Lecture 3: Factor models and FAVARs

Models for large cross-sections

- Here we will study models which allows us to use many economic series: FAVAR and Structural Factor Models.
- Why is information important?
- Problem of non-fundamentalness: if econometrician has less information than he cannot estimate the u_t, the structural shocks (see Hansen and Sargent, 1991, Lippi and Reichlin, 1993).

The Factor Model

Forni, Giannone, Lippi and Reichlin (Econometric Theory 2009). Let us assume

$$
\begin{aligned}
x_t &= Af_t + \xi_t, && (1) \\
D(L)f_t &= \epsilon_t && (2) \\
\epsilon_t &= Ru_t
\end{aligned}
$$

where

- x_t – a vector containing the n variables of the panel.
- Af_t – the common component.
- f_t – a vector containing $r < n$ unobserved factors.
- u_t – a vector containing $q < r$ structural macro shocks.
- R – a $r \times q$ matrix of coefficients.
- $D(L)$ – a $r \times r$ matrix of polynomials in the lag operator.
- ξ_t – a vector of n idiosyncratic components (orthogonal to the common one, poorly correlated in the cross-sectional dimension.

The Factor Model

From (1)-(2) We can derive the dynamic representation of the model (in terms of structural shocks)

$$x_t = B(L)u_t + \xi_t$$

where $B(L) = AD(L)^{-1}R$ – a $n \times q$ matrix of impulse response functions to structural shocks.

Notice that the fact that $q < r$ makes $D(L)^{-1}$ a rectangular matrix where the conditions for fundamentalness are different from the standard conditions.

Identification

- $B(L)$ is identified up to an orthogonal $(q \times q)$ matrix H (such that $HH' = I$) since $B(L)u_t = C(L)v_t$ where $B(L) = C(L)H$ and $v_t = H'u_t$.
- In this context identification consists in imposing economically-based restrictions on $B(L)$ to determine a particular H. This is the same as in VAR but restriction can be imposed on a $n \times q$ matrix of responses.
- In practice, given a matrix of nonstructural impulse response functions $C(\hat{L})$ obtained as described in the estimation one has to choose H by imposing some restrictions on $B(L)$.
- Same types of restrictions used in VAR: Cholesky, long run, signs etc.

Consistent estimator of impulse response functions

- $\hat{\Gamma}^x$ the sample variance-covariance matrix of the data. Loadings $\hat{A} = (\hat{a}_1' \hat{a}_2' \cdots \hat{a}_n')'$ is the $n \times r$ matrix having on the columns the normalized eigenvectors corresponding to the first largest $\hat{r}$ eigenvalues of $\hat{\Gamma}^x$. Factors are $\hat{f}_t = \hat{A}'(x_{1t} x_{2t} \cdots x_{nt})'$.

- VAR(p) for $\hat{f}_t$ gives $\hat{D}(L)$.

- $\hat{\Gamma}^\epsilon$ the sample variance-covariance matrix of $\hat{\epsilon}_t$ $\hat{\mu}_j^\epsilon$ eigenvalue. $\hat{\mathcal{M}}$ the $q \times q$ diagonal matrix with $\sqrt{\hat{\mu}_j^\epsilon}$ as its (j, j) entry, $\hat{K}$ the $r \times q$ matrix with the corresponding normalized eigenvectors on the columns.
$$\hat{C}(L) = \hat{A}\hat{D}(L)^{-1}\hat{K}\hat{\mathcal{M}}. \tag{4}$$

- Finally, $\hat{H}$ and $\hat{b}_i(L) = \hat{c}_i(L)\hat{H}$ $i = 1, \ldots, n$ are obtained by imposing the identification restrictions on
$$\hat{B}(L) = \hat{C}(L)\hat{H}. \tag{5}$$

Inference

Confidence bands are obtained by a standard non-overlapping block bootstrap technique.

- Let $X = [x_{it}]$ be the $T \times n$ matrix of data. Such matrix is partitioned into S sub-matrices X_s (blocks), $s = 1, \ldots, S$, of dimension $\tau \times n$, τ being the integer part of T/S.

- An integer h_s between 1 and S is drawn randomly with reintroduction S times to obtain the sequence $h_1, \ldots, h_S$.

- A new artificial sample of dimension $\tau S \times n$ is then generated as $X^* = \left[X'_{h_1} X'_{h_2} \cdots X'_{h_S}\right]'$ and the corresponding impulse response functions are estimated.

- A distribution of impulse response functions is obtained by repeating drawing and estimation.

Determination of the number of factors

There are criteria available for the determination of the number of both static and dynamic factors.

- **# of static factors** r Bai and Ng (2002) proposes consistent criteria. The most common one is the $IC_{p2}(r)$. r should be chosen in order to minimize

$$IC_{p2}(r) = \ln V(r, \hat{f}_t) + r\left(\frac{n+T}{nT}\right)\ln\left(Min(n,T)\right)$$

where $V(r, \hat{f}_t)$ is the sum of residuals (divided by (nT)) from the regression of x_i on the r factors for all i,

$$V(r, \hat{f}_t) = \min_A \sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it} - A_i^r f_t^r)^2$$

- **# of dynamic factors** q
  - Bai and Ng (2007) based on the rank of the residual covariance matrix.
  - Amengual and Watson (2008). Regress x on $\hat{f}_t$ and apply Bai and Ng (2002) to the new obtained residuals to study the number of dynamic factors.

Monetary policy and exchange rates, Forni and Gambetti (2010, JME)

- Motivation: standard theory of monetary policy predicts that after a contractionary policy shock:
  - Prices fall
  - The real exchange rate immediately appreciates and then depreciates (overshooting theory)
- With VAR puzzling results:
  - Prices increase (price puzzle)
  - The real exchange rate appreciates with a long delay (delayed overshooting puzzle)
- Here: we study the effects of monetary policy shocks within a SFM.
- Why: information could be the key.
- Main result: both of them solved IRF behave like theory predicts.

Monetary policy and exchange rates, Forni and Gambetti (2010, JME)

- Data: 112 US monthly series from March 1973 to November 2007. Most series are those of the Stock-Watson, we added a few real exchange rates and short-term interest rate spreads between US and some foreign countries.
- The monetary policy shock is identified by the following assumptions:
  1. the monetary policy shock is orthogonal to all other structural shocks,
  2. the monetary policy shock has no contemporaneous effect on prices and output (Cholesky scheme).

Monetary policy and exchange rates, Forni and Gambetti (2010, JME)

Table 1: Variance decomposition SVAR (*)

	k=0	k=6	k=12	k=48
Ind. production	0 (0)	0.0361 (0.0634)	0.1129 (0.1388)	0.3062 (0.1737)
CPI	0 (0)	0.0483 (0.0300)	0.0461 (0.0364)	0.0170 (0.0358)
Federal funds rate	0.9209 (0.0205)	0.5435 (0.0182)	0.3996 (0.0208)	0.1854 (0.0322)
Swi/US real ER	0.0275 0.0313	0.0685 (0.0420)	0.0923 (0.0497)	0.1434 (0.0607)

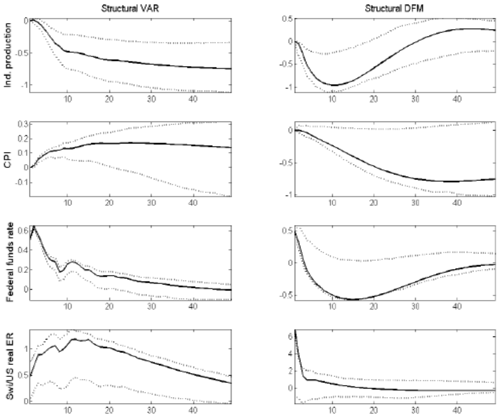
(*) Months after the shocks on the columns.

Table 2: Variance decomposition SDFM (*)

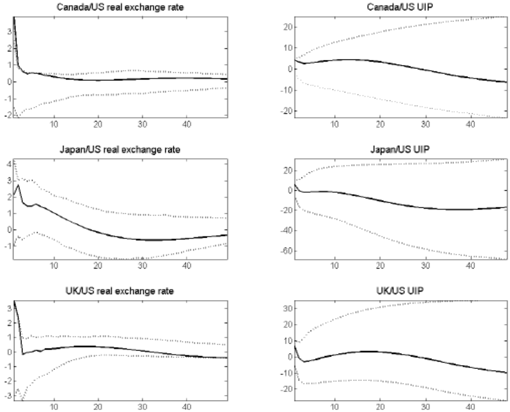
	k=0	k=6	k=12	k=48
Ind. production	0 (0)	0.0657 (0.0465)	0.1299 (0.0674)	0.1346 (0.0710)
CPI	0 (0)	0.0057 (0.0243)	0.0333 (0.0608)	0.1634 (0.1679)
Federal funds rate	0.5345 (0.2335)	0.1463 (0.2036)	0.1986 (0.1676)	0.2989 (0.1575)
Swi/US real ER	0.5227 (0.2704)	0.4330 (0.2123)	0.4041 (0.2028)	0.3836 (0.1666)
Can/US real ER	0.7541 (0.2605)	0.3474 (0.1825)	0.2523 (0.1794)	0.1643 (0.1580)
Jap/US real ER	0.1885 (0.2897)	0.2371 (0.2101)	0.2092 (0.2013)	0.1746 (0.1765)
UK/US real ER	0.2313 (0.2165)	0.1463 (0.1841)	0.1227 (0.1795)	0.1200 (0.1543)

(*) Months after the shocks on the columns.

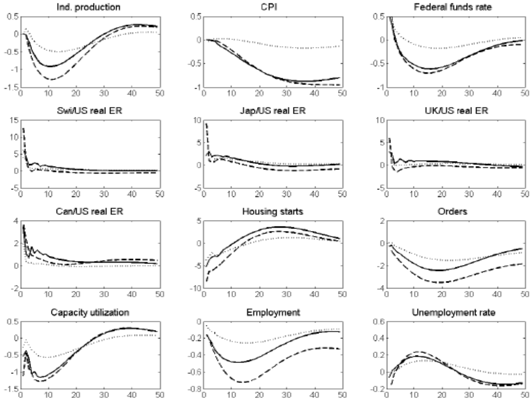
Monetary policy and exchange rates, Forni and Gambetti (2010, JME)



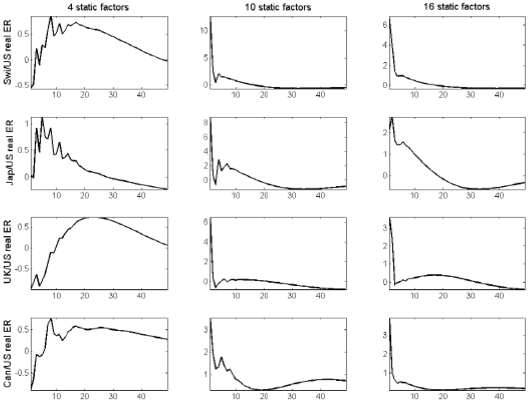
Monetary policy and exchange rates, Forni and Gambetti (2010, JME)



Monetary policy and exchange rates, Forni and Gambetti (2010, JME)



Monetary policy and exchange rates, Forni and Gambetti (2010, JME)



FAVAR

- Similar to factor models.
- Two main differences:
  1. Same number of dynamic and static factors $q = r$.
  2. Possibility of including observed factors in the VAR for the factors.

FAVAR and Monetary policy shocks - BBE (QJE 2005)

- ...remember the price puzzle?
- Bernanke Boivin and Eliasz (2002) use a FAVAR model to study the effects of a monetary policy shock.
- x_t consists of a panel of 120 monthly macroeconomic time series. The data span from January 1959 through August 2001.
- The federal funds rate is the only observable factor.
- The model is estimated with 13 lags.
- 3 and 5 unobservable factors are used.
- Identification of the monetary policy shock similar to CEE

FAVAR and Monetary policy shocks - BBE (QJE 2005)

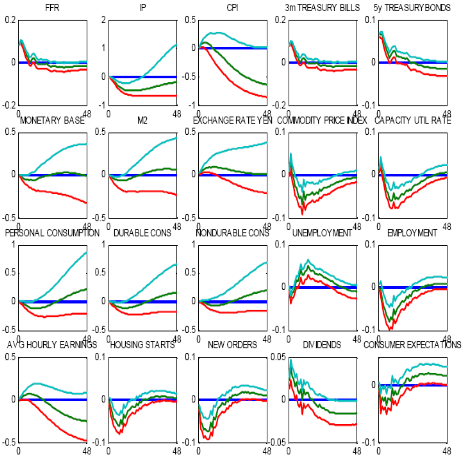


Figure 1. Impulse responses generated from FAVAR with 3 factors and FFR estimated by principal components with 2 step bootstrap.

FAVAR and Monetary policy shocks - BBE (QJE 2005)

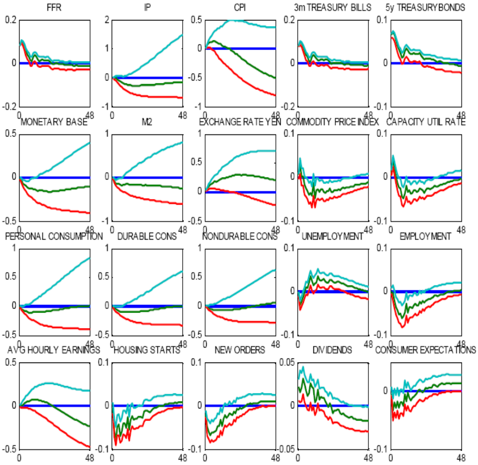


Figure 3. Impulse responses generated from FAVAR with 5 factors and FFR estimated by principal components with 2 step bootstrap.

FAVAR and Monetary policy shocks - BBE (QJE 2005)

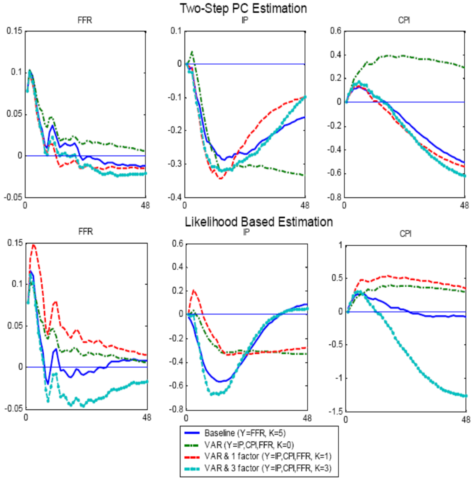


Figure 5. VAR – FAVAR comparison. The top panel displays estimated responses for the two-step principal component estimation and the bottom panel for the likelihood based estimation.

FAVAR and Monetary policy shocks - BBE (QJE 2005)

Table 1. Contribution of the policy shock to variance of the common component

Variables	Variance Decomposition	R^2
Federal funds rate	0.4538	*1.0000
Industrial production	0.0763	0.7074
Consumer price index	0.0441	0.8699
3-month treasury bill	0.4440	0.9751
5-year bond	0.4354	0.9250
Monetary Base	0.0500	0.1039
M2	0.1035	0.0518
Exchange rate (Yen/$)	0.2816	0.0252
Commodity price Index	0.0750	0.6518
Capacity utilization	0.1328	0.7533
Personal consumption	0.0535	0.1076
Durable consumption	0.0850	0.0616
Non-durable cons.	0.0327	0.0621
Unemployment	0.1263	0.8168
Employment	0.0934	0.7073
Aver. Hourly Earnings	0.0965	0.0721
Housing Starts	0.0816	0.3872
New Orders	0.1291	0.6236
S&P dividend yield	0.1136	0.5486
Consumer Expectations	0.0514	0.7005

The column entitled "Variance Decomposition" reports the fraction of the variance of the forecast error of the common component, at the 60-month horizon, explained by the policy shock. "R^2" refers to the fraction of the variance of the variable explained by the common factors, $(\hat{F}_t, Y_t)$. See text for details.

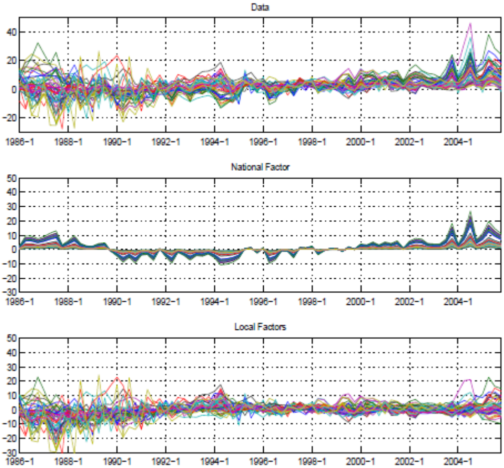
*This is by construction.

99 Luftballoons Del Negro and Otrok (JME 2007)

- Importance of common and local components for house prices in the US.
- Use a factor model to disentangle the two components.
- Data on house prices for 48 US states 1986-2005.
- Study the role of monetary policy for house prices fluctuations.
- Main results
  - fluctuations house prices mainly driven by the local component.
  - period 2001-2005 increase in house prices is a national phenomenon
  - effects of policy shocks on house prices are small.

99 Luftballoons Del Negro and Otrok (JME 2007)

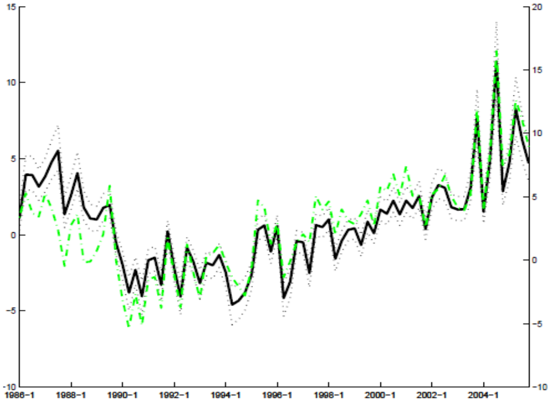
Figure 2: STATE-LEVEL REAL HOUSE PRICE GROWTH: NATIONAL AND LOCAL FACTORS



Source: 99 Luftballons: Monetary Policy and the House Price Boom Across U.S. States Del Negro and Otrok, JME 2007.

99 Luftballoons Del Negro and Otrok (JME 2007)

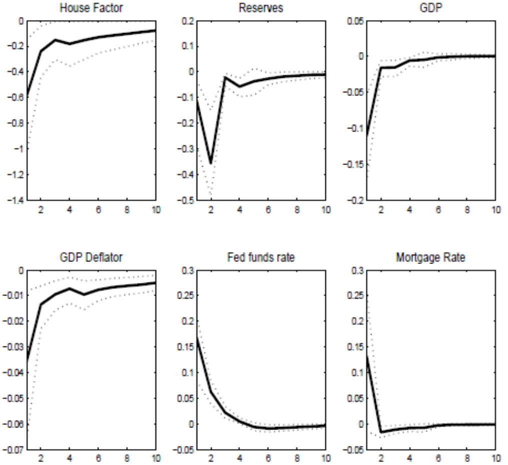
Figure 4: The National House Price Factor and the U.S. OFHEO House Price Index



Notes: The figure plots the national housing factor f_t^0 (black, scale on the left axis), the ninety percent bands (dotted lines), as well as the OFHEO U.S. price index (gray, right axis). f_t^0 is the median posterior estimate of the factor from equation (1).

Source: 99 Luftballons: Monetary Policy and the House Price Boom Across U.S. States Del Negro and Otrok, JME 2007.

99 Luftballoons Del Negro and Otrok (JME 2007)

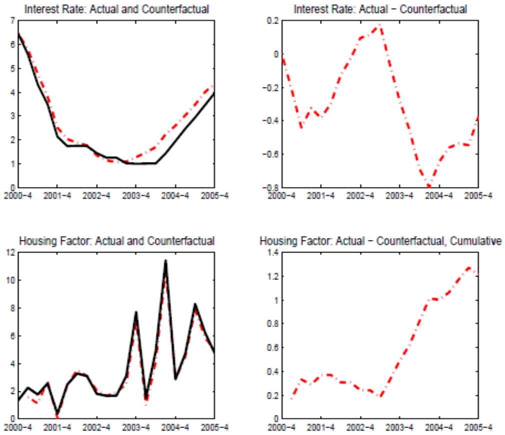


Notes: The figure displays the impulse response function of all of the variables to the monetary policy shock, along with the 68 percent posterior coverage intervals. The VAR is estimated with quarterly data from QI-2006 to QIV-2005.

Source: 99 Luftballons: Monetary Policy and the House Price Boom Across U.S. States Del Negro and Otrok, JME 2007.

99 Luftballoons Del Negro and Otrok (JME 2007)

Figure 6: Actual and Counterfactual Interest Rate and Housing Factor



Notes: The figure shows the actual (solid line) and the counterfactual (dash-and-dotted line) paths for the Fed Funds rate and the housing factor. The counterfactual paths are obtained by shutting down monetary policy shocks from QI-2001 to the end of the sample.

Source: 99 Luftballons: Monetary Policy and the House Price Boom Across U.S. States Del Negro and Otrok, JME 2007.

Credit Shocks Boivin, Giannone and Stevanovic 2013

- The paper studies the effects of credit shocks, unexpected deteriorations of credit market conditions.
- Use a FAVAR model.
- Main results
  - increase credit spreads
  - persistent reduction in economic activity
  - effects are quantitatively important.
- 124 monthly economic/financial time series 1959-2009.
- the shock:
  - No impact effects on inflation, unemployment and the federal funds rate
  - impact effects on the credit spread: the difference between BAA bond yields and Treasury bond yields.

Credit Shocks Boivin, Giannone and Stevanovic 2013

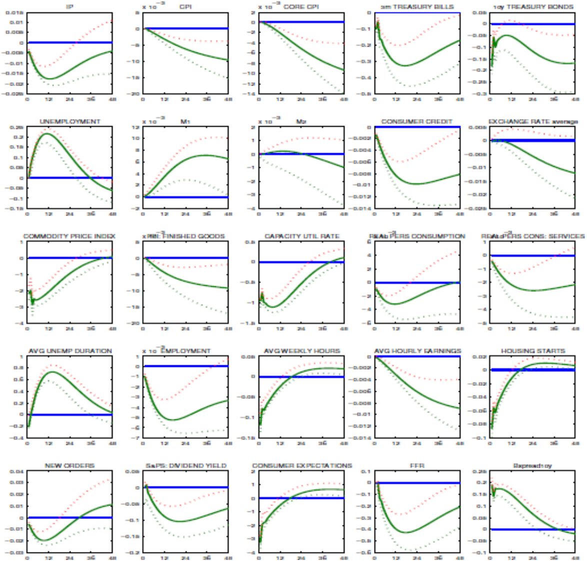


Figure 2: Dynamic responses of monthly variables to credit shock in FAVAR 1

Credit Shocks Boivin, Giannone and Stevanovic 2013

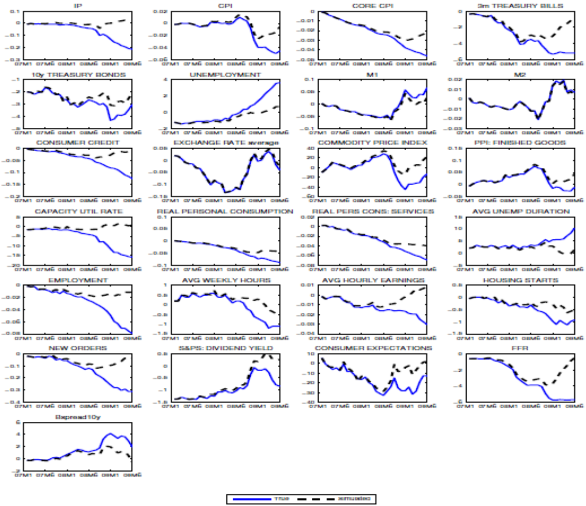


Figure 4: Simulated monthly data without credit shocks from FAVAR 1

Notes: The figure plots the actual and simulated series of interest from 2007M1 to 2009M6, the date at which the recession officially ended. The data are simulated from the structural factor representation excluding the credit shock.

Credit Shocks Boivin, Giannone and Stevanovic 2013

Table 2: Variance decomposition and R^2 in FAVAR 1

Variables	Variance decomposition	R^2
Industrial production	0.5289	0.7140
CPI: total	0.0591	0.7966
CPI: core	0.1223	0.6123
T-Bill: 3-month	0.1509	0.8839
T-Bond: 5-year	0.1144	0.9132
Unemployment rate	0.2615	0.7089
M1	0.1418	0.0919
M2	0.0308	0.1149
Consumer credit	0.6492	0.1778
Exchange rate: average	0.0326	0.0530
Commodity price index	0.3135	0.5214
PPI: finished goods	0.0424	0.5949
Capacity utilization rate	0.7469	0.7476
Real Pers. Cons.	0.2360	0.1401
Real Pers. Cons.: services	0.2343	0.1283
Avg. unemployment duration	0.4248	0.7597
Employment	0.5946	0.2879
Avg weekly hours	0.4948	0.3819
Avg hourly earnings	0.3949	0.2164
Housing starts	0.6002	0.4676
New orders	0.4452	0.2473
S&P's CCS: dividend yield	0.1605	0.7529
Consumer expectations	0.3188	0.5338
FFR	0.1347	0.8957
B-spread: 10y	0.7727	0.6574

Notes: The second column reports for key macroeconomic series, $x_{i,t}$, the contribution of the credit shock to the variance of the forecast error of the respective series at a 48-month horizon. The third column contains the fraction of the variability of this series explained by the common factors, i.e., the R^2 obtained from the regression of $x_{i,t}$ on $\lambda_i' F_t$ for each indicator i, where λ_i' denotes the i-th row of matrix Λ in equation (??).

No news in business cycle, Forni, Gambetti and Sala (2011)

- Motivation: news shocks can give raise to nonfundamentalness (recall example at the beginning).
- VAR models like Beaudry and Portier AER can have an hard time in estimating news shocks.
- Here:
  - Test whether the news shock is fundamental for TFP and stock prices, i.e. are fundamental for the variable in BP.
  - Estimate the shocks using a FAVAR model.

Testing for fundamentalness

Use the Forni and Gambetti (2011) orthogonality test:

1. estimate a VAR with a given set of variables y_t and identify the relevant shock, w_t;
2. test for orthogonality of w_t with respect to the lags of the factors (F-test);
3. the null of fundamentalness is rejected if and only if orthogonality is rejected.

The factors are not observed and we estimate them using the principal components of a dataset composed of 107 US quarterly macroeconomic series, covering the period 1960-I to 2010-IV.

Testing for fundamentalness

We consider the following VAR specifications.

2-variable VAR							
S1	TFP adj.	Stock P					
S2	TFP	Stock P					
4-variable VAR							
S3	TFP adj.	Stock P	Cons	Hours			
S4	TFP	Stock P	Cons	Hours			
S5	TFP adj.	Output	Cons	Hours			
7-variable VAR							
S6	TFP adj.	Stock P	Output	Cons	Hours	Confidence	Inflation

Testing for fundamentalness

- We apply the Forni and Gambetti test.
- For each specification we use two identifications of the news shock:
  - The news shock is the shock that does not move TFP on impact and (for specifications from $S3$ to $S6$) has maximal effect on TFP at horizon 40.
  - The news shock is identified is the only shock with a non-zero effect on TFP in the long run.

Results of the test: Identification 1

		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

Results of the fundamentalness test. 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.

Results of the test: Identification 2

		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

Results of the fundamentalness test. 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.

Identifying news shocks

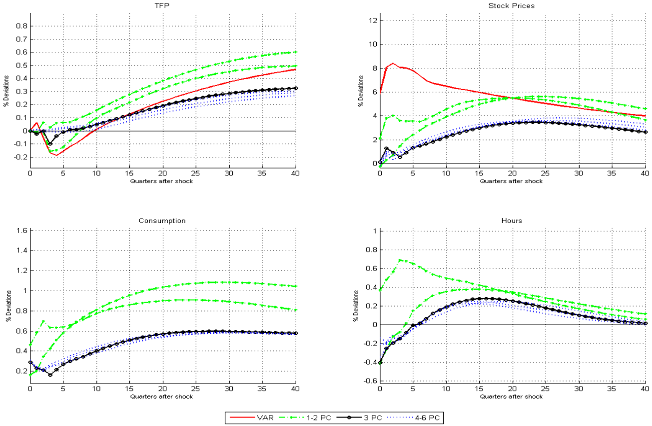
- We study the effects of news shocks with a FAVAR model.
- As in Beaudry and Portier (2006) stock prices and TFP are treated as observable factors.
- The news shock is identified by assuming that
  1. does not have a contemporaneous impact on TFP;
  2. has a maximal effect on the level of TFP at the 60-quarter horizon.
- We also identify a standard technology shock by assuming that
  1. is the only shock that affects TFP on impact.

How many factors?

FAVAR with h factors	Principal components (from $h+1$ to j) 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

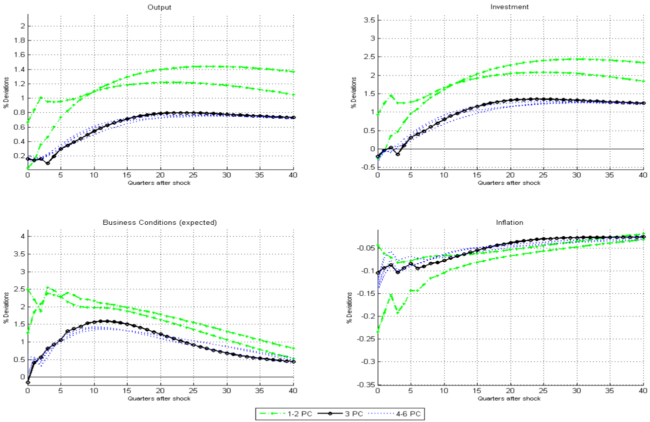
Results of the test for the number of principal components to be included in FAVAR models in specification $S1$. Each entry of the table reports the p-value of the F-test in a regression of the news shock on two lags of the principal components from the $h+1$-th to j-th, $j = h+1, \ldots, 10$. The news 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.

The effects of enlarging the information set



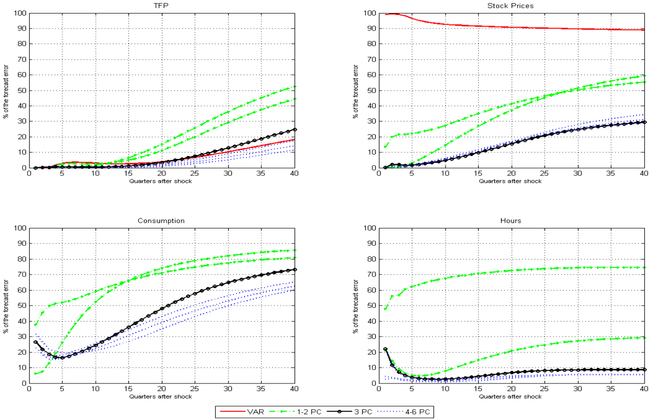
Impulse response functions to a news shock. Solid (only in the upper boxes): VAR, specification $S1$. Dash-dotted: FAVAR 1-2 principal components. Solid with circles: FAVAR, 3 principal components. Dashed: FAVAR, 4-6 principal components.

The effects of enlarging the information set



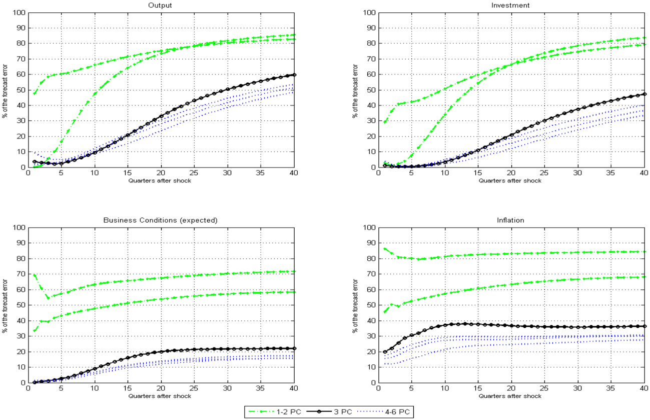
Impulse response functions to a news shock (continued). Dash-dotted: FAVAR 1-2 principal components. Solid with circles: FAVAR, 3 principal components. Dashed: FAVAR, 4-6 principal components.

The effects of enlarging the information set



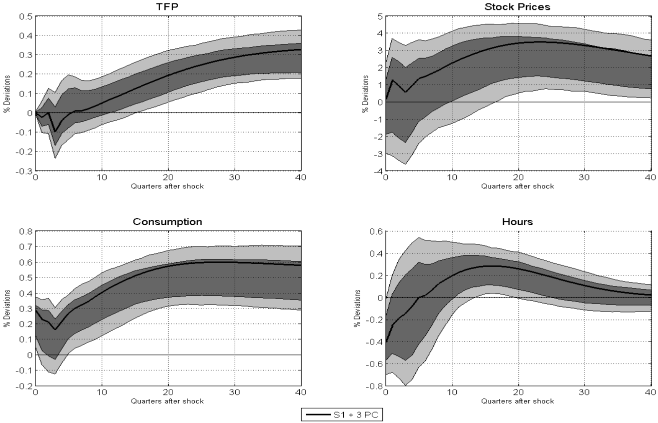
Variance decomposition for the news shock. Solid (only in the upper boxes): VAR, specification $S1$. Dash-dotted: FAVAR 1-2 principal components. Solid with circles: FAVAR, 3 principal components. Dashed: FAVAR, 4-6 principal components.

The effects of enlarging the information set



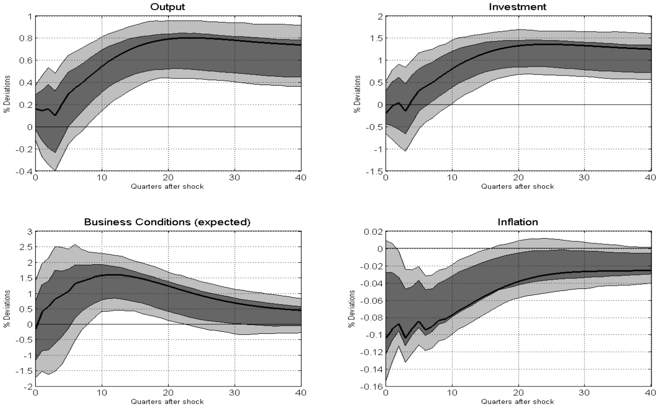
Variance decomposition for the news shock. Dash-dotted: FAVAR 1-2 principal components. Solid with circles: FAVAR, 3 principal components. Dashed: FAVAR, 4-6 principal components.

The effects of news shocks



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.

The effects of news shocks



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.

Variance decomposition

Variables	Horizons						BC freq.
	0	4	8	16	24	40	
TFP adj. [93]	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)

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.