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Abstract

Using a large information Bayesian VAR, we approximate the flow of information received by economic agents to investigate the effects of government spending. We document robust evidence that insufficiency of information in conventional models could explain inconsistent results across samples and identifications (Recursive Structural VAR and Expectational VAR). Furthermore, we report heterogeneous effects of government spending components. While aggregate government spending does not appear to produce a strong stimulative effect with output multiplier around 0.7, government investment components have multipliers well above unity. Also, state and local consumption, which captures investment in education and health, elicits a strong response.

JEL classification: C32, E32, E62.
Keywords: fiscal shocks, government spending, fiscal foresight, Survey of Professional Forecasters, Structural VARs, Expectational VARs, Large Bayesian VARs.

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1 Introduction

The severity and duration of the economic downturn stemming from the 2007-2008 global financial crisis has been unprecedented in recent history. With conventional monetary policy instruments facing a binding zero lower bound, fiscal policy has experienced renewed interest as a tool for economic stabilisation and growth. In the immediate aftermath of the financial crisis, many developed countries implemented large fiscal stimulus packages. Subsequently, the protracted economic stagnation coupled with high levels of public debt in many countries has raised questions about the long-run sustainability of government budgets and focused attention on fiscal adjustment measures.

Ideally, policy makers would like to engineer stimulus packages that elicit strong positive responses from the economy, and fiscal adjustments that result in only mild contractionary effects. Hence, the timing and composition of fiscal maneuvers have been intensely debated (see Alesina et al. (2012), and Blanchard and Leigh (2013)). In particular, during the recent downturn much attention has been devoted to government investment, such as in *infrastructure*, aimed at stimulating economic activity (see e.g., Fernald (1999) and Leeper et al. (2010)).

Unfortunately, academic research has provided no clear guidance on the macroeconomic impact of fiscal shocks, with disagreement on the size and even the sign of the responses of private aggregate demand components. Importantly, there is still a high degree of uncertainty regarding the potentially heterogeneous macroeconomic effects of different fiscal instruments and their compatibility with policy objectives.

Policy-makers often use *multipliers* as summary measures of the response of macroeconomic variables to fiscal instruments such as government spending components, transfers and taxes.[1] As a result, the empirical measurement of multipliers has been a major objective for research on fiscal policy. While different identification strategies and em-

[1] For example, *government spending multipliers* are defined as the ratios of changes in output, consumption, or investment to changes in government spending.

pirical settings have been used to isolate fiscal shocks and to estimate their effects, to date a consensus view has not emerged. Reported government spending multipliers are vastly different across identifications, highly unstable and sensitive to the choice of sample periods, ranging from around 0.6 to 1.8. The empirical literature in this area is vast and a detailed review is beyond the scope of this paper. Recent surveys on government spending multipliers can be found in Ramey (2011b), Hall (2009) and Parker (2011).[2]

This paper uses a large information approach to make two main contributions to the literature on government spending multipliers: (1) we examine *informational insufficiency* as the potential source of inconsistencies in previously reported results; and (2) we investigate the *heterogeneous* effects of different components of government spending. In particular, we disaggregate U.S. government spending into *consumption* and *investment* components of *federal defense*, *federal non-defense*, and *state and local* spending. As a result, we outline a more complete and coherent picture of the macroeconomic effects of government spending shocks on a comprehensive set of macroeconomic variables.

A key understanding underlying modern economic theory is that agents base their decisions on all information currently available to them. This crucial fact, well embedded in stylised economic models, has been generally overlooked in empirical research. In fact, prior literature in empirical fiscal policy has mostly used small information sets and a *marginal approach* to measure the effects of a change in government spending (see Christiano et al. (1996)).

An obvious requirement for the empirical analysis to be meaningful is that the vari-

[2]From a theoretical point of view, the effects of an increase in government spending are ambiguous and model dependent. While the neoclassical Real Business Cycle (RBC) and the old Keynesian and neo-Keynesian models are broadly consistent with regard to the effect of expansionary government spending on output, they reach different conclusions on the magnitude of the multiplier based on the sign of the response of consumption, investment and real wages. In particular, the RBC model generally predicts that consumption is negatively related to government spending while the Keynesian and some neo-Keynesian models predict a positive relation (e.g., Baxter and King (1993), and Galí et al. (2007)). A large number of recent theoretical papers have studied the effectiveness of an increase in government spending in various settings (see Woodford (2011), Hall (2009), Christiano et al. (2011), Monacelli and Perotti (2008), Corsetti et al. (2011), among others).

ables incorporated in the model convey all of the relevant information available to economic agents. Therefore, we apply a comprehensive large information approach with full Bayesian VAR techniques to study the economic effects of fiscal policy shocks. As shown by Banbura et al. (2010), a Large Bayesian VAR allows the econometrician to significantly expand the dataset in order to analyse shocks, possibly aligning the information set used in the econometric analysis with that of economic agents.[3]

There are three possible explanations for the inconsistent results previously reported in the literature on government spending. First, the identification of fiscal shocks is challenging due to potential anticipation effects of fiscal policy changes and their lagged implementation, as highlighted by Ramey (2011a). Second, aggregate spending may conceal changes in the composition of government spending over time. In fact, policy-makers can activate a variety of fiscal instruments including government spending components, and each may elicit potentially different effects. Finally, a growing number of papers convincingly point out that government spending multipliers are not structural constants, but rather the responses of endogenous variables to shocks in government spending. As such, there is no single government spending multiplier and its value is likely to depend on the interaction between fiscal and monetary policy, the degree of openness of the market, the way in which spending is financed, the budget deficit level, as well as the economic phase. These three issues can be viewed as three facets of the same underlying problem: the misalignment of the information sets of the econometrician and the agents.

Our large information approach allows us to expand the econometric information set to control for fiscal foresight, heterogeneity in fiscal instruments, and relevant omitted variables. A key intuition is that anticipated fiscal shocks are captured by forward looking variables (e.g., commodity prices, financial markets, inventories, consumer and

[3]Banbura et al. (2010) show that by applying Bayesian shrinkage, it is possible to handle large unrestricted VARs that allow application of the VAR framework to empirical problems that require the analysis of large data sets, potentially solving the issue of omitted variable bias.

business confidence, among others).[4]

We document that: (1) fiscal shocks identified using a marginal approach in standard recursive fiscal SVARs and Expectational VARs (EVARs) are likely to have been anticipated by economic agents, and are forecastable using factors extracted from a larger information set. (2) The previously reported inconsistent multipliers can be partly explained by missing information. In fact, recursive SVARs and EVARs deliver virtually identical estimates of dynamic responses when a large information dataset is used. Also, government spending multipliers are stable across samples and the well known sample instability of the estimates for the multipliers appears to be reduced to a statistically insignificant level. (3) In the aggregate, government spending does not appear to produce a strong stimulative effect with multipliers well below unity. Consumption, private investment and real wages are mostly unresponsive to slightly negative. The positive responses previously found in small VARs are possibly due to informational insufficiency. (4) We estimate fiscal multipliers for disaggregated components of government spending at federal and state and local levels, and report remarkably heterogeneous dynamic responses. In fact, non-defense and state and local components generally produce larger responses than the defense components. Significantly, investment components have large multipliers, hinting at a positive effect of public capital on economic activity. In addition, state and local consumption multipliers are around 4 in the long-run. Since a large portion of state and local spending is on education, this can be seen as investment in human capital.

Our paper is closely related, in spirit, to Forni and Gambetti (2010), in which government spending shocks are studied using a large factor model and sign restrictions. The common underlying intuition is that large dimension datasets incorporating forward looking variables are necessary to close the gap between the information sets of economic

[4]The informational sufficiency of the set of variables in a VAR is testable (see Giannone and Reichlin (2006), and Forni and Gambetti (2011)). Using this test we verify that our information set conveys sufficient information to identify fiscal shocks.

agents and the econometrician. The advantage of using a Large Bayesian VAR is that we are able to treat variables in a more transparent manner, bridging the gap between different identification strategies and reconciling previously reported inconsistencies. In fact, our model is able to nest previously used models and identifications (recursive and expectational). More generally, factor models are less general than VAR models and impose restricted VAR relations among variables.

Our paper adds robust evidence to the recent literature studying heterogeneous effects of fiscal instruments. Mertens and Ravn (2013) study the effects of personal and corporate income tax changes, while several papers study the different effects of investment and consumption, or federal and state and local government spending components, using a small information marginal approach (for example, Perotti (2011), Pappa (2009), Bénétrix (2012), and Bouakez et al. (2013)).

The remainder of our paper proceeds as follows. Section 2 discusses the identification of fiscal shocks and motivates our use of the large information information approach, Section 3 introduces our large information fiscal Bayesian VAR, Section 4 presents our empirical findings and Section 5 concludes.

2 Identification of Fiscal Shocks

Empirical identification of government spending shocks requires isolating innovations that are uncorrelated with other contemporaneous economic shocks, and that are distinct from systematic business cycle variations.

Prior literature on fiscal shocks using time-series techniques has almost exclusively used small information sets, resorting to a *marginal approach.* Typically, in this approach a small VAR model is developed with a core set of variables. The effects of fiscal shocks are examined on these variables, and other variables that are added one at a time (see Christiano et al. (1996)). This approach may present two issues: (1) the potential omission of relevant variables; and (2) limited comparability among the impulse response functions.

These issues are related to the general problem of *informational insufficiency* of the econometric model due to the misalignment of the information sets available to the agents and the econometrician. In the case of fiscal shocks, this misalignment can be related to missing information in the econometric model about: (1) the flow of information about the future path of fiscal variables (*fiscal foresight* and *non-fundamentalness*); (2) heterogeneity of fiscal instruments (*heterogeneity* of components and *instability* of aggregate government spending); and (3) various variables interacting with fiscal policy, such as monetary policy, credit and financial market conditions, and openness of the markets, among others (*omitted variables*). This misalignment has relevant implications not only for the estimate of the transmission parameters but also for the correct identification of fiscal shocks.

2.1 Small Information Marginal Approach

Following the influential paper of Blanchard and Perotti (2002), works using *Structural Vector Autoregressions (SVARs)* have identified fiscal shocks using restrictions motivated by economic theory, e.g., recursive identification (see Perotti (2005, 2008) and Galí et al. (2007)) or sign restrictions (see Mountford and Uhlig (2009)).

As summarised by Hall (2009) and Ramey (2011b), prior empirical literature using SVARs generally finds output multipliers in the range from 0.6 to 1.8, and consumption multipliers in the range from somewhat negative to 0.5. These studies also usually find that a positive government spending shock raises worked hours and real wages, while having a negligible impact on private investment.

Building on the narrative approach, Ramey (2011a) argues that estimated government spending shocks in SVARs are likely to be anticipated. This can lead to a spurious finding of a positive effect of government spending shocks on consumption and real wages.

Economic agents receive a constant flow of information about future changes in fiscal policy, informed by the institutional process through which they are implemented. In particular, changes in fiscal policy occur after two lags: the first between the initial proposal of a new fiscal measure and its approval (*decision lag*), and the second between enactment of the legislation and its actual implementation (*implementation lag*).

While economic agents react to the announcement of policy changes occurring in future periods, the econometrician only observes the innovation produced in fiscal variables by the lagged implementation of the new policy. This phenomenon, known as *fiscal foresight*, poses significant challenges for identification of fiscal shocks.

VAR models always implicitly assume *informational sufficiency.* This implies that structural economic shocks can be recovered as linear combinations of the residuals from the linear projection of a vector of economic variables onto their past values.

However, in the presence of fiscal foresight, to recover the true fiscal shocks hitting the economy the econometrician should relate present changes in macroeconomic variables to future innovations in fiscal variables. Therefore, fiscal shocks and their dynamic responses cannot be estimated from current and past fiscal data, as assumed in conventional dynamic econometric models and the structural shocks are said to be *non-fundamental* for the VAR specification (Hansen and Sargent (1980), Lippi and Reichlin (1993), Leeper et al. (2013), Mertens and Ravn (2010)).[5,6]

Non-fundamentalness can be framed as a problem of *informational insufficiency*, originating from the misalignment of the respective information sets of the econometrician and agents. In the context of fiscal foresight, this misalignment is due to news flow about future policy changes conveyed by the institutional implementation process that is not observed by the econometrician. The natural solution to deal with non-

[5]A comprehensive review on non-fundamentalness in structural econometric models can be found in Alessi et al. (2011).

[6]In a dynamic stochastic general equilibrium (DSGE), fiscal foresight can produce a non-invertible moving-average (MA) component into the equilibrium process, as discussed in Leeper et al. (2013).

fundamentalness is to include more information in the econometrician's information set; this idea underpins most of the solutions proposed in the empirical literature on fiscal shocks.[7]

One solution proposed in Ramey (2011a) is to augment the VAR with variables that can proxy for changes in agents' expectations about the present value of government spending, developing an Expectational VAR (EVAR). In Ramey (2011a) two different measures of expectations are proposed: a *military news variable* based on narrative evidence for defense spending and a *fiscal expectations variable* based on the Survey of Professional Forecasters (SPF). Using this approach, Ramey (2011a) finds that fiscal shocks have a positive effect on GDP upon impact, but crowd out private consumption and investment. Other proxy variables for fiscal expectations have been proposed by Leeper et al. (2013) using the spread between municipal and treasury bonds and Fisher and Peters (2010) using stock returns of U.S. defense contractors. The disadvantage of using proxy variables for expectations is that, to some extent, whether these variables are able to correctly capture agents' expectations or not is a matter of assumptions.

2.2 Heterogeneity of Fiscal Shocks

Informational insufficiency can also be due to the components of government spending that could appear as potentially relevant omitted variables. First, the composition of spending has undergone a remarkable shift through time, raising doubts about the *stability* of the macroeconomic properties of the aggregate government spending variable. Table 1 presents the breakdown of U.S. government spending on consumption

[7] A different approach, proposed in Lippi and Reichlin (1994) consists of applying appropriate Blaschke matrices to the VAR innovations in order to retrieve the fundamental shocks. The Blaschke matrices transform the recovered innovations into linear combinations of past and future innovations, allowing a non-fundamental MA representation to be mapped into a fundamental one. Mertens and Ravn (2010) have estimated the effects of government spending shocks using Blaschke matrices. The disadvantage of this approach is the non-uniqueness of Blaschke matrices. Additional restrictions derived from theoretical models are necessary to identify the correct MA component among different possible MA representations.

and investment over the last 50 years. Defense spending has fallen from 45.7 percent of total government spending in 1960 to 27.6 percent in 2010, while federal non-defense spending has stayed at around 10 percent. During the same period, state and local spending has increased from 45.2 percent in 1960 to 58.9 percent in 2010, with most of the increase stemming from consumption expenditures. However, during the most recent period (2010) continued post-9/11 military spending, crisis related fiscal stimulus and contracting state budgets have reversed this trend, increasing the relative size of federal spending. Investment components of spending, especially defense investment, were high during the 1960s and subsequently declined, as also reported by Fernald (1999).[8]

Second, government consumption and investment includes the purchase of a large variety of goods and services that may activate demand and supply channels differently. In particular, civilian investment components can have a direct effect on the aggregate production function and can be a source of *externalities*. Other categories of spending such as education, healthcare and public safety can have both productive effects (e.g., through the accumulation of human capital) and effects on marginal rates of substitution by entering in the utility function of economic agents. Table 1 reports the functional decomposition of federal and state and local spending. Over the last 50 years, federal spending has tilted towards civilian spending on healthcare and public safety, and away from defense spending. During the same time, the composition of state and local spending shows a decline in transportation and an increase in general public service and public safety. Education is the largest component of state and local spending at around 43 percent. The presence of spending components with productive effects and externalities creates challenges in understanding the channels through which spending operates and in interpreting multipliers.

[8] It is worth noting that in national accounts, defense investment captures both the building of military infrastructure, as well as the acquisition of military equipment and stockpiling of weapons that provide a flow of future national security services but may have reduced productive effects.

2.3 Large Information Approach

A comprehensive theoretical approach to deal with insufficient information and non-fundamentalness has been proposed in Giannone and Reichlin (2006). The key idea is to use large datasets to address non-fundamentalness and to detect informational insufficiency with Granger causality tests.[9] As proved in Giannone and Reichlin (2006), structural shocks are correctly recovered using large information under the assumptions that the shocks of interest are pervasive throughout the cross-section and that they generate heterogeneous dynamics. The remaining shocks need not propagate too widely and therefore, can meaningfully be considered idiosyncratic. In our case, the intuition for this approach is that anticipated fiscal shocks can be captured by including forward looking variables such as commodity prices, financial markets, inventories, consumer and business confidence, among others.

Informational sufficiency and non-fundamentalness can be assessed by testing whether the VAR residuals of the variables of interest are weakly exogenous with respect to potentially relevant additional variables or factors extracted from them. The intuition for this test, proposed in Forni and Gambetti (2011), is that if additional variables contain relevant information useful to forecast innovations to the economic variables of interest, then this information may have been used by economic agents.

The most suitable econometric models to incorporate large datasets are Factor Augmented VARs (e.g., Bernanke et al. (2004)), dynamic factor models (Forni et al. (2000, 2009)), and the recently proposed Large Bayesian VARs (see De Mol et al. (2008); Banbura et al. (2010)).

In this paper we adopt a Large Bayesian VAR approach that allows a transparent treatment of variables, facilitates a comparison of different identification strategies, and nests different empirical models.

[9]Very large dataset ($N \sim 100$) are considered to be a good approximation for the whole economy.

3 A Large Bayesian Fiscal Structural VAR

3.1 Empirical Model

A natural solution for this is to expand the information set used in the econometric analysis. In particular, we would like to expand the set of variables to include: (1) the components of government spending as well as other relevant fiscal variables to control for the issue of heterogeneity of fiscal instruments and instability of the aggregate; (2) a number of forward looking variables that may capture the flow of information received by agents to deal with the fiscal foresight and non-fundamentalness issue; and (3) other omitted variables (e.g., variables related to financial markets, credit markets, monetary policy, international trade, etc.) that may be relevant in determining the economic environment and agents' decisions.

Unfortunately, in standard VAR models, the estimation of the parameters of models with a large number of variables is obstructed by the *curse of dimensionality.* Large Bayesian VARs offer a viable solution to this problem. Banbura et al. (2010) show that by applying Bayesian techniques, it is possible to handle large unrestricted VARs. This allows the VAR framework to be applied to empirical problems that require large data sets, potentially solving the issue of informational insufficiency. In particular, they show that for the analysis of data sets characterised by strong collinearity, which is typically the case for macroeconomic time series, it is possible to increase the cross-sectional dimension by consistently setting the informativeness of the priors in relation to the size of the model. Large Bayesian VARs have proven to be competitive with factor models in terms of forecasting ability, and allow for a more flexible and transparent treatment of large information datasets (Banbura et al. (2010); Giannone et al. (2012); Koop (2011)). Moreover, they have a clear interpretation in terms of factor analysis and of Mixed Thail estimation (De Mol et al. (2008)).

We consider different specifications of the following VAR(4) model:

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

where ε_t is an n-dimensional Gaussian white noise, with covariance matrix Σ_ε, y_t is a $n \times 1$ vector of endogenous variable and C, A_1,..., A_4 and Σ_ε are matrices of suitable dimensions containing the model's unknown parameters. In our setting, the dimension of y_t can be large. Following Banbura et al. (2010), we embed prior beliefs in the form of *dummy observations* to artificially expand the length of our sample, as done in Banbura et al. (2010). In particular, we use a natural conjugate variant of the *Minnesota priors* proposed in Doan et al. (1983) and Litterman (1979). These priors assumes that in first approximations all the variables behave independently either as random walks or white noises.[10] We also adopt a refinement of the Minnesota prior known as *sum-of-coefficients* prior (Sims (1980)).[11] The informativeness of the priors, i.e., the relative weight of priors with respect to actual observations, is controlled by *hyperparameters*.

In selecting the value of the hyperparameters of our priors, we adopt the pure Bayesian method proposed in Giannone et al. (2012). From a purely Bayesian perspective, the informativeness of the prior distribution is one of the many unknown parameters of the model that can be inferred given the conditional posterior distribution of the observed data. In particular, the hyperparameters can be optimally chosen by maximising the one-step-ahead out-of-sample forecasting ability of the model. Using frequentist intuition, this method effectively reduces the estimation error while generating only relatively small biases in the estimates of the parameters.[12]

[10]This prior shrinks all VAR coefficients towards zero except for coefficients on own lags of each dependent variable. The latter is either set to one - for those variables which are thought to be relatively persistent - or zero, otherwise.

[11]This prior works to suppress initial transients, and also provides an approximate representation of widely shared prior beliefs that unit roots are present in macroeconomic datasets.

[12]The use of our Bayesian priors introduces a bias toward zero in the estimates of the VAR coefficients and hence of the IRFs (except for coefficients on own lags of each dependent variable). For this reason, our estimated multipliers can be better framed as lower bounds, in absolute values, on the value of the

In a Technical and Data Appendix, we discuss the econometric approach in detail. Also, we present a simple model to illustrate the issue of non-fundamentalness and motivate the use of a large information approach.

3.2 Identification

To identify fiscal shocks, we employ two different approaches: a Structural VAR (SVAR) with recursive identification and an Expectational VAR (EVAR) using government spending forecasts from the Survey of Professional Forecasters (SPF). Recursive identification exploits decision lags in fiscal policy-making to identify unexpected fiscal shocks. Specifically, in the different versions of our SVAR the shock variable is always ordered first.[13]

Following Ramey (2011a), in our EVAR we use SPF forecast data to control for agents' expectations of government spending. Unfortunately, it is not possible to include these SPF forecasts in levels in the VAR, as would be natural to do, since the base year changes several times in the sample. To overcome this issue, the surprises in government spending are defined as

$$\Delta g_t^{f.err.} = \Delta g_t - \Delta g_{t|t-1}^e = (g_t - g_{t-1}) - (g_{t|t-1}^e - g_{t-1|t-1}^e) \tag{2}$$

where $\Delta g_t^{f.err.}$ is the forecast error in the growth rate of government spending, Δg_t and $\Delta g_{t|t-1}^e$ are the realised growth rate and the forecasted growth rate one quarter before, respectively. This definition assumes that the SPF forecasts are good proxies for the representative agent's expectations. Moreover, it also assumes that agents know the value of government spending in the current quarter.

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multipliers. However, by selecting the informativeness of the priors optimally, the bias introduced is not substantially larger than the small sample bias of the standard flat-prior VAR (see Giannone et al. (2012)).

[13] A fixed ordering of the government spending components with defense spending components ordered first does not alter the results.

Perotti (2011) has noted that professional forecasters in SPF do not know the value of g_t. For this reason he proposes to decompose these forecast errors as

$$\Delta g_t^{f.err.} = \Delta g_t - \Delta g_{t|t-1}^e = \underbrace{(\Delta g_t - \Delta g_{t|t}^e)}_{\text{time t's surprise in } \Delta g_t} + \underbrace{(\Delta g_{t|t}^e - \Delta g_{t|t-1}^e)}_{\text{revision of expectation of } \Delta g_t} \quad (3)$$

where the first term captures the realisation of government spending growth over its expectations in t and the second term captures the revision of the agent's expectations about Δg_t. While the first term is not in the information set of agents at time t, the second term is the actual shock to expectations and could proxy for the news in the information flow of agents, as proposed in neoclassical models.

In our EVAR, the *forecast errors* defined in eq. (2) and the *expectation revision* expressed in eq. (3) are ordered first, and used as shock variables.

3.3 Data Description

Our main macroeconomic variables of interest are consumption and investment components of federal, and state and local government spending, gross domestic product, the Barro-Redlick marginal tax rate, real wages, total worked hours, output per hour, personal consumption of durables, nondurables, and services, real private investment, real rates, and the real exchange rate. We use quarterly data from 1959Q1 to 2012Q1 in real log per capita levels for all variables except those expressed in rates. Real rates are measured using the three-month U.S. Treasury Bill rate adjusted for changes in the consumer price index. The Barro-Redlick marginal tax rate is the income weighted average marginal tax rate that is made available by the National Bureau of Economic Research.

We consider the following VAR specifications:

- Small VAR: In the base specification, this is a 5 variable VAR with a fixed set of variables including government spending (or one of its components), marginal tax rate, gross domestic product, and real rates, as well as a rotating fifth variable of interest including real wages, total worked hours, output per hour, personal consumption of durables, nondurables, and services, real private investment, and the real exchange rate.

- Large VAR: In addition to the variables in the Small VAR, this specification includes as many forward-looking variables as possible in order to approximate the flow of information received by economic agents. These include tax, savings, credit, consumer sentiment, asset prices, inventories, production costs, and housing among others (see Table 5 for a complete list of variables).[14] The baseline specification with aggregate government spending has 43 variables while the expanded specification with government spending components has 48 variables.

- Small and Large EVARs: In the Expectational VAR specifications where the SPF data are used, the components of government spending are combined to conform with the level of aggregation in the SPF data.

Furthermore, we collect 128 macroeconomic variables, including sectoral components which are used to extract commonalities using factor analysis. A brief description of all the variables used in our study is presented in a Technical and Data Appendix. In Table 5 we indicate the variables that we apply logarithms to, as well as the variables with assumed random walk priors. The variables used in the various VAR specifications are also indicated.

Our 1959Q1-2012Q1 sample period delivers a rich macroeconomic dataset, and excludes the large military spending shocks related to the Korea War and WWII. We split this sample period into two subsamples: 1959Q1-1981Q4 and 1982Q1-2012Q1.[15]

[14]Following the conjecture in Banbura et al. (2010), we exclude regional and sectoral components of macroeconomic variables as they appear to not be relevant in order to capture economy-wide structural shocks. In robustness tests, we include many regional or sectoral variables in our Large VAR and find unchanged responses lending support to the conjecture.

[15]In robustness checks we also use a shortened sample (1959Q1-2005Q4) excluding the recent financial crisis and economic recession and obtain similar results.

The 1982Q1 split point is chosen in order to assess the subsample instability claimed in Perotti (2008) and is consistent with a large stream of literature that finds a structural break in the U.S. economy in the early 1980s. This split point also enables comparability of the SVAR and EVAR specifications.

4 The Dynamic Effects of Fiscal Shocks

In this section, we present our empirical results. First, we contrast the effects of shocks to *disaggregated* components of government spending with shocks to *aggregate* government spending. Second, we test the informational content of our Large VAR using factors extracted from a large dataset of 128 macroeconomic variables. Third, we compare SVARs with EVARs that incorporate Survey of Professional Forecasters' expectations for government spending. Finally, we check the robustness of our results across subsamples.

4.1 Aggregate Versus Disaggregate Government Spending

We start by examining the effects of shocks to aggregate government spending. Figure 1 compares the IRFs obtained for an aggregate government spending shock using the standard fiscal Small VAR and our Large VAR. The dynamic responses of macroeconomic variables of interest are plotted for a one percent shock in government spending. The IRFs can be interpreted as elasticities since the variables are in log–levels. To make the IRFs easier to read, we only show posterior cover intervals for one standard deviation. The results remain unchanged at the 0.9 level.

Aggregate Spending Shocks in Small VAR. Looking at the standard fiscal Small VAR IRFs one would conclude that a positive aggregate government spending shock elicits a positive and sustained response from GDP and output per hour as well as from consumption components. Also, real wages initially drop and subsequently increase, peaking after four quarters, while worked hours start increasing after eight quarter. Investment drops on impact and remains in negative territory for sixteen quarters.

Aggregate Spending Shocks in Large VAR. The Large VAR recounts a different story. An aggregate government spending shock results in a positive but short lived stimulus in GDP and output per hour. Crucially, IRFs for consumption components are generally unresponsive and flat if not negative. Similarly, real wages and worked hours do not increase following a fiscal spending shock. At the same time, investment drops on impact, being crowded out by government spending for the entire horizon, even though not significantly. The income-weighted average marginal tax rate rises on impact, peaks after a couple of quarters and then declines. Real rates drop upon impact and then recover after a few quarters, while the real exchange rate increases on impact (appreciation) and then stabilises after a few quarters. IRFs of the Small VAR are quite often outside the posterior coverage intervals, and deliver biased estimations.

The fiscal multipliers can be recovered by taking the product of elasticities shown in the IRFs and the average dollar ratio of the interest variable to the government shock variable. Multipliers from the Large VAR are reported in Table 2. The GDP multiplier for aggregate government spending from the Large VAR is 0.72 upon impact and remains positive and statistically significant for about 4 quarters. The impact multipliers for durables, nondurables and services consumption are not significantly different from zero.

However, the aggregate government spending shocks do not tell a complete story since they mask the underlying heterogeneity of the dynamic responses to different components of spending.

Disaggregate Spending Shocks in Large VAR. The IRFs for shocks to consumption expenditures components of federal defense, federal non-defense and state and local spending are presented in Figure 2. Focusing on the Large VAR IRFs, the three components of government spending appear to induce very different reactions from macroeconomic variables. Federal defense consumption elicits a positive, significant but short lived response from GDP, with an impact multiplier of 0.89, while private consumption is unresponsive and investment is negative. Following a federal non-defense spending shock GDP drops (not significant), while durables consumption and investment are crowded out. Finally, state and local consumption shocks produce a slowly increasing response from GDP, from the components of consumption as well as from investment that peaks after about 2 to 3 years. The associated GDP multiplier after eight quarters is 4.38. In addition, nondurables, services consumption, and investment peak multipliers are above unity, providing a strong feedback effect. As in the aggregate spending IRFs, the Small VAR delivers biased results.

Investment components of government spending produce starkly different effects on the variables of interest (see Figure 3). While defense investment has a negative effect on output, non-defense investment at federal and state and local level appears to provide strong economic stimulus. A federal non-defense investment shock produces a slowly rising hump-shaped response that peaks after 2 years, while the largest effect of state and local investment is upon impact.

The GDP multipliers reported in Table 2 reflect this result with federal defense investment yielding large negative multipliers within a year. Non-military investment components result in large statistically significant impact multipliers of 2.66 and 5.76 for state and local and federal non-defense investment, respectively. In addition, federal non-defense investment has large multipliers, even though estimated with large standard errors. The consumption IRFs and multipliers are generally close to zero and insignificant upon impact, except the durables consumption multiplier for state and local investment. In addition, private investment responds strongly to federal non-defense investment with impact and medium-run multipliers well over 1. This may suggest the activation of a supply channel possibly sparked by increased public capital.

Finally, we assess whether the GDP multipliers for each component are significantly different from each other by performing pair-wise tests of differences. The results reported in Table 3 show that at different horizons, many of the multipliers are statistically different from each other.

The above results show that the different components of government spending elicit remarkably heterogeneous responses from output, consumption and investment. Generally, the non-defense and state and local components produce more positive responses while the same does not hold true for defense components. In particular, investment components have larger multipliers than consumption components hinting at a direct productive effect on economic activity.

4.2 Fiscal Foresight and Informational Sufficiency

The presence of fiscal foresight and non-fundamentalness in the different empirical models can be examined using the information sufficiency test proposed in Forni and Gambetti (2011). The test can be implemented by extracting factors from a large dataset assumed to encompass all macroeconomic information, and checking for Granger causality of the identified fiscal shocks. The intuition supporting this test is that if the factors contain relevant information useful for forecasting fiscal shocks, then economic agents could have used this information to alter their behaviour prior to the realisation of the forecasted spending shock.

We use this informational sufficiency test to assess different empirical specifications. First, we test informational sufficiency of the Small VAR and the Large VAR. Then, we verify the forecastability of SPF forecast errors, the "Ramey" military spending news variable, and the residuals from a small EVAR.

We use a large dataset of 128 variables to extract five factors that explain over 99 percent of the variance in the data.[16] We use these five factors to conduct Granger

[16]We used several criteria to assess the appropriate number of factors to extract, including variance explained, the criteria proposed in Bai and Ng (2002), and the Onatski (2009) test. We chose the largest number proposed in the different tests. Factors are extracted using an EM algorithm.

causality tests on the residuals of government spending and the components of government spending from the Small and Large VARs for the full sample and the two subsamples.

Table 4 reports the results for the Granger causality tests. In the Small VAR with total government spending, Factor 3 Granger causes the residuals for the full sample as well as for the 1959Q1 to 1981Q4 subsample. Similarly, in the Small VAR with the components of government spending, Factor 3 appears to Granger cause the residuals from defense, non-defense and state and local investment and state and local consumption. In addition, Factor 4 Granger causes the residuals from defense and state and local investment, while Factor 5 those from state and local consumption and investment. Most are significant at the 5 percent level. These results suggest that fiscal shocks are non-fundamental in the Small VAR possibly due to fiscal foresight. Using a different test, Forni and Gambetti (2010) report similar strong non-fundamentalness results for a 6 variable VAR.

We test whether the variables that proxy for expectations of government spending proposed in Ramey (2011a) can convey information sufficient to correctly pin down the timing of fiscal shocks. We conduct Granger causality tests on "Ramey" forecast errors and VAR residuals, using SPF forecast data on federal and state and local spending, as well as expectation revisions as defined in Perotti (2011). Overall, the factors Granger cause the "Ramey" federal and state and local spending forecast errors mostly at 5 percent significance level. Also the Small EVAR residuals associated with government spending forecast errors appear to be Granger caused, albeit at around 15 percent significance level. Similarly, the expectation revisions for federal spending are Granger caused by Factor 1 and Factor 3, while expectation revisions for state and local spending are Granger cause by Factor 3 as well. Finally, we also conduct a Granger causality test using the "Ramey" military spending news variable and find that it is Granger caused by Factor 2 at the 5 percent significance level.[17]

Although the expectation proxy variables may provide some additional information useful to approximate the agents' information set, this approach is most likely still not able to correctly identify fiscal shocks. Instead, expanding the set of variables to the Large VAR appears to provide sufficient information to correctly identify fiscal shocks, overcoming fiscal foresight issues. Indeed, none of the factors appear to Granger cause the Large VAR residuals of government spending in any specification or subsample.

In order to better understand these result we study the partial correlations of the factors with the variables in the dataset. These correlations confirm the importance of including forward looking variables in the VAR specifications in order to approximate the agents' information set: Factor 1 is correlated with public finances variables (debt and deficit) and rates; Factor 2 with commodity and producer price indices as well as consumer sentiment; Factor 3 with taxes, public finance variables, labour and credit market variables, inventories and money supply; Factor 4 with CEO confidence, housing starts, industrial production and private investment; and Factor 5 with equity market returns and industrial activity indices.[18]

4.3 SVAR versus EVAR

To test the potential source of disagreement between the SVAR and EVAR as proposed in Ramey (2011a), we compare IRFs from recursive and expectation identifications (incorporating SPF data) estimated using the small and large models. Informational sufficiency of the dataset incorporated in the Large VAR would imply that the proxy variables for expectations should not provide additional information. Provided that

[17]The *military news variable* has very low predictive power for post-1955 samples, that exclude WWII and the Korea War, as discussed in Ramey (2011a).

[18]The relevance of including forward looking variables, such as commodity prices, in the VAR specification to capture agents' expectations is recognised since the seminal work of Sims (1992). Moreover, Favero and Giavazzi (2007) argue in favour of including the path of public debt in the VAR in order to correctly recover fiscal shocks.

fiscal shocks are correctly identified under both specifications, a Large Structural VAR and a Large Expectational VAR should yield the same results and IRFs in statistical terms.

The results for aggregate federal spending are shown in Figure 4.[19] The IRFs show the dynamic response of macroeconomic variables to a shock in "Ramey" forecasts errors normalised such that federal government spending peaks at one, as done in Perotti (2011). Using this methodology allows a direct comparison of IRFs from the SVARs and the EVARs.

The Large SVARs and EVARs deliver strikingly similar results, while the Small SVARs and EVARs deliver different results. This suggests that missing information may explain the different results obtained from different identifications.[20] This also corroborates our findings from the Granger causality tests and provides a strong indication of the informational sufficiency of the Large SVAR specification. A complementary possible explanation for these results, as observed in Perotti (2011) is that the strong predictive power of "Ramey" forecast error for government spending reported in Ramey (2011a) is partially due to the low predictive power of expected government spending growth. The forecast error is almost equivalent to actual spending growth less some noise.

The IRFs reported in the first two columns of Figure 4 compare results for Small and Large SVARs and EVARs for aggregate federal spending. The Small EVAR IRFs are similar to those reported by Ramey (2011a), but we find shallower troughs for the Large EVAR, although not always significant. However, in the Large VARs aggregate state and local spending shocks result in positive hump-shaped IRFs for output, consumption and investment, as well as real wages.

[19]In the VAR specifications where the forecast errors are used, they are ordered first. For the federal spending VAR, the various components of federal spending (consumption and investment components of federal defense and non-defense) are aggregated as the SPF forecasts are at an aggregate level.

[20]For the sake of brevity, only federal spending results are reported. Large SVARs and EVARs for state and local spending also deliver almost identical results.

Finally, we explore a different specification of the EVARs that includes agents' expectation revisions as defined by Perotti (2011). IRFs for aggregate federal spending are reported in the last columns of Figures 4. The shapes of the IRFs are intriguingly different from the Ramey EVAR specification and may suggest the stimulative effect of news on fiscal spending. Also, they seem to indicate that revisions of expectations affect agents' behaviour in real-time. However, the low statistical significance of the IRFs also points to the high level of noise contained in this alternative measure for expectations. See Ricco (2013) who uses a refined measure for fiscal news and reports consistent results.

4.4 Subsample Instability

Finally, we examine the issue of sample instability of dynamic responses to fiscal shocks that has been highlighted by numerous studies. A common finding using U.S. data is that the government spending multipliers vary depending on the sample studied (e.g., Perotti (2008), Ramey (2011b), Hall (2009)). This instability could be caused either by the presence of structural breaks (e.g., credit market developments or changes in the fiscal-monetary policy regime), or by variations in the composition of government spending over time. Another possible source of instability may be omitted variables and non-fundamentalness of structural shocks in the empirical model. Therefore, as robustness check, we investigate potential sample instability by splitting our full sample period of 1959Q1 to 2012Q1 into two subsamples, covering 1959Q1 to 1981Q4 and 1982Q1 to 2012Q1.

Figure 5 presents the impulse responses to a shock in total government spending over 24 quarters for the full sample as well as for the two subsamples. The plots also show the posterior coverage intervals at the 0.68 and 0.9 levels. While the IRFs for the Small VAR exhibit subsample instability, the Large VAR IRFs do not. In particular, the Small VAR shows subsample instability across all the variables we study, including

GDP, durables and nondurables consumption, investment and real rates. Conversely, in the Large VAR the IRFs for both subsamples are within the posterior coverage interval at the 0.68 level for virtually all the horizons. The residual variation across subsamples may be accounted for by the changing composition of government spending over time.[21]

The Large VAR responses to a shock in government spending are positive and significant for GDP, insignificant for nondurables and durables consumption and investment, and negative and significant for real rates.[22]

Overall, these results for the Large VAR suggest that the previously reported subsample instability is not due to structural changes but instead points to an omitted variable problem. Also, given the consistency of results, the Large VAR can be used for different subsamples without loss of validity (e.g., our analysis of government expectations over 1982Q2-2012Q1).

4.5 Discussion of Results

Our empirical results confirm the intuition that given the forward looking behaviour of agents "information matters" in order to understand the effects of fiscal policy. Therefore, it is necessary to enlarge the information set used in the econometric analysis to capture the flow of information in the economy.

In the aggregate, government spending appears to stimulate output with a less then unity multiplier, due to the crowding out of investment and unresponsiveness of consumption. However, our Large VAR uncovers multipliers that crucially depend on the component of government spending as they manifest starkly heterogenous effects. Consumption components appear to have short lived and relatively weak effects. State and

[21]Results are robust to the exclusion of the recent financial crisis. Also, the results for the subsample 1982Q1-2012Q1 are robust to the inclusion of additional potentially forward-looking variables, including Conference Board CEO confidence index, Conference Board consumer confidence index, U.S. housing price index and NASDAQ returns. These variables are not available for the full sample.

[22]The subsample instability is also not present in the Large VAR for shocks to the components of government spending.

local consumption stands out as providing a slow growing but sustained stimulus to output, consumption components and investment. A large portion of state and local spending is devoted to education, which can be framed as investment in human capital. This could be a possible explanation for both the large multipliers and the slow growing pass-through effect.

Non-defense investment components, that are considered to be directly productive, provide large stimulative effects on economic activity, boosting consumption and investment. The accumulation of public capital and its impact on the aggregate production function may account for these responses. Similar results on government investment have been reported in Aschauer (1989) and in Auerbach and Gorodnichenko (2012). Also, from a theoretical perspective, Baxter and King (1993) consider the multiplier effects of an increase in investment in public capital in a neoclassical setting. In line with our findings, they show that in the case of public capital that raises the marginal product of private inputs, multipliers can be quite large, somewhere between 4 and 13 in the long run.

Defense investment depresses economic activity. As surprising as it may appear, it could be explained by recalling that in national accounting purchases of military hardware meant to be stocked and used in the future are accounted for as investment. Possibly this component of defense investment accounts for a large portion of its variation.

Our results suggest that fiscal foresight can be effectively dealt with by incorporating a rich macroeconomic dataset in a Large Bayesian Structural VAR. Findings indicate a possible direction to reconcile findings previously reported in the literature. First, informational sufficiency tests show that small VARs using a marginal approach are generally misspecified and prone to non-fundamentalness and fiscal foresight issues. In fact, the fiscal shocks recovered from these models appear to be forecastable using a larger information set, confirming Ramey's criticism of this approach. Proposed proxy variables for expectations of government spending still do not fully account for the flow of macroeconomic information received by the agents, and are again predictable using a broader set of variables.

Second, our Large VAR is robust across identifications of fiscal shocks: structural recursive and expectation augmented specifications deliver the same results. Furthermore, the recovered shocks appear to be true fiscal innovations, lending credibility to the use of Large BVARs as a suitable tool for fiscal policy analysis. Finally, the stability of our results over different samples provides strong indication of the robustness of our findings, explaining the previously reported instability as an omitted variables artifact.

Our approach suffers from limitations largely common to the SVAR and EVAR literature. Using a static linear VAR approach, we estimate time-invariant and linear (marginally constant and symmetric with respect to the sign of the shock) government multipliers. Therefore, we implicitly assume through our choice of the econometric model that government spending multipliers are independent of the state of the economy, do not change with the magnitude of the shock, and that positive and negative shocks impinge on the economy in a symmetric way (a thoughtful discussion on this point can be found in Parker (2011)).

However, the government spending multipliers cannot be thought of as deep structural parameters of the economy. There is no single government spending multiplier and its value is likely to depend on the country, the economic phase, the interaction between monetary and fiscal policy regimes in place, and the degree of openness of the economy (e.g. Woodford (2011); Ilzetzki et al. (2010); Auerbach and Gorodnichenko (2012); Hall (2009)). Our IRFs and estimated multipliers should be interpreted as statistical averages over largely different economic conditions and policies.

5 Conclusions

In examining the effects of government spending as an active fiscal policy instrument, we make two main contributions in this paper. First, we show that it is possible to meaningfully identify government spending shocks using an expanded information set and Bayesian VAR techniques. We document that fiscal shocks identified using standard recursive fiscal SVARs and EVARs suffer from informational insufficiency. In fact, fiscal innovations identified using these models are likely to have been anticipated by economic agents, and are forecastable using a larger information set. In contrast, Bayesian VAR techniques with a rich dataset yield multipliers and IRFs that are stable across samples and identifications, overcoming issues of fiscal foresight and non-fundamentalness.

Second, we estimate fiscal multipliers for different components of government spending at federal and state and local level, and uncover significant heterogeneity in the responses of macroeconomic variables. While aggregate government spending does not appear to produce a strong stimulative effect, federal non-defense investment, and state and local consumption and investment components generally have output multipliers well above unity. These findings may help to inform the current fiscal policy debate.

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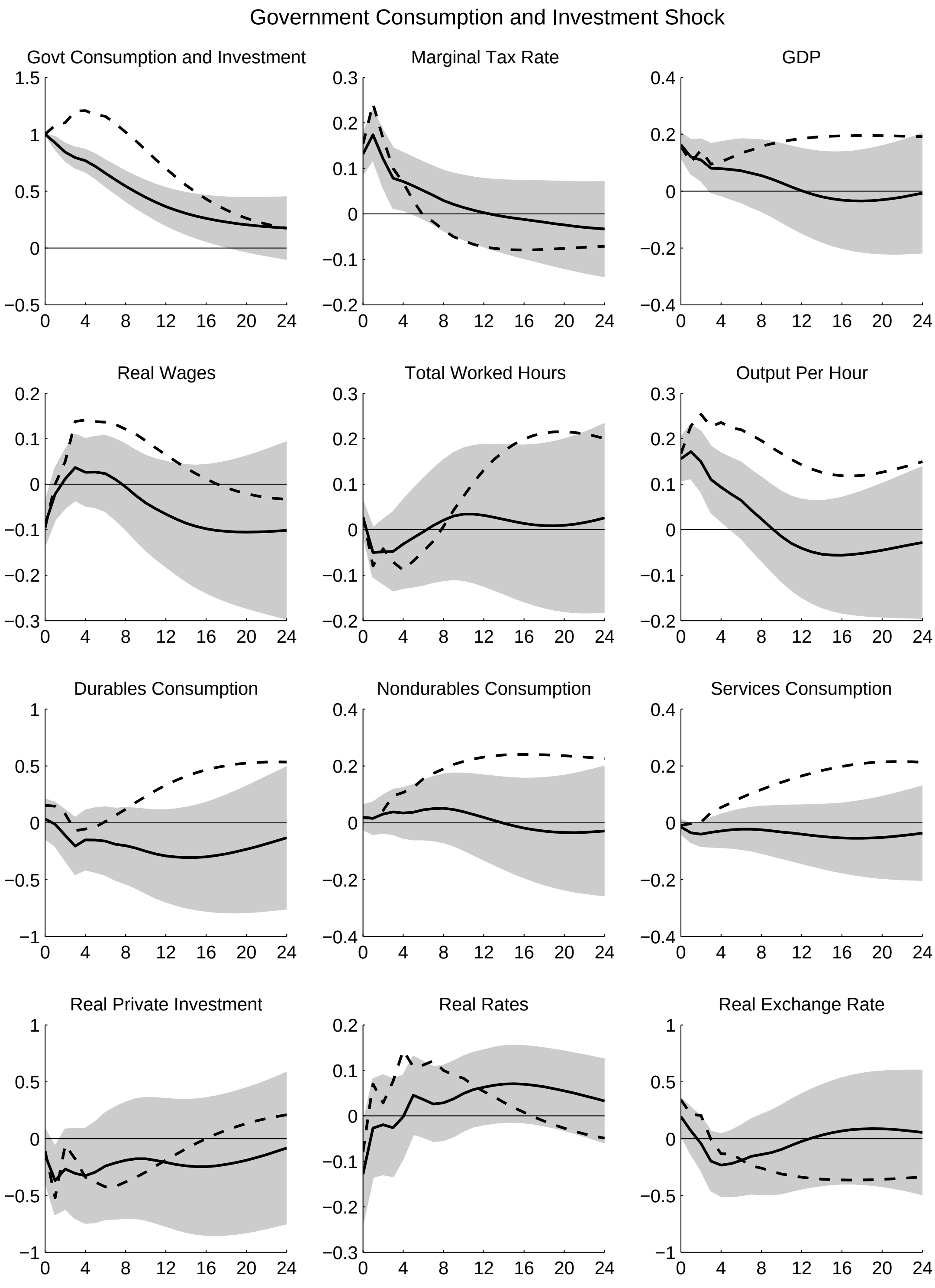

Figure 1: **Large and Small VAR (1959Q1:2012Q1)**. This figure presents the impulse response functions to a shock in Government Consumption and Investment. Each chart shows the Large VAR response for the period 1959Q1 to 2012Q1 as a solid line with shaded posterior coverage intervals at the 0.68 level. The dashed line in each chart is the response for the Small VAR for the same period.

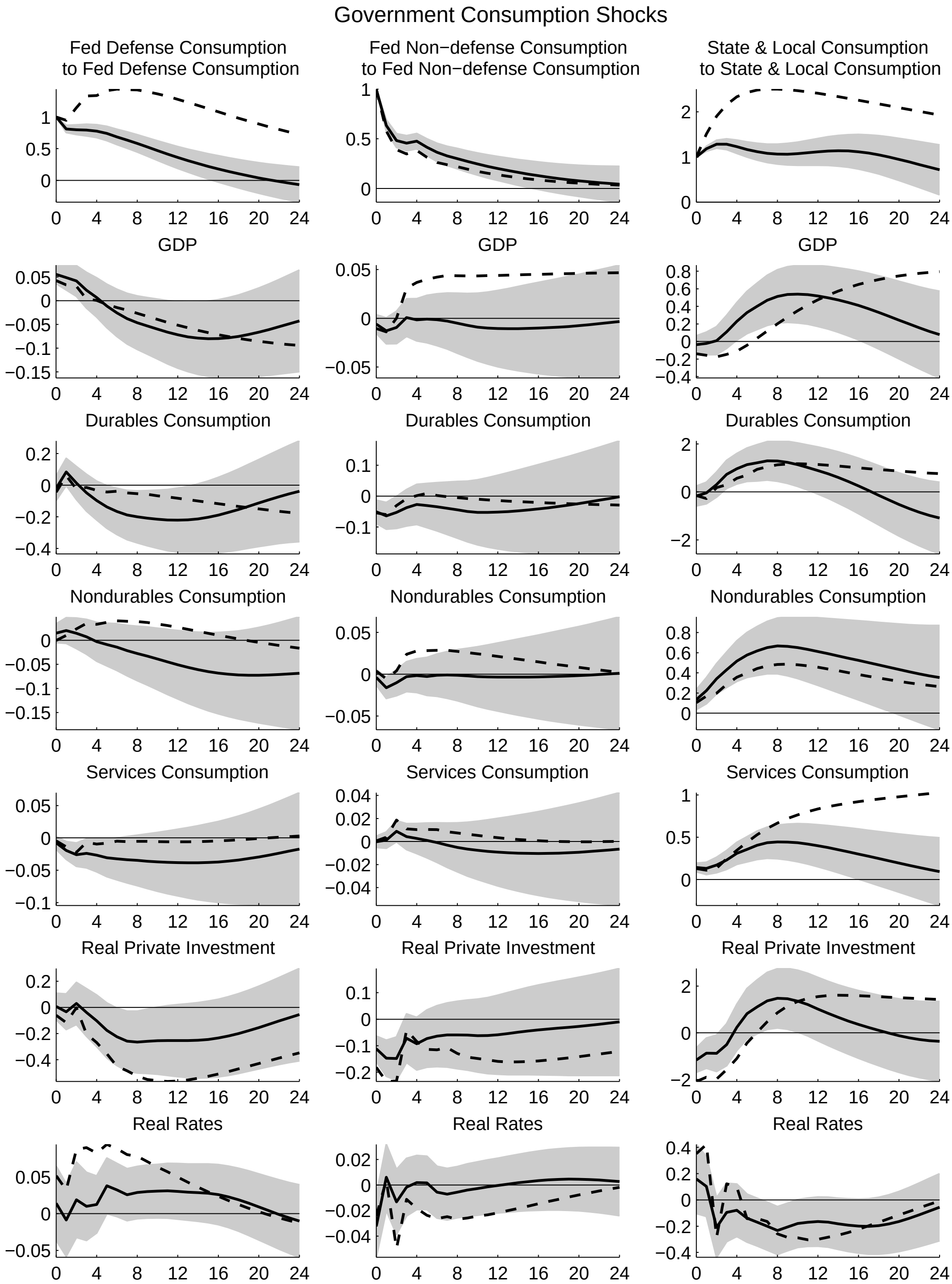

Figure 2: **Large and Small VAR – Government Consumption Components (1959Q1:2012Q1)**. This figure presents the impulse response functions to a shock in a specified component of government consumption. The left, middle and right columns of plots depict the responses to a shock in federal defense consumption, federal non-defense consumption, and state and local consumption, respectively. Each chart shows the Large VAR response for the period 1959Q1 to 2012Q1 as a solid line with shaded posterior coverage intervals at the 0.68 level. The dashed line in each chart is the response for the Small VAR for the same period.

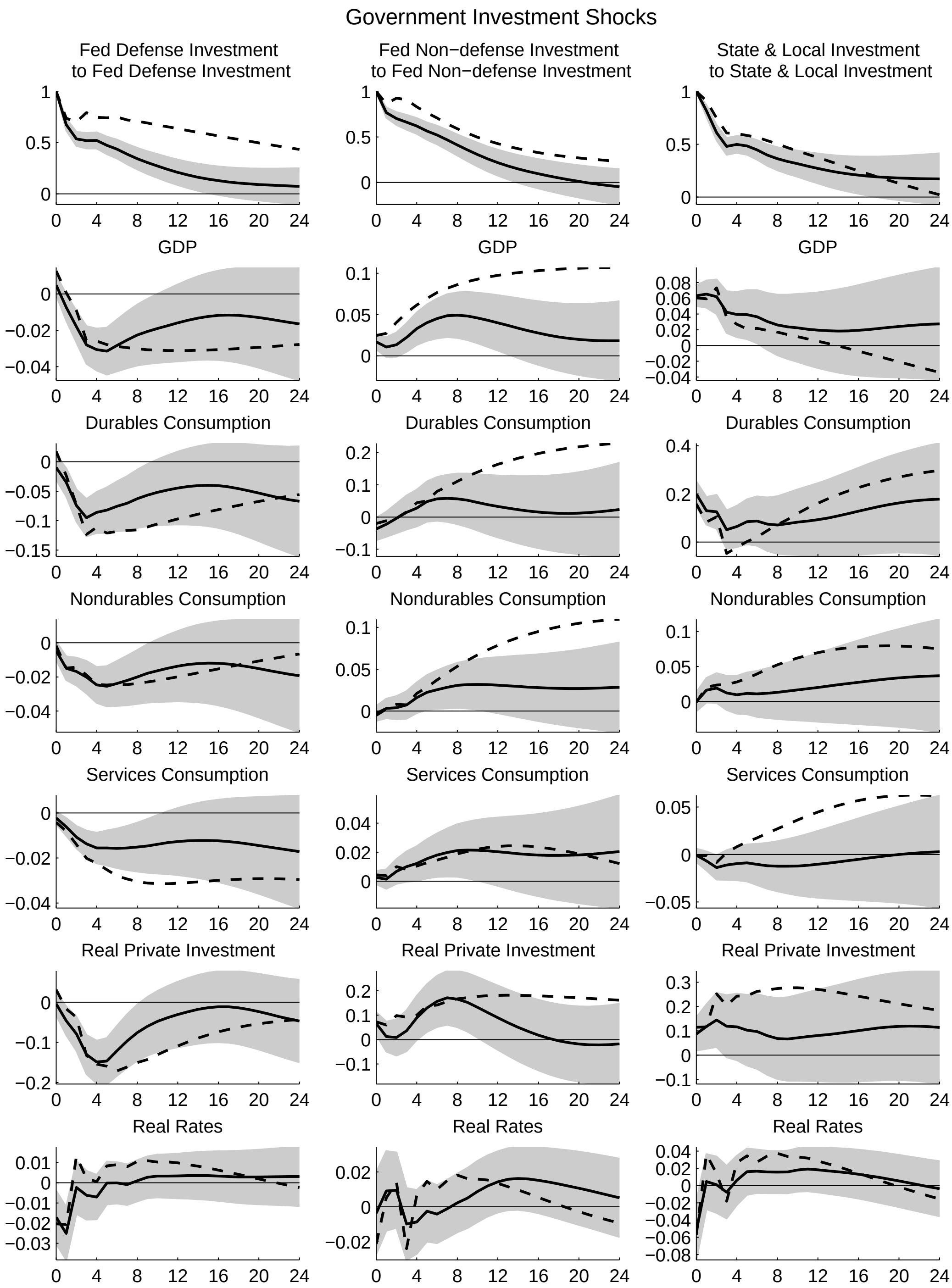

Figure 3: **Large and Small VAR – Government Investment Components (1959Q1:2012Q1)**. This figure presents the impulse response functions to a shock in a specified component of government investment. The left, middle and right columns of plots depict the responses to a shock in federal defense investment, federal non-defense investment, and state and local investment, respectively. Each chart shows the Large VAR response for the period 1959Q1 to 2012Q1 as a solid line with shaded posterior coverage intervals at the 0.68 level. The dashed line in each chart is the response for the Small VAR for the same period.

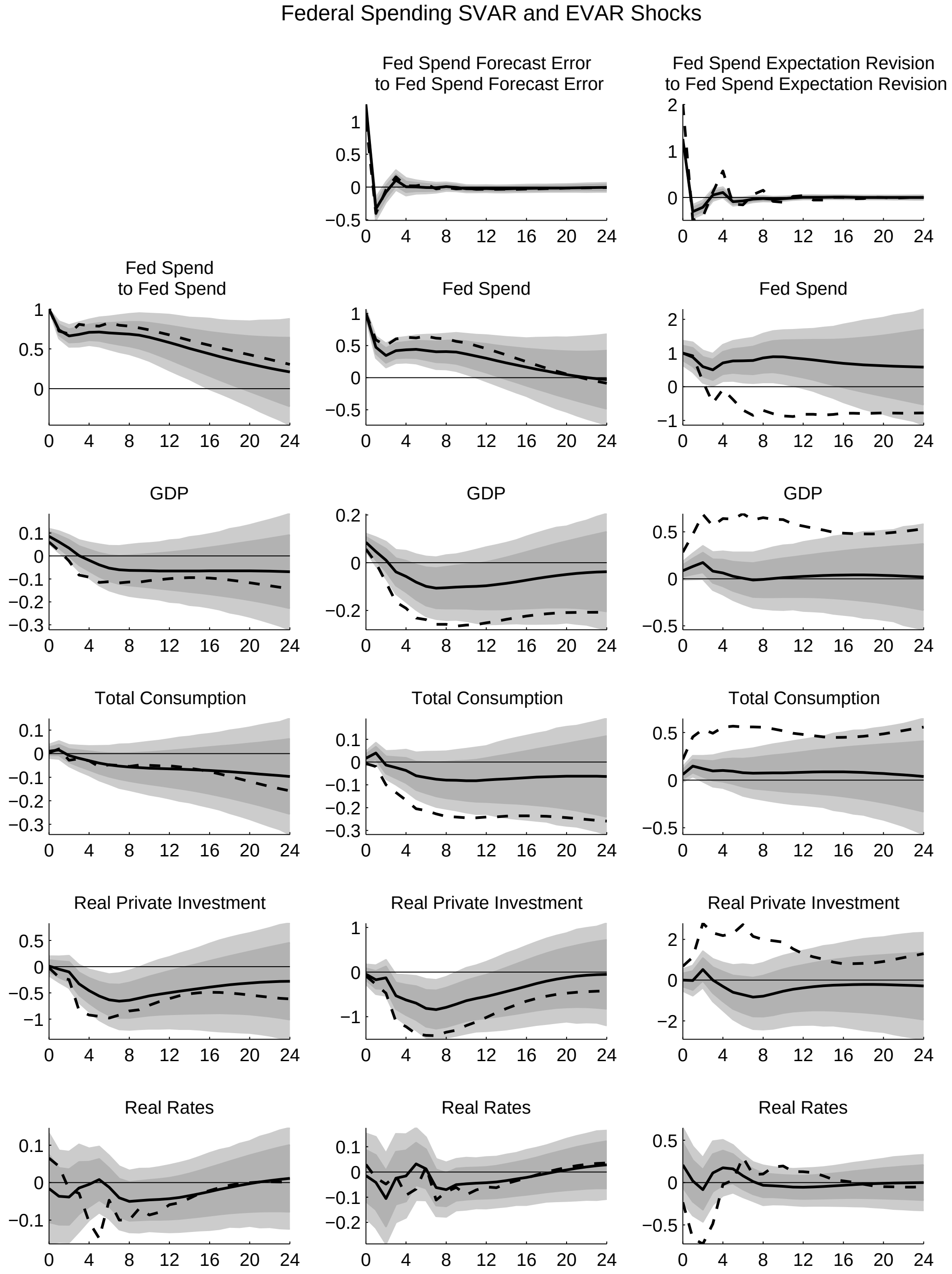

Figure 4: **Federal Spending SVAR and EVAR (1982Q1:2012Q1)**. This figure presents the impulse response functions to a shock in federal spending and federal spending forecasts. The left, middle and right columns of plots depict the responses to a shock in federal spending, federal spending forecast error, and federal spending expectation revision, respectively. Each chart shows the Large VAR response for the period 1982Q1 to 2012Q1 as a solid line with shaded posterior coverage intervals at the 0.68 and 0.9 level. The dashed line in each chart is the response for the Small VAR for the same period.

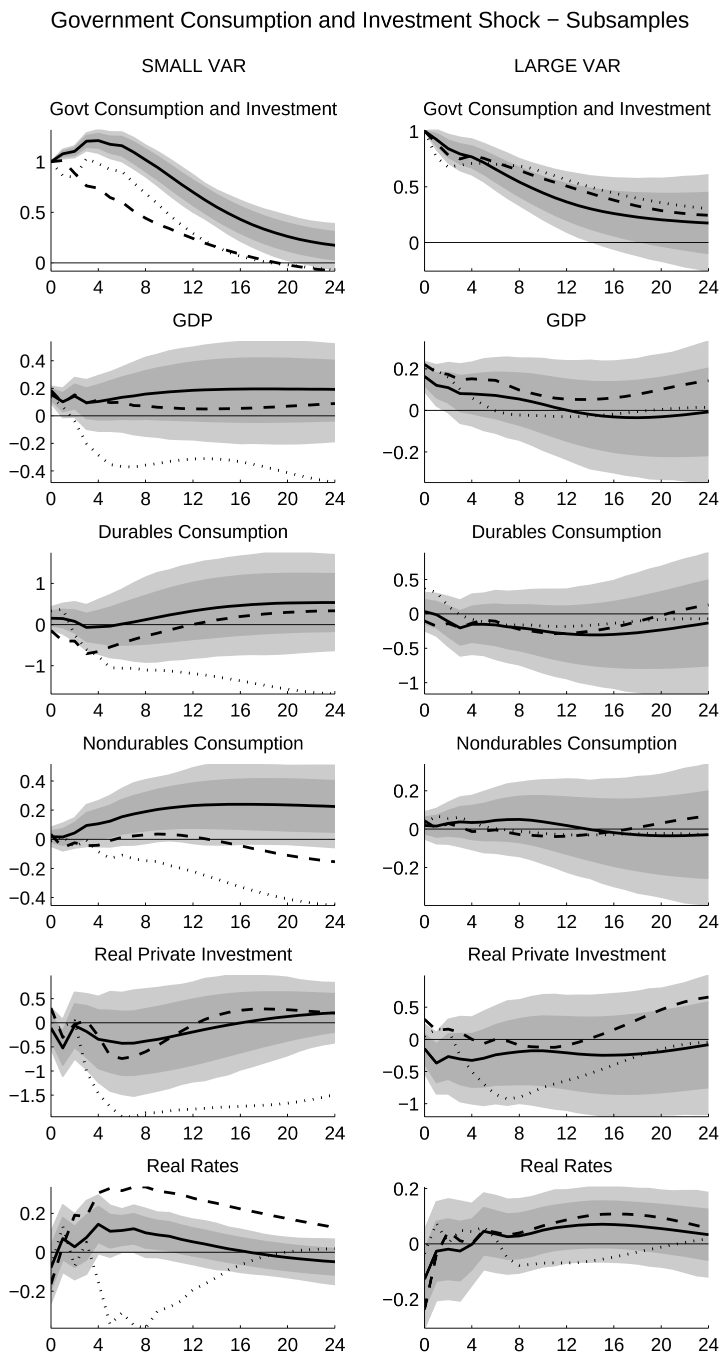

Figure 5: **Government Consumption and Investment Shocks for Subsamples**. The subsample 1959Q1 to 2012Q1 is plotted as a solid line with shaded posterior coverage intervals at the 0.68 and 0.9 level. The dashed line and dotted lines in each chart are the responses for the periods 1982Q1 to 2012Q1, and 1959Q1 to 1981Q4, respectively. The left column of plots shows the Small VAR responses and the right column presents the Large VAR plots for each subsample.

Table 1: **Government Spending Decomposition (1960 – 2010)**

	1960	**1970**	**1980**	**1990**	**2000**	**2010**
Government Spending ($ bn)	870.5	1,233.6	1,358.6	1,863.7	2,097.9	2,605.8
Government Spending (%)						
Federal Government	53.8	46.7	40.9	42.8	33.3	41.3
Defense Consumption Expenditures	40.7	36.5	26.6	27.2	19.2	23.4
Defense Gross Investment	5.0	2.6	2.3	4.0	2.4	4.2
Non-defense Consumption Expend.	8.2	9.5	12.1	10.3	10.1	11.8
Non-defense Gross Investment	0.8	0.8	1.2	1.3	1.5	1.9
State and Local Government	45.2	53.0	59.3	57.0	66.7	58.9
S&L Consumption Expenditures	34.5	42.0	49.9	47.2	54.0	48.3
S&L Gross Investment	10.0	10.4	9.5	9.8	12.7	10.6
Federal Government Spending (%)	100.0	100.0	100.0	100.0	100.0	100.0
(Functional Decomposition)						
General Public Service	4.2	4.5	6.4	5.3	4.6	5.6
National Defense	84.6	79.6	68.5	73.2	65.0	66.6
Public Order and Safety	0.5	0.7	1.5	2.0	4.6	4.9
Transportation	2.0	2.2	3.0	2.6	3.3	3.1
Economic Affairs (excl. Transport)	6.0	7.8	11.4	9.5	11.1	8.9
Housing and Community Services	0.1	0.2	0.2	0.1	0.0	0.2
Health	2.5	3.6	6.2	5.9	8.5	7.7
Recreation and Culture	0.4	0.4	0.6	0.4	0.6	0.5
Education	0.3	0.6	0.6	0.5	1.0	0.7
Income Security	0.5	1.0	2.2	1.1	1.5	1.7
State and Local Govt. Spending (%)	100.0	100.0	100.0	100.0	100.0	100.0
(Functional Decomposition)						
General Public Service	6.7	8.4	10.2	11.4	11.6	11.6
Public Order and Safety	11.7	11.2	13.1	14.5	15.2	15.9
Transportation	23.4	18.8	15.5	14.2	13.5	11.8
Economic Affairs (excl. Transport)	5.2	4.9	5.1	4.0	3.5	3.6
Housing and Community Services	5.3	4.5	4.2	3.9	2.9	3.4
Health	3.7	3.6	3.5	4.2	2.9	4.1
Recreation and Culture	1.6	2.0	2.0	2.1	2.1	2.0
Education	40.8	43.5	42.9	41.9	43.6	43.3
Income Security	1.6	2.7	3.7	3.9	4.6	4.4

Source: Bureau of Economic Analysis NIPA Tables Section 3

Table 2: **Multipliers for GDP, Consumption and Investment.** Standard errors are italicised. Inv is Investment and Dur, ND, and Svs are durables, nondurables and services consumption, respectively. The asterisks *, **, *** denote statistical significance at 20 percent, 10 percent and 5 percent levels.

		GDP		**Dur**		**ND**		**Svs**		**Inv**	
On Impact	Govt. Spend	0.72***	*(0.19)*	0.01	*(0.05)*	0.01	*(0.03)*	-0.03	*(0.05)*	-0.09	*(0.14)*
	Def Cons	0.89***	*(0.31)*	-0.02	*(0.07)*	0.04	*(0.05)*	-0.05	*(0.07)*	0.01	*(0.22)*
	Def Inv	0.68	*(0.76)*	-0.08	*(0.17)*	-0.11	*(0.12)*	-0.14	*(0.17)*	-0.08	*(0.53)*
	Non-def Cons	-0.25	*(0.40)*	-0.13*	*(0.10)*	-0.03	*(0.07)*	0.00	*(0.09)*	-0.64***	*(0.28)*
	Non-def Inv	5.76*	*(3.08)*	-0.75	*(0.71)*	-0.15	*(0.50)*	0.39	*(0.69)*	3.03*	*(2.10)*
	S&L Cons	-0.34	*(0.94)*	-0.10	*(0.23)*	0.21*	*(0.15)*	0.59***	*(0.21)*	-1.49***	*(0.66)*
	S&L Inv	2.66***	*(0.54)*	0.51***	*(0.13)*	0.00	*(0.10)*	-0.02	*(0.13)*	0.50	*(0.39)*
4 Quarters	Govt. Spend	0.36	*(0.38)*	-0.05	*(0.07)*	0.03	*(0.06)*	-0.07	*(0.10)*	-0.19	*(0.24)*
	Def Cons	0.35	*(0.60)*	-0.05	*(0.11)*	0.02	*(0.10)*	-0.17	*(0.16)*	-0.08	*(0.40)*
	Def Inv	-3.88***	*(1.43)*	-0.79***	*(0.26)*	-0.47***	*(0.22)*	-0.85***	*(0.36)*	-2.47***	*(0.92)*
	Non-def Cons	0.03	*(0.81)*	-0.10	*(0.15)*	-0.02	*(0.13)*	0.08	*(0.21)*	-0.41	*(0.53)*
	Non-def Inv	7.52*	*(5.80)*	0.29	*(1.07)*	0.42	*(0.92)*	1.52	*(1.57)*	1.65	*(3.86)*
	S&L Cons	1.02	*(1.74)*	0.41	*(0.33)*	0.67***	*(0.27)*	0.96***	*(0.46)*	-0.65	*(1.15)*
	S&L Inv	1.78*	*(1.11)*	0.13	*(0.20)*	0.09	*(0.17)*	-0.21	*(0.29)*	0.68	*(0.73)*
8 Quarters	Govt. Spend	0.28	*(0.52)*	-0.05	*(0.08)*	0.04	*(0.08)*	-0.04	*(0.15)*	-0.13	*(0.30)*
	Def Cons	-0.61	*(0.85)*	-0.18	*(0.15)*	-0.06	*(0.14)*	-0.24	*(0.25)*	-0.57	*(0.50)*
	Def Inv	-3.50*	*(2.15)*	-0.59*	*(0.39)*	-0.51*	*(0.34)*	-0.96*	*(0.60)*	-1.83*	*(1.26)*
	Non-def Cons	-0.12	*(1.21)*	-0.10	*(0.22)*	-0.01	*(0.20)*	-0.06	*(0.36)*	-0.34	*(0.70)*
	Non-def Inv	16.43**	*(8.71)*	1.18	*(1.49)*	1.61	*(1.42)*	2.98	*(2.48)*	7.90*	*(5.08)*
	S&L Cons	4.38**	*(2.66)*	0.73*	*(0.45)*	1.01***	*(0.40)*	1.81***	*(0.76)*	1.74	*(1.55)*
	S&L Inv	1.29	*(1.52)*	0.19	*(0.28)*	0.08	*(0.25)*	-0.22	*(0.45)*	0.46	*(0.92)*

Table 3: **Multipliers Mean Differences Test.** This table reports t-statistics for pairwise differences in government spending multipliers for GDP. The asterisks *, **, *** denote statistical significance at two-tailed 10 percent, 5 percent and 1 percent levels, respectively.

		(1)	(2)	(3)	(4)	(5)	(6)
On Impact	Govt. Spend (1)						
	Defense Cons (2)	0.47					
	Defense Inv (3)	-0.05	-0.26				
	Nondefense Cons (4)	-2.2**	-2.25**	-1.08			
	Nondefense Inv (5)	1.63*	1.57	1.6	1.93*		
	State & Local Cons (6)	-1.1	-1.24	-0.84	-0.09	-1.89*	
	State & Local Inv (7)	3.37***	2.81***	2.12**	4.31***	-0.99	2.75***
4 Quarters	Govt. Spend (1)						
	Defense Cons (2)	0.00					
	Defense Inv (3)	-2.87***	-2.73***				
	Nondefense Cons (4)	-0.37	-0.32	2.38			
	Nondefense Inv (5)	1.23	1.23*	1.91**	1.28*		
	State & Local Cons (6)	0.37	0.36	2.17**	0.51	-1.07	
	State & Local Inv (7)	1.22	1.13	3.13***	1.28	-0.97	0.37
8 Quarters	Govt. Spend (1)						
	Defense Cons (2)	-0.88					
	Defense Inv (3)	-1.71*	-1.25				
	Nondefense Cons (4)	-0.3	0.33	1.37			
	Nondefense Inv (5)	1.85*	1.95*	2.22**	1.88*		
	State & Local Cons (6)	1.51	1.79*	2.3**	1.54	-1.32	
	State & Local Inv (7)	0.63	1.09	1.82*	0.72	-1.71*	-1.01

Table 4: **Granger causality Tests.** This table reports F-statistics and p-values for Granger causality tests. Five factors are extracted from a dataset with 128 macroeconomic variables and we test whether these factors Granger-cause VAR residuals and expectational proxies. The asterisks *, **, *** denote statistical significance at two-tailed 20 percent, 10 percent and 5 percent levels, respectively.

	Factor 1	*p-value*	Factor 2	*p-value*	Factor 3	*p-value*	Factor 4	*p-value*	Factor 5	*p-value*
Small SVAR (1959 – 2012)	0.26	*(0.906)*	0.03	*(0.998)*	1.73*	*(0.145)*	1.04	*(0.389)*	0.89	*(0.472)*
Defense Consumption	0.49	*(0.743)*	0.06	*(0.992)*	0.09	*(0.985)*	0.09	*(0.984)*	0.41	*(0.803)*
Defense Investment	0.85	*(0.495)*	0.04	*(0.997)*	2.35**	*(0.055)*	1.85*	*(0.120)*	1.20	*(0.311)*
Non-defense Consumption	1.60*	*(0.176)*	0.36	*(0.840)*	0.04	*(0.998)*	0.08	*(0.988)*	0.23	*(0.919)*
Non-defense Investment	1.19	*(0.317)*	0.15	*(0.965)*	1.57*	*(0.185)*	1.11	*(0.354)*	1.25	*(0.292)*
State & Local Consumption	0.46	*(0.762)*	0.05	*(0.996)*	3.26***	*(0.013)*	0.73	*(0.575)*	4.65***	*(0.001)*
State & Local Investment	0.58	*(0.677)*	0.05	*(0.996)*	3.98***	*(0.004)*	2.62***	*(0.036)*	2.51***	*(0.043)*
Small SVAR (1982 – 2012)	1.11	*(0.356)*	0.42	*(0.796)*	0.34	*(0.849)*	1.48	*(0.213)*	0.23	*(0.919)*
Small SVAR (1959 – 1981)	0.82	*(0.515)*	0.31	*(0.871)*	1.77*	*(0.143)*	1.04	*(0.394)*	0.25	*(0.912)*
Fed Spend Forecast Error	2.99***	*(0.034)*	0.57	*(0.639)*	3.95***	*(0.010)*	2.97***	*(0.035)*	0.58	*(0.628)*
Small EVAR Residuals	1.36	*(0.232)*	1.50*	*(0.178)*	0.95	*(0.473)*	0.45	*(0.866)*	1.63*	*(0.137)*
Fed Spend Expectation Revision	1.73*	*(0.135)*	1.02	*(0.412)*	2.13**	*(0.068)*	1.32	*(0.261)*	1.38	*(0.239)*
Small EVAR Residuals	0.40	*(0.849)*	0.53	*(0.755)*	1.67*	*(0.150)*	1.34	*(0.254)*	0.86	*(0.508)*
S&L Spend Forecast Error	5.19***	*(0.001)*	9.43***	*(0.000)*	2.70***	*(0.035)*	0.96	*(0.432)*	3.12***	*(0.018)*
Small EVAR Residuals	0.69	*(0.703)*	1.11	*(0.365)*	0.61	*(0.768)*	0.73	*(0.663)*	1.66*	*(0.120)*
S&L Spend Expectation Revision	0.32	*(0.812)*	0.69	*(0.561)*	2.76***	*(0.046)*	2.06*	*(0.111)*	0.27	*(0.850)*
Small EVAR Residuals	1.52*	*(0.178)*	1.14	*(0.347)*	0.93	*(0.476)*	1.51*	*(0.181)*	0.64	*(0.695)*
Ramey News Variable	1.03	*(0.392)*	2.85***	*(0.025)*	0.34	*(0.848)*	1.35	*(0.254)*	0.65	*(0.628)*
Large SVAR (1959 – 2012)	0.05	*(0.996)*	0.29	*(0.885)*	0.49	*(0.744)*	0.67	*(0.615)*	0.05	*(0.995)*
Defense Consumption	0.15	*(0.963)*	0.05	*(0.996)*	0.08	*(0.988)*	0.21	*(0.933)*	0.02	*(0.999)*
Defense Investment	0.24	*(0.918)*	0.39	*(0.816)*	0.25	*(0.910)*	0.45	*(0.770)*	0.04	*(0.997)*
Non-defense Consumption	0.56	*(0.694)*	0.16	*(0.958)*	0.13	*(0.973)*	0.62	*(0.649)*	0.04	*(0.997)*
Non-defense Investment	0.39	*(0.819)*	0.10	*(0.984)*	0.13	*(0.971)*	0.46	*(0.762)*	0.32	*(0.862)*
State & Local Consumption	0.85	*(0.496)*	0.08	*(0.989)*	0.31	*(0.871)*	0.42	*(0.797)*	0.38	*(0.823)*
State & Local Investment	0.09	*(0.986)*	0.26	*(0.901)*	0.68	*(0.607)*	0.82	*(0.516)*	0.79	*(0.535)*
Large SVAR (1982 – 2012)	0.21	*(0.930)*	0.23	*(0.923)*	0.24	*(0.915)*	0.17	*(0.951)*	0.24	*(0.914)*
Large SVAR (1959 – 1981)	0.17	*(0.984)*	0.05	*(1.000)*	0.56	*(0.762)*	0.98	*(0.443)*	0.07	*(0.999)*

Table 5: List of Variables

Mnemonic	Variable Description / Short Label	Small	Large	Small SPF	Large SPF	Factors	Log	RW Prior
RFEDGOV_FE	SPF Real Federal Govt Spend Forecast Error / Fed Spend Forecast Error			•	•			
RSLGOV_FE	SPF Real State & Local Govt Spend Forecast Error / S&L Spend Forecast Error			•	•			
RFEDGOV_ER	SPF Real Federal Govt Spend Expectation Revision / Fed Spend Expectation Revision			•	•			
RSLGOV_ER	SPF Real State & Local Spend Expectation Revision / S&L Spend Expectation Revision			•	•			
GCEC96	Real Govt. Consumption Exp.& Gross Invest. / Govt Consumption and Investment	•	•			•	•	•
DEFCONS	Federal Defense Consumption Expenditures / Fed Defense Consumption	•	•			•	•	•
DGI	Federal Defense Gross Investment / Fed Defense Investment	•	•			•	•	•
CIVCONS	Federal Non-defense Consumption Expenditures / Fed Civil Consumption	•	•			•	•	•
NDGI	Federal Non-defense Gross Investment / Fed Civil Investment	•	•			•	•	•
SLCONS	State & Local Consumption Exp. / State & Local Consumption	•	•			•	•	•
SLINV	State & Local Gross Investment / State & Local Investment	•	•			•	•	•
SLCE	State & Local Consumption Exp. & Gross Investment / S&L Spend (Cons + Inv)			•	•		•	•
FEDSPEND	Federal Defense and Non-defense Consumption Expenditures / Fed Spend (Cons + Inv)			•	•		•	•
FGRECPT	Federal Government Tax Receipts		•		•	•	•	•
PERSTAX	Personal Current Taxes		•		•	•	•	•
MTR	Barro-Redlick Income Weighted Avg. Marginal Tax Rate / Marginal Tax Rate	•	•	•	•	•		•
FGDEF	Net Federal Government Saving (Deficit)		•		•	•		•
PUBDEBT	US Total Treasury Securities Outstanding (Public Debt)		•		•	•	•	•
GDPC96	Real Gross Domestic Product / GDP	•	•	•	•	•	•	•
UNRATE	Civilian Unemployment Rate		•		•	•		•
CE16OV	Civilian Employment		•		•	•	•	•
UEMPMEAN	Average (Mean) Duration of Unemployment		•		•	•	•	•
HOABS	Business Sector: Hours of All Persons / Total Worked Hours	•	•	•	•	•	•	•
TOTALSL	Total Consumer Credit Outstanding		•		•	•	•	•
BUSLOANS	Commercial and Industrial Loans at All Commercial Banks		•		•	•	•	•
REALLN	Real Estate Loans at All Commercial Banks		•		•	•	•	•
OILPRICE	Spot Oil Price: West Texas Intermediate (Dollar Per Barrel)		•		•	•	•	•
UMCSENT	University of Michigan: Consumer Sentiment Index		•		•	•		
GPSAVE	Gross Private Saving		•		•	•	•	•
DSPIC96	Real Disposable Personal Income		•		•	•	•	•
RCPHBS	Business Sector: Real Compensation Per Hour / Real Wages	•	•	•	•	•	•	•
PCECTPI	Personal Consumption Expenditures: Chain-type Price Index (Percent Change)		•		•	•	•	•
PCDG	Personal Consumption Expenditures: Durable Goods / Durables Consumption	•	•	•	•	•	•	•
PCND	Personal Consumption Expenditures: Nondurable Goods / Nondurables Consumption	•	•	•	•	•	•	•
PCESV	Personal Consumption Expenditures: Services / Services Consumption	•	•	•	•	•	•	•
NAPMNOI	ISM Manufacturing: New Orders Index		•		•	•		
NAPMII	ISM Manufacturing: Inventories Index		•		•	•		
CPATAX	Corporate Profits After Tax with IVA and CCAdj		•		•	•	•	•
INDPRO	Industrial Production Index		•		•	•	•	•
PPIACO	Producer Price Index: All Commodities		•		•	•	•	•
OPHPBS	Business Sector: Output Per Hour of All Persons / Output Per Hour	•	•	•	•	•	•	•
HOUST	Housing Starts: Total: New Privately Owned Housing Units Started		•		•	•	•	
GPDIC96	Real Gross Private Domestic Investment / Real Private Investment	•	•	•	•	•	•	•
EXPGSC96	Real Exports of Goods & Services		•		•	•	•	•
IMPGSC96	Real Imports of Goods & Services		•		•	•	•	•
RER	Real Exchange Rate USD (3 month average closing) / Real Exchange Rate	•	•	•	•	•	•	•

List of Variables *(Continued)*

Mnemonic	Variable Description / Short Label	Small	Large	Small SPF	Large SPF	Factors	Log	RW Prior
SP500	S&P 500 Stock Market Index (Percent Change)		•		•	•		•
DJIA	Dow Jones Industrial Average Stock Price Index (Percent Change)		•		•	•		•
AAA	Moody's Seasoned Aaa Corporate Bond Yield		•		•	•		•
GS10	10-Year Treasury Constant Maturity Rate		•		•	•		•
M2SL	M2 Money Stock (Growth Rate)		•		•	•		•
FEDFUNDS	Effective Federal Funds Rate		•		•	•		•
REALRATES	Real Interest Rates (3m T-Bill minus Inflation) / Real Rates	•	•	•	•	•		•
GNPC96	Real Gross National Product					•	•	•
PCEPILFE	Personal Consumption Exp.: Chain-Type Price Index Less Food and Energy					•	•	•
CPIAUCSL	CPI for All Urban Consumers: All Items					•	•	•
CPIUFDSL	CPI for All Urban Consumers: Food					•	•	•
CPIMEDSL	CPI for All Urban Consumers: Medical Care					•	•	•
CPIAPPNS	CPI for All Urban Consumers: Apparel					•	•	•
CPIENGNS	CPI for All Urban Consumers: Energy					•	•	•
CUUR0000SEHA	CPI for All Urban Consumers: Rent of primary residence					•	•	•
CPITRNSL	CPI for All Urban Consumers: Transportation					•	•	•
CUSR0000SAD	CPI for All Urban Consumers: Durables					•	•	•
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					•		•
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					•	•	•

List of Variables *(Continued)*

Mnemonic	Variable Description / Short Label	Small	Large	Small SPF	Large SPF	Factors	Log	RW Prior
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					•	•	•
PNFI	Private Nonresidential Fixed Investment					•	•	•
PRFI	Private Residential Fixed Investment					•	•	•
ULCBS	Business Sector: Unit Labour Cost					•	•	•
HOABS	Business Sector: Hours of All Persons					•	•	•
IPDCONGD	Industrial Production: Durable Consumer Goods					•	•	•
IPBUSEQ	Industrial Production: Business Equipment					•	•	•
IPCONGD	Industrial Production: Consumer Goods					•	•	•
IPNCONGD	Industrial Production: Nondurable Consumer Goods					•	•	•
IPDMAT	Industrial Production: Durable Materials					•	•	•
IPNMAT	Industrial Production: Nondurable Materials					•	•	•
NAPM	ISM Manufacturing: PMI Composite Index					•	•	•
NAPMSDI	ISM Manufacturing: Supplier Deliveries Index					•	•	•
NAPMEI	ISM Manufacturing: Employment Index					•	•	•
NAPMPI	ISM Manufacturing: Production Index					•	•	•
NAPMPRI	ISM Manufacturing: Prices Index					•	•	•
PPIFGS	Producer Price Index: Finished Goods					•	•	•
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 Authorised 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					•	•	•

Technical and Data Appendix to*
Government Spending Reloaded:
Informational Sufficiency and Heterogeneity in Fiscal VARs

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A Technical Appendix

In this technical appendix, we discuss the issue of non-fundamentalness and the details of our econometric model and estimation strategy. In section A.1, we discuss how non-fundamentalness is related to fiscal foresight. In section A.2, we present a simple model to develop some intuition on how a large information approach may help to address non-fundamentalness. Finally, in sections A.3 and A.4 we provide details of our Large Bayesian VAR model and the estimation strategy.

A.1 Non-fundamentalness in Fiscal SVAR models

Let us assume that the *true* equilibrium solution of the equations describing the economy, at any point in time, can be approximated by a VARMA process solution to the reduced form system of equilibrium equations,

$$\Phi(L)Y_t = \Theta(L)u_t \ , \qquad u_t \sim w.n.(0, I_q) \tag{1}$$

where Y_t is an N-dimensional vector of macroeconomic variables and u_t is a q-dimensional vector of orthonormal white noise processes, that can be thought of as structural shocks.[1] The AR and MA filters are polynomial matrices defined as $\Phi(L) = I_N + \sum_{k=1}^{p_1} \phi_k L^k$ and $\Theta(L) = \sum_{k=0}^{p_2} \theta_k L^k$, respectively, where I_n is the n-dimensional identity matrix and L is the lag operator. The AR component is generally assumed to be causal and stationary.

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[1] Y_t can be either an N-dimensional vector whose entries are $I(0)$ or k-differences of $I(k)$ processes.

This condition amounts to requiring that all the complex roots of the determinants of the AR matrix lie outside the unit circle.

Given the assumption of stationarity, the process Y_t always admits a Wold representation, that is a decomposition in $\epsilon_t \equiv Y_t - P(Y_t|\{Y_{t-1}, Y_{t-2}, \dots\})$, the linear forecast errors of Y_t,

$$Y_t = \delta_t + \Psi(L)\epsilon_t \qquad \epsilon_t \sim w.n.(0, \Sigma_q) \tag{2}$$

where $\Psi(L) = I_N + \sum_{k=1}^{\infty} \psi_k L^k$ and δ_t is a deterministic process.

If we assume that the MA component is also invertible – i.e., all the complex roots of the determinants of the MA matrix lie outside the unit circle – then ϵ_t and u_t belong to the space generated by present and past values of Y_t. The structural shocks u_t are a linear combination of innovations ϵ_t, and we say that u_t is Y_t-fundamental.

If instead the determinant of the MA matrix has at least one root inside the unit circle, than ϵ_t and u_t do not live in the same space. In particular, u_t does not belong to the space generated by present and past Y_t and we say that u_t is Y_t-non-fundamental.[2]

A crucial point is that fundamental and non-fundamental MA components are observationally equivalent. Two ARMA processes with the same AR component and with MA components such that

$$\Theta(L)u_t = \tilde{\Theta}(L)\tilde{u}_t \tag{3}$$

$$\Theta(z)\Theta(z^{-1})' = \tilde{\Theta}(z)\tilde{\Theta}(z^{-1})' \tag{4}$$

have identical covariance generating functions and spectra. All the observationally equivalent representations are generated by Blaschke transformations (see Lippi and Reichlin (1994)).[3]

Essentially, a Blaschke transformation is the product of rotations and transformations that flip fundamental roots into non-fundamental ones, and vice versa. While simple rotations account for the form of non-uniqueness that Sims (1980) describes and that require an appropriate selection of an identification scheme (e.g., recursive identification, sign restrictions, long run restriction, etc.), more general Blaschke transformations relate fundamental to non-fundamental representations.

Non-fundamentalness can appear in the estimation of economic models either endogenously – a common feature of rational expectations models (see Hansen and Sargent (1980)) – or exogenously, due to the dynamics of exogenous variables (e.g., technology shocks in Lippi and Reichlin (1993)). In the case of fiscal shocks, non-fundamentalness may arise endogenously due to the anticipation of fiscal shocks by forward-looking agents. It is worth noting that non-fundamentalness is an issue only when estimating structural models and not for forecasting. In the latter case, only the estimate of the innovations' space is necessary.

To understand how endogenous non-fundamentalness can plague the estimation of fiscal policy shocks, we need to acknowledge that the econometrician only observes a

[2]If at least one of the roots of the determinant of the MA matrix lie on the unit circle, the MA component is non-invertible but is not necessarily non-fundamental.

[3]A complex-valued matrix is a Blaschke matrix if it has no poles inside the unit circle and $B(z)B(z^{-1})' = I$. It can be shown that a generic n-dimensional Blaschke matrix can be expanded into the product of a finite number of constant orthogonal matrices and of diagonal matrices with a Blaschke factor $R(\alpha, z) = \mathrm{diag}(\frac{z-\alpha}{1-\bar{\alpha}z}, I_{n-1})$.

subset y_t of the vector of variables fully describing the economy, Y_t. Structural shocks affecting the economy Y_t, will typically also affect the subset of macroeconomic variables, y_t. However, a Y_t-fundamental structural shock u_t can become y_t-non-fundamental when observing only a limited amount of information about the economy-wide process Y_t.

The standard econometric practice consists of estimating an approximated VAR(p) model with data about a small number of variables, y_t,

$$y_t = A(L)y_{t-1} + \varepsilon_t \ , \qquad \varepsilon_t \sim w.n.(0, \Sigma_\varepsilon) \ , \qquad t \in \mathbb{Z} \tag{5}$$

where $A(L)$ is a $n \times n$ filter such that $\det(I_n - A(z))$ has roots only outside the unit circle. This condition is equivalent to the assumptions of causality and stationarity for the VAR model. In the SVAR literature it is usually assumed that structural shocks are y_t-fundamental. For y_t-fundamental shocks, innovations ε_t coincide with u_t up to an orthogonal transformation. Therefore, once eq. (5) is estimated, the structural shocks can be obtained as $\hat{u}_t = \hat{R}\hat{\varepsilon}_t$, for an appropriately selected rotation matrix R, such that $RR^T = I_n$, where the estimate $\hat{R}$ of R is obtained by imposing $n(n-1)/2$ restrictions derived from economic theory.

There are two possible issues in the standard SVAR econometric procedure. First, a finite lag VAR representation of the underlying process may not exist and therefore a VAR(p) model may estimate biased impulse response functions. Second, the assumption of fundamentalness of structural shocks with respect to the observed variables may not hold since crucial state variables do not appear in the VAR.

In the context of fiscal SVARs, the anticipation of fiscal shocks can introduce non-fundamentalness in the structural shocks. Forward-looking agents incorporate information about future fiscal shocks in their expectations and would react to announcements of policy changes. An econometrician estimating a standard SVAR would miss the true structural shocks (the signals about future changes in taxes or government spending), and would instead identify actual policy implementation which likely lags the announcement. In this case, structural shocks u_t would belong to the space spanned by future values of y_t as well. This phenomenon is called *fiscal foresight* and is at the core of the Ramey (2011) critique of traditional fiscal SVAR.

This criticism is well founded in economic theory. Using a neoclassical growth model with two shocks, Leeper et al. (2013) show that fiscal foresight poses formidable challenges to the econometrician. Even in a very simple setting, anticipation effects can distort interpretation of the identified shocks. In particular, they show that the MA representation of any pair of variables selected from capital, taxes and technology, is non-fundamental.

A.2 A Simple Model

In order to illustrate the large information approach to address the issue of fundamentalness, let us consider a simple model derived from the ones in Perotti (2011) and Leeper et al. (2013)[4]

$$\text{Max}\,\mathbb{E}_t \sum_{i=0}^{\infty} \beta^i \log C_{t+i} \tag{6}$$

$$\text{s.t. } C_t + K_t + G_t = Z_t K_{t-1}^{\alpha} \tag{7}$$

where C_t, K_t and G_t are consumption, capital and government expenditure, respectively. The productivity factor Z_t follows a lognormal process with mean zero and variance σ_z^2. The agent's Euler equation is

$$\mathbb{E}_t \left[\beta(1+R_{t+1}) \frac{C_t}{C_{t+1}} \right] = 1 \tag{8}$$

and at the non-stochastic steady state $1+R_{ss} = 1/\beta$ and $K_{ss} = (\alpha\beta)^{\frac{1}{1-\alpha}}$. Log-linearising around the steady state we get

$$c_t - \mathbb{E}_t[c_{t+1}] + \mathbb{E}_t[z_{t+1}] + (\alpha - 1)k_t = 0 \tag{9}$$

where the lower case letters denote log deviations from the steady state. Linearising the budget constraint and substituting it into the Euler equation, we find the equilibrium equation for k_t. For sufficiently small government consumption at the steady state, G, the equation admits a stable solution

$$k_t - \lambda_1 k_{t-1} = -\frac{1}{\lambda_2 \alpha\beta} \sum_{i=0}^{\infty} \frac{1}{\lambda_2^i} \mathbb{E}_t \left[((G+\alpha\beta) z_{t+i+1} - z_{t+i}) + G(g_{t+1+i} - g_{t+1}) \right] \tag{10}$$

where $\lambda_1 < 1$ and $\lambda_2 > 1$ are the roots of the characteristic equation.

We assume that log deviations for government consumption expenditure follow an exogenous process specified by

$$g_t = \gamma_{t|t-1} \tag{11}$$

where $\gamma_{t|t-1}$ is a white noise shock that is known at time $t-1$. We assume that due to an implementation lag the innovation is known to the agent one lag before being realised.

The equilibrium solution for k_t is

$$k_t - \lambda_1 k_{t-1} = \frac{1}{\lambda_2 \alpha\beta} z_t - \frac{G}{\lambda_2 \alpha\beta} \gamma_{t|t-1} + \frac{G}{\lambda_2 \alpha\beta} \left(1 - \frac{1}{\lambda_2}\right) \gamma_{t+1|t} \; . \tag{12}$$

We can rewrite the equation in more compact form as

$$k_t - \lambda_1 k_{t-1} = \delta z_t + \pi_0 \gamma_{t|t-1} + \pi_1 \gamma_{t+1|t} \tag{13}$$

where the coefficients are defined as in the prior equation.

The VARMA representation is

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1-\lambda_1 L \end{pmatrix} \begin{pmatrix} g_t \\ z_t \\ k_t \end{pmatrix} = \begin{pmatrix} L & 0 \\ 0 & 1 \\ \pi_1 + \pi_0 L & \delta \end{pmatrix} \begin{pmatrix} \gamma_{t+1|t} \\ z_t \end{pmatrix} \tag{14}$$

[4]A similar argument has been proposed in Forni and Gambetti (2010) for factor models.

Given the invertibility of the AR component, we can reformulate the system in the MA representation

$$\begin{pmatrix} g_t \\ z_t \\ k_t \end{pmatrix} = \begin{pmatrix} L & 0 \\ 0 & 1 \\ \frac{\pi_1+\pi_0 L}{1-\lambda_1 L} & \frac{\delta}{1-\lambda_1 L} \end{pmatrix} \begin{pmatrix} \gamma_{t+1|t} \\ z_t \end{pmatrix} \tag{15}$$

The MA component for the square subsystem given by capital and government consumption expenditure is non-fundamental.

$$\begin{pmatrix} g_t \\ k_t \end{pmatrix} = \begin{pmatrix} L & 0 \\ \frac{\pi_1+\pi_0 L}{1-\lambda_1 L} & \frac{\delta}{1-\lambda_1 L} \end{pmatrix} \begin{pmatrix} \gamma_{t+1|t} \\ z_t \end{pmatrix} \tag{16}$$

To verify that the structural shocks are non-fundamental, it is sufficient to observe that the determinant of the relative squared MA component is equal to $\frac{\delta z}{1-\lambda z}$ and has root equal to zero, inside the unit circle. This is also true for the other two-by-two subsystems

$$\begin{pmatrix} g_t \\ z_t \end{pmatrix} = \begin{pmatrix} L & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \gamma_{t+1|t} \\ z_t \end{pmatrix} \tag{17}$$

$$\begin{pmatrix} z_t \\ k_t \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ \frac{\pi_1+\pi_0 L}{1-\lambda_1 L} & \frac{\delta}{1-\lambda_1 L} \end{pmatrix} \begin{pmatrix} \gamma_{t+1|t} \\ z_t \end{pmatrix} \tag{18}$$

for which the determinants of the MA matrix are z and $\frac{\pi_1+\pi_0 z}{1-\lambda z}$, respectively and have roots 0 and $-\pi_1/\pi_0$, both less than one in modulus.

To recover fundamental representations of the two-by-two system for z_t and g_t we could apply the following Blaschke matrix

$$\begin{pmatrix} 1 & 0 \\ 0 & \frac{z+\frac{\pi_1}{\pi_0}}{1+\frac{\pi_1}{\pi_0}z} \end{pmatrix} . \tag{19}$$

Note that *a priori* it is difficult to guess the exact form of the transformation needed.

Instead, including the larger set of variables, we get a finite order VAR(2) (of reduced rank) for the VARMA representation for which the structural shocks are fundamental:

$$\begin{pmatrix} 1+\frac{\pi_0}{\pi_1}L & \frac{\delta}{\pi_1}L & -\frac{1}{\pi_1}L+\frac{\lambda_1}{\pi_1}L^2 \\ 0 & 1 & 0 \\ -\frac{\pi_0}{\pi_1} & -\frac{\delta}{\pi_1} & \frac{1}{\pi_1}-\frac{\lambda_1}{\pi_1}L \end{pmatrix} \begin{pmatrix} g_t \\ z_t \\ k_t \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ 0 & 1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} \gamma_{t+1|t} \\ z_t \end{pmatrix} . \tag{20}$$

Adding an unanticipated shock (the structural shock of interest) to government spending

$$g_t = \gamma_{t|t-1} + \varepsilon_t \ , \tag{21}$$

we get the equilibrium solution for k_t

$$k_t - \lambda_1 k_{t-1} = \delta z_t + \pi_0 \gamma_{t|t-1} + \pi_1 \gamma_{t+1|t} + \pi_0 \varepsilon_t \ . \tag{22}$$

The VAR(2) representation is now:

$$\begin{pmatrix} 1+\frac{\pi_0}{\pi_1}L & \frac{\delta}{\pi_1}L & -\frac{1}{\pi_1}L+\frac{\lambda_1}{\pi_1}L^2 \\ 0 & 1 & 0 \\ -\frac{\pi_0}{\pi_1} & -\frac{\delta}{\pi_1} & \frac{1}{\pi_1}-\frac{\lambda_1}{\pi_1}L \end{pmatrix} \begin{pmatrix} g_t \\ z_t \\ k_t \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ z_t \\ \gamma_{t+1|t} \end{pmatrix}. \tag{23}$$

We can observe that the unanticipated fiscal shocks can be recovered with a recursive identification since the matrix of contemporaneous correlations is:

$$A_0 = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ -\frac{\pi_0}{\pi_1} & -\frac{\delta}{\pi_1} & \frac{1}{\pi_1} \end{pmatrix} \qquad C = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}. \tag{24}$$

A.3 A Large Fiscal Bayesian VAR

Banbura et al. (2010) show that by applying Bayesian shrinkage, it is possible to handle large unrestricted VARs. This allows the VAR framework to be applied to empirical problems that require large data sets, potentially solving the issue of omitted variable bias. In particular, De Mol et al. (2008) prove that for the analysis of data sets that are characterised by strong collinearity, which is typically the case for macroeconomic time series, it is possible to increase the cross-sectional dimension by consistently setting the degree of shrinkage in relation to the size of the model. In this way, it is possible to control for over-fitting while preserving the relevant sample information.

We consider the following VAR(4) model:

$$y_t = C + A_1 y_{t-1} + A_2 y_{t-2} + A_3 y_{t-3} + A_4 y_{t-4} + \varepsilon_t \tag{25}$$

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

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

$$\Sigma \sim IW(\Psi, d) \tag{26}$$

$$\beta|\Sigma \sim N(b, \Sigma \otimes \Omega) \tag{27}$$

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

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

- **Minnesota prior:** This prior is based on the assumption that each variable follows a random walk process, possibly with drift. This is quite a parsimonious, though reasonable approximation of the behaviour of economic variables. Following Kadiyala and Karlsson (1997), we set the degrees of freedom of the Inverse-Wishart distribution to $d = n + 2$ which is the minimum value that guarantees the existence of the prior mean of Σ.[5] Moreover, we assume Ψ to be a diagonal matrix with $n \times 1$ elements ψ along the diagonal. The coefficients $A_1, \ldots, A_4$ are assumed to be *a priori* independent. Under these assumptions, the following first and second moments analytically characterise this prior:

$$E[(A_k)_{i,j}] = \begin{cases} \delta_i & j = i, \; k = 1 \\ 0 & \text{otherwise} \end{cases} \tag{28}$$

$$V[(A_k)_{i,j}] = \begin{cases} \frac{\lambda^2}{k^2} & j = i \\ \vartheta \frac{\lambda^2}{k^2} \frac{\psi_i}{\psi_j/(d-n-2)} & \text{otherwise.} \end{cases} \tag{29}$$

These can be casted in the form of (27). The coefficients δ_i that were originally set by Litterman were $\delta_i = 1$ reflecting the belief that all the variables of interest follow a random walk. However, it is possible to set the priors in a manner that incorporates the specific characteristics of the variables. We set $\delta_i = 0$ for variables that in our prior beliefs follow a white noise process and $\delta_i = 1$ for those variables that in our prior beliefs follow a random walk process.[6] We assume a diffuse prior on the intercept. The factor $1/k^2$ is the rate at which prior variance decreases with increasing lag length. The coefficient ϑ weights the lags of the other variables with respect to the variable's own lags. We set $\vartheta = 1$. The hyperparameter λ controls the overall tightness of the prior distribution around the random walk or white noise process. A setting of $\lambda = \infty$ corresponds to the ordinary least squares (OLS) estimates. For $\lambda = 0$, the posterior equals the prior and the data does not influence the estimates.

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

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

where $J_p = diag(1, 2, ..., p)$.[7] In this setting, the first block of dummies in the matrices imposes priors on the autoregressive coefficients, the second block implements priors for the covariance matrix and the third block reflects the uninformative prior for the intercept (ε is a very small number).

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

[6]Details of our prior selection are provided in Appendix B where we describe the dataset used.

[7]This amounts to specifying the parameter of the Normal-Inverse-Wishart prior as

$$b = (x_d' x_d)^{-1} x_d' y_d, \Omega_0 = (x_d' x_d)^{-1}, \Psi = (y_d - x_d B_0)'(y_d - x_d B_0)$$

.

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

$$\begin{aligned} y_d &= \text{diag}(\delta_1\mu_1, ..., \delta_n\mu_n)/\tau \\ x_d &= ((1_{1\times p}) \otimes \text{diag}(\delta_1\mu_1, ..., \delta_n\mu_n)/\tau \ \ 0_{n\times 1})\,. \end{aligned} \tag{30}$$

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

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

The adoption of these priors has been shown to improve the forecasting performance of VAR models, effectively reducing the estimation error while introducing only relatively small biases in the estimates of the parameters (e.g. Banbura et al. (2010); De Mol et al. (2008); Sims and Zha (1996)).

The regression model augmented with the dummies can be written as a VAR(1) process

$$y_* = x_* B + e_* \tag{31}$$

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

The resulting posteriors are:

$$\Sigma|y \sim IW\left(\tilde{\Psi}, T_d + 2 + T - k\right) \tag{32}$$

$$\beta|\Sigma, y \sim N\left(\hat{\beta}, \Sigma \otimes ({x_*}'x_*)^{-1}\right) \tag{33}$$

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

A.4 Prior Selection

In selecting the value of the hyperparameters of our priors, we adopt the pure Bayesian method proposed in Giannone et al. (2012).[8]

[8]In prior literature, a number of heuristic methodologies have been proposed to set the hyperpriors either by maximising the out-of-sample forecasting performance of the model (see Doan et al. (1983))

From a purely Bayesian perspective, the informativeness of the prior distribution is one of the many unknown parameters of the model that can be inferred given the conditional posterior distribution of the observed data. Therefore, hyperparameters can be optimally chosen by maximising the posterior distribution given by the product of the maximum likelihood (ML) of the observed data conditional on the hyperparameters, $p(y|\gamma)$, and the hyperprior distribution $p(\gamma)$

$$p(\gamma|y) \propto \ p(y|\gamma) \cdot p(\gamma) \tag{34}$$

The hyperprior can be viewed as a level two prior on the hyperparameters, while the maximum likelihood is the probability of the data as a function of the hyperparameter obtained by integrating over the VAR coefficients

$$p(y|\gamma) = \int p(y|\theta,\gamma)p(\theta|\gamma)d\theta \ . \tag{35}$$

For a flat hyperprior, the posterior coincides with the ML, hence the choice of the hyperparameters can be thought of as maximising the one-step-ahead out-of-sample forecasting ability of the model. This proposed procedure selects the optimal amount of shrinkage given the sample and the model. The selected priors are tighter when the model features many unknown coefficients relative to the available data.

In order to use this methodology for a large information set, we make additional assumptions to reduce the number of hyperparameters to be estimated and the uncertainty in the estimation of the VAR coefficients.[9]

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

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

Following Giannone et al. (2012), we adopt a Gamma distribution with mode equal to 0.2 (the value recommended by Sims and Zha (1996)) and standard deviation equal to 0.4 as hyperprior density for λ.[10] Given the choice of conjugate priors, the ML is available in closed form and the selection of the tightness of λ amounts to maximising a closed form posterior (see Giannone et al. (2012)).

or by controlling for over-fitting by choosing the shrinkage parameters that yields a desired in-sample fit (see Banbura et al. (2010)).

[9]In the largest specification of our Large VAR we have about 50 scalar hyperparameters controlling the tightness of the priors.

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

B Data Appendix

We identify the relevant components of U.S. national income for our study using the National Income and Product Accounts (NIPA) which are made available by the Bureau of Economic Analysis of the U.S. Department of Commerce on their website.[11]

All data for the macroeconomic variables used in our model specifications are from publicly available sources. The primary source for the macroeconomic series is FRED Economic Data available from the website of the Federal Reserve Board of St. Louis (FRED).[12] Where available we use the real economic series from FRED, all of which are chained to 2005 dollars. Where the length of the real series is shorter than our sample period, we collect the nominal series and deflate it using the relevant chained-type price deflators which are all indexed at 100 in 2005. These various deflators are available on the website of the Bureau of Economic Analysis.[13]

The total public debt series (PUBDEBT) is collected from the website of the U.S. Department of Treasury.[14]

We use the consumer sentiment index developed by the University of Michigan available on their website.[15] The survey data is also available as part of the FRED Economic Data.

We collect federal government and state and local government spending forecasts published in the Survey of Professional Forecasters available on the website of the Federal Reserve Bank of Philadelphia.[16]

The Barro-Redlick marginal tax rate is the income weighted average marginal tax rate from the website of the National Bureau of Economic Research.[17]

The Real Exchange Rate is the average of the prior 3 month real effective exchange rate index for U.S. Dollars calculated by the Bank for International Settlements (BIS) and made available on the BIS website.[18] BIS calculates the real effective exchange rate as geometric weighted averages of bilateral exchange rates adjusted by relative consumer prices. The weighting pattern is time-varying, and is based on bilateral trade data. Since the data series begins in Q1:1964, we compute the real exchange rate for the period Q1:1959 to Q4:1963 using the methodology described by BIS.

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

[12] `research.stlouisfed.org/fred2/`

[13] `http://www.bea.gov/itable/index.cfm`

[14] `http://www.treasury.gov/resource-center/data-chart-center/Pages/index.aspx`

[15] `http://www.sca.isr.umich.edu/`

[16] `http://www.phil.frb.org/research-and-data/real-time-center/`

[17] `http://users.nber.org/~taxsim/barro-redlick/currentp1.html`

[18] `http://www.bis.org/statistics/eer/index.htm`

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