Fiscal Foresight and the Effects of Government Spending*

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Abstract

We study the effects of government spending by using a structural, large dimensional, dynamic factor model. We find that the government spending shock is non-fundamental for the variables commonly used in the structural VAR literature, so that its impulse response functions cannot be consistently estimated by means of a VAR. Government spending raises both consumption and investment, with no evidence of crowding out. The impact multiplier is 1.7 and the long run multiplier is 0.6.

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1 Introduction

Understanding the effects of discretionary fiscal policy actions is key to assessing competing theories of the business cycle and providing guidance to policymakers. Recent developments in the conduct of fiscal policy in the US and other industrialized countries have sparked a renewed interest in the topic. Little consensus however has emerged over the last years: economists disagree about the sign of the response of private aggregate demand components, in particular consumption, and, as a consequence, the magnitude of the government spending multiplier. In their seminal paper, Blanchard and Perotti (2002) use a VAR model and identify a government spending shock by imposing that government spending is not affected on impact by the other shocks. The main finding is that government spending leads to a large increase in consumption. Similar results are obtained by Fatas and Mihov (2001), Gali, Lopez Salido, and Valles (2007), Mountford and Uhlig (2002), and Perotti (2002, 2007), which may be included in the so-called "government spending innovation approach". On the contrary, Ramey and Shapiro (1998), using a dummy variables identification approach, find that consumption falls, implying a very small value for the government spending multiplier. Burnside, Eichenbaum, and Fisher (2004), Cavallo (2005), Edelberg, Eichenbaum, and Fisher (1999) and Eichenbaum and Fisher (2005) find similar results.

Recently, a few works have convincingly argued that one of the intrinsic characteristic of fiscal policy actions is that they are anticipated (see e.g. Yang, 2007, Leeper, Walker and Yang, 2008, Mertens and Ravn, 2009). That is, private agents receive signals about future changes in taxes and government spending before these changes actually take place. The reason is the existence of legislative and implementation lags: it takes time for a policy action to be passed and implemented. The phenomenon is called "fiscal foresight"; empirical estimates of the lag range from a few months to a couple of years.

Leeper, Walker and Yang (2008) show that fiscal foresight poses a formidable challenge to the econometrician. The authors consider a simple neoclassical growth model with two shocks, a technology and an anticipated tax shock. They show that the MA representation of any pair of variables among capital, taxes and technology, is *non-fundamental*; that is, the determinant of the MA matrix has roots smaller than one in modulus. The implication is that the variables do not have a VAR representation in the structural shocks, so that the true fiscal policy shock and the related impulse response functions cannot be found by estimating a VAR.

The problem can be reformulated in terms of information sets. Typically, economic agents can see the structural shocks. By contrast, the econometrician can only observe the economic variables. Obviously, such variables convey information about the shocks, but if the impact effects are small and the delayed effects are large, such information is not enough to recover the shocks (Lippi and Reichlin, 1993).

Persuasive evidence that the information set used in the VAR fiscal policy literature is indeed too poor is provided in Ramey (2009). Ramey shows that the fiscal policy shock obtained by using a VAR similar to the one in Perotti (2007) is not an innovation with respect to available macroeconomic information, being Granger-caused by the forecast of government spending from the Survey of Professional Forecasters.

In recent years a few works have tried to overcome the problem posed by fiscal foresight. Two different strategies have been adopted. On the one hand, Mertens and Ravn (2009) estimate the effects of government spending shocks using the methodology proposed by Lippi and Reichlin (1994), based on Blaschke matrices. On the other hand, some authors augment the VAR with variables presumably conveying better information about discretionary fiscal policy actions. Ramey (2009) constructs two series for exogenous government spending shocks: one is based on narrative evidence for defense spending, the second is based on the Survey of Professional Forecasters. Fisher and Peters (2009) identify government spending shocks with statistical innovations to the accumulated excess returns of large US military contractors. Both approaches have shortcomings. The former requires many restrictions, some of them relying on the correct specification of the theoretical model; moreover, the structural shocks cannot be estimated consistently. As for the latter, it is hard to judge whether the additional variables included in the VAR are fully successful in capturing the relevant information.

In this paper we depart from the VAR approach and use instead a large structural factor model. The motivation is that, as argued in Forni, Giannone, Lippi and Reichlin (2009), large factor models are not affected by the non-fundamentalness problem. The basic intuition is that these models typically use most of the available macroeconomic information and this helps in closing the gap between the information set of the econometrician and that of economic agents.

To better understand how non-fundamentalness arises and how the factor model can avoid the problem, let us start from a vector MA representation, obtained from a DSGE model. Typically the number of variables is larger than the number of shocks, so that we have a rectangular, "tall" MA system. As we shall show, for such systems, observing the variables is equivalent to observing the shocks, and the non-fundamentalness problem is not there. In the model of Leeper, Walker and Yang (2008), for instance, the tall system made up by the three state variables and the two shocks is fundamental (see Section 2).

Unfortunately, a rectangular system cannot be estimated by using standard VAR techniques. This is because observed series do not have reduced dynamic rank: by estimating a VAR with n variables, we end up with n linearly independent residuals and find too many structural shocks. In order to estimate a VAR we have to ignore some variables and "cut" the tall system to get a square one. But in such a way we open the door to non-fundamentalness.

The factor model follows an alternative strategy to handle the reduced rank problem. It retains all of the variables and adds measurement errors. Since the number of variables is very large, and the errors are poorly correlated across section, we can get rid of them by taking suitable linear combinations of the variables (the principal components). In such a way we end up with a fundamental, rectangular system which can be estimated consistently by means of a reduced rank VAR technique.

Let us now summarize our main findings.

To begin, we find that the government spending shock is non-fundamental for the variables commonly used in the structural VAR literature. Precisely, we select a few square sub-matrices of our tall impulse-response matrix, corresponding to standard VAR specifications. Then we compute the smallest root of the determinant and find that in most cases it is smaller than one in modulus.

Then we identify a government spending shock by using sign restrictions (Uhlig, 2005). More specifically, an expansionary government spending shock is defined as a shock having a positive effect on government expenditure, output, prices, the prime rate, the government primary deficit and tax receipts (the last inequality is imposed to distinguish the government spending shock from a tax shock). All restrictions are imposed only on responses delayed by six months (the third coefficient of the impulse response functions), so that the impact effect on all variables, and in particular government expenditure, is left unrestricted to avoid the fiscal-foresight criticism.

The main results are the following. First, our estimated shock, unlike the VAR shock, passes Ramey's Granger-causation test, i.e. it is not caused by the forecast of government spending from the Survey of Professional Forecasters. Second, the shape of the impulse response functions suggests that actually there is a great deal of anticipation. After an immediate and significant increase, government spending gradually rises and reaches its maximum, which is about two times larger than the initial effect, after a couple of years. By contrast, the effect on consumption is transitory and reaches its maximum on impact. Finally, there is no evidence of crowding-out. Consumption reacts positively to the fiscal shock. More surprisingly, the reaction of total investment is positive and significant on impact and becomes negative only in the long-run. Our estimated multiplier is 1.7 on impact, reaches its maximum, 2.2, after 3 quarters and then declines towards its long-run value, about 0.6.

The remainder of the paper is organized as follows: Section 2 discusses non-fundamentalness; Section 3 presents the factor model; Section 4 shows results; Section 5 concludes.

2 Fundamentalness, structural VARs and fiscal foresight

2.1 Fundamentalness in square and tall systems

Let us consider the statistical MA representation

$$\chi_t = B(L)u_t, \tag{1}$$

where $\chi_t = (\chi_{1t} \cdots \chi_{nt})'$ is an n-vector of weakly stationary variables, $B(L)$ is a $(n \times q)$ matrix of rational functions in the lag operator L, with $n \geq q$, and $u_t = (u_{1t} \cdots u_{qt})'$ is a q-dimensional white-noise normalized to have identity variance-covariance matrix.

By equation (1), χ_t lies in the space spanned by present and past values of u_t, i.e. $\chi_t \in H_t^u = \overline{\text{span}}(u_{,}j = 1, \ldots, q, \tau \leq t)$. However, the converse does not necessarily hold. If it does, i.e. $u_t \in H_t^\chi$, we say that representation (1) is fundamental and u_t is fundamental for χ_t. In such a case, observing χ_t is equivalent to observing u_t, in the sense that $H_t^u = H_t^\chi$. Moreover, by the uniqueness of the orthogonal decomposition, $(B(L) - B(0))u_t$ is the projection of χ_t onto its own past H_{t-1}^χ and $B(0)u_t$ is the residual, i.e. the innovation of the information set H_t^χ. [1] A fundamental white noise is not unique, but it is easily seen that if v_t is also fundamental, then it is a linear transformation of u_t. By contrast, non-fundamental white-noise vectors can be obtained from u_t by applying linear filters that involve the future of u_t and the so-called Blaschke matrices (see e.g. Lippi and Reichlin, 1994).

If $B(z)$ is rational, as assumed above, we can characterize fundamentalness in terms of its rank: representation (1) is fundamental if, and only if, the rank of $B(z)$ is q for all z such that $|z| < 1$ (see e.g. Rozanov, 1967, Ch. 1, Section 10, and Ch. 2, p. 76). In the particular case $n = q$, such condition reduces to the requirement that $\det B(z)$ does not vanish within the unit circle in the complex plane.[2]

Our main point here is that, as argued in Forni, Giannone, Lippi and Reichlin (2009), there is a substantial difference between the case $n = q$, on one hand, and $n > q$, on the other hand. In the former case, the determinant is a rational function, which generally vanishes somewhere and may well vanish within the unit circle. In the latter case, $B(z)$ is a "tall", rectangular matrix; its rank is less than q for some z only if all of the $(q \times q)$ sub-matrices of $B(z)$ are singular. Hence in general $B(z)$ is "zeroless", i.e. has rank q for all z, and non-fundamentalness is very unlikely. More precisely, letting p be the l-vector whose entries are the parameters of $B(L)$ and $\Pi \in \mathbb{R}^l$ the set of all possible p, in the case $n > q$ fundamentalness holds *generically* (i.e. the subset of Π where fundamentalness does not hold is *meagre*), whereas in the case $n = q$ fundamentalness is not generic.

[1] Conversely, if $B(0)u_t$ is the innovation of H_t^χ, u_t is fundamental for χ_t.

[2] Observe that invertibility implies fundamentalness, but the converse does not hold, because if the rank falls for some unit modulus z, we do not have invertibility.

Consider for instance the simple case $n = 2$, $q = 1$, $\chi_{1t} = u_t + b_1 u_{t-1}$, $\chi_{2t} = u_t + b_2 u_{t-1}$. Now consider the square subsystem made up by the first equation: u_t is non-fundamental for χ_{1t} if and only if $|b_1| > 1$. In this case, the fundamental representation is $\chi_{1t} = \eta_t + b_1^{-1}\eta_{t-1}$, $\eta_t = \left((1 + b_1 L)/(b_1 + L^{-1})\right) u_t$.[3] Similarly u_t is non-fundamental for χ_{2t} if and only if $|b_2| > 1$. However, the tall system made up by both equation is non-fundamental if and only if $b_1 = b_2$ and $|b_1| > 1$. Observe that u_t is generally fundamental for χ_t even if it is non-fundamental for both χ_{1t} and χ_{2t}.

2.2 Fundamentalness and VAR models

Now let us assume that (1) is derived as the solution of a DSGE model, so that the variables in χ_t are the macroeconomic variables of interest, the entries of u_t are structural shocks and $B(L)$ is a matrix of impulse-response functions (whose coefficients are functions of the deep parameters of the model). The number of variables n is typically larger than the number of shocks q, so that $B(L)$ is a tall matrix and χ_t is dynamically singular (i.e. its spectral density matrix has reduced rank q).

u_t is the innovation of the information set of economic agents. This is quite reasonable even if u_t is not directly observable, because, as noted above, u_t will be fundamental for χ_t, except for negligible cases, implying that $B(0)u_t$ is the residual of the projection of χ_t, which we assume observable, onto its own past H_{t-1}^{χ}.

At this stage the economist passes on the baton to the econometrician. The aim is to estimate $B(L)$ and u_t, starting from the information in H_t^{χ}. Unfortunately, macroeconomic series are not dynamically singular, perhaps because χ_t is observed with error. By estimating an n-dimensional VAR we would end up with n linearly independent shocks, in conflict with the theory. The standard strategy is then the following: (i) selecting a square, q-dimensional subsystem, say

$$\chi_t^* = B^*(L)u_t; \tag{2}$$

(ii) estimating the VAR $A(L)\chi_{1t} = \epsilon_t$ to find out the innovations $\epsilon_t = B^*(0)u_t$ and the MA filter $A(L)^{-1} = B^*(L)B^*(0)^{-1}$; (iii) identifying $B^*(0)$, and therefore representation (2), by imposing the normalization $B^*(0)B^*(0)^{-1} = \Sigma_\epsilon$ along with identifying restrictions derived from theoretical considerations.

However, as argued above, the square subsystem could be non-fundamental, or, equivalently, the reduced information space used by the econometrician, $H_t^{\chi^*}$, could be smaller than the one of the agents, H_t^u. In such a case, u_t is not a linear transformation of ϵ_t, so that step (ii) is wrong and the VAR cannot produce the correct result, whatever be the identification scheme adopted in (iii). Obviously, the choice of the subsystem in

[3] Observe that the Blaschke factor $b(L) = \left((1 + b_1 L)/(b_1 + L^{-1})\right)$ is such that $b(z)b(z^{-1}) = 1$, so that the spectral density of η_t is constant and η_t is white noise.

step (i) may be relevant, but, as shown in the example below, a fundamental subsystem does not necessarily exist.

2.3 A fiscal foresight example

Leeper, Walker and Yang (2008) show that fiscal shock non-fundamentalness in VAR models naturally arises in an economy with fiscal foresight.[4] Starting with a standard growth model with log preferences and inelastic labor supply, the authors obtain the equilibrium capital accumulation equation

$$k_t = \lambda_1 k_{t-1} - \lambda_2^{-1} \sum_{i=0}^{\infty} \theta^i E_t(\nu_0 a_{t+i+1} - \nu_1 a_{t+i} + \psi \tau_{t+i+1}) \tag{3}$$

where k_t, a_t and τ_t denote the log of capital, the log of technology and the tax rate, respectively, in deviation from the steady state. The parameters appearing in the above equation are functions of the deep parameters of the model; from the theory we know that $|\theta| < 1$ (θ is a discount rate). Technology and taxes follow the exogenous law of motions

$$\begin{aligned} a_t &= u_{A,t} \\ \tau_t &= u_{\tau,t-2} \end{aligned}$$

where $u_{\tau,t}$ and $u_{A,t}$ are i.i.d. shocks that economic agents can observe. The second equation says that the effect of fiscal policy on taxes is delayed by two periods.

Solving for k_t we get[5]

$$\begin{pmatrix} a_t \\ k_t \\ \tau_t \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ \frac{-\lambda_2^{-1}\psi(L+\theta)}{1-\lambda_1 L} & \frac{\lambda_2^{-1}\nu_1}{1-\lambda_1 L} \\ L^2 & 0 \end{pmatrix} \begin{pmatrix} u_{\tau,t} \\ u_{A,t} \end{pmatrix} = B(L) u_t$$

Let us consider the square subsystem given by the first two rows (technology and capital): the determinant $\frac{\lambda_2^{-1}\psi(z+\theta)}{1-\lambda_1 z}$ vanishes for $z = -\theta$, which is less than 1 in modulus. Similarly, the determinant of the submatrix given by the first and the last rows of $B(z)$ (technology and taxes) is z^2, which vanishes for $z = 0$. Finally, the determinant of the subsystem formed by the second and the last row (capital and taxes) also vanishes for $z = 0$. In conclusion, $u_t = (u_{\tau,t} u_{A,t})'$ is non-fundamental for any pair of variables on the left-hand side, implying that standard VAR techniques are unable to correctly estimate the fiscal shock. To better appreciate the role of anticipation, observe that with

[4]Simple examples of non-fundamentalness in economic models can also be found in Lippi and Reichlin (1993) and Fernández-Villaverde, Rubio-Ramirez, Sargent and Watson (2006).

[5]Strictly speaking the system is just a block of the model since for simplicity we abstract from consumption. However the implications discussed later remain unchanged.

no implementation delay ($\tau_t = u_{\tau,t}$), u_t would be fundamental for all of the subsystems, whereas, with a one-period delay ($\tau_t = u_{\tau,t-1}$), fundamentalness would still hold for the subsystem with taxes and capital. Intuitively, the variables convey information about the current values of the fiscal shock, as long as they are contemporaneously affected by such shock. In presence of implementation delay, taxes are not affected on impact, and therefore do not provide useful information. Capital is more helpful; however, if the delay is larger than one period, its contribution is not sufficient to recover the shock.

Let us now consider the whole system. u_t is fundamental for χ_t, since $B(z)$ is zeroless, i.e. has rank 2 everywhere in the complex plane. In fact, it is easily seen that χ_t has the reduced rank VAR representation[6]

$$\begin{pmatrix} 1 & 0 & 0 \\ \lambda_2^{-1}\psi L & 1-\lambda_1 L & 0 \\ \frac{\nu_1(L-\theta)L^2}{\psi\theta^2} & \frac{(L-\theta)(1-\lambda_1 L)L^2}{\lambda_2^{-1}\psi\theta^2} & 1-\frac{L^2}{\theta^2} \end{pmatrix} \begin{pmatrix} a_t \\ k_t \\ \hat{\tau}_t \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ -\lambda_2^{-1}\psi\theta & \lambda_2^{-1}\nu_1 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} u_{\tau,t} \\ u_{A,t} \end{pmatrix}.$$

Put differently, present and past values of the three variables, capital, taxes and technology, are sufficient to estimate the two shocks. Unfortunately, standard VAR techniques cannot be used to this end. In the next section we present a structural factor model, whose core is a tall system like the one above. Such a system can be consistently estimated through appropriate procedures.

3 The large factor model

3.1 Representation

In the present section we provide a presentation of our model and estimation procedure. For additional details see Forni, Giannone, Lippi and Reichlin (2009), FGLR from now on.

A convenient assumption, which is standard in the large factor model literature, is that there are infinitely many variables x_{it}, $i \in \mathbb{N}$. The econometrician observes the first n of them, and consistency results are obtained for both n and T (the number of time observation) going to infinity.

Each macroeconomic variable is the sum of two mutually orthogonal unobservable components, the common component χ_{it} and the idiosyncratic component ξ_{it}:

$$x_{it} = \chi_{it} + \xi_{it}. \tag{4}$$

The idiosyncratic components are poorly correlated in the cross-sectional dimension (see FGLR, Assumption 5 for a precise statement). They arise from shocks or sources

[6]Notice that the VAR representation has finite order. Existence of a finite VAR representation is a general property for zeroless tall rational systems (Anderson and Deistler 2008).

of variation which considerably affect only a single variable or a small group of variables; in this sense, we could say that they are not "macroeconomic" shocks. For variables related to particular sectors, like industrial production indexes or production prices, the idiosyncratic component may reflect sector-specific variations (with a slight abuse of language we could say "microeconomic" fluctuations); for strictly macroeconomic variables, like GDP, investment or consumption, the idiosyncratic component must be interpreted essentially as a measurement error. With equation (1) in mind it is easily seen that the factor model can be interpreted as the log-linear solution of a DSGE model augmented with a measurement error.[7]

The common components are responsible for the main bulk of the co-movements between macroeconomic variables, being linear combinations of a relatively small number r of factors $f_{1t}, f_{2t}, \cdots, f_{rt}$, not depending on i:

$$\chi_{it} = a_{1i} f_{1t} + a_{2i} f_{2t} + \cdots + a_{ri} f_{rt} = a_i f_t. \tag{5}$$

Such factors can be interpreted as the state variables of the economic system.

The dynamic relations between the macroeconomic variables arise from the fact that the vector f_t follows the relation

$$f_t = N(L) u_t, \tag{6}$$

where $N(L)$ is a $r \times q$ matrix of rational functions in the lag operator L and $u_t = (u_{1t} \ u_{2t} \ \cdots \ u_{qt})'$ is a q-dimensional vector of orthonormal white noises, with $q < r$. Such white noises are the structural macroeconomic shocks.[8]

Since $N(L)$ is tall, the discussion in the previous section motivate the assumption that $N(z)$ is zeroless, i.e. $\text{rank} N(z) = q$ for any z, which implies fundamentalness. This ensure that f_t has the finite order VAR representation (Anderson and Deistler, 2008)

$$D(L) f_t = \epsilon_t = R u_t, \tag{7}$$

where $D(L)$ is a $r \times r$ matrix of polynomials such that $D(L)^{-1} R = N(L)$ and $R = N(0)$.

From equations (4) to (7) it is seen that the model can be written in the dynamic form

$$x_{it} = b_i(L) u_t + \xi_{it}, \tag{8}$$

[7] See also Altug, 1989, Sargent, 1989, and Ireland 2004 for the link between factor models and DSGE models.

[8] In the large dynamic factor model literature they are sometimes called the "common" or "primitive" shocks or "dynamic factors" (whereas the entries of f_t are the "static factors"). Equations (4) to (6) need further qualification to ensure that all of the factors are loaded, so to speak, by enough variables with large enough loadings (see FGLR, Assumption 4); this "pervasiveness" condition is necessary to have uniqueness of the common and the idiosyncratic components, as well as the number of static factors r and dynamic factors q.

where

$$b_i(L) = a_i N(L) = a_i D(L)^{-1} R. \tag{9}$$

The entries of the q-dimensional vector $b_i(L)$ are the impulse-response functions.

Observe that, under appropriate regularity conditions on the factor loadings a_i,[9] the linear space spanned by the χ's includes the factors, so that u_t is fundamental for the χ's. Moreover, since the idiosyncratic components are poorly correlated across sections and the x's are infinite in number, by taking appropriate averages of the x's we can kill the idiosyncratic components and obtain the factor without error. We can restate this by saying that u_t is fundamental for the x's.

3.2 Identification

Representation (8) is not unique, since the impulse-response functions and the related primitive shocks are not identified. In particular, if H is any orthogonal $q \times q$ matrix, then Ru_t in (7) is equal to Sv_t, where $S = RH'$ and $v_t = Hu_t$, so that $\chi_{it} = c_i(L)v_t$, with $c_i(L) = b_i(L)H' = a_i D(L)^{-1} S$. However, assuming mutually orthogonal structural shocks, post-multiplication by H' is the only admissible transformation, i.e. the impulse-response functions are unique up to orthogonal transformations, just like in structural VAR models (FGLR, Proposition 2). As a consequence, structural analysis in factor models can be carried on along lines very similar to those of standard SVAR analysis.

To be precise, let us assume with no loss of generality that economic theory implies a set of restrictions on the impulse-response functions the first $m \leq n$ variables, n being the number of variables in the data set. Let us write such functions in matrix notation as $B_m(L) = (b_1(L)' b_2(L)' \cdots b_m(L)')'$. Given any non-structural representation

$$\begin{pmatrix} \chi_{1t} \\ \vdots \\ \chi_{mt} \end{pmatrix} = C_m(L) v_t, \tag{10}$$

along with the relation

$$B_m(L) = C_m(L) H, \tag{11}$$

if theory-based restrictions on $B_m(L)$ are sufficient to obtain H, then $B_n(L)$ is uniquely determined (global identification). If the researcher, as is the case in the fiscal foresight literature, is interested in identifying just a single shock, along with the related impulse response functions (partial identification), the target is to determine the entries of a single column of the matrix H, say H_1, which is enough to get the first column of $B_n(L)$, say $B_{n1}(L)$.

[9] see FGLR, Assumption 4.

In the present paper we do not identify uniquely the shock and the impulse-response functions; rather, following Uhlig (2005), we identify a distribution of shocks and related impulse-response functions by imposing a set of sign restrictions on the impulse-response functions themselves.[10] The first column H_1 of the matrix H is a point on the unit sphere S^{q-1}. Given the non-structural representation $C_n(L)v_t$, the sign restrictions that we impose on $B_{m1}(L)$ define an admissible region Θ on the unit sphere, such that for $H_1 \in \Theta$ $B_{m1}(L) = C_n(L)H_1$ satisfies such inequalities. Following Uhlig (2005), we assume a uniform *a priori* probability density in the region Θ. This in turn implies a density and the associated confidence bounds for each coefficient of the impulse-response functions.

3.3 Estimation

As for estimation, we proceed as follows. First, starting with an estimate $\hat{r}$ of the number of static factors, we estimate the static factors themselves by means of the first $\hat{r}$ principal components of the variables in the data set, and the factor loadings by means of the associated eigenvectors. Precisely, let $\hat{\Gamma}^x$ be the sample variance-covariance matrix of the data: our estimated loading matrix $\hat{A}_n = (\hat{a}_1' \hat{a}_2' \cdots \hat{a}_n')'$ is the $n \times r$ matrix having on the columns the normalized eigenvectors corresponding to the first largest $\hat{r}$ eigenvalues of $\hat{\Gamma}^x$, and our estimated factors are $\hat{f}_t = \hat{A}_n'(x_{1t}x_{2t} \cdots x_{nt})'$. The intuition behind this estimation method is that by taking appropriate linear combinations of a large number of variables (the principal components), the idiosyncratic components vanish, owing to their poor cross-sectional correlation. Therefore we are left with r independent linear combinations of the χ's, which are a basis of the linear space spanned by the factors.[11]

Second, we set a number of lags $\hat{p}$ and run a VAR($\hat{p}$) with $\hat{f}_t$ to get $\hat{D}(L)$ and $\hat{\epsilon}_t$. Now, let $\hat{\Gamma}^\epsilon$ be the sample variance-covariance matrix of $\hat{\epsilon}_t$. As the third step, having an estimate $\hat{q}$ of the number of dynamic factors, we obtain an estimate of a non-structural representation of the common components by using the spectral decomposition of $\hat{\Gamma}^\epsilon$. Precisely, let $\hat{\mu}_j^\epsilon$, $j = 1, \ldots, \hat{q}$, be the j-th eigenvalue of $\hat{\Gamma}^\epsilon$, in decreasing order, $\hat{\mathcal{M}}$ the $q \times q$ diagonal matrix with $\sqrt{\hat{\mu}_j^\epsilon}$ as its (j, j) entry, $\hat{K}$ the $r \times q$ matrix with the corresponding normalized eigenvectors on the columns. Setting $\hat{S} = \hat{K}\hat{\mathcal{M}}$, our estimated matrix of non-structural impulse response functions is

$$\hat{C}_n(L) = \hat{A}_n \hat{D}(L)^{-1} \hat{S}. \tag{12}$$

Consistency of the above estimation procedure (as both the cross-sectional and the

[10] The precise set of restrictions that we impose is discussed below.

[11] Indeed, the factors are identified only up to linear transformations. What we estimate is a basis of the factor space.

time dimension go to infinity) is proven in FGLR.

To account for estimation uncertainty, we adopt the following standard non-overlapping block bootstrap technique. Let $X = [x_{it}]$ be the $T \times n$ matrix of data. Such matrix is partitioned into S sub-matrices X_s (blocks), $s = 1, \ldots, S$, of dimension $\tau \times n$, τ being the integer part of T/S.[12] An integer h_s between 1 and S is drawn randomly with reintroduction S times to obtain the sequence $h_1, \ldots, h_S$. A new artificial sample of dimension $\tau S \times n$ is then generated as $X^* = \left[X'_{h_1} X'_{h_2} \cdots X'_{h_S}\right]'$ and the corresponding impulse-response functions are estimated. A set of non-structural impulse-response functions is obtained by repeating drawing and estimation.

Finally, we obtain a distribution of impulse-response functions by imposing our sign identification restrictions. Precisely, we proceed as follows. For each artificial sample X^* we compute the corresponding non-structural impulse response functions $\hat{C}_n(L)$. Then we draw N times a vector H_1 by drawing its q entries from a standard normal distribution and normalize by dividing by its Euclidean norm and retain the related vector of impulse response functions $\hat{B}_{n1}(L) = \hat{C}_n(L)H_1$ as long as it satisfies the sign restrictions. This gives a distribution of estimated $\hat{B}_{n1}(L)$'s. We get a point estimate and the related confidence bands by retaining the mean along with the relevant percentiles of such a distribution.[13]

3.4 Discussion

FGLR is a special case of the generalized dynamic factor model proposed by Forni, *et al.* (2000, 2004, 2005) and Forni and Lippi (2001, 2010). This model differs from the traditional dynamic factor model of Sargent and Sims (1977) and Geweke (1977) in that the number of cross-sectional variables is infinite and the idiosyncratic components are allowed to be mutually correlated to some extent, along the lines of Chamberlain (1983), Chamberlain and Rothschild (1983) and Connor and Korajczyk (1988). Closely related models have been studied by Forni and Reichlin (1998), Stock and Watson (2002a, 2002b, 2005), Bai and Ng (2002, 2007), Bai (2003) and Bernanke *et al.* (2005).

Factor models impose a considerable amount of structure on the data, implying restricted VAR relations among variables (see Stock and Watson, 2005 for a comprehensive analysis). In this sense, they are less general than VAR models. The advantage is that factor models are much more parsimonious in terms of parameters to estimate, so that they can handle a large number of time series. This is crucial in the present

[12]Note that τ has to be large enough to retain relevant lagged auto- and cross-covariances In the present paper we set $\tau = 19$.

[13]Here we impose an upper bound (10) to the number of impulse-response functions to retain for each step of the bootstrap procedure in order to avoid that a single bootstrap provide a disproportionately large number of functions.

context, since, as shown in the previous section, non-fundamentalness arises from information deficiency. As a matter of fact, large dimensional factor models have proven useful in solving well known VAR puzzles (Bernanke *et al.*, 2005, Forni and Gambetti, 2010).

To gain some additional insight about the reason why the factor model solves the non-fundamentalness problem, let us go back to the economic model (1). We have seen that, if it contains only q variables, χ_{jt}, $j = 1, \ldots, q$, fundamentalness of u_t is not ensured, the reason being possible superior information of the agents with respect to present and past values of χ_{jt}, $j = 1, \ldots, q$. However, the informational advantage of the agents disappears if the econometrician observes additional macroeconomic variables. Intuitively, this is because, when shifting from a square system to a tall one, we are enlarging information, without adding sources of uncertainty. The generating processes of χ_{jt}, $j = q + 1, \ldots, n$, have impulse response functions which, in all likelihood, are sufficiently heterogeneous, with respect to the first q, to prevent the rank reduction which is equivalent to non-fundamentalness. The χ's are only observed with error; however, we also assume that n is large, so that we can get rid of them using large-dimensional factor-model techniques.

It should be clear from the previous subsection that the core of our estimation procedure is (i) estimation of the factor space trough principal components and (ii) estimation of the VAR (7) with the principal components. One may wonder why such VAR is not affected by the non-fundamentalness problem. The answer is that the VAR for the principal components is singular (i.e. the residuals are asymptotically singular). This would not be the case for a VAR with r variables, otherwise we could directly estimate system (1).

Let us notice here that the FAVAR model proposed by Bernanke *et al.* (2005), while being similar in some respects to the factor model used here, assumes $r = q$. This feature of the model, besides being at odds with empirical data according to existing information criteria (see below), is particularly unappealing in light of the above arguments.

Finally let us stress again that, as already argued in Section 2, the q-dimensional square submatrices of $N(z) = D(z)^{-1}R$ appearing in equation (6) can be singular for values of z within the unit circle, without hurting consistency of estimation. Similarly, if we take a q-dimensional vector of integers I, such that $I_i \leq n$, $i = 1, \ldots, q$, then u_t can be non-fundamental for the subvector $(\chi_{I_1 t} \cdots \chi_{I_q t})' = B_I(L)u_t = A_I N(L)u_t$ and $\det B_I(z)$ can vanish within the unit circle.

This is interesting because we can estimate the smallest root of some selected square subsystems and verify whether the corresponding impulse response functions are indeed non-fundamental, implying a problem for VAR estimation.

4 Empirics

4.1 Data and model specification

The data set contains 106 quarterly macroeconomic series spanning from 1959:I to 2007:IV. It includes fiscal policy variables, GDP and components, industrial production indexes, labor market variables, stock market variables, surveys, leading indicators, price indexes and deflators, money and credit aggregates, long- and short-term interest rates. The data are transformed to reach stationarity, as required by the model. The full list of variables along with the corresponding transformations is reported in the Appendix. All series are taken from FRED Database, Federal Reserve Bank of St. Louis.

Before estimation we need to specify the number of static factor, $\hat{r}$, the number of shocks, $\hat{q}$, and the number of lags, $\hat{p}$. To determine $\hat{r}$ we use the IC_{p2} criterion of Bai and Ng (2002), which gives $\hat{r} = 13$. We fix $\hat{p} = 3$.

As for $\hat{q}$, Table 1 shows the results of the test proposed by Onatski (2009). Each cell reports the probability value of the null of just k (columns) shocks against the alternative of j (rows) shocks, with $k + 1 \leq j \leq h$.[14] For instance, the element 2,2 in the matrix is the p-value of the test of the null of $k = 1$ against the alternative of $j = 2$. The null of $k = 1, ..., 5$ shocks is rejected at the 10% level against the alternative of six shocks. For $k = 4, 5$ the null is rejected even at the 5%. However the null $k = 6$ is not rejected against any of the alternatives. These results support a six-shock model specification.

The number of shocks can also be determined by a few consistent information criteria. Here we use three groups of criteria, proposed by Amengual and Watson (2007), Bai and Ng (2007) and Hallin and Liska (2007). The criterion $\hat{BN}^{ICP}(\hat{y}^A)$ by Amengual and Watson gives 6 primitive factors in the IC_{p1} version and 4 primitive factors in the IC_{p2} version (with $\hat{r} = 13$ and $\hat{p} = 3$). The four criteria of Bai and Ng (2007), namely q_1, q_2, q_3 and q_4, give 5, 6, 5 and 4 shocks respectively (with $\hat{r} = 13$ and $\hat{p} = 3$).[15] Finally, the log criterion proposed by Hallin and Liska gives 3 shocks for all of the proposed penalty functions (independently of the initial random permutation). In summary, information criteria do not provide a unique result, the number of shocks being between 3 and 6. Here we conclude in favor of a six-shock specification, which results from the Onatski tests and is consistent with the range emerging from available

[14] The test has two parameters identifying the lower and the upper bound of the frequencies of interest. Since we are mainly interested in business cycle fluctuations, we set these parameters in such a way as to include waves of periodicity between 2 and 12 years.

[15] The Bai and Ng criteria have two parameters. We set $\delta = .1$ for all criteria and $m(q_1) = 1.1$, $m(q_2) = 1.9$, $m(q_3) = 1.8$, $m(q_4) = 4$. Such values produced good results in our simulations (not shown here).

information criteria.

4.2 The smallest root of some selected sub-systems

In this subsection we investigate whether the government spending shock is fundamental for the variables which have been commonly used in the VAR literature.

We consider seven different variables specifications (listed in Table 2a) corresponding to seven different choices of I (see Section 3.4), denoted I^j $j = 1, ..., 6$. For each specification we compute the modulus of the smallest root of the determinant of the corresponding impulse response functions $B_{I^j}(L)$. The roots are computed for the real data as well as all the bootstrap repetitions, so that the whole distribution is available.

Table 1b shows the mean, the median, a few percentiles of the distribution and the point estimate. For all j the mean is smaller than one, ranging from 0.57 to 0.89. For the first three specifications, the probability of the smallest root to be smaller than one in modulus is higher than 90%. Notice that specification 2 is quite common and similar to that used in Ramey (2009). For the last two specifications the percentiles are slightly higher. In particular stock prices seem particularly helpful in capturing the fiscal shock, since for the specification including this variable ($j = 5$) the median is nearly one. Notice also that for $j = 5, 6$ the point estimate is slightly larger than one.

We also consider two four-variable specifications (recall that $\hat{q} = 4$ is within the range indicated by the information criteria). Both include government spending, output and taxes. One includes consumption, the other investment. These two specifications are particularly interesting because correspond to those used in Blanchard and Perotti (2002) and Gali et al. (2007). In both cases the mean and the median of the modulus of the smallest root are around 0.5 and the 90th percentile is smaller than one. Moreover the point estimate is much smaller than one. Again, strong evidence in favor of non-fundamentalness of the government spending shock for standard VAR specifications emerges.

We conclude that, first, standard VAR models are unable to properly recover the effects of government spending shocks, independently of the identification scheme adopted; second, including forward looking variables like stock prices in the VAR can be helpful to estimate the shock.

4.3 Identifying restrictions

Identification of the government spending shock is achieved by means of sign restrictions (Uhlig, 2005).[16] Precisely, an expansionary shock is defined as a shock having a positive effect on government expenditure, output (GDP and industrial production),

[16] Sign restrictions for the identification of government spending shocks are used also in Pappa (2009).

prices (CPI and the GDP deflator), the prime rate, the government primary deficit and tax receipts. The positive effect on output and prices is imposed to distinguish the shock from a systematic spending reaction to a recessionary shock stemming from the private sector. An increasing deficit is imposed to exclude expenditures entirely financed with additional receipts. The last inequality is imposed to distinguish the government spending shock from a tax shock. All of the restrictions are imposed only on the responses delayed by six months (the third coefficient of the impulse response functions), so that the impact effect on all variables, and in particular government spending, is left unrestricted to avoid the fiscal-foresight criticism.

Having defined the relevant sign restrictions, we proceeded as explained at the end of Section 3.2 to get a set of admissible impulse response functions (satisfying the restrictions) and a set of corresponding fiscal shock series. We obtained 350 admissible shock series out of 20,000 drawings of the rotation parameters. We took the simple average of such series as our estimate of the fiscal shock.

Finally we performed the bootstrapping procedure explained at the end of Section 3.3 to get a posterior density distribution for the impulse response functions. We generated 300 artificial samples X^* and for each one of them we drew 1,000 rotation vectors H_1. We retained 1,029 admissible sets of impulse response functions. In the pictures below we show the average along with the 16th and the 84th percentiles of the related distribution.

4.4 Granger causation and anticipation

Having obtained our estimate of the government spending shock we verify whether such shock passes Ramey's Granger-causation test. As already noted, Ramey (2008) shows that the government spending shock obtained with a VAR similar to that of Perotti (2007) is Granger-caused by the government spending forecast from the Survey of Professional Forecasters. Here we perform a similar exercise using our estimated shock. Specifically, we regress the government spending shock on four lags of the shock itself and four lags of the government spending forecast. Table 4 shows the results. None of the parameters is statistically significant. The F-statistic obtained under the null hypothesis that the parameters of the lags of the forecast variable are jointly zero is 1.862, which is very much smaller than the 10% critical value. In conclusion, our government spending shock is not Granger-caused by the government spending forecast series.

Let us now go deeper into the analysis of government spending anticipation by examining the estimated impulse response functions. Figures 1-3 depict the reaction profile of several variables of interest to a government spending shock which raises government spending by one percent of GDP as the maximum effect (horizon 8). Consistently with the existence of implementation lags, government spending increases slowly, reaching the maximal level after two years. About one half of the total spending takes place immediately, half is delayed by one quarter or more. By contrast, consumption and investment reach their maximal level either on impact (consumption), or 1-2 quarters after the shock (GDP and investment). Hence, the spending is spread over time, whereas economic agents react immediately. This seems to fit the story that agents receive signals about changes in taxes and government spending, and react to them, before these changes are fully in place.

4.5 Crowding-out and the multiplier

Now let us look at the reaction of GDP and its components. GDP reacts immediately, increasing by 2%. The response stays at that level for about one year and starts decreasing afterward, the effects being no longer significant after 6 quarters. Given the normalization imposed, the impulse response function represents the government spending multiplier. The estimated multiplier is 1.7 on impact, reaches its maximum, 2.2, after 3 quarters and then declines towards its long-run value, about 0.6. Confidence bands show that the multiplier is significantly above one at horizon 2, while is not different from zero in the long run.

The size and shape of the multiplier can be explained by looking at the response of private consumption and investment. Both consumption and investment immediately and significantly increase by about 1% and 3% respectively. The response of consumption is very short-lived, declining and becoming not significant after the second quarter. On the contrary, the response of investment appears to be more persistent, the effect vanishing only after about six quarters. In the long run, the point estimate of the response of both variables is negative, although not significant.

By inspecting the disaggregated components (Fig. 2), it is clear that the response of aggregate investment is mainly driven by non-residential investment while residential investment is crowded out after the nearly zero impact effect. As far as consumption is concerned, the three components react positively and significantly on impact. Government spending crowds-in, in the short run, private components of aggregate demand.

Results for consumption stand in sharp contrast with the standard prediction of RBC models, where government spending shock generate negative wealth effect that depresses consumption. They are consistent with the evidence in Blanchard and Perotti (2002), with the remarkable difference that here the response is temporary and short-lived, with the maximal effects observed on impact.

The response of investment contradicts the standard textbook crowding-out effect triggered by the increase in the interest rate. A positive response of investment, however, is the outcome predicted in Baxter and King (1993) after a permanent government spending shock. There, the increase in investment is caused by an increase in the marginal productivity of capital following a sharp increase in employment which is also found here (see Fig. 3).[17]

4.6 Variance decomposition

Table 2 shows the variance decomposition for several variables of interest. Columns 2-5 report the percentage of forecast error variance of the variables listed in column 1, accounted for by the shock at various horizons. Column 6 reports the percentage of the variance of the series, transformed to reach stationarity (e.g. inflation instead of prices), accounted for by the shock. The shock accounts for about 25% of the variance of government spending (both federal and total) and about 10% of the variance of deficit and taxes. At a first sight, these numbers could seem small but recall that (i) we are ruling out tax shocks; (ii) we are ruling out spending not increasing current deficit; and (iii) this is *discretionary* policy, in that it excludes systematic reactions to shocks stemming from the private sector.

The shock accounts for about 16%, 13% and 16% of the variance of GDP, investment and consumption, respectively. Interestingly, the shock is more important in the very short run (on impact it explains 21% 14% and 20% of the three variables, respectively) than at longer horizons (at horizon 20 percentages are 9%, 8% and 9%, respectively.

4.7 Robustness

This subsection studies the robustness of the results to changes in model specification.

First let us compare the results of our benchmark specification ($r = 13$, $q = 6$) with five alternative specifications: 1) $r = 10$, $q = 6$; 2)$r = 16$, $q = 6$; 3)$r = 10$, $q = 4$; 4)$r = 13$, $q = 4$; 5)$r = 16$, $q = 4$. Figure 4 displays the impulse response functions of consumption and investment for the six different specifications. The first column depicts the responses for the 4 dynamic shock specification, the second those for the 6 dynamic shock specification. Overall the results are remarkably similar both from a qualitative and from a quantitative point of view. The only minor difference is that the effects tend to be slightly larger in the 10 static factor specification and slightly smaller in the 16 factor specification than in our benchmark.

We also made several other checks listed below.

1) We used the federal funds rate and the 10 year bond rate instead of the prime rate to identify the shock.

2) We used federal government spending instead of and together with total government

[17]However, unlike Baxter and King (1993), here the persistent increase in labor cannot be caused by a negative wealth effect, given that consumption increases.

spending to identify the shock.
3) We did not restrict the interest rate.
4) We used two instead of three lags in the VAR for the factors.
5) We imposed the identifying restriction for periods 4 or/and 5.
6) We used the second (instead of first) differences of the log of prices and other nominal variables.
7) We used the estimation procedure proposed by Forni and Lippi (2010).
In all these experiments we found the same results obtained in the benchmark model.

Overall results seem to be robust to changes in model specification.

5 Conclusions

This paper studied the effects of government spending shocks in the US using a structural, large dimensional, dynamic factor model. The main motivation is that in this model, unlike in VARs, the shocks are fundamental even in presence of fiscal foresight. We find that the government spending shock is non-fundamental for the variables commonly used in the structural VAR literature, so that its impulse response functions cannot be consistently estimated by means of a VAR. Government spending raises both consumption and investment, with no evidence of crowding out. The impact multiplier is 1.7 and the long run multiplier is 0.6.

Appendix: Data

Transformations: 1=levels, 2= first differences of the original series, 5= first differences of logs of the original series, 5= second differences of logs of the original series.

no.series	Transf.	Mnemonic	Long Label
1	5	GDPC1	Real Gross Domestic Product, 1 Decimal
2	5	GNPC96	Real Gross National Product
3	5	NICUR/GDPDEF	National Income/GDPDEF
4	5	DPIC96	Real Disposable Personal Income
5	5	OUTNFB	Nonfarm Business Sector: Output
6	5	FINSLC1	Real Final Sales of Domestic Product, 1 Decimal
7	5	FPIC1	Real Private Fixed Investment, 1 Decimal
8	5	PRFIC1	Real Private Residential Fixed Investment, 1 Decimal
9	5	PNFIC1	Real Private Nonresidential Fixed Investment, 1 Decimal
10	5	GPDIC1	Real Gross Private Domestic Investment, 1 Decimal
11	5	PCECC96	Real Personal Consumption Expenditures
12	5	PCNDGC96	Real Personal Consumption Expenditures: Nondurable Goods
13	5	PCDGCC96	Real Personal Consumption Expenditures: Durable Goods
14	5	PCESVC96	Real Personal Consumption Expenditures: Services
15	5	GPSAVE/GDPDEF	Gross Private Saving/GDP Deflator
16	5	FGCEC1	Real Federal Consumption Expenditures & Gross Investment, 1 Decimal
17	5	FGEXPND/GDPDEF	Federal Government: Current Expenditures/ GDP deflator
18	5	FGRECPT/GDPDEF	Federal Government Current Receipts/ GDP deflator
19	2	FGDEF	Federal Real Expend-Real Receipts
20	1	CBIC1	Real Change in Private Inventories, 1 Decimal
21	5	EXPGSC1	Real Exports of Goods & Services, 1 Decimal
22	5	IMPGSC1	Real Imports of Goods & Services, 1 Decimal
23	5	CP/GDPDEF	Corporate Profits After Tax/GDP deflator
24	5	NFCPATAX/GDPDEF	Nonfinancial Corporate Business: Profits After Tax/GDP deflator
25	5	CNCF/GDPDEF	Corporate Net Cash Flow/GDP deflator
26	5	DIVIDEND/GDPDEF	Net Corporate Dividends/GDP deflator
27	5	HOANBS	Nonfarm Business Sector: Hours of All Persons
28	5	OPHNFB	Nonfarm Business Sector: Output Per Hour of All Persons
29	5	UNLPNBS	Nonfarm Business Sector: Unit Nonlabor Payments
30	5	ULCNFB	Nonfarm Business Sector: Unit Labor Cost
31	5	WASCUR/CPI	Compensation of Employees: Wages & Salary Accruals/CPI
32	5	COMPNFB	Nonfarm Business Sector: Compensation Per Hour
33	5	COMPRNFB	Nonfarm Business Sector: Real Compensation Per Hour

no.series	Transf.	Mnemonic	Long Label
34	5	GDPCTPI	Gross Domestic Product: Chain-type Price Index
35	5	GNPCTPI	Gross National Product: Chain-type Price Index
36	5	GDPDEF	Gross Domestic Product: Implicit Price Deflator
37	5	GNPDEF	Gross National Product: Implicit Price Deflator
38	5	INDPRO	Industrial Production Index
39	5	IPBUSEQ	Industrial Production: Business Equipment
40	5	IPCONGD	Industrial Production: Consumer Goods
41	5	IPDCONGD	Industrial Production: Durable Consumer Goods
42	5	IPFINAL	Industrial Production: Final Products (Market Group)
43	5	IPMAT	Industrial Production: Materials
44	5	IPNCONGD	Industrial Production: Nondurable Consumer Goods
45	2	AWHMAN	Average Weekly Hours: Manufacturing
46	2	AWOTMAN	Average Weekly Hours: Overtime: Manufacturing
47	2	CIVPART	Civilian Participation Rate
48	5	CLF16OV	Civilian Labor Force
49	5	CE16OV	Civilian Employment
50	5	USPRIV	All Employees: Total Private Industries
51	5	USGOOD	All Employees: Goods-Producing Industries
52	5	SRVPRD	All Employees: Service-Providing Industries
53	5	UNEMPLOY	Unemployed
54	5	UEMPMEAN	Average (Mean) Duration of Unemployment
55	2	UNRATE	Civilian Unemployment Rate
56	5	HOUST	Housing Starts: Total: New Privately Owned Housing Units Started
57	2	FEDFUNDS	Effective Federal Funds Rate
58	2	TB3MS	3-Month Treasury Bill: Secondary Market Rate
59	2	GS1	1-Year Treasury Constant Maturity Rate
60	2	GS10	10-Year Treasury Constant Maturity Rate
61	2	AAA	Moody's Seasoned Aaa Corporate Bond Yield
62	2	BAA	Moody's Seasoned Baa Corporate Bond Yield
63	2	MPRIME	Bank Prime Loan Rate
64	5	BOGNONBR	Non-Borrowed Reserves of Depository Institutions
65	5	TRARR	Board of Governors Total Reserves, Adjusted for Changes in Reserve
66	5	BOGAMBSL	Board of Governors Monetary Base, Adjusted for Changes in Reserve
67	5	M1SL	M1 Money Stock
68	5	M2MSL	M2 Minus
69	5	M2SL	M2 Money Stock

no.series	Transf.	Mnemonic	Long Label
70	5	BUSLOANS	Commercial and Industrial Loans at All Commercial Banks
71	5	CONSUMER	Consumer (Individual) Loans at All Commercial Banks
72	5	LOANINV	Total Loans and Investments at All Commercial Banks
73	5	REALLN	Real Estate Loans at All Commercial Banks
74	5	TOTALSL	Total Consumer Credit Outstanding
75	5	CPIAUCSL	Consumer Price Index For All Urban Consumers: All Items
76	5	CPIULFSL	Consumer Price Index for All Urban Consumers: All Items Less Food
77	5	CPILEGSL	Consumer Price Index for All Urban Consumers: All Items Less Energy
78	5	CPILFESL	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy
79	5	CPIENGSL	Consumer Price Index for All Urban Consumers: Energy
80	5	CPIUFDSL	Consumer Price Index for All Urban Consumers: Food
81	5	PPICPE	Producer Price Index Finished Goods: Capital Equipment
82	5	PPICRM	Producer Price Index: Crude Materials for Further Processing
83	5	PPIFCG	Producer Price Index: Finished Consumer Goods
84	5	PPIFGS	Producer Price Index: Finished Goods
85	5	OILPRICE	Spot Oil Price: West Texas Intermediate
86	5	USSHRPRCF	US Dow Jones Industrials Share Price Index (EP) NADJ
87	5	US500STK	US Standard & Poor's Index if 500 Common Stocks
88	5	USI62...F	US Share Price Index NADJ
89	5	USNOIDN.D	US Manufacturers New Orders for Non Defense Capital Goods (BCI 27)
90	5	USCNORCGD	US New Orders of Consumer Goods & Materials (BCI 8) CONA
91	1	USNAPMNO	US ISM Manufacturers Survey: New Orders Index SADJ
92	5	USVACTOTO	US Index of Help Wanted Advertising VOLA
93	5	USCYLEAD	US The Conference Board Leading Economic Indicators Index SADJ
94	5	USECRIWLH	US Economic Cycle Research Institute Weekly Leading Index
95	2	GS10-FEDFUNDS	
96	2	GS1-FEDFUNDS	
97	2	BAA-FEDFUNDS	
98	5	GEXPND/GDPDEF	Government Current Expenditures/ GDP deflator
99	5	GRECPT/GDPDEF	Government Current Receipts/ GDP deflator
100	2	GDEF	Governnent Real Expend-Real Receipts
101	5	GCEC1	Real Government Cons. Expenditures & Gross Investment, 1 Decimal
102	5		Real Federal Cons. Expenditures & Gross Investment National Defense
103	2		Federal primary deficit
104	5		Real Federal Current Tax Revenues
105	5		Real Government Current Tax Revenues
106	2		Government primary deficit

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Tables

Table 1:

	1	2	3	4	5	6	7
0	0.004	0.007	0.009	0.012	0.014	0.017	0.02
1		0.107	0.192	0.258	0.317	0.085	0.099
2			0.144	0.259	0.345	0.072	0.085
3				0.825	0.821	0.056	0.072
4					0.503	0.041	0.056
5						0.023	0.041
6							0.852

Table 1: Onatsky's test results.

j	Variables (I^j)(*)
Four shocks:	
1	GDP(1), Gov. Cons & Inv.(101), Taxes(105), Cons.(11)
2	GDP(1), Gov. Cons & Inv.(101), Taxes(105), Inv.(7)
Six shocks:	
1	GDP(1), Gov. Cons & Inv.(101), Taxes(105), Cons.(11), Real Wage(33), Inv. (7)
2	GDP(1), Gov. Cons & Inv.(101), Taxes(105), Cons.(11), Hours(27), Inv. (7)
3	GDP(1), Gov. Cons & Inv.(101), Taxes(105), Cons.(11), Real Wage(33), Hours(27)
4	GDP(1), Gov. Cons & Inv.(101), Taxes(105), Cons.(11), Inv.(7), CPI(75)
5	GDP(1), Gov. Cons & Inv.(101), Taxes(105), Cons.(11), Stock Prices(87), CPI(75)
6	GDP(1), Gov. Cons & Inv.(101), Taxes(105), Cons.(11), New Orders(90), Int. Rate(58)

(*) The numbers correspond to those in the Appendix.

Table 2a: Variables

j	Mean	Median	68%	84%	90%	95%	97.5%	Point est.
Four shocks:								
1	0.5013	0.472	0.7337	0.9074	0.9741	1.029	1.0599	0.2785
2	0.5878	0.6153	0.7313	0.8501	0.8989	0.9628	0.9894	0.6146
Six shocks:								
1	0.5836	0.6197	0.7608	0.8749	0.9277	0.9835	1.0223	0.5274
2	0.5712	0.5919	0.7689	0.8975	0.9516	1.0082	1.0434	0.1428
3	0.6762	0.752	0.8673	0.9619	0.9947	1.0319	1.0615	0.8780
4	0.6779	0.7427	0.9064	1.0157	1.0413	1.0703	1.0919	0.6130
5	0.8963	1.0098	1.0562	1.0832	1.0967	1.1098	1.1208	1.0463
6	0.7739	0.8546	0.9624	1.0309	1.0581	1.084	1.1019	1.0920

Table 2b: Smallest roots

Variables (*)	0	4	8	20	All
1	21.4561	13.7573	10.9514	8.9521	16.9648
7	14.1079	8.5233	7.6718	8.4006	13.1848
8	11.8079	9.7168	11.2048	13.06	13.3988
9	16.1903	10.5417	8.3779	7.6225	13.2872
11	20.5571	11.0635	9.3388	9.162	16.3087
12	23.0693	12.7522	10.3883	9.3846	17.1243
13	16.9267	10.0162	9.7537	10.7016	15.7915
14	21.7078	14.6437	12.0405	10.9197	15.9382
50	19.1684	14.4823	11.4959	10.0345	13.9778
27	17.1343	10.8643	8.822	8.1776	13.0418
92	18.6997	12.8397	10.6455	9.6934	13.9604
55	18.3024	11.6769	9.0163	8.3928	13.8712
28	17.4842	12.514	10.6369	10.5767	16.0935
33	14.574	12.8693	12.371	12.3721	14.108
36	10.9488	16.1708	17.1008	17.5155	17.2489
38	16.0135	10.7028	8.5468	7.8771	13.7549
75	13.2069	16.7301	17.22	17.3897	16.7211
58	13.2993	16.8603	15.9178	15.2425	15.2697
101	25.6751	27.1914	26.7907	22.9072	23.3843
105	7.0648	6.1469	5.577	5.652	8.997
106	7.2143	4.0555	6.0209	10.2174	9.4434
16	26.1293	28.2298	29.1133	28.7177	24.3966
103	9.6831	6.1579	8.155	12.6393	11.0775
104	7.5744	7.328	7.0476	6.9643	9.3025

(*) The numbers correspond to those in the Appendix.

Table 3: Variance decomposition

i	$\hat{\beta}_i$	$\hat{\gamma}_i$
1	-0.0553 (0.1090)	-0.1488 (0.2695)
2	-0.0548 (0.1105)	0.0080 (0.2567)
3	0.0382 (0.1116)	0.0146 (0.2570)
4	-0.0958 (0.1116)	0.1531 (0.2571)
F-test	$H_0 : \gamma_i = 0, i = 1, ..., 4$	F=1.862

Table 4: Granger causality. The regression is
$shock_t = \alpha + \sum_{i=1}^{4} \beta_i shock_{t-i} + \sum_{i=1}^{4} \gamma_i spf_{t-i} + \varepsilon_t$. Standard errors in parenthesis.

Figures

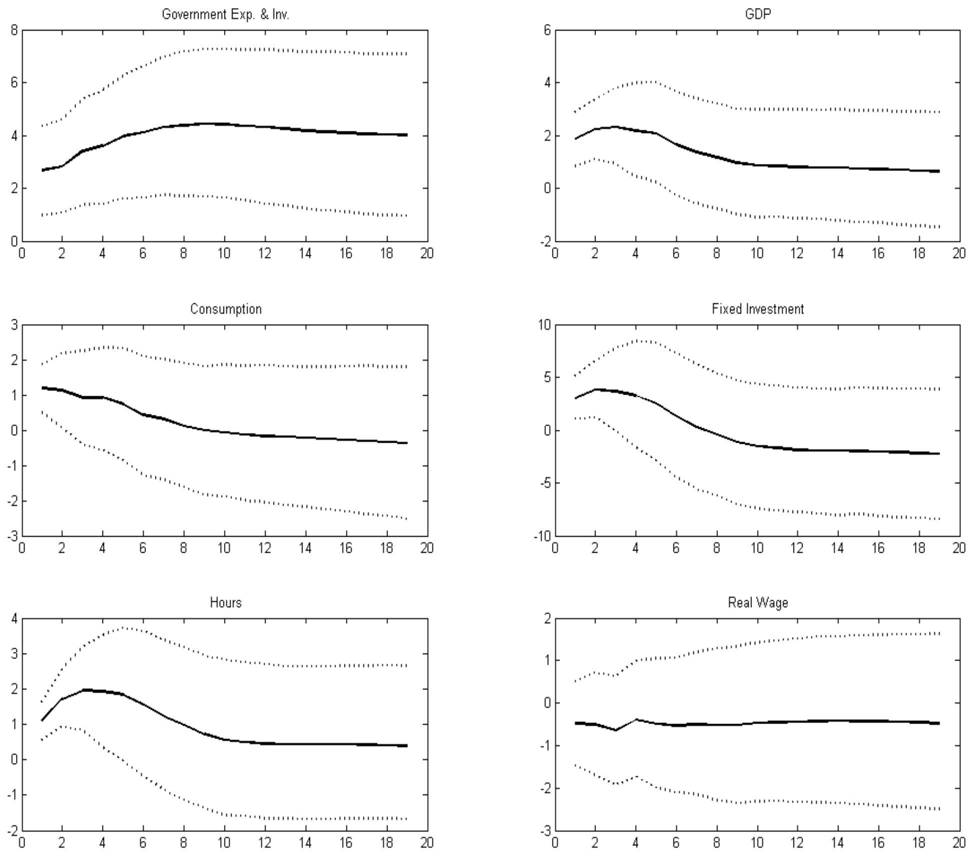

Figure 1: Impulse response functions

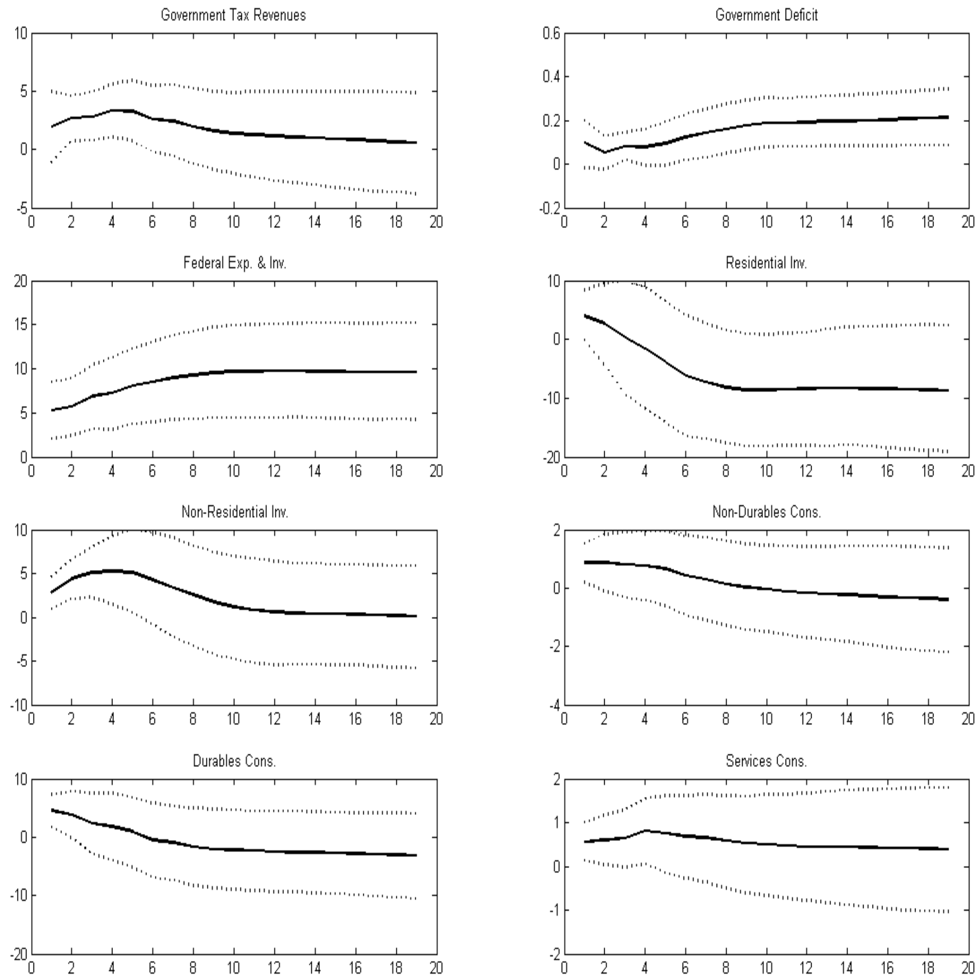

Figure 2: Impulse response functions.

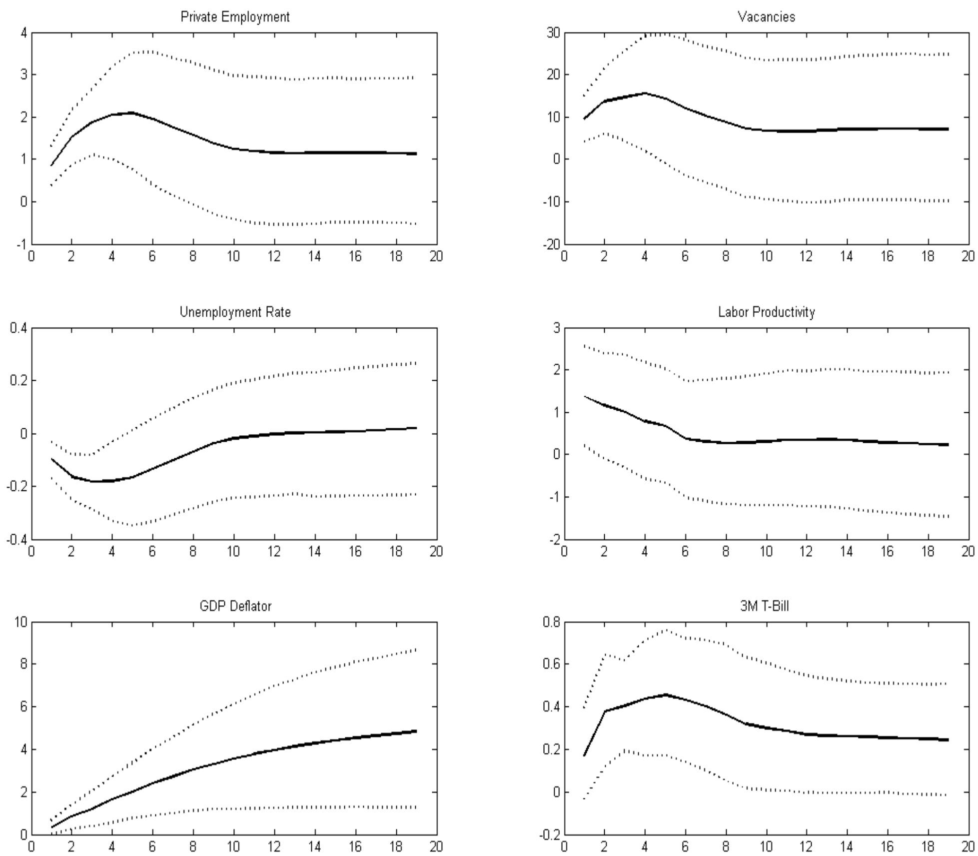

Figure 3: Impulse response functions.

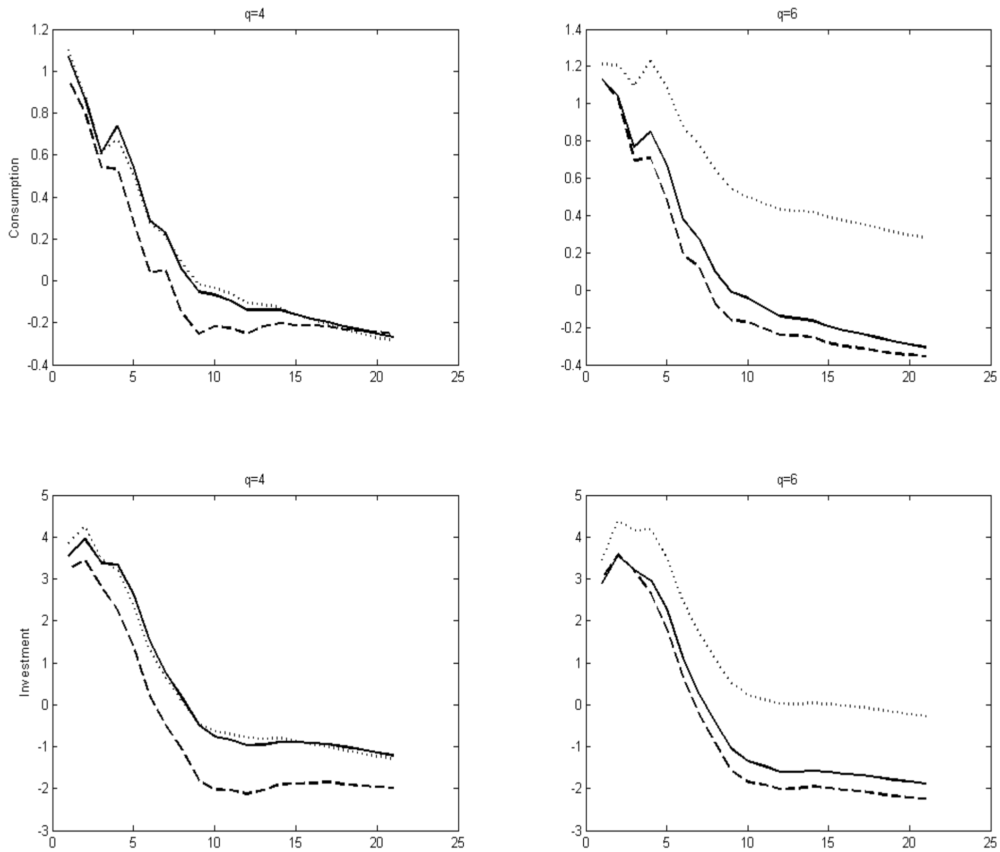

Figure 4: Robustness: 13 factors (solid line), 10 factors (dotted line), 16 factors (dashed line).