Macroeconomic Shocks and the Business Cycle: Evidence from a Structural Factor Model

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March 22, 2010

Abstract

We use a dynamic factor model to provide a semi-structural representation for 101 quarterly US macroeconomic series. We find that (i) the US economy is well described by a number of structural shocks between two and six. Focusing on the four-shock specification, we identify, using sign restrictions, two non-policy shocks, demand and supply, and two policy shocks, monetary and fiscal. We obtain the following results. (ii) Both supply and demand shocks are important sources of fluctuations; supply prevails for GDP, while demand prevails for employment and inflation. (ii) Policy matters: Both monetary and fiscal policy shocks have sizeable effects on output and prices, with little evidence of crowding out; both monetary and fiscal authorities implement important systematic countercyclical policies reacting to demand shocks. (iii) Negative demand shocks have a large long-run positive effect on productivity, consistently with the Schumpeterian "cleansing" view of recessions.

JEL classification: C32, E32, E52, F31.

Keywords: structural factor model, sign restrictions, monetary policy, fiscal policy, demand, supply

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1 Introduction

What and how many are the shocks that drive economic fluctuations? What is the relative importance of supply and demand disturbances? What are the effects of macroeconomic policies? These questions have been at the core of macroeconomic research for more than half a century, since the answer is key to assessing competing theories of the business cycle and the implied policy recommendations.

Since Sims' (1980) seminal paper, structural vector autoregressive models (SVAR) have been a major tool to address the questions above. Such models replaced large scale econometric models, their main advantage being that they do not require the imposition of "incredible" identifying restrictions. Over the last three decades, SVAR literature have substantially contributed to improve our knowledge of macroeconomic dynamics, providing evidence often used as a guideline by both policymakers and theorists. Nonetheless, we believe that SVAR models have an important limitation: the amount of information that they can handle is perforce small, owing to the so-called "curse of dimensionality". The relevance of this information issue is stressed in several papers, including Quah (1990), Sims (1992), Lippi and Reichlin (1993, 1994), Bernanke and Boivin (1993), Bernanke *et al.* (2005). If, as plausible, both policy makers and private economic agents base their decisions on all of the available macroeconomic information, structural shocks should be innovations with respect to a large information set, perhaps larger than the one that can be included in a standard VAR.

An alternative to SVAR models is given by a new generation of large dimensional models: the "generalized" or "approximate" dynamic factor models introduced by Forni *et al.* (2000), Forni and Lippi (2001), Stock and Watson (2002a, 2002b) and recently proposed for structural economic analysis (Stock and Watson, 2005, Forni *et al.*, 2009). Such models have been successful in solving well known VAR puzzles (Bernanke *et al.*, 2005, Forni and Gambetti, 2010). Their key advantage is that they combine a large number of macroeconomic variables with a reduced number of macroeconomic shocks. Two basic features distinguish large factor models from old-fashioned large scale models. First, identification can be reached in just the same way as in VAR models, without relying on "incredible" restrictions. Second, the forecasting performance is good (Stock and Watson 2002a, 2002b, Altissimo *et al.*, 2010).

In this paper we use a large structural factor model to address the questions raised at the beginning of this introduction. Specifically, we apply the model and the estimation method of Forni *et al.* (2009) to 101 US quarterly series, covering the period 1959-I to 2007-IV. Following Uhlig (2005), we adopt an identification scheme based on inequality constraints. Such constraints are milder than the traditional zero restrictions commonly used in the VAR literature, in that only the sign of the impulse response functions at a few specific lags is imposed. Sign restrictions are particularly appropriate in our data-rich framework, since they can be imposed on a broad set of variables and this, in turn, is likely to deliver a better characterization of the shocks.

As a first step in our analysis we answer the question: how many shocks are there in the macroeconomy? This question has largely been ignored in the empirical literature, probably because it is not meaningful within a VAR framework, where the number of economic shocks is determined by the number of variables included in the model. We find that the US economy can be well described by a number of shocks between 2 and 6, contrary to both theories relying on a single source of fluctuations, like early RBC models, and models with many macroeconomic shocks, like the one in Smets and Wouters (2007).

We then focus on a four-shock specification and identify two non-policy shocks, demand and supply, and two policy shocks, monetary and fiscal. All shocks are normalized as expansionary by imposing positive effects on output (GDP and industrial production). We further impose that supply reduce prices, whereas the other three shocks raise prices (CPI and GDP deflator). Moreover, we impose that expansionary monetary policy reduces the federal fund rate and expansionary fiscal policy raises federal deficit.

Our main findings are the following. First, both supply and demand shocks explain a considerable fraction of the fluctuations in real variables. However, their relative importance depends on the specific variable considered. Supply shocks explain most of GDP volatility, while demand shocks prevail for employment and other labor market variables. Demand shocks are less persistent than supply shocks and their long-run effect on GDP is not significant. Concerning inflation, both supply and demand have relevant effects; but demand shocks prevail, particularly in the long-run.

Second, policy is important. Discretionary monetary policy shocks have sizeable effects on output and prices and are responsible for the early 80s recession and disinflation. Discretionary fiscal policy shocks have sizeable effects on GDP and do not have important crowding-out effects on private consumption and investment, with the sole exception of residential investment. As for systematic policy, there is evidence of a strong countercyclical response of both monetary and fiscal authorities to demand and, to a lesser extent, supply shocks.

Finally, negative demand shocks have a persistent positive effect on labor productivity. This finding, while being at odds with most of the business cycle literature, is consistent with a stream of empirical and theoretical work concerning the interactions between growth and cycle and the Schumpeterian view of recessions as providing a cleansing mechanism for reducing organizational inefficiencies and resource misallocations.

The remainder of the paper is organized as follows. Section 2 presents the model. Section 3 shows results concerning the number of shocks and presents in detail the definition of the shocks and the identification scheme. Section 4 presents the main results. Section 5 concludes.

2 Theory

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.

2.1 The factor model

We assume that each variable x_{it} of our macroeconomic data set is the sum of two mutually orthogonal unobservable components, the common component χ_{it} and the idiosyncratic component ξ_{it}:

$$x_{it} = \chi_{it} + \xi_{it}. \tag{2.1}$$

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 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:

$$\chi_{it} = a_{1i} f_{1t} + a_{2i} f_{2t} + \cdots + a_{ri} f_{rt} = a_i \boldsymbol{f}_t. \tag{2.2}$$

The dynamic relations between the macroeconomic variables arise from the fact that the vector $\boldsymbol{f}_t$ of the common factors follows the VAR relation

$$\begin{aligned} \boldsymbol{f}_t &= D_1 \boldsymbol{f}_{t-1} + \cdots + D_p \boldsymbol{f}_{t-p} + \boldsymbol{\epsilon}_t \\ \boldsymbol{\epsilon}_t &= R \boldsymbol{u}_t, \end{aligned} \tag{2.3}$$

where R is a $r \times q$ matrix and $\boldsymbol{u}_t = (u_{1t}\ u_{2t}\ \cdots\ u_{qt})'$ is a q-dimensional vector of orthonormal white noises, with $q \leq r$. Such white noises are the "common" or "primitive" shocks or "dynamic factors" (whereas the entries of $\boldsymbol{f}_t$ are the "static factors"). [1]

From equations (2.1) to (2.3) it is seen that the model can be written in the dynamic form

$$x_{it} = b_i(L) \boldsymbol{u}_t + \xi_{it}, \tag{2.4}$$

where

$$b_i(L) = a_i (I - D_1 L - \cdots - D_p L^p)^{-1} R. \tag{2.5}$$

The dynamic factors $\boldsymbol{u}_t$ and $b_i(L)$ are "structural" macroeconomic shocks and impulse-response functions respectively.[2]

[1]Observe that, if $q < r$, the residuals of the above VAR relation have a singular variance covariance matrix. Equations (2.1) to (2.3) 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.

[2]Unlike the dynamic factors, the static factors do not have a structural economic interpretation; rather, they are a statistical tool which is useful to model the dynamics of the system. Loosely speaking, given the number of primitive shocks q, the number of "static factors" r governs the "degree of heterogeneity" of the impulse-response functions. For instance, in the simple case $q = 1$, if $r = 1$ all the impulse-response functions are proportional. On the other hand, if r is larger, different variables can load the shock with

2.2 Identification

Representation (2.4) 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 $R\boldsymbol{u}_t$ in (2.3) is equal to $S\boldsymbol{v}_t$, where $S = RH'$ and $\boldsymbol{v}_t = H\boldsymbol{u}_t$, so that $\boldsymbol{\chi}_{it} = c_i(L)\boldsymbol{v}_t$, with $c_i(L) = b_i(L)H' = a_i(I - D_1L - \cdots - D_pL^p)^{-1}S$. 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 that economic theory implies a set of restrictions on the impulse-response functions of some variables, the first $m \leq n$ with no loss of generality. 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

$$\boldsymbol{\chi}_{mt} = C_m(L)\boldsymbol{v}_t, \tag{2.6}$$

along with the relation

$$B_m(L) = C_m(L)H, \tag{2.7}$$

if theory-based restrictions on $B_m(L)$ are sufficient to obtain H, then $b_i(L)$ is uniquely determined for any i (just identification).

In the present paper however we do not identify uniquely the shocks 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. Formally, let b_{ik} be the coefficient of the term of degree k of $b_i(L)$. We impose $b_{ik} > 0$ for $i \in \mathcal{I}$, $k \in \mathcal{K}$ and $b_{jh} < 0$ for $j \in \mathcal{J}$, $h \in \mathcal{H}$, where $\mathcal{I}$, $\mathcal{K}$, $\mathcal{J}$ and $\mathcal{H}$ are sets of integers. The precise set of restrictions that we impose in the present paper is discussed below.

A quite natural parameterization of the orthogonal matrices H is given by the hyperspherical coordinates of the unit sphere S^w of dimension $w = (q^2 - q)/2$, i.e. $H = H(\theta)$, θ being a w-dimensional vector of angles such that $0 \leq \theta_j < \pi$, $j = 1, \ldots, w-1$, $0 \leq \theta_w < 2\pi$.

different delays, so that we may have leading, coincident and lagging variables. If r is large enough, any (finite order) MA dynamics can be written in the form (2.1)-(2.3) (FGLR, Section 2).

Given the non-structural representation $C_n(L)\boldsymbol{v}_t$, the sign restrictions above define an admissible region Θ on the unit sphere, such that for $\theta \in \Theta$ $B_n(L) = C_n(L)H(\theta)$ satisfies such inequalities. Following Uhlig (2005), we assume that the true shocks and impulse-response functions are associated with a point θ with uniform probability density in the region Θ. This in turn implies upper and lower bounds and a probability density for each coefficient of the impulse-response functions $B_n(L)$.

2.3 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 $\hat{r}$ ordinary 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 $\boldsymbol{f}_t = \hat{A}_n'(x_{1t}x_{2t} \cdots x_{nt})'$.

Second, we set a number of lags $\hat{p}$ and run a VAR($\hat{p}$) with $\boldsymbol{f}_t$ to get estimates of $D(L)$ and the residuals $\boldsymbol{\epsilon}_t$, say $\hat{D}(L)$ and $\hat{\boldsymbol{\epsilon}}_t$.

Now, let $\hat{\Gamma}^\epsilon$ be the sample variance-covariance matrix of $\hat{\boldsymbol{\epsilon}}_t$. 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

$$\hat{C}_n(L) = \hat{A}_n\hat{D}(L)^{-1}\hat{S}. \tag{2.8}$$

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 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.[3] 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 of angles θ with dimension $w = (q^2 - q)/2$ from a uniform distribution in the range $0 \leq \theta_j < \pi$, $j = 1, \ldots, w-1$, $0 \leq \theta_w < 2\pi$ and retain the related $\hat{B}_n(L) = C_n(L)H(\theta)$ as long as they satisfy the sign restrictions. This gives a distribution of estimated $\hat{B}_n(L)$'s. We get a point estimate and the related confidence bands by retaining the mean along with the relevant percentiles of such a distribution.[4]

2.4 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, 2008). 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).

Large statistical factor models are compatible with a variety of economic models, including both neo-classical and neo-keynesian DSGE models, augmented with measurement errors (see Sargent and Sims, 1977, Sargent, 1989; Altug, 1989; Ireland, 2004, Giannone *et al.*, 2006 and the literature mentioned therein). However, in the present work we do not

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

[4]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.

propose a fully developed economic model characterized by “deep” parameters. Rather, our approach is very much in the spirit of the “structural” VAR literature. Our impulse response functions can indeed be labeled as “semi-structural”, rather than “structural”: while not being reduced form coefficients, they are still a mixture of behavioral and policy parameters, so that we cannot tell, say, what would happen in absence of systematic fiscal or monetary policy. The results of the present paper should then be interpreted essentially as stylized facts, conditional on the identified shocks.

Why use a structural factor model rather than a structural VAR? 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. On the other hand, factor models have a few advantages which may be important in the present context.

First, within a factor model we can study how many shocks there are in the macro economy, an interesting question which does not even make sense within the statistical VAR framework, where the number of shocks is necessarily equal to the number of variables that the econometrician chooses to include in the data set. Determining the number of shocks is important since it can provide useful guidelines for building macroeconomic models.

Second, being much more parsimonious in terms of parameters, factor models can handle a much larger amount of information. The data set used here, for instance, includes about one hundred variables. A VAR model with the same number of series would have too many parameters to estimate, given the number of observations available in the time dimension.

Having a large data set is important for three reasons. First, we can study the impulse response functions of virtually all relevant macro variables within a unified framework. We exploit this opportunity here by showing results for 23 key macro variables.

Second, it enables us to impose identifying restrictions on several variables, reducing the region of admissible impulse response functions and causing the confidence bands to shrink. For instance, we identify an expansive demand shock by imposing positive effects on output and prices; as output series we use both GDP and the industrial production index, while prices are measured by both the GDP deflator and the CPI.

Last, but not least, large information is likely to produce better results. The relevance of the information issue is stressed in several influential papers, including Quah (1990), Sims (1992), Lippi and Reichlin (1993, 1994), Bernanke and Boivin (1993), Bernanke *et al.* (2005). Central Banks, fiscal policy authorities and private economic agents base their decisions on all of the available macroeconomic information. Hence structural shocks should be innovations with respect to a large information set, which can hardly be included in a standard VAR model. If the VAR information set is too poor, the true structural shocks and the corresponding impulse response functions cannot be obtained from the VAR residuals, even if the identifying assumptions are correct. 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).

3 Empirics I: Identifying the structural shocks

In this section we describe the data, identify the number and the nature of structural shocks and describe the set of inequality restrictions used to estimate the impulse response functions.

3.1 Data, data treatment and specification of r

Our data set is made up of 101 US quarterly series, covering the period 1959-I to 2007-IV. Most series are taken from the FRED data base. A few stock market and leading indicators are taken from Data Stream. Some series have been constructed by ourselves as transformations of the original FRED series. The series include both national accounting data like GDP, investment, consumption and the GDP deflator, which are available only at quarterly frequency, and series like industrial production indices, CPI, PPI and employment, which are produced monthly. Monthly data have been temporally aggregated to get quarterly figures.

As required by the model, the data are transformed to obtain stationarity. Following Stock and Watson (2005), prices and nominal variables are taken in second differences of logs, rather than first differences of logs, and interest rates in first differences, rather than in levels. With these transformations all variables are stationary according to both the ADF and the KPSS tests.[5]

[5] Outliers were detected as values differing from the median more than 6 times the interquartile difference and replaced with the median of the five previous observations.

The full list of variables along with the corresponding transformations is reported in the Appendix.

The number of static factors r was set to 12 by taking the simple average of the popular tests IC1 ($r = 14$) and IC2 ($r = 10$), proposed by Bai and Ng (2002). As a robustness check, we repeated the analysis below for $r = 8$ and $r = 16$ and obtained similar results (not reported here).

Finally, the number of lags p to include in the VAR which is part of our estimation procedure was set to 2, the average of AIC (3 lags) and BIC (1 lag).

3.2 The number of shocks and their "demand" or "supply" nature

Determining the number of shocks, besides being a step needed for the specification of our model, has an intrinsic economic interest. Early real business cycle models assume the existence of just one supply shock driving economic fluctuations, whereas, on the other extreme, Smets and Wouters (2007) propose a new Keynesian DSGE model with no less than ten structural shocks. The fact that economic theories disagree about the number of shocks driving the economy is partly due to the lack of empirical evidence that can guide this choice. In the present factor-model framework we have both tests and consistent information criteria which can provide useful indications for economic modeling.

Table 1 shows the results of the test proposed by Onatski (2009). Each cell reports the probability value of the null of just k shocks against the alternative of j shocks, with $k + 1 \leq j \leq h$.[6] The null of no shocks (first row) is rejected at the 5% level against all of the alternatives $h = 1, 2, \ldots, 7$. The same result holds for the null of just one shock (second row). The null of two shocks is not rejected against the alternative of three shocks, but is rejected at the 5% level against the alternative of 3 or 4 shocks. The null of three shocks is rejected at the 5% level against the alternative of 4 shocks. The null of 4 shock is not rejected against any alternative. These results suggest a four-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

[6] 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 such parameters in such a way as to include waves of periodicity between 2 and 12 years.

(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 2 primitive factors in the IC_{p2} version (with $\hat{r} = 12$ and $p = 2$). The four criteria of Bai and Ng (2007), namely q_1, q_2, q_3 and q_4, give 4, 5, 5 and 4 shocks respectively (with $\hat{r} = 12$ and $p = 2$).[7] Finally, the log criterion proposed by Hallin and Liska gives 2 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 2 and 6. Here we conclude in favor of a four-shock specification, which results from the Onatski tests and is consistent with the range emerging from available information criteria.

Overall, the above results are in line with what is found by Giannone *et al*, (2004) with more informal methods. They are compatible with small scale New-Keynesian models like Galı´ (1999) or RBC models extended to include other types of shocks in addition to the technology shock.

Shocks can be classified as either "demand" or "supply", according to the conditional correlation of output and prices: an expansionary demand shock raises prices, whereas an expansionary supply shock reduces prices. This observation is the basis for the following exercise, which provides some evidence about the nature of the structural shocks.

First, we normalize the sign of all of the shocks by imposing that they have a positive effect on output. As measures of output we take both GDP and the industrial production index. Then we require that one shock be "supply" by imposing a negative effect on prices, and one shock be "demand", by imposing a positive effect on prices. As measures of prices we take both the GDP deflator and the consumption price index.[8] The effect of the remaining shocks on prices is left unrestricted. Finally we estimate the model as explained in Section 2.3 to obtain the impulse response function of prices. We find that both the average and the median response of both the GDP deflator and the CPI are positive for both the unrestricted shocks, suggesting that they are demand shocks.

Next, we impose the additional requirement that one out of the two previously unrestricted shocks be a demand shock (i.e. has a positive effect on both the GDP deflator and

[7]The Bai and Ng criteria have two parameters. We set $\delta = .1$ for all criteria and $m(q_1) = 1.25$, $m(q_2) = 2.5$, $m(q_3) = 2$, $m(q_4) = 4.5$. Such values produced good results in our simulations (not shown here).

[8]All sign restrictions are imposed only on the second-lag coefficient of the impulse response functions, for reasons that will be clarified below.

the CPI), so that there are two demand shocks and one supply shock, whereas the fourth shock is left unrestricted. Again, we find that both the average and the median response of both the GDP deflator and the CPI are positive for the unrestricted shock, suggesting that it is a demand shock.

3.3 Identifying restrictions

Although the positive effects on prices are not significant, the above exercise provides some evidence in favor of a specification with three demand shocks and just one supply shock. We find particularly appealing a characterization of the demand shocks as "discretionary fiscal policy", "discretionary monetary policy" and "private" or "non-policy" demand.

To characterize such shocks we adopt the following definitions. The expansionary monetary policy shock is defined as a shock having a positive effect on both output and prices, but a negative effect on the federal fund rate. We expect that expansionary monetary policy will enlarge money aggregates, but prefer not to impose such a restriction as part of the definition of the shock, in order to keep the definition itself as simple as possible.

An obvious logical implication of the above characterization is that private demand and fiscal policy do not have a negative effect on the federal fund rate. Despite this, we do not impose such constraints, since in the present framework imposing a non-negative effect is equivalent to imposing a significant positive effect, which would be unnecessarily restrictive. Nonetheless, private demand and fiscal policy are well defined only if their effect on the federal fund rate is not significantly negative, i.e. is either significantly positive or not significant. We need to verify whether such condition is satisfied by the estimated impulse response functions.

The expansionary fiscal policy shock is defined as a shock having a positive effect on output, prices and the real federal deficit.[9] The logical complement of this definition is that the other demand shocks, or at least expansionary private demand, do not have a significant positive effect on the federal deficit. Again, we do not impose a non-positive constraint, since *de facto* it would rule out a zero effect, which is not inconsistent with our definitions. We shall verify that private demand and monetary policy do not raise significantly the real

[9]The real federal deficit is constructed as the difference between current federal expenditures and current federal receipts, divided by the GDP deflator

federal deficit, so that our shocks are well defined.

Most of the restrictions above are imposed on the first three coefficients of the impulse response functions, i.e. on the impact effect as well as the effects delayed by one and two quarters. However, there are two exceptions. First, we do not impose any restriction on the impact effects of monetary policy on output and prices. This is because both output and prices might react to monetary policy with some delay. In the structural VAR literature such a delayed reaction is commonly assumed to identify monetary policy (see Christiano *et al.*, 1999 for a review). Second, the positive effects of expansionary fiscal policy on the federal deficit, output and prices are imposed only on lag 2. The reason is the following. On the one hand, the effects of fiscal policy decisions on public expenditures or receipts are often delayed by several months (see e.g. the discussion in Leeper *et al.*, 2008). On the other hand, the sign and the size of the impact effects of such decisions on output and prices are not obvious. For instance, consumers might anticipate a larger income in the near future, but also a reduced public expenditure or higher taxes in the medium run. If public expenditure is delayed and consumption does not increase on impact, output and prices do not necessarily increase at lag 0.

Summing up, the supply shock increases GDP and industrial production and reduces the GDP deflator and the CPI at lags 0, 1 and 2; the private demand shock increases GDP, industrial production, the GDP deflator and the CPI at lags 0, 1 and 2; the monetary policy shock reduces the federal fund rate at lags 0, 1 and 2 and increases GDP, industrial production, the GDP deflator and the CPI at lags 1 and 2; the fiscal policy shock increases GDP, industrial production, the GDP deflator, the CPI and the real federal deficit at lag 2.

Such constraints are not sufficient *per se* to guarantee that all shocks are well defined. In addition we need that (i) the private demand shock does not reduce the federal fund rate for at least one of the lags 0, 1, 2; (ii) the private demand shock does not increase the real federal deficit at lag 2; (iii) at least one of the following conditions holds: (iii.1) the monetary policy shock does not increase the federal deficit at lag 2, (iii.2) the fiscal policy shock does not reduce the federal fund rate for at least one of the lags 0, 1, 2. Conditions (i) and (ii) are needed to characterize the private demand shock, whereas condition (iii) is needed to distinguish monetary from fiscal policy.

4 Empirics II: Main results

In this section we present our main findings. We begin by showing a few results validating our identification scheme. Then we show results concerning the size and the timing of the effects of supply and demand shocks. Finally, we address policy issues and discuss the effects of demand on productivity.

4.1 Validating the identification of structural shocks

The purpose of this subsection is to validate our identification procedure along two dimensions. First, we check whether the inequality restrictions are sufficient to get a full characterization of the structural shocks, i.e., conditions (i)-(iii) above are satisfied. Second, we show that the response of some relevant variables conform to the consensus view.

Figure 1, left column, shows the mean impulse response functions (solid lines) of the federal funds rate to the four shocks, along with the 68% confidence bands (dotted lines). The non-policy demand shock generates an immediate and significant positive effect on the federal funds rate. A similar finding, but with a smaller response in terms of magnitude, is obtained for the fiscal policy shock. Hence conditions (i) and (iii.2) are satisfied. Moreover, deficit significantly reduces at all horizons after a non-policy demand shock, thus ensuring condition (ii), whereas it is essentially unaffected by the monetary policy shock, the effects being remarkably small and not significant at all horizons, consistently with condition (iii.1) (Fig. 2). These findings ensure that the identifying restrictions are sufficient for a proper characterization of the structural shocks.

Next we show the effect of our identified shocks on a few selected variables, in order to verify whether they conform to some basic features emerging from previous literature and to gain additional insights about their sources and their nature.

The non-policy demand shock is the only one that affects significantly, on impact, both new orders and real exports (Fig. 3). While new orders capture mainly the increase in domestic demand, real exports indicates that the shock is also related to external factors. The demand shock is the primary source of unexpected change in investment on impact, explaining almost one half of the forecast error variance at lag 0 (as against 20% of consumption, see Table 3a). This is very much in line with the idea that investment is largely driven by "animal spirits" (even if the supply component is also important).

Concerning the supply shock, Figure 3 shows that both the producer price index of crude materials and the unit labor cost immediately and significantly fall, indicating that the supply shocks are partly made up of unexpected changes in some key production costs. Moreover, Figure 9 shows a large and significant positive impact on labor productivity, in line with the consensus view that supply shocks include an important technological component.

An expansionary monetary policy shock increases monetary aggregates, as predicted by the theory of the liquidity effect (the response function of M2 is shown in Figure 1). Moreover, the impact effects on output and prices are small and not significant, consistently with the zero identifying restrictions often imposed in the SVAR literature (Fig. 4).

Finally, the fiscal policy shock immediately and significantly increases federal government expenditures (Fig. 2). Note also the different reaction of current receipts to fiscal policy and private demand shocks. While both shocks significantly affect GDP on impact and the size of the effects are similar (Fig. 4), non-policy demand significantly raises federal receipts, whereas fiscal policy does not, suggesting the presence of a tax reduction component compensating for the increase in GDP.

4.2 The relative importance of supply and demand shocks

Table 2 shows the variance decomposition of (the stationary transformation of) some selected series. Columns 2 to 6 report the percentages of variance explained by the monetary policy shock (MP), the fiscal shock (FS), the supply shock (S), the non-policy demand shock (D) and the two policy shocks jointly (MP+FS).

Supply shocks explain around 55% of the variance of GDP growth, being slightly more important for consumption than for investment. Such result is in line with King *et al.* (1991). Policy shocks account for about 26% of the variance, while non-policy demand shocks explain only 18%. The picture however changes substantially when other variables are considered. Regarding industrial production, for instance, the contribution of supply reduces to 37%, as against 39% of non-policy demand. This is consistent with the fact that, as already noted, private-demand shocks primarily concern investment and exports, which mainly involve goods, rather than services. The importance of demand is even larger for labor market variables, such as employment, hours worked or the unemployment rate.

Focusing on employment, for instance, the percentage of variance accounted for by supply shocks reduces to 35%, while the one accounted for by non-policy demand shocks is raised up to 42%. Such a large difference between employment and GDP variance decompositions is probably due to the technology component of supply shocks. While demand affects output mainly through employment changes, supply largely affects GDP through the important impact on productivity already noted above.

Tables 3a-3c display the decomposition of the forecast error variance at different horizons. The previous results are confirmed. In particular, supply shocks explain most of GDP variance, while demand shocks prevail as far as employment is concerned. On impact ($k = 0$) such dichotomy is particularly pronounced: supply shocks explain 63% of output as against 11% of employment, whereas non-policy demand accounts for 58% of employment but only 13% of output. From Tables 3a-3c it also emerges clearly that, in the long run, the effects of non-policy demand on all real variables reduce, while the effects of supply increase, consistently with the consensus view that supply shocks are more persistent.

Considering prices, the bulk of fluctuations in the GDP deflator is accounted for by the three demand shocks, which, taken together, account for about 70% of the variance of the two series. The result is confirmed by Tables 3a-3c: demand shocks account for about 68%, 75% and 84% at horizons 0, 4 and 24 quarters, respectively.

Figure 4 plots the impulse response functions of GDP and the GDP deflator to the four shocks. Several interesting features emerge. First, all of the shocks except monetary policy affect significantly output on impact. The effect is particularly large for supply shocks. Second, both fiscal policy and non-policy demand shocks have temporary effects on output, whereas the supply shock has large and significant permanent effects. Long-run neutrality of demand on output is consistent with mainstream theory and is adopted as an identifying assumption in the SVAR literature, starting with the seminal work of Blanchard and Quah (1989). Third, despite this, demand is not long-run neutral on all real variables, persistency being particularly pronounced for employment. We will come back to this point below. Fourth, the GDP deflator significantly increases at all horizons for the three demand shocks and reduces significantly at all horizons for the supply shock.

To get some additional insights about the relative importance of structural shocks, Figure 5 and 6 plot the historical decomposition of output growth and inflation. The dotted lines refer to the original series, while the solid line refers to the series of inflation generated using the particular component specified in the title of each panel.[10] As noted above, both demand and supply shocks have an important role in shaping economic fluctuations. However, their relative importance is not constant over time. In the 70s supply shocks seem to have a primary role. Actually, they are responsible for the two recessions of 1971 and 1974. Supply appears to be very important also in the last part of the sample, from the early 90s onward. The 1991 recession, in particular, is mainly attributable to the supply component. These results are consistent with the narrative literature attributing to supply factors such as increases in commodity prices the two recessions of the 70s and the recession of 1991. On the other hand, demand shocks play a relevant role during the 80s. In particular the recession of the early 80s is attributable to both policy and non-policy demand factors.

As discussed above, demand shocks are by far the primary source of fluctuations in prices. The last row of Figure 6 shows that demand shocks very well track the series of inflation, with the exception of the two peaks in inflation dated 1975 and 1979, which correspond to the two oil shocks and are driven by supply. The left panel of the last row plots the component of inflation changes obtained using only the fiscal policy and non-policy demand components. In the first half of the 80s this series lies always above the actual series, whereas the two series almost exactly overlap when also the monetary policy component is added (right panel). The monetary policy shock correctly captures the Volcker disinflation episode, where a strongly anti-inflationary monetary policy stance was adopted to fight inflation.

In summary, both supply and demand shocks are important sources of macroeconomic fluctuations, but the relative importance differs substantially for different variables. Supply prevails for GDP, whereas demand prevails for labor market variables, industrial production and prices. Demand shocks are less persistent than supply shocks for all real variables. While being long-run neutral for output, neutrality does not hold for employment. Finally, policy shocks have sizeable effects on output and prices. In particular the former seems to be

[10]This component is computed as follows. First, we estimate a non-structural orthogonal representation for the original data as explained in Section 2. Then we draw randomly the candidate rotation matrices and retain the impulse response functions satisfying our sign restriction along with the corresponding shocks (we got about 2000 admissible impulse response functions). Finally we filter each shock with the corresponding response function to get the component and average across components.

responsible for the early 80s recession and disinflation. This picture is more complex than the one emerging from the VAR literature, where the limited dimension makes it difficult to compare all of the relevant series.

4.3 Macroeconomic policies

This sub-section addresses three key policy questions. First, what and how big are the effects of monetary and fiscal discretionary policies on GDP and prices? Second, are consumption and investment crowded out by discretionary fiscal policy? Third, do monetary and fiscal authorities react systematically to macroeconomic shocks?

Monetary policy and fiscal shocks account for about 9% and 17% of the fluctuations in GDP, respectively (see Table 2). Fiscal policy shocks are more important in the short run (25% at $k = 0$ and 5% at $k = 24$), while monetary policy shocks produce bigger effects at long horizons (3% at $k = 0$ and 9% at $k = 24$). This is due to the different shape of the impulse response functions (Fig. 4). On the one hand, the response of GDP to a monetary policy shock is persistent but has a nearly zero impact effect. On the other hand, the response to a fiscal fiscal policy shock reaches the maximal level on impact and is relatively short lived. As far as inflation is concerned, monetary and fiscal policy shocks explain around 27% and 7% of the volatility of the growth rates of the GDP deflator, respectively. Percentages are similar at all horizons.

In conclusion, both fiscal and monetary policy have non-negligible effects on output and prices; fiscal policy seems to be more relevant for output fluctuations, while monetary policy is dominant for fluctuations in prices.

Figure 7, line 2, plots the impulse response functions of investment, residential investment and nonresidential investment to a unit variance fiscal policy shock. The responses of nonresidential and residential investment differ substantially. The former increases significantly for the first year (in the long run the point estimate is positive but not significant). The latter, after a nearly zero initial effect, reduces significantly in the long run. The difference could be attributable to a different sensitivity of the two types of investment to the interest rate, which permanently and significantly increases (see below). On aggregate, investment increases significantly on impact and for the first quarter after the shock, despite the increase of interest rates.

Figure 8, line 2, plots the impulse response functions of consumption, durable consumption and nondurable consumption to a unit variance fiscal policy shock. The three responses have similar shapes, with a positive impact effect, followed by a reduction. The impact effect is much larger for durables (0.3% as against 0.06%). On aggregate the impact effect is small (0.1% as compared to 0.3% of investment). All effects are (borderline) significant only on impact. All of the three responses are very similar, both quantitatively and qualitatively, to the corresponding ones of non-policy demand. Such picture is different to that of Blanchard and Perotti (2002), where consumption is found to considerably increase, but is also different to those of Ramey and Shapiro (1998) and Ramey (2009), where consumption is found to significantly fall. The small reaction of nondurable consumption (and hence aggregate consumption) to both the fiscal policy and the non-policy demand shocks seems in line with standard permanent income theory, provided that, at least in part, consumers correctly perceive the increase of income as transitory. The positive sign of the response is in contrast with theoretical predictions from standard RBC models.

Overall, there is little evidence of crowding-out of private expenditure after a fiscal policy shock, with the relevant exception of residential investment.

Let us now study whether there is evidence of a systematic monetary and fiscal policy reacting to our structural shocks.

Let us consider first monetary policy. After both a non-policy demand and a fiscal policy shock the federal funds rate immediately and permanently increases (Fig. 1). The effect is significant in both cases, although, from a quantitative point of view, the effect of the non-policy demand shock is about two times larger than that of fiscal policy. As for money aggregates, a significant reduction of M2 is found in both cases, the reduction being particularly large for the non-policy demand shock (Fig. 1). This suggests a very active countercyclical behavior of monetary policy, which is consistent with standard Taylor rules implying systematic policy reaction to increases in prices and output.

On the contrary, the federal funds rate responds negatively to the supply shock on impact, although the effect is not significant. However, the effect becomes positive and significant after about one year, converging to 0.4% in the long run. Taking as benchmark a standard Taylor rule, the result indicates that while in the very short run the opposite effects of output and inflation offset each other, in the long run the effects on inflation reduce and the federal funds rate seems to follow the pattern of output.

Let us now come to systematic fiscal policy (Fig. 2). Government spending essentially does not react to monetary policy and supply shocks, the effect of such shocks being not significant at any horizon. On the contrary, the non-policy demand shock induces a strong countercyclical behavior of fiscal authorities. Government spending reduces significantly at all horizons by about 0.4%. We can get some idea of the effects of such policy by looking at Table 2. The fraction of variance of GDP growth explained by the non-policy demand shock (18%) is sizeably smaller than the one of its components: investment (35%), consumption (19%), and government expenditure (27%). This is attributable to the negative comovement of private demand components and government spending.

There is little evidence, however, of an active behavior of fiscal authorities on the receipt side, since current receipts essentially follow GDP changes. Both supply and demand bring about a significant positive and permanent increase in current receipts which reduces government deficit.

In summary, the evidence suggests a strong countercyclical systematic response of both monetary and fiscal authorities to demand shocks. Given that discretionary policy has sizeable effects on both output and prices, systematic policy could be effective in controlling inflation and reducing output fluctuations arising from non-policy demand. As a consequence, output fluctuations originated by non-policy demand, which, as documented above, are fairly small in comparison with supply-driven variations, could be much larger if systematic policy where not in place. Unfortunately, with the present model we cannot proceed to evaluate the quantitative importance of stabilization policies, nor we can say whether the corresponding variance reduction over-compensates for discretionary policies, which, as we have seen, are non-negligible sources of additional fluctuations.

4.4 Demand shocks and labor productivity

As shown above, the non-policy demand shock does not have permanent effects on GDP. This however does not mean that demand is long-run neutral, since the private demand shock has permanent effects on several real variables. In particular, an expansionary shock increases employment and hours worked and reduces unemployment and the unemployment rate (the effect on employment is reported in Figure 9). Since output does not increase in the long run, labor productivity (non-farm business sector, output per hour of all persons) significantly decreases (Figure 9). Such an effect is quantitatively important. A unit-variance shock, increasing GDP by 0.2 per cent on impact, reduces labor productivity by almost 0.4% in a couple of years: a change which, in absolute value, is even larger than that of the supply shock. Table 3c confirms such ranking: private demand explains about 45% of the forecast error variance at a six-year horizon, as against the 35% explained by the supply shock. Moreover, the wage rate (nonfarm business sector, real compensation per hour) decreases substantially as far as the point estimate is concerned, even though the effect is not significant, owing to the large confidence bands (not shown).

The findings above, while being at odds with most of the business cycle literature, are consistent with a stream of empirical and theoretical work concerning the interactions between growth and cycle. Empirical evidence of a long-run negative effect of a positive demand shock on productivity is reported in Bean (1990), Saint-Paul (1993) and Galıánd Hammour (1991), where an impulse response function almost identical to the one obtained here is found by using a structural VAR approach. Possible explanations are provided by theoretical works which, in various ways, revive the Schumpeterian view of recessions as providing a cleansing mechanism for reducing organizational inefficiencies and resource misallocations. During recessions, less efficient firms become unprofitable and shut down, thus improving average productivity (Caballero and Hammour, 1993). Moreover, the opportunity cost of undertaking productivity-enhancing activities are lower, so that recessions are the right time to reorganize production, and/or improve the matching between workers and firms, implement new technologies, invest in human capital (Davis and Haltiwanger, 1992, Hall, 1991, Aghion and Saint-Paul, 1991). Such efficiency effects are long-lasting.[11]

Let us highlight two relevant implications of the above findings. The first one is related to empirical economic research. A widespread practice in structural VAR literature is to identify technology shocks as the only ones having long-run effects on productivity (Galı, 1999, Christiano *et al.*, 2003). But if demand also affects productivity, this identification assumption may produce a mixture of true positive technology shocks and negative demand

[11]According to the above explanations, productivity is related to the business cycle, rather than demand *per se*). This is consistent with our estimated response of productivity to supply shocks, which reaches its maximum after about one year and then declines sharply, dissipating about one half of the impact effect in the following six quarters (see Figure 9).

shocks, leading to incorrect conclusions. For instance, the finding that technology reduces hours worked (Galí, 1999) could be due to the negative demand component. Indeed, our supply shock have a significant positive impact on hours worked (not shown). Moreover, the puzzling finding that technology has little effect on investment (Christiano *et al.*, 2003) may result from positive technology effects canceling out with negative demand effects. Actually with our identification procedure supply shocks account for about 72% of fluctuations in investment at the 4-year horizon (see Table 3c).

The second implication is a policy one. Systematic counter-cyclical policies, if successful in reducing fluctuation, may have long-run 'side effects'. Specifically, expansive measures following negative demand shocks, while not hurting GDP growth, may permanently support employment on one hand, and reduce per-capita GDP and real wages, on the other hand. On balance, such effects are not necessarily undesirable. But policy makers should be fully aware of the efficiency issues related to public support for employment and shaky companies, in order to design intervention properly.

5 Conclusions

This paper studies the sources of the business cycle and the role of macroeconomic policies using a structural factor model. Our main results are the following.

First, theories based on the existence of a single source of fluctuations as well as theories relying on a large number of shocks are inconsistent with our evidence. The US economy can be well described by a number of shocks between 2 and 6.

Second, by specifying a four-shock model we find that both demand and supply components are important to explain fluctuations in real macroeconomic variables, although the relative importance varies, depending on the specific variable considered. Supply explains most of GDP volatility while demand prevails for employment and other labor market variables. Fluctuations in prices are mostly explained by demand shocks.

Third, policy is important. Discretionary policies produce sizeable effects on output and prices, with little evidence of crowding out effects of public expenditure. Both fiscal and monetary authorities follow systematic policy rules reacting mainly to private demand shocks. Such stabilization policies could in principle be very effective in reducing demand-driven fluctuations.

Finally, non-policy demand shocks, while being long run neutral on GDP, have a large and permanent negative effect on productivity. Such a result is consistent with the Schumpeterian view of crises as providing a "cleansing" device for reducing inefficiencies and resource misallocations.

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	6	COMPNFB	Nonfarm Business Sector: Compensation Per Hour
33	5	COMPRNFB	Nonfarm Business Sector: Real Compensation Per Hour

no.series	Transf.	Mnemonic	Long Label
34	6	GDPCTPI	Gross Domestic Product: Chain-type Price Index
35	6	GNPCTPI	Gross National Product: Chain-type Price Index
36	6	GDPDEF	Gross Domestic Product: Implicit Price Deflator
37	6	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	6	BOGNONBR	Non-Borrowed Reserves of Depository Institutions
65	6	TRARR	Board of Governors Total Reserves, Adjusted for Changes in Reserve
66	6	BOGAMBSL	Board of Governors Monetary Base, Adjusted for Changes in Reserve
67	6	M1SL	M1 Money Stock
68	6	M2MSL	M2 Minus
69	6	M2SL	M2 Money Stock

no.series	Transf.	Mnemonic	Long Label
70	6	BUSLOANS	Commercial and Industrial Loans at All Commercial Banks
71	6	CONSUMER	Consumer (Individual) Loans at All Commercial Banks
72	6	LOANINV	Total Loans and Investments at All Commercial Banks
73	6	REALLN	Real Estate Loans at All Commercial Banks
74	6	TOTALSL	Total Consumer Credit Outstanding
75	6	CPIAUCSL	Consumer Price Index For All Urban Consumers: All Items
76	6	CPIULFSL	Consumer Price Index for All Urban Consumers: All Items Less Food
77	6	CPILEGSL	Consumer Price Index for All Urban Consumers: All Items Less Energy
78	6	CPILFESL	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy
79	6	CPIENGSL	Consumer Price Index for All Urban Consumers: Energy
80	6	CPIUFDSL	Consumer Price Index for All Urban Consumers: Food
81	6	PPICPE	Producer Price Index Finished Goods: Capital Equipment
82	6	PPICRM	Producer Price Index: Crude Materials for Further Processing
83	6	PPIFCG	Producer Price Index: Finished Consumer Goods
84	6	PPIFGS	Producer Price Index: Finished Goods
85	6	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 Consumption Expenditures & Gross Investment, 1 Decimal

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Tables

Table 1:

0	1	2	3	4	5	6	7
0	0.001	0.002	0.003	0.003	0.004	0.005	0.006
1		0.012	0.021	0.028	0.036	0.042	0.05
2			0.927	0.107	0.147	0.183	0.215
3				0.06	0.107	0.147	0.183
4					0.852	0.982	0.746
5						0.746	0.595
6							0.336

Table 2: Explained variances

	MP		FP		S		D		MP+FP
Variable	% var	std	% var	std	% var	std	% var	std	% var
GDP	8.95	5.78	17.25	9.28	55.81	13.45	17.98	10.63	26.21
Investment	7.75	6.10	9.76	6.52	47.96	14.71	34.54	13.22	17.50
Consumption	10.80	7.38	11.34	7.67	58.56	13.08	19.30	9.73	22.14
Gov. Exp.&Inv.	17.91	17.23	37.77	19.95	17.07	14.38	27.26	18.48	55.68
Deficit	16.40	12.17	19.88	12.19	17.19	9.10	46.53	14.21	36.28
Industrial Production	8.32	6.32	14.98	9.98	37.68	11.74	39.01	12.99	23.30
Employment	11.10	7.57	11.02	8.23	35.23	13.82	42.64	14.51	22.13
Unemployment Rate	7.25	6.22	10.87	6.77	42.20	13.20	39.68	12.95	18.12
Labor Productivity	11.39	8.47	22.05	12.43	51.37	13.52	15.18	5.62	33.44
GDP Deflator	26.80	18.76	7.02	8.56	29.65	16.27	36.53	18.92	33.82
PPI	19.65	13.81	34.68	17.23	29.77	13.92	15.90	12.27	54.33
Federal Funds Rate	18.97	11.70	17.43	10.96	18.73	8.90	44.86	12.05	36.40
New Orders	11.09	7.51	12.12	6.74	32.10	9.75	44.69	11.34	23.22

Table 3a: Explained forecast error variances at horizon $k = 0$

	MP		FP		S		D		MP+FP
Variable	% var	std	% var	std	% var	std	% var	std	% var
GDP	3.23	6.01	19.96	13.84	62.87	18.47	13.93	14.83	23.20
Investment	2.29	4.11	8.71	9.89	41.36	20.93	47.63	22.73	11.01
Consumption	6.91	8.49	9.06	12.01	63.94	20.52	20.09	19.12	15.98
Gov. Exp.&Inv.	16.08	21.18	39.26	25.55	15.53	18.04	29.13	22.21	55.34
Deficit	15.38	16.76	18.71	16.11	7.38	10.98	58.53	20.45	34.10
Industrial Production	4.59	7.50	18.99	16.00	28.11	17.17	48.31	20.73	23.58
Employment	14.88	18.73	15.27	17.54	11.16	12.01	58.69	25.95	30.16
Unemployment Rate	2.24	3.80	13.15	11.45	28.43	16.47	56.18	19.68	15.39
Labor Productivity	7.26	11.45	22.53	16.92	64.90	18.15	5.30	6.08	29.80
GDP Deflator	30.80	23.28	5.77	9.86	32.70	18.04	30.74	21.79	36.57
PPI	16.60	16.21	35.88	22.45	35.53	17.67	12.00	15.24	52.48
Federal Funds Rate	26.93	16.92	19.95	18.70	8.72	10.41	44.40	22.31	46.88
New Orders	7.84	8.89	10.97	12.12	10.22	12.02	70.96	21.43	18.81

Table 3b: Explained forecast error variances at horizon $k = 4$

	MP		FP		S		D		MP+FP
Variable	% var	std	% var	std	% var	std	% var	std	% var
GDP	6.89	7.48	7.39	8.26	73.55	16.81	12.16	13.35	14.28
Investment	7.00	7.88	3.96	4.99	64.97	20.35	24.07	18.18	10.96
Consumption	11.10	10.19	5.29	5.93	76.03	14.52	7.58	8.48	16.39
Gov. Exp.&Inv.	13.17	17.13	41.92	25.29	14.63	15.37	30.29	23.50	55.09
Deficit	10.59	10.69	9.80	9.57	18.36	15.27	61.25	18.95	20.38
Industrial Production	6.18	6.22	7.19	7.76	54.03	18.67	32.60	17.93	13.37
Employment	7.68	7.41	6.68	8.03	38.12	20.57	47.52	21.26	14.36
Unemployment Rate	4.86	5.97	5.35	6.42	54.25	19.89	35.54	19.01	10.21
Labor Productivity	9.52	11.02	11.14	10.97	58.08	16.85	21.26	12.97	20.66
GDP Deflator	27.36	22.22	4.86	8.53	25.70	17.49	42.09	21.33	32.21
PPI	29.26	23.46	34.03	25.49	23.87	18.96	12.84	15.12	63.29
Federal Funds Rate	7.10	6.31	16.27	12.47	10.39	7.69	66.24	14.90	23.37
New Orders	5.65	6.58	4.96	5.40	44.10	20.91	45.29	20.79	10.61

Table 3c: Explained forecast error variances at horizon $k = 24$

	MP		FP		S		D		MP+FP
Variable	% var	std	% var	std	% var	std	% var	std	% var
GDP	8.82	9.64	4.97	6.98	78.61	14.70	7.60	9.03	13.79
Investment	9.34	10.43	5.19	5.77	72.03	18.95	13.44	14.19	14.53
Consumption	12.00	11.44	6.34	7.14	72.15	15.16	9.51	9.37	18.34
Gov. Exp.&Inv.	12.37	17.10	41.08	27.13	19.19	19.82	27.36	24.77	53.45
Deficit	11.85	12.93	15.46	12.94	28.60	20.51	44.08	23.07	27.32
Industrial Production	8.87	8.92	4.77	6.54	67.77	18.72	18.59	16.11	13.64
Employment	9.80	9.72	4.75	5.98	54.82	23.37	30.63	21.38	14.56
Unemployment Rate	7.56	8.95	4.06	5.37	68.82	20.43	19.56	17.26	11.62
Labor Productivity	10.17	12.34	10.49	12.27	34.67	18.61	44.67	19.52	20.66
GDP Deflator	31.30	24.72	4.59	8.86	16.26	17.19	47.85	22.78	35.89
PPI	30.05	25.88	26.47	25.95	31.20	26.60	12.28	13.18	56.52
Federal Funds Rate	5.29	5.61	10.53	10.71	25.37	16.56	58.82	17.95	15.82
New Orders	7.42	9.57	5.60	5.49	60.18	22.28	26.81	20.66	13.02

Figures

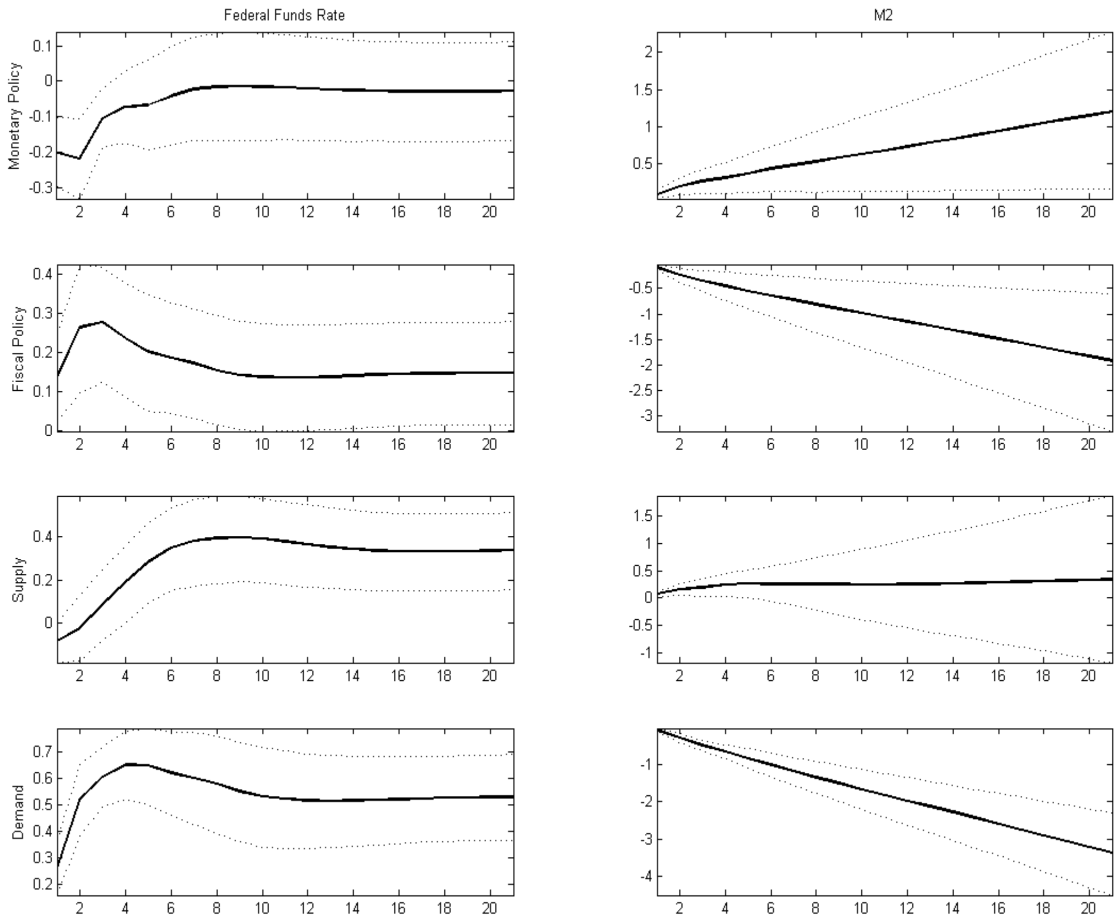
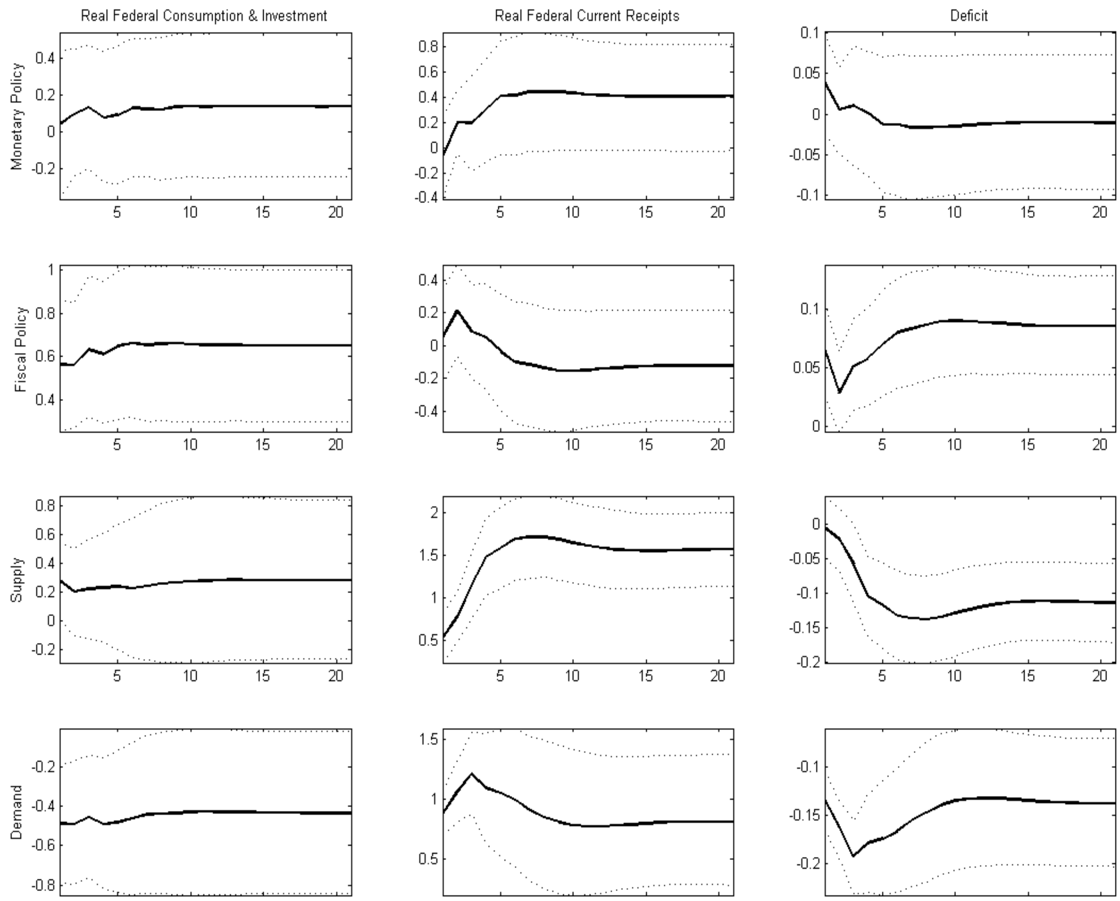


Figure 1



Real Federal Consumption & Investment
Real Federal Current Receipts
Deficit
Monetary Policy
Fiscal Policy
Supply
Demand

Figure 2

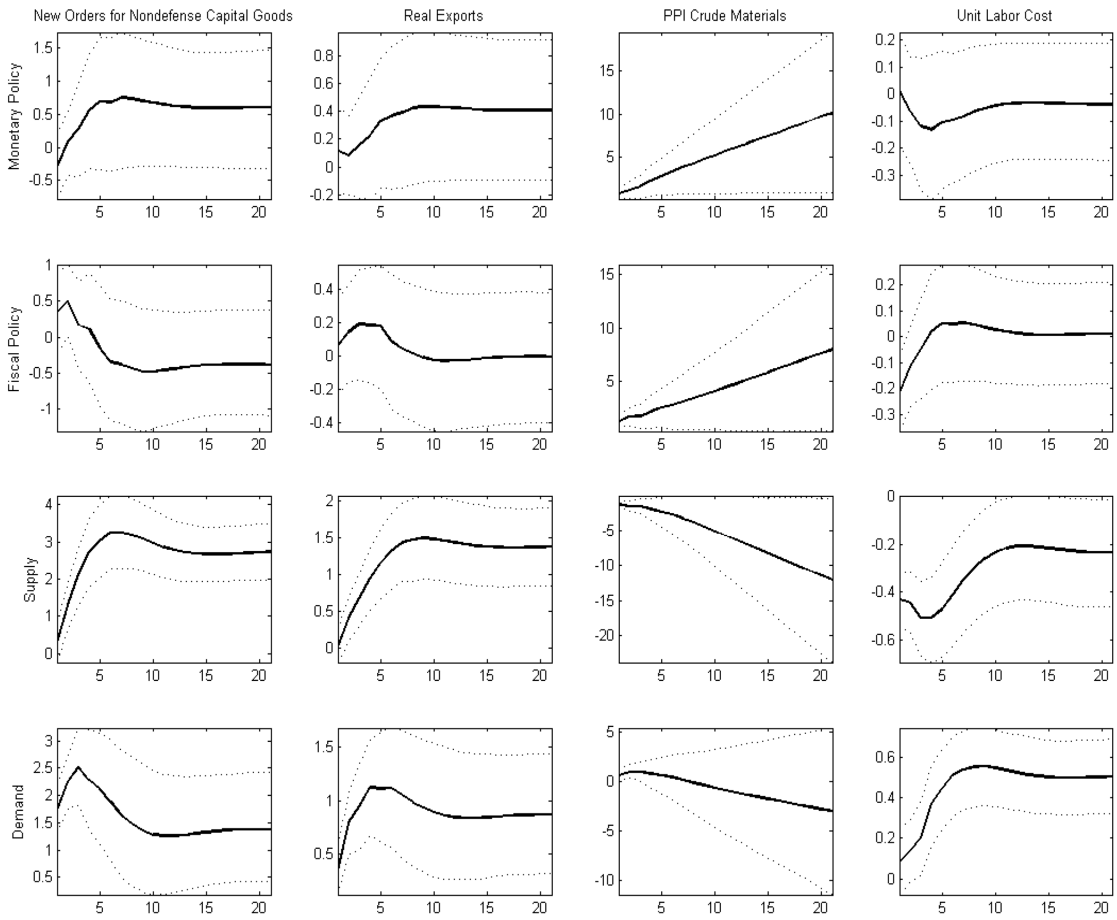

New Orders for Nondefense Capital Goods
Real Exports
PPI Crude Materials
Unit Labor Cost
Monetary Policy
Fiscal Policy
Supply
Demand

Figure 3

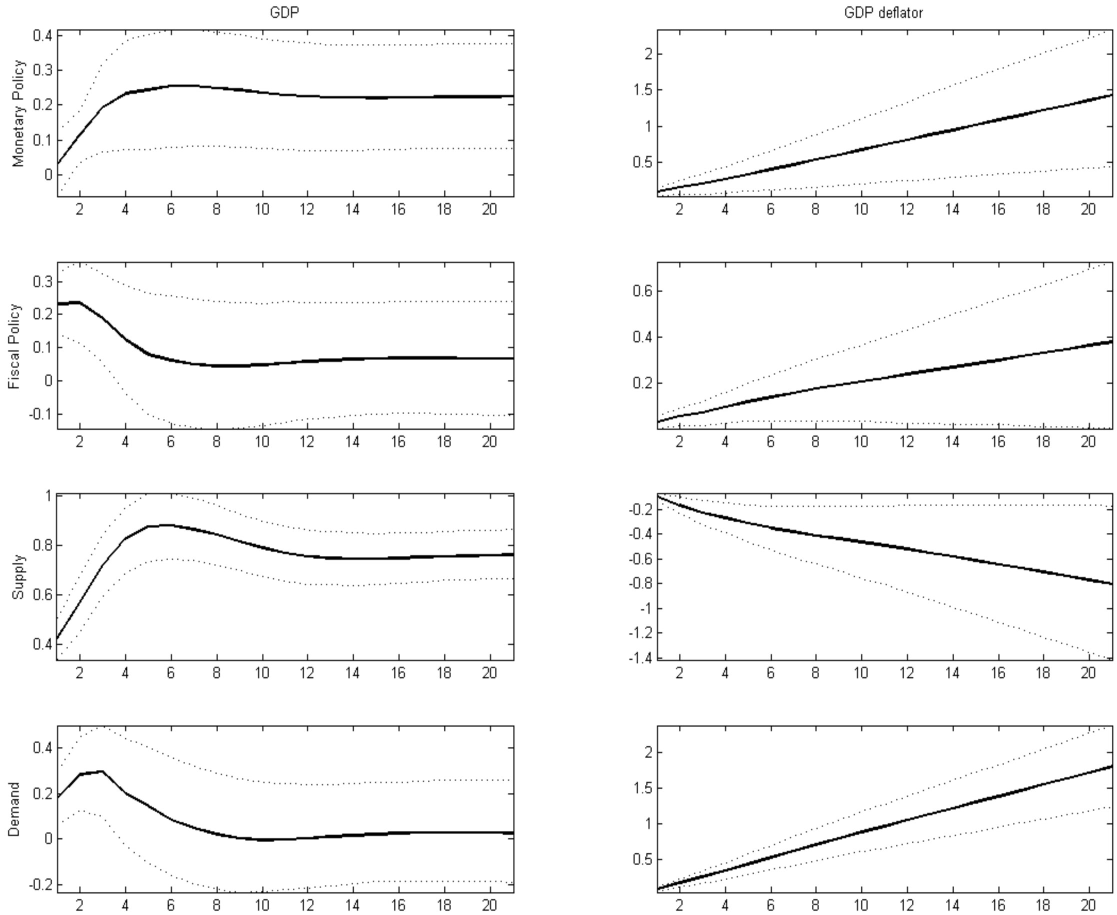

GDP
GDP deflator
Monetary Policy
Fiscal Policy
Supply
Demand

Figure 4

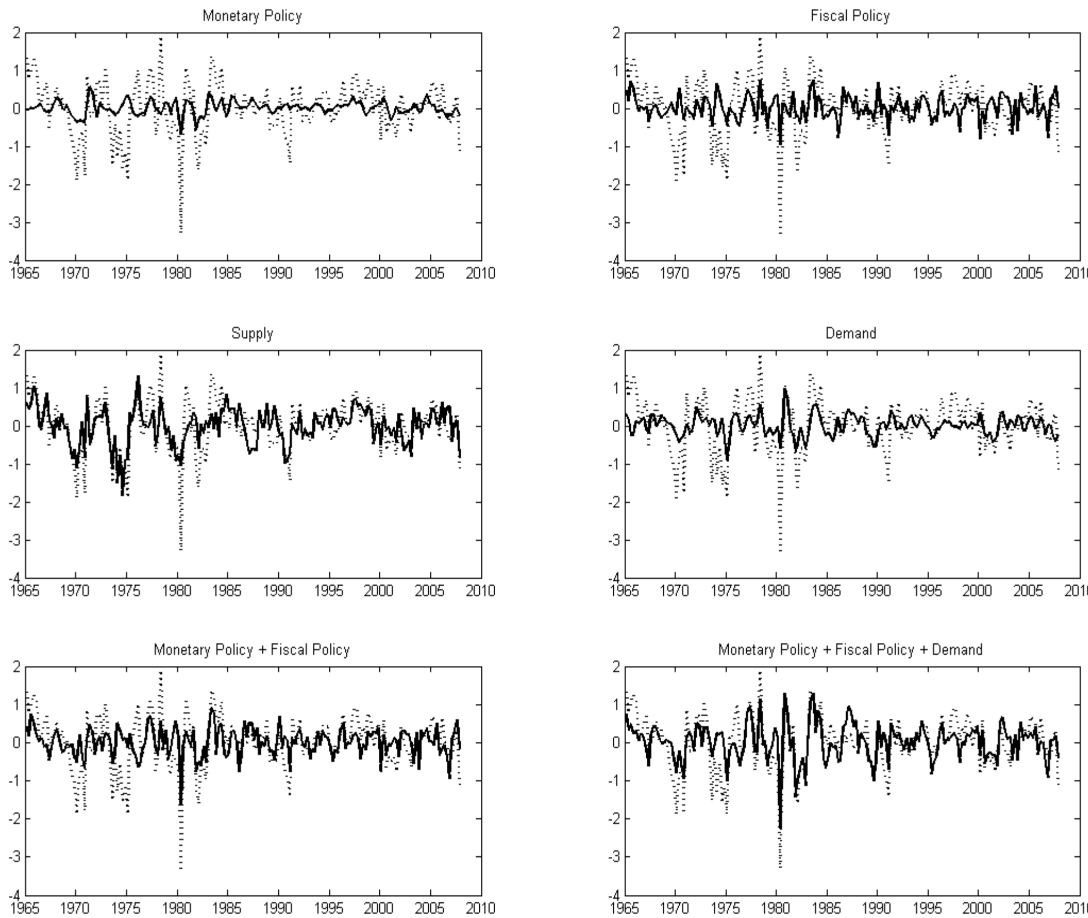

Monetary Policy
Fiscal Policy
Supply
Demand
Monetary Policy + Fiscal Policy
Monetary Policy + Fiscal Policy + Demand
2
1
0
-1
-2
-3
-4
1965
1970
1975
1980
1985
1990
1995
2000
2005
2010

Figure 5

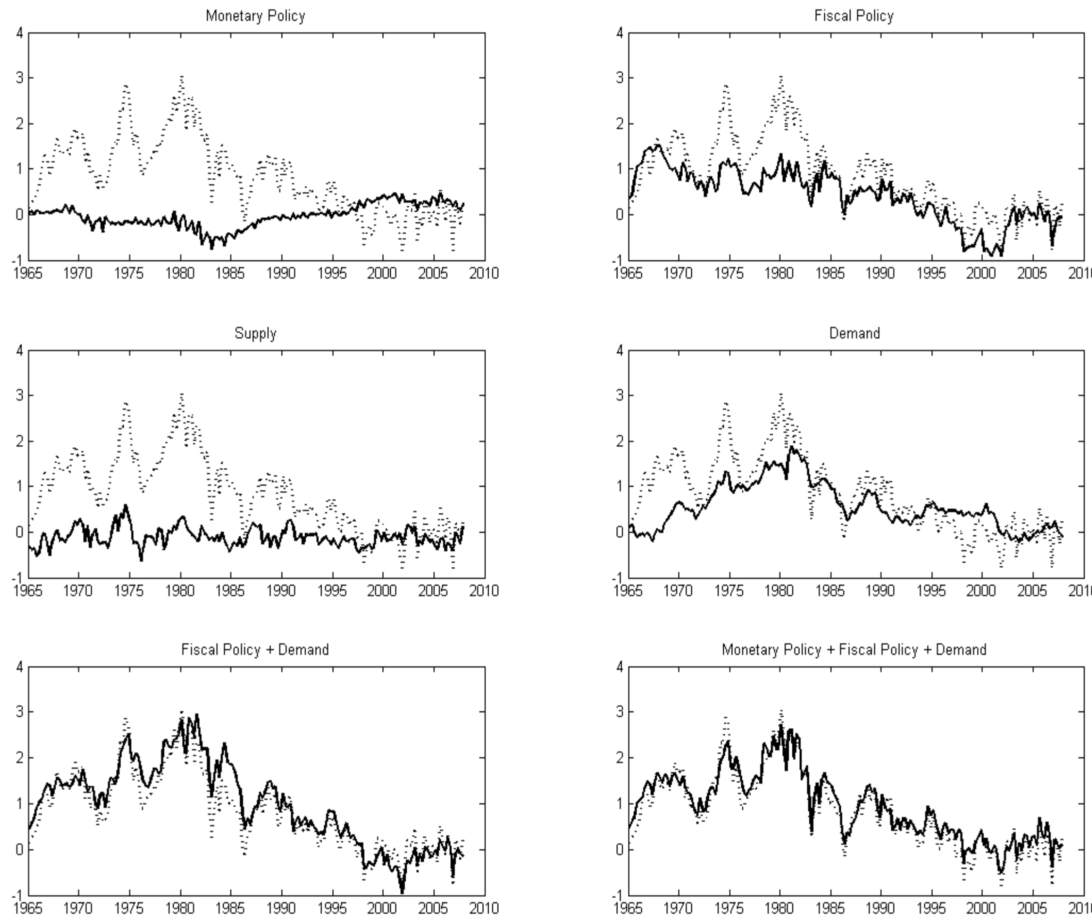
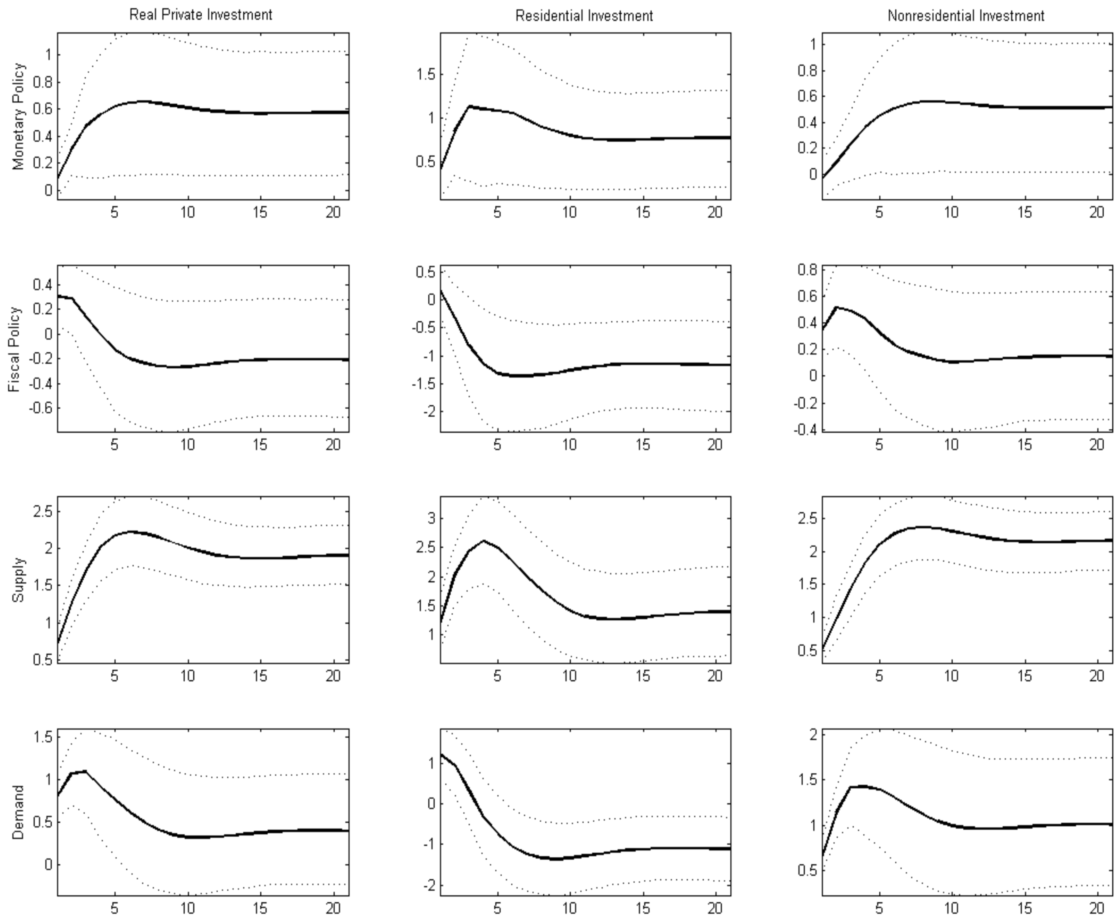
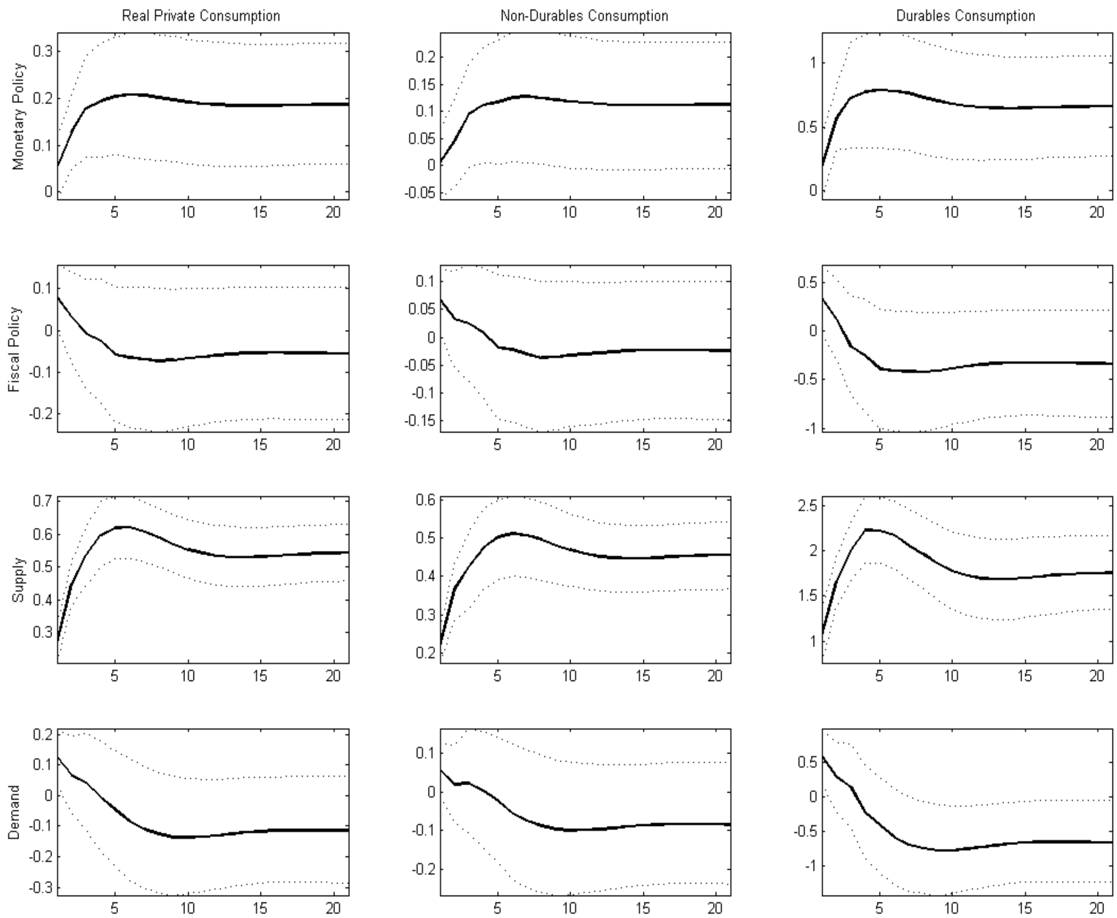

Monetary Policy
Fiscal Policy
Supply
Demand
Fiscal Policy + Demand
Monetary Policy + Fiscal Policy + Demand
4
3
2
1
0
-1
1965
1970
1975
1980
1985
1990
1995
2000
2005
2010

Figure 6



Real Private Investment
Residential Investment
Nonresidential Investment
Monetary Policy
Fiscal Policy
Supply
Demand

Figure 7



Real Private Consumption
Non-Durables Consumption
Durables Consumption
Monetary Policy
Fiscal Policy
Supply
Demand

Figure 8

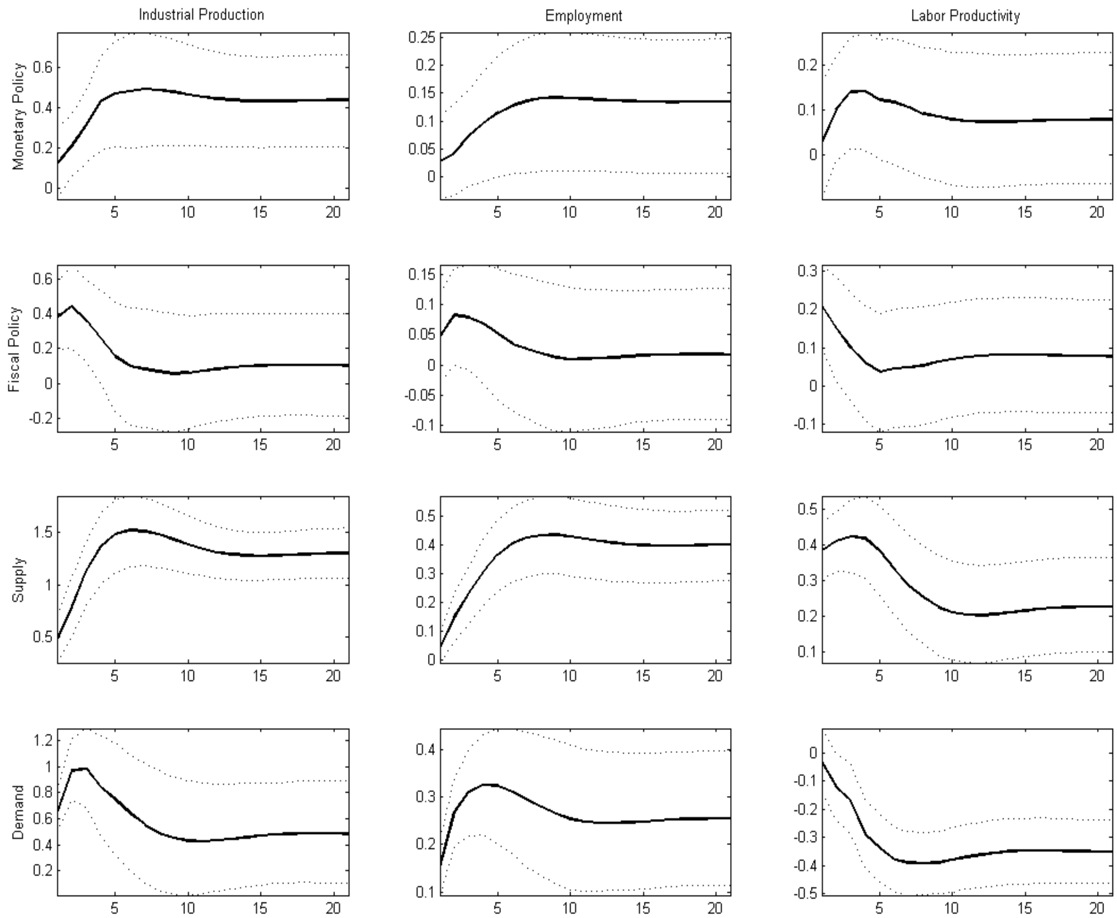

Industrial Production
Employment
Labor Productivity
Monetary Policy
Fiscal Policy
Supply
Demand

Figure 9