Fiscal Foresight and the Effects of Government Spending*

Mario Forni[†]
Università di Modena e Reggio Emilia
CEPR and RECent

Luca Gambetti[‡]
Universitat Autonoma de Barcelona

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Abstract

The contribution of this paper is twofold. First, we investigate whether fiscal foresight poses an issue for the empirical analysis conducted with VAR models. The answer is yes: the government spending shock is non-fundamental for the variables commonly used in the VAR literature, so that its impulse response functions cannot be consistently estimated with a VAR. Second, we study the effects of government spending by using a structural, large dimensional, dynamic factor model. The key advantage of our approach is that this class of models is not affected by the non-fundamentalness problem. We find that the multiplier is above one in the short run and around zero in the long run.

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†Contact: Dipartimento di Economia Politica, via Berengario 51, 41100, Modena, Italy. Tel. +39 0592056851; e-mail: mario.forni@unimore.it

‡The financial support from the Spanish Ministry of Science and Innovation through grant ECO2009-09847 and the Barcelona Graduate School Research Network is gratefully acknowledged. Contact: Office B3.1130 Departament d'Economia i Historia Economica, Edifici B, Universitat Autonoma de Barcelona, Bellaterra 08193, Barcelona, Spain. Tel (+34) 935814569; e-mail: luca.gambetti@uab.cat

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 any other shock. 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), Eichenbaum and Fisher (2005) and Ramey (2009) 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, 2008, Leeper, Walker and Yang, 2008, Mertens and Ravn, 2010). 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 big 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 observe 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 might not be enough to recover the shocks (Lippi and Reichlin, 1993).

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 (2010) 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 (2010) 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.

The contribution of this paper is twofold. First, we investigate whether fiscal foresight represents an issue for the empirical analysis conducted with VAR models. To this end we perform two tests of fundamentalness to establish whether VAR specifications typically used in the literature convey enough information to estimate fiscal policy shocks. The first test is the test of informational sufficiency proposed in Forni and Gambetti (2011). The second is a test directly based on the estimated roots of the MA representation of certain variables. We find that none of the set of variables typically used in the literature to study the effects of government spending, including those used in Perotti (2007) and Ramey (2009), contain enough information to recover the structural shocks.

We also test the orthogonality between the estimated government spending shock and the forecast of government spending from the Survey of Professional Forecasters. We find that the government spending shock obtained with Perotti's (2007) identification scheme is not orthogonal to the Survey of Professional Forecasters, consistently with Ramey (2009). The shock obtained using Ramey's defense spending variable is less correlated with the Survey, although the null of orthogonality is still rejected in some specification.

We conclude that the information sets used in the VAR fiscal policy literature are too poor.

Second, we study the effects of government spending shocks by using a large structural factor model. The main 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, consider the MA representation associated to the log-linear solution of a DSGE model. Typically the number of variables is larger than the number of shocks, so that such a representation is a "tall" system. Therefore in order to estimate a VAR we have to ignore some of the 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.

Identification in presence of fiscal foresight is an hard task. We prefer not to rely on identification schemes *á la* Perotti, since they are not consistent with fiscal foresight. Rather, following Mountford and Uhlig (2009), Canova and Pappa (2007) and Pappa (2009), we use a set of sign restrictions. Precisely, a positive government spending shock is defined as a shock having a positive effect on government and federal expenditure, government and federal primary deficit, employment (hours and private employment), prices (CPI and the GDP deflator) and the 3-months treasury bills rate. Such restrictions are not imposed on impact but rather on the responses delayed by one year (the fifth coefficient of the impulse response functions), to be consistent with the presence and the timing of fiscal foresight.

The main results are the following. First, the estimated shock is orthogonal to the forecasts of the Survey of Professional Forecasters. Second, the shape of the impulse response functions suggests that actually there is anticipation. Government spending gradually rises reaching its maximum, which is about two times larger than the initial effect, after a couple of years. On the contrary, consumption, GDP and investment react immediately and reach their maximal value after one or two quarters. The government spending shock increases both consumption and investment in the short run, although the former not significantly, and reduce them in the long run. This produces an estimated multiplier above one in the short run and zero in the long run. Hours significantly increase and the real wage falls.

The remainder of the paper is organized as follows: Section 2 discusses non-fundamentalness; Section 3 presents the factor model; Section 4 and 5 shows results; Section 6 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-dimensional 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. $\chi_t \in H_t^u = \overline{\text{span}}(u_{j\tau}, j = 1, \ldots, q, \tau \leq t)$. 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 $H_t^u = H_t^\chi$.[1]

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.

Consider for instance the simple case $n = 2$, $q = 1$,

$$\begin{aligned} \chi_{1t} &= u_t + b_1 u_{t-1} \\ \chi_{2t} &= u_t + b_2 u_{t-1}. \end{aligned}$$

[1] 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. Conversely, if $B(0)u_t$ is the innovation of H_t^χ, u_t is fundamental for χ_t. A fundamental white noise is not unique, but it is easily seen that if v_t is also fundamental, then it is a linear, contemporaneous 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).

[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.

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 $\chi_{1t} = \eta_t + b_1^{-1}\eta_{t-1}$, where $\eta_t = (1+b_1 L)/(b_1 + L^{-1})u_t$.[3] Hence if we estimate an autoregressive model with χ_{1t}, we do not get (a consistent estimate of) the structural shock u_t, but η_t, which is a linear combination of present and past values of u_t. Similarly, u_t is non-fundamental for χ_{2t} if and only if $|b_2| > 1$. However, the tall system made up by both equations is non-fundamental if and only if $b_1 = b_2$ and $|b_1| > 1$. If there are no *a priori* economic reasons why the former equality should hold, non-fundamentalness should be considered a zero-probability event.

Observe that u_t is generally fundamental for χ_t even if it is non-fundamental for both χ_{1t} and χ_{2t}. In fact, if $b_1 \neq b_2$, u_t is a linear contemporaneous combination of χ_{1t} and χ_{2t}, i.e. $u_t = (b_2\chi_{1t} - b_1\chi_{2t})/(b_2 - b_1)$.

2.2 Fundamentalness and VAR models

Now let us assume that (1) is derived as the solution of a DSGE model, so that χ_t includes the macroeconomic variables, the entries of u_t are structural shocks, observed by economic agents, 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). The discussion in the previous section motivates the fundamentalness assumption, i.e. $H_t^{\chi} = H_t^{u}$.

The econometrician wants to estimate the structural shocks and the impulse response function, starting from the information in H_t^{χ}. The structural VAR strategy is the following: (i) selecting a square, q-dimensional subsystem, say

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

(ii) estimating the VAR $A(L)\chi_t^* = \epsilon_t$ 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 step

[3] Observe that the Blaschke factor $b(L) = (1 + b_1 L)/(b_1 + L^{-1})$ 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.

(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 non-fundamentalness in VAR models naturally arises in an economy with fiscal foresight. Let us shortly rivisit their example in the light of the previous discussion. Our contribution here is to show that the tall system is fundamental, even if all square subsystems are not.[4] Starting with a standard growth model with log preferences and inelastic labor supply, the authors obtain the equilibrium capital accumulation equation

$$k_t = \alpha k_{t-1} + a_t - \kappa \sum_{i=0}^{\infty} \theta^i E_t \tau_{t+i+1} \tag{3}$$

where $\kappa = (1-\theta)\left(\frac{\tau}{1-\tau}\right)$, τ being the steady state tax rate, and k_t, a_t and τ_t are the log deviations from the steady state of capital, technology and the tax rate, respectively. 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]

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

Let us consider the square subsystem given by the first two rows (technology and capital): the determinant $\frac{-\kappa(L+\theta)}{1-\alpha L}$ 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

[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 (2007).

[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.

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.

However u_t is fundamental for the three variables all together since $B(z)$ is zeroless, i.e. has rank 2 everywhere in the complex plane. In fact χ_t has the reduced rank VAR representation[6]

$$\begin{pmatrix} 1 & 0 & 0 \\ L\phi + \frac{\alpha L}{1-\alpha L} & 1 + \phi(1-\alpha L) & \frac{\kappa\phi L}{L-\theta} \\ -\frac{L^2(L-\theta)}{\kappa\theta^2} & \frac{L^2(L-\theta)(1-\alpha L)}{\kappa\theta^2} & 1 - \frac{L^2}{\theta^2} \end{pmatrix} \begin{pmatrix} a_t \\ k_t \\ \hat{\tau}_t \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ -\kappa\theta & 1 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} u_{\tau,t} \\ u_{A,t} \end{pmatrix}.$$

with $\phi = \frac{(1+\theta\alpha)(L-\theta)}{(1-\alpha L)\theta^2}$. Put differently, present and past values of the three variables capital, taxes and technology, are sufficient to estimate the two shocks.

This example illustrates out point. Enlarging the information available to the econometrician, without increasing the sources of uncertainty is crucial for the correct estimation of structural shocks. This however opens the door to a reduced rank problem that cannot be handled within a VAR model. In the next section we present a structural factor model, whose core is a tall system like the one above and that 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.[7]

Each macroeconomic variable [8] 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 of

[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).

[7]FGLR is a special case of the generalized dynamic factor model proposed by Forni, *et al.* (2000) and Forni and Lippi (2001). 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).

[8]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.

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.

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:

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

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.[9] Under (5), (4) and (6) form a state space model like the one resulting from the log-linear solution of a DSGE model.[10]

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

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

where

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

[9] 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.

[10] See also Altug (1989) Sargent (1989) and Ireland (2004) for the link between factor models and DSGE models.

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,[11] 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 $B_{n1}(L)$.

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

[11] see FGLR, Assumption 4.

functions themselves.[12] 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.[13]

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 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

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

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

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.[14] 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.[15]

3.4 Testing for fundamentalness

The factor model described earlier provides the basis for testing procedures designed to establish whether a particular set of variables contains enough information to estimate the structural shocks by means of a VAR, i.e. the shocks are fundamental. We describe three different procedures which will be applied in the empirical part of the paper.

A first test is based on the estimated matrix of impulse response functions. As already observed, while the whole system $B_n(L)$ is fundamental, the q-dimensional square sub-matrices of $B_n(L)$ corresponding to selected subsets of variables can be singular for values of z within the unit circle (without hurting consistency of estimation). Precisely, considering a q-dimensional vector of integers I, with elements I_i, $i = 1, \ldots, q$, u_t is fundamental for the sub-vector $\chi_{It} = (\chi_{I_1 t} \cdots \chi_{I_q t})' = B_I(L)u_t$ if $\det B_I(z)$ does not vanish within the unit circle.

A test for fundamentalness of a particular square subsystem can then be performed by looking at the estimated distribution of the modulus ρ of the smallest root. We reject the null of fundamentalness ($\rho \geq 1$) against the alternative of non-fundamentalness ($\rho < 1$) at the significance level α as long as the frequency of values larger than 1 is smaller than α.

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

[15]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.

Rejection of fundamentalness implies that an hypothetical VAR model using χ_{It} would be misspecified. In principle, such an implication cannot be directly extended to the true VAR setting, where x_{It} is used in place of χ_{It}. In practice however the idiosyncratic components are usually very small, so that rejection (acceptance) of fundamentalness provides a useful indication against (in favor of) a particular VAR specification.

A second test is the 'informational sufficiency' test proposed in Forni and Gambetti (2011). The test is based on a proposition stating that, in an economy that admits a state space representation like (4), (5) and (7), a set of variables conveys enough information to estimate the structural shocks if, and only if, it is not Granger caused by the factors f_t.

The test is implemented as follows. First, set a maximum number of factors P and estimate them as the first P principal components of the large dataset. Second, perform a sequence of Granger causality tests to see whether the first h principal components, $h = 1, ..., P$, Granger cause the variables of interest. If the null of no causality is rejected, the set of variables under consideration does not contain enough information to estimate the structural shocks. On the other hand, if the null is rejected for all h, the variables have a fundamental representation and can be used to recover the shocks.

A final check to determine if a shock is fundamental is the orthogonality test proposed in Forni and Gambetti (2011). The test is a test of orthogonality between the estimated shock and the lagged values of the factors or any other variable.The idea behind the test is that structural shocks are unpredictable. Therefore rejecting the null of orthogonality implies that the estimated shock cannot be structural. Absence of rejection however does not implies fundamentlaness.

Notice that this last test requires identification of the shock. On the contrary the previous tests are completely independent of the type of identification adopted.

4 Empirics I: Fundamentalness

In this section we describe our large data set and the specification of the factor model and show results concerning fundamentalness of the sets of variables most commonly used in the fiscal policy VAR literature.

4.1 Data and model specification

The data set contains 118 quarterly macroeconomic series spanning from 1960: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.

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 shocks, with $k + 1 \leq j \leq h$, h being on the rows.[16] For instance, the element 2,3 in the matrix is the p-value of the test of the null of $k = 1$ against the alternative of j being either 2 or 3. The null of $k = 1, ..., 5$ shocks is rejected at the 10% level against the alternative of j shocks, $k < j \leq 6$. For $k = 4, 5$ the null is rejected even at the 5%. However the null $k = 6$ is not rejected against the 7-shock alternative. 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. 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.[17] 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 information criteria. In the following subsection we present also some results for the 4-shock specification.

4.2 The smallest root test

First of all we apply the test of the smallest root. We consider seven variables specifications (listed in Table 2), corresponding to different choices of the information set I (see Section 3.4), denoted by I^j $j = 1, ..., 7$. The variables included in the information sets $I^1 - I^6$ are among those typically used in the VAR literature to estimate the government spending shock. The set I^7 is considered for the sake of comparison. It includes two

[16] 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.

[17] 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).

variables intended to complete the information set: the 3-month Treasury Bill Rate and a leading indicator of economic activity (the Help Wanted Advertising Index). For each specification, we compute the modulus of the smallest root of the determinant of the corresponding impulse response functions $B_{Ij}(L)$. The roots are computed for the real data as well as all the bootstrap repetitions, so that the whole distribution is available.

Table 3 shows the point estimate, the median and a few percentiles of the distribution. The point estimate is much smaller than one for all but the last specification. Fundamentalness is outside the 84% confidence level for specifications 1, 2, 4, 5 and 6 and outside the 68% level for specification 3. The last specification cannot be rejected even at the 68% confidence level.

We also consider two four-variable specifications. 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 median and the point estimate of the modulus of the smallest root are smaller than one and the 68th percentile is smaller than one.

To understand how relevant in terms of results is the problem of non-fundamentalness we compare the impulse response functions obtained by applying Perotti's (2007) identification scheme in both a VAR and the factor model. The shock is defined as the only one having a non-zero impact effect on government spending. The variables used in the VAR are those of specification 1, i.e. government spending, GDP, fixed private investment, consumption, the real wage and hours worked in the non-farm business sector. Figure 1 plots the results. The dashed lines are the VAR impulse response functions while the solid lines are the factor model impulse response functions. Differences are substantial. In the factor model the reduction of investment is much less pronounced, the response of real wage is negative and so is the response of consumption in the short run.

4.3 The 'informational sufficiency' test

Let us now turn to the informational sufficiency test. This test does not require that the number of variables in the VAR be equal to the number of shocks in the factor model, nor that such variables belong in the factor model data set. Hence, besides the specifications of Table 2, we can test for six additional specifications used in literature, i.e. the five considered in Ramey (2009) and the one of Perotti (2009). All of the Ramey specifications include the news military variable, real government spending, real GDP, the three months T-bills rate and the Barro-Redlick average marginal tax rate. The specifications differ for the last variable which is in turn: total hours (specification 1), real wage (2), real total consumption (3), real nondurable consumption (4) and real fixed investment (5). The Perotti VAR includes: real government spending, real GDP, real nondurable plus services consumption, real fixed investment, total hours, the Barro-Redlick average marginal tax rate and the real wage.[18]

The Granger causality tests are performed by using the Gelper and Croux (2007) multivariate extension of the out-of-sample test proposed by Harvey *et al.*(1998). Table 4 shows the p-values. On the rows we report the number of principal components used in the test; on the columns we have the VAR specifications. Columns 1-7 refer to the six-variable specifications of Table 2; specifications 1-6 are strongly rejected, whereas, consistently with the smaller root test, specification 7 cannot be rejected. Columns 8-13 show results for the additional specifications. The first three principal components of our large dataset Granger cause all of the VAR specifications at the 5% significance level, so that informational sufficiency is always rejected.

4.4 The orthogonality test

Finally we preform the orthogonality test. Specifically we regress the shock estimated with the VAR specifications described in the previous subsection onto the forecast of federal spending from the Survey of Professional Forecasters. In Ramey's VARs the shock is the first one in a Cholesky ordering where the news variable is ordered first. In Perotti's VAR the shock is the first one in a Cholesky ordering where the real government spending is ordered first.[19]

Table 5 reports the results. The first column reports the forecasting horizon. For instance $h = 2$ refers to the forecast of government spending at time t made at time $t - 2$. For the shock obtained with Perotti's VAR, orthogonality is rejected at the 5% significance level at all forecasting horizons. As for Ramey's shock, orthogonality can be rejected at the 10% level only for the two periods ahead forecast.

The shock obtained in the Perotti's VAR clearly cannot be the government spending shock since it is predictable. As for Ramey's shock, evidence is much less clear. However, it should be noticed that the news variable, which in practice is the shock, is poorly correlated to the forecast of federal spending, as well as federal expenditure itself, at all leads and lags. In fact, its average squared coherence with the forecasts at horizons 1-5 is 0.06, 0.18, 0.26, 0.17, 0.24, respectively, and its average square coherence with federal spending is 0.09. Hence orthogonality may depend on the fact that the variable, rather than anticipating federal spending, is almost unrelated to it (at least during the period for which we have the professional forecasts).

From the above tests we conclude that non-fundamentalness represents a serious threat for the analysis conducted with standard VAR models. This motivates the inves-

[18]For this test we use the data kindly provided by Valerie Ramey. GDP and components and hours worked are expressed in per-capita terms and taken in differences of logs.

[19]We estimated all VARs with 4 lags.

tigation presented in the next section.

5 Empirics II: The effects of government spending

In this section we study the effects of a government spending shock by using the factor model.

5.1 Identifying restrictions

Identifying government spending shocks in presence of fiscal foresight is an hard task. First of all we prefer not to rely identification schemes *á la* Perotti since they are not fully consistent with fiscal foresight. The reason is that in presence of fiscal foresight the government spending shock could be precisely one of the shocks that has no impact effect on government spending.

Rather we take a different approach and use a mix of zero and sign restrictions. Sign restrictions have been recently used to identify fiscal policy shock by Mountford and Uhlig (2009), Canova and Pappa (2007) and Pappa (2009). Precisely, we define an expansionary government spending shock as a shock having a positive effect on government and federal expenditure, government and federal primary deficit, employment (hours and private employment), prices (CPI and the GDP deflator) and the 3-months treasury bills rate.

An increasing deficit is imposed to exclude expenditures entirely financed with additional receipts. The positive effect on labor variables and prices are imposed to distinguish the shock from a systematic spending reaction to a recessionary shock stemming from the private sector. The positive effect on the interest rate may be helpful in distinguishing the shock from an expansionary monetary policy shock. As argued in Pappa (2009) the above restrictions are robust in the sense that they are shared by different theoretical models (even if the mechanisms, in particular for hours worked, are different for neo-Keynesian and neo-classical models).

The key feature of our identification scheme is that such restrictions are not imposed on impact but rather on the responses delayed by one year (the fifth coefficient of the impulse response functions) to be consistent with the presence and the timing of fiscal foresight.

We augment such a set of sign restrictions with the additional constraint that the government spending shock does not raise total factor productivity on impact. Such a restriction is motivated by the observation that government spending growth and TFP are positively correlated in our dataset. However, we believe there are no reasons why TFP should improve immediately after an increase in government spending. So the restriction can actually help in defining the government spending shock, by narrowing the set of admissible impulse response functions which under pure sign restrictions schemes are very large.

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.

5.2 Impulse response functions

Having identified the government spending shock, as a first step of our analysis we perform the same orthogonality test we did in section 4.4 using our estimated shock. The last column of Table 5 reports the p-values of the test. Orthogonality is never rejected.

Figure 2-4 plot the impulse response functions of several variable of interest to a shock that increases government spending by 1% of GDP after two years, the peak of the response of government spending. Consider first the reaction of GDP and its components. GDP reacts immediately and significantly, increasing by 1.4%. Given the normalization imposed, the impulse response function represents the multiplier. The response stays around that level for about one year and starts decreasing afterward, the effects being no longer significant after 6 quarters. In the long run the multiplier is not significantly different from zero.

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 increase by about 1.2% and 3.6% respectively. The response of consumption is very short-lived and never significant. On the contrary, the response of investment appears to be significant for the first year after the shock. In the long run both variables are crowded out, the point estimate of the response being negative.

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, disaggregated components display a behavior similar to that of the aggregate variables.

A persistent and significant increase of hours worked is accompanied by a fall of real wages at all horizons.

Finally, 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.

All in all the picture that emerges is that private aggregate demand components are crowded in in the short run and crowded out in the long run. Moreover the short run reaction of investment is higher than that of consumption.

Such results are hard to reconcile with standard RBC or neo-Keynesian models. In the former consumption is always predicted to fall because of a negative wealth effect triggered by expected higher future taxes while in the latter investment is predicted to fall because of the increase in the interest rate. In a recent paper Furlanetto (2011) combines the model in Gali, Lopez-Salido and Valles (2005) with rule-of-thumb consumers and sticky wages. What he finds is that under reasonable parametrizations, consumption and investment are both predicted to increase after a government spending shock.

5.3 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 11-15% of fiscal policy variables. 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 with balanced budget; and (iii) this is *discretionary* policy, in that it excludes systematic reactions to shocks stemming from the private sector. The shock accounts for about 7%, 9% and 10% of the variance of GDP, investment and consumption, respectively. The percentages of explained variances are similar across horizons.

5.4 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 did not restrict the interest rate.

3) We used two instead of three lags in the VAR for the factors.

4) We imposed the identifying restriction for period 3 instead of 5.

5) We used the second (instead of first) differences of the log of prices and other nominal variables.

6) 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.

6 Conclusions

This paper studied the empirical relevance of fiscal foresight in VAR analysis. 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.

Motivated by this result we investigate the effects of government spending shocks in the US by using a large dynamic factor model. In this model the structural shocks are likely fundamental even in presence of fiscal foresight. We find that the government spending shock raises both consumption and investment in the short run, although the effects are small. The multiplier is above one in the short run and around zero in the long run.

Appendix: Data

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

no.series	Transf.	Mnemonic	Long Label
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
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	

no.series	Transf.	Mnemonic	Long Label
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
107	1		Real rate 10YRate-inflation
108	1		Personal Finance Current (Michigan Consumer Survey)
109	1		Personal Finance Expected (Michigan Consumer Survey)
110	1		Expected Business Condition 12 Months (Michigan Consumers Survey)
111	1		Expected Business Condition 5 Years (Michigan Consumers Survey)
112	1		Buying Conditions (Michigan Consumers Survey)
113	1		Sentiment Index (Current) (Michigan Consumers Survey)
114	1		Sentiment Index (Expected) (Michigan Consumers Survey)
115	5		Consumption non-durables +services
116	5		hours worked (27) divided by population
117	1		Fernald's TFP growth rate CU adjusted
118	1		Fernald's TFP growth rate

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Tables

0	1	2	3	4	5	6	7
0	0.003	0.006	0.008	0.010	0.012	0.015	0.017
1	0	0.086	0.156	0.211	0.261	0.043	0.051
2	0	0	0.305	0.545	0.692	0.036	0.043
3	0	0	0	0.425	0.726	0.029	0.036
4	0	0	0	0	0.813	0.021	0.029
5	0	0	0	0	0	0.012	0.021
6	0	0	0	0	0	0	0.822

Table 1: Onatsky's test results. In the first column there is the number of shocks under the null. On the first row there is the number of shocks in the alternative.

j	Variables (I^j)					
			Four Shocks			
1	GDP(1)	Gov. (101)	Taxes(105)	Cons.(116)		
2	GDP(1)	Gov. (101)	Taxes(105)	Inv.(7)		
			Six Shocks			
1	GDP(1)	Gov.Exp.(101)	Taxes(105)	Cons.(11)	Real Wage(33)	Inv.(7)
2	GDP(1)	Gov.EXp.(101)	Taxes(105)	Cons.(11)	Hours(27)	Inv. (7)
3	GDP(1)	Gov.Exp.(101)	Taxes(105)	Cons.(11)	Real Wage(33)	Hours(27)
4	GDP(1)	Gov.Exp.(101)	Taxes(105)	Inv.(7)	Real Wage(33)	Hours(27)
5	GDP(1)	Gov.Exp.(101)	Deficit(106)	Cons.(11)	Hours(27)	Inv. (7)
6	GDP(1)	Gov.Exp.(101)	Deficit(106)	Inv.(7)	Real Wage(33)	Hours(27)
7	GDP(1)	Gov.Exp.(101)	Deficit(106)	Hours(27)	Help Wanted(92)	Int. Rate(58)

Table 2: Subsets of variables (I) used in the test described in Section 3.4. The numbers in brackets correspond to those in the Appendix.

j	Point est.	Median	68%	84%	90%
		Four Shocks			
1	0.23	0.71	0.98	1.11	1.13
2	0.57	0.59	0.73	0.86	0.90
		Six Shocks			
1	0.37	0.58	0.76	0.95	1.05
2	0.18	0.58	0.75	0.99	1.05
3	0.27	0.64	0.84	1.02	1.06
4	0.19	0.59	0.79	0.94	1.01
5	0.18	0.61	0.81	0.98	1.03
6	0.20	0.56	0.79	0.96	1.00
7	1.13	0.98	1.07	1.10	1.12

Table 3: Moduli of the smallest root of the determinant of the sub-matrices $B_I(L)$ defined in Table 2.

	Six-variable VARs of Table 2							Ramey's VARs					Perotti's
	1	2	3	4	5	6	7	1	2	3	4	5	VAR
1	0.01	0.03	0.13	0.01	0.13	0.01	0.88	0.77	0.34	0.78	0.12	0.24	0.34
2	0.02	0.01	0.01	0.02	0.01	0.02	0.86	0.11	0.06	0.18	0.02	0.06	0.12
3	0.00	0.01	0.00	0.00	0.01	0.00	0.90	0.01	0.04	0.02	0.00	0.02	0.01
4	0.00	0.01	0.00	0.00	0.00	0.01	0.78	0.01	0.03	0.01	0.00	0.07	0.00
5	0.00	0.00	0.00	0.01	0.00	0.05	0.57	0.00	0.00	0.00	0.00	0.01	0.00

Table 4: P-values of the Forni and Gambetti (2011) test for sufficient information. In the first column we report the number of principal components included in the test.

	Ramey's VARs					Perotti's VAR	Factor model
h	1	2	3	4	5		
1	0.42	0.41	0.44	0.32	0.42	0.01	0.76
2	0.06	0.08	0.08	0.07	0.05	0.03	0.33
3	0.23	0.28	0.22	0.24	0.19	0.01	0.40
4	0.32	0.28	0.40	0.35	0.25	0.01	0.83
5	0.13	0.18	0.17	0.17	0.11	0.05	0.70

Table 5: P-values of the orthogonality test of the government spending shock. In the first column we report the horizon of the forecast of government spending.

Variables	0	4	8	20	All
1	4.365	5.466	4.860	5.157	7.767
7	8.414	4.836	4.971	7.253	9.520
8	7.536	8.736	11.751	16.155	11.563
9	11.117	6.819	5.419	5.218	9.793
11	10.175	7.062	6.626	7.576	10.600
12	10.926	6.642	6.300	7.969	11.278
13	7.304	6.385	7.068	9.679	9.896
14	18.009	12.668	11.477	10.774	15.207
50	13.423	9.641	8.141	6.921	11.195
27	12.046	7.682	6.483	6.061	10.349
92	15.329	9.418	8.284	7.529	11.919
55	11.835	5.868	4.516	5.234	10.627
28	1.226	4.518	5.627	7.725	5.439
33	19.606	18.305	18.417	18.904	17.455
36	19.375	23.855	25.657	27.468	24.599
38	14.262	8.213	6.372	6.200	12.211
75	16.799	20.575	22.921	25.342	21.675
58	12.520	12.325	11.299	9.911	12.705
101	9.992	11.609	10.934	8.845	11.214
105	11.384	5.999	4.944	6.406	11.989
106	13.886	5.998	6.225	9.652	13.981
16	12.415	14.340	14.154	13.297	13.274
103	16.312	8.497	8.439	11.505	15.859
104	10.773	6.365	5.314	5.855	11.826

Table 6: Variance decomposition. The numbers in brackets correspond to those in the Appendix.

Figures

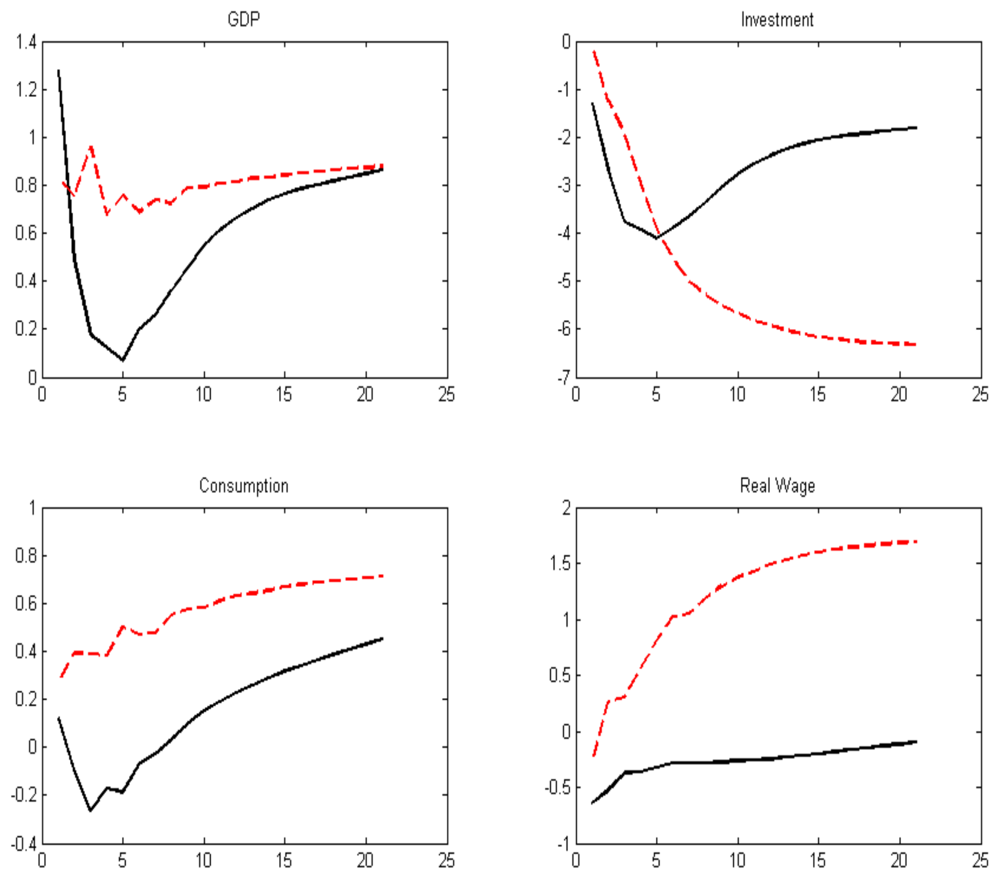

Figure 1: Perotti identification. red dashed - VAR. black solid - Factor model.

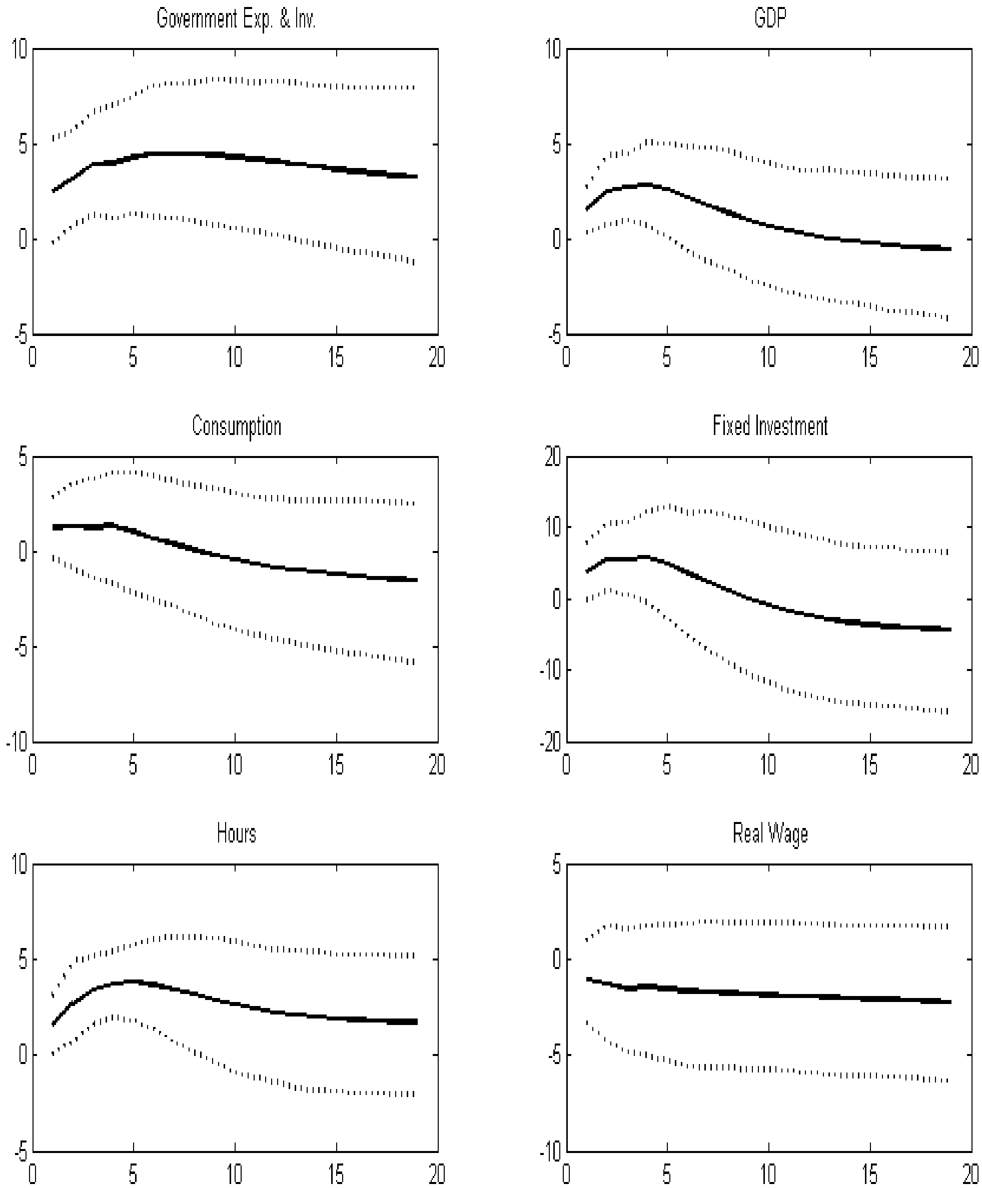

Figure 2: Impulse response functions

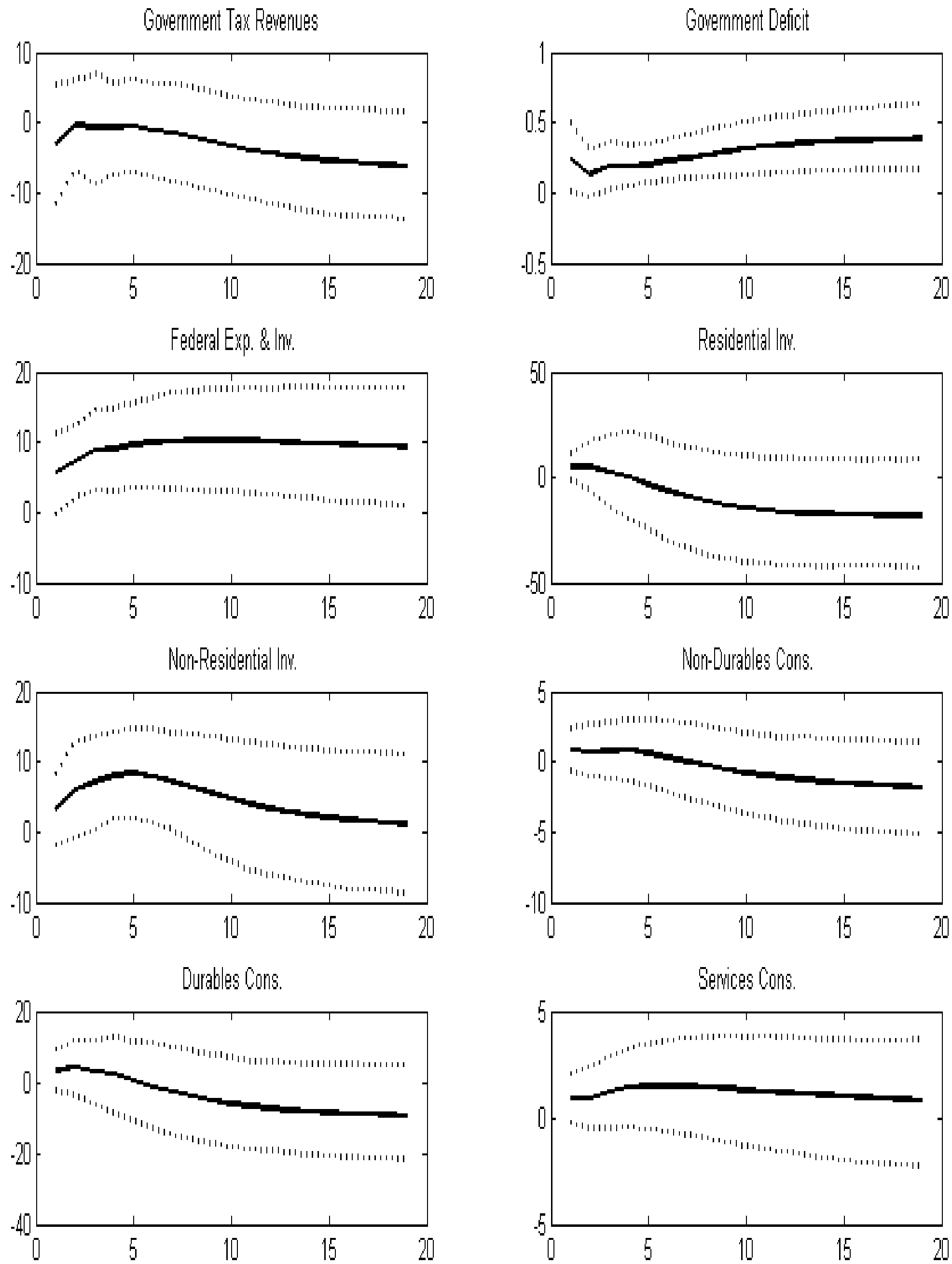

Figure 3: Impulse response functions.

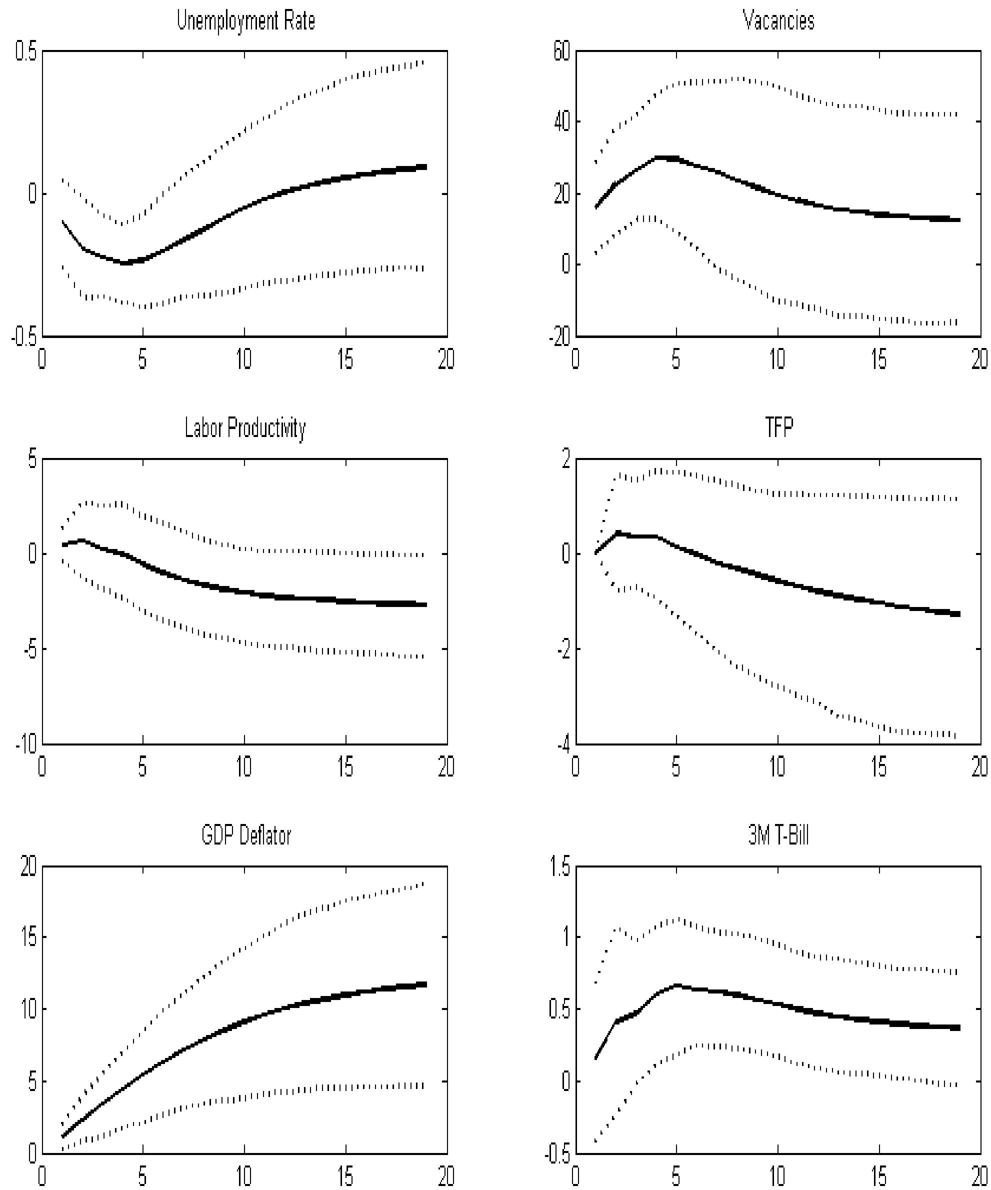

Figure 4: Impulse response functions.

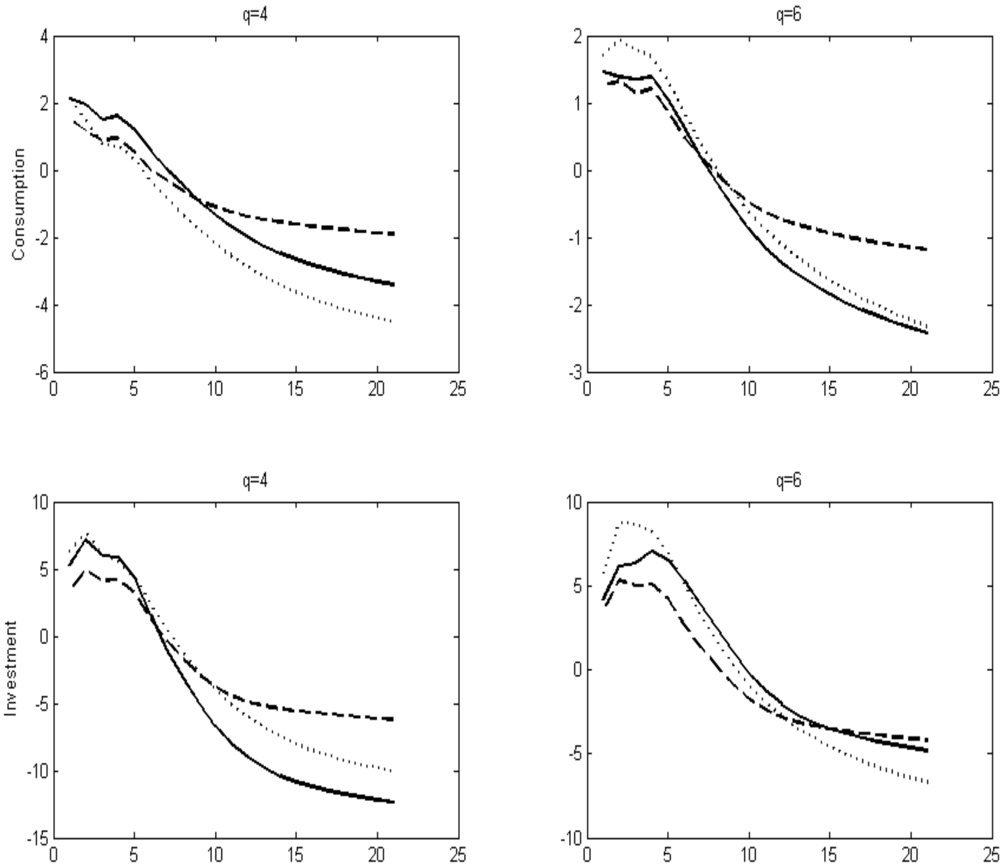

Figure 6: Robustness: 13 factors (solid line), 10 factors (dotted line), 16 factors (dashed line) with q=4.