# No News in Business Cycles

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February 21, 2011

**Abstract**

This paper uses a structural, large dimensional factor model to evaluate the role of 'news' shocks (shocks with a delayed effect on productivity) in generating the business cycle. We find that (i) existing small-scale VECM models are affected by 'non-fundamentalness' and therefore fail to recover the correct shock and impulse response functions; (ii) news shocks have a limited role in explaining the business cycle; (iii) their effects are in line with what predicted by standard neoclassical theory; (iv) the bulk of business cycle fluctuations are explained by shocks unrelated to technology.

JEL classification: C32, E32, E62.
Keywords: structural factor model, news shocks, invertibility, fundamentalness.

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# 1 Introduction

In recent years there has been a renewed interest in the idea that business cycles could be generated by changes in expectations (this idea dates back to Pigou, 1927). The literature has focused on shocks having delayed effects on technology, the so-called 'news shocks'. The seminal paper by Beaudry and Portier (2006) finds that positive news shocks have a positive impact on stock prices, consumption, investment and hours worked and account for more than half of output fluctuations (see Figure 10 in Beaudry and Portier, 2006).[1] These results do not square with standard neoclassical one-sector models, in which good news about future technology trigger a wealth effect that affects positively consumption but negatively hours, output and investment on impact. Beaudry and Portier (2007), Jaimovich and Rebelo (2009), Schmitt-Grohe and Uribe (2008) propose models that can reconcile the theory with the above results.

Existing evidence has been obtained by using small-scale VAR or VECM models. This is problematic, because when structural shocks have delayed effects on macroeconomic variables, VAR models using such variables may be affected by non-fundamentalness (Lippi and Reichlin, 1994, Leeper, Walker and Yang, 2008, Forni and Gambetti, 2010b, Feve, Matheron and Sahuc, 2009). Non-fundamentalness means that the variables used by the econometrician do not contain enough information to recover the structural shocks and the related impulse response functions. The question is essentially whether the structural MA representation of such variables can be inverted or not. If not, the variables do not have a VAR representation in the structural shocks, implying that such shocks cannot be obtained by estimating a VAR with these variables.[2]

To get an intuition of the problem, assume that the news shock affects total factor productivity (TFP) with a one-period delay. Clearly, by observing TFP at time $t$ we get information about news arrived in $t-1$, but do not learn anything about the current shock. Coupling TFP with a series affected by the shock on impact (like stock prices) does not necessarily solve the problem, as shown in Section 2.

In this paper we present new evidence on the effects of news shocks by estimating a large-dimensional factor model with US quarterly data. Large factor models, including Factor Augmented VARs (FAVARs), can be used for structural economic analysis just like VAR models, as in Giannone, Reichlin and Sala (2004), Bernanke, Boivin and Eliasz (2005), Stock and Watson (2005), Forni, Giannone, Lippi and Reichlin (2009), Forni

[1] Beaudry and Lucke (2009) and Beaudry, Portier and Dupaigne (2008) confirm the same empirical findings.

[2] A partial list of references on non-fundamentalness includes Lippi and Reichlin (1993), Hansen and Sargent (1991), Chari, Kehoe and McGrattan (2005), Fernandez-Villaverde, Rubio-Ramirez, Sargent and Watson (2005), Giannone, Reichlin and Sala (2006).

and Gambetti (2010a).[3] Their advantage in the present context is that they are not affected by the non-fundamentalness problem, as shown in Forni, Giannone, Lippi and Reichlin (2009).[4] The intuition is that large factor models, unlike VARs, include a large amount of information (virtually all available macroeconomic series), so that insufficient information is unlikely. As a matter of fact, factor models have been successful in explaining well known VAR puzzles like the 'price' puzzle and the 'exchange rate' puzzle (Bernanke, Boivin and Eliasz, 2005, Forni and Gambetti, 2010a). In addition, the factor model enables us to verify whether a given VAR information set is affected by non-fundamentalness or not. Our testing procedure is explained in Section 3.5.

Our results are the following.

First, we estimate a two-shock factor model and apply the above test to the two variables in the benchmark model of Beaudry and Portier (TFP and stock prices). We find that the structural MA representation of TFP and stock prices is non-fundamental. Then we identify the news shock as in Beaudry and Portier (2006), by assuming a zero impact effect on TFP and find that the impulse responses and variance decompositions obtained with the factor model are completely different from those obtained by imposing the same identification scheme to a bivariate VECM. In particular, the effects on stock prices are much smaller.

Then we focus on our preferred factor model specification (a six-shock specification). We identify the news shock by imposing both a zero impact effect and a maximal long-run effect on TFP. The latter condition corresponds to the idea that news shocks should explain the main bulk of technology in the long-run. We find that: (i) hours worked, investment and output have negative impact responses, whereas consumption and stock prices are essentially unaffected on impact; (ii) investment, consumption, output and stock prices increase gradually as TFP increases; (iii) news shocks account for about 20-25% of business-cycle fluctuations in investment, consumption and GDP. Such effects are essentially in line with what predicted by a standard neoclassical model.

Finally, we identify a standard technology shock, having non-zero impact effect on productivity, by imposing that no other shock affects TFP contemporaneously. We find that the news and the technology shocks explain together almost all of TFP volatility at all frequencies, but only 25-35% of business-cycle fluctuations in investment, consumption and GDP, leaving substantial room for sources of volatility unrelated to technology.

[3]Large 'generalized' or 'approximate' dynamic factor models are specifically designed to handle a large amount of information. Early references are Forni and Reichlin (1998), Forni, Hallin, Lippi and Reichlin (2000), Forni and Lippi (2001), Stock and Watson (2002a, 2002b), Bai and Ng (2002).

[4]This result holds true provided that economic agents can see the structural shocks, as assumed in most of the current theoretical literature. A recent noticeable exception is Lorenzoni (2009), where agents can only observe technology 'news' disturbed by an aggregate 'noise'. We are not concerned with this interesting case in the present paper.

Overall, our results are fairly similar to those obtained by Barsky and Sims (2009) with a six-variable VAR including inflation, a short term interest rate, consumption and a consumer sentiment index, in addition to TFP and stock prices. Consistently with this, our test is not able to reject fundamentalness for such variables.

The paper is structured as follows. In Section 2 we provide a simple analytical example that shows how non-fundamentalness can arise in the presence of news shocks. In Section 3 we present the factor model, argue why it is not subject to the non-fundamentalness problem, and describe our fundamentalness test. Section 4 presents empirical results. Section 5 concludes.

## 2 Non-fundamentalness and News Shocks

In this Section we present a simple example, in which non-fundamentalness appears as a consequence of the presence of news shocks. Measured TFP, $\theta_t$, is assumed to follow the non-stationary process:

$$\theta_t = \theta_{t-1} + \varepsilon_{t-2} + u_t \tag{1}$$

where $\varepsilon_t$ is the news shock and $u_t$ is the 'standard' technology shock, affecting TFP on impact. Agents observe the shock $\varepsilon_t$ at time $t$ and react to it immediately, while the shock will affect TFP only at time $t+2$. Therefore the econometrician will not be able to identify $\varepsilon_t$ by observing $\theta_t$ .

The representative consumer maximizes

$$E_t \sum_{t=0}^{\infty} \beta^t C_t,$$

where $C_t$ is consumption and $\beta$ is a discount factor, subject to the constraint

$$C_t + P_t S_{t+1} = (P_t + \theta_t) S_t,$$

where $P_t$ is the price of a share, $S_t$ is the number of shares and $(P_t + \theta_t)S_t$ is the total amount of resources available at time $t$. The equilibrium value for asset prices is given by:

$$P_t = E_t \sum_{j=1}^{\infty} \beta^j \theta_{t+j}$$

Considering (1), the above equation can be solved to get the following structural MA representation

$$\begin{pmatrix} \Delta\theta_t \\ \Delta P_t \end{pmatrix} = \begin{pmatrix} L^2 & 1 \\ \frac{\beta^2}{1-\beta} + \beta L & \frac{\beta}{1-\beta} \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ u_t \end{pmatrix}. \tag{2}$$

The determinant is

$$-\frac{\beta^2}{1-\beta} - \beta z + \frac{\beta}{1-\beta} z^2$$

which vanishes for $z = 1$ and $z = -\beta$. As $\beta < 1$, the moving average is non invertible and the two shocks $u_t$ and $\varepsilon_t$ are non-fundamental for the variables $\Delta P_t$ and $\Delta \theta_t$. Not even a very forward-looking variable like stock prices conveys enough information to recover the shock.

# 3 The structural factor model

In this paper we use the factor model presented in Forni, Giannone, Lippi and Reichlin (2009, FGLR henceforth).[5] Here we provide a short presentation of the model, discuss the relation with non-fundamentalness and explain our fundamentalness test.

## 3.1 Representation

We assume that each macroeconomic variable $x_{it}$ is the sum of two mutually orthogonal unobservable components, the common component $\chi_{it}$ and the idiosyncratic component $\xi_{it}$:

$$x_{it} = \chi_{it} + \xi_{it}. \tag{3}$$

The idiosyncratic components are poorly correlated in the cross-sectional dimension.[6] They arise from shocks or sources of variation which considerably affect only a single variable or a small group of variables. For variables related to particular sectors, like industrial production indexes or production prices, the idiosyncratic component may reflect sector specific variations; for strictly macroeconomic variables, like GDP, investment or consumption, the idiosyncratic component can be interpreted as a measurement error.[7]

The common components account for the bulk of the co-movements between macroeconomic variables, being linear combinations of a relatively small number $r$ of factors

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

[6]See FGLR, Assumption 5 for a precise statement.

[7]Altug, (1989), Sargent, (1989), and Ireland (2004) show that the model can be interpreted as the linear solution of a DSGE model with measurement error.

$f_{1t}, f_{2t}, \cdots, f_{rt}$, not depending on $i$:

$$\chi_{it} = a_{1i} f_{1t} + a_{2i} f_{2t} + \cdots + a_{ri} f_{rt} = a_i f_t. \tag{4}$$

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

$$f_t = N(L) u_t, \tag{5}$$

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 $q \leq r$. Such white noises are the structural macroeconomic shocks.[8]

The discussion in Section 3.4 motivates the assumption that $N(z)$ is zeroless, i.e. $\text{rank}(N(z)) = q$ for any $z$, which implies fundamentalness. This ensures that $f_t$ has the finite order VAR representation (Anderson and Deistler, 2008)

$$D(L) f_t = \epsilon_t = R u_t, \tag{6}$$

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

Combining equations (3) to (6), the model can be written in dynamic form

$$x_{it} = b_i(L) u_t + \xi_{it}, \tag{7}$$

where

$$b_i(L) = a_i D(L)^{-1} R. \tag{8}$$

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

### 3.2 Identification

Representation (7) 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

$$\chi_{it} = c_i(L) v_t$$

where $c_i(L) = b_i(L) H'$ and $v_t = H u_t$. 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).

[8] In the large dynamic factor model literature they are sometimes called the "common" or "primitive" shocks or "dynamic factors" (whereas the entries of $f_t$ are the "static factors"). Equations (3) to (5) 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 $q$.

As a consequence, structural analysis in factor models can be carried on along lines very similar to those of standard structural VAR analysis. Specifically $q(q-1)/2$ restrictions have to be imposed on the matrix of impulse response functions $B_n(L) = (b_1(L)'b_2(L)' \cdots b_n(L)')'$, with $n$ the number of variables, to pin down all the elements of $H$.

If the researcher is interested in identifying just a single shock, the target is to determine the entries of a single column of the matrix $H$, say $H_1$, which is enough to obtain the first column of $B_n(L)$, say $B_{n1}(L)$.

### 3.3 Estimation

Estimation proceeds through the following steps.

1. Starting with an estimate $\hat{r}$, the static factors are estimated by means of the first $\hat{r}$ principal components of the variables in the dataset, and the factor loadings by means of the associated eigenvectors. Precisely, let $\hat{\Gamma}^x$ be the sample variance-covariance matrix of the data: the 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 the estimated factors are $\hat{f}_t = \hat{A}_n'(x_{1t}x_{2t} \cdots x_{nt})'$. [9]

2. $\hat{D}(L)$ and $\hat{\epsilon}_t$ are obtained by running a VAR($\hat{p}$) with $\hat{f}_t$ where the number of lags $\hat{p}$ is chosen according to some criterion.

3. Let $\hat{\Gamma}^\epsilon$ be the sample variance-covariance matrix of $\hat{\epsilon}_t$. Having an estimate $\hat{q}$ of the number of dynamic factors, an estimate of a non-structural representation of the common components is obtained 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, and $\hat{K}$ the $r \times q$ matrix with the corresponding normalized eigenvectors on the columns. The estimated matrix of non-structural impulse response functions is

$$\hat{C}_n(L) = \hat{A}_n\hat{D}(L)^{-1}\hat{K}\hat{\mathcal{M}}. \tag{9}$$

To account for estimation uncertainty, the following non-overlapping block bootstrap technique is adopted. 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 $\tau \times n$, $\tau$ being the

[9] The factors are identified only up to linear transformations. What is estimated is a basis of the factor space.

integer part of $T/S$.[10] 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, $\hat{C}_n(L)$, are estimated and the identifying assumptions are imposed to get $H_1$ and the corresponding impulse response functions $\hat{B}_{n1}(L) = \hat{C}_n(L)H_1$. A set of structural impulse response functions is obtained by repeating drawing, estimation and identification. Confidence bands are obtained by taking the relevant percentiles of the point-wise distributions.

### 3.4 Tall systems and fundamentalness

Here we discuss why the assumption of fundamentalness is justified in the factor model. Let us go back to equation (5)

$$f_t = N(L)u_t,$$

where $N(L)$ is a $(r \times q)$ matrix of rational functions in the lag operator $L$, with $r \geq q$. Under what conditions are the shocks $u_t$ fundamental for $f_t$? A necessary and sufficient condition is that the rank of $N(z)$ be $q$ for all $z$ such that $|z| < 1$ (see e.g. Rozanov, 1967, Ch. 1, Section 10, and Ch. 2, p. 76).

Let us first focus on the particular case $r = q$, and interpret $f_t$ as a vector of observable variables to be used in a VAR. The above fundamentalness condition reduces to the requirement that the determinant of $N(z)$ does not vanish within the unit circle in the complex plane. If this condition holds, then the shock $u_t$ can be found using a VAR for $f_t$. In general, however, there is no guarantee that the condition holds, as shown in Section 2.

Now let us turn to the case $r > q$, which is the normal case in the factor model. In such case $N(z)$ is a "tall", rectangular matrix. Its rank is less than $q$ for some $z$, i.e. the shock is non-fundamental, only if all of the $(q \times q)$ sub-matrices of $N(z)$ are singular. Clearly this is a very special case, since it requires $\begin{pmatrix} r \\ q \end{pmatrix} - 1$ equalities to be satisfied. Therefore, in general, when $r > q$, $N(z)$ has rank $q$ for all $z$ and the representation can be assumed fundamental.

As a very elementary example, consider the case $q = 1$, $r = 2$, $f_{1t} = u_t + 2u_{t-1}$, $f_{2t} = 2u_{t-1}$. Here $u_t$ is non-fundamental for both $f_{1t}$ and $f_{2t}$, and cannot be found as a linear combination of present and past values of a single factor. However, $u_t$ is fundamental for the vector $f_t$, since $u_t = f_{1t} - f_{2t}$.

Observe that fundamentalness of representation (5) implies fundamentalness of the

[10] Note that $\tau$ has to be large enough to retain relevant lagged auto- and cross-covariances.

system

$$\chi_t = B_n(L)u_t,$$

where $\chi_t = (\chi_{1t} \cdots \chi_{nt})'$ and $B_n(L) = A_n D(L)^{-1} R$, $A_n = (a_1' \ a_2' \cdots \ a_n')'$ (provided that $A_n$ has full column rank).

### 3.5 Testing for fundamentalness

While the whole system $B_n(L)$ is fundamental, the $q$-dimensional square submatrices 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 subvector $\chi_{It} = (\chi_{I_1 t} \cdots \chi_{I_q t})' = B_I(L)u_t$ 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 $\rho$ 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 $\alpha$ as long as the frequency of values larger than 1 is smaller than $\alpha$.

Rejection of fundamentalness implies that an hypothetical VAR model using $\chi_{It}$ 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 $\chi_{It}$. 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.

## 4 Empirics

### 4.1 Data and model specification

Our data set is composed of 116 US quarterly series, covering the period 1959-I to 2007-IV. Most series are taken from the FRED database. A few stock market and leading indicators are taken from Datastream. 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, TFP and consumers sentiment 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 in 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.[11]

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

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 $\hat{p} = 2$ based on the AIC criterion. The number of shocks is 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.[12] 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. In the following Sections we provide evidence for the two extreme cases, $q = 2$ and $q = 6$ and robustness checks.

### 4.2 The two-shock model

In this subsection we investigate the properties of a two-shock model. We begin our analysis from a two-shock model for two reasons. First, $q = 2$ is the lower bound for the number of shocks identified by information criteria and therefore it is an empirically relevant choice; second, we want to compare our results to those in Beaudry and Portier (2006) in which the benchmark specification is a bivariate VECM.

We start by testing along the lines explained in Section 3.5 whether the two variables used by Beaudry and Portier (stock prices and TFP) have a fundamental representation in terms of our estimated shocks. We compute the modulus of the smallest root of the determinant of selected sub-blocks $B_I^j(L)$ of our 'tall' system of impulse-response functions. The roots are computed for the point estimate as well as all the bootstrap repetitions, so that the whole distribution is available. As shown in the upper part of Table 1, we consider two specifications that differ for the definition of TFP; the first uses a measure of TFP not corrected for capital utilization (indexed as variable 103 in our data set), the second uses a measure of TFP that controls for variable capital utilization

[11]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.

[12]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).

(indexed as variable 104 in our dataset) (see Basu, Fernald and Kimball, 2006).

Table 2 shows the mean, the median, some selected percentiles of the distribution and the point estimate. For both specifications, the point estimate, the mean and the median are all much smaller than one. Since confidence bands are rather large, in all this paper we adopt the 68% convention. At this confidence level, the null of fundamentalness can be rejected in both cases. We conclude that the bivariate VECM model in Beaudry and Portier is unable to properly recover the effects of news shocks.

We then identify the news shock in the factor model assuming that it has no contemporaneous effect on TFP, as in Beaudry and Portier (2006). The shock with a non-zero impact effect on TFP can be regarded as a 'traditional' technology shock. For comparison, we compute impulse responses from a VECM model estimated by using the common components of TFP and stock prices, in which shocks are identified as in the factor model.[13] We use the common components instead of the variables themselves to be sure that the differences with respect to the factor model are due to non-fundamentalness, rather than the idiosyncratic components. However, estimation of the VECM using actual data obtains very similar results.

The left column of Figure 1 shows impulse responses to the technology shock in the factor model (solid) and in the VECM (dashed) together with 68% confidence bands (dotted) from the factor model. The top panel shows the responses of TFP; the bottom panel the responses of stock prices. The right column shows impulse responses to the news shock. It is seen that impulse responses from the factor model and the VECM are substantially different. The VECM, not surprisingly, produces results similar to the ones of Beaudry and Portier (2006). In particular, news have a huge impact effect on stock prices. The factor model response of stock prices is much smaller at all horizons and not significant on impact.

Let us turn to variance decompositions, reported in Table 3. While in the bivariate VECM news shocks explain a considerable fraction of the volatility of TFP (34% at 40 periods horizon) and almost all of the volatility of stock prices (93% at the 40 quarters horizon), in the factor model these figures are much smaller, 7% and 63%, respectively.

The conclusions we draw from this section are the following. The two variables considered in Beaudry and Portier have a non-fundamental representation. Non-fundamentalness, far from being a statistical detail, has important consequences in terms of the estimated impulse responses and variance decompositions.

[13] The VECM is estimated with 3 lags and 1 cointegration relation.

### 4.3 The six-shock model

We now extend our analysis by considering a factor model driven by six common shocks. Such specification is in line with the criteria proposed by Bai and Ng (2007) and Amengual and Watson (2007).

We identify the news shocks as a shock that (i) does not have a contemporaneous impact on TFP and (ii) has a maximal effect on the level of TFP in the long run (at the 40 quarters horizon).[14] In addition, we identify a 'standard' technology shock is as the only one shock having a non-zero impact effect on TFP.

Condition (i) is obvious. Condition (ii) corresponds to the idea that the news shock should explain an important fraction of TFP in the long-run. Maximizing the effect may seem arbitrary to some extent. Observe however that, by reducing the long-run effect on TFP, the effects on the business cycle would be further reduced, and our conclusions would be strengthened.

In Figure 2 we report the impulse responses of selected variables to the news shock. Let us comment first the last row. The index of consumer sentiment about current economic conditions does not move on impact, while the consumer sentiment on expected conditions has a large positive and significant jump. We think that this is a convincing confirmation that the shock that we have identified is in fact related to good news about the future.

Turning to the first panel, TFP grows monotonically, without reaching a maximum in the first 6 years after the impact. This is consistent with the idea that the diffusion of technical progress may take much time. Investment and GDP drop significantly on impact and then gradually grow to a new long run level. Consumption, on the other side, does not move on impact and only after the first quarter starts to significantly increase. Hours fall in the short run with a significant impact effect. Overall, such results are fairly consistent with what predicted by a standard neoclassical model: in response to a news shock that is expected to move TFP in the future, agents feel richer, consume more and work less. Given the level of technology, the reduction in hours worked implies a fall in output. As output is falling and consumption is growing, investment has to go down.

Figure 3 presents the responses of the 'traditional', non anticipated technology shock. TFP, GDP, consumption and investment move up significantly on impact and then converge to their higher long run level. These impulse responses are in line with existing evidence on the effect of a technology shocks and with the predictions of standard neoclassical models.

Table 4 shows the variance decompositions for selected variables. The top part of the

[14] Maximization is obtained numerically by using the matlab routine fminsearch.

Table pertains to the news shocks. The bottom part reports results for the technology shock. The first four columns, labeled with the letter (a), report forecast error variance decompositions for the variables in levels. Column (b) shows the fraction of the unconditional variance of the variable transformed to get stationarity. Column (c) shows the fraction of the unconditional variance located at business cycle frequencies (periodicity within 2 and 8 years) explained by the two shocks.

Results show that the news shock, despite being obtained by maximizing the long run effect on TFP, explains only 30% of the forecast error variance of TFP at a 10-year horizon. Focusing on (b) it is seen the news shock explains only 8% of the unconditional variance of the growth rate of TFP, 15% of the variance of the growth rate of GDP and around 20-25% of the volatility of consumption and investment. The technology shock explains a larger fraction of volatility of TFP and GDP, namely 80% and 38%, 18% of the variance of consumption and only 6% of the variance of investment.

If one considers the volatility at business cycle frequencies, the two shocks together account for almost all the variance of TFP (90.9%), while accounting for only 31%, 34% and 23% of the business cycle volatility of GDP, consumption and investment, respectively. This leaves the door open to other shocks not related to TFP in generating the business cycle.

Overall, our results are fairly similar to those obtained by Barsky and Sims (2009) with a six-variable VAR. This raises the question whether the variables used in such work have a fundamental representation or not, and, more generally, whether our results can be obtained within a VAR approach. We address these question by using the fundamentalness test.

We consider five different sub-blocks (listed in the bottom part of Table 1) corresponding to five different information sets $I$ (see Section 3.4), denoted $I^j$ $j = 1, ..., 5$. The specifications include the variables typically used in the empirical literature on news shocks. Table 2 reports the modulus of the smallest root of the determinant of the impulse response matrix. For each modulus are reported the point estimate, the mean, the median and some selected percentiles of the bootstrap distribution.

For the first four information sets, the mean, the median, the point estimate and the 68th percentile are all smaller than one, implying non-fundamentalness. On the other hand, for Specification 5 the point estimate is about 1.1, and also the 68th percentile is larger than one, so that fundamentalness cannot be rejected. Such specification is the one used in Barsky and Sims (2009). The difference with respect to other specifications is given by the inclusion of the Consumer Sentiment Index about expected economic conditions, a forward-looking variable which seems to provide important additional information and solves the invertibility problem.

### 4.4 Robustness

In this section we analyze the robustness of our results to different specification choices.

We first estimate the model by setting the number of static factors to 8 and 18 ($\pm 5$ with respect to the benchmark). We also estimate the model by setting the number of lags in the VAR for the static factors to 1 and 3 ($\pm 1$ with respect to the benchmark). Figures 4 and 5 shows that impulse responses are almost unaffected by such modifications.

In Figure 6 we display the impulse responses obtained from both the two-shock model discussed in Section 4.2 and the six-shock model. Results change somewhat but the main conclusions are the same. Finally, we estimated the model with 4 shocks and get impulse responses almost identical to those of the six-shock model (not shown).

## 5 Conclusions

In this paper we use a large dimensional, structural factor model to analyze the effect of news shocks on the business cycle. We find that existing VARs suffer from non-fundamentalness and therefore produce misleading results. By using the factor model we solve the non-fundamentalness problem. We find that news shocks behave as predicted by standard neoclassical theory and have a limited role in generating the business cycle. The bulk of cyclical fluctuations is explained by shock unrelated to TFP.

## Appendix: Data

Transformations: 1=levels, 2= first differences of the original series, 5= first differences of logs of the original series, 6= 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 |
| 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 |

| no.series | Transf. | Mnemonic | Long Label |
|---|---|---|---|
| 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 |
| 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 |

| no.series | Transf. | Mnemonic | Long Label |
|---|---|---|---|
| 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 |
| 102 | 1 | | Fernald's TFP growth CU adjusted |
| 103 | 1 | | Fernald's TFP growth |
| 104 | 5 | | DOW JOONES/GDP DEFL |
| 105 | 5 | | S&P500/GDP DEFL |
| 106 | 1 | | Fernald's TFP growth - Investment |
| 107 | 1 | | Fernald's TFP growth - Consumption |
| 108 | 1 | | Fernald's TFP growth CU - Investment |
| 109 | 1 | | Fernald's TFP growth CU - Consumption |
| 110 | 1 | | Personal Finance Current |
| 111 | 1 | | Personal Finance Expected |
| 112 | 1 | | Business Condition 12 Months |
| 113 | 1 | | Business Condition 5 Years |
| 114 | 1 | | Buying Conditions |
| 115 | 1 | | Consumer's sentiment: Current Index |
| 116 | 1 | | Consumer's sentiment: Expected Index |

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## Tables

| $j$ | Variables ($I^j$) | | | | | |
|---|---|---|---|---|---|---|
| | | | Two Shocks | | | |
| 1 | TFP (102) | Stock P (105) | | | | |
| 2 | TFP (103) | Stock P (105) | | | | |
| | | | Six Shocks | | | |
| 1 | TFP (102) | Stock P (105) | Non Dur. C (12) | Inv. (7) | Hours (27) | GDP (1) |
| 2 | TFP (103) | Stock P (105) | Non Dur. C (12) | Inv. (7) | Hours (27) | GDP (1) |
| 3 | TFP (102) | Stock P (105) | Non Dur. C (12) | GDP (1) | CPI (75) | 3M T-Bill (58) |
| 4 | TFP (102) | Stock P (105) | Non Dur. C (12) | Hours (27) | CPI (75) | 3M T-Bill (58) |
| 5 | TFP (102) | Stock P (105) | Non Dur. C (12) | Sentiment (116) | CPI (75) | 3M T-Bill (58) |

Table 1: Subsets of variables ($I$) used in the test described in Section 3.5. The numbers in brackets correspond to those in the Appendix.

| $j$ | Mean | Median | 68% | 90% | 95% | Point est. |
|---|---|---|---|---|---|---|
| | | | Two Shocks | | | |
| 1 | 0.531 | 0.515 | 0.768 | 1.060 | 1.086 | 0.481 |
| 2 | 0.711 | 0.812 | 0.940 | 1.102 | 1.128 | 0.861 |
| | | | Six Shocks | | | |
| 1 | 0.692 | 0.763 | 0.934 | 1.084 | 1.125 | 0.459 |
| 2 | 0.636 | 0.665 | 0.878 | 1.023 | 1.066 | 0.279 |
| 3 | 0.645 | 0.666 | 0.835 | 1.051 | 1.083 | 0.755 |
| 4 | 0.557 | 0.546 | 0.712 | 0.966 | 1.041 | 0.294 |
| 5 | 0.856 | 0.952 | 1.072 | 1.161 | 1.192 | 1.099 |

Table 2: Moduli of the smallest root of the submatrices $B_I(L)$ defined in Table 1.

| Variables | Horizons | | | |
|---|---|---|---|---|
| | 0 | 4 | 8 | 40 |
| Factor model | | | | |
| TFP (102) | 0.0 | 6.5 | 7.2 | 7.4 |
| Stock Prices (105) | 16.1 | 55.2 | 61.2 | 63.4 |
| VECM | | | | |
| TFP (102) | 0 | 0.7 | 0.6 | 33.9 |
| Stock Prices (105) | 99.7 | 97.6 | 96.5 | 93.4 |

Table 3: Explained forecast error variance (percentages) at various horizons in the two-shock factor model and the bivariate VAR for the common components using the Cholesky identification (levels). The numbers in brackets correspond to those in the Appendix.

| Variables | Horizons (a) | | | | % Total Variance | % Variance 2-8 Years |
|---|---|---|---|---|---|---|
| | 0 | 4 | 8 | 40 | (b) | (c) |
| | | | News shock | | | |
| TFP (102) | 0.0 | 11.1 | 17.6 | 29.9 | 7.8 | 14.6 |
| GDP (1) | 6.2 | 11.0 | 11.3 | 15.3 | 15.2 | 19.9 |
| Consumption (11) | 2.9 | 17.0 | 27.0 | 40.2 | 25.0 | 25.0 |
| Investment (7) | 8.0 | 14.1 | 12.3 | 12.5 | 20.0 | 20.3 |
| Hours (27) | 26.1 | 14.4 | 17.5 | 15.7 | 21.9 | 19.9 |
| Stock Prices (105) | 6.9 | 7.0 | 8.1 | 9.8 | 10.0 | 10.1 |
| Sentiment current (115) | 7.0 | 14.7 | 21.5 | 24.4 | 24.4 | 22.1 |
| Sentiment expected (116) | 26.4 | 31.1 | 36.0 | 37.9 | 37.9 | 32.3 |
| Prices (75) | 19.5 | 23.9 | 20.6 | 15.5 | 23.7 | 27.1 |
| 3M T-Bill (58) | 28.5 | 25.5 | 20.5 | 18.4 | 25.4 | 25.6 |
| | | | Technology shock | | | |
| TFP (102) | 100.0 | 85.7 | 79.2 | 69.2 | 80.4 | 76.3 |
| GDP (1) | 64.2 | 22.4 | 20.8 | 23.6 | 38.1 | 12.0 |
| Consumption (11) | 30.7 | 16.2 | 16.0 | 16.5 | 17.8 | 9.2 |
| Investment (7) | 8.7 | 2.6 | 2.4 | 3.8 | 6.1 | 2.9 |
| Hours (27) | 0.7 | 0.9 | 1.0 | 0.9 | 2.2 | 1.6 |
| Stock Prices (105) | 0.5 | 0.8 | 1.0 | 1.3 | 2.7 | 1.4 |
| Sentiment current (115) | 3.3 | 3.0 | 3.6 | 4.0 | 4.0 | 3.0 |
| Sentiment expected (116) | 13.8 | 8.0 | 7.8 | 7.9 | 7.9 | 6.1 |
| Prices (75) | 1.0 | 1.1 | 1.4 | 1.6 | 2.9 | 1.4 |
| 3M T-Bill (58) | 2.6 | 1.5 | 1.4 | 1.3 | 4.0 | 1.7 |

Table 4: Variance decomposition. (a) Fraction of the variance of the forecast error for the levels of the variables at different horizon (b) Percentage of variance of the variables transformed to get stationarity explained by the shock (c) Percentage of cyclical variance (of periodicity between 2 to 8 years) explained by the shock. The numbers in brackets correspond to those in the Appendix.

# Figures

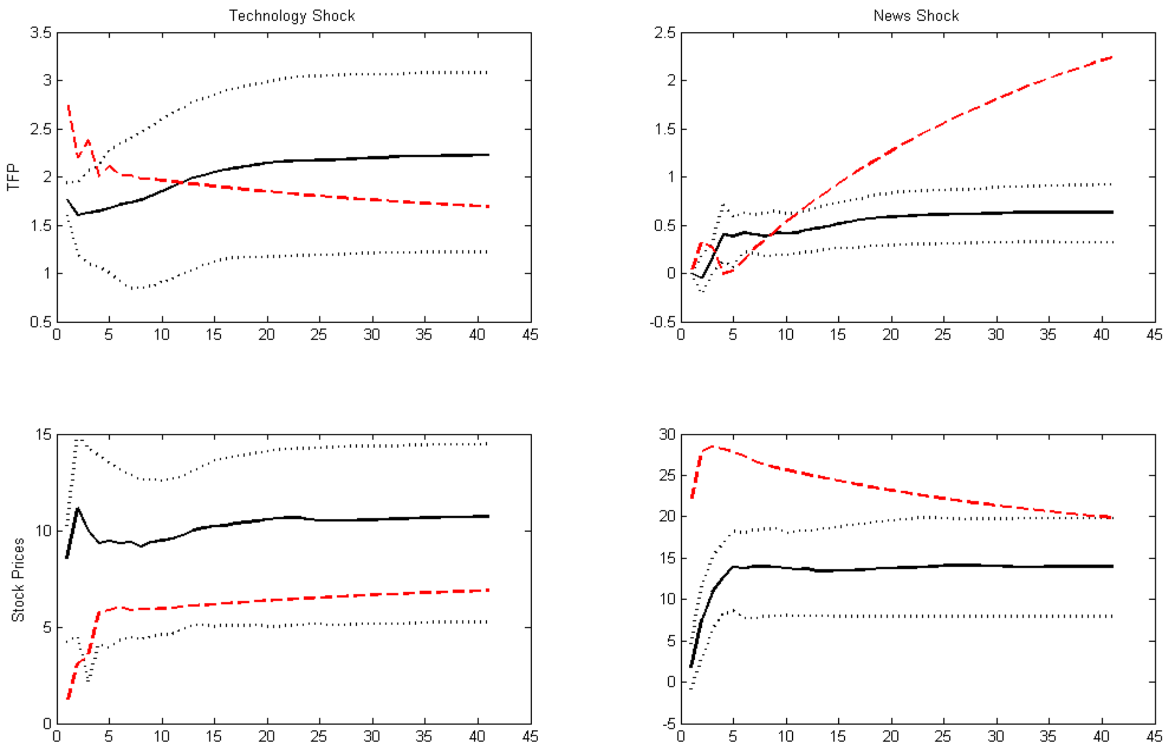


Figure 1: Impulse response functions in the two-shocks model. Left column: technology shock, right column: news shock. Upper row: response of TFP; Lower row: rsponses of stock prices. Solid: factor model (median). Dotted: factor model 68% confidence bands. Dashed: VECM for the common components.

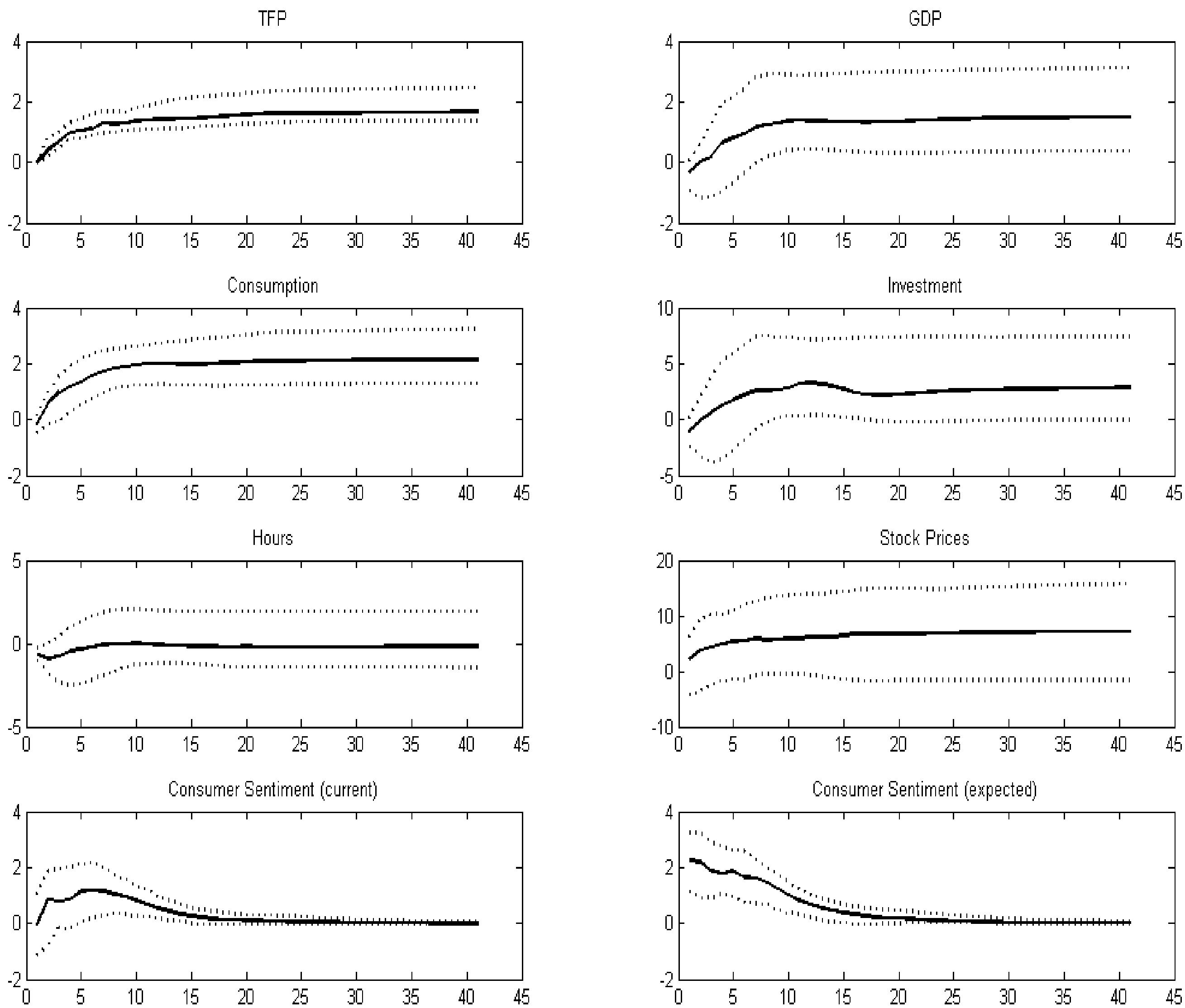


Figure 2: Impulse response functions to a news shock in the six-shocks model. Solid: factor model (median). Dotted: factor model 68% confidence bands.

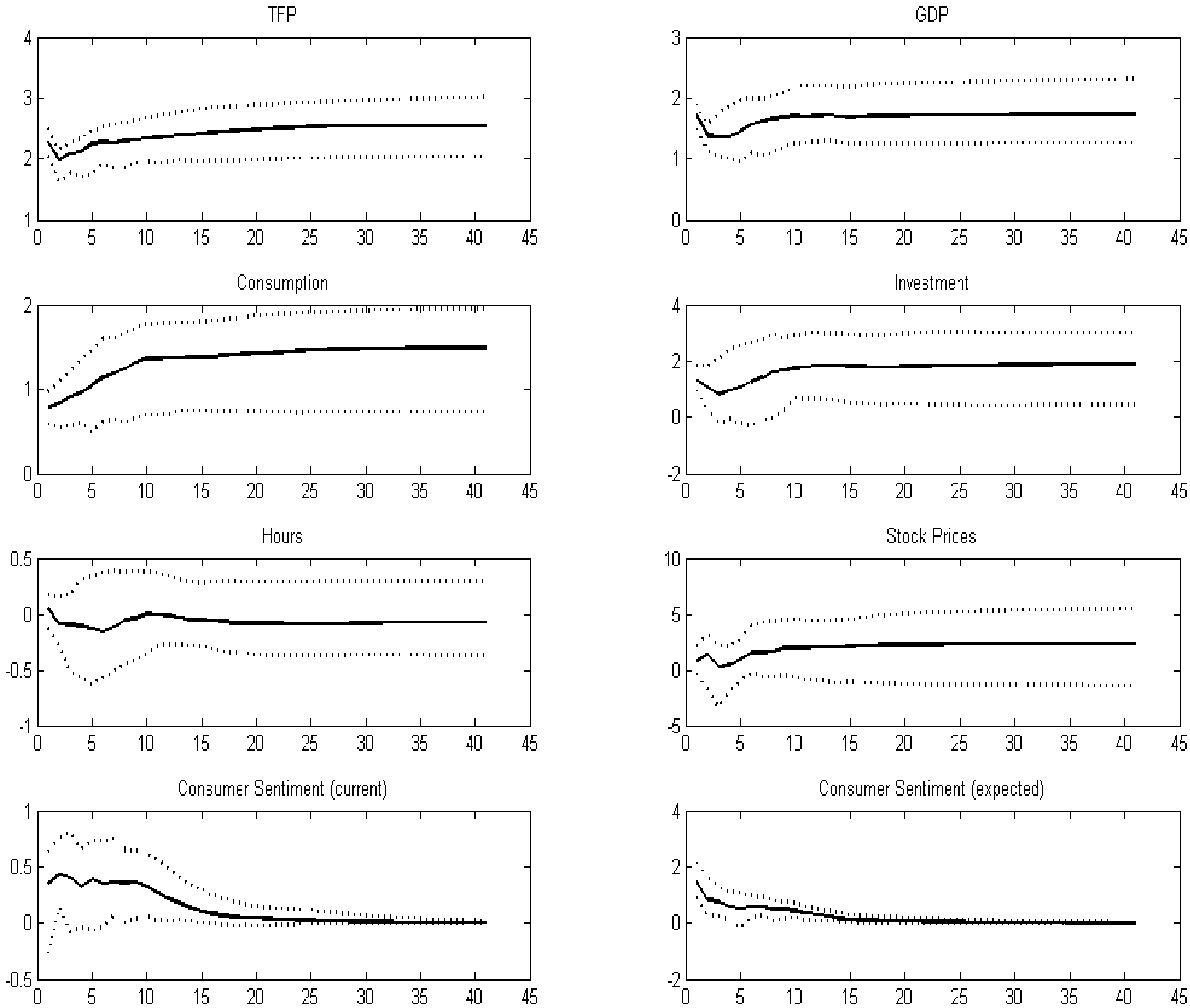


Figure 3: Impulse response functions to a technology shock in the six-shocks model. Solid: factor model (median). Dotted: factor model 68% confidence bands.

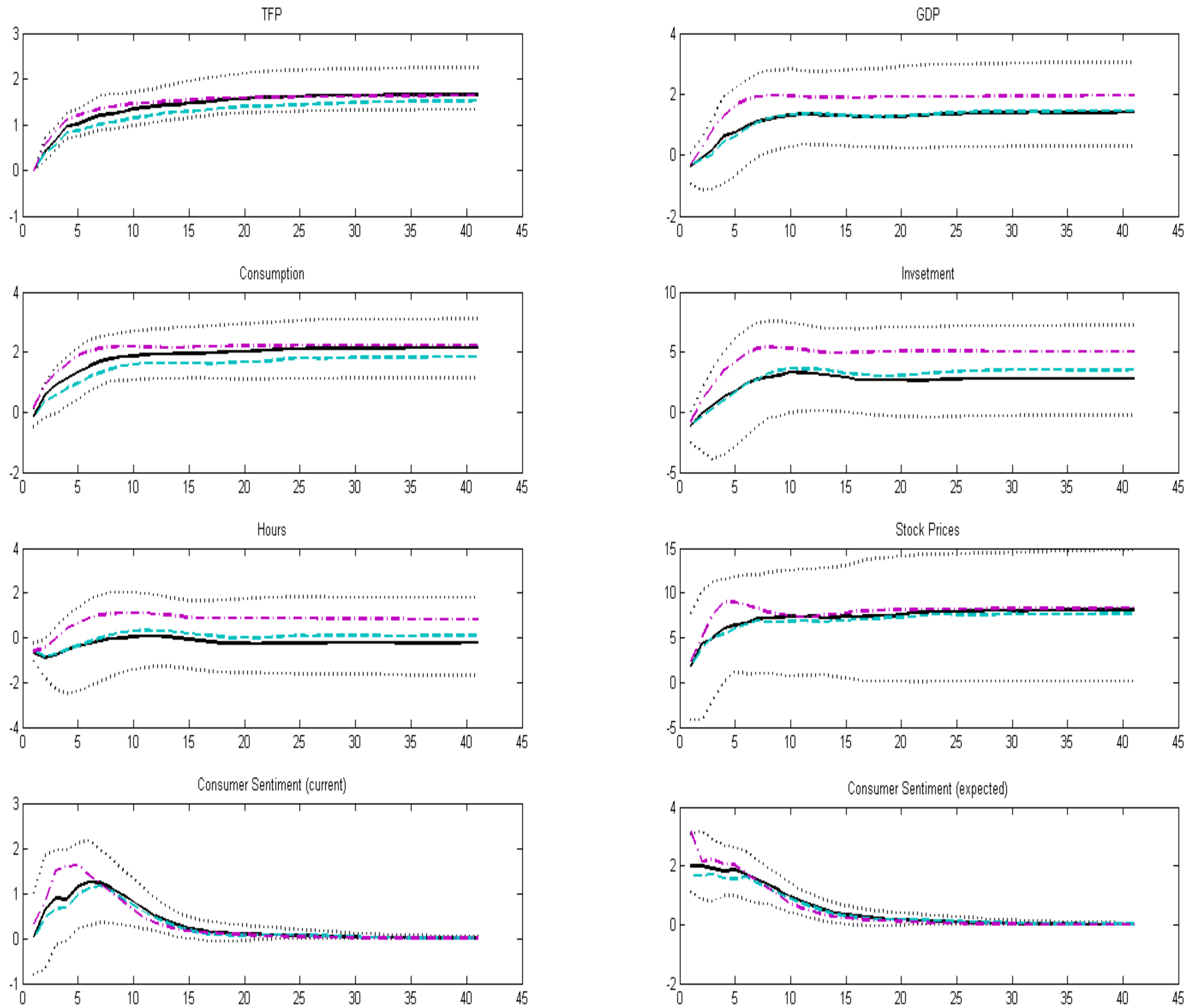


Figure 4: Impulse response functions with different values of $\hat{r}$. Solid: benchmark, $\hat{r} = 13$ - dashed: $\hat{r} = 8$ - dash-dotted: $\hat{r} = 18$.

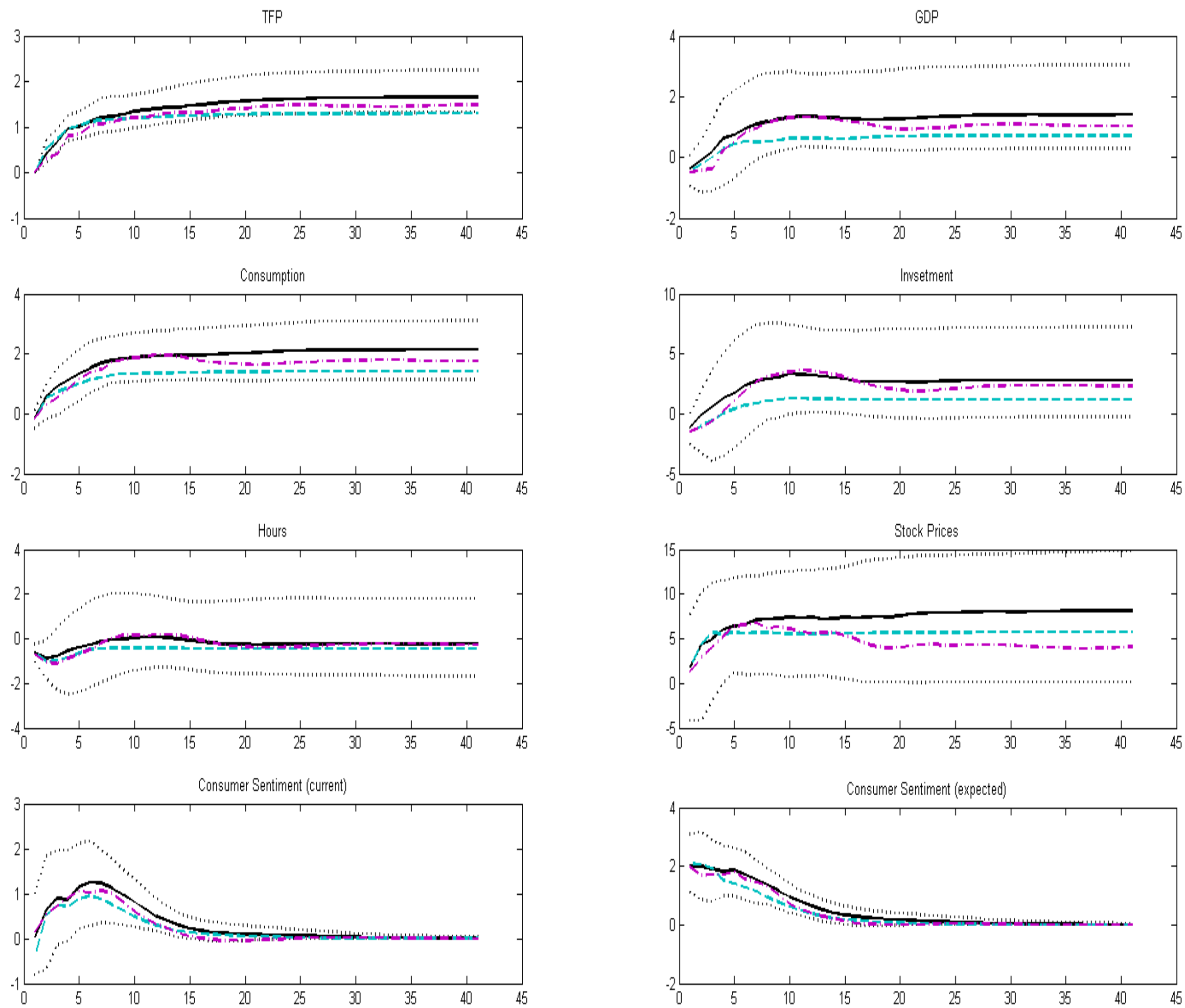


Figure 5: Impulse response functions with different values of $\hat{p}$. Solid: benchmark, $\hat{p} = 2$ - dashed: $\hat{p} = 1$ - dash-dotted: $\hat{p} = 3$.

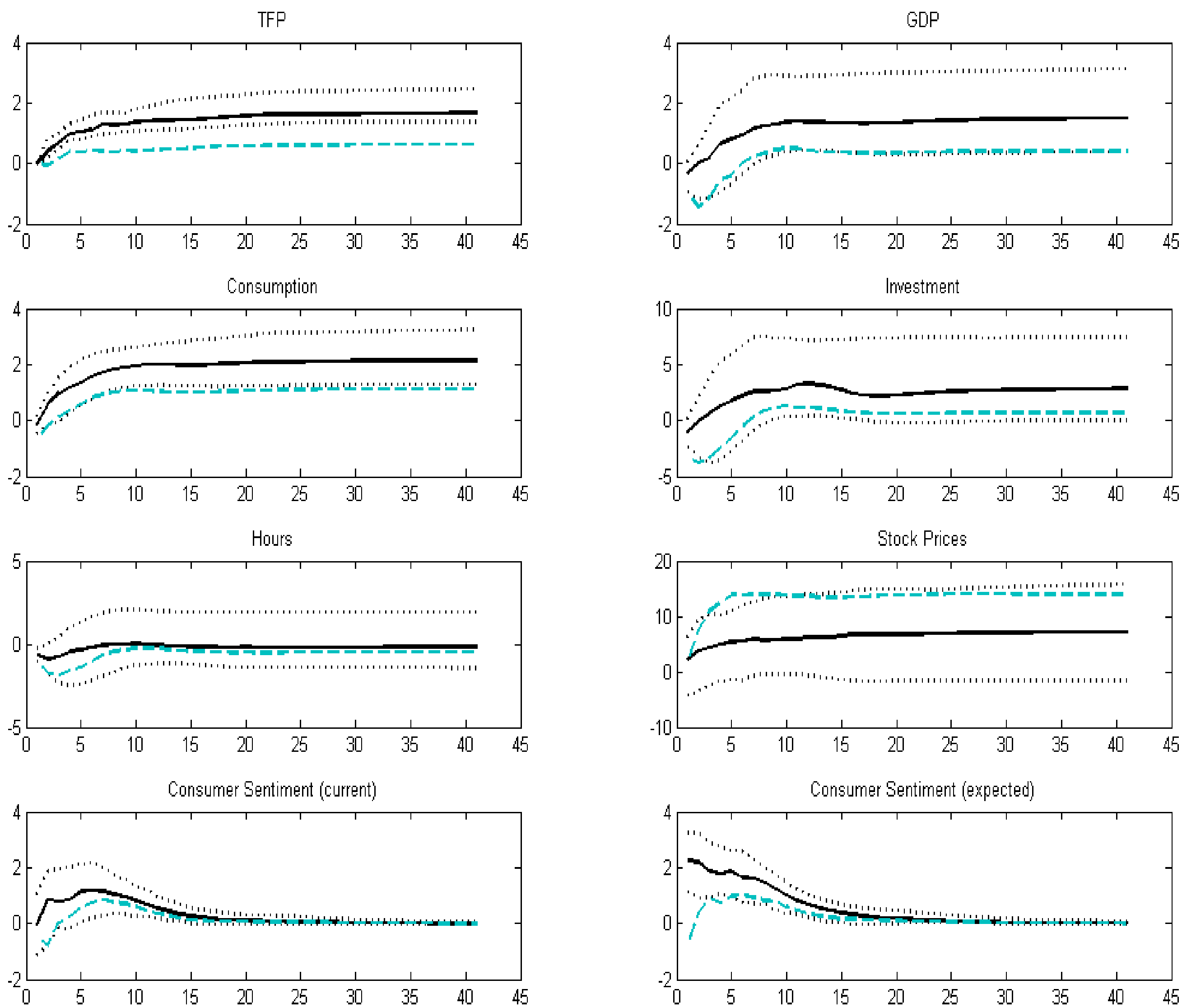


Figure 6: Impulse response functions to news shocks in factor models with $\hat{q} = 6$ (solid) and $\hat{q} = 2$ (dashed). The two shocks model is identified with a zero contemporaneous restriction on TFP (as in Section 4.2).