No News in Business Cycles

Mario Forni*
Università di Modena e Reggio Emilia
CEPR and RECent

Luca Gambetti†
Universitat Autonoma de Barcelona and Barcelona GSE

Luca Sala‡
Università Bocconi and IGIER

March 16, 2012

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 VAR 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) a substantial fraction of business cycle fluctuations are explained by shocks unrelated to technology.

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

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

‡Contact: Universitá Bocconi, Via Roentgen 1, 20136, Milan, Italy. Tel. +39 0258363062; e-mail: luca.sala@unibocconi.it

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

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.[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.

Most of the 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 used to estimate the effects of shocks may be affected by non-fundamentalness (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,

[1] Beaudry and Lucke, 2009, and Dupaigne and Portier, 2006, find similar results.

[2] A partial list of references on non-fundamentalness includes Hansen and Sargent, 1991, Lippi and Reichlin, 1993, 1994, Chari, Kehoe and McGrattan, 2005, Fernandez-Villaverde, Rubio-Ramirez, Sargent and Watson, 2007, Giannone, Reichlin and Sala, 2006, and Forni and Gambetti, 2011.

Stock and Watson, 2005, Forni, Giannone, Lippi and Reichlin, 2009, Forni 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, as explained below, our data-rich environment enables us to test whether the different VAR specifications used in the literature are in fact affected by non-fundamentalness or not.

We start our empirical analysis by applying the fundamentalness test suggested in Forni and Gambetti, 2011. The idea is to verify whether the estimated structural shock is an innovation with respect to available information. Precisely, we summarize the information in our dataset by computing the principal components; then, we estimate the news shock with different VAR specifications and identification schemes; finally, we test for orthogonality of the estimated shocks with respect to the lags of the principal components. We find that fundamentalness is strongly rejected for all existing small-scale VARs. The only VAR specification surviving the test is the seven variables specification in Barsky and Sims, 2011.

We then estimate our large factor model and identify the news shock as the shock that best anticipates TFP in the long-run and does not move it on impact. We find that: (i) on impact, hours worked have a significant negative response, whereas consumption has a significant positive reaction; (ii) investment and output have small impact effects, increasing gradually as TFP increases; (iii) news shocks account for about 11% and 25% of the forecast-error variance of output at the 1-year and the 2-year horizon, respectively. Such effects are essentially in line with what predicted by the standard neoclassical model and similar to those obtained by Barsky and Sims, 2011, consistently with the fundamentalness test above.

[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.

Finally, we identify a second shock, which we call TFP shock, as the only shock allowed to have a non-zero impact effect on productivity. We find that the news and the TFP shocks explain together almost all of TFP volatility at all horizons, but only 26% of GDP fluctuations at the 2-year horizon, leaving substantial room for sources of volatility unrelated to technology.

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 and the fundamentalness test. Section 4 presents empirical results. Section 5 concludes.

2 Non-fundamentalness and News Shocks

In this Section we present a simple textbook formulation of the Lucas' tree model, in which non-fundamentalness arises from news shocks. Total factor productivity, a_t, is assumed to follow the exogenous process:

$$a_t \quad = \quad a_{t-1} + \varepsilon_{t-2} + \eta_t \tag{1}$$

where ε_t is the news shock and η_t is a shock affecting TFP on impact. Agents observe the shock ε_t at time t and react to it immediately, while the shock will affect TFP only at time $t+2$. The representative consumer maximizes $E_t \sum_{t=0}^{\infty} \beta^t c_t$, where c_t is consumption and β is a discount factor, subject to the constraint $c_t + p_t n_{t+1} = (p_t + a_t) n_t$, where p_t is the price of a share, n_t is the number of shares and $(p_t + a_t) n_t$ is the total amount of resources available at time t. The equilibrium value for asset prices is given by:

$$p_t = \sum_{j=1}^{\infty} \beta^j E_t a_{t+j} \tag{2}$$

Considering (1), we have

$$\begin{aligned} E_t a_{t+1} &= a_t + \varepsilon_{t-1}, \\ E_t a_{t+j} &= a_t + \varepsilon_{t-1} + \varepsilon_t, \quad \text{for } j \geq 2, \end{aligned}$$

so that equation (2) reads

$$p_t = \frac{\beta}{1-\beta} a_t + \frac{\beta}{1-\beta} (\beta \varepsilon_t + \varepsilon_{t-1}).$$

Stock prices and productivity are therefore cointegrated and the deviation of $\beta^{-1}(1-\beta)p_t$ from a_t is the stationary process $z_t = \beta\varepsilon_t + \varepsilon_{t-1}$. Since the discount factor β is smaller than 1, such moving average is not invertible, and the news shock ε_t is not a linear combination of present and past values of z_t. In fact, ε_t is a linear combination of *future* values of z_t: $\varepsilon_t = \sum_{j=1}^{\infty}(-\beta)^{-j} z_{t+j}$.

Similarly, equation (2) can be solved to obtain the structural moving average representation for Δa_t and Δp_t:

$$\begin{pmatrix} \Delta a_t \\ \Delta p_t \end{pmatrix} = \begin{pmatrix} L^2 & 1 \\ \frac{\beta^2}{1-\beta} + \beta L & \frac{\beta}{1-\beta} \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ u_t \end{pmatrix} \tag{3}$$

whose determinant

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

vanishes for $L = 1$ and $L = -\beta$. As $\beta < 1$, the moving average is not invertible and the two shocks u_t and ε_t are non-fundamental for the variables Δp_t and Δa_t. The econometrician observing productivity and stock prices cannot recover ε_t by estimating a VAR on Δa_t and Δp_t. As an alternative explanation, observe that the joint dynamics of a_t and p_t can be represented in the state-space form studied by Fernandez-Villaverde, Rubio-Ramirez, Sargent and Watson, 2007, as

$$\begin{pmatrix} a_t \\ \varepsilon_t \\ \varepsilon_{t-1} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} a_{t-1} \\ \varepsilon_{t-1} \\ \varepsilon_{t-2} \end{pmatrix} + \begin{pmatrix} 0 & 1 \\ 1 & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix} \tag{4}$$

$$\begin{pmatrix} a_t \\ p_t \end{pmatrix} = \begin{pmatrix} 1 & 0 & 1 \\ \delta & \delta & \delta \end{pmatrix} \begin{pmatrix} a_{t-1} \\ \varepsilon_{t-1} \\ \varepsilon_{t-2} \end{pmatrix} + \begin{pmatrix} 0 & 1 \\ \delta\beta & \delta \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix}. \tag{5}$$

where $\delta = \beta/(1-\beta)$. It is easy to see from the transition equation (4) that the structural shocks can be obtained as the residuals of a VAR on the state variables. Unfortunately, the state vector includes ε_t and ε_{t-1}, which are not observable. By observing p_t the econometrician can obtain some information about the missing states but cannot tell apart ε_t and ε_{t-1}.[5,6]

[5] On this point, see also Sims, 2011.

[6] Indeed, in the system above the condition for invertibility given in Fernandez-Villaverde *et al.*, 2007 is violated.

In the stylized example above we have just two observable variables, productivity and stock prices. In a more complex economy, however, the invertibility problem can be solved by adding information. In Section 3.2 below we show that going the factor route reveals the hidden aspect of the state vector and allows to recover the shocks.

3 The structural factor model

3.1 Representation

Following Bai, 2004, we assume that each macroeconomic variable x_{it} is either stationary or difference-stationary, and can be represented as the sum of two mutually orthogonal unobservable components, the common component χ_{it} and the idiosyncratic component ξ_{it}:

$$x_{it} = \chi_{it} + \xi_{it}. \tag{6}$$

The idiosyncratic components are assumed to be stationary and poorly correlated in the cross-sectional dimension.[7] 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.

The common components (which can be either stationary or integrated of order 1) account for the bulk of the co-movements between macroeconomic variables, being linear combinations of a relatively small number r of factors $f_{1t}, f_{2t}, \dots, f_{rt}$, not depending on i:

$$\chi_{it} = \alpha_{1i} f_{1t} + \alpha_{2i} f_{2t} + \cdots + \alpha_{ri} f_{rt} = \alpha_i f_t \tag{7}$$

As in Forni, Giannone, Lippi and Reichlin, 2009, (FGLR henceforth), we assume that the dynamic relations between macroeconomic variables arise from the fact that the vector f_t follows a VAR

$$G(L) f_t = \epsilon_t = R u_t, \tag{8}$$

where $G(L)$ is a $r \times r$ matrix of polynomials 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

[7] See Bai, 2004, Assumption C, for a precise statement.

the structural macroeconomic shocks.[8]

Combining equations (6) to (8), the model can be written in dynamic form as

$$x_{it} = \beta_i(L)u_t + \xi_{it}, \tag{9}$$

where

$$\beta_i(L) = \alpha_i G(L)^{-1} R. \tag{10}$$

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

3.2 The factor model, the $ABCD$ model and fundamentalness

The factor model can be interpreted as the linear solution of a DSGE model augmented with measurement errors (Altug, 1989, Sargent, 1989, Ireland, 2004). To show this, let us start from the $ABCD$ state-space representation of a macroeconomic equilibrium studied in Fernandez-Villaverde *et al.*, 2007:

$$s_t = As_{t-1} + Bu_t \tag{11}$$

$$\chi_t = Cs_{t-1} + Du_t \tag{12}$$

where $\chi_t = (\chi_{1t}\ \chi_{2t}\ \cdots\ \chi_{nt})'$, s_t is an l-dimensional vector of "state" variables; A, B, C and D are conformable matrices of parameters and B has a left inverse B^{-1} such that $B^{-1}B = I_q$.

Observe that the macroeconomic shocks are linear combinations of present and lagged states, since, pre-multiplying (11) by B^{-1} we get

$$u_t = B^{-1}s_t - B^{-1}As_{t-1}. \tag{13}$$

Equation (13) shows that the states contain enough information to recover the shocks, or, in other words, that the shocks are always fundamental with respect to the states. The fundamentalness problem arises from the fact that the information used by the econometrician can be strictly smaller than the information spanned by the state variables.

Substituting (13) into (12) and rearranging gives

$$\chi_t = DB^{-1}s_t + (C - DB^{-1}A)s_{t-1}. \tag{14}$$

[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").

Now let us assume that the econometrician observes $x_{it} = \chi_{it} + \xi_{it}$, ξ_{it} being a measurement error (which can be zero) and define $x_t = (x_{1t}\ x_{2t}\ \cdots\ x_{nt})'$, $\xi_t = (\xi_{1t}\ \xi_{2t}\ \cdots\ \xi_{nt})'$. From equation (14) one can see that x_t follows the factor model

$$x_t = \Lambda f_t + \xi_t, \tag{15}$$

where $\Lambda = (\hat{\alpha}_1'\ \hat{\alpha}_2'\ \cdots\ \hat{\alpha}_n')' = \begin{pmatrix} DB^{-1} & C - DB^{-1}A \end{pmatrix}$ and $f_t = \begin{pmatrix} s_t' & s_{t-1}' \end{pmatrix}'$. Since the factors f_t include the states, the structural shocks are always fundamental with respect to the factors as long as the macroeconomic equilibrium can be represented in the form (11)–(12).

3.3 Identification

Going back to the factor model, observe that representation (9) is not unique, i.e. the impulse response functions and the related shocks are not identified. In particular, if H is any orthogonal $q \times q$ matrix, then Ru_t in (8) is equal to Sv_t, where $S = RH'$ and $v_t = Hu_t$, so that

$$\chi_{it} = \gamma_i(L)v_t = \beta_i(L)H'v_t = \alpha_i G(L)^{-1} S v_t. \tag{16}$$

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 structural VAR analysis. Specifically $q(q-1)/2$ restrictions have to be imposed on the matrix of impulse response functions $B(L) = (\beta_1(L)'\beta_2(L)'\cdots\beta_n(L)')'$ 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 relevant column of $B(L)$, say $B_1(L)$, and the relevant shock $u_{1t} = H_1'v_t$.

3.4 Estimation

Estimation proceeds through the following steps.

1. Starting with an estimate of the number of factors, $\hat{r}$, the factors are estimated as the first $\hat{r}$ principal components of the variables in the dataset, taken in levels, centered and standardized, and the factor loadings with the associated eigenvectors. Precisely,

let $\hat{\Gamma}^x$ be the sample variance-covariance matrix of the data: the estimated loading matrix $\hat{\Lambda} = (\hat{\alpha}_1' \ \hat{\alpha}_2' \ \cdots \ \hat{\alpha}_n')'$ is the $n \times \hat{r}$ 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 $\hat{f}_t = \hat{\Lambda}'(x_{1t} \ x_{2t} \ \cdots \ x_{nt})'$. The associated estimate of the idiosyncratic component $\hat{\xi}_{it}$ is given by $x_{it} - \hat{\alpha}_i \hat{f}_t$. The theoretical basis for this procedure is provided by the consistency results in Bai, 2004.[9]

2. $\hat{G}(L)$ 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 information 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, $\hat{M}$ the $\hat{q} \times \hat{q}$ diagonal matrix with $\sqrt{\hat{\mu}_j^\epsilon}$ as its (j, j) entry, and $\hat{K}$ the $\hat{r} \times \hat{q}$ matrix with the corresponding normalized eigenvectors on the columns. Setting $\hat{S} = \hat{K}\hat{M}$, the estimated matrix of non-structural impulse response functions is
$$\hat{C}(L) = \hat{\Lambda}\hat{G}(L)^{-1}\hat{S}. \tag{17}$$
and the estimated non-structural shocks are
$$\hat{v}_t = \hat{S}^{-1}\hat{\epsilon}_t.$$

4. The structural impulse response functions are estimated as $\hat{B}_1(L) = \hat{C}_(L)H_1$ and the structural shock is estimated as $\hat{u}_{1t} = H_1'\hat{v}_t$, where the vector H_1 is determined by imposing suitable restrictions on $\hat{B}_1(L)$ (see below).

To account for estimation uncertainty, the following bootstrap technique is adopted. First, an artificial sequence of shocks v_t^1, $t = 1, \ldots, T$ is obtained by sampling with replacement the columns of the estimated matrix $(\hat{v}_1 \ \hat{v}_2 \ \cdots \ \hat{v}_T)$. Next, artificial factors f_t^1, $t = 1, \ldots, T$, are produced as $f_t^1 = \hat{f}_t$, for $t = 1, \ldots, \hat{p}$, and $f_t^1 = [(I - \hat{G}(L))/L]f_{t-1}^1 + \hat{S}v_t^1$, for $t = \hat{p} + 1, \ldots, T$. Then artificial data are produced as $x_{it}^1 = \hat{\alpha}_i f_t^1 + \hat{\xi}_{it}$. The procedure is repeated m times to produce the artificial data sets x^h, $h = 1, \ldots, m$ and the corresponding estimated impulse response functions $\hat{B}_1^h(L)$. Confidence bands are obtained by taking suitable percentiles of the point-wise distributions.

[9]See Proposition 1. Consistency is reached for both the time dimension and the cross-sectional dimension n going to infinity.

3.5 Testing for fundamentalness

To verify whether the news shock estimated with a given VAR specification can be a structural shock, we use the orthogonality test proposed in Forni and Gambetti, 2011. Let y_t be a subvector of $(x_{1t}\ x_{2t}\ \cdots\ x_{nt})'$ and ω_t the vector of the residuals of the projection of y_t on its past values y_{t-k}, $k > 0$. Consider an econometrician trying to identify a single structural shock, say u_{1t}, as $w_t = \alpha'\omega_t$. From equation (8) it is seen that the structural shocks in u_t are orthogonal to the lags of the factors f_{t-k}, $k > 0$ (as well as the lags of all variables). Hence orthogonality of w_t with respect to the lags of the factors is necessary for w_t being equal to u_{1t}.

Moreover, Proposition 4 in Forni and Gambetti, 2011, establishes a converse result, which holds under the assumption that the economic equilibrium can be represented in the $ABCD$ form: if w_t is orthogonal to f_{t-k}, $k > 0$, then it is a linear combination of the structural shocks. Hence $w_t = u_{1t}$, provided that identification is correct.

On the basis of the above results, fundamentalness can be verified as follows. First, estimate a VAR with y_t and identify the relevant shock. Then test for orthogonality of such shock with respect to the lags of the principal components. The null of fundamentalness is rejected if, and only if, orthogonality is rejected.

4 Empirics

4.1 Data and model specification

Our data set is composed of 107 US quarterly series, covering the period 1960-I to 2010-IV. The series include both national accounting data like GDP, investment, consumption and the GDP deflator, TFP and consumers sentiment which are available 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. Most series are taken from the FRED database. TFP data are taken from the Federal Reserve Bank of San Francisco 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. National accounting data have been expressed in per capita terms, dividing by population aged 16 years or more (Civilian Noninstitutional Population) and stock market data have been deflated and expressed in per capita terms.

According to the model, data are not transformed to get stationarity. Since the series must be either $I(0)$ or $I(1)$, prices and other nominal data are taken in log-differences, whereas real non-stationary data are taken in log-levels. The full list of variables along with the corresponding transformations is reported in the Appendix.

4.2 Fundamentalness of alternative VAR specifications

In this Section we employ the approach proposed in Forni and Gambetti, 2011, to test whether news shocks estimated with a variety of VARs proposed in the literature are indeed fundamental. The VAR specifications we employ are presented in Table 1. The bivariate specifications denoted as $S1$ and $S2$ and the four-variable specifications $S3$ and $S4$ have been studied by Beaudry and Portier (2006); the four-variable specification $S5$ and the seven-variable specification $S6$ have been proposed by Barsky and Sims (2011).

We estimate the above VAR models and identify the news shock in two alternative ways. In the first one, we assume that the news shock (i) does not move TFP on impact and (ii) has maximal impact on TFP in the long run (at the 40 quarters horizon). The idea is to define the news shock as the shock that best anticipates TFP, conditionally on not impacting it in the present. This identification scheme is the one we use below for the factor model and is very similar to the one proposed in Barsky and Sims, 2011. Observe that, for the bivariate specifications $S1$ and $S2$, this scheme reduces to condition (i), which is used in Beaudry and Portier, 2006. In the second scheme, which is used, among others, by Beaudry and Portier, 2006, identification is obtained by imposing that the news shock is the only one having a non-zero effect on TFP in the long run.[10]

In Table 2 we report the results for the first identification scheme; in Table 3 we report results for the second. Column n reports the p-values of the F-test of the regression of the news shock on the lags of the first n principal components. In all specifications but one orthogonality is clearly rejected at the 5% level for both identification methods. The only shock that passes the fundamentalness test is the one obtained with the seven-variable specification $S6$ of Barsky and Sims, 2011. Comparing $S6$ and $S5$ it is seen that the role of the "information" variables stock prices, confidence index and inflation rate is crucial to obtain fundamentalness. Below we show that this failure of fundamentalness, far from being a statistical detail, affects significantly inference on impulse responses and variance decompositions.

[10] VAR models are estimated with variables in levels. We also estimated VECM and identified shocks following closely the original papers, obtaining the same results.

4.3 Results from the structural factor model

Before estimation we need to specify the number of static factor, $\hat{r}$, the number of shocks, $\hat{q}$, and the number of lags, $\hat{p}$. Following Bai, 2004, we use the IC_{p2} criterion of Bai and Ng, 2002, applied to the first difference of the data, to determine $\hat{r}$. This gives $\hat{r} = 8$. We set $\hat{p} = 2$ following the AIC criterion. The number of shocks is determined by applying Bai and Ng (2007) criteria to the first difference of the data. The four criteria, namely q_1, q_2, q_3 and q_4, give 6, 6, 7 and 6 shocks respectively.[11] We then set $\hat{q} = 6$.

We focus our attention on the measure of TFP corrected for capacity utilization, introduced by Basu, Fernald and Kimball, 2006. As anticipated above, we define the news shocks as the 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). We also identify a second shock, which we label TFP shock, as the only one having a non-zero impact effect on TFP.

Figures 1 and 2 shows impulse responses of selected variables to a positive news shock, together with 68% (dark gray) and 90% (light gray) confidence intervals. All responses are expressed in percentage terms. TFP increases significantly right after the shock and reaches the new long run level very quickly, after approximately one year from the shock. Consumption significantly jumps up on impact and remains significantly positive since then. GDP and investment do not respond significantly in the short run. They become significant after few quarters and remain so thereafter. Hours worked significantly fall on impact and then revert to equilibrium. Stock prices jump up on impact and remain positive though they become less significant after 5-6 years. Interestingly, the confidence indicator on current conditions stays put while the confidence indicator on expected conditions jumps up on impact, though only marginally significant. We interpret this as a confirmation that the shock we have identified is in fact related to good news about the future.

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 muted response in output. As output stays put and consumption grows, investment does not increase.

Tables 4 and 5 show the forecast error variance decompositions of selected variables to a news shock and a TFP shock, respectively. The numbers in brackets are standard

[11] The Bai and Ng, 2007, criteria have two parameters. We use the parameters suggest by the authors.

deviations across bootstrap simulations. Not surprisingly, the news shock, being obtained by maximizing the long run effect on TFP, explains an important fraction of the forecast error variance of output at the 40 quarters horizon. However, in the short-run the effect is much smaller, about 4% on impact, 12% at the 1-year horizon and 25% at the 2-year horizon. Similar percentages are found for investment, hours worked and stock prices, whereas the reaction of consumption is considerably larger (about 40%). Such numbers, albeit not negligible, are much smaller than those reported in Beaudry and Portier (2006, Figure 10), in which the news shock explains 25-40% of the forecast error of investment, 45-65% of output and hours worked, 70-90% of consumption, and over 90% of stock prices.

Turning to the TFP shock, Table 5 shows that it explains a large fraction of the volatility of TFP, a number ranging between 90%, at the one-year horizon, and 54%, at the ten-year horizon, while it explains a smaller fraction of the variance of output, consumption and investment, ranging from 2-3% to 30% at 1 and 2 years horizon. If the two shocks are considered together, they account for almost all the variance of TFP (more than 90% uniformly across horizons), while accounting for only 26%, 48% and 24% of the forecast error variance of GDP, consumption and investment, respectively, at the one-year horizon. This leaves the door open to other shocks unrelated to TFP in generating the business cycle.

We now compare results from non-fundamental VARs with those obtained with the factor model. Figure 3 and Table 6 show impulse responses and variance decompositions to a news shock obtained from specification $S1$, discussed in Section 4.2, and a triangular identification, together with those from the factor model. The bivariate VAR generates responses of stock prices and TFP to a news shock that are very different from those obtained with the factor model. The variance decomposition is also very different in the two models for both variables. From these results, we conclude that non-fundamentalness has important consequences on the effects and the importance of news shocks.

We conclude this Section by presenting some robustness checks. We first estimate the model by setting the number of static factors to 9 and 7 (± 1 with respect to the benchmark). We also estimate the model by setting the number of lags in the VAR for the factors f_t to 1 and 3 (± 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 by setting the number of shocks to 5 and 7 (± 1 with respect to the benchmark). Overall, the three Figures show that the main results are robust to variations in the model's specification.

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 news shocks about TFP lead to impulse responses of macro variables that are largely consistent with the implications of a standard one sector real business cycle model — when good news hits, consumption rises and hours worked decline. In terms of variance decomposition, news shocks explain a moderate amount of output fluctuations at business cycle horizons. A substantial fraction (around 50%) of business cycle fluctuations is due to shocks unrelated to TFP. These results are in line with those presented in Barsky and Sims, 2011 and differ from previous findings based on small-scale VAR specifications. This is because small-scale VARs do not contain enough information, as testified by the fact that the news shock estimated with these VARs are not orthogonal to the lags of the factors.

Appendix: Data

Transformations: 1 = levels, 2 = logs, 3 = first differences of logs. Most series are taken from the FRED database. TFP data are taken from the Federal Reserve Bank of San Francisco database. A few stock market and leading indicators are taken from Datastream. Monthly data have been temporally aggregated to get quarterly figures. CNP = Civilian Noninstitutional Population (Fred mnemonic: CNP16OV).

no.series	Transf.	Mnemonic	Long Label
1	2	GDPC1/CNP	Real Gross Domestic Product/CNP
2	2	GNPC96/CNP	Real Gross National Product/CNP
3	2	(NICUR/GDPDEF)/CNP	(National Income/GDP Deflator)/CNP
4	2	DPIC96/CNP	Real Disposable Personal Income/CNP
5	2	OUTNFB/CNP	Nonfarm Business Sector: Output/CNP
6	2	FINSLC1/CNP	Real Final Sales of Domestic Product/CNP
7	2	(FPIC1+PCNDGC96)/CNP	(Real Private Fixed Inv. + Real Durables Cons.)/CNP
8	2	PRFIC1/CNP	Real Private Residential Fixed Investment/CNP
9	2	PNFIC1/CNP	Real Private Nonresidential Fixed Investment/CNP
10	2	GPDIC1/CNP	Real Gross Private Domestic Investment/CNP
11	2	(PCNDGC96+PCESVC96)/CNP	(Real Pers. Cons. Exp.: Non Durables + Services)/CNP
12	2	PCNDGC96/CNP	Real Pers. Cons. Exp.: Nondurable Goods /CNP
13	2	PCDGCC96/CNP	Real Pers. Cons. Exp.: Durable Goods/CNP
14	2	PCESVC96/CNP	Real Pers. Cons. Exp.: Services/CNP
15	2	(GSAVE/GDPDEF)/CNP	(Gross Saving/GDP Deflator)/CNP
16	2	FGCEC1/CNP	Real Federal Cons. Exp. & Gross Investment/CNP
17	2	(FGEXPND/GDPDEF)/CNP	(Federal Gov.: Current Exp./ GDP Deflator)/CNP
18	2	(FGRECPT/GDPDEF)/CNP	(Federal Gov. Current Receipts/ GDP Deflator)/CNP
19	1	CBIC1	Real Change in Private Inventories
20	2	EXPGSC1/CNP	Real Exports of Goods & Services /CNP
21	2	IMPGSC1/CNP	Real Imports of Goods & Services /CNP
22	2	CP/GDPDEF	Corporate Profits After Tax/GDP Deflator
23	2	NFCPATAX/GDPDEF	Nonfin. Corp. Bus.: Profits After Tax/GDP Deflator
24	2	CNCF/GDPDEF	Corporate Net Cash Flow/GDP Deflator
25	2	DIVIDEND/GDPDEF	Net Corporate Dividends/GDP Deflator
26	2	HOANBS/CNP	Nonfarm Business Sector: Hours of All Persons/CNP
27	2	OPHNFB	Nonfarm Business Sector: Output Per Hour of All Persons
28	2	UNLPNBS	Nonfarm Business Sector: Unit Nonlabor Payments
29	2	ULCNFB	Nonfarm Business Sector: Unit Labor Cost
30	2	WASCUR/CPI	Compensation of Employees: Wages & Salary Accruals/CPI
31	3	COMPNFB	Nonfarm Business Sector: Compensation Per Hour
32	2	COMPRNFB	Nonfarm Business Sector: Real Compensation Per Hour
33	3	GDPCTPI	Gross Domestic Product: Chain-type Price Index
34	3	GNPCTPI	Gross National Product: Chain-type Price Index
35	3	GDPDEF	Gross Domestic Product: Implicit Price Deflator
36	3	GNPDEF	Gross National Product: Implicit Price Deflator
37	2	INDPRO	Industrial Production Index
38	2	IPBUSEQ	Industrial Production: Business Equipment
39	2	IPCONGD	Industrial Production: Consumer Goods

no.series	Transf.	Mnemonic	Long Label
40	2	IPDCONGD	Industrial Production: Durable Consumer Goods
41	2	IPFINAL	Industrial Production: Final Products (Market Group)
42	2	IPMAT	Industrial Production: Materials
43	2	IPNCONGD	Industrial Production: Nondurable Consumer Goods
44	1	AWHMAN	Average Weekly Hours: Manufacturing
45	1	AWOTMAN	Average Weekly Hours: Overtime: Manufacturing
46	1	CIVPART	Civilian Participation Rate
47	2	CLF16OV	Civilian Labor Force
48	2	CE16OV	Civilian Employment
49	2	USPRIV	All Employees: Total Private Industries
50	2	USGOOD	All Employees: Goods-Producing Industries
51	2	SRVPRD	All Employees: Service-Providing Industries
52	2	UNEMPLOY	Unemployed
53	2	UEMPMEAN	Average (Mean) Duration of Unemployment
54	1	UNRATE	Civilian Unemployment Rate
55	2	HOUST	Housing Starts: Total: New Privately Owned Housing Units Started
56	1	FEDFUNDS	Effective Federal Funds Rate
57	1	TB3MS	3-Month Treasury Bill: Secondary Market Rate
58	1	GS1	1- Year Treasury Constant Maturity Rate
59	1	GS10	10-Year Treasury Constant Maturity Rate
60	1	AAA	Moody's Seasoned Aaa Corporate Bond Yield
61	1	BAA	Moody's Seasoned Baa Corporate Bond Yield
62	1	MPRIME	Bank Prime Loan Rate
63	3	M1SL	M1 Money Stock
64	3	M2MSL	M2 Minus
65	3	M2SL	M2 Money Stock
66	3	BUSLOANS	Commercial and Industrial Loans at All Commercial Banks
67	3	CONSUMER	Consumer (Individual) Loans at All Commercial Banks
68	3	LOANINV	Total Loans and Investments at All Commercial Banks
69	3	REALLN	Real Estate Loans at All Commercial Banks
70	3	TOTALSL	Total Consumer Credit Outstanding
71	3	CPIAUCSL	Consumer Price Index For All Urban Consumers: All Items
72	3	CPIULFSL	Consumer Price Index for All Urban Consumers: All Items Less Food
73	3	CPILEGSL	Consumer Price Index for All Urban Consumers: All Items Less Energy
74	3	CPILFESL	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy
75	3	CPIENGSL	Consumer Price Index for All Urban Consumers: Energy
76	3	CPIUFDSL	Consumer Price Index for All Urban Consumers: Food
77	3	PPICPE	Producer Price Index Finished Goods: Capital Equipment
78	3	PPICRM	Producer Price Index: Crude Materials for Further Processing
79	3	PPIFCG	Producer Price Index: Finished Consumer Goods
80	3	PPIFGS	Producer Price Index: Finished Goods
81	3	OILPRICE	Spot Oil Price: West Texas Intermediate
82	3	USSHRPRCF	US Dow Jones Industrials Share Price Index (EP) NADJ
83	2	US500STK	US Standard & Poor's Index if 500 Common Stocks
84	2	USI62...F	US Share Price Index NADJ
85	2	USNOIDN.D	US Manufacturers New Orders for Non Defense Capital Goods (B CI 27)
86	2	USCNORCGD	US New Orders of Consumer Goods & Materials (BCI 8) CONA
87	1	USNAPMNO	US ISM Manufacturers Survey: New Orders Index SADJ

no.series	Transf.	Mnemonic	Long Label
88	2	USCYLEAD	US The Conference Board Leading Economic Indicators Index S ADJ
89	2	USECRIWLH	US Economic Cycle Research Institute Weekly Leading Index
90	2	GEXPND/GDPDEF/CNP	(Government Current Expenditures/ GDP Deflator)/CNP
91	2	GRECPT/GDPDEF/CNP	(Government Current Receipts/ GDP Deflator)/CNP
92	2	GCEC1/CNP	Real Government Consumption Expenditures & Gross Investment/CNP
93	2		Fernald's TFP growth CU adjusted
94	2		Fernald's TFP growth
95	2		(DOW JONES/GDP Deflator)/Civilian Noninstitutional Population
96	2		(S&P500/GDP Deflator)/Civilian Noninstitutional Population
97	2		Fernald's TFP growth - Investment
98	2		Fernald's TFP growth - Consumption
99	2		Fernald's TFP growth CU - Investment
100	2		Fernald's TFP growth CU - Consumption
101	1		Michigan Consumer Sentiment: Personal Finance Current
102	1		Michigan Consumer Sentiment: Personal Finance Expected
103	1		Michigan Consumer Sentiment: Business Condition 12 Months
104	1		Michigan Consumer Sentiment: Business Condition 5 Years
105	1		Michigan Consumer Sentiment: Buying Conditions
106	1		Michigan Consumer Sentiment: Current Index
107	1		Michigan Consumer Sentiment: Expected Index

References

[1] Altug, S., 1989, "Time-to-build and aggregate fluctuations: some new evidence", International Economic Review 30, pp. 889-920.

[2] Bai, J., 2004, "Estimating cross-section common stochastic trends in nonstationary panel data", Journal of Econometrics 122, pp. 137-183.

[3] Bai, J. and Ng, S., 2002, "Determining the number of factors in approximate factor models", Econometrica 70, pp. 191-221.

[4] Bai, J. and Ng, S., 2007, "Determining the number of primitive shocks in factor models", Journal of Business and Economic Statistics 25, pp. 52-60.

[5] Basu, S., Fernald, L. and Kimball, M., 2006, "Are technology improvements contractionary?", American Economic Review, vol. 96(5), pp. 1418-1448.

[6] Barsky, R.B. and Sims, E.R., 2011, "News shocks and business cycles", Journal of Monetary Economics 58, pp. 273-289.

[7] Beaudry, P. and Lucke, B., 2009, "Letting different views about business cycles compete", NBER Macroeconomics Annual.

[8] Beaudry, P. and Portier, F., 2006, "Stock prices, news, and economic fluctuations", American Economic Review, vol. 96(4), pp. 1293-1307.

[9] Beaudry, P. and Portier, F., 2007, "When can changes in expectations cause business cycle fluctuations in neo-classical settings?", Journal of Economic Theory, 135, pp. 458-477.

[10] Bernanke, B. S., Boivin, J. and Eliasz, P., 2005, "Measuring monetary policy: a factor augmented autoregressive (FAVAR) approach", The Quarterly Journal of Economics 120, pp. 387-422.

[11] Dupaigne, M. and Portier, F., 2006, ""News" shocks in international business cycles", 2006 Meeting Papers 473, Society for Economic Dynamics.

[12] Fernandez-Villaverde J., Rubio-Ramirez, J.F. , Sargent, T.J. and Watson, M.W. , 2007, ABCs (and Ds) of understanding VARs, American Economic Review, 97(3), pp. 1021-1026.

[13] Feve, P., Matheron, J. and Sahuc, J.G. , 2009, "On the dynamic implications of news shocks", Economics Letters 102, pp. 96-98.

[14] Forni, M. and Gambetti, L., 2010a, "The dynamic effects of monetary policy: a structural factor model approach", Journal of Monetary Economics 57, pp. 203-216.

[15] Forni, M. and Gambetti, L., 2010b, "Fiscal foresight and the effects of government spending", CEPR Discussion Paper Series no. 7840.

[16] Forni, M. and Gambetti, L., 2011, "Sufficient information in structural VARs," Center for Economic Research (RECent) 062, University of Modena and Reggio Emilia, Dept. of Economics.

[17] Forni, M., Giannone, D., Lippi, M. and Reichlin, L., 2009, "Opening the black box: structural factor models with large cross-sections", Econometric Theory 25, pp. 1319-1347.

[18] Forni, M., Hallin, M., Lippi, M. and Reichlin, L., 2000, "The generalized dynamic factor model: identification and estimation", The Review of Economics and Statistics 82, pp. 540-554.

[19] Forni, M. and Lippi, M., 2001, "The generalized dynamic factor model: representation theory", Econometric Theory 17, pp. 1113-1141.

[20] Forni, M. and Reichlin, L., 1998, "Let's get real: a factor analytical approach to disaggregated business cycle dynamics", Review of Economic Studies 65, pp. 453-473.

[21] Giannone, D., Reichlin, L. and Sala, L., 2004, "Monetary policy in real time", NBER Macroeconomics Annual 2004, Volume 19, pp. 161-224.

[22] Giannone, D., Reichlin, L., and Sala, L., 2006, "VARs, common factors and the empirical validation of equilibrium business cycle models", Journal of Econometrics 127, pp. 257-279.

[23] Ireland, P. N., 2004, "A method for taking models to the data", Journal of Economic Dynamics and Control 28, pp. 1205-1226.

[24] Jaimovich, N. and Rebelo, S., 2009, "Can news about the future drive the business cycle?", American Economic Review, vol. 99(4), pp. 1097-1118

[25] Leeper, E.M., Walker, T.B. and Yang, S.S. , 2008, "Fiscal foresight: analytics and econometrics", NBER Working Paper No. 14028.

[26] Lippi, M. and Reichlin, L., 1993, "The dynamic effects of aggregate demand and supply disturbances: comment", American Economic Review 83, pp. 644-652.

[27] Lippi, M. and Reichlin, L., 1994, "VAR analysis, non fundamental representation, Blaschke matrices", Journal of Econometrics 63, pp. 307-325.

[28] Lorenzoni, G. (2009) "A theory of demand shocks", American Economic Review, 99(5), pp. 2050-84.

[29] Pigou, A. C., 1927, "Industrial fluctuations", London, Macmillan.

[30] Sargent, T. J., 1989, "Two models of measurements and the investment accelerator", The Journal of Political Economy 97, pp. 251-287.

[31] Schmitt-Grohe, S. and Uribe, M., 2008, "What's news in business cycles", NBER Working Paper no. 14215.

[32] Sims, E., 2011, "News, non-invertibility, and structural VARs", mimeo, University of Notre Dame.

[33] Stock, J. H. and Watson, M. W., 2002a, "Macroeconomic forecasting using diffusion indexes", Journal of Business and Economic Statistics 20, pp. 147-162.

[34] Stock, J. H. and Watson, M. W., 2002b, "Forecasting using principal components from a large number of predictors", Journal of the American Statistical Association 97, pp. 1167-1179.

[35] Stock, J. H. and Watson, M. W. , 2005, "Implications of dynamic factor models for VAR analysis", NBER Working Paper no. 11467.

	2 variables ($S1$, $S2$: Beaudry and Portier, 2006)				lags
$S1$	TFP adj. (93)	Stock Prices (96)			5
$S2$	TFP (94)	Stock Prices (96)			5
	4 variables ($S3$, $S4$: Beaudry and Portier, 2006 - $S5$: Barsky and Sims, 2011)				
$S3$	TFP adj. (93)	Stock Prices (96)	Consumption (11)	Hours Worked (26)	5
$S4$	TFP (94)	Stock Prices (96)	Consumption (11)	Hours Worked (26)	5
$S5$	TFP adj. (93)	Output (5)	Consumption (11)	Hours Worked (26)	3
	7 variables ($S6$: Barsky and Sims, 2011)				
$S6$	TFP adj. (93)	Output (5)	Consumption (11)	Hours Worked (26)	
	Stock Prices (96)	Confidence (104)	Inflation (71)		3

Table 1: VAR specifications used to identify news shocks. Numbers in brackets correspond to the series in the data appendix.

		Principal components (from 1 to n)							
spec	lags	1	2	3	4	5	6	7	8
$S1$	2	0.29	0.43	0.13	0.04	0.05	0.06	0.04	0.06
	4	0.38	0.17	0.03	0.03	0.05	0.04	0.03	0.06
$S2$	2	0.51	0.54	0.06	0.01	0.02	0.02	0.01	0.02
	4	0.64	0.54	0.08	0.04	0.08	0.04	0.02	0.03
$S3$	2	0.06	0.02	0.03	0.02	0.03	0.02	0.04	0.05
	4	0.23	0.06	0.04	0.07	0.15	0.15	0.23	0.30
$S4$	2	0.30	0.03	0.08	0.06	0.10	0.06	0.10	0.10
	4	0.57	0.04	0.07	0.17	0.28	0.25	0.30	0.32
$S5$	2	0.51	0.15	0.26	0.45	0.19	0.14	0.12	0.16
	4	0.22	0.05	0.08	0.13	0.01	0.01	0.03	0.05
$S6$	2	0.60	0.83	0.94	0.98	0.79	0.56	0.27	0.39
	4	0.08	0.23	0.42	0.51	0.32	0.40	0.37	0.53

Table 2: Results of the fundamentalness test described in Section 3.5. Each entry of the table denotes the p-value of the F-test in a regression of the news shock estimated using specifications $S1$ to $S6$ on 2 or 4 lags of the first n factors. The news shock is identified as the shock that does not move TFP on impact and (for specifications from $S3$ to $S6$) has maximal effect on TFP at horizon 40.

		Principal components (from 1 to n)							
spec	lags	1	2	3	4	5	6	7	8
$S1$	2	0.62	0.37	0.17	0.01	0.03	0.05	0.03	0.06
	4	0.55	0.08	0.01	0.00	0.01	0.01	0.00	0.01
$S2$	2	0.46	0.22	0.03	0.01	0.02	0.02	0.02	0.03
	4	0.77	0.13	0.02	0.02	0.02	0.01	0.02	0.03
$S3$	2	0.05	0.01	0.03	0.02	0.04	0.03	0.05	0.06
	4	0.2	0.04	0.04	0.07	0.15	0.14	0.22	0.27
$S4$	2	0.41	0.02	0.07	0.06	0.10	0.10	0.18	0.17
	4	0.52	0.02	0.06	0.13	0.24	0.31	0.43	0.42
$S5$	2	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	4	0.13	0.01	0.02	0.00	0.00	0.00	0.00	0.00
$S6$	2	0.84	0.58	0.75	0.75	0.57	0.42	0.49	0.58
	4	0.39	0.20	0.48	0.58	0.38	0.35	0.26	0.29

Table 3: Results of the fundamentalness test described in Section 3.5. Each entry of the table denotes the p-value of the F-test in a regression of the news shock estimated using specifications $S1$ to $S6$ on 2 or 4 lags of the first n factors. The news shock is identified as the only shock with a non-zero effect on TFP in the long run.

Variables	Horizons					
	0	4	8	16	24	40
TFP adj. (93)	0	5.3	11.0	22.1	29.5	38.4
	(0.0)	(4.5)	(8.4)	(12.5)	(13.1)	(13.1)
GDP (1)	4.6	11.6	25.5	35.9	36.0	38.5
	(15.1)	(16.3)	(20.4)	(20.1)	(18.7)	(18.2)
Consumption (11)	37.6	40.6	45.7	50.4	48.9	50.6
	(22.4)	(22.0)	(22.6)	(20.6)	(19.1)	(18.3)
Investment (7)	0.4	9.7	21.2	32.1	32.5	34.6
	(11.6)	(17.2)	(19.5)	(18.3)	(16.9)	(16.5)
Hours (26)	16.0	12.5	7.2	5.6	4.8	5.8
	(12.5)	(12.6)	(10.4)	(9.8)	(9.7)	(9.5)
Stock Prices (96)	23.2	23.6	23.6	25.2	22.3	20.7
	(17.9)	(17.9)	(17.9)	(17.5)	(16.9)	(16.6)
Sentiment current (106)	2.1	3.7	7.3	6.9	6.8	7.6
	(10.8)	(11.4)	(13.2)	(12.6)	(11.9)	(11.5)
Sentiment expected (107)	2.7	9.8	10.7	8.4	7.8	7.8
	(12.7)	(15.4)	(15.3)	(13.7)	(13)	(12.7)
Inflation (35)	24.2	29.4	24.2	17.6	16.4	17.6
	(14.9)	(15.5)	(14.7)	(12.9)	(12.5)	(12.6)
3M T-Bill (57)	53.5	49.8	47.7	39.5	36.7	37.1
	(21.3)	(21.1)	(20)	(17.8)	(17.3)	(17.3)

Table 4: Variance decomposition to a news shock. Fraction of the variance of the forecast error for the levels of the variables at different horizon. Numbers in parenthesis are standard deviations across bootstrap simulations. Numbers in brackets correspond to the series in the data appendix.

Variables	Horizons					
	0	4	8	16	24	40
TFP adj. (93)	100	92.9	84.5	69.5	61.6	53.9
	(0.0)	(8.6)	(12.6)	(14.4)	(13.4)	(12.5)
GDP (1)	2.9	1.0	1.1	10.6	23.4	29.1
	(17.3)	(9.5)	(8.9)	(11.9)	(14.1)	(14.7)
Consumption (11)	6.8	2.5	2.2	11.9	23.9	29.0
	(13.1)	(9.3)	(8.7)	(11.7)	(14.0)	(14.9)
Investment (7)	21.3	5.0	2.8	10.3	22.0	26.6
	(19.9)	(10.8)	(8.1)	(10.1)	(12.3)	(13.1)
Hours (26)	42.6	29.6	22.3	22.6	30.0	32.2
	(16.5)	(13.1)	(13.2)	(14.3)	(14.4)	(13.8)
Stock Prices (96)	8.2	27.9	35.9	47.0	56.3	58.4
	(15.8)	(16.5)	(17.1)	(18.1)	(18.3)	(18.3)
Sentiment current (106)	22.6	13.6	14.5	28.2	33.5	33.5
	(13.1)	(12.3)	(13.1)	(13.9)	(13.5)	(13.1)
Sentiment expected (107)	31.9	31.4	39.6	54.4	57.5	57.3
	(17.3)	(17.1)	(17.6)	(17.4)	(16.7)	(16.3)
Inflation (35)	25.7	30.2	41.3	50.2	49.3	47.4
	(16.5)	(15.7)	(15.6)	(15.1)	(14.9)	(14.9)
3M T-Bill (57)	26.7	16.1	11.8	16.8	18.6	19.7
	(11.7)	(7.6)	(6.4)	(8.6)	(9.7)	(10.8)

Table 5: Variance decomposition to a technology shock. Fraction of the variance of the forecast error for the levels of the variables at different horizon. Numbers in parenthesis are standard deviations across bootstrap simulations. Numbers in brackets correspond to the series in the data appendix.

Variables	Horizons					
	0	4	8	16	24	40
			Factor model			
TFP (93)	0.0	5.3	11.0	22.1	29.5	38.4
Stock Prices (96)	23.2	23.6	23.6	25.2	22.3	20.7
			VAR			
TFP (93)	0.0	3.0	3.2	2.9	6.7	19.0
Stock Prices (96)	98.9	96.4	93.1	91.2	90.2	88.9

Table 6: Explained forecast error variance (percentages) of news shocks at various horizons in bivariate VAR $S1$ (TFP and Stock Prices). The news shock in the VAR has been identified with a Choleski decomposition. Numbers in brackets correspond to the series in the data appendix.

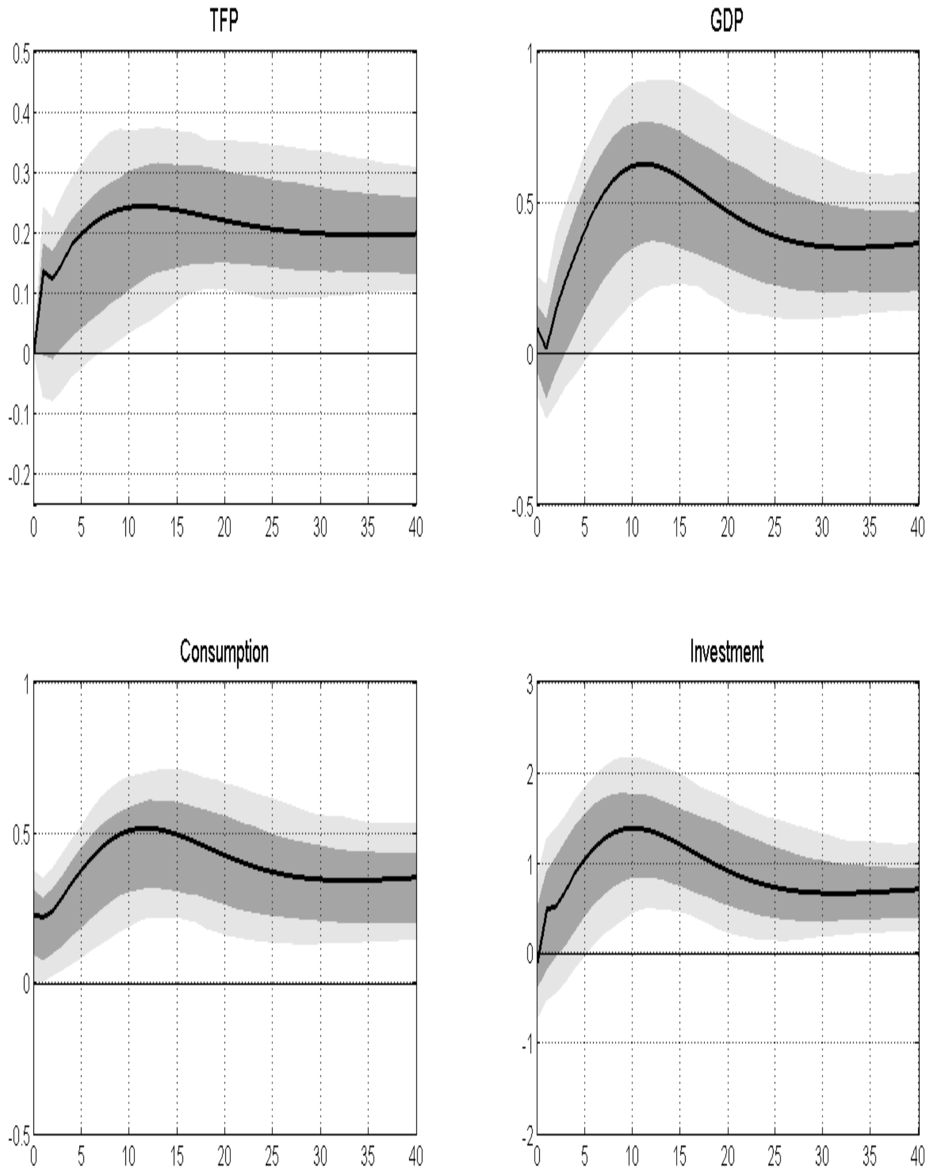

Figure 1: Impulse response functions to a news shock. Solid: factor model. Dark gray areas denote 68% confidence intervals. Light gray areas denote 90% confidence intervals.

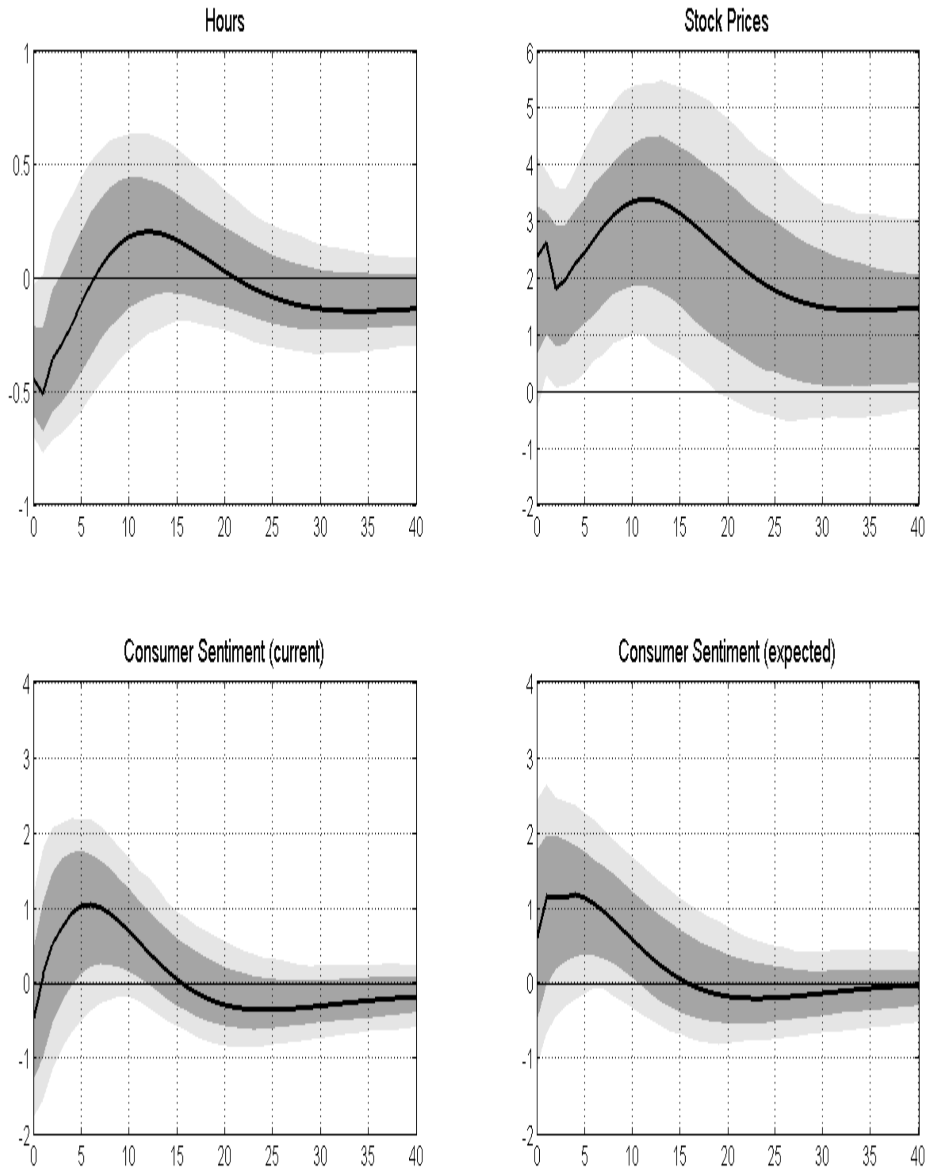

Figure 2: Impulse response functions to a news shock (continued). Solid: factor model. Dark gray areas denote 68% confidence intervals. Light gray areas denote 90% confidence intervals.

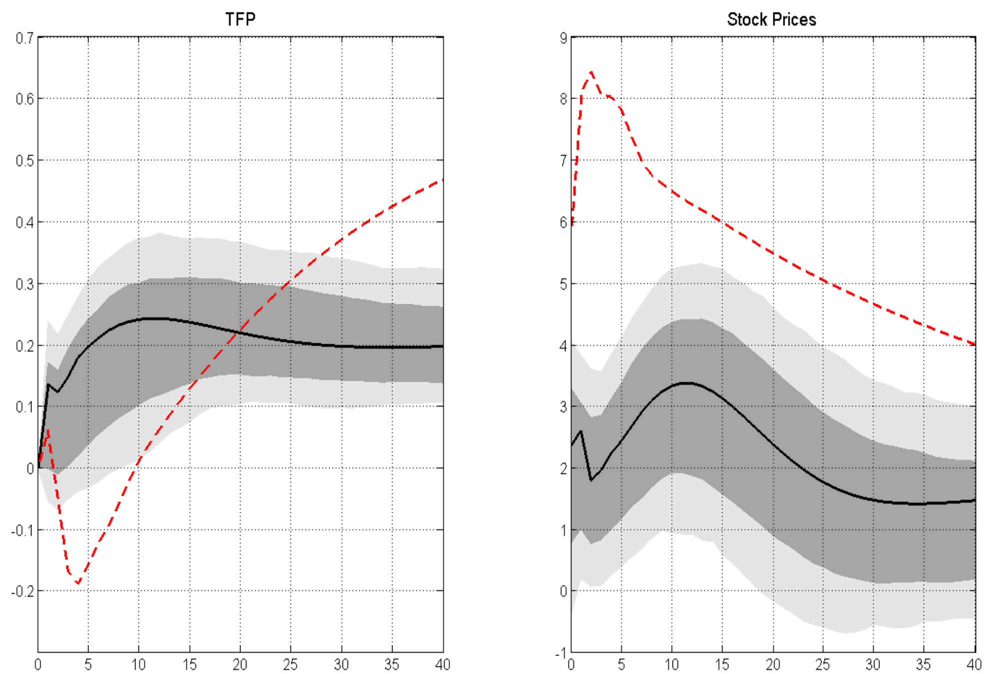

Figure 3: Comparison of impulse responses to a news shock. The dashed lines are the impulse responses obtained from a bivariate VAR (with 5 lags) identified with a Choleski decomposition (as in Beaudry and Portier, 2006). The solid lines are impulse responses obtained with the benchmark factor model. Dark gray areas denote 68% confidence intervals. Light gray areas denote 90% confidence intervals.

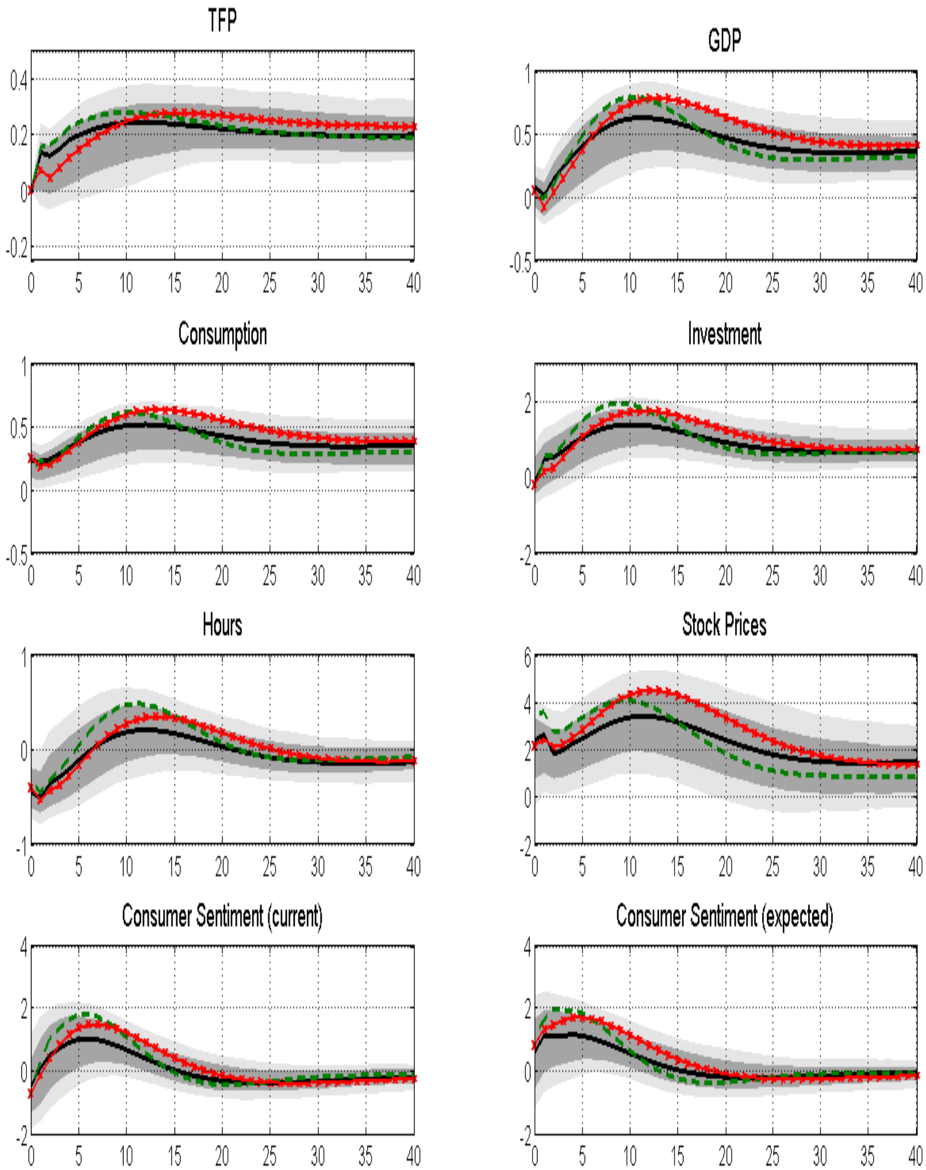

Figure 4: Impulse response functions with different values of $\hat{r}$. Solid: benchmark, $\hat{r} = 8$ - dashed: $\hat{r} = 9$ - Starred: $\hat{r} = 7$.

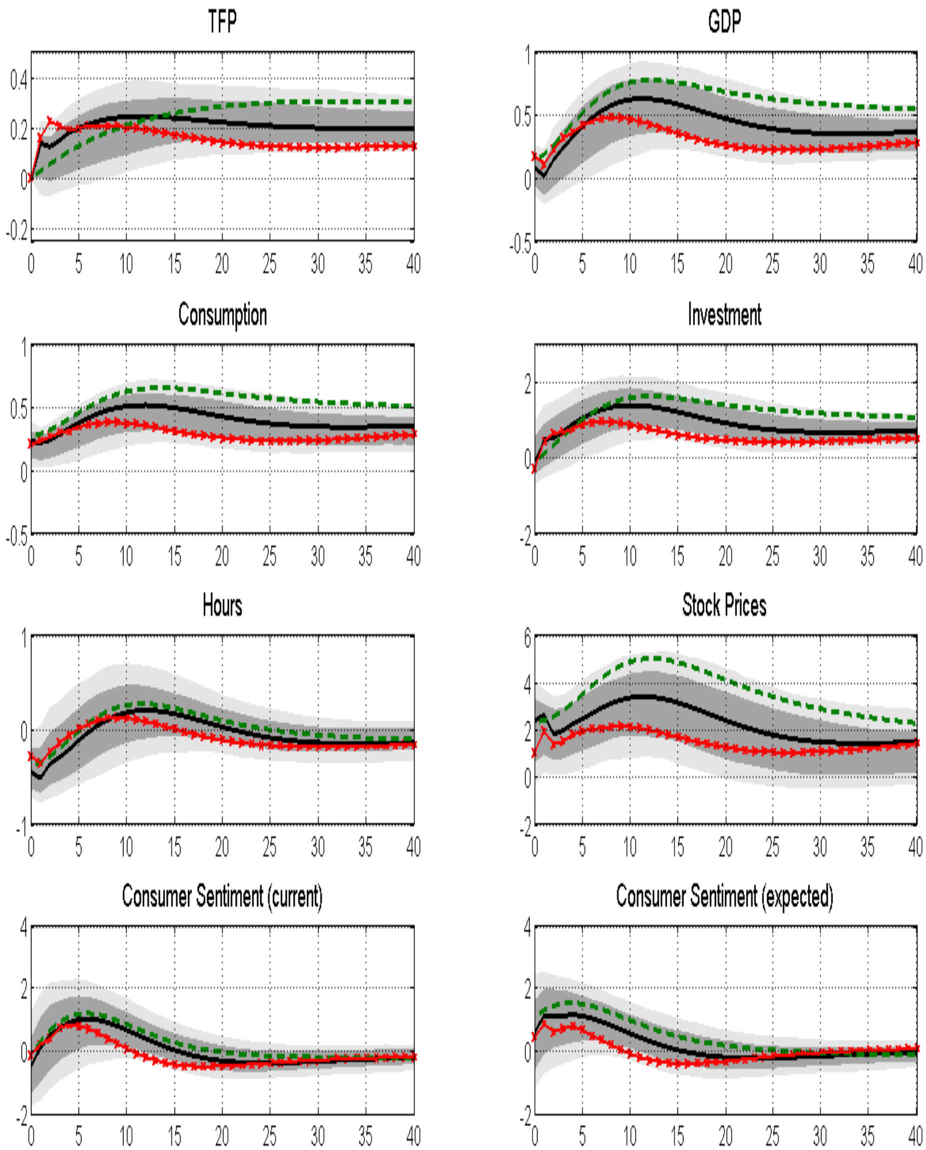

Figure 5: Impulse response functions with different values of $\hat{p}$. Solid: benchmark, $\hat{p} = 2$ - dashed: $\hat{p} = 1$ - starred: $\hat{p} = 3$.

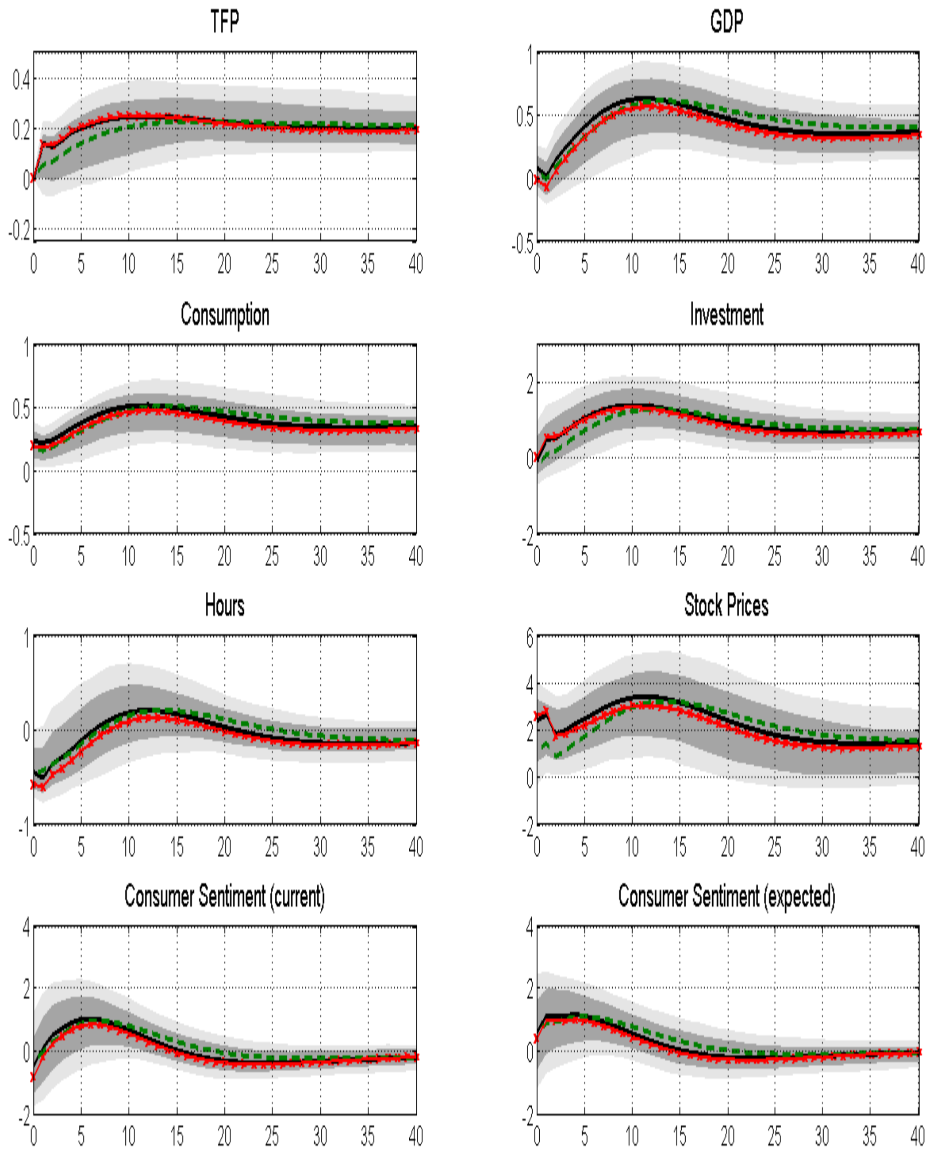

Figure 6: Impulse response functions with different values of $\hat{q}$. Solid: benchmark, $\hat{q} = 6$ - dashed: $\hat{q} = 7$ - starred: $\hat{q} = 5$.