implementation lags, that suggest that government spending does not react contemporaneously to shocks hitting the economy. Fragetta and Melina (2011) show that this hypothesis is also consistent from a statistical point of view.

[6] See Ramey (2011b, p.24).

[7] The dataset and codes of Ramey (2011b) are available via her webpage.

However, exactly due to the legislation and implementation lags that motivate the identification strategy above, it might be the case that the identified shock to government spending g_t is not news to actual agents in the economy. If this is the case, one can expect that any measure of news about fiscal policy to both the agents in the actual economy and the econometrician, say $\mathcal{N}_t$, should Granger (1969) cause the shock in g_t as argued in Ramey (2011b). In this case there is the problem of fiscal foresight.

Alternately to a VAR with the vector (5), one can estimate a VAR with the specification

$$Y_t' = [\mathcal{N}_t \; g_t \; ...],$$

where $\mathcal{N}_t$ is a variable that contains news about fiscal policy to both the agents in the actual economy and the econometrician as outlined above in Section 3.1.[8]

Depending on the particular instrument $\mathcal{N}_t$, variations of the analysis are possible as illustrated in Ramey (2011b) and Auerbach and Gorodnichenko (2010). First, one can consider shocks in $\mathcal{N}_t$. In the context of Ramey (2009)'s defense news $\mathcal{N}_t = D_t$ these innovations are labeled "defense shocks". Second, the series $\mathcal{N}_t$ can be forecast errors of agents in the actual economy with regard to government spending g_t and therefore the forecast errors $\mathcal{N}_t = FE_t$ are unanticipated. In analogy to the defense shocks, we label innovations to the forecast

[8]Note that incorporating $\mathcal{N}_t$ directly into Y_t and considering shocks to $\mathcal{N}_t$ goes back to Edelberg et al. (1999). Alternatively one might consider to separate $\mathcal{N}_t$ from Y_t in a *VARX approach* as in Lütkepohl (2005, p.396ff.). At least asymptotically there is no difference in those two approaches as outlined in Edelberg et al. (1999, p.172).

error "forecast shocks". Third, $\mathcal{N}_t$ can represent growth in the forecast of government spending g_t, thus $\mathcal{N}_t = \triangle g_{t|t-1}$. In consequence, one can consider shocks in g_t ordered as second variable. An innovation in g_t ordered after $\triangle g_{t|t-1}$ in a Cholesky ordering is orthogonal to the latter by construction. Everything about government spending that could have been anticipated by agents in the actual economy should be reflected in $\triangle g_{t|t-1}$. We label the latter kind of innovations as "purified spending shocks".

In Section 4 below we will consider defense shocks. Our robustness analysis in Section 5 will give reasons to examine forecast shocks and purified spending shocks therein.

3.3. Data: the Large Panel of Informational Time Series

We utilize a large panel of informational time series in order to extract the factors F_t via (3) for estimation of (1). Table 6 in Appendix A below gives detailed information on the 62 time series in our informational dataset. We restrict the analysis to these 62 time series as they are publicly available from the Federal Reserve Bank of St. Louis' FRED® Economic Data base from 1948Q1 to 2008Q4 on a monthly or quarterly basis.

Note that before we test for the number of factors and extract the factors, all series are transformed to ensure stationarity according to Dickey and Fuller (1979) and Kwiatkowski et al. (1992) tests.

In order to test for the number of static factors, we make use of the methods outlined in Bai and Ng (2002, 2007). More specifically, we use their IC_{p2} criterion to test for the number of static factors. The test suggests five static factors for the sample length 1948Q1 to 2008Q4 and three static factors for shorter sample lengths in our analyses in Section 5.

3.4. Data: a Comment on Sample Length

Ramey (2011b) in parts of her analysis considers observations from 1947Q1 to 2008Q4. Given data availability for the large informational dataset used to extract factors, we need to reduce the sample length and start from 1948Q1 to 2008Q4 in order to compare VAR and FAVAR estimates in Section 4.[9]

Next, the extraction of factors from X_t requires that all series therein are stationary. Adequate transformations[10] yield an effective sample ranging from 1948Q3 to 2008Q4.[11] We do not expect a major drawback from this change. The defense news variable should still be informative as we keep the Korean War in our sample, which might be important as emphasized by Ramey (2011b).

3.5. Multiplier Calculation

We present results for three different types of multipliers. All multipliers are based on the normalized median impulse response of output to a unit shock. Responses are normalized such that the government spending response to a shock in $\mathcal{N}_t$ is equal to unity at its peak. Thus, the level of the impulse response at any point in time h can be interpreted as the implied elasticity of output at time h, $y(h)$, with respect to the government spending peak g_P, which we denote $\varepsilon_{y|g_P}(h)$. Furthermore, based on the definition of an elasticity $\varepsilon_{z|x} \equiv (dz/z)/(dx/x)$ of two variables z and x an implied output multiplier at time horizon h can be calculated

[9] Our motivation is to include indicators of unemployment and producer price indices in the large informational dataset.

[10] More details on the transformations are listed in Table 6 below.

[11] Note that Ramey (2011b)'s main analysis is based on a sample from 1939Q1 to 2008Q4, but this is not feasible for us due to the lack of informational time series that go back to 1939.

by

$$\frac{dy}{dg} = \varepsilon_{y|g_P}(h) \times \frac{1}{g/y},$$

where $\varepsilon_{y|g_P}(h)$ is the value of the impulse response function at time h and g/y is the average share of nominal government spending in nominal GDP over the sample.

Similar to Ramey (2011b) we report

$$\varepsilon_{y|g_P}(P) \times \frac{1}{g/y},$$

which is the multiplier based on the implied elasticity of the peak in output with respect to the peak in government spending.

The second approach of Ramey (2011b) is to take the integral under the impulse response of GDP over the time horizon $h = 1, 2, ..., H$. Ramey (2011b) reports a discrete approximation

$$\frac{\sum_{h=1}^{H} \varepsilon_{y|g_P}(h)}{\sum_{h=1}^{H} \varepsilon_{g|g_P}(h)} \times \frac{1}{g/y},$$

which we denote "Integral 1". Alternatively, one can numerically integrate the intervals and calculate

$$\frac{\int_1^H \varepsilon_{y|g_P}(h)dh}{\int_1^H \varepsilon_{g|g_P}(h)dh} \times \frac{1}{g/y}.$$

We expect numerical integration to yield more accurate approximations of the integrals. The multipliers using *Trapezoidal / Simpson's Rule* are denoted "Integral 2" and "Integral 3" respectively.

Finally, we calculate the present value multiplier as in Mountford and Uhlig (2009, p.15) by

$$\frac{\sum_{h=1}^{H}(1+i)^{-h+1}\varepsilon_{y|g_P}(h)}{\sum_{h=1}^{H}(1+i)^{-h+1}\varepsilon_{g|g_P}(h)} \times \frac{1}{g/y},$$

where i is the average interest rate over the sample.

4. Results for Defense Shocks

Figures 1 and 2 show the impulse response functions to a defense shock in the VAR and FAVAR specification respectively. Similar to Ramey (2011b) we facilitate comparison of results by normalizing the responses so that the log change of government spending is 1% at its peak in both the VAR and the FAVAR specification. In all figures we report the median impulse response and the 68% as well as 90% standard error bands based on bootstrap standard errors. Nevertheless, we base the discussion of results on the 68% standard error bands for the sake of clarity.[12]

It appears that the responses of government spending, output, tax rate, interest rates, and manufacturing product wage are qualitatively consistent across the two specifications. The responses of the 3-month Treasury bill rate and the tax rate are largely insignificant in both specifications. The latter fact indicates that the defense shock is deficit-financed. This feature is important to relate our results to the existing literature as for example reviewed in Ramey (2011a).

[12] A direct comparison to Ramey (2011b)'s VAR results is not feasible for two reasons. First, the sample length is slightly different and second, Ramey (2011b) does not report confidence intervals, but solely point estimates for her results based on the sample 1947-2008.

In more detail, government spending response to the defense shock is hump-shaped. It peaks 5 quarters after the shock in the VAR and 6 quarters after the shock in the FAVAR.

Most notably, with a value of 0.32 on impact and 0.41 at the peak in the second quarter after the shock, the output response in the VAR is lower and less persistent than its counterpart in the FAVAR. Therein, output responds with 0.45 on impact and 0.53 at its peak in the sixth quarter after the shock.

As far as the different types of output multipliers based on Section 3.5 are concerned, the response pattern of output just mentioned carries over. As listed in Table 1, the peak multiplier in the VAR is 2.04, which is lower compared to a peak multiplier of 2.61 in the FAVAR. This insight remains true for the integral multiplier (1.67 vs. 4.13, 1.58 vs. 3.85, 1.58 vs. 3.78) and the present value multiplier (2.00 vs. 4.25).

Next, the response of the real BAA bond rate is negative on impact with -0.24 in the VAR and -0.39 in the FAVAR.

From our perspective, the observations with regard to output are an indicator that the limited information problem might play an important role in quantifying the effects of fiscal policy.

The response of the real manufacturing product wage is another remarkable similarity across the two specifications. In the VAR, the wage significantly decreases on impact by -0.31, whereas with -0.38 in the FAVAR the decrease on impact is larger in magnitude. Nevertheless, the decrease in more persistent in the VAR. In contrast, in the FAVAR the decrease is only significant on impact.

Among the striking differences among the VAR and the FAVAR are the responses of components of consumption. In the VAR, durable consumption increases on impact and decays to zero after two quarters, whereas nondurable and services consumption do not respond significantly. In the FAVAR nondurable, durable and services consumption have significantly and persistent positive responses after four, eleven, and one quarter respectively which contrasts the VAR results. The significant peaks are at 0.28, 0.4, and 0.27 respectively. One might conclude that in a FAVAR consumption is crowded-in, which can in part explain the larger output multipliers found in the FAVAR specification.

Moreover, in the FAVAR residential investment is stimulated with a significant peak at 1.12 after seven quarters whereas the initial stimulus in nonresidential investment fades out immediately. Thus, at least residential investment appears to be crowded-in. In contrast, the VAR leads to an ambiguous conclusion with regard to investment, as residential investment is countercyclical, whereas non-residential investment is procyclical.

Finally, there is also an enormous difference in the responses of total hours worked. In the VAR, the latter behaves procyclically, which would be in line with Neoclassical production theory. In fact, total hours peak significantly three quarters after the shock at a level of 0.18. On the contrary, in the FAVAR total hours do not respond significantly. Such a response could be justified by relatively inelastic labour supply. Alternative explanations could be a small intertemporal substitution effect of leisure in response to a small decrease in the real interest rate or an increase in total factor productivity via productivity enhancing government expenditures. Another possible reason could be labour hoarding or underutilization of labour by firms.

After comparing responses for both specifications, one can conclude that the incorporation of factors gives opposing answers with regard to key variables such as components of consumption, investment and total hours worked. In turn, if indeed there is a limited information problem in the VAR that is surmounted by the FAVAR, then it is obvious that the interpretation of the empirical evidence based on a VAR could have dramatic consequences for the judgement of empirical validity of theoretical models.

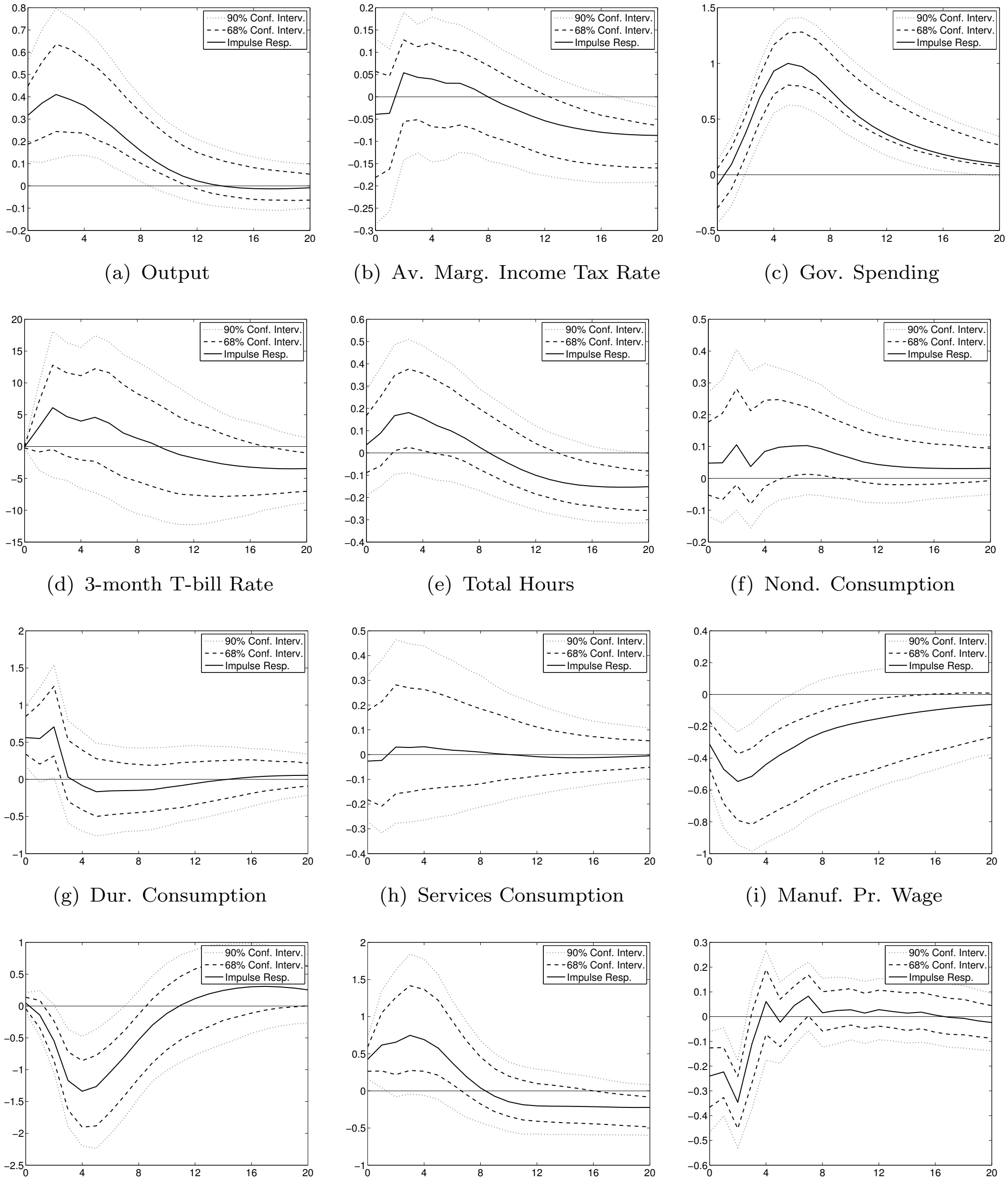
5. Robustness of Results

The comparison above suggests that inference from a FAVAR produces implications for key variables antipodal to what we find in a related VAR. Before drawing ultimate conclusions from the results above, we consider robustness of our results along three dimensions. First, we perform basic specification tests to find out the more desirable specification from a statistical point of view. Second, we examine whether a Narrative VAR approach is enough to align information sets or whether the effort of a Narrative FAVAR approach is necessary to guarantee fundamentalness of the government spending shock. Clearly, in the latter case we should rely on inference from a FAVAR specification as in the VAR there would be a limited information problem. Third we apply the variations of our analysis as motivated in Section 3.2 above in order to analyse robustness of our results with respect to the narrative measure and identification strategy.

5.1. Basic Specification Tests

In order to evaluate the VAR and FAVAR specifications from a purely statistical point of view, one possibility is to perform a Portmanteau autocorrelation test. In particular, we test the null hypothesis of no autocorrelation considering twenty lags. For example, if the p-value is lower than a value of 0.05 one rejects the null hypothesis at the 5% significance level. The p-values for different VAR and FAVAR specifications are listed below in Table 2.

For the VAR, p-values indicate that the specification with non-durable consumption, non-residential investment and total hours worked present a dynamic



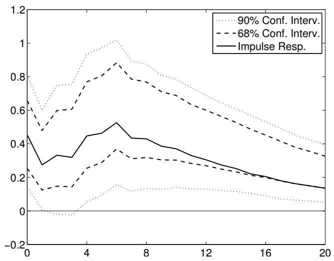
(a) Output (b) Av. Marg. Income Tax Rate (c) Gov. Spending

(d) 3-month T-bill Rate (e) Total Hours (f) Nond. Consumption

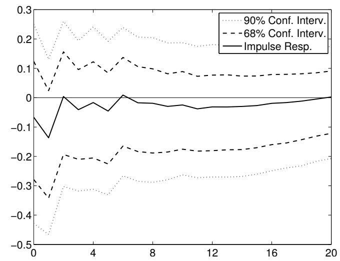
(g) Dur. Consumption (h) Services Consumption (i) Manuf. Pr. Wage

(j) Res. Investment (k) Nonres. Investment (l) Real BAA Bond Rate

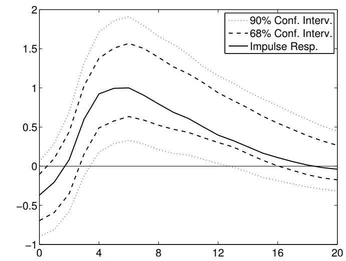
Figure 1: Effect of Defense Shocks in a *VAR*, 1948-2008



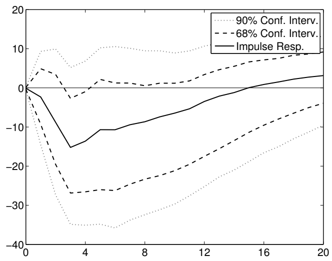
(a) Output



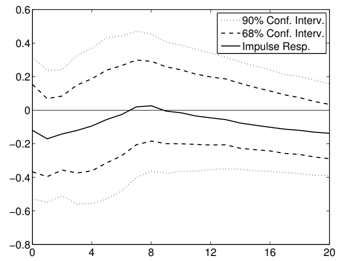
(b) Av. Marg. Income Tax Rate



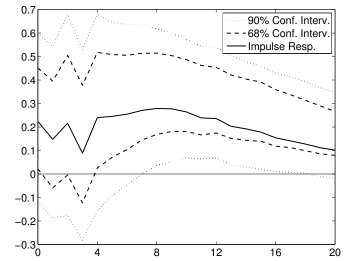
(c) Gov. Spending



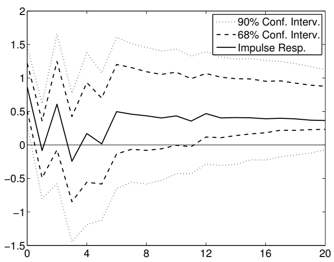
(d) 3-month T-bill Rate



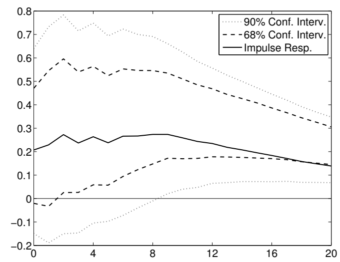
(e) Total Hours



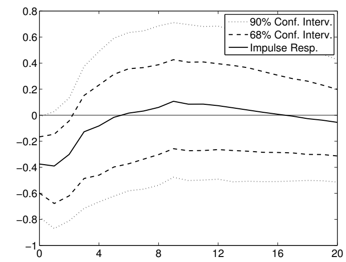
(f) Nond. Consumption



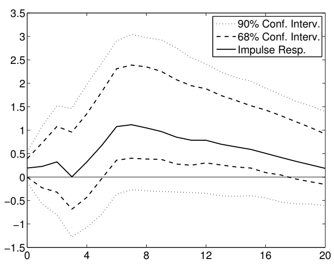
(g) Dur. Consumption



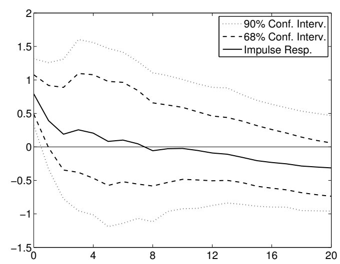
(h) Services Consumption



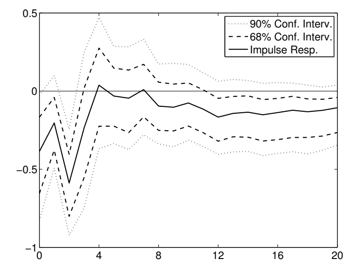
(i) Manuf. Pr. Wage



(j) Res. Investment



(k) Nonres. Investment



(l) Real BAA Bond Rate

Figure 2: Effect of Defense Shocks in a *FAVAR*, 1948-2008

misspecification in terms of autocorrelation. Moreover, for any specification, the p-value for the FAVAR exceeds the p-value for the VAR and the null is never rejected at any conventional level for the FAVAR.

Next, we calculate the Akaike (1974) Information Criterion (AIC) for all VAR and FAVAR specifications and the very same lag length, see Table 3. Specifications with a smaller AIC are preferable from a statistical point of view. It turns out, that again the FAVAR specifications outperform the VAR specifications.

Thus, the basic specification tests clearly favour the FAVAR approach.

5.2. Test for (Non-)Fundamentalness of the Government Spending Shock

Determining whether a shock is fundamental can be done by the orthogonality test (i.e. F-test) proposed in Forni and Gambetti (2011). The procedure tests for orthogonality between the estimated shock and the lagged values of the factors or any other variable. The idea behind is that structural shocks are unpredictable. Therefore rejecting the null of orthogonality implies that the estimated shock cannot be structural, but can be predicted by factors. It is important to point out that acceptance of the null does not state fundamentalness of the shock. But it turns out that in factor models there is no problem of non-fundamentalness by construction. By incorporating factors, we take into account the information of a large set of variables that states a suitable representation of economic activity in the US. The latter is arguably true in case of the vector X_t that we consider herein. It contains various measures of employment, prices indexes, income, savings etc.

In Ramey (2011b)'s VARs the shock hits her new measure of defense news, which is the first variable in a Cholesky ordering. One can therefore derive the structural shock without factors and test whether the structural shock is orthogonal to the lagged factors. We conduct the test for the five static factors suggested by the Bai and Ng (2002) statistic. The first row in Table 4 considers the different specification used in Ramey (2011b), starting with the baseline Ramey (2011b) model for then rotating one variable per time. P-values for the F-test are reported with the null of orthogonality. The null of orthogonality is rejected either at the 1% significance level or at least at 5% significance level for all specifications except for services consumption rejected at 10% significance level.

Next we derive the defense news structural shock including the first 5 factors of the large panel of informational time series. Then we test whether the first 6 up to 10 factors are orthogonal to the structural shock. The first column in Table 5 reports the number of factors utilised in the test. As can be seen, the null of orthogonality is not rejected at the routinely considered 5% or 10% level.

Given the orthogonality test, defense news suffer of a non fundamentalness problem, but remains a valid instrument in a FAVAR specification, as long as the variables from which we extract factors are representative of the economic activity. Furthermore, we continue to assume that contemporaneous factors and explicit variables cannot linearly predict defense news. It is this assumption that allows us to consider defense news as first variable in Y_t. We motivate this assumption by the results of Fragetta and Melina (2011), who have shown that government spending does not react to contemporaneous shocks hitting the economy from a statistical point of view. From our perspective, it is reasonable to assume that this is likely to be true for defense spending as well.

Nevertheless, our FAVAR results are based on defense news and could vary with the choice of the instrument and identification strategy. For this reason we consider alternative ways to control for fiscal foresight in the subsequent analysis.

5.3. Results for Forecast Shocks

Ramey (2011b) concludes that the defense news variable is a weak instrument, once the sample does not include the Korean War. This motivates her usage of forecast errors based on a spliced series of forecasts. The results based on that variable suggest that forecast shocks do not stimulate the economy.

The idea to utilize forecast errors is convincing, but from our point of view Ramey (2011b)'s spliced series exhibits an inconsistency that calls her result into question. In particular, here instrument is a combined series of forecasts for defense spending (1968Q4 to 1981Q2) and for federal government spending (1981Q3 to 2008Q4).

Recall that according to Ramey (2011b) the defense news variable should be regarded as "an approximation to the changes in expectations at the time", where expectations are about government spending. Thereby Ramey (2011b) implicitly assumes that the approximation of the changes in expectations (or anticipation effects) in the actual economy works via discounting news about (or the change in) future defense spending. In reality the relation between defense news and the change in expectations about future government spending in the actual economy could work differently or via various channels, i.e. there could exist different approximation regimes.

Unfortunately, the combined series of Ramey (2011b) means that there is a change in the approximation scheme, i.e. about the way that agents process information and form expectations about future government spending. Ramey (2011b) assumes that before 1981Q3, agents use defense spending forecasts and from 1981Q3 onwards, they use federal government spending forecasts for their approximation. But why should agents change their expectations formation process? A likely reason could be a structural change, but then she would need to account for that in her specification.

Fortunately, Auerbach and Gorodnichenko (2010) have constructed a consistent variable of forecast errors based on the Survey of Professional Forecasters and the government spending (Greenbook) forecasts prepared for FOMC meetings. Thus, we utilize the Auerbach and Gorodnichenko (2010) variable of forecast errors in this section.[13]

In particular, our specification of the vector of explicit variables is now given by $Y_t = [FE_t, g_t, y_t, i_t, \tau_t, \bullet_t]'$ where FE_t are the forecast errors. Moreover, in this and the subsequent section, we consider the business wage instead of the product wage to rotate into Y_t. Ramey (2011b) suggests to do so, as the product wage might be more appropriate in the context of defense news, as those news are concentrated in few industries. In contrast, now we deal with forecasts for federal government spending and therefore the business wage might be more appropriate.

Before we discuss the empirical results for this specification, we want to point the readers attention to the specification test results for this model. Comparisons of second against fifth row in Tables 2 and 3 reveal that the FAVAR is again the favourable specification from a statistical perspective. Moreover, opposed to the case of defense shocks, we cannot find explicit evidence for non-fundamentalness in case of forecast shocks, as the second row in Table 4 indicates.

In brief, FAVAR impulse responses to a forecast shock produce slightly different results compared to the defense shock. Most of the impulse responses in Figure 3 are qualitatively the same, but it is important to highlight some details.

The response of the 3-month Treasury bill rate is not significantly negative on impact. Next, the tax rate responds significantly positive on impact and significantly negative later on. This observation raises the question, whether we have to interpret the results as responses to a deficit-financed increase in spending? We calculate the integrals over the response of the tax rate similar to the ones for the output multipliers and find that they are close to zero. Thus,

[13] We are indebted to Yuriy Gorodnichenko for providing us with their dataset.

we keep on interpreting our results as responses to a deficit-financed increase in spending.

Government spending response to a forecast error shock turns out to be as expected, but more persistent compared to what we found in the FAVAR with defense shocks. The response peaks 4 quarters after the shock and is significantly positive even after 5 years.

The positive significant response of output is evidence that opposed to Ramey (2011b)'s findings, forecast shocks do stimulate the economy. As listed in Table 1, the implied output multipliers in the FAVAR are in the range of 0.77 to 1.58, depending on the type of multiplier.

An important difference, compared to the results for defense shocks is the significant and persistent increase in total hours with a peak of 0.23 not until 6 quarters after impact. This result is consistent with a Neoclassical production function.

With regard to the responses of consumption, we find that the pattern of significant crowding-in remains stable for non-durable consumption and, with a lag of one year, for services consumption. Non-durable consumption responds significantly positive on impact and is zero otherwise.

The business wage increases significantly up to 0.23 only 6 quarters after the shock.

Both, residential and non-residential investment are crowded out by a tax-financed increase in spending. It is remarkable that the response of non-residential investment decreases by up to -1.00 and that the decrease is still present 5 years after impact.

A possible explanation for the crowding-out could be that now the response of the real BAA bond rate is positive on impact with a significant peak at 0.36

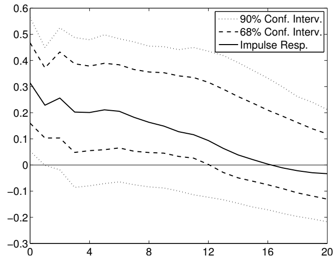
after 3 quarters.

5.4. Results for Purified Spending Shocks

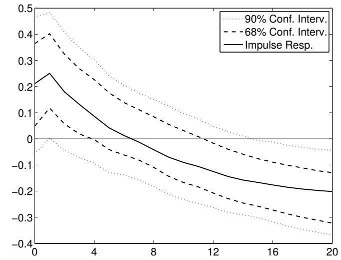
As argued before, an alternative way to control for expectation, is an identification strategy suggested by Auerbach and Gorodnichenko (2010). It consists in augmenting the baseline SVAR with one variable pertaining to the forecast of government spending. In consequence, the vector of explicit variables now is given by $Y_t = [\triangle g_{t|t-1}, g_t, y_t, i_t, \tau_t, \bullet_t]'$ where $\triangle g_{t|t-1}$ is the forecast for the growth rate of government spending at time t made at time $t-1$. It is intuitively clear that an innovation in g_t is orthogonal to $\triangle g_{t|t-1}$, i.e. unanticipated. Obviously, whatever is anticipated for period t by agents in period $t-1$ should be in their forecast $\triangle g_{t|t-1}$. In addition, the third row in Table 4 indicates that there is no explicit evidence that purified spending shocks suffer from non-fundamentalness. Moreover, the statistical perspective favours the FAVAR, as comparisons of third against sixth row in Tables 2 and 3 reveal.

The analysis in this subsection allows us to compare two different identification strategies related to the Narrative approach for the same sample size. According to Figure 4, purified spending shocks reveal no qualitative differences compared to forecast shocks with regard to output, tax rate, government spending, 3-month T-bill Rate, non-durable consumption, non-residential investment and the real BAA bind rate. Output is significantly stimulated and the implied multipliers in the FAVAR are in the range of 0.89 to 1.38 as can be seen in Table 4. Moreover, non-durable consumption is significantly crowded in.

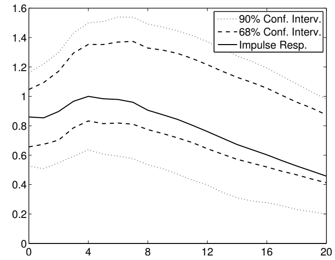
Among the differences, compared to forecast shocks, are the fact that durable consumption is significantly crowded in on impact and not different from zero only until 11 quarters after the shock. Solely services cosumption is significantly and persistently crowded out. Next, total hours are not significantly different



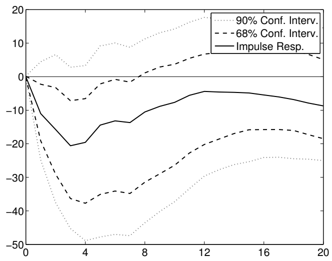
(a) Output



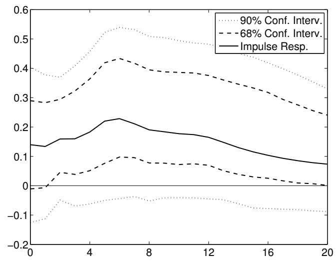
(b) Av. Marg. Income Tax Rate



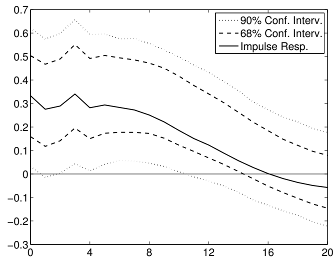
(c) Gov. Spending



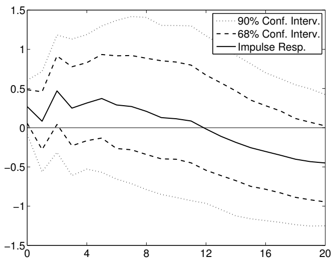
(d) 3-month T-bill Rate



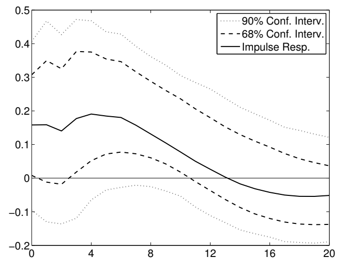
(e) Total Hours



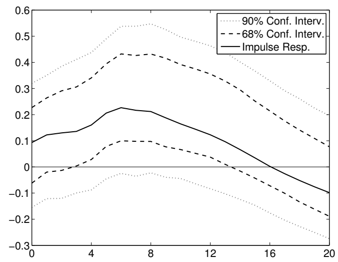
(f) Nond. Consumption



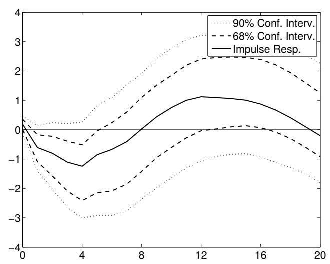
(g) Dur. Consumption



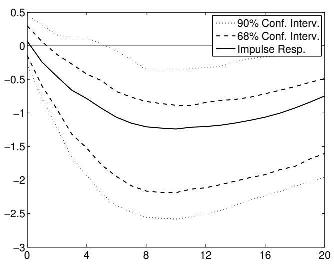
(h) Services Consumption



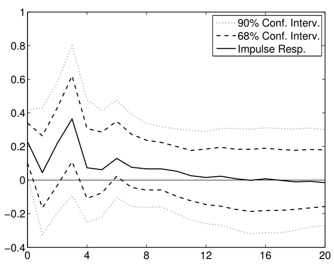
(i) Business Wage



(j) Res. Investment



(k) Nonres. Investment



(l) Real BAA Bond Rate

Figure 3: Effect of Forecast Shocks in a *FAVAR*, 1966-2008

from zero for most of the time horizon and the business wage does no respond to the shock at all. Finally, residential investment is significantly crowded out on impact and thereafter, but becomes significantly positive later on.

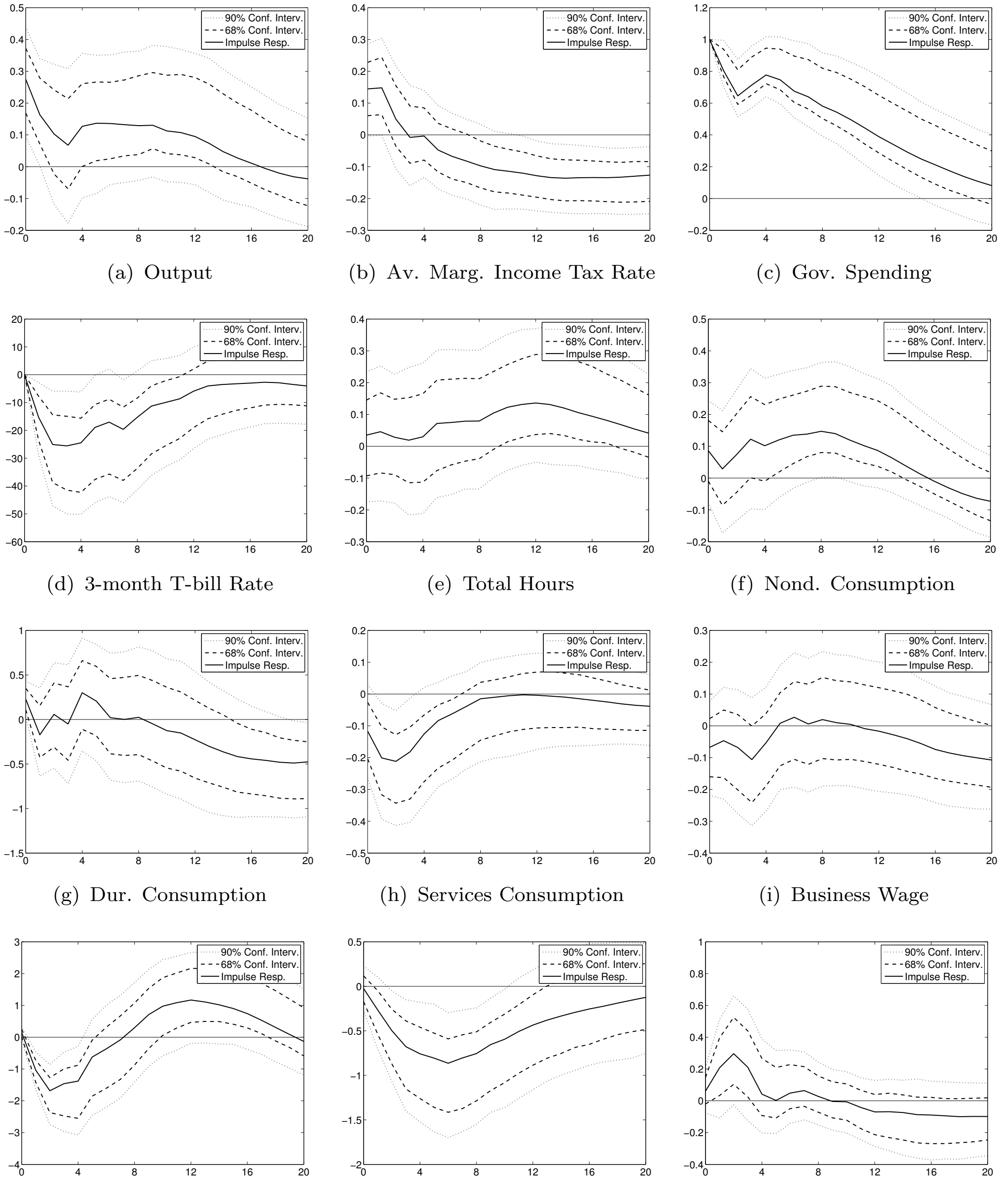
6. Discussion of Results

The limited information problem appears to play an important role as it produces striking differences in empirical results for VAR and FAVAR estimation. Moreover, it appears that alternatives to control for fiscal foresight produce slightly different responses in a FAVAR framework even for the same sample.

Nevertheless, there are some patterns in the FAVAR that remain stable independent of considering defense-, forecast-, or purified spending shocks. Among them is the fact that output is stimulated and implied peak multipliers are larger than one. Furthermore, for tax-financed forecast- or purified spending shocks, integral and present value multipliers can be smaller than one. However, except for the case of the peak multiplier for purified spending shocks, FAVAR multipliers exceed VAR multipliers in all cases. Thus, by accounting for the limited information problem we routinely obtain larger fiscal multipliers, which suggests that reported multipliers in the empirical literature might be underestimated.

Next, hours respond positively or are not different from zero. We also find that the components of consumption tend to be either significantly crowded in or not different from zero. Likewise, the real wage increases or is not different from zero. Finally, investment has significant ambiguous responses, that make it difficult to reconcile investment responses with either the Neoclassical or (New-)Keynesian view.

According to Ramey (2011a), the Neoclassical view predicts that in response to a deficit-financed positive government spending shock, output should increase



(a) Output (b) Av. Marg. Income Tax Rate (c) Gov. Spending

(d) 3-month T-bill Rate (e) Total Hours (f) Nond. Consumption

(g) Dur. Consumption (h) Services Consumption (i) Business Wage

(j) Res. Investment (k) Nonres. Investment (l) Real BAA Bond Rate

Figure 4: Effect of Purified Spending Shocks in a *FAVAR*, 1966-2008

with an implied multiplier below unity. In addition, hours worked, investment and the real interest rate should increase, while consumption and the real wage should decrease.

Clearly, our empirical evidence cannot be reconciled with the Neoclassical view, as key facts such as the output multipliers, as well as the responses of consumption and real wage differ from the predictions of the Neoclassical view. This appears to be a surprising result, as the Narrative approach tends to produce results that support the empirical validity of the Neoclassical view, see Ramey (2011a).

Equivalently, one can ask to what extent our results give empirical validity to the (New-)Keynesian view? Table 1 reveals that the multipliers in case of defense shocks are larger than one. This results appears to be in line with the IS-LM model. Similarly, the fact that consumption tends to be crowded in and a decrease in the real wage cannot be found in our results, can be reconciled with the IS-LM model.

However, in case of the shorter sample for forecast- and purified spending shocks, multipliers can be below unity. This observation can be explained by the strong crowding out effects on nonresidential investment. The latter is a prediction consistent with the Keynesian view. Likewise the weaker multipliers suggest that the stimulating effect of public spending is changing over time.

Overall, our results tend to provide empirical validity for the (New-)Keynesian view.

7. Concluding Remarks

Our paper proposes an empirical strategy to surmount the fiscal foresight problem and the limited information problem inherent in fiscal VARs that are widely used to quantify the effects of shocks to government spending.

We argue that the Narrative approach may be able to overcome the fiscal foresight problem, but not the limited information problem. Therefore, we propose FAVAR specifications that incorporate Narrative identification strategies. Such an approach represents a novelty to the empirical literature on quantifying the effects of fiscal policy. It is important to emphasize that this literature has largely neglected the generic limited information problem of VAR estimation. We are only aware of Forni and Gambetti (2011) who address the limited information problem by a related but distinct approach.

In contrast to the Narrative approach in a VAR, our approach can insulate the analysis from both the fiscal foresight problem and limited information problem. Furthermore, our approach is favoured from a statistical point of view as the robustness analysis suggests.

Our single most important result emerges by a comparison of the results for VAR and a FAVAR estimates for defense shocks. We demonstrate that striking qualitative and quantitative differences in the empirical results emerge.

We find that in a FAVAR, where both the fiscal foresight problem and limited information problem are resolved, it turns out that in the US consumption is crowded-in for a sample ranging from 1948 to 2008. Likewise, output is stimulated and the implied multipliers are in the range from 0.77 to 4.25 depending on the specification and definition. A comparison of multipliers suggests that FAVAR multipliers routinely exceed their VAR counterparts.

It is remarkable that the Narrative approach applied in a FAVAR produces evidence that overturns the impression that the Narrative approach only produces results in favour of the Neoclassical view as outlined in Ramey (2011a). Our results support the view that, next to its direct effect, government spending has (indirect) multiplier effects.

Thus, our main conclusion is simple and well known. In advance of assessing the empirical validity of a certain theoretical model, one should be cautious with respect to the empirical evidence. However, our results suggest that it is not only the identification approach, or more obvious issues such as sample length, the nature of financing the government spending increase, or the state of the economy in which the shock occurs, that create non-trivial differences in empirical results. We add the limited information problem to this set of issues that require a careful treatment.

Finally, we would like to emphasize that the FAVAR approach is just one strategy to overcome the limited information problem. It is fair to say that before one draws ultimate conclusions, it is necessary that future research compares different approaches to overcome the limited information problem and examines, whether they all lead to similar qualitative and quantitative results.

A. Data

The Table 6 below gives detailed information on the 62 time series in our informational dataset.

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Tables

Identification	**Peak**		**Integral 1**		**Integral 2**		**Integral 3**		**Present Value**	
	VAR	FAVAR	VAR	FAVAR	VAR	FAVAR	VAR	FAVAR	VAR	FAVAR
D_t	2.04	2.61	1.67	4.13	1.58	3.85	1.58	3.78	2.00	4.25
FE_t	1.55	1.58	0.50	0.79	0.49	0.78	0.48	0.77	0.66	0.94
$\triangle g_{t\|t-1}$	1.52	1.38	0.72	0.91	0.70	0.90	0.70	0.89	0.91	0.96

Table 1: Implied output multipliers in VAR and FAVAR specifications

	BASELINE	LRCDUR	LRCND	LRCSV	LRNRI	LRRES	LRWMFG	LTOTH	RINTBAA
VAR									
D_t	0.1821	0.163	0.070	0.180	0.008	0.145	0.875	0.045	0.737
FE_t	0.006	0.020	0.009	0.001	0.000	0.000	0.039	0.009	0.169
$\triangle g_{t\|t-1}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.016
FAVAR									
D_t	0.718	0.563	0.609	0.609	0.563	0.490	0.639	0.404	0.687
FE_t	0.407	0.484	0.251	0.252	0.316	0.051	0.219	0.423	0.584
$\triangle g_{t\|t-1}$	0.117	0.126	0.029	0.010	0.112	0.011	0.053	0.189	0.308

Table 2: Portmanteau autocorrelation test for various specifications

	BASELINE	LRCDUR	LRCND	LRCSV	LRNRI	LRRES	LRWMFG	LTOTH	RINTBAA
VAR									
D_t	-45.11	-52.49	-55.04	-56.33	-53.36	-52.16	-54.14	-55.29	-53.21
FE_t	-36.72	-44.24	-48.08	-48.01	-45.08	-46.13	-46.49	-47.04	-44.51
$\triangle g_{t\|t-1}$	-38.84	-46.17	-48.80	-50.05	-47.21	-46.13	-48.68	-49.09	-46.55
FAVAR									
D_t	-63.01	-70.47	-73.06	-74.09	-71.22	-70.08	-73.38	-73.26	-72.41
FE_t	-45.97	-53.64	-57.28	-57.18	-56.45	-54.31	-55.81	-56.30	-55.09
$\triangle g_{t\|t-1}$	-48.01	-55.49	-58.06	-59.22	-56.45	-55.36	-58.04	-58.40	-57.18

Table 3: AIC information criteria for various specifications

	BASELINE	LRCDUR	LRCND	LRCSV	LRNRI	LRRES	LRWMFG	LTOTH	RINTBAA
DN_t	0.005	0.0030	0.0126	0.0526	0.0048	0.0110	0.0036	0.0008	0.0442
FE_t	0.4773	0.3862	0.4228	0.4406	0.4327	0.3949	0.5933	0.4864	0.2504
$\triangle g_{t\|t-1}$	0.5700	0.6064	0.6618	0.4860	0.4860	0.5666	0.6325	0.6572	0.7456

Table 4: p-values of specification test for VARs with different variable ordered first

K	BASELINE	LRCDUR	LRCND	LRCSV	LRNRI	LRRES	LRWMFG	LTOTH	RINTBAA
6	0.404	0.442	0.349	0.350	0.266	0.462	0.3409	0.3689	0.566
7	0.822	0.811	0.787	0.813	0.720	0.888	0.784	0.801	0.866
8	0.201	0.607	0.204	0.268	0.122	0.403	0.161	0.223	0.457
9	0.241	0.609	0.229	0.353	0.161	0.458	0.173	0.301	0.442
10	0.165	0.431	0.167	0.248	0.121	0.355	0.114	0.171	0.290

Table 5: p-values of specification test for factor-augmented VARs with defense shocks

No.	Mnemonic	Description	Unit	Freq.	Seas. Adj.	Tcode
1	AAA	Moody's Seasoned Aaa Corporate Bond Yield	%	M	NA	2
2	AHECONS	Average Hourly Earnings Of Production and Nonsupervisory Employees: Construction	USD per Hour	M	NSA	6
3	AWHMAN	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing	Hours	M	SA	2
4	BUSLOANS	Commercial and Industrial Loans at All Commercial Banks	Bil. of USD	M	SA	6
5	CBI	Change in Private Inventories	Bil. of USD	Q	SAAR	2
6	CIVA	Corporate Inventory Valuation Adjustment	Bil. of USD	Q	SAAR	2
7	CNCF	Corporate Net Cash Flow	Bil. of USD	Q	SAAR	5
8	CONSUMER	Consumer (Individual) Loans at All Commercial Banks	Bil. of USD	M	SA	6
9	CP	Corporate Profits After Tax	Bil. of USD	Q	SAAR	5
10	CPIAUCSL	Consumer Price Index for All Urban Consumers: All Items	Index 1982-84=100	M	SA	6
11	CPIUFDSL	Consumer Price Index for All Urban Consumers: Food	Index 1982-84=100	M	SA	6
12	CPIULFSL	Consumer Price Index for All Urban Consumers: All Items Less Food	Index 1982-84=100	M	SA	6
13	CURRSL	Currency Component of M1	Bil. of USD	M	SA	6
14	FINSLC96	Real Final Sales of Domestic Product, 3 Decimal	Bil. of Chn. 2005 USD	Q	SAAR	5
15	GDPCTPI	Gross Domestic Product: Chain-type Price Index	Index 2005=100	Q	SA	6
16	GSAVE	Gross Saving	Bil. of USD	Q	SAAR	5
17	HOABS	Business Sector: Hours of All Persons	Index 2005=100	Q	SA	5
18	HOANBS	Nonfarm Business Sector: Hours of All Persons	Index 2005=100	Q	SA	5
19	INDPRO	Industrial Production Index	Index 2007=100	M	SA	6
20	INVEST	Total Investments at All Commercial Banks	Bil. of USD	M	SA	6
21	LOANINV	Total Loans and Investments at All Commercial Banks	Bil. of USD	M	SA	5
22	LOANS	Total Loans and Leases at Commercial Banks	Bil. of USD	M	SA	6
23	MANEMP	All Employees: Manufacturing	Thous.	M	SA	6
24	NAPM	ISM Manufacturing: PMI Composite Index	Index	M	SA	1
25	NDMANEMP	All Employees: Nondurable goods	Thous.	M	SA	6
26	NONREVSL	Total Nonrevolving Credit Outstanding	Bil. of USD	M	SA	6
27	OILPRICE	Spot Oil Price: West Texas Intermediate	USD per Barrel	M	NA	5
28	OTHSEC	Other Securities at All Commercial Banks	Bil. of USD	M	SA	5
29	PFCGEF	Producer Price Index: Finished Consumer Goods Excluding Foods	Index 1982=100	M	SA	6
30	PPIACO	Producer Price Index: All Commodities	Index 1982=100	M	NSA	5
31	PPICPE	Producer Price Index: Finished Goods: Capital Equipment	Index 1982=100	M	SA	6
32	PPICRM	Producer Price Index: Crude Materials for Further Processing	Index 1982=100	M	SA	5
33	PPIENG	Producer Price Index: Fuels & Related Products & Power	Index 1982=100	M	NSA	5
34	PPIFCF	Producer Price Index: Finished Consumer Foods	Index 1982=100	M	SA	5
35	PPIFCG	Producer Price Index: Finished Consumer Goods	Index 1982=100	M	SA	5
36	PPIFGS	Producer Price Index: Finished Goods	Index 1982=100	M	SA	5
37	PPIIDC	Producer Price Index: Industrial Commodities	Index 1982=100	M	NSA	5
38	PPIITM	Producer Price Index: Intermediate Materials: Supplies & Components	Index 1982=100	M	SA	5
39	RCPHBS	Business Sector: Real Compensation Per Hour	Index 2005=100	Q	SA	6
40	REALLN	Real Estate Loans at All Commercial Banks	Bil. of USD	M	SA	5
41	SRVPRD	All Employees: Service-Providing Industries	Thous.	M	SA	6
42	TB3MS	3-Month Treasury Bill: Secondary Market Rate	%	M	NA	2
43	TOTALSL	Total Consumer Credit Outstanding	Bil. of USD	M	SA	6
44	UEMP15OV	Civilians Unemployed - 15 Weeks & Over	Thous. of Persons	M	SA	5
45	UEMP15T26	Civilians Unemployed for 15-26 Weeks	Thous. of Persons	M	SA	5
46	UEMP27OV	Civilians Unemployed for 27 Weeks and Over	Thous. of Persons	M	SA	5
47	UEMP5TO14	Civilians Unemployed for 5-14 Weeks	Thous. of Persons	M	SA	5
48	UEMPLT5	Civilians Unemployed - Less Than 5 Weeks	Thous. of Persons	M	SA	5
49	ULCBS	Business Sector: Unit Labor Cost	Index 2005=100	Q	SA	5
50	ULCNFB	Nonfarm Business Sector: Unit Labor Cost	Index 2005=100	Q	SA	5
51	USEHS	All Employees: Education & Health Services	Thous.	M	SA	6
52	USFIRE	All Employees: Financial Activities	Thous.	M	SA	6
53	USGOVT	All Employees: Government	Thous.	M	SA	6
54	USGSEC	US Government Securities at All Commercial Banks	Bil. of USD	M	SA	6
55	USINFO	All Employees: Information Services	Thous.	M	SA	5
56	USLAH	All Employees: Leisure & Hospitality	Thous.	M	SA	5
57	USPBS	All Employees: Professional & Business Services	Thous.	M	SA	5
58	USPRIV	All Employees: Total Private Industries	Thous.	M	SA	5
59	USSERV	All Employees: Other Services	Thous.	M	SA	6
60	USTPU	All Employees: Trade, Transportation & Utilities	Thous.	M	SA	5
61	USTRADE	All Employees: Retail Trade	Thous.	M	SA	6
62	USWTRADE	All Employees: Wholesale Trade	Thous.	M	SA	6

Frequency (Freq): Q = Quarterly, M = Monthly

Seasonal Adjustment (Seas Adj): SA = Seas. Adj., NSA = Not Seas. Adj., SAAR = Seas. Adj. Annual Rate, NA = Not Applicable

Tcode: 1 = Level, 2 = First Difference, 3 = Second Difference, 4 = Log-Level, 5 = Log-First-Difference, 6 = Log-Second-Difference

Source: Federal Reserve Bank of St. Louis' FRED® Economic Data

Table 6: Data used to extract factors