Government Spending Reloaded: Fundamentalness and Heterogeneity in Fiscal SVARs

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Abstract

Using a large information approach and full Bayesian VAR techniques, we study the economic effects of fiscal policy shocks in the U.S. over the last five decades. We find that omitted variables can explain the well known sample instability of the estimates for the fiscal multiplier. We also find evidence of fiscal foresight and anticipation of the government spending shocks recovered from small Structural VARs (SVARs). Despite incorporating forecasts of government spending, Expectational VARs (EVARs) also show signs of fiscal foresight and anticipation. Conversely, the fiscal shocks recovered from a large information BVAR do not exhibit the same problem. Moreover, large information SVARs and EVARs deliver identical dynamic responses to fiscal shocks. Finally, we report multipliers and impulse response functions for aggregate government spending as well as for components of government spending, and find remarkably heterogeneous responses.

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1 Introduction

The economic consequences of the 2007-2012 global financial crisis have reignited interest in fiscal stimulus packages as tools for economic stabilisation. This reflects the unprecedented scale of the downturn in terms of duration and severity, and the limits that monetary policy is experiencing with nominal short-term safe interest rates down to zero. Many developed world governments boosted fiscal spending and enacted tax reductions with the aim to stimulate consumption, production and investment.

However, despite extensive research there is still a high degree of uncertainty regarding the macroeconomic impact of these measures. Differently from the effects of monetary policy changes for which there is substantial consensus, the effects of fiscal policy shocks remain controversial. Indeed, not only the size but also the sign of the responses of private aggregate demand components is debated. In particular, there is inconsistent evidence regarding consumption which is a crucial determinant of the magnitude of the government spending multiplier. Empirical literature has used different identification strategies and different empirical settings in order to isolate fiscal shocks and to estimate their effects without reaching a consensus view. Structural Vector Autoregression (SVAR) models in which identification is usually obtained by assuming decision lags in government spending find rather consistently that an unexpected increase in government spending raises not only GDP and worked hours, but also consumption and the real wage (e.g., Blanchard and Perotti (2002), Fatás and Mihov (2001), Galí et al. (2007), Perotti (2008)).[1] On the contrary, analyses using a narrative identification of government spending shocks typically find that while government spending raises GDP and worked hours, it lowers consumption and the real wage (e.g., Ramey and Shapiro (1998), Ramey (2011a), Barro and Redlick (2009)). Moreover, multiplier estimates appear to be highly unstable and sensitive to the choice of the sample periods. As pointed out in Perotti (2008, 2011) and in Ramey (2011b), changes in the sample specification can lead to largely different results.

As pointed out in Ramey (2011a), the identification of fiscal shocks has also proven challenging due to potential anticipation effects of fiscal policy changes and their lagged implementation. While economic agents react to the announcement of the policy changes, the econometrician only observes the economic variables and the innovation produced by the implementation of the new policy. This phenomenon, known as *fiscal foresight*, poses significant challenges to the econometrician generating non-fundamental Moving Average (MA) components in the equilibrium processes (see Leeper et al. (2008)). This implies that fiscal shocks and the relative dynamic responses cannot be estimated using a standard SVAR (see Hansen and Sargent (1980), Lippi and Reichlin (1993)).

The study of the consequences of fiscal expansions is also an intriguing problem from a theoretical point of view. The effects of an increase in government spending are ambiguous and depend on the assumed model. While the neoclassical Real Business Cycle (RBC) and the old Keynesian and neo-Keynesian models are broadly

[1] A thoughtful survey on fiscal SVAR can be found in Caldara and Kamps (2006, 2008).

consistent with regard to the effect of expansionary government spending on output, they reach different conclusions on the magnitude of the multiplier and on the sign of the response of consumption and real wages. Neoclassical models (e.g., Baxter and King (1993)) generally imply a smaller multiplier than neo-Keynesian models and, crucially, according to these models the size of the multiplier is sensitive to how the spending is financed. In particular, the multiplier is smaller if spending is financed by distortionary taxes rather than by lump sum taxes. Moreover, 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., Galí et al. (2007)).

A growing number of papers convincingly point out that government spending multipliers cannot be thought of as structural constants but as the responses of endogenous variables to shocks in government purchases. In this respect, there is no single government spending multiplier and its value is likely to depend on the country, the economic phase, 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, the expectation about future policy adjustments as well as the nature, direction and magnitude of the shock.[2,3]

Prior literature has mostly used small information sets to measure the effects of a change in government spending. Recently, several studies have argued that it is necessary to incorporate more information in standard SVARs in order to account for agents' expectations and to overcome the issue of fiscal foresight (e.g., Ramey (2011a), Leeper et al. (2011) and Fisher and Peters (2010)) or to control for potentially omitted variables such as the public debt dynamics (e.g., Favero and Giavazzi (2007) and Ilzetzki (2011)), the level of economic development, the exchange rate regime, and the openness to trade (e.g., Ilzetzki et al. (2010), Born et al. (2012)).

Our paper applies a large information approach and full Bayesian VAR techniques to study the economic effects of fiscal policy shocks using U.S. data from 1959 to 2010. A large Bayesian VAR allows us to significantly expand the dataset used in order to analyse shocks to government spending.[4] This approach aims to align the respective information sets of the econometrician and of the economic agents. Indeed, large information datasets are generally considered good approximations of the whole economy and allow a more careful study of fiscal shocks while controlling for issues of non-fundamentalness, and more generally for omitted variable problems.

The key findings of our paper can be summarised as follows. First, the well known

[2]A large number of recent theoretical papers have studied the effectiveness of an increase in government consumption in various settings (see Woodford (2011), Hall (2009), Christiano et al. (2011), Monacelli and Perotti (2008), Corsetti et al. (2011), among others).

[3]A relevant empirical paper studying the variation of fiscal multipliers across the business cycle is Auerbach and Gorodnichenko (2012).

[4]Banbura et al. (2010) show that by applying Bayesian shrinkage, it is possible to handle large unrestricted VARs that allow the VAR framework to be applied to empirical problems that require the analysis of 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.

sample instability of the estimates for the fiscal multipliers appear to be significantly mitigated using a large information approach and is reduced to a statistically insignificant level, given the confidence level delivered by our econometric tools. After controlling for changes in monetary policy, fiscal policy, budget structure, credit access, financial markets and the openness of the economy, the dynamic responses of macroeconomics variables appear to be virtually the same across subsamples. This result seems to indicate that using a large information set it is possible to fully control for policy changes, revealing that the behaviour of economic agents is more stable over time than previously reported.

Second, the traditional SVAR approach shows signs of non-fundamentalness for small VARs (similar findings have been reported in Forni and Gambetti (2010)). While the issue of non-fundamentalness appears to be somewhat mitigated using a moderate number of variables, the more general problem of omitted variables likely remains, resulting in biased IRFs to fiscal shocks.

Third, the Expectational VAR (EVAR) approach proposed in Ramey (2011a) to overcome non-fundamentalness in small VARs still seems to suffer from non-fundamentalness. In fact, using a large information set the dynamic responses to shocks in expectations, as defined in Ramey (2011a), appear to be identical to the IRFs produced using the SVAR approach.

Fourth, the use of a large information set seems to overcome the non-fundamentalness issues. Using a large Bayesian VAR, the macroeconomic variables related to output, consumption and investment show a remarkably heterogeneous dynamic response to shocks in different components of government consumption and investment. In particular, defence spending appears to elicit dynamic responses that are qualitatively different compared with nondefence spending. Dynamic responses and multipliers for fiscal shocks are broadly consistent to those in standard VAR literature. However, the responses are difficult to reconcile with standard Real Business Cycle models, and are also not fully consistent with neo-Keynesian predictions.

Our paper is closely related to the paper of Forni and Gambetti (2010), in which fiscal shocks are studied using a large factor model and sign restrictions. The common underlying intuition is that large dimension datasets are necessary to close the gap between the information sets of economic agents and of the econometrician. The results in Forni and Gambetti (2010) and in our paper are broadly consistent.

To correctly interpret our results, it is important to remember that applying a static linear VAR approach, we estimate time-invariant and linear (marginally constant and symmetric with respect to the sign of the shock) government spending multipliers. Therefore, we implicitly assume through our choice of the econometric model that the 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)). For this reason, our IRFs and multipliers needs to be thought of as statistical averages over largely different economic conditions and policies.

The remainder of our paper proceeds as follows. Section 2 discusses the identification of fiscal shocks and previous literature, Section 3 motivates our use of the different components of government spending, Section 4 covers the issue of non-fundamentalness in fiscal VARs, Section 5 introduces our large information fiscal Bayesian VAR, Section 6 presents our empirical findings and Section 7 concludes.

2 Identification of Fiscal Shocks

Empirical identification of fiscal shocks requires the econometrician to isolate innovations in the fiscal policy variable of interest (for example, government spending) that are uncorrelated with contemporaneous economic shocks and are separate from systematic variations related to the business cycle.

Prior literature has identified fiscal shocks by employing three main strategies[5]. The first strategy involves estimating *Structural Vector Autoregressive Regressions (SVARs)*, using orthogonality assumptions to identify innovations in fiscal policy along the lines of Blanchard and Perotti (2002). Using mainly quarterly data, a large number of studies have employed this approach supplemented with a number of theoretically motivated identification assumptions, to analyse fiscal policy shocks over a large number of countries (e.g., Perotti (2008); Galí et al. (2007); Burriel et al. (2010)). The shocks are identified by exploiting decision lags in policy-making and information about the elasticity of fiscal variables to economic activity. A different agnostic identification procedure based on sign restrictions has been applied in Mountford and Uhlig (2009) to identify and estimate the effects of a balanced budget and a deficit spending shock. The results of this study suggest that government spending has a negative impact on both residential and non-residential investment, but does not affect consumption which shows a small and insignificant response. As summarised by Hall (2009), prior empirical literature using SVARs finds output multipliers in the range from 0.5 to 1.0, and consumption multipliers in the range from somewhat negative to 0.5. Studies also usually find that a positive government spending shock raises hours worked and real wages, while having a negligible impact on private investments.

The second strategy relies on developing a *narrative identification* of the fiscal shocks. Proponents of narrative identification argue that the SVAR approach fails to deal with the endogeneity and anticipation of fiscal shocks. In the narrative approach, the correct timing of fiscal shocks is recovered using historical narrative about major military events and proxy measures of agents' expectations of policy changes. Most studies adopting narrative identifications have focused on defence spending and follow Barro (1981) in arguing that fluctuations in military spending in the United States during major wars can be thought of as completely exogenous. Ramey and Shapiro (1998) use dummy variables in order to identify the correct timing of the shocks to defence spending and find that consumption falls, implying a very small value for the government spending multiplier. Barro and Redlick (2009) use data starting in 1917, including the two World Wars, to estimate that the output multiplier ranges from 0.6 to 0.8. Their estimates of the consumption multiplier are close to zero.

Starting from a narrative approach, Ramey (2011a) argues that in the SVAR approach the government spending shocks estimated by the econometrician are likely

[5] An in-depth survey of the state of knowledge about the government spending multiplier can be found in Ramey (2011c).

to be anticipated, and that this can lead to a spurious finding of a positive effect of these shocks on consumption and real wages. The general issue originates from the fact that the information sets of the private agents and the econometrician may be misaligned. In the case of fiscal policy anticipation, this would mean that private agents have a broader information set relative to the *ex-post* variables observed by the econometrician. The fiscal policy shocks cannot be recovered since the MA representation is non-invertible or non-fundamental for the variables used in the VAR, due to fiscal foresight.

Given this criticism there would be little basis to use a SVAR approach, unless it could be demonstrated that in practice anticipation issues are not present in the estimation of fiscal policy shocks (possibly due to liquidity constraints agents, rational-inattentive consumers, or high uncertainty in the future path of taxes and spending) or that it is possible to formulate econometric techniques to overcome the non-fundamentalness issue.[6]

The solution proposed in Ramey (2011a) is to use a direct measure of change in the expectations of the present value of government spending to obtain an Expectational VAR (EVAR). Using this approach, private sector forecast revisions appear to have a strong negative effect on consumption and a low multiplier for GDP.

The third strategy uses *natural experiments* as sources of exogenous variations in government spending, taxes or transfers that are uncorrelated with other contemporaneous macroeconomic events. Natural experiments have been used in different settings that range from regional to internationally funded development programs. Nakamura and Steinsson (2011) focus on cross-state variations in U.S. military spending activity that are likely to be uncorrelated with state-level economic conditions. Regional fiscal GDP multipliers estimated using this identification strategy are large and above unity. Fishback and Kachanovskaya (2010) also study the state-level effects of federal spending, but focus on the New Deal period using a measure of swing voting behaviour as an instrument. The output multiplier is estimated between 0.9 to 1.7. Acconcia et al. (2011) exploit anti-mafia legislation outcomes on municipal budget spending in Italy and find estimated spending multipliers ranging from 1.4 to 2.0. Kraay (2010) uses World Bank project-level disbursement data to isolate the component of World Bank-financed government spending in a given year that is associated with past project approval decisions and then uses this as an instrument for total government spending, in order to estimate spending multipliers in a sample of 29 primarily low-income countries. The estimated GDP multiplier is fairly low and around 0.5. Using data from the Consumer Expenditure Survey, Johnson et al. (2006), Parker et al. (2011), and Misra and Surico (2011) have exploited the randomised timing of the receipt of payments to estimate the effects of the fiscal stimulus payments on consumption expenditures for the tax rebate episodes of 2001

[6]Burriel et al. (2010) report that, using a standard SVAR approach with U.S. and Euro area data, the identified government spending shocks can be interpreted in light of historical episodes. Moreover, the tax shocks of the VAR in the case of the U.S. seem to reproduce the episodes identified by Romer and Romer (2010) with their natural experiment approach. Ilzetzki et al. (2010) provide some evidence that fiscal shocks are not foreseen. Using data revisions by central banks, for which time series of government consumption data of different vintages are available – Bulgaria, Ecuador, and Uruguay – the authors show that errors in the central banks preliminary estimate of government consumption are clearly correlated with the VAR residuals.

and 2008. Besley et al. (2012) employ evidence from a stamp duty holiday in U.K. to identify the effects of a transactions tax. Other studies have used changes in Congressional committee chairmanships to identify changes in federal spending at the state level in the U.S. (Cohen et al. (2010)); Medicaid transfers to U.S. states during the 2009 fiscal stimulus (Chodorow-Reich et al. (2012)); variation across U.S. states in enforcing a balanced-budget (Clemens and Miran (2010)); and variation in federal spending at local levels due to sharp changes in population estimates stemming from methodological changes in census years (Serrato and Wingender (2010)).

3 Heterogeneity in Government Spending

As noted in Oh and Reis (2011), macroeconomic research on fiscal shocks has primarily studied the effects of increases in government purchases (consumption plus investment).[7] This choice is motivated by the fact that this component of spending is viewed as the most exogenous component of total government spending relative to the business cycles and likely does not affect intertemporal consumption choices or marginal rates of substitutions between consumption and work.

Extant research pursuing a narrative approach has argued that only military spending is truly *exogenous* being caused by geopolitical events uncorrelated with other economic shocks. Changes in defence spending have been large in magnitude and are arguably unpredictable. The historically high variance of these shocks allows them to be readily identified and their economic consequences to be assessed. Military shocks also present the interesting feature that they can be considered as purely unproductive, *thrown-in-the-ocean*, spending, offering the possibility of discriminating between the predictions of different neo-Keynesian and neoclassical models.

However, one possible criticism of the results obtained in the narrative literature is that the evidence comes primarily form the huge defence spending spikes related to World War II and the Korea War, and may not be relevant for today economy. Prior literature has noted that significant military spending due to major military events are historically associated with command-type interventions in the economy, including rationing (see Hall (2009)). These can result in issues of *validity* and a failure of the identifying assumptions.

Conversely, the SVAR approach mainly uses aggregate government spending and often the time series used excludes WWII. In these samples fiscal shocks are smaller and the parameters are poorly estimated. Moreover, SVARs use components of government spending that may not be completely exogenous even in absence of fiscal foresight, potentially suffering from *endogeneity problems*. Finally, components of nondefence government spending may enter either the aggregate production function or the utility function of agents, producing *externalities*. Hence, results from this

[7]Government expenditures are the sum of purchases, transfers and interest payments. While the latter component of the budget is small the first two are relatively large although the second is the most countercyclical one. For example, in the U.S. from the end of 2007 until the end of 2009, only one quarter of the increase government expenditures is accounted for by government purchases, while three quarters of the increase is due to increases in transfers. Unfortunately, there is a dearth of empirical research on the macroeconomic effects of transfers.

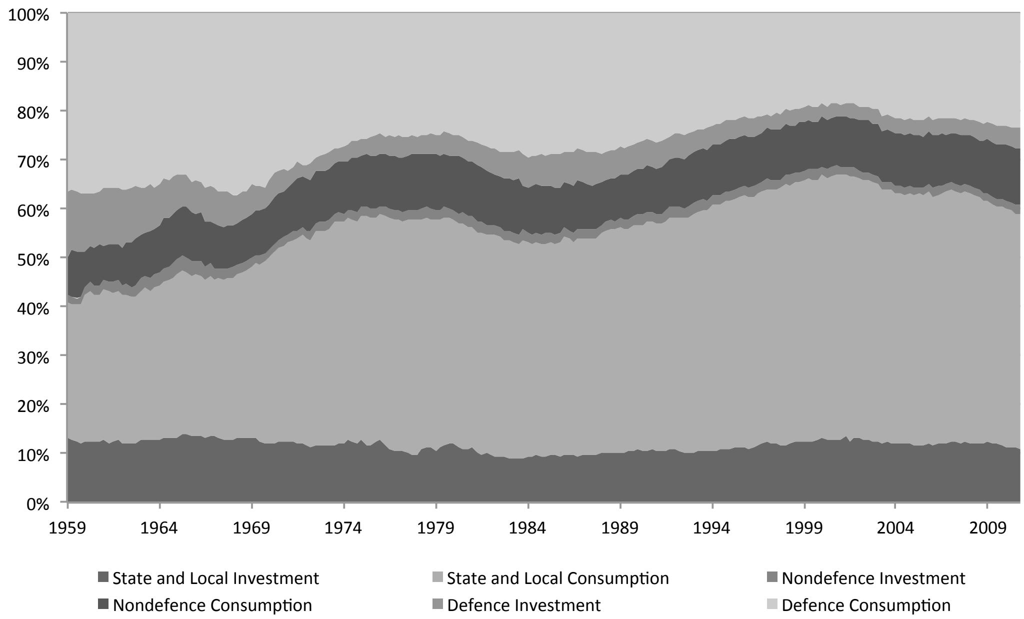

Figure 1: Government Spending Breakdown (billions of U.S. dollars).

	1959	1981	2010
State and Local Investment	13.3	10.0	11.1
State and Local Consumption	27.6	44.7	47.9
Nondefence Investment	1.6	2.0	1.8
Nondefence Consumption	7.7	11.2	11.7
Defence Investment	13.2	4.8	4.2
Defence Consumption	36.6	27.3	23.2
State and Local Spending	40.9	54.7	59.1
Nondefence Spending	9.3	13.2	13.5
Defence Spending	49.8	32.1	27.5

Table 1: Government Spending Breakdown

SVAR methodology may not be useful to discriminate between competing economic theories.

Furthermore, in the last fifty years, defence spending has fallen from almost 50 percent of government spending to 28 percent in 2010 (see Figure 1 and Table 1). While federal nondefence spending is a trivial part of overall government spending, state and local spending has become significantly more important, equaling 59 percent in 2010. The expansion in state and local spending is mostly related to spending on education, health and public services which may enter the aggregate production function. The varying composition of government expenditure over time, the potentially differential effects of the various components of spending and their interaction, could result in an omitted variable problem in studies that do not control for these sources of heterogeneity.

4 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.[8] 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. 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.[9]

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.[10]

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

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

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

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

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

[10] 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.

have identical covariance generating functions and spectra. All the observationally equivalent representations are generated by Blaschke transformations (see Lippi and Reichlin (1994)).[11]

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 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 estimated 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.

[11] 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 $R(\alpha, z) = \mathrm{diag}(\frac{z-\alpha}{1-\bar{\alpha}z}, I_{n-1})$.

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 (2011a) critique of traditional fiscal SVAR.

This criticism is well founded in economic theory. Using a neoclassical growth model with two shocks, Leeper et al. (2008) 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.

4.1 Back to Fundamentals

Non-fundamentalness can always be framed as a problem of omitted variables, originating from the misalignment of the respective information sets of the econometrician and the agent.

Two solutions are possible to solve the issue of non-fundamentalness. The first 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.

The second approach consists of enlarging the econometrician's information space; this idea underpins most of the solutions proposed in the empirical literature on fiscal shocks.[12]

There are two possibilities to enlarge the econometrician information space: one in the time dimension (including observations from future time periods), and the other in the cross-sectional dimension (enlarging the dataset with additional variables). The first method has been initially proposed in Blanchard and Perotti (2002) and then used in a more systematic way in Tenhofen and Wolff (2007). They allow present output and consumption to depend on one forward lag of fiscal variables, assuming perfect foresight of fiscal shocks one quarter ahead. Unfortunately, this assumption

[12] A different possibility unexploited in fiscal SVAR is proposed in Lanne and Saikkonen (2011) and is represented by Non-causal VARs. The assumption of causality (invertibility of the AR matrix) can be relaxed and the observable variables can also be allowed to depend on future values of the associated disturbance process. Non-causal VARs can be seen as approximated representations of VARMA models with non-invertible MA representations.

is quite strong and rather arbitrary.

The solution proposed in Ramey (2011a) is to enlarge the VAR using variables that may proxy for the agent's expectations (EVAR) (see Perotti (2011); Ramey (2011b)). In Ramey (2011a) two different measures of expectations are proposed: a *military news variable* based on narrative evidence for defence spending and a *fiscal expectations variable* based on the Survey of Professional Forecasters (SPF).[13] Along similar lines, Leeper et al. (2011) propose using the spread between municipal and treasury bonds as a measure of the anticipation of future tax changes.[14] Fisher and Peters (2010) use stock returns of large U.S. defence contractors to identify government spending shocks. The disadvantage in using proxy variables for expectations is that to some extent whether these variables are able to correctly capture the agent's expectations is a matter of assumptions.

More generally, Giannone and Reichlin (2006) assess the possibility of using larger data sets when dealing with non-fundamental models, proposing a criterion to detect non-fundamentalness based on Granger causality (an updated discussion can be found in Forni and Gambetti (2011)). Non-fundamentalness can be assessed empirically by testing whether the variables of interest are weakly exogenous with respect to potentially relevant additional variables, under the conditions that the additional variables are driven by the same structural shocks influencing the variables of interest, plus possible additional structural shocks.

Very large dataset ($N \sim 100$) are considered to be a good proxy for the whole economy and therefore, the correct treatment of such an information set should allow the econometrician to better assess and overcome issues of non-fundamentalness. As proved in Giannone and Reichlin (2006)), the 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. Remaining shocks need not propagate too widely and therefore, can meaningfully be considered idiosyncratic. 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)). While non-fundamentalness is a generic feature of standard VARs, for models with reduced rank ($N > q$) (e.g., factor models) non-fundamentalness is a non-generic issue (see Forni et al. (2009)).

In this respect, a large information approach is the most natural way to deal with the non-fundamentalness issue in the identification of fiscal shocks. Forni and Gambetti (2010) use a large structural factor model to study fiscal shocks, finding indications that the government spending shock is non-fundamental for the variables commonly used in the SVAR literature. Factor models are less general than VAR models and impose restricted VAR relations among variables.

In this paper we adopt a large Bayesian VAR approach. Large Bayesian VARs offer a natural solution to the *curse of dimensionality* problem, have proven to be

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

[14] They exploit a feature of the U.S. tax code that exempts municipal bonds from federal income tax and argue that the implicit tax rate at which the investor is indifferent between the tax exempt and taxable bond could predict subsequent movements in individual tax rates.

competitive with factor models, and allow for a more flexible and transparent treatment of large information datasets (Banbura et al. (2010); Giannone et al. (2012)). Moreover, they have a clear interpretation in terms of factor analysis (De Mol et al. (2008)). In Appendix A we present a simplified model to illustrate the issues of non-fundamentalness and to motivate the use of a large information set to deal with this issue.

5 A Large Information 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:

$$y_t = C + A_1 y_{t-1} + A_2 y_{t-2} + A_3 y_{t-3} + A_4 y_{t-4} + \varepsilon_t \tag{6}$$

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

$$\begin{aligned} \Sigma &\sim IW(\Psi, d) & (7)\\ \beta|\Sigma &\sim N(b, \Sigma \otimes \Omega) & (8) \end{aligned}$$

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.[15] Moreover, we assume Ψ to

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

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:

$$E[(A_k)_{i,j}] = \begin{cases} \delta_i & j = i,\ k = 1 \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

$$V[(A_k)_{i,j}] = \begin{cases} \frac{\lambda^2}{k^2} & j = i \\ \vartheta \frac{\lambda^2}{k^2} \frac{\psi_i}{\psi_j/(d-n-2)} & \text{otherwise.} \end{cases} \tag{10}$$

These can be casted in the form of (8). 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.[16] 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*

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

where $J_p = diag(1, 2, ..., p)$.[17] In this setting, the first block of dummies in the matrices imposes priors on the autoregressive coefficients, the second block implements priors for the covariance matrix and the third block reflects the uninformative prior for the intercept (ε is a very small number).

- **Sum-of-coefficients prior:** To further favour unit roots and cointegration and to reduce the importance of the deterministic component implied by the estimation of the VAR conditioning on the first observations, we adopt a refinement of the Minnesota prior known as *sum-of-coefficients* prior (Sims (1980)).

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

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

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

.

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:

$$\begin{aligned} y_d &= \mathrm{diag}(\delta_1\mu_1, ..., \delta_n\mu_n)/\tau \\ x_d &= ((1_{1\times p}) \otimes \mathrm{diag}(\delta_1\mu_1, ..., \delta_n\mu_n)/\tau \;\; 0_{n\times 1})\,. \end{aligned} \tag{11}$$

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. Sims and Zha (1996); De Mol et al. (2008); Banbura et al. (2010)). The regression model augmented with the dummies can be written as a VAR(1) process

$$y_* = x_* B + e_* \tag{12}$$

where the starred variables are obtained by stacking $y = (y_1, \ldots, y_T)'$, $x = (x_1, \ldots, x_T)'$ for $x_t = (y'_{t-1}, \ldots, y'_{t-4}, 1)'$, and $\varepsilon = (\varepsilon_1, \ldots, \varepsilon_T)$ 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:

$$\Sigma | y \sim IW\left(\tilde{\Psi}, T_d + 2 + T - k\right) \tag{13}$$

$$\beta | \Sigma, y \sim N\left(\hat{\beta}, \Sigma \otimes \left({x_*}' x_*\right)^{-1}\right) \tag{14}$$

where $\hat{\beta} = \mathrm{vec}(\hat{B})$, $\hat{B} = ({x_*}'x_*)^{-1}{x_*}'y_*$ 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_*.

5.1 Prior Selection

In selecting the value of the hyperparameters of our priors, we adopt the pure Bayesian method proposed in Giannone et al. (2012).[18]

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

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

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 $p(\gamma)$

$$p(\gamma|y) \propto \ p(y|\gamma) \cdot p(\gamma) \tag{15}$$

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

$$p(y|\gamma) = \int p(y|\theta, \gamma) p(\theta|\gamma) d\theta \ . \tag{16}$$

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.[19]

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 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.[20] 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)).

6 The Dynamic Effects of Fiscal Shocks

6.1 Data Description

The main macroeconomic variables of interest in our study are government consumption expenditures and investment (spending), gross domestic product, personal current taxes, hourly wages, personal consumption expenditures and gross private domestic investment. For government spending, we separately collect data for federal

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

[20]Using a flat hyperprior for λ we obtain similar numerical results.

defence, federal nondefence and state and local governments. For personal consumption expenditures, we collect data for durables, nondurables and services.

As is standard in prior literature, we collect quarterly data and use real log per capita for the output, investment and consumption variables, except those variables expressed in rates. We use the three-month U.S. Treasury Bill rate adjusted for changes in the consumer price index to calculate real short-term interest rates.

We expand the dataset to include labour, consumer sentiment, equity market, credit market, housing, production, business activity, exchange rate and monetary variables, as well as consumer and producer price indices. We also collect components of some of these variables as well as additional relevant macroeconomic variables to develop a large dataset of 128 variables which is used to extract commonalities using factor analysis. A brief description of all the variables used in our study is presented in Appendix B. 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.

We collect quarterly data for the period from 1959Q1 to 2010Q4, balancing the aim of assembling a large data set with a sufficiently long time series. We split our full sample period of 1959Q1 to 2010Q4 into two subsamples, covering 1981Q1 to 2010Q4, and 1959Q1 to 1981Q1.[21] The 1981Q1 split point is chosen in order to assess the subsample instability claimed in Perotti (2008) and is in agreement with a large stream of literature that finds a structural break in the U.S. economy in the early 1980s. This split point allows us to expand our dataset for the subsample 1981Q1 to 2010Q4 by including federal government and state and local government spending forecasts published in the Survey of Professional Forecasters (SPF) of the Federal Reserve Bank of Philadelphia. We exclude periods prior to 1959 in order not to have the Korea War and WWII in our sample, thus avoiding possible issues of validity associated with large military spending shocks in these periods.

We identify fiscal shock using a generalised recursive identification. We consider the following VAR specifications:

- SMALL: This is a small fiscal VAR with 3 variables including government consumption expenditures and investment (GCEC96), personal current taxes (PERSTAX) and gross domestic product (GDPC96).
- MEDIUM: In the base specification, this is a 9 variable VAR including government consumption expenditures and investment (GCEC96), personal current taxes (PERSTAX), gross domestic product (GDPC96), hourly wages (RCPHBS), personal consumption expenditures on durables (PCDG), nondurables (PCND) and services (PCESV), gross private domestic investment (GPDIC96), and real rates (REALRATES). In VAR specifications where the components of government consumption expenditures and investment are used, this is a 14 variable VAR including federal defence consumption and expenditures (DEFSPEND), federal defence investment (DGI), federal nondefence consumption and expenditures (CIVSPEND), federal nondefence investment (NDGI), state and local

[21] In robustness checks we also use a shortened sample from 1959Q1 to 2005Q4 to exclude the recent financial crisis and economic recession.

consumption and expenditures (SLSPEND), and state and local investment (SLINV) in addition to the other variables. In each specification where the components are used, the shock variable is ordered first. In the specifications where the SPF government federal spending forecasts are used, the various components of federal spending are aggregated. Along with the relevant spending forecast variable to which a shock is applied, these specifications have 10 variables. A similar approach is used for the VAR specifications where state and local spending forecasts are used.

- LARGE: In the base specification, this is a 39 variable VAR. In addition to the variables in the MEDIUM VAR, this specification includes federal government current receipts (FGRECPT), net federal government saving (deficit) (FGDEF), total public debt (PUBDEBT), unemployment rate (UNRATE), average duration of unemployment (UEMPMEAN), total consumer credit outstanding (TOTALSL), commercial and industrial loans at commercial banks (BUSLOANS), real estate loans at commercial banks (REALLN), oil price per barrel (OILPRICE), consumer sentiment index (UMCSENT), gross private saving (GPSAVE), disposable personal income (DSPIC96), personal consumption price index (PCECTPI), new orders index (NAPMNOI), inventories index (NAPMII), after-tax corporate profits (CPATAX), industrial production index (INDPRO), producer price index (PPIACO), productivity (OPHPBS), housing starts (HOUST), exports of goods and services (EXPGSC96), imports of goods and services (IMPGSC96), Euro to U.S. Dollar exchange rate (EUDOLLDR), S&P 500 stock market returns (SP500), Dow Jones Industrial Average stock market returns (DJIA), AAA corporate bond yield (AAA), 10-year U.S. Treasury rate (GS10), growth in M2 money stock (M2SL), and effective federal funds rate (FEDFUNDS). In VAR specifications where the components of government consumption expenditures and investment are used, this is a 44 variable VAR with each component to which the shock is applied ordered first. In specifications where the SPF government spending forecasts are used (federal or state and local), this is a 40 variable VAR.

6.2 Subsample Instability

Our first set of analyses is related to the sample instability highlighted by Perotti (2008) who finds inconsistency in the response of consumption to government spending depending on the subsample used. For example, he finds a positive and statistically significant response in the 1960s and 1970s, but an insignificant response in the 1980s and 1990s. Similar results are reported in several other studies. Therefore, we split our full sample period of 1959Q1 to 2010Q4 into two subsamples, covering 1981Q1 to 2010Q4, and 1959Q1 to 1981Q1.

We use the MEDIUM and LARGE VAR specifications to assess the sample instability issue. Figure 2 presents the impulse response function for the full sample and the two subsamples. The plots also depict the posterior coverage intervals at the 0.68 and 0.9 levels. While the IRFs for the MEDIUM VAR show subsample instability, the LARGE VAR does not exhibit significant subsample instability. In particular,

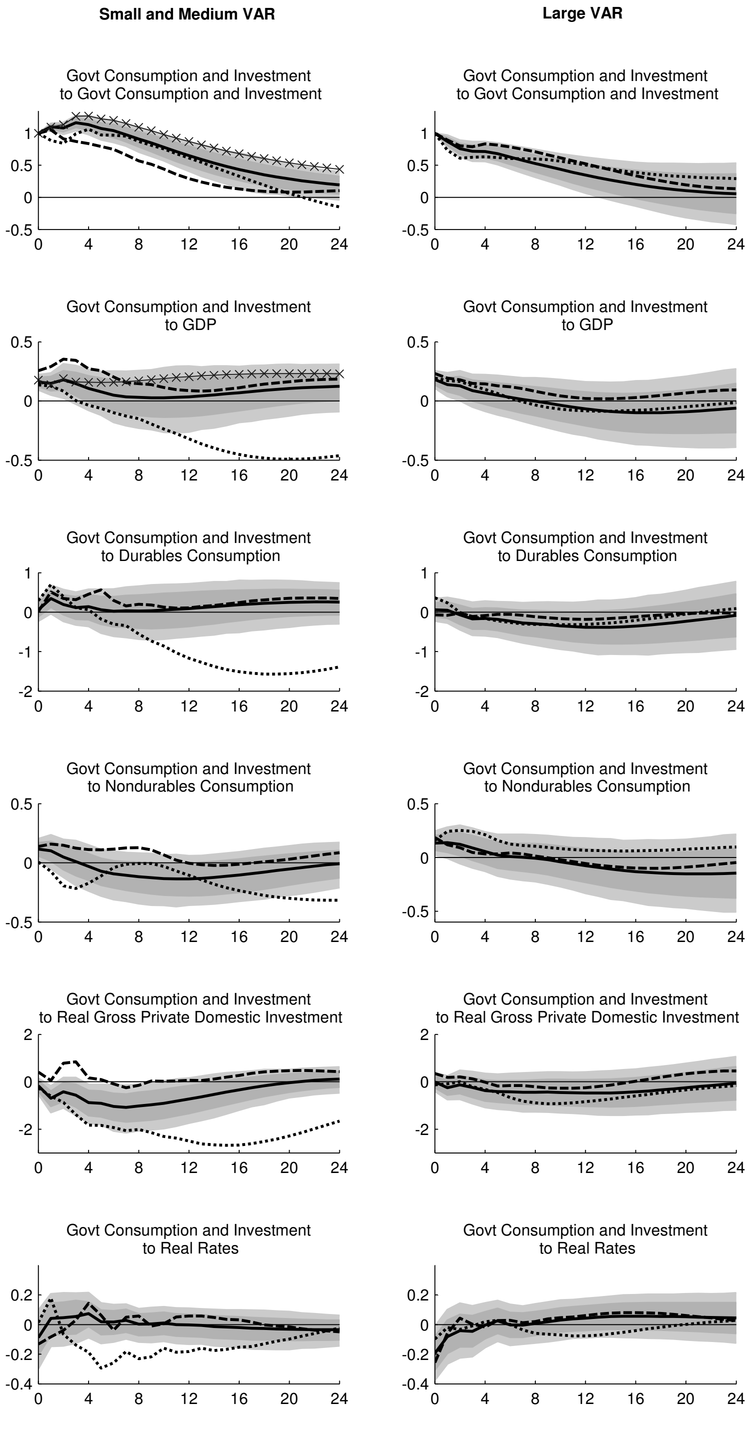

Figure 2: **IRFs to a shock in total Government Consumption for Subsamples**. The subsample 1959Q1 to 2010Q4 is plotted as a solid line with shaded posterior coverage intervals at the 0.68 and 0.9 level. The dashed line and dotted lines in each chart are the responses for the periods 1981Q1 to 2010Q4, and 1959Q1 to 1981Q1, respectively. The left column of plots shows the MEDIUM VAR responses, with the SMALL VAR responses for the period 1959Q1 to 2010Q4 superimposed as lines with crosses on the plots for Government Consumption and Investment and GDP. The right column of plots presents the LARGE VAR plots for each subsample.

the MEDIUM VAR shows subsample instability across all the variables we study, including GDP, durables and nondurables consumption, investment and real rates. In the LARGE VAR, the IRFs for both subsamples are within the posterior coverage interval at the 0.68 level for most of the horizon. The LARGE VAR responses to a shock in government spending are positive and significant for GDP and nondurables consumption, insignificant for durables consumption and investment, and negative and significant for real rates. The subsample instability is also not present in the LARGE VAR for shocks to the components of government spending. The results for the components are included in the Technical Appendix to this paper. Overall, the results for the LARGE VAR suggest that the previously reported subsample instability may be due to an omitted variable problem. Therefore, we can use the LARGE VAR specifications for different subsamples without loss of validity.

6.3 Fundamentalness

In order to assess the issue of non-fundamentalness, we use the large dataset of 128 variables to extract five factors that explain over 99 percent of the variance in the data.[22] We use these five factors to conduct Granger causality tests on the residuals of government spending and the components of government spending from the SMALL, MEDIUM and LARGE VARs for the full sample and the two subsamples. Table 2 reports the results for the Granger causality tests. Factor 1 Granger causes the residuals in the SMALL VAR for the 1959Q1 to 1981Q1 subsample, while Factor 2 Granger causes the residuals in the SMALL VAR for the full sample period and for the 1981Q1 to 201Q4 subsample. The results are mostly significant at the 5 percent level.

Although the 9 variable MEDIUM VAR performs better, the null hypothesis that the factors do not Granger cause the residuals of government spending cannot be rejected with a high confidence level. For example, for the 1981Q1 to 2010Q4 subsample, Factor 1 appears to Granger cause the residuals of government spending, although only at the 20 percent significance level. This result provides further evidence that the subsample instability is caused by an omitted variable problem. Similarly, looking at the components of government spending, Factor 4 appears to Granger cause the residuals from defence investment, again at the 20 percent significance level. Overall, the Granger causality results do not provide strong evidence of fundamentalness in the MEDIUM VAR. Using a different approach, Forni and Gambetti (2010) report stronger non-fundamentalness results for a 6 variable VAR.

Expanding the information set to the LARGE VAR significantly improves the Granger causality results. None of the factors appear to Granger cause the residuals of government spending or the components of government spending in any specification or subsample for the LARGE VAR. Hence, there is no indication of non-fundamentalness in the LARGE VAR. Subsequently, using the Survey of Professional Forecasters data on federal and state and local spending forecasts, we conduct Granger causality tests on "Ramey" forecast errors as well as expectation revisions

[22]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.

Table 2: **Granger causality Tests.** This table reports F-statistics for Granger causality test. The asterisks $*$, $**$, $***$ denote statistical significance at 20 percent, 10 percent and 5 percent level, respectively.

	Factor 1	Prob.	Factor 2	Prob.	Factor 3	Prob.	Factor 4	Prob.	Factor 5	Prob.
SMALL VAR (1959 – 2010)	0.53	*(0.757)*	2.69***	*(0.022)*	1.85	*(0.105)*	0.66	*(0.653)*	1.04	*(0.395)*
SMALL VAR (1981 – 2010)	2.46***	*(0.038)*	0.92	*(0.471)*	0.71	*(0.621)*	0.25	*(0.939)*	1.10	*(0.363)*
SMALL VAR (1959 – 1981)	0.52	*(0.760)*	2.34**	*(0.051)*	0.21	*(0.955)*	0.50	*(0.775)*	1.34	*(0.256)*
MEDIUM VAR (1959 – 2010)	0.20	*(0.961)*	1.15	*(0.336)*	0.33	*(0.896)*	0.30	*(0.910)*	0.28	*(0.922)*
Defence Consumption	0.35	*(0.885)*	0.66	*(0.655)*	0.93	*(0.462)*	0.07	*(0.997)*	0.27	*(0.932)*
Defence Investment	1.01	*(0.414)*	0.86	*(0.511)*	0.18	*(0.970)*	1.76*	*(0.124)*	0.57	*(0.727)*
Nondefence Consumption	1.16	*(0.333)*	0.60	*(0.704)*	0.45	*(0.812)*	0.12	*(0.989)*	0.14	*(0.982)*
Nondefence Investment	1.25	*(0.286)*	0.15	*(0.981)*	0.24	*(0.943)*	0.56	*(0.733)*	0.38	*(0.862)*
State & Local Consumption	0.97	*(0.437)*	1.01	*(0.415)*	0.32	*(0.898)*	0.77	*(0.576)*	0.59	*(0.709)*
State & Local Investment	0.41	*(0.839)*	0.98	*(0.429)*	0.16	*(0.976)*	1.03	*(0.400)*	1.31	*(0.261)*
MEDIUM VAR (1981 – 2010)	1.54*	*(0.186)*	0.98	*(0.433)*	0.35	*(0.882)*	0.24	*(0.943)*	0.72	*(0.611)*
MEDIUM VAR (1959 – 1981)	0.15	*(0.981)*	1.34	*(0.254)*	0.57	*(0.719)*	0.06	*(0.998)*	0.51	*(0.771)*
LARGE VAR (1959 – 2010)	0.04	*(0.999)*	0.63	*(0.676)*	0.13	*(0.986)*	0.26	*(0.933)*	0.20	*(0.963)*
Defence Consumption	0.17	*(0.973)*	0.64	*(0.670)*	0.56	*(0.730)*	0.23	*(0.949)*	0.23	*(0.948)*
Defence Investment	0.49	*(0.785)*	0.67	*(0.648)*	0.25	*(0.937)*	0.42	*(0.833)*	0.19	*(0.965)*
Nondefence Consumption	0.45	*(0.811)*	0.95	*(0.452)*	0.15	*(0.980)*	0.26	*(0.932)*	0.08	*(0.995)*
Nondefence Investment	0.46	*(0.803)*	0.09	*(0.994)*	0.08	*(0.995)*	0.42	*(0.834)*	0.07	*(0.997)*
State & Local Consumption	0.21	*(0.960)*	0.43	*(0.827)*	0.79	*(0.558)*	0.66	*(0.652)*	1.14	*(0.343)*
State & Local Investment	0.32	*(0.903)*	0.55	*(0.739)*	0.09	*(0.993)*	0.60	*(0.701)*	0.48	*(0.790)*
LARGE VAR (1981 – 2010)	0.68	*(0.641)*	0.52	*(0.759)*	0.17	*(0.975)*	0.12	*(0.987)*	0.66	*(0.658)*
LARGE VAR (1959 – 1981)	0.13	*(0.985)*	0.91	*(0.479)*	0.12	*(0.988)*	0.44	*(0.818)*	0.85	*(0.516)*
Fed Spend Forecast Error	4.44***	*(0.001)*	1.84	*(0.111)*	0.96	*(0.449)*	0.79	*(0.560)*	1.87	*(0.107)*
Fed Spend Expectation Revision	2.72***	*(0.024)*	3.37***	*(0.007)*	3.00***	*(0.015)*	0.50	*(0.776)*	2.13**	*(0.067)*
S&L Spend Forecast Error	1.21	*(0.311)*	0.98	*(0.431)*	1.09	*(0.369)*	0.93	*(0.464)*	0.69	*(0.631)*
S&L Spend Expectation Revision	0.69	*(0.634)*	1.98**	*(0.088)*	0.74	*(0.598)*	0.90	*(0.481)*	1.07	*(0.379)*
Ramey News Variable	0.79	*(0.555)*	0.22	*(0.954)*	2.30***	*(0.047)*	0.63	*(0.676)*	0.33	*(0.895)*

defined in Perotti (2011). The results are presented at the bottom of Table 2. Factor 1 Granger causes the “Ramey” federal spending forecast errors at the 1 percent significance level. Similarly, the expectation revisions for federal spending are Granger caused by four of the five factors. Factor 2 also Granger causes expectation revisions for state and local spending at the 10 percent significance level.

Finally, we also conduct a Granger causality test using the “Ramey” military spending news variable (PDVMIL) and find that it is Granger caused by Factor 3 at the 5 percent significance level. This result suggests that the approach adopted in Ramey (2011a) most likely is not able to recover structural shocks.

6.4 Heterogeneity of Government Spending Components

We study the dynamic responses of our macroeconomic variables of interest to a one percent shock in the related government spending variable. Since we are applying logarithms to the variables, the IRFs can be interpreted as elasticities. The multipliers can be recovered by taking the product of these elasticities and the ratio of the average dollar level of the interest variable to the average dollar level of the shock variable (government spending or the relevant component).

First, we study the dynamic responses to aggregate government spending shocks. The IRFs are presented in Figure 3 for the MEDIUM and LARGE VARs and all the related multipliers are reported in Tables 3 and 4, respectively. Although, the responses for GDP, durables consumption and real rates are similar for the two specifications, the MEDIUM VAR generally delivers a biased estimation of the impulse response functions and hence, the multipliers. The GDP multiplier for aggregate government spending from the LARGE VAR is 0.79 upon impact and remains positive and statistically significant for up to 4 quarters. The impact multipliers for durables consumption and services consumption are not significantly different from zero, while the impact multiplier for nondurables consumption is positive (0.11) and statistically significant. Wages and private domestic investment do not respond significantly to shocks in aggregate government spending, while rates decline upon impact before recovering over the subsequent 4 and 8 quarters.

Next, we study the potentially different responses of output, consumption and investment to the heterogeneous components of government spending. The IRFs for shocks to consumption expenditures components of federal defence, federal nondefence (civil) and state and local spending are presented in Figure 4. As in the aggregate spending IRFs, the MEDIUM VAR delivers biased results. Focusing on the LARGE VAR IRFs, the response of GDP to a shock in defence and state and local consumption is positive and significant, whereas the response to a shock in nondefence consumption is negative but statistically insignificant. The GDP impact multiplier for state and local consumption is strongly above one at 1.61. The responses of all personal consumption components to shocks are generally small in magnitude and not significantly different from zero, except for shocks to state and local consumption that elicit a positive and significant response from all three personal consumption components. The related impact multipliers are 0.50, 1.73 and 0.71 for durables, nondurables and services consumption, respectively. The response of private domestic investment to shocks in consumption components of government

Table 3: **Multipliers for GDP and Consumption – MEDIUM VAR.** Standard errors are italicised. D, ND, and S are durables, nondurables and services consumption, respectively.

		GDP		**D**		**ND**		**S**	
On Impact	Government Spend	0.71	*(0.19)*	0.02	*(0.06)*	0.09	*(0.05)*	0.10	*(0.05)*
	Defence Spend	1.07	*(0.34)*	0.06	*(0.10)*	0.17	*(0.09)*	-0.03	*(0.08)*
	Defence Investment	1.23	*(0.65)*	0.20	*(0.20)*	0.28	*(0.15)*	0.12	*(0.12)*
	Nondefence Spend	-0.34	*(0.53)*	-0.10	*(0.17)*	0.01	*(0.14)*	0.17	*(0.13)*
	Nondefence Inv	6.37	*(2.46)*	0.04	*(0.78)*	1.01	*(0.64)*	0.85	*(0.54)*
	S&L Spend	2.28	*(0.89)*	0.96	*(0.31)*	1.64	*(0.22)*	0.64	*(0.22)*
	S&L Investment	2.27	*(0.61)*	0.55	*(0.22)*	0.15	*(0.16)*	0.24	*(0.14)*
After 4 Quarters	Government Spend	0.64	*(0.45)*	0.04	*(0.11)*	0.01	*(0.09)*	0.12	*(0.11)*
	Defence Spend	1.15	*(0.78)*	0.13	*(0.19)*	0.16	*(0.17)*	0.24	*(0.19)*
	Defence Investment	-1.46	*(1.32)*	-0.63	*(0.34)*	-0.08	*(0.28)*	-0.33	*(0.32)*
	Nondefence Spend	2.56	*(1.21)*	0.47	*(0.29)*	0.11	*(0.24)*	0.42	*(0.31)*
	Nondefence Inv	6.68	*(6.40)*	-1.05	*(1.46)*	2.03	*(1.17)*	0.79	*(1.59)*
	S&L Spend	0.02	*(2.10)*	0.46	*(0.44)*	0.13	*(0.41)*	0.77	*(0.50)*
	S&L Investment	0.15	*(1.16)*	-0.22	*(0.31)*	0.08	*(0.29)*	-0.27	*(0.29)*
After 8 Quarters	Government Spend	0.15	*(0.61)*	0.01	*(0.15)*	-0.08	*(0.09)*	0.16	*(0.17)*
	Defence Spend	0.88	*(0.92)*	0.03	*(0.25)*	0.07	*(0.14)*	0.35	*(0.28)*
	Defence Investment	-2.96	*(1.54)*	-0.81	*(0.38)*	-0.22	*(0.24)*	-0.51	*(0.48)*
	Nondefence Spend	4.09	*(1.46)*	0.79	*(0.36)*	0.46	*(0.24)*	0.70	*(0.39)*
	Nondefence Inv	8.39	*(8.72)*	-1.17	*(2.10)*	1.19	*(1.51)*	0.35	*(2.51)*
	S&L Spend	2.96	*(2.37)*	1.43	*(0.47)*	0.02	*(0.46)*	1.18	*(0.61)*
	S&L Investment	-0.49	*(1.37)*	-0.03	*(0.36)*	-0.02	*(0.23)*	-0.35	*(0.40)*

Table 4: **Multipliers for GDP and Consumption – LARGE VAR.** Standard errors are italicised. D, ND, and S are durables, nondurables and services consumption, respectively.

		GDP		**D**		**ND**		**S**	
On Impact	Government Spend	0.79	*(0.20)*	0.02	*(0.07)*	0.11	*(0.05)*	0.02	*(0.05)*
	Defence Spend	0.94	*(0.37)*	0.00	*(0.13)*	0.14	*(0.10)*	-0.13	*(0.09)*
	Defence Investment	0.66	*(0.57)*	-0.06	*(0.19)*	0.17	*(0.15)*	-0.11	*(0.13)*
	Nondefence Spend	-0.29	*(0.46)*	-0.14	*(0.16)*	0.12	*(0.12)*	0.04	*(0.11)*
	Nondefence Inv	4.99	*(2.52)*	-0.66	*(0.86)*	-0.13	*(0.61)*	0.79	*(0.57)*
	S&L Spend	1.61	*(0.98)*	0.50	*(0.32)*	1.73	*(0.24)*	0.71	*(0.22)*
	S&L Investment	2.89	*(0.58)*	0.73	*(0.21)*	0.23	*(0.16)*	0.22	*(0.15)*
After 4 Quarters	Government Spend	0.38	*(0.38)*	-0.07	*(0.10)*	0.07	*(0.09)*	-0.07	*(0.09)*
	Defence Spend	0.39	*(0.72)*	-0.16	*(0.20)*	0.07	*(0.17)*	-0.19	*(0.18)*
	Defence Investment	-2.93	*(1.10)*	-0.88	*(0.29)*	-0.20	*(0.28)*	-0.66	*(0.27)*
	Nondefence Spend	-0.03	*(0.95)*	-0.09	*(0.26)*	0.16	*(0.23)*	0.11	*(0.22)*
	Nondefence Inv	6.53	*(4.61)*	0.68	*(1.28)*	0.98	*(1.13)*	1.61	*(1.13)*
	S&L Spend	-0.62	*(1.71)*	-0.33	*(0.47)*	0.71	*(0.43)*	0.47	*(0.44)*
	S&L Investment	1.76	*(1.13)*	0.23	*(0.31)*	0.36	*(0.29)*	-0.13	*(0.28)*
After 8 Quarters	Government Spend	0.05	*(0.51)*	-0.10	*(0.12)*	0.00	*(0.10)*	-0.12	*(0.14)*
	Defence Spend	-0.66	*(0.99)*	-0.28	*(0.25)*	-0.13	*(0.20)*	-0.28	*(0.28)*
	Defence Investment	-3.30	*(1.63)*	-0.73	*(0.42)*	-0.39	*(0.35)*	-0.72	*(0.45)*
	Nondefence Spend	0.27	*(1.39)*	-0.03	*(0.35)*	0.15	*(0.29)*	0.00	*(0.39)*
	Nondefence Inv	15.57	*(6.35)*	2.11	*(1.67)*	2.76	*(1.40)*	2.52	*(1.82)*
	S&L Spend	-0.65	*(2.55)*	-0.14	*(0.63)*	0.19	*(0.52)*	0.00	*(0.69)*
	S&L Investment	0.86	*(1.62)*	0.11	*(0.40)*	0.22	*(0.35)*	-0.21	*(0.45)*

spending indicates that investment is crowded out by public spending. The response of real rates is negative upon impact and then generally recovers in 4 to 8 quarters.

Similarly, the IRFs for shocks to investment components of federal defence, federal nondefence (civil) and state and local spending are presented in Figure 5. The LARGE VAR IRFs for GDP are positive and significant upon impact across the three investment components of government spending. While the GDP response to shocks in federal nondefence and state and local investment components is persistent, the response to federal defence investment turns negative immediately after impact. The GDP multipliers reflect this result. While the GDP multipliers for both federal nondefence and state and local investment are significantly above one for several quarters, the multiplier for defence investment is mildly positive upon impact and becomes significantly negative soon after impact. The consumption responses and multipliers are generally close to zero and insignificant upon impact, except state and local investment. While the defence investment component of government spending elicits a negative and significant response from the three personal consumption components in the medium run, nondefence investment and state and local investment stimulate a positive and persistent response. The same holds true for private domestic investment. The consumption multipliers for nondefence investment and state and local investment are quite high.

The above results show that the different components of government spending elicit remarkably heterogeneous responses from the various output, consumption and investment variables that we study. Generally, the nondefence and state and local components produce positive responses while the same does not hold true for defence components. This heterogeneity of the responses may partially explain the subsample instability due to the changing composition of government spending over time.

6.5 Expectation Augmented Large VAR

To further analyse the results uncovered by our Granger causality tests, we expand the MEDIUM and LARGE VAR specifications to incorporate "Ramey" forecasts errors and expectation revisions as defined by Perotti (2011) using quarterly forecasts of real federal spending and real state and local spending from the Survey of Professional Forecasters (SPF). Unfortunately, it is not possible to include these 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 in Perotti (2011) as

$$\Delta g_t^{f.err.} = \Delta g_t - \Delta g^e_{t|t-1} = (g_t - g_{t-1}) - (g^e_{t|t-1} - g^e_{t-1|t-1}) \tag{17}$$

where $\Delta g_t^{f.err.}$ is the forecast error in the growth rate of government spending and $\Delta g_t - \Delta g^e_{t|t-1}$ 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 is also assumed that the agent knows the value of government spending in the current quarter. In reality, professional forecasters in SPF do not know the value of g_t. For this reason Perotti

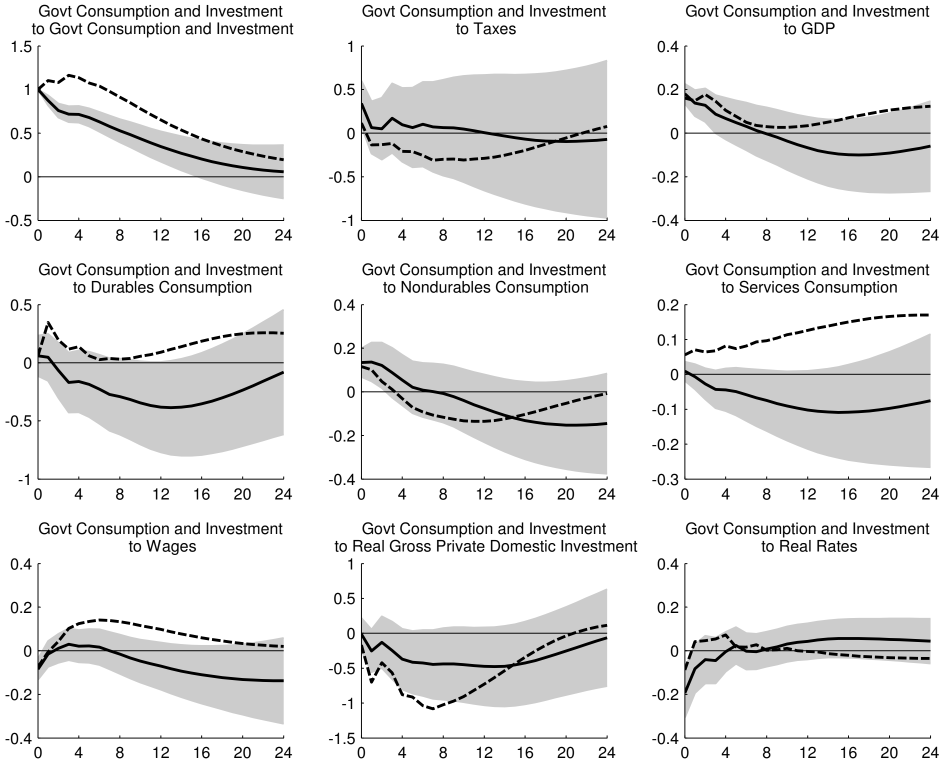

Figure 3: **Large and Medium VAR (1959Q1:2010Q4)**. This figure presents the impulse response functions to a shock in Government Consumption and Investment. Each chart shows the LARGE VAR response for the period 1959Q1 to 2010Q4 as a solid line with shaded posterior coverage intervals at the 0.68. The dashed line in each chart is the response for the MEDIUM VAR for the same period.

(2011) proposes to decompose these forecast errors as

$$\Delta g_t^{f.err.} = \Delta g_t - \Delta g^e_{t|t-1} = \underbrace{(\Delta g_t - \Delta g^e_{t|t})}_{\text{time t's surprise in } \Delta g_t} + \underbrace{(\Delta g^e_{t|t} - \Delta g^e_{t|t-1})}_{\text{revision of expectation of } \Delta g_t} \tag{18}$$

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 the agent at time t, the second term is the actual shock to expectations and could proxy for the news in the information flow of the agent, as proposed in neoclassical models.

In our VAR specification, we use both of these definitions to encapsulate forward-looking expectations of the agent. The results for federal spending are shown in Figure 6, while the state and local spending results are shown in Figure 7.[23]

[23] In the VAR specifications where the forecast errors and expectation revisions are used, they are ordered first. For the federal spending VAR, the various components of federal spending (consumption and investment components of federal defence and nondefence) are aggregated as the SPF forecasts are at an aggregate level. A similar approach is adopted for state and local spending.

Following Perotti (2011), the IRFs show the dynamic response of macroeconomic variables of interest to a shock in the relevant expectations variable normalised such that the respective government spend (federal or state and local) peaks at one over the horizon. Using this methodology allows a direct comparison of these IRFs with the IRFs from the SVARs. Using the "Ramey" forecast errors, the MEDIUM SVAR and EVAR deliver broadly similar results, while the LARGE SVAR and EVAR deliver a strikingly similar result. This confirms the Granger causality results that the "Ramey" forecast errors are not fundamental. The intuition 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 due to the extremely low predictive power of expected government spending growth. The forecast error is almost equivalent to actual spending growth less some noise. This can explain the almost identical impulse responses of SVARs and EVARs when applied to the same dataset.

6.6 Robustness of Results

The results reported in this paper are robust to using flat hyperpriors as well as an in-sample methodology to fixing λ as discussed in Banbura et al. (2010) . Moreover the results are similar over a wide range of values for τ and λ.

The results for the subsample 1981Q1-2010Q4 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. These variables are not available for the full sample. We also considered additional variables such as new job advertisements, sovereign CDS spreads, employment and real estate related Web searches; unfortunately these variables are not available even for the shorter subsample.

We also included in our dataset a stock and a flow measure of the public debt level. Our results are robust to the exclusion of these two variables. Finally, the results are robust to the exclusion of the recent financial and economic crisis.

7 Conclusions

Using a Large Bayesian VAR approach it is possible to significantly expand the information set used to analyse shocks to government spending. Large information datasets are generally considered good approximations of the whole economy. For this reason, we believe that Large Bayesian VAR techniques allow for a more careful study of fiscal shocks while controlling for issues of non-fundamentalness and more generally for omitted variable problems.

The key results of our paper can be distilled as follows. First, the subsample instability previously reported appears to be significantly mitigated using a large information approach and is reduced to a statistically insignificant level, given the confidence level delivered by our econometric tools. After controlling for changes in monetary policy, fiscal policy, budget structure, credit access, financial markets and openness of the economy, the dynamic responses of macroeconomics variables appear to be essentially the same across subsamples. This could be an indication that *deep* *habits* of economic agents – that are embedded in structural parameters – might be more stable and persistent across time than previously reported. To verify this conjecture it would be interesting for future research to apply the same methodology to different settings. The results on structural breaks in the U.S. economy reported in many recent papers contrast with our findings. If validated, a possible interpretation of our results is that studies conducted using limited information capture policy and market structure changes rather than changes in *deep structural parameters* of the economy. However, we recognise this difference can be quite nuanced and depends on the model adopted.

Second, the traditional SVAR approach shows signs of non-fundamentalness for small VARs (similar findings have been reported in Forni and Gambetti (2010)). While the issue of non-fundamentalness appears to be mitigated using a moderate number of variables (for example, our nine-variable MEDIUM VAR), the more general problem of omitted variables remains, resulting in biased IRFs to fiscal shocks.

Third, the EVAR approach proposed in Ramey (2011a) to overcome non-fundamentalness in small VARs seems to suffer from the same issue. Moreover, using a large information set the dynamic responses to shocks in expectations, as defined in Ramey (2011a), appear to be identical to the IRFs produced using the SVAR approach. This result was conjectured in Perotti (2011) and holds partially true using smaller VARs as well (for example, our MEDIUM VAR).

Fourth, our LARGE VAR seems to overcome the non-fundamentalness issues present in all of the other specifications. Using this LARGE VAR the macroeconomic variables related to output, consumption and investment show a remarkably heterogeneous dynamic response to shocks in different components of government consumption and investment. In particular, defence spending appears to elicit dynamic responses qualitatively different compared with nondefence spending. This result, partially reported in previous studies, raises issues of validity when using defence shocks to identify the dynamic effects of public spending. In general terms, this may be related to the issue of aggregation of macroeconomic variables.

Our results are broadly consistent with previous findings from SVARs, as stated in Hall (2009): "the output multiplier is in the range from 0.5 to 1.0 and [...] the consumption multiplier is somewhat positive". Generally, consumption components and private investment appear to be rather unresponsive to shocks in government spending, at odds with neoclassical theory. Conversely, investment components that are thought to be directly productive generally elicit large positive responses in GDP, consumption and investment. The same holds true for the state and local consumption components where social spending is likely to be more localised. In this respect, state and local public spending generates services, such as health and education, which enter either in the production function or in the consumers' utility function, or both. These findings can therefore be explained in a neoclassical framework as well.

This study suffers from two main limitations, largely common to the SVAR and EVAR literature, and leaves many questions open. The results on multipliers and IRFs presented in this paper need to be read in light of these limitations.

First, government spending shocks have been identified via a generalised recursive identification with the shocks always ordered first. We believe this identification is largely sensible and is chosen with the aim of assessing previous findings with the SVAR and EVAR approaches that apply this methodology in different settings. However, this assumption of the *exogeneity* of government spending with respect to contemporaneous shocks to other macroeconomic variables could be incorrect. In this respect, it is reassuring that results in Forni and Gambetti (2010) obtained using a different approach and a sign restriction identification are broadly consistent with our findings.

Second, 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)). Applying 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 assumed through our choice of the econometric model that the 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)). All these previous assumptions are likely to be false. Hence, the only correct way to interpret our IRFs and multipliers is as statistical averages over largely different economic conditions and policies.

The results presented by Auerbach and Gorodnichenko (2012) obtained using a small nonlinear VAR to analyse fiscal shocks in expansions and recessions could be seen as providing complementary evidence to ours. While their nonlinear VAR is able to address issues related to the variation of multipliers across business cycles, they use a very small information set, potentially prone to omitted variables. Finally, results from natural experiments that aim to bridge the gap between microeconomic and macroeconomic levels are complementary evidence necessary to put our results in the correct perspective (e.g., in Acconcia et al. (2011); Nakamura and Steinsson (2011); Wilson (2010)).

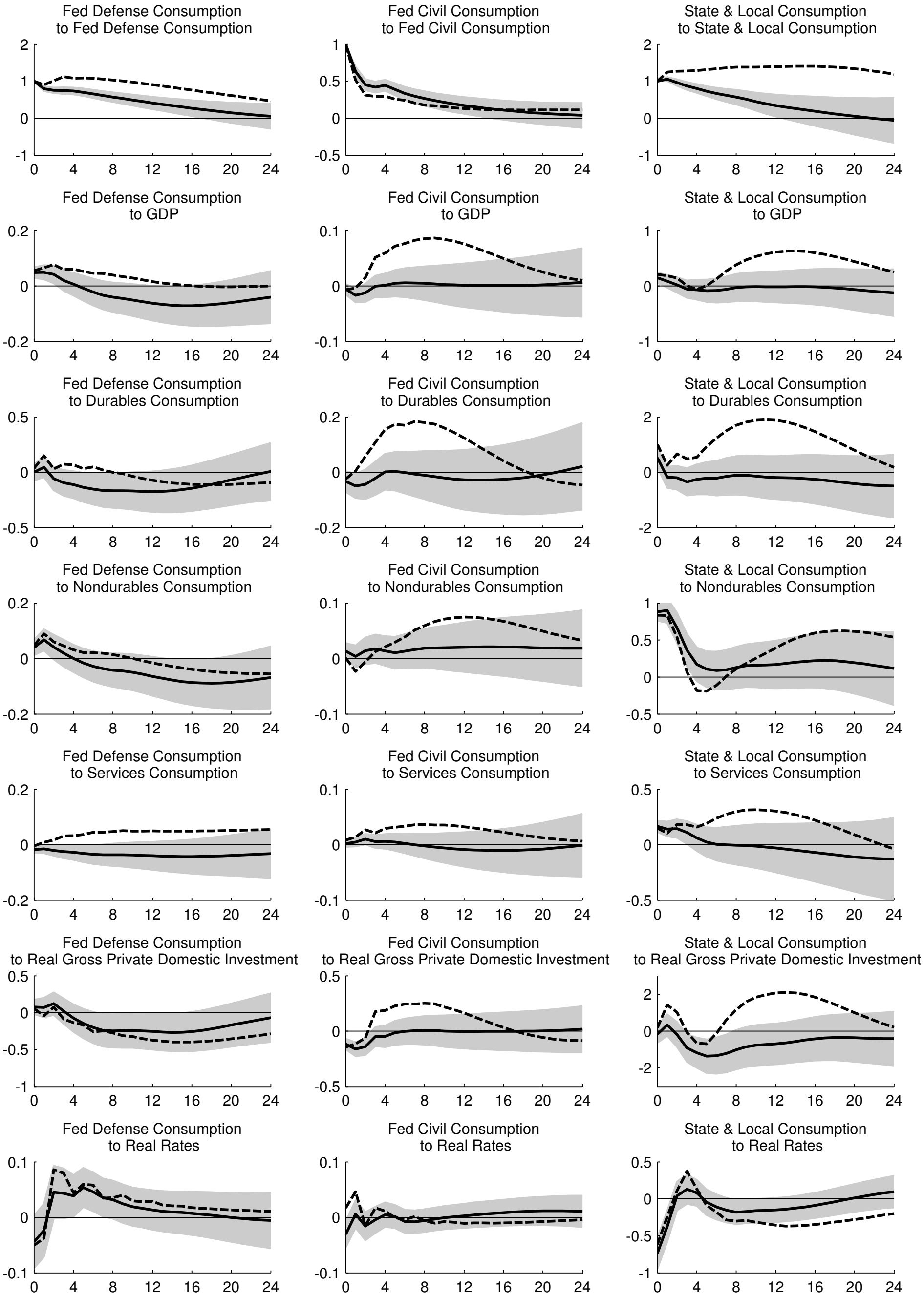

Figure 4: **Large and Medium VAR – Government Consumption Components (1959Q1:2010Q4)**. This figure presents the impulse response functions to a shock in a specified component of Government Consumption and Expenditures. The left, middle and right columns of plots depict the responses to a shock in federal defence consumption, federal nondefence (civil) consumption, and state and local consumption, respectively. Each chart shows the LARGE VAR response for the period 1959Q1 to 2010Q4 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 MEDIUM VAR for the same period.

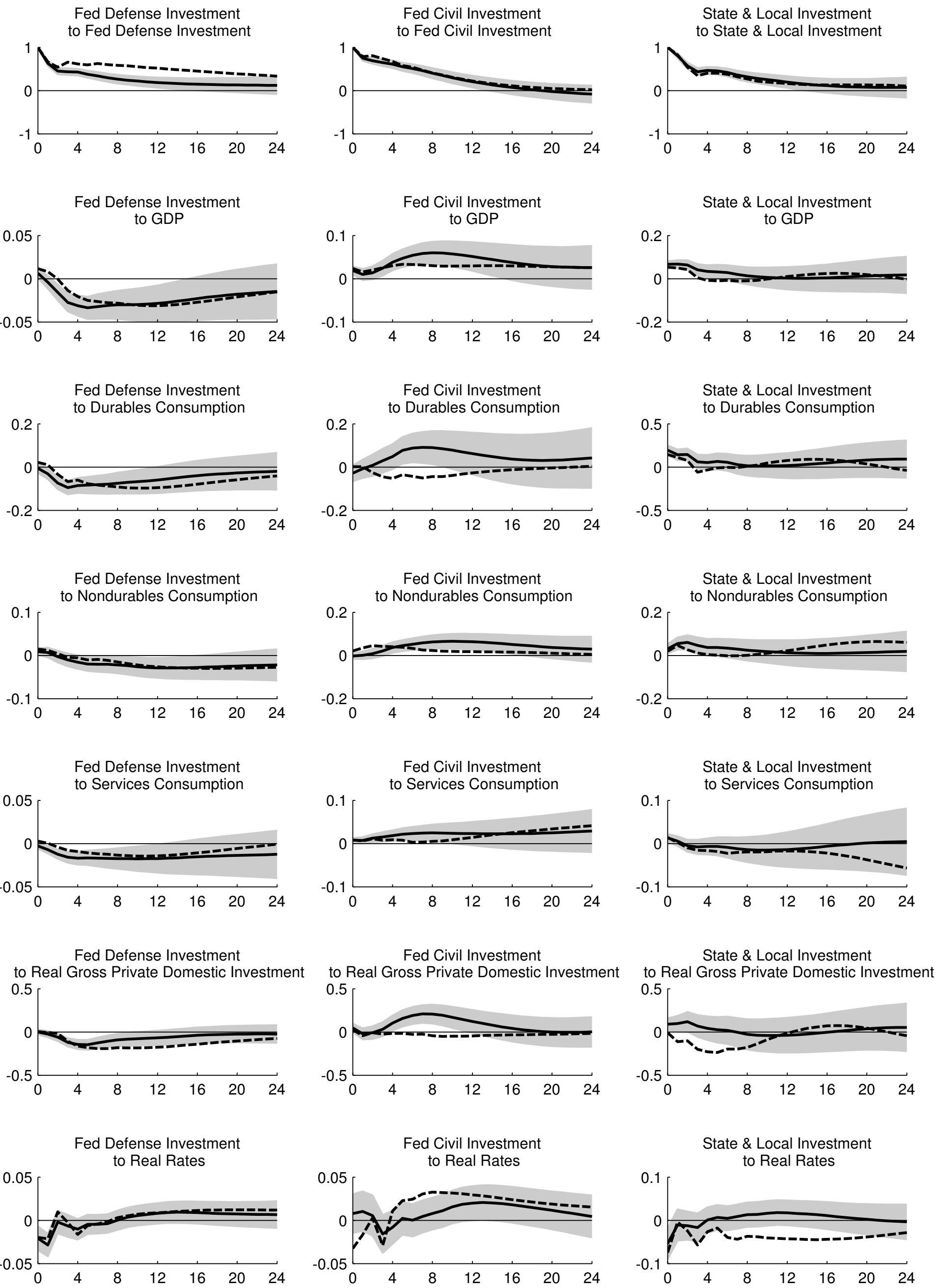

Figure 5: **Large and Medium VAR – Government Investment Components (1959Q1:2010Q4)**. This figure presents the impulse response functions to a shock in a specified component of Government Investment. The left, middle and right columns of plots depict the responses to a shock in federal defence investment, federal nondefence (civil) investment, and state and local investment, respectively. Each chart shows the LARGE VAR response for the period 1959Q1 to 2010Q4 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 MEDIUM VAR for the same period.

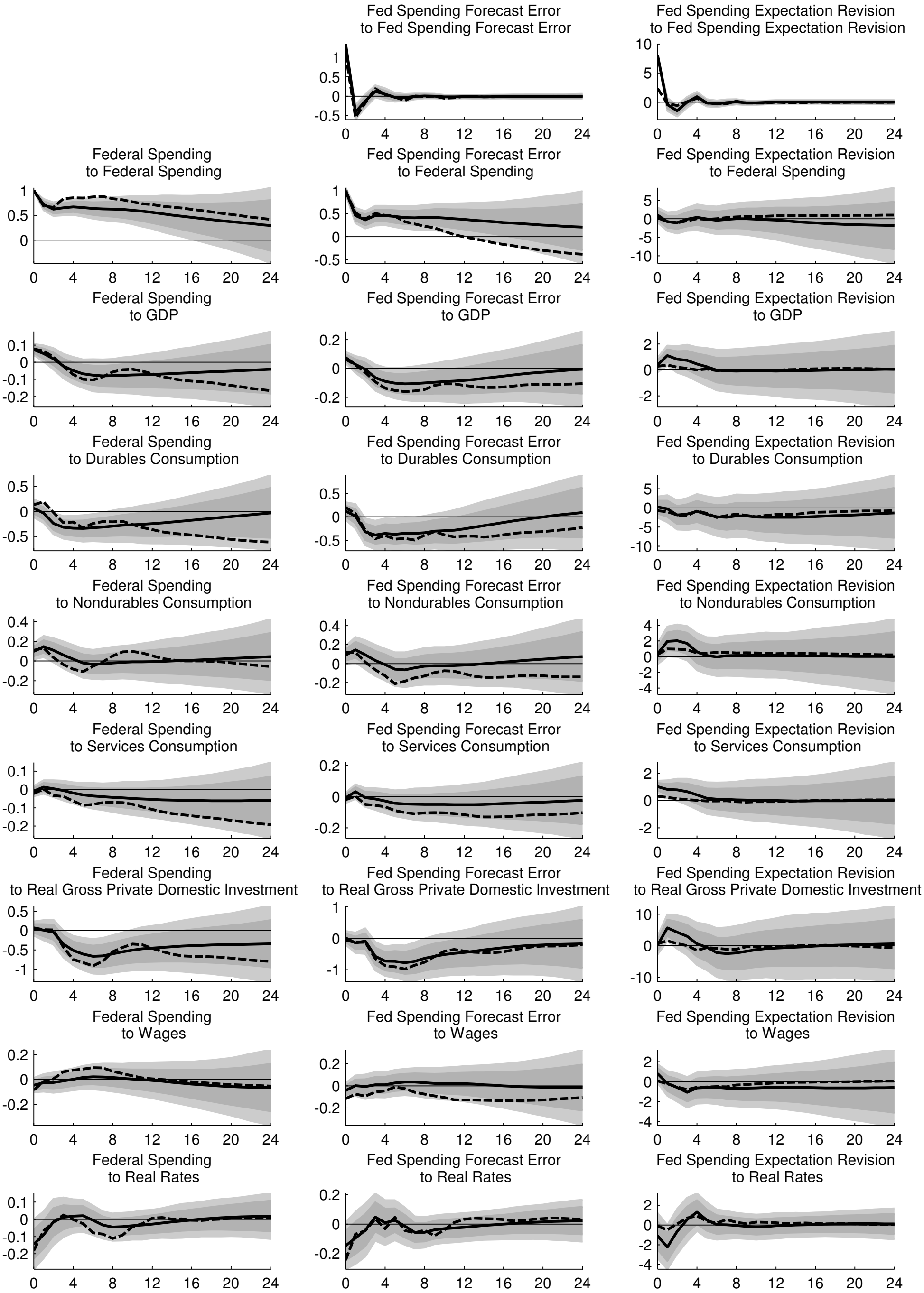

Figure 6: **Large and Medium VAR SPF – Federal Spending (1982Q1:2010Q4)**. This figure presents the impulse response functions to a shock in federal spending and federal spending forecasts. The left, middle and right columns of plots depict the responses to a shock in federal spending, federal spending forecast error, and federal spending expectation revision, respectively. Each chart shows the LARGE VAR response for the period 1982Q1 to 2010Q4 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 MEDIUM VAR for the same period.

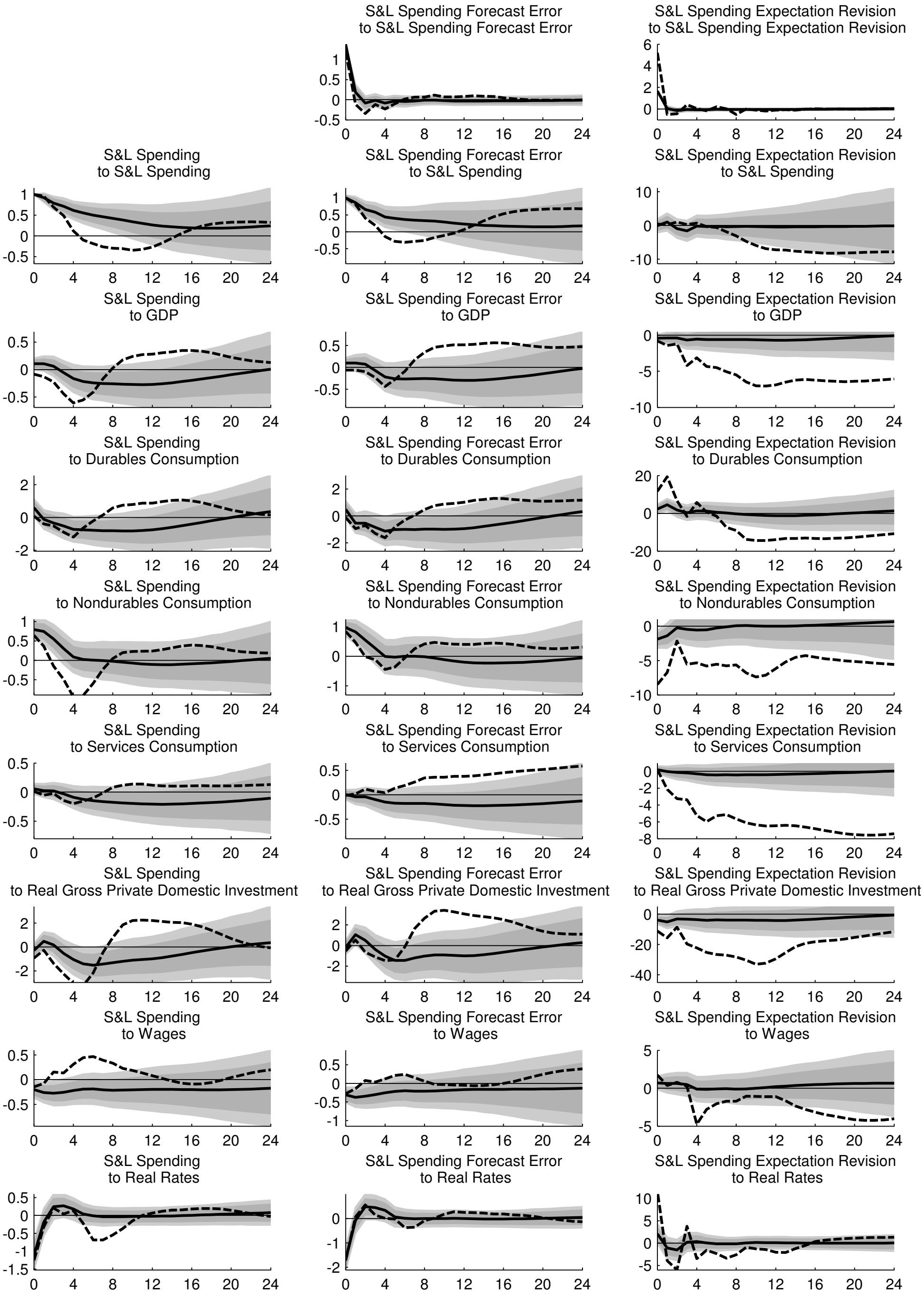

Figure 7: **Large and Medium VAR SPF – State and Local Spending (1982Q1:2010Q4)**. This figure presents the impulse response functions to a shock in state and local spending and state and local spending forecasts. The left, middle and right columns of plots depict the responses to a shock in state and local spending, state and local spending forecast error, and state and local spending expectation revision, respectively. Each chart shows the LARGE VAR response for the period 1982Q1 to 2010Q4 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 MEDIUM VAR for the same period.

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A A Simple Model

In order to illustrate the large information approach to address the issue of fundamentalness, let us consider the simple model proposed in Perotti (2011) and derived from Leeper et al. (2008)[24]

$$\text{Max}\, E_t \sum_{i=0}^{\infty} \beta^i \log C_{t+i} \tag{19}$$

$$\text{s.t. } C_t + K_t + G_t = Z_t K_{t-1}^{\alpha} \tag{20}$$

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

$$E_t \left[\beta(1 + R_{t+1}) \frac{C_t}{C_{t+1}} \right] = 1 \tag{21}$$

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

$$c_t - E_t[c_{t+1}] + E_t[z_{t+1}] + (\alpha - 1)k_t = 0 \tag{22}$$

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

$$k_t - \lambda_1 k_{t-1} = -\frac{1}{\lambda_2 \alpha\beta} \sum_{i=0}^{\infty} \frac{1}{\lambda_2^i} E_t \left[((G + \alpha\beta) z_{t+i+1} - z_{t+i}) + G(g_{t+1+i} - g_{t+1}) \right] \tag{23}$$

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

$$g_t = \gamma_{t|t-1} \tag{24}$$

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

$$k_t - \lambda_1 k_{t-1} = \frac{1}{\lambda_2 \alpha\beta} z_t - \frac{G}{\lambda_2 \alpha\beta} \gamma_{t|t-1} - \frac{G}{\lambda_2 \alpha\beta} \left(1 - \frac{1}{\lambda_2}\right) \gamma_{t+1|t} \; . \tag{25}$$

We can rewrite the equation in more compact form as

$$k_t - \lambda_1 k_{t-1} = \delta z_t + \pi_0 \gamma_{t|t-1} + \pi_1 \gamma_{t+1|t} \tag{26}$$

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

where the coefficients are defined as in the prior equation.

The VARMA representation is

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1-\lambda_1 L \end{pmatrix} \begin{pmatrix} g_t \\ z_t \\ k_t \end{pmatrix} = \begin{pmatrix} L & 0 \\ 0 & 1 \\ \pi_1 + \pi_0 L & \delta \end{pmatrix} \begin{pmatrix} \gamma_{t+1|t} \\ z_t \end{pmatrix} \tag{27}$$

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

$$\begin{pmatrix} g_t \\ z_t \\ k_t \end{pmatrix} = \begin{pmatrix} L & 0 \\ 0 & 1 \\ \frac{\pi_1+\pi_0 L}{1-\lambda_1 L} & \frac{\delta}{1-\lambda_1 L} \end{pmatrix} \begin{pmatrix} \gamma_{t+1|t} \\ z_t \end{pmatrix} \tag{28}$$

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

$$\begin{pmatrix} g_t \\ k_t \end{pmatrix} = \begin{pmatrix} L & 0 \\ \frac{\pi_1+\pi_0 L}{1-\lambda_1 L} & \frac{\delta}{1-\lambda_1 L} \end{pmatrix} \begin{pmatrix} \gamma_{t+1|t} \\ z_t \end{pmatrix} \tag{29}$$

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 and is inside the unit circle. This is also true for the other two-by-two subsystems

$$\begin{pmatrix} g_t \\ z_t \end{pmatrix} = \begin{pmatrix} L & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \gamma_{t+1|t} \\ z_t \end{pmatrix} \tag{30}$$

$$\begin{pmatrix} z_t \\ k_t \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ \frac{\pi_1+\pi_0 L}{1-\lambda_1 L} & \frac{\delta}{1-\lambda_1 L} \end{pmatrix} \begin{pmatrix} \gamma_{t+1|t} \\ z_t \end{pmatrix} \tag{31}$$

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.

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

$$\begin{pmatrix} 1 & 0 \\ 0 & \frac{z+\frac{\pi_1}{\pi_0}}{1+\frac{\pi_1}{\pi_0}z} \end{pmatrix} . \tag{32}$$

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:

$$\begin{pmatrix} 1+\frac{\pi_0}{\pi_1}L & \frac{\delta}{\pi_1}L & -\frac{1}{\pi_1}L+\frac{\lambda_1}{\pi_1}L^2 \\ 0 & 1 & 0 \\ -\frac{\pi_0}{\pi_1} & -\frac{\delta}{\pi_1} & \frac{1}{\pi_1}-\frac{\lambda_1}{\pi_1}L \end{pmatrix} \begin{pmatrix} g_t \\ z_t \\ k_t \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ 0 & 1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} \gamma_{t+1|t} \\ z_t \end{pmatrix} . \tag{33}$$

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

$$g_t = \gamma_{t|t-1} + \varepsilon_t \ , \tag{34}$$

we get the equilibrium solution for k_t

$$k_t - \lambda_1 k_{t-1} = \delta z_t + \pi_0 \gamma_{t|t-1} + \pi_1 \gamma_{t+1|t} + \pi_0 \varepsilon_t \ . \tag{35}$$

The VAR(2) representation is now:

$$\begin{pmatrix} 1 + \frac{\pi_0}{\pi_1} L & \frac{\delta}{\pi_1} L & -\frac{1}{\pi_1} L + \frac{\lambda_1}{\pi_1} L^2 \\ 0 & 1 & 0 \\ -\frac{\pi_0}{\pi_1} & -\frac{\delta}{\pi_1} & \frac{1}{\pi_1} - \frac{\lambda_1}{\pi_1} L \end{pmatrix} \begin{pmatrix} g_t \\ z_t \\ k_t \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ z_t \\ \gamma_{t+1|t} \end{pmatrix} \ . \tag{36}$$

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

$$A_0 = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ -\frac{\pi_0}{\pi_1} & -\frac{\delta}{\pi_1} & \frac{1}{\pi_1} \end{pmatrix} \qquad C = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \ . \tag{37}$$

B Data and Description of Variables

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.[25]

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.[26] 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 GDP deflator (GDPDEF) which is indexed at 100 in 2005.

The total public debt series (PUBDEBT) is collected from the website of the U.S. Department of Treasury.[27]

We use the consumer sentiment index developed by the University of Michigan available on their website.[28] 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.[29]

[25] `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`

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

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

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

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

Table 5: Appendix: Description of the Dataset

Mnemonic	Description	Log	Small	Medium	Large	M SPF	L SPF	Factors	RW Prior
RFEDGOV_FE	SPF Real Fed Govt Expenditures and Investment – Forecast Error					•	•		•
RSLGOV_FE	SPF Real State & Local Expenditures and Investment – Forecast Error					•	•		•
RFEDGOV_FE	SPF Real Fed Govt Expenditures and Investment – Expectation Revision					•	•		•
RSLGOV_FE	SPF Real State & Local Expenditures and Investment – Expectation Revision					•	•		•
GCEC96	Real Government Consumption and Expenditures & Gross Investment	•	•	•	•			•	•
DEFSPEND	National Defence Consumption and Expenditures	•		•	•			•	•
DGI	Federal National Defence Gross Investment	•		•	•			•	•
CIVSPEND	Federal Nondefence Consumption and Expenditures	•		•	•			•	•
NDGI	Federal Nondefence Gross Investment	•		•	•			•	•
SLSPEND	State & Local Consumption and Expenditures	•		•	•			•	•
SLINV	State & Local Gross Investment	•		•	•			•	•
SLCE	State & Local Consumption and Expenditures & Gross Investment	•				•	•		•
FEDSPEND	Federal Defence and Nondefence Consumption and Expenditures	•				•	•		•
FGRECPT	Federal Government Current Receipts	•			•		•	•	•
PERSTAX	Personal Current Taxes	•	•	•	•	•	•	•	•
FGDEF	Net Federal Government Saving (Deficit)				•		•	•	•
PUBDEBT	U.S. Total Treasury Securities Outstanding (Public Debt)	•			•		•	•	•
GDPC96	Real Gross Domestic Product	•	•	•	•	•	•	•	•
UNRATE	Civilian Unemployment Rate				•		•	•	•
CE16OV	Civilian Employment	•			•		•	•	•
UEMPMEAN	Average (Mean) Duration of Unemployment	•			•		•	•	•
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	•		•	•	•	•	•	•
PCECTPI	Personal Consumption Expenditures: Chain-type Price Index				•		•	•	•
PCDG	Personal Consumption Expenditures: Durable Goods	•		•	•	•	•	•	•
PCND	Personal Consumption Expenditures: Nondurable Goods	•		•	•	•	•	•	•
PCESV	Personal Consumption Expenditures: Services	•		•	•	•	•	•	•
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	•			•		•	•	•
HOUST	Housing Starts: Total: New Privately Owned Housing Units Started	•			•		•	•	
GPDIC96	Real Gross Private Domestic Investment	•		•	•	•	•	•	•
EXPGSC96	Real Exports of Goods & Services, 3 Decimal	•			•		•	•	•
IMPGSC96	Real Imports of Goods & Services, 3 Decimal	•			•		•	•	•
EUDOLLR	Currency Exchange Rate: (EURO TO U.S. $)	•			•		•	•	•
SP500	S&P 500 Stock Market Index (Percent Change)				•		•	•	•
DJIA	Dow Jones Industrial Average Stock Price Index (Percent Change)	•			•		•	•	•

Table 6: Appendix: Description of the Dataset *(Continued)*

Mnemonic	Description	Log	Small	Medium	Large	M SPF	L SPF	Factors	RW Prior
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)			•	•	•	•	•	•
FDEFX	National Defence Consumption and Expenditures & Gross Investment	•						•	•
FNDEFX	Federal Nondefence Consumption and Expenditures & Gross Investment	•						•	•
GNPC96	Real Gross National Product	•						•	•
PCEPILFE	Personal Consumption Expenditures: Chain-Type Price Index Less Food and Energy	•						•	•
CPIAUCSL	Consumer Price Index for All Urban Consumers: All Items	•						•	•
CPIUFDSL	Consumer Price Index for All Urban Consumers: Food	•						•	•
CPIMEDSL	Consumer Price Index for All Urban Consumers: Medical Care	•						•	•
CPIAPPNS	Consumer Price Index for All Urban Consumers: Apparel	•						•	•
CPIENGNS	Consumer Price Index for All Urban Consumers: Energy	•						•	•
CUUR0000SEHA	Consumer Price Index for All Urban Consumers: Rent of primary residence	•						•	•
CPITRNSL	Consumer Price Index for All Urban Consumers: Transportation	•						•	•
CUSR0000SAD	Consumer Price Index for All Urban Consumers: Durables	•						•	•
CPILFENS	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy	•						•	•
CUUR0000SETA01	Consumer Price Index for All Urban Consumers: New vehicles	•						•	•
CUUR0000SETD	Consumer Price Index for All Urban Consumers: Motor vehicle maintenance and repair	•						•	•
CUSR0000SAS	Consumer Price Index for All Urban Consumers: Services	•						•	•
CUUR0000SAN	Consumer Price Index 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	Average Hourly Earnings Of Production And Nonsupervisory Employees: Manufacturing	•						•	•
AHECONS	Average Hourly Earnings Of Production And Nonsupervisory Employees: Construction	•						•	•
CEU3100000008	Average Hourly Earnings of Production and Nonsupervisory Employees: Durable Goods	•						•	•
CES3200000008	Average Hourly Earnings of Production and Nonsupervisory Employees: Nondurable Goods	•						•	•
CEU0600000008	Average Hourly Earnings of Production and Nonsupervisory Employees: Goods-Producing	•						•	•

Table 7: Appendix: Description of the Dataset *(Continued)*

Mnemonic	Description	Log	Small	Medium	Large	M SPF	L SPF	Factors	RW Prior
CEU1000000008	Average Hourly Earnings of Production and Nonsupervisory Employees: Mining and Logging	•						•	•
WASCUR	Compensation of Employees: Wages & Salary Accruals	•						•	•
FINSLC96	Real Final Sales of Domestic Product, 3 Decimal	•						•	•
CBIC96	Real Change in Private Inventories, 3 Decimal							•	•
GPDICTPI	Gross Private Domestic Investment: Chain-type Price Index	•						•	•
PNFI	Private Nonresidential Fixed Investment	•						•	•
PRFI	Private Residential Fixed Investment	•						•	•
ULCBS	Business Sector: Unit Labor Cost	•						•	•
HOABS	Business Sector: Hours of All Persons	•						•	•
IPDCONGD	Industrial Production: Durable Consumer Goods	•						•	•
IPBUSEQ	Industrial Production: Business Equipment	•						•	•
IPCONGD	Industrial Production: Consumer Goods	•						•	•
IPNCONGD	Industrial Production: Nondurable Consumer Goods	•						•	•
IPDMAT	Industrial Production: Durable Materials	•						•	•
IPNMAT	Industrial Production: Nondurable Materials	•						•	•
NAPM	ISM Manufacturing: PMI Composite Index	•						•	•
NAPMSDI	ISM Manufacturing: Supplier Deliveries Index	•						•	•
NAPMEI	ISM Manufacturing: Employment Index	•						•	•
NAPMPI	ISM Manufacturing: Production Index	•						•	•
NAPMPRI	ISM Manufacturing: Prices Index	•						•	•
PPIFGS	Producer Price Index: Finished Goods	•						•	•
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	•						•	•
USDOLLR	Currency Exchange Rate: (U.S. $ TO U.K. GBP)	•						•	•