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No News in Business Cycles

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Abstract

A structural Factor-Augmented VAR model is used to evaluate the role of "news" shocks 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 smaller role in explaining the business cycle than previously found in the literature; (iii) their effects are essentially in line with what predicted by standard theories; (iv) a substantial fraction of business cycle fluctuations are explained by shocks unrelated to technology.

JEL classification: C32, E32, E62.

Keywords: Factor-augmented VAR, 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). Much attention has been paid on shocks having delayed effects on productivity, 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 the predictions of standard models, like simple RBC 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, Den Haan and Kaltenbrunner, 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

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

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 delay of two periods. Clearly, observed TFP at time t conveys information about the news arrived in $t-2$, but not about the current shock. Coupling TFP with a series that reacts to 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 model with US quarterly data. Models that can process large datasets, like latent factor models and 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 and Gambetti, 2010a.[3] Their advantage in the present context is that they are not affected by the non-fundamentalness problem (see Forni, Giannone, Lippi and Reichlin, 2009).[4] The intuition is that factor models, unlike VARs, include a large amount of information (virtually all available macroeconomic series), so that insufficient information is unlikely. As a

[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.

[3]Early references on large "generalized" or "approximate" dynamic factor models 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 treat this kind of non-fundamentalness in Forni, Gambetti, Lippi and Sala, 2013.

matter of fact, such 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 structural shock estimated with a VAR is an innovation with respect to available information. We summarize the information in our dataset by computing the principal components; we then 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 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 FAVAR models by adding principal components to different VAR specifications 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 and tracking the response of TFP; (iii) news shocks account for about 3% and 26% of the forecast-error variance of output at the 1-year and 4-year horizons respectively, and 20% of the volatility of output at business cycle frequencies; such numbers, though not negligible, are much smaller than those reported in

Beaudry and Portier, 2006. The findings, which are similar to those obtained by Barsky and Sims, 2011, are in line with the predictions of standard DSGE models, including both simple RBC and New Keynesian models, in terms of impulse response functions and point to a relatively small role for news shocks as a source of cyclical fluctuations.

Finally, we identify a second shock, which we call TFP surprise shock, as the only shock having a non-zero impact effect on productivity. We find that news and TFP surprise shocks explain together almost all of TFP volatility at all horizons, but only 25-30% 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 fundamentalness test. Section 4 presents empirical results. Section 5 concludes.

2 Non-fundamentalness and news shocks

2.1 A stylized example

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:

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

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: $\varepsilon_t = \sum_{j=1}^{\infty} (-\beta)^{-j} z_{t+j}$.

From (1) and (2) the structural moving average representation in equation (3) can be obtained as:

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

The determinant of the matrix on the right-hand side, i.e.

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

vanishes for $L = 1$ and $L = -\beta$. As $|\beta| < 1$, the shocks η_t and ε_t are non-fundamental for the variables Δp_t and Δa_t. Hence, 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 easily seen 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]

2.2 The role of large information sets

In the stylized example above there are just two observable variables, productivity and stock prices. In a more complex economy, however, the invertibility problem can be solved by adding information.

To show this, let us start from the $ABCD$ state-space representation of a macroeconomic equilibrium studied in Fernandez-Villaverde *et al.*, 2007:

$$s_t = As_{t-1} + Bu_t \tag{6}$$

$$\chi_t = Cs_{t-1} + Du_t \tag{7}$$

where $\chi_t = (\chi_{1t}\ \chi_{2t}\ \cdots\ \chi_{nt})'$, is an n-dimensional vector of macroeconomic variables; s_t is an l-dimensional vector of "state" variables, $l \leq n$; u_t is a q-dimensional vector, $q \leq l$, of serially uncorrelated structural shocks, orthogonal to s_{t-k}, $k = 1, \ldots, \infty$; 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 shocks in u_t are linear combinations of present and lagged states,

[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.

as pre-multiplying (6) by B^{-1} we get

$$u_t = B^{-1}s_t - B^{-1}As_{t-1}. \tag{8}$$

Equation (8) 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 (8) into (7) and rearranging gives

$$\chi_t = DB^{-1}s_t + (C - DB^{-1}A)s_{t-1}. \tag{9}$$

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 (9) it is seen that x_t follows the factor model

$$x_t = \Lambda f_t + \xi_t, \tag{10}$$

where $\Lambda = \begin{pmatrix} DB^{-1} & C - DB^{-1}A \end{pmatrix}$ 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 (6)–(7).[7] Depending on the assumptions about the observability of f_t, equation (10) can be a

[7] Several authors have already made the point that the factor model can be interpreted as the linear solution of a DSGE model augmented with measurement errors (Altug, 1989, Sargent, 1989, Ireland, 2004).

pure latent factor model (when none of the factors is observable) or a FAVAR (when some variables have zero measurement error and are entries of f_t). In the following sections we use a FAVAR model, which enables us to make a closer comparison with existing VAR specifications.

3 Testing for fundamentalness

3.1 The testing procedure

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. We briefly review the main idea of the testing procedure. Assume that the economy follows (6)-(7). Let y_t be an m-dimensional sub-vector of x_t and ω_t the vector of the residuals of the theoretical projection of y_t onto its past values $y_{t-1}, ..., y_{t-k}$, $k > 0$. Consider an econometrician trying to identify a single structural shock, say u_{1t}, by estimating a VAR on y_t. By rotating the residuals the econometrician obtains $e_t = \beta'\omega_t$, where β is an m-dimensional column vector.

Under what conditions is e_t equal to the desired shock u_{1t}? From equations (6) and (10) it is seen that u_{1t} (as well as the other entries of u_t) is orthogonal to the lags of the factors f_{t-k}, $k > 0$ (as well as the lags of all variables). Hence orthogonality of e_t with respect to the lags of the factors is a necessary condition. Moreover, Proposition 4 in Forni and Gambetti, 2011, establishes a converse result: assuming that y_t is free of measurement errors, if e_t is orthogonal to f_{t-k}, $k > 0$, then it is a linear combination of the structural shocks. Hence $e_t = u_{1t}$, provided that identification is correct.

The factors are not necessarily observable; however, they can be consistently estimated by the principal components (Stock and Watson, 2002, Bai, 2004). Fundamentalness can be verified as follows. First, estimate a VAR with y_t and identify the shock of interest. Then collect a large macroeconomic data set – the vector x_t of equation (10) – and compute the principal components. Finally, test for orthogonality of the estimated shock with respect to the lags of the principal components. The null of fundamentalness is rejected if, and only if, orthogonality is rejected.[8]

3.2 Data set and data treatment

We use a dataset composed of 107 US quarterly macroeconomic series, covering the period 1960-I to 2010-IV. The series include both quarterly data, like national accounting data, the GDP deflator, TFP and consumers' sentiments, and monthly series, like industrial production indexes, CPI, PPI and employment. 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 Non-institutional

[8]Forni and Gambetti, 2011, propose a fundamentalness test based on Granger causality. The orthogonality test, however, is more appropriate than the Granger causality test in the present case, since we are interested in a single shock, rather than the whole vector of structural shocks. In fact, as shown in the paper above, a VAR may contain enough information to recover a shock of interest, even if the whole vector cannot be found.

Population) and stock market data have been deflated by using the GDP deflator. The consumption series refers to consumption of non durable goods and services, whereas the investment series includes consumption of durable goods.

Data are not transformed to get stationarity. The basis for this procedure is Bai, 2004, where it is shown that, under suitable conditions, the principal components are consistent estimates of the factors,[9] provided that the variables are either $I(0)$ or $I(1)$. To match this condition, 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.

3.3 Results

We apply the above testing procedure to a number of VARs used in the literature. We consider the following specifications (see also Table 1):

$S1$ - Total factor productivity adjusted for capacity utilization and real stock prices.

$S2$ - Total factor productivity not adjusted for capacity utilization and real stock prices.

$S3$ - Total factor productivity adjusted for capacity utilization, real stock prices, real consumption and hours worked.

$S4$ - Total factor productivity not adjusted for capacity utilization, real stock prices, real consumption and hours worked.

[9] More precisely, the principal components converge to a basis of the factor space.

$S5$ - Total factor productivity adjusted for capacity utilization, real output, real consumption and hours worked.

$S6$ - Total factor productivity adjusted for capacity utilization, real output, real consumption, hours worked, real stock prices, a component of the Michigan consumer sentiment index (business conditions expected for the next five years) and the inflation rate.

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 (in levels) with the same number of lags used in the original papers (see the last column of Table 1) and identify the news shock in two alternative ways. In the first identification, we assume that the news shock (i) does not move TFP on impact and (ii) has maximal impact on TFP at the 60 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 very similar to the one proposed in Barsky and Sims, 2011. Observe that, for the bivariate specifications $S1$ and $S2$, the scheme reduces to a Choleski decomposition with TFP ordered first, as in Beaudry and Portier, 2006.

In the second scheme, which is used 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 Tables 2 and 3 we report the results of the test for the first and the second identification scheme, respectively. Column j in both tables reports the p-values of the F-test of the regression of the estimated news shock on the lags of the first j first-differenced 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 test is the one obtained with the seven-variable specification $S6$ of Barsky and Sims, 2011. Comparing $S6$ and $S5$, it can be seen that the forward-looking variables stock prices, expected business conditions and the inflation rate play a crucial role in amending the information set. Below we show that non-fundamentalness, far from being a statistical detail, affects significantly the estimates of impulse responses and variance decompositions.

4 The effects of news shocks

4.1 Model specification and identification

In this section, we estimate the effects of news shocks using a FAVAR model where TFP and stock prices are assumed to be observable factors. We choose this FAVAR specification, instead of a pure latent factor model, because results will be more directly comparable with those obtained in Beaudry and Portier, 2006, and the effect of enlarging the information set will emerge more clearly.

[10]In practice, given that we work with variables in levels, we impose zero effects of all the other shocks on TFP at the 100 quarters horizon. We also estimated VECM and identified shocks following closely the original papers, obtaining similar results.

Let y_t be a sub-vector of x_t, including TFP and stock prices as in S1. Let g_{jt} be the j-th principal component of x_t and let $w_t^h = (y_t\ g_{1t}\ \cdots\ g_{ht})'$. We estimate a VAR for w_t^h, and identify the news shock by imposing that (i) it does not have a contemporaneous impact on TFP and (ii) it has a maximal effect on the level of TFP at the 60 quarters horizon. Notice that, in bivariate systems, condition (i) is sufficient to get identification, so that our criterion reduces to the Choleski scheme used in Beaudry and Portier, 2006. In larger systems, our criterion turns out to be very similar to the long-run identification in Beaudry and Portier, 2006, where the news shock is the only one having a permanent effect on TFP.

The FAVAR approach allows us to estimate also the impulse response functions of all of the x_t's as $\hat{\Lambda}\hat{B}(L)$, where the entries of $\hat{\Lambda}$ are the coefficients of the OLS projection of x_t on w_t^h (see equation (10)) and the entries of $\hat{B}(L)$ are the estimated impulse response functions of the VAR for w_t^h.

4.2 Results

The first question to be addressed is how much information has to be added to specification S1 in order to obtain a shock which passes the orthogonality test.[11] To do that, we augment S1 by one principal component at a time and repeat for each specification w_t^h, $h = 1, \dots, 9$, the orthogonality test with respect to the remaining first-differenced principal components (from the $h+1$-th to the 10-th)[12]. For each FAVAR specification we set the number of lags according to the AIC criterion under

[11]Table A1 displays the percentage of the variance of some variables of interest explained by the FAVAR S1 when the number of principal components increases.

[12]We use first-differenced principal components, as the variables on the right-hand side of the testing regression have to be stationary.

the constraint that the number of lags cannot be larger than 4. Table 4 reports the p-values of the tests. For instance, the number 0.04 in the second row is the p-value of the test that the shock estimated using S1 plus one principal component is orthogonal to the second and the third first-differenced principal components. The results is that 3 principal components must be added to obtain fundamentalness. For all specifications including three or more principal components, orthogonality is never rejected.

To get a clearer picture of how information affects the estimation of the news shock and the impulse responses, we report in Figures 1 and 2 the estimated impulse response functions of the specification S1 (solid line) and the FAVAR specifications w_t^h, $h = 1, ..., 6$. The dash-dotted lines refer to the FAVAR with 1 and 2 principal components; the solid line with circles refers to the FAVAR with 3 principal components; the dashed lines refer to FAVAR models with 4, 5 and 6 principal components.

Results change dramatically when three principal components are added. The responses of GDP, consumption, investment, hours and stock prices become much smaller. On impact, the responses of both investment and hours worked become negative. Notice that, consistently with the results of the test, the impulse response functions do not change any longer when adding further principal components.[13]

Comparing results for S1 with two principal components and S1 with three principal components, it appears that the third principal component (PC3) plays an important role in amending the information set. To gain further insight into this

[13]Results for the FAVAR specifications with 7 to 10 principal components, not reported in the figure, are similar to those of the specifications with 3 to 6 principal components.

result, we compute the (contemporaneous) correlation of PC3[14] with the variables of our data set and find a sizable correlation with expected business conditions (0.41) and the overall expected consumer confidence index (0.46), confirming what already observed above about specification S6. PC3 anticipates hours worked, since the correlation coefficients of PC3 lagged by one, two and four quarters with current hours worked are 0.77, 0.75 and 0.64, respectively. This explains the dramatic change of the impulse-response function of hours worked obtained when including PC3 in the information set.

Figures 3 and 4 report the variance decomposition of the above models. Models are denoted as in Figures 1 and 2, where dash-dotted lines refer to the FAVAR with 1 and 2 principal components; the solid line with circles refers to the FAVAR with 3 principal components; the dashed lines refer to FAVAR models with 4, 5 and 6 principal components. The percentage of the forecast error variance of GDP, consumption, investment, hours and stock prices explained by the news shock dramatically falls in all FAVAR specifications including three or more principal components. In all fundamental specifications the shock has important effects in the long run but a much smaller role at short horizons.

Now let us focus on the FAVAR with three principal component, w_t^3. For this specification we use 4 lags, following the truncated AIC criterion. Figures 5 and 6 depict the impulse response functions of selected variables to a positive news shock, together with 68% (dark gray) and 90% (light gray) confidence intervals.[15] All re-

[14]Notice that PC3 is stationary according to the ADF(k) test with $k = 0, 1, 2, 3, 4$.

[15]Confidence intervals are constructed by bootstrapping the FAVAR model, generating new observations and re-estimating the entire model.

sponses are expressed in percentage terms. TFP stays close to zero for about two years and then increases slowly, turning significantly positive after 3-4 years and reaching the long-run level after approximately 8-10 years. The response suggests an S-shape pattern in the diffusion of technology. Consumption significantly jumps on impact and remains positive at all lags. Output and investment do not react significantly in the short run, with the point estimate of investment negative, but their response become significant only after about one year, tracking the behavior of TFP. Hours worked fall significantly on impact and start increasing after about one year before reverting to the pre-shock level. Stock prices turn significantly positive after approximately 2 years and remain positive since then. The inflation rate decreases significantly. The above results are similar to those of Barsky and Sims, 2011, with the exception of the impulse-response function of TFP, which increases more slowly (see Barsky and Sims, 2011, figure 4). This is consistent with the finding that specification S6 passes the orthogonality test.

Table 5 reports the forecast error variance decompositions for the news shock. The numbers in brackets are standard deviations across bootstrap simulations. Not surprisingly, the news shock explains an important fraction of the forecast error variance of output at the 40-quarter horizon. However, in the short-run the effect is much smaller: about 4% on impact, 3%, 8% and 26% at the 1-year, 2-year and 4-year horizons, respectively. Smaller percentages are found for investment, hours worked and stock prices, whereas the reaction of consumption is larger (about 20% at the 2-year horizon and 40% at the 4-year horizon). Such numbers, albeit not negligible, are much smaller than those reported in Beaudry and Portier, 2006, figure 10, for horizons between 0 and 4 years, where the news shock is found to explain about 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. The last column of the table reports the explained variance at the business cycle frequencies.[16] The role of the shock is fairly limited for output and investment (20.6% and 16.5% of the cyclical variance, respectively) and more important for consumption (43.2%).

Figure 7 reports the impulse response functions for the surprise TFP shock. The news and the surprise shocks have very different effects on the series of interest. In particular, unlike the news shock, the surprise shock has transitory effects on all real variables, in line with Barsky and Sims, 2011. Table 6 reports the forecast error variance decompositions for the surprise TFP shock. The shock explains a large fraction of the volatility of TFP, a number ranging between 94%, at the one-year horizon, and 64%, at the ten-year horizon, while it explains only a small portion of the variance of output, consumption and investment, ranging from 14% to 30% at the 1-year and 4-year horizons. Also at the cyclical frequencies (first column) the role of the shock is very limited, explaining only 8%, 12.5% and 14% of the cyclical variance of output, investment and consumption, respectively.

While the two shocks together account for almost all the variance of TFP (more than 90% uniformly across horizons) and a substantial portion of the cyclical variance of consumption (around 57%), they fail in explaining the bulk of fluctuations in output and investment. Indeed, for these two variables, the cyclical variance ex-

[16]The variance at cyclical frequencies is obtained as the ratio of the integral of the spectrum computed using the impulse response functions of the news shock to the integral of the spectrum at frequencies corresponding to 6 to 32 quarters.

plained by the two shocks is below 30%. This leaves the door open to other shocks, unrelated to TFP, as important sources of business cycle fluctuations.

We conclude this section with a comparison between our benchmark FAVAR specification with other VAR specifications, in particular S3 and S5. Figure (8) depicts the benchmark impulse response functions along with the impulse response functions estimated with S3 and S5, for the variables included in these VAR specifications. Differences are apparent: the two VAR specifications overestimate substantially the effects of the shock. In line with the impulse response functions, the forecast error decompositions are radically different from what obtained with our specification. According to S3 and S5, the news shocks explains 90% and 93%, respectively, of the forecast error variance of consumption at the two-year horizon (as against 22% obtained with S1+3, see Table 5). According to S5 (S3 does not include output), the news shock explains 71% of the forecast error variance of output at the same horizon (as against 8% obtained with S1+3). On the other hand, when S3 and S5 are augmented with three principal components results become very similar to those obtained with S1+3.[17]

4.3 Robustness

A few robustness checks have been implicitly discussed in the previous section. Let us summarize them. First, the impulse response functions and the variance decompositions are similar for all FAVAR specifications that include at least the first three principal components. Second, results are similar for the FAVAR specifications S1+3,

[17] In S3+3 and S5+3, 3 and 4 lags are used, according to the AIC criterion.

S3+3 and S5+3.

Here, we check the robustness of the results along another dimension, which is the maximization horizon. Remind that our identification procedure requires the choice of the horizon at which the effect of news on TFP is maximal. In our benchmark specification we select 15 years; Figure (9) plots the benchmark impulse response functions and the relative confidence bands, along with the point estimate of the impulse response functions obtained using 10 and 20 years (dashed and dotted-dashed lines respectively). The results of the three alternative identifications are similar.

In a previous version of the paper we used a pure factor model instead of a FAVAR and variables were taken in first differences rather than in levels (see Forni, Gambetti and Sala, 2011). The main results were similar to those obtained here.

5 Conclusions

We use a large dimensional information set 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 standard DSGE models, including the 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 60%) 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 principal components extracted from our dataset.

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 Non-institutional 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

Variables	no. of principal components						
	0	1	2	3	4	5	6
TFP adj. [93]	100	100	100	100	100	100	100
Stock Prices [96]	100	100	100	100	100	100	100
Consumption [11]	98.4	99.6	99.6	99.7	99.7	99.7	99.7
Hours [26]	26.2	45.2	58.3	78.6	81.7	87.6	91.0
Output [5]	98.1	99.7	99.8	99.8	99.8	99.8	99.8
Investment [7]	97.7	98.5	98.7	98.9	98.9	99.0	99.0
Business Condition [104]	52.4	57.5	64.3	75.1	78.5	79.1	82.4
CPI Inflation [71]	27.3	33.1	83.2	85.5	93.1	93.5	94.5

Table A1: Percentage of the variance of the variables of interest explained by the FAVAR S1 with 0 to 6 principal components. Numbers in square brackets correspond to the series in the data appendix.

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	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 j)									
spec	lags	1	2	3	4	5	6	7	8	9	10
S1	1	0.12	0.30	0.07	0.02	0.04	0.04	0.02	0.04	0.06	0.06
	4	0.37	0.19	0.04	0.06	0.10	0.03	0.06	0.09	0.12	0.02
S2	1	0.31	0.60	0.03	0.01	0.01	0.01	0.00	0.00	0.01	0.01
	4	0.56	0.61	0.09	0.06	0.12	0.04	0.08	0.11	0.13	0.04
S3	1	0.02	0.01	0.02	0.03	0.06	0.02	0.02	0.03	0.04	0.03
	4	0.20	0.09	0.07	0.20	0.12	0.08	0.08	0.10	0.12	0.21
S4	1	0.21	0.02	0.04	0.04	0.06	0.02	0.03	0.02	0.02	0.03
	4	0.48	0.03	0.08	0.13	0.03	0.03	0.08	0.08	0.06	0.08
S5	1	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	4	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
S6	1	0.55	0.19	0.35	0.30	0.41	0.36	0.43	0.53	0.58	0.32
	4	0.43	0.24	0.53	0.52	0.49	0.72	0.58	0.66	0.72	0.72

Table 2: Results of the fundamentalness test described in Section 3. Each entry of the table reports the p-value of the F-test in a regression of the news shock estimated using specifications $S1$ to $S6$ on 1 and 4 lags of the first differences of the first j principal components, $j = 1, \ldots, 10$. 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 60.

		Principal components (from 1 to j)									
spec	lags	1	2	3	4	5	6	7	8	9	10
S1	1	0.54	0.82	0.36	0.23	0.34	0.24	0.08	0.12	0.17	0.08
	4	0.18	0.02	0.00	0.01	0.01	0.00	0.01	0.02	0.03	0.01
S2	1	0.32	0.60	0.38	0.12	0.15	0.05	0.04	0.06	0.09	0.04
	4	0.34	0.02	0.01	0.02	0.02	0.01	0.03	0.05	0.08	0.03
S3	1	0.02	0.01	0.02	0.04	0.07	0.02	0.02	0.03	0.04	0.03
	4	0.20	0.08	0.06	0.19	0.10	0.06	0.08	0.09	0.11	0.20
S4	1	0.28	0.01	0.02	0.03	0.05	0.02	0.03	0.02	0.03	0.04
	4	0.52	0.02	0.07	0.12	0.03	0.05	0.13	0.14	0.10	0.09
S5	1	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	4	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
S6	1	0.54	0.22	0.37	0.26	0.37	0.36	0.42	0.51	0.57	0.37
	4	0.25	0.15	0.41	0.37	0.35	0.58	0.48	0.54	0.60	0.60

Table 3: Results of the fundamentalness test described in Section 3. Each entry of the table reports the p-value of the F-test in a regression of the news shock estimated using specifications $S1$ to $S6$ on 1 and 4 lags of the first differences of the first j principal components, $j = 1, \ldots, 10$. The news shock is identified as the only shock with a non-zero effect on TFP in the long run.

FAVAR with	Principal components (from $h+1$ to j)									
h factors	1	2	3	4	5	6	7	8	9	10
0	0.12	0.30	0.07	0.02	0.04	0.04	0.02	0.04	0.06	0.06
1	-	0.17	0.04	0.08	0.10	0.15	0.19	0.20	0.02	0.01
2	-	-	0.79	0.96	0.96	0.97	0.79	0.47	0.16	0.04
3	-	-	-	0.49	0.46	0.56	0.65	0.52	0.60	0.69
4	-	-	-	-	0.95	0.99	0.98	0.82	0.91	0.95
5	-	-	-	-	-	0.71	0.84	0.75	0.87	0.92
6	-	-	-	-	-	-	0.76	0.40	0.59	0.74
7	-	-	-	-	-	-	-	0.10	0.26	0.43
8	-	-	-	-	-	-	-	-	0.59	0.72
9	-	-	-	-	-	-	-	-	-	0.63

Table 4: Results of the test for the number of principal components to be included in FAVAR models, described in Section 3 in specification $S1$. Each entry of the table reports the p-value of the F-test in a regression of the news shock on one lag of the first-differenced principal components from the h+1-th to j-th, $j = h+1, \ldots, 10$. The news shock is estimated from a FAVAR with h principal components; it is identified as the shock that does not move TFP on impact and has maximal effect on TFP at horizon 60.

Variables	Horizons						BC freq.
	0	4	8	16	24	40	
TFP adj. [93]	0.0 (0)	0.6 (2.2)	0.4 (2.8)	1.8 (4.6)	7.5 (8.4)	25.8 (12.2)	15.1 (8.1)
Stock Prices [96]	0.0 (13.3)	1.7 (13.1)	4.0 (13.3)	12.0 (14.2)	20.8 (14.6)	29.7 (14.6)	8.6 (11.5)
Consumption [11]	26.5 (15.9)	16.4 (13.7)	22.4 (15.0)	40.9 (18.0)	57.8 (17.2)	73.7 (14.3)	43.2 (12.8)
Hours [26]	22.1 (16.5)	3.8 (9.9)	2.5 (8.9)	5.4 (8.3)	8.1 (8.4)	8.6 (8.3)	4.8 (9.6)
Output [5]	3.7 (7.9)	2.5 (9.4)	7.7 (11.6)	25.7 (14.7)	43.0 (14.4)	60.4 (13.1)	20.6 (9.7)
Investment [7]	1.1 (5.1)	0.3 (8.1)	2.5 (9.6)	14.9 (13.3)	30.2 (14.1)	47.9 (13.8)	16.5 (9.4)
Business Condition [104]	0.2 (7.8)	2.6 (10.5)	7.5 (11.7)	17.9 (11.7)	21.3 (11.0)	22.1 (11.0)	4.4 (8.8)
CPI Inflation [71]	19.9 (15.1)	30.6 (16.0)	36.2 (15.2)	37.2 (13.7)	36.0 (13.2)	36.4 (13.1)	20.3 (11.5)

Table 5: Variance decomposition to a news shock. Columns 2-7: fraction of the variance of the forecast error at different horizon. Column 8: fraction of the variance at business cycle frequencies (between 2 and 8 years). It is obtained as the ratio of the integral of the spectrum computed using the impulse response functions of the news shock to the integral of the spectrum at frequencies corresponding to 6 to 32 quarters. Numbers in brackets are standard deviations across bootstrap simulations. Numbers in square brackets correspond to the series in the data appendix.

Variables	Horizons						BC freq.
	0	4	8	16	24	40	
TFP adj. [93]	100 (0)	88.4 (5.8)	85.9 (7.5)	83.9 (8.7)	76.8 (10.6)	60.0 (12.2)	62.0 (9.5)
Stock Prices [96]	0.0 (0.7)	1.0 (2.2)	0.7 (2.9)	3.0 (4.9)	7.6 (7.1)	15.1 (8.7)	6.8 (3.3)
Consumption [11]	45.1 (12.9)	29.5 (12.0)	28.8 (11.8)	19.2 (10.2)	13.0 (8.4)	8.5 (7.1)	14.0 (9.7)
Hours [26]	3.7 (4.8)	4.6 (4.4)	3.2 (3.9)	3.5 (4.3)	5.2 (4.7)	6.6 (4.9)	3.9 (4.2)
Output [5]	43.2 (9.8)	17.0 (8.3)	17.8 (9.1)	14.1 (8.1)	10.5 (6.7)	7.8 (6.0)	7.9 (6.8)
Investment [7]	55.1 (14.4)	24.5 (12.7)	24.3 (12.5)	19.6 (10.6)	15.5 (8.8)	12.3 (7.4)	12.5 (10.0)
Business Condition [104]	2.8 (5.1)	0.6 (3.3)	0.7 (4.0)	6.2 (6.6)	12.5 (7.8)	17.2 (8.3)	1.8 (4.4)
CPI Inflation [71]	0.0 (1.3)	0.6 (2.0)	2.6 (3.8)	10.4 (6.8)	14.4 (7.6)	16.2 (7.9)	4.3 (5.3)

Table 6: Variance decomposition to a technology shock. Columns 2-7: fraction of the variance of the forecast error at different horizon. Column 8: fraction of the variance at business cycle frequencies (between 2 and 8 years). It is obtained as the ratio of the integral of the spectrum computed using the impulse response functions of the news shock to the integral of the spectrum at frequencies corresponding to 6 to 32 quarters. Numbers in brackets are standard deviations across bootstrap simulations. Numbers in square brackets correspond to the series in the data appendix.

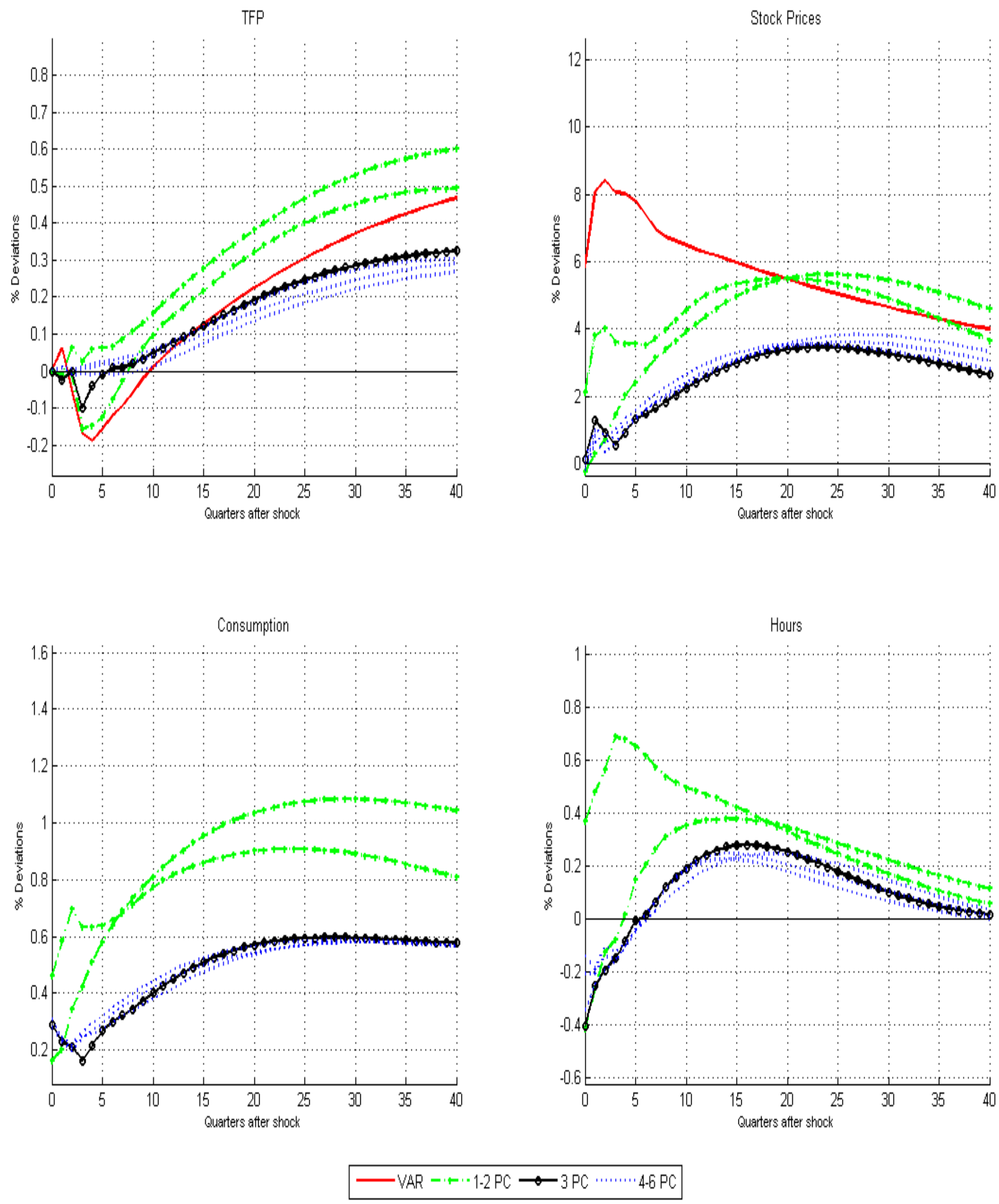

Figure 1: Impulse response functions to a news shock. Solid (only in the upper boxes): VAR, specification $S1$. Dash-dotted: FAVAR 1-2 principal components. Solid with circles: FAVAR, 3 principal components. Dashed: FAVAR, 4-6 principal components.

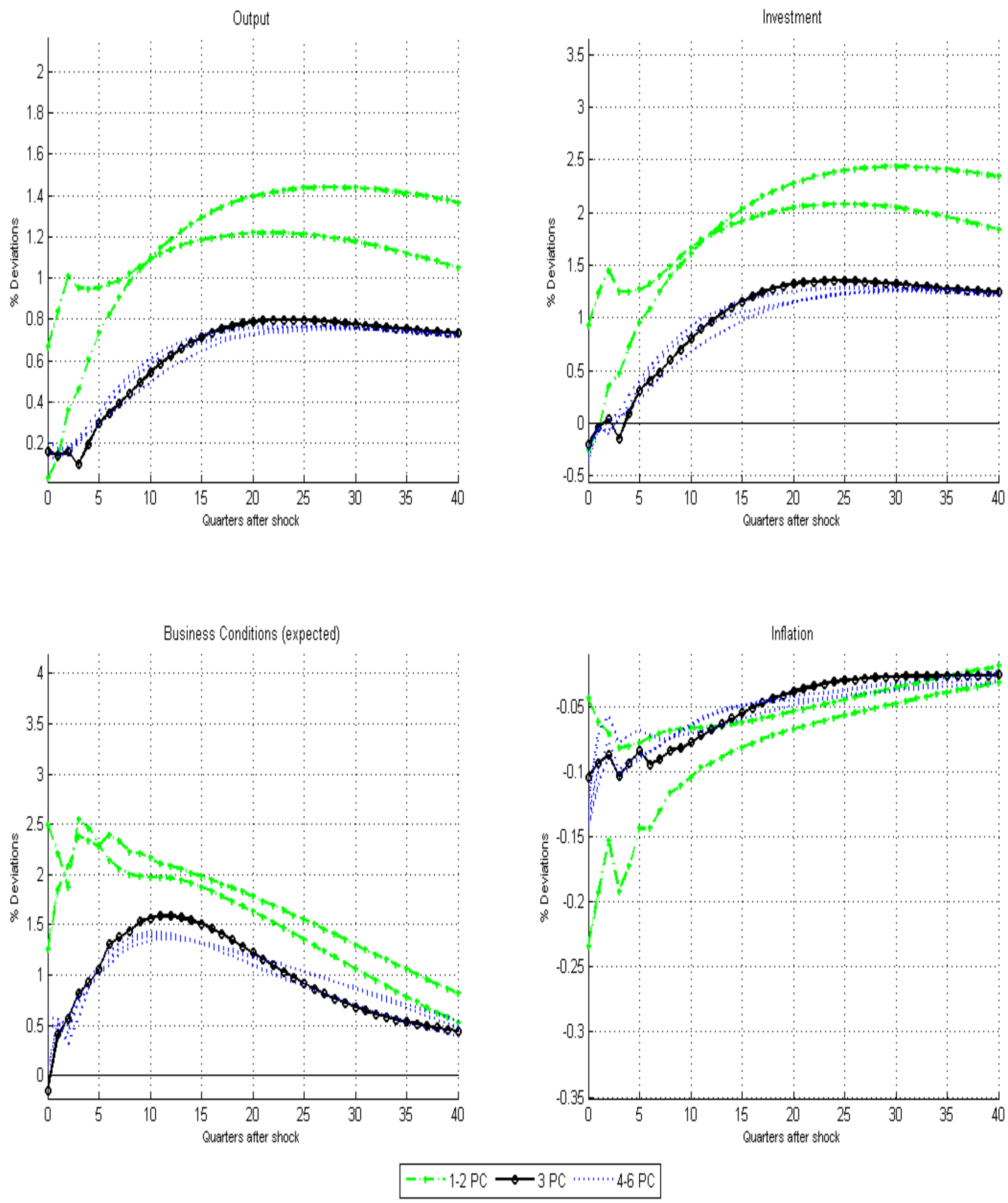

Figure 2: Impulse response functions to a news shock (continued). Dash-dotted: FAVAR 1-2 principal components. Solid with circles: FAVAR, 3 principal components. Dashed: FAVAR, 4-6 principal components.

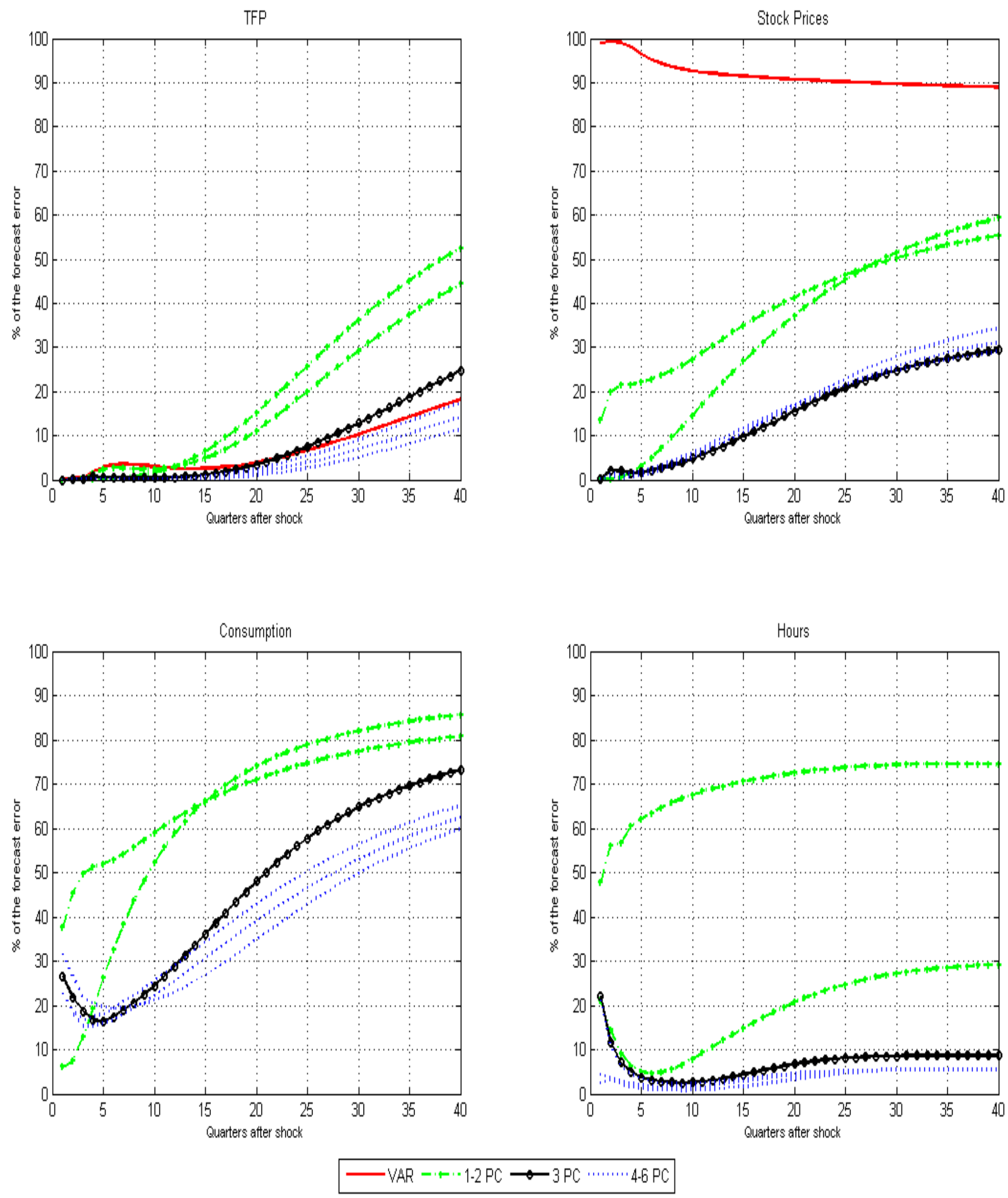

Figure 3: Variance decomposition for the news shock. Solid (only in the upper boxes): VAR, specification $S1$. Dash-dotted: FAVAR 1-2 principal components. Solid with circles: FAVAR, 3 principal components. Dashed: FAVAR, 4-6 principal components.

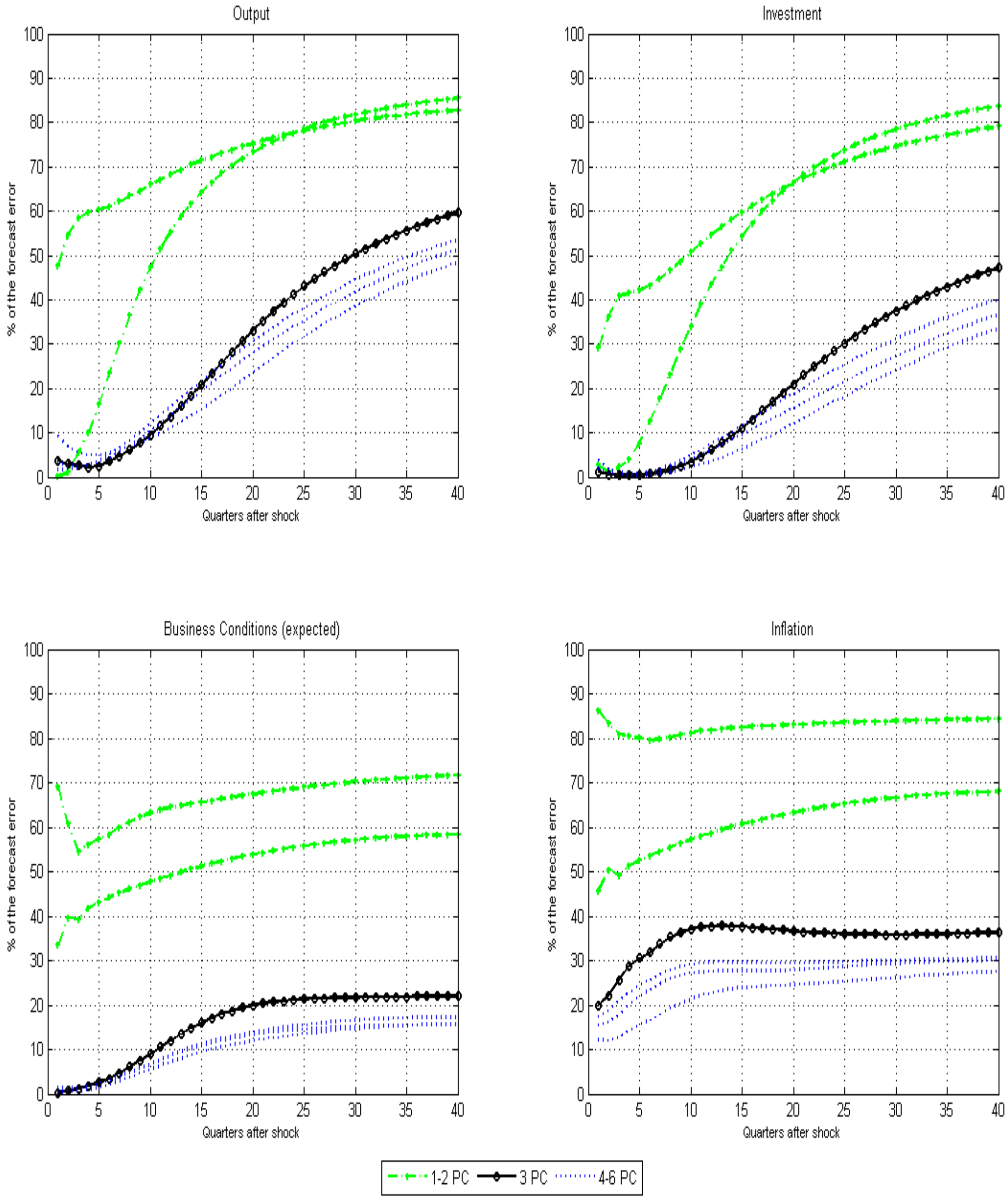

Figure 4: Variance decomposition for the news shock (continued). Dash-dotted: FAVAR 1-2 principal components. Solid with circles: FAVAR, 3 principal components. Dashed: FAVAR, 4-6 principal components.

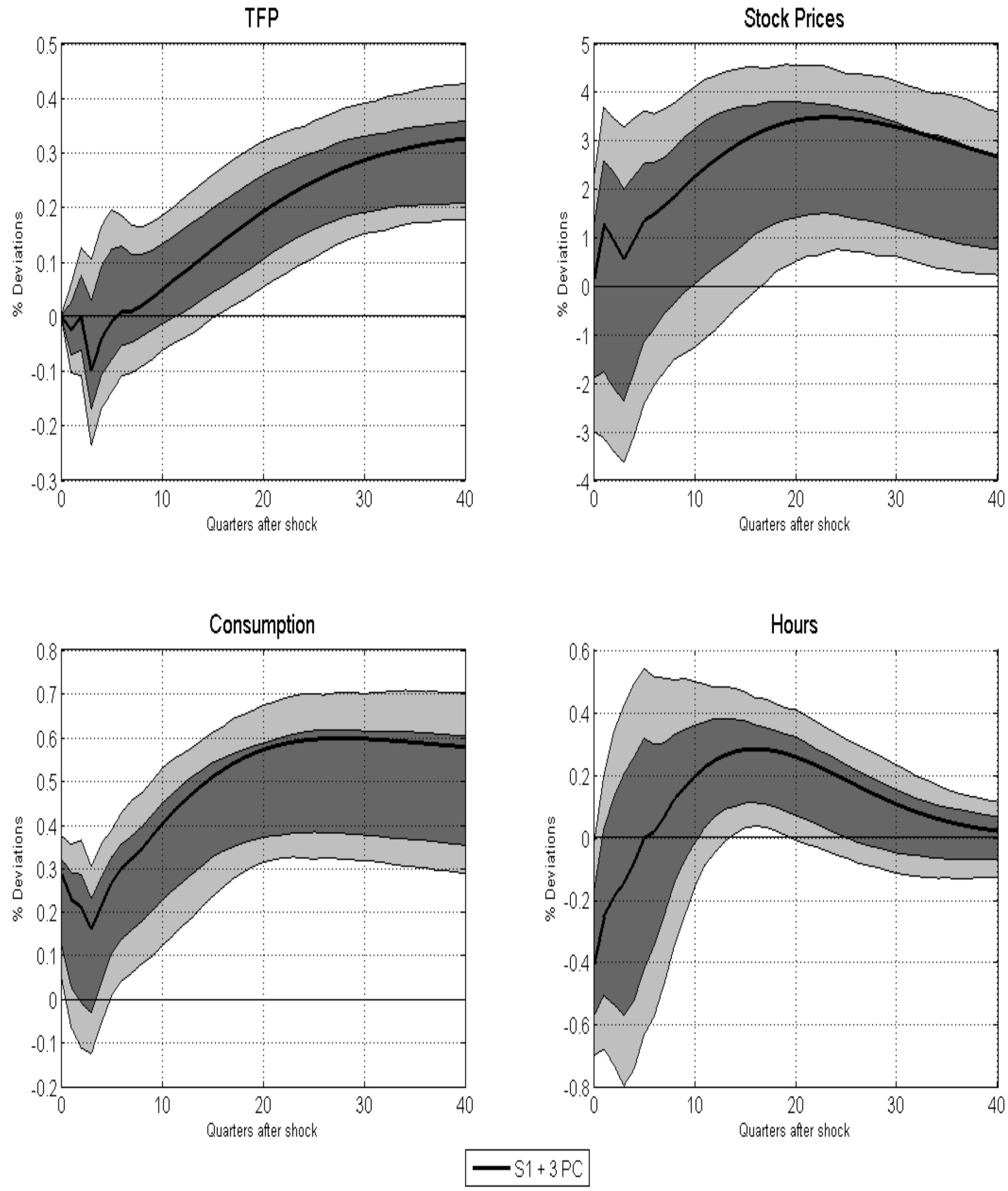

Figure 5: Impulse response functions to a news shock. Solid: FAVAR model, specification $S1$ + 3 principal components. Dark gray areas denote 68% confidence intervals. Light gray areas denote 90% confidence intervals.

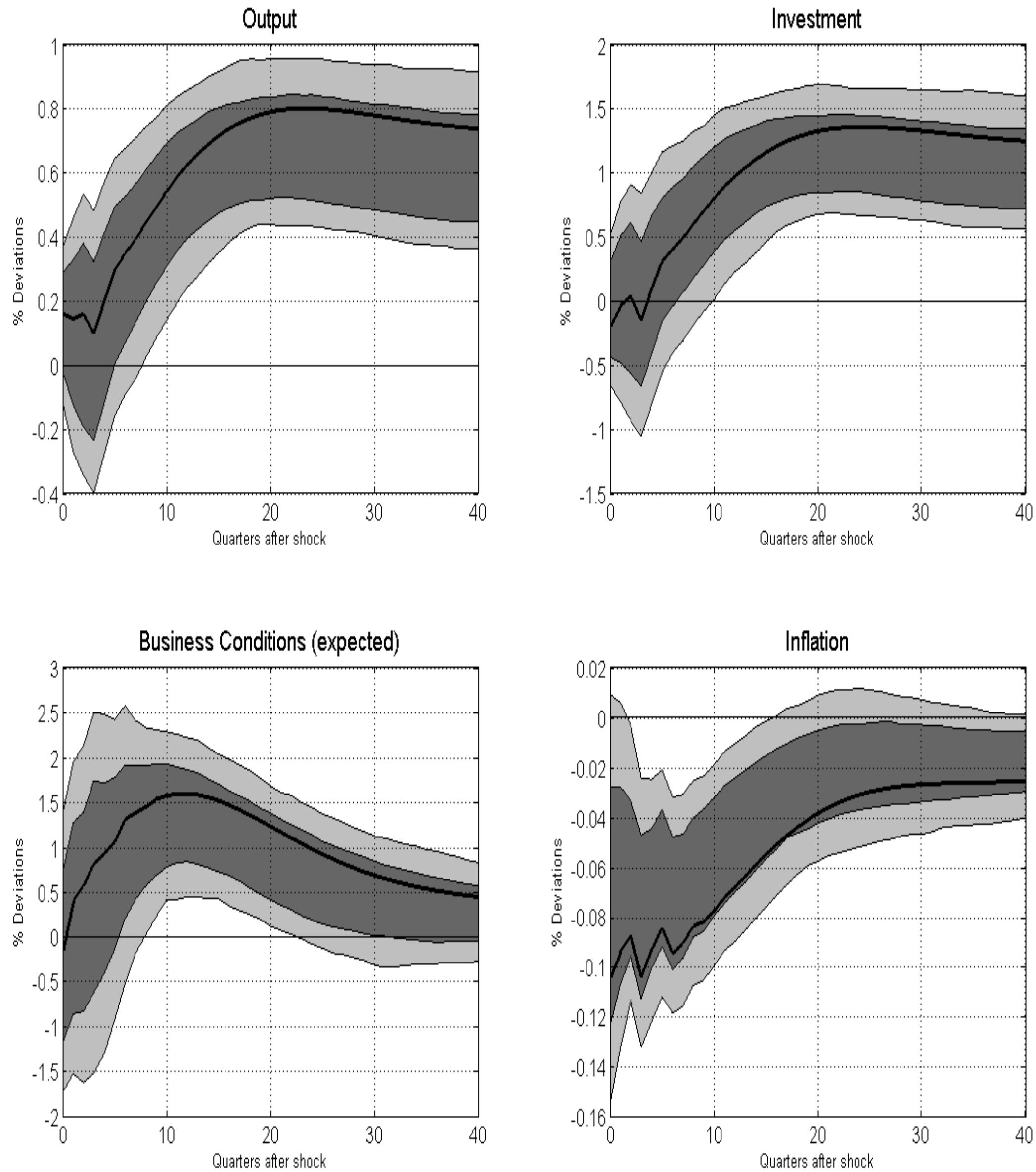

Figure 6: Impulse response functions to a news shock (continued). Solid: FAVAR model, specification $S1$ + 3 principal components. Dark gray areas denote 68% confidence intervals. Light gray areas denote 90% confidence intervals.

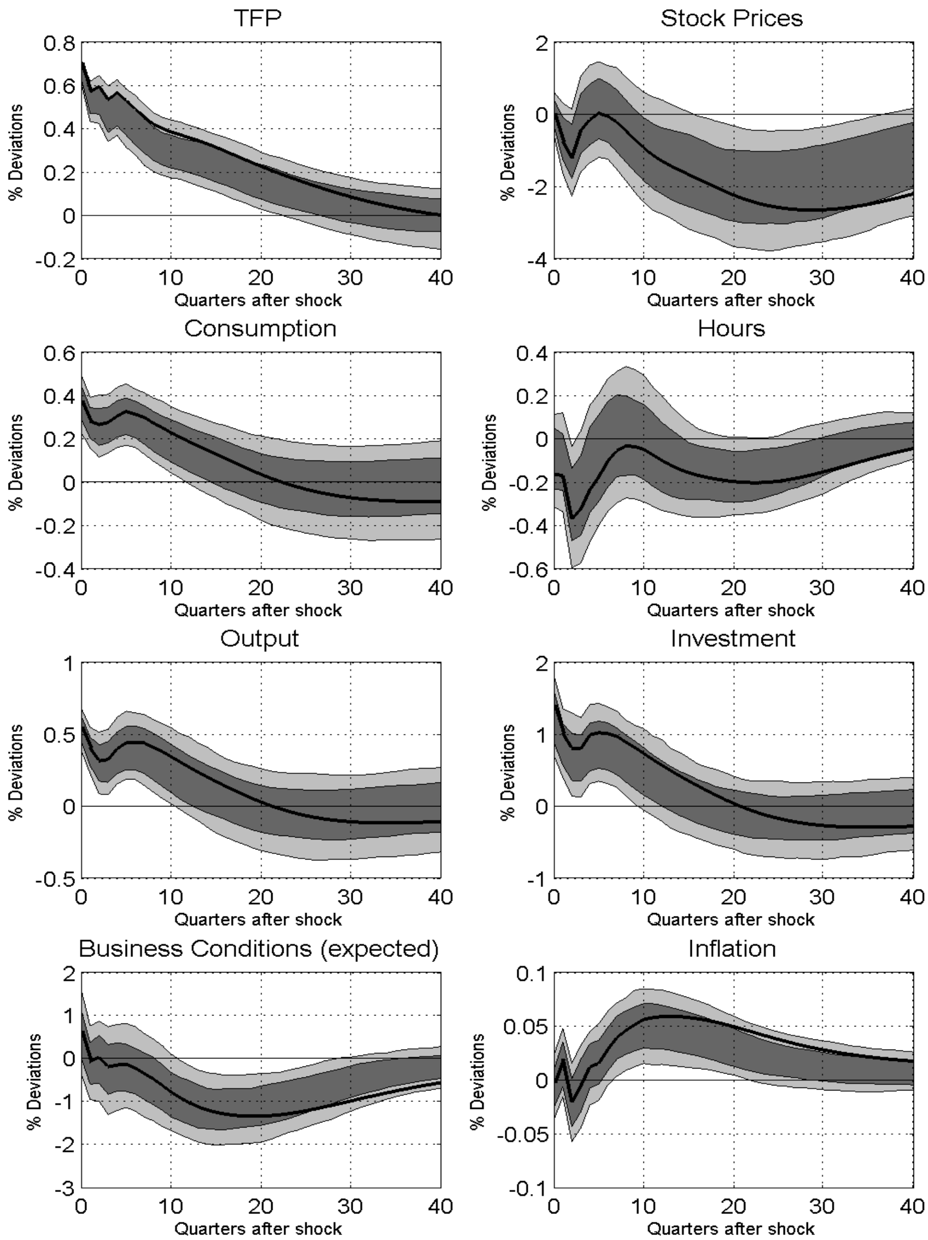

Figure 7: Impulse response functions to a surprise TFP shock. Solid: Benchmark specification S1+3. Dark gray areas denote 68% confidence intervals. Light gray areas denote 90% confidence intervals.

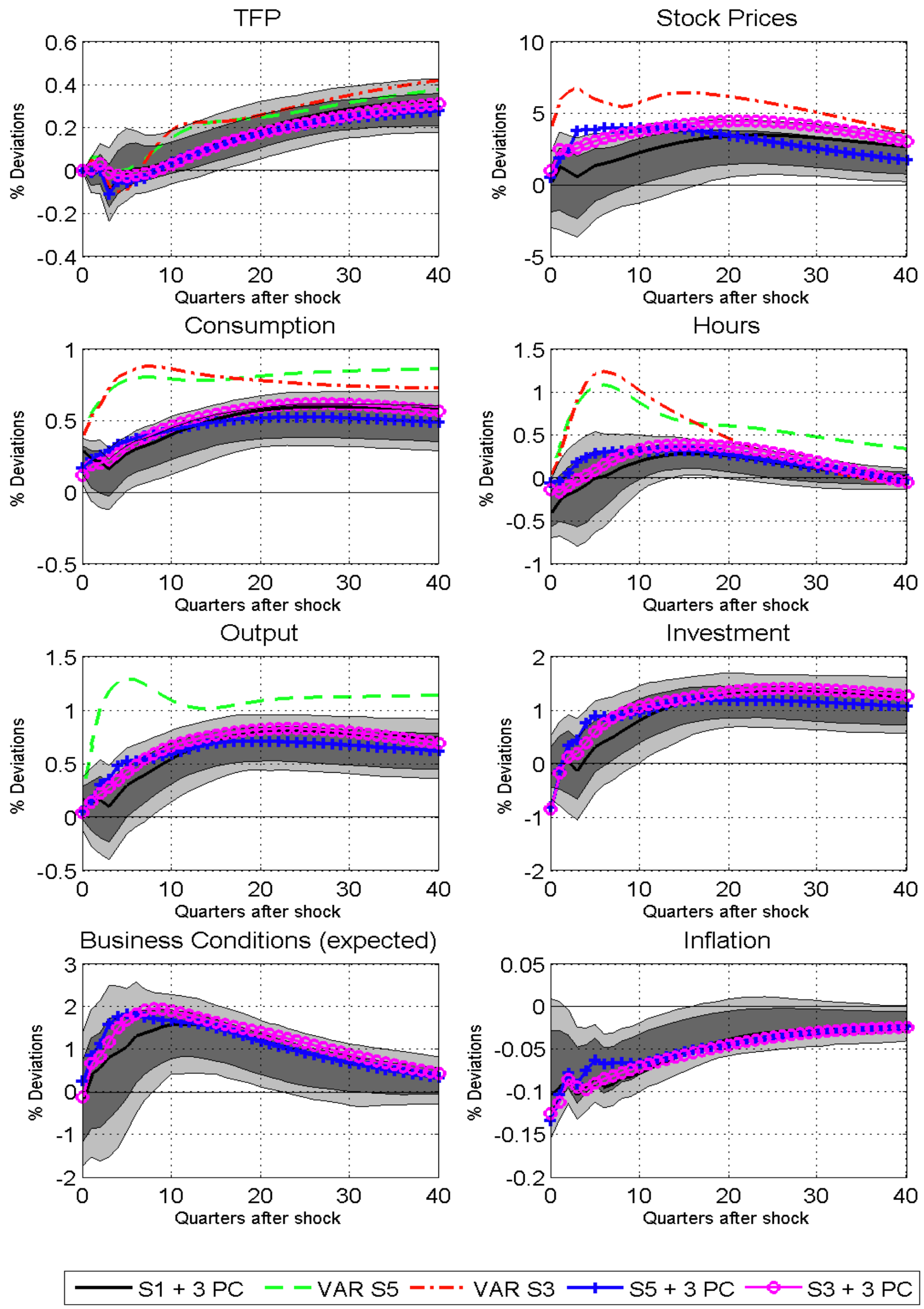

Figure 8: Impulse response functions to a news shock. Solid: Benchmark specification S1+3. Dark gray areas denote 68% confidence intervals. Light gray areas denote 90% confidence intervals. Dashed: VAR S5. Dash-Dotted: VAR S3. Solid with crosses: FAVAR specification S5+3. Solid with circles: FAVAR specification S5+3.

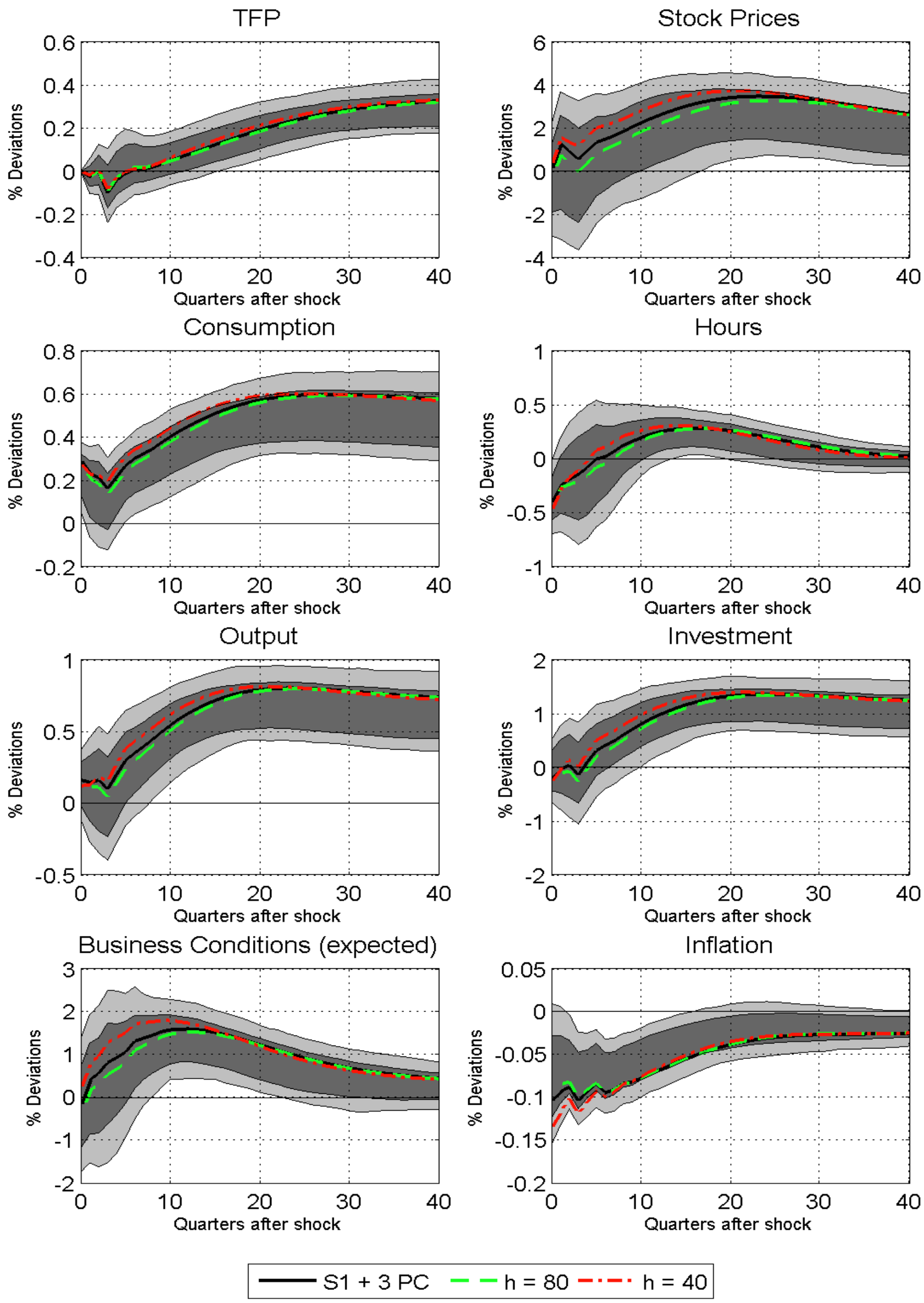

Figure 9: Impulse response functions to a news shock. Solid: Benchmark specification S1+3. Dark gray areas denote 68% confidence intervals. Light gray areas denote 90% confidence intervals. Dashed: maximization horizon 80 quarters. Dash-Dotted: maximization horizon 40 quarters.