News Shocks: Different Effects in Boom and Recession?

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Introduction

'News' is defined in the literature as exogenous changes in the information sets that economic agents use to form their perceptions regarding future economic activity.

The news-driven business cycle hypothesis assumes that business cycles can arise because of changes in expectations of future fundamentals.

Research question

Are the effects of news about future productivity state-dependent?

We take an empirical approach to test whether the reactions to a news shock are state-dependent and/or asymmetric.

In this paper we...

... estimate a logistic smooth transition VAR model.

... identify the news shock with a medium-run identification scheme.

... use generalized impulse responses to analyze the effect of a news shock in different states of the economy.

... use generalized forecast error variance decomposition to estimate the contribution of the news shock to the forecast error variance of the variables.

Related empirical news literature

Short-run restrictions: Beaudry and Portier (AER, 2006)

Medium-run restrictions: Barsky and Sims (JME, 2011), Beaudry and Portier (JEL, 2014)

Non-fundamentalness: Sims (AE, 2012), Forni and Gambetti (JME, 2014)

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Contributions

Main contribution:

- Analysis of the state-dependent and asymmetric effects of news shocks.

Methodological contributions:

- Estimation of different smooth transition processes - in the mean and the variance equation, respectively.
- Application of the maximum forecast error variance identification method in a nonlinear model.
- Comparison of short-run and medium-run identification methods in a nonlinear setting.

Main results

The effect of the news shock is...

- qualitatively independent of the state of the economy.
- quantitatively different in expansions and recessions.
- not significantly asymmetric (sign/magnitude).
- affecting the probability of regime transition (e.g. escaping a recession).

Data

In our model we include:

- Total Factor Productivity: adjusted for factor utilization (Basu, Fernald and Kimball (2006)) (logged)
- Measure of consumer confidence: Index of Consumer Sentiment from the Michigan Survey of Consumers
- Output: GDP nonfarm (logged, real, per capita)
- Inflation Rate: annualized log-difference of the GDP price deflator nonfarm
- Stock Prices: S&P 500 (logged, real, per capita)

We estimate the model using quarterly data for the US for the sample period 1955Q1-2012Q4 with four lags.

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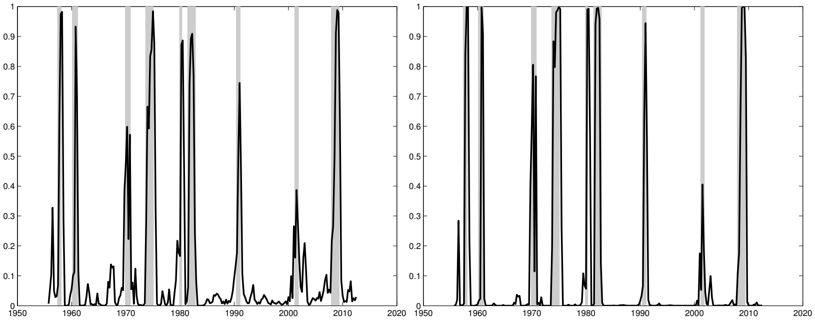
Logistic transition function

$$F_i(s_t) = \frac{exp(-\gamma_i(s_t - c_i))}{1 + exp(-\gamma_i(s_t - c_i))}, \ \gamma_i > 0, \ \text{for } i = M, V$$

Estimation results:
$\hat{\gamma}_M = 3.00, \ \hat{c}_M = -0.61; \ \hat{\gamma}_V = 6.31, \ \hat{c}_V = -0.52$

Transition functions



Left: F_M ($\hat{\gamma}_M = 3.00$, $\hat{c}_M = -0.61$), Right: F_V ($\hat{\gamma}_V = 6.31$, $\hat{c}_V = -0.52$)

Logistic smooth transition VAR

$$Y_t = (1 - F_M(s_{t-1}))\Pi'_E X_t + F_M(s_{t-1})\Pi'_R X_t + \epsilon_t$$
$$\epsilon_t \sim N(0, \Sigma_t)$$
$$\Sigma_t = \Sigma_E(1 - F_V(s_{t-1})) + \Sigma_R F_V(s_{t-1})$$

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Generalized impulse responses

The generalized impulse response function (GIRF) allows for the response to depend not only on the history Θ_{t-1} but also on the magnitude and sign of the shock ξ_{it}.

$$GIRF(h, \xi_{it}, \Theta_{t-1}) = E\left\{Y_{t+h} \mid \xi_{it} = \delta, \Theta_{t-1}\right\} - E\left\{Y_{t+h} \mid \xi_{it} = 0, \Theta_{t-1}\right\}$$

The responses are grouped according to the state indicated by $F_M(s_{t-1})$, $(s_{t-1} \in \Theta_{t-1})$.

REC: $F_M(s_{t-1}) \geq 0.5$ and EXP: $F_M(s_{t-1}) < 0.5$

The economy spends $\sim 15\%$ of the time in recession.

Medium-run identification scheme

News shock: The shock with no impact effect on TFP, *that has the largest contribution to the GFEVD of TFP in the medium-run (in 10 years)*.

Generalized forecast error variance decomposition:

$$\lambda_{ij,\Theta_{t-1}}(h) = \frac{\sum_{l=0}^{h} GIRF(l,\xi_{it},\Theta_{t-1})_j^2}{\sum_{i=1}^{K}\sum_{l=0}^{h} GIRF(l,\xi_{it},\Theta_{t-1})_j^2}, \qquad i,j = 1,\ldots,m$$

Generalized forecast error variance decomposition

		Impact	One year	Two years	Ten years
TFP	Linear	0	0.13	0.95	38.67
	Expansion	0	6.82	12.14	53.68
	Recession	0	42.66	42.65	67.54
Confidence	Linear	56.06	72.09	75.5	71.76
	Expansion	47.43	73.81	77.58	67.83
	Recession	86.79	70.14	70.61	61.77
Output	Linear	25.21	57.21	69.27	78.96
	Expansion	24.65	54.49	70.63	72.11
	Recession	1.25	39.9	64.57	71.48
Inflation	Linear	44.28	41.1	43.31	48.57
	Expansion	51.04	52.61	54.11	49.65
	Recession	84.86	72.68	70.92	66.55
Stock Prices	Linear	18.24	30.75	40.1	63.11
	Expansion	13.77	37.79	50.67	59.11
	Recession	69.62	79.2	79.12	72.14

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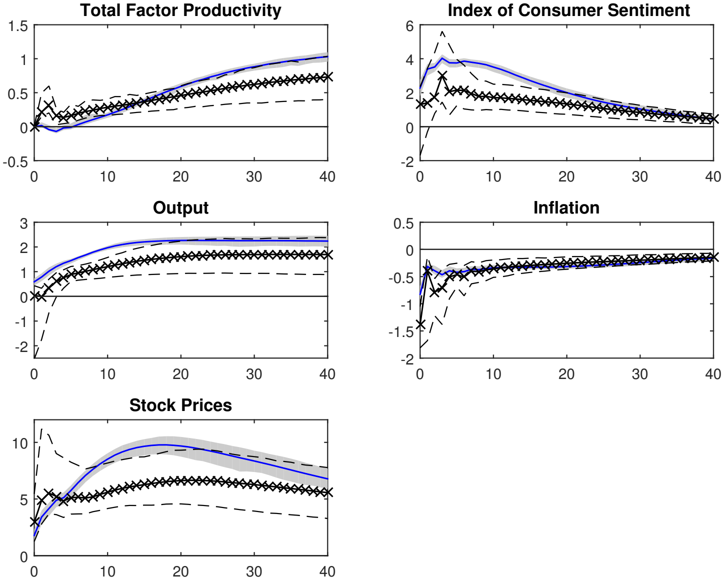
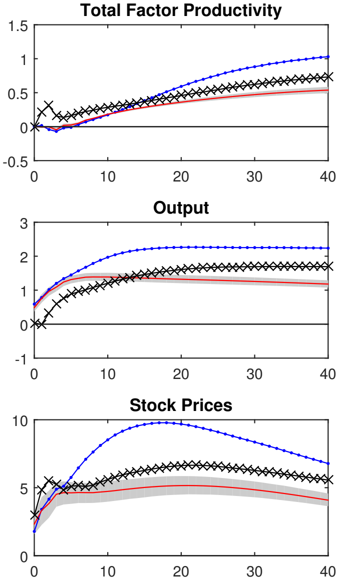
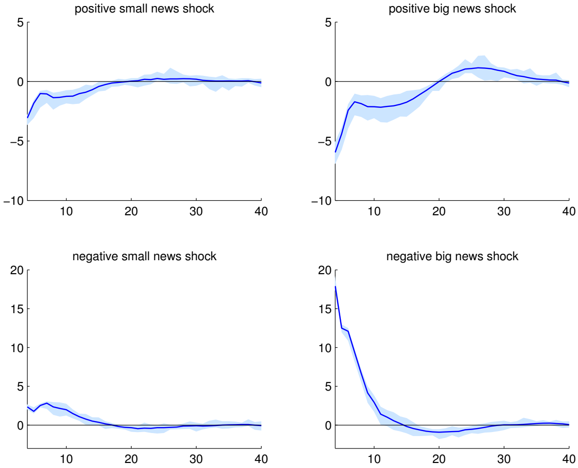
Generalized impulse responses to a news shock



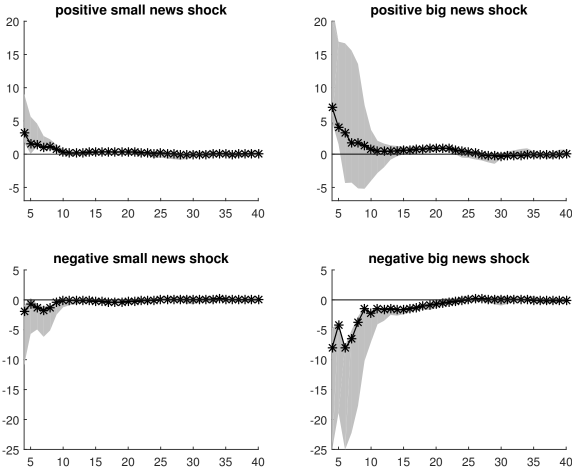
Robustness check: Comparison with the linear IRFs



Switching probability: Expansion



Switching probability: Recession



Conclusions

- The news shock leads to business cycle movements, independent of the state of the economy.
- Stronger effects of news shocks in expansion than in recession.
- No evidence in favour of asymmetries.
- The probability of regime transition is strongly influenced by the news shock.

Linear model

$$Y_t = \Pi_0' + \sum_{j=1}^{p} \Pi_j' Y_{t-j} + \epsilon_t = \Pi' X_t + \epsilon_t, \quad \epsilon_t \sim N(0, \Sigma)$$

where $Y_t = (Y_{1,t}, \ldots . Y_{m,t})'$ is an $m \times 1$ vector of endogenous variables, Π_0 is an $1 \times m$ intercept vector, Π_j is a $m \times m$ parameter matrix. $X_t = (\mathbf{1}, Y_{t-1}, \ldots, Y_{t-p})'$.

MA representation:

$$Y_t = B(L)\epsilon_t$$

Structural MA representation:

$$Y_t = C(L)u_t$$

Identification

Short-run identification

Linear mapping between innovations and structural shocks:

$$\epsilon_t = Au_t \quad AA' = \Sigma$$

- PS: The only shock that affects TFP on impact.
- NS: The shock with no impact effect on TFP, *that has an impact effect on consumer confidence*.

Medium-run identification

- PS: The only shock that affects TFP on impact.
- NS: The shock with no impact effect on TFP, *that has the largest effect on TFP in the medium-run (in 10 years)*.

*

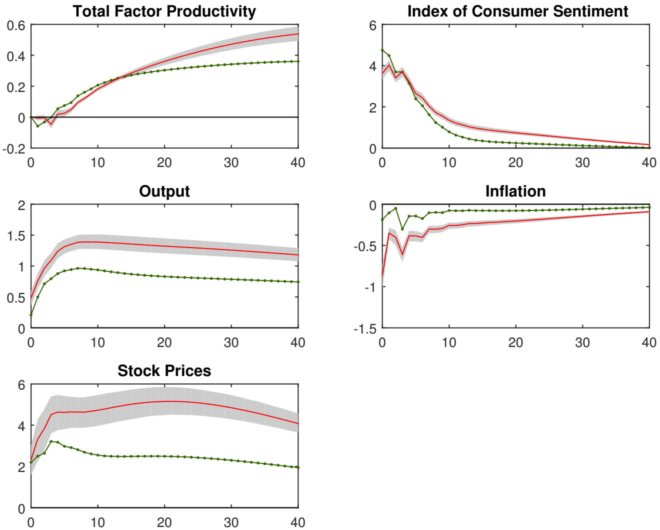
Medium-run identification

- h-step ahead forecast error:
  $Y_{t+h} - Y_{t+h|t-1} = \Sigma_{\tau=0}^{h} B_\tau \tilde{A} D u_{t+h-\tau}, \quad DD' = I$
- Contribution of shock j to the variance of variable i at horizon h:

$$\Xi_{i,j}(h) = \frac{e_i'(\Sigma_{\tau=0}^{h} B_\tau \tilde{A} D e_j e_j' D' \tilde{A}' B_\tau') e_i}{e_i'(\Sigma_{\tau=0}^{h} B_\tau \tilde{A} \tilde{A}' B_\tau') e_i} = \frac{(\Sigma_{\tau=0}^{h} B_{i,\tau} \tilde{A} \theta \theta' \tilde{A}' B_{i,\tau}')}{(\Sigma_{\tau=0}^{h} B_{i,\tau} \tilde{A} \tilde{A}' B_{i,\tau}')}$$

- Choose θ such that $\Xi_{1,NS}(h)$ is maximized at horizon $h = 40$ quarters.

Comparison of IRFs to a news and a confidence shock



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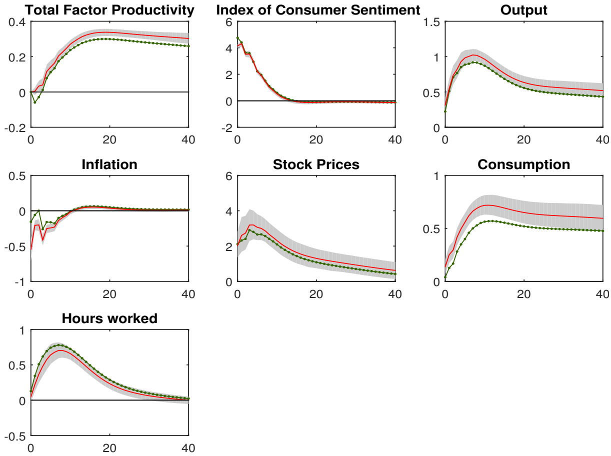
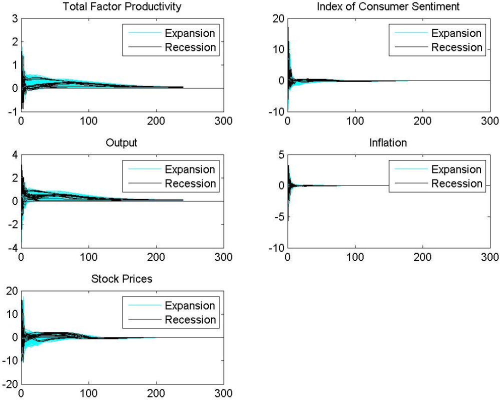
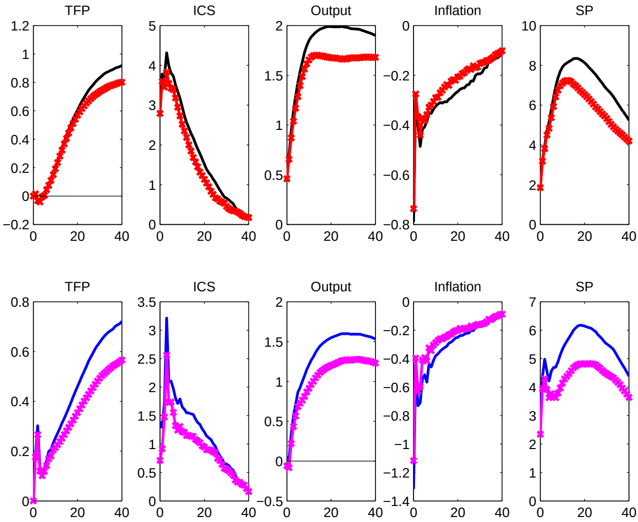


Stability check



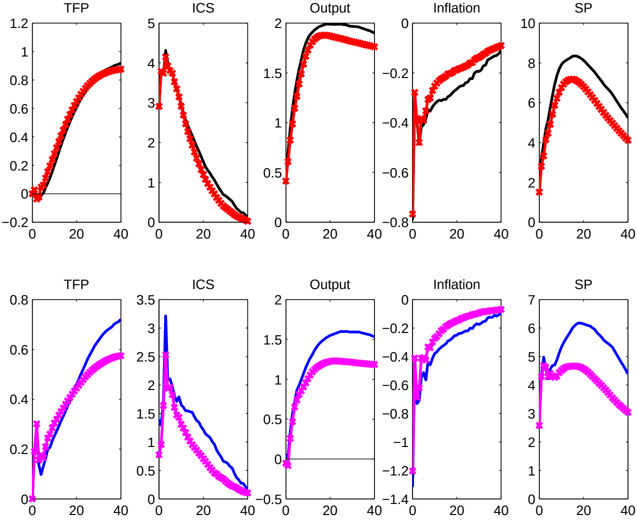
Counterfactuals

GIRFs: Positive small vs negative small news shocks



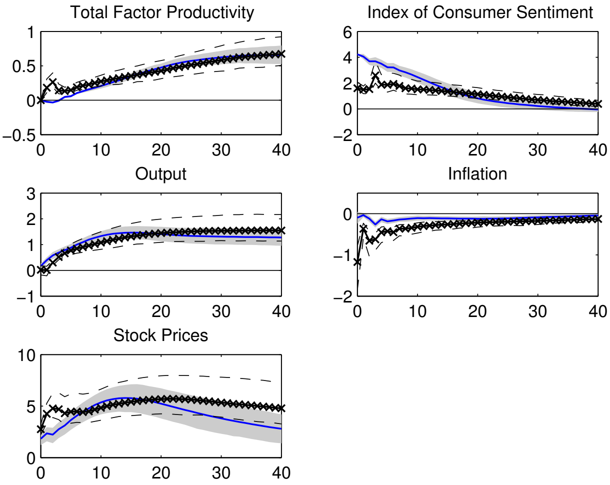
Top: Expansion, black = positive news, red=negative news
Bottom: Recession, bue = positive news, purple=negative news

GIRFs: Positive small vs positive big news shocks



Top: Expansion, black = small news, red=big news
Bottom: Recession, bue = small news, purple=big news

GIRFs to a confidence shock (on ICS)



GFEVD for the confidence shock

		Impact	One year	Two years	Ten years
TFP	Linear	0	0.38	2.16	23
	Expansion	0	4.62	8.76	27.98
	Recession	0	23.56	25.77	46.7
Confidence	Linear	96.46	88.46	83.29	68.38
	Expansion	98.59	76.35	65.31	44.29
	Recession	92.51	54.46	51.88	43.29
Output	Linear	4.61	28.14	33.79	33.1
	Expansion	3.29	20.83	29.43	28.14
	Recession	0.63	24.83	43.48	47.73
Inflation	Linear	2.05	4.26	4.93	5.92
	Expansion	0.64	5.5	7.61	13.3
	Recession	52.28	45.78	45.06	43.58
Stock Prices	Linear	16.32	16.18	17.89	17.32
	Expansion	14.76	16.29	20.68	20
	Recession	49.48	52.12	52.83	48.17

Orthogonality test

1. We take a large dataset Q_t, which contains 87 quarterly macroeconomic series for the U.S. from 1955Q1 to 2012Q4.
2. We set the maximum number of factors $p = 10$ and compute the first p principal components of Q_t. We use the principal components to obtain the unobserved factors.
3. We test whether the estimated shock is orthogonal to the past of the principal components, p (we use lags 1, 4, and 6), by regressing the critical structural shock (news shock) on the past of the principal components and performing an F-test of the null hypothesis that the coefficients are jointly zero.

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Linearity test of Teräsvirta and Yang (2014)

$$H_0 : \quad \Pi_1 = \Pi_2,$$
$$H_1 : \quad \Pi_{1,j} \neq \Pi_{2,j}, \text{ for at least one } j \in \{0, ..., p\}.$$

We approximate the logistic function by a third order Taylor expansion. We then perform an LM test:

1. Estimate the model under the null hypothesis (the linear model). Compute the matrix residual sum of squares, $SSR_0 = \tilde{E}'\tilde{E}$.
2. Estimate the auxiliary regression, by regressing Y (or $\tilde{E}$) on X and the interaction terms. Compute $SSR_1 = \hat{E}'\hat{E}$.
3. Compute the asymptotic χ^2 test statistic:

$$LM_{\chi^2} = T(m - tr\left\{SSR_0^{-1} SSR_1\right\})$$

We reject the null hypothesis of linearity at all significance levels.

Constancy of the error covariance matrix

We use the test of Yang (2014). First, we estimate the model under the null hypothesis assuming the error covariance matrix to be constant over time. Similar to the linearity test for the dynamic parameters, the alternative hypothesis is approximated by a third-order Taylor approximation given the transition variable. The LM statistic is then computed as follows:

$$LM = \sum_{i=1}^{p} T \frac{SSG_i - RSS_i}{SSG_i},$$

where SSG_i is the sum of squared $\tilde{g}_{it}$, and the RSS_i the corresponding residual sum of squares in the auxiliary regression.

Estimation

The parameters of the LSTVAR model are estimated using NLS. The error terms are normally distributed, thus the NLS estimator is equivalent to the maximum likelihood estimator of the parameters $\Psi = \{\gamma_V, c_V, \gamma_M, c_M, \Sigma_E, \Sigma_R, \Pi_E, \Pi_R\}$:

$$\hat{\Psi} = \arg\min_{\Psi} \sum_{t=1}^{T} \epsilon_t' \Sigma_t^{-1} \epsilon_t$$

For given $\gamma_V, c_V, \gamma_M, c_M$, Σ_E, and Σ_R, estimates of Π can be obtained by weighted least squares (WLS), with weights given by Σ_t^{-1}.

The procedure iterates on $\{\gamma_F, c_F, \gamma_M, c_M, \Sigma_E, \Sigma_R\}$, yielding Π and the likelihood, until an optimum is reached. We perform the estimation using a MCMC method - the MH algorithm. *