News, Uncertainty and Economic Fluctuations

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Motivation

- Two separate streams of literature on the sources of economic fluctuations.
- News shocks: Beaudry and Portier (BP, 2004, 2006), Lorenzoni (2007), Barski and Sims (2011).
- Uncertainty shocks: Bloom (2009) Rossi and Sekhposyan (2015), Jurado et al. (2015), Ludvigson et al. (2015), Baker et al. (2016).

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- In this paper:
  - news and uncertainty are closely connected
  - uncertainty arises from news
  - big news (either good or bad) generates big uncertainty.

Some preliminary evidence

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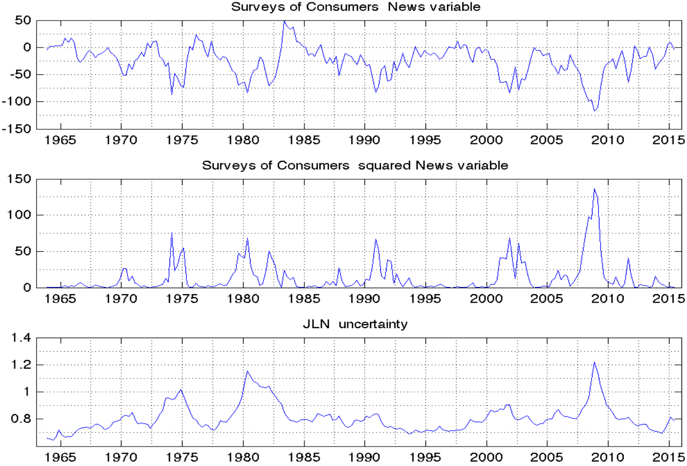
- Answers: Favorable News, Unfavorable News, No Mentions
- We construct a single "news" variable as the difference

  News = % Favorable News - % Unfavorable News
- Then we construct a "Big News" variable as the square of this News variable

Squared Michigan News and JLN3 Uncertainty



Some preliminary evidence

	VXO	VIX	JLN 3-month	JLN 1-month
No Mention	-0.30	-0.38	-0.53	-0.54
Squared News	0.62	0.67	0.67	0.69
Squared centered News	0.61	0.69	0.48	0.50
Absolute News	0.55	0.58	0.68	0.69

Table: Contemporaneous correlation coefficients.

Big news are associated with high uncertainty. Why?

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- Simple method to estimate non-linear effects of shocks
- We show that:
  - news shocks and uncertainty shocks are closely related
  - news shocks have quadratic effects, which have been so far ignored in the news shock literature;
  - such effects account for a sizable part of economic fluctuations;
  - no news is good news;
  - big bad news has larger effects than big good news.

Simple model

- Total Factor Productivity a_t (TFP) follows the model

$$\Delta a_t = \mu + \epsilon_{t-1} \quad \epsilon_t \sim iid. \tag{1}$$

where ϵ_t reflects news occurring at time t, but having its effect only at time $t+1$.

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- The percentage error

$$v_t = \frac{\epsilon_t - s_t}{s_t} \tag{2}$$

  is zero mean iid, independent of agents' information set.

Implications

- Hence the forecast error of a_{t+1} is proportional to s_t

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- The multiplicative structure of the expectation error is in line with a simple idea:
  - When nothing happens, agents see that there is no news. Both ϵ_t and s_t are small and the error $\epsilon_t - s_t$ is small.
  - If important events take place, both ϵ_t and s_t are generally large and the error is potentially large.

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- In a more general setup, uncertainty is still a function of s_t^2.

More general model

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- Uncertainty

$$U_t^k = \sigma_v^2 \sum_{h=0}^{\infty} (R_{k+h}^k)^2 (s_{t-h}^2 - 1) + \sigma_v^2 \sum_{h=0}^{k-1} (R_h^k)^2 + \sum_{h=0}^{k-1} C_h^2. \tag{7}$$

Econometric approach

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- Two linear VARs yielding nonlinear IRF.

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- Joint representation of Δa_t and z_t as

$$\begin{pmatrix} \Delta a_t \\ z_t \end{pmatrix} = \begin{pmatrix} d(L) & c(L) & 0 \\ m(L)\sigma_u & n(L) & P(L) \end{pmatrix} \begin{pmatrix} u_t/\sigma_u \\ s_t \\ w_t \end{pmatrix} \tag{8}$$

$m(L)$, $n(L)$ are vectors of impulse-response functions, 0 an n_w-dimensional row vector and $P(L)$ an $n_z \times n_w$ matrix of impulse response functions.

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- Estimate (8) with structural VAR (VAR 1).
- News shock identifiction: (i) u_t is the only one shock affecting a_t on impact; (ii) u_t and s_t are the only two shocks affecting a_t in the long-run. Forni, Gambetti and Sala (2014) and Beaudry et al. (2016)

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- Include both s_t and s_t^2 (or U_t^k) into a new VAR (VAR 2), aimed at estimating the impulse response function representation

$$\begin{pmatrix} s_t^2 - 1 \\ s_t \\ \Delta y_t \end{pmatrix} = \begin{pmatrix} \sigma_{s^2} & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ f(L) & [c(L) + g(L)] & d(L)\sigma_u & h(L) \end{pmatrix} \begin{pmatrix} \frac{s_t^2 - 1}{\sigma_{s^2}} \\ s_t \\ u_t/\sigma_u \\ w_t \end{pmatrix}, \tag{9}$$

Remarks on step 2

- If s_t serially independent and with symmetric distribution, then s_t^2 and s_t are jointly white noise. Implication: identification can be carried out by means of a standard Cholesky scheme (ordering of s_t and $s_t^2 - 1$ irrelevant).

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- Problem: the distribution of s_t is not symmetric (larger bad news), correlation coefficient of s_t and s_t^2 is -0.2. Identification problem.
- Solution: Cholesky scheme with s_t^2 ordered first and s_t ordered second (reverse ordering gives the same results).

Simulations

Simulation I:

$$\begin{pmatrix} \Delta a_t \\ z_{1t} \\ z_{2t} \end{pmatrix} = \begin{pmatrix} 1 & L & 0 \\ 1 + m_1 L & 1 + n_1 L & 0 \\ 1 + m_2 L & 1 + n_2 L & 1 + p_2 L \end{pmatrix} \begin{pmatrix} u_t / \sigma_u \\ s_t \\ \frac{s_t^2 - 1}{\sigma_{s^2}} \end{pmatrix}. \tag{10}$$

were z_{1t} and z_{2t} are two variables containing information about s_t, shocks gaussian iid.

Parameter values:
$m_1 = 0.8,\ m_2 = 1,\ n_1 = 0.6,\ n_2 = -0.6,\ p_1 = 0.2,\ p_2 = 0.4.$

2000 artificial series of length $T = 200$.

VAR 1 Identification: s_t is the second shock of the Cholesky representation.

Simulations

VAR 2: Using the same 2000 realizations of $[u_t \; s_t \; s_t^2]'$ we generate Δy_t from the equation

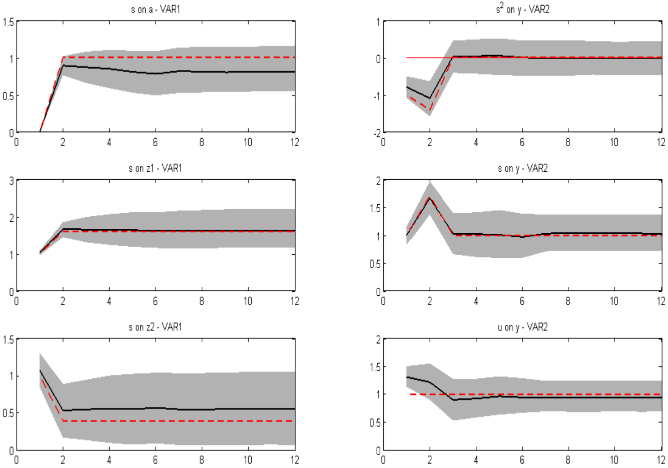
$$\Delta y_t = u_t + (1 + g_1 L - g_1 L^2 + L)s_t - (1 + (f_1 - 1)L - f_1 L^2)\frac{s_t^2 - 1}{\sigma_{s^2}},$$

with $g_1 = 0.7$ and $f_1 = 1.4$.

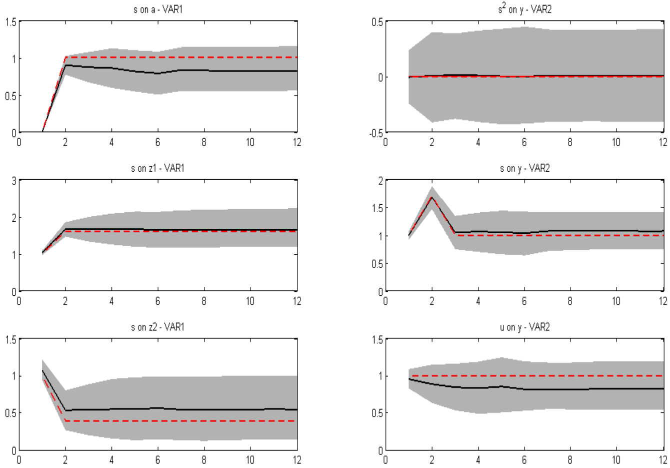
We estimate a VAR with $[\hat{s}_t \; \hat{s}_t^2 \; \Delta y_t]'$ and apply a Cholesky identification. The first shock is the news shock the second shock is the uncertainty shock.

Simulation II is identical to Simulation I but for the fact that s_t^2 has no effect on y_t

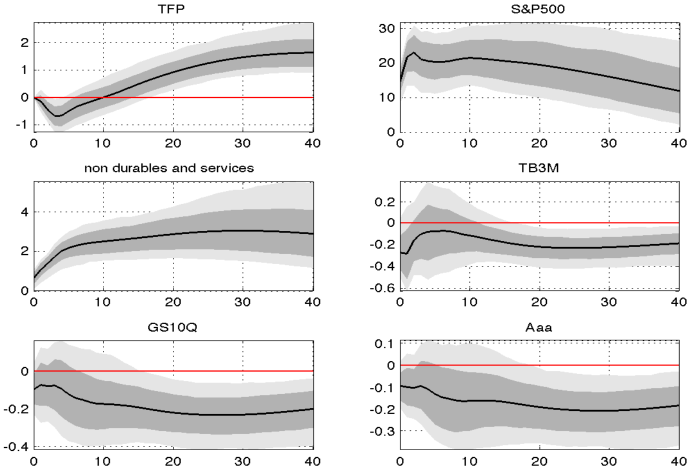
Simulation I: result



Simulation II: result



IRF to news shocks (VAR 1)

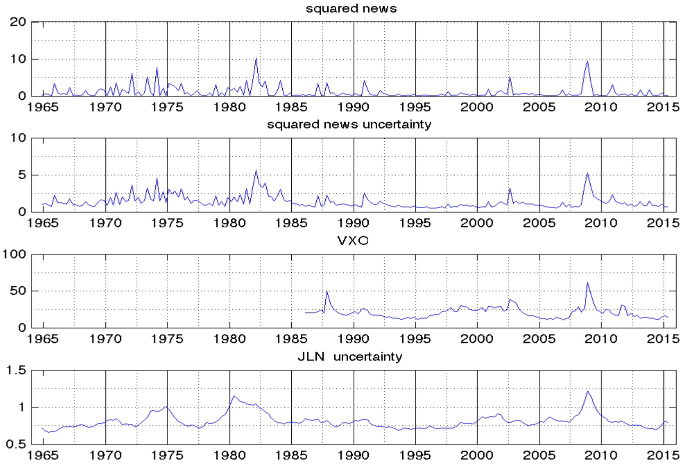


Variance decomposition

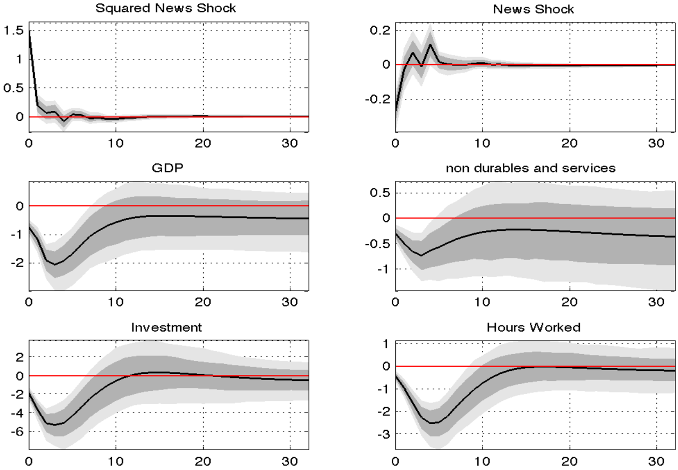
Variable	Horizon				
	Impact	1-Year	2-Years	4-Years	10-Years
TFP	0.0	2.5	3.2	2.8	29.5
S&P500	68.6	74.5	79.0	80.8	72.9
E5Y	4.8	25.3	35.4	41.3	38.8
Non durables and services	20.6	56.0	65.0	75.7	79.0
TB3M	15.4	4.5	2.9	5.2	18.8
GS10Q	4.4	1.6	3.7	8.9	26.6
Aaa	7.7	5.3	6.7	9.9	26.0

Table: Variance decomposition for VAR 1. The entries are the percentage of the forecast error variance explained by the news shock.

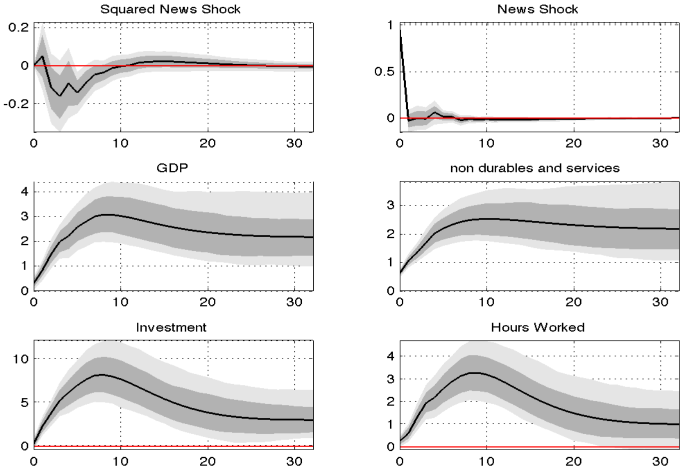
Uncertainty measures



IRF to uncertainty shocks (VAR 2)



IRF to news shocks (VAR 2)

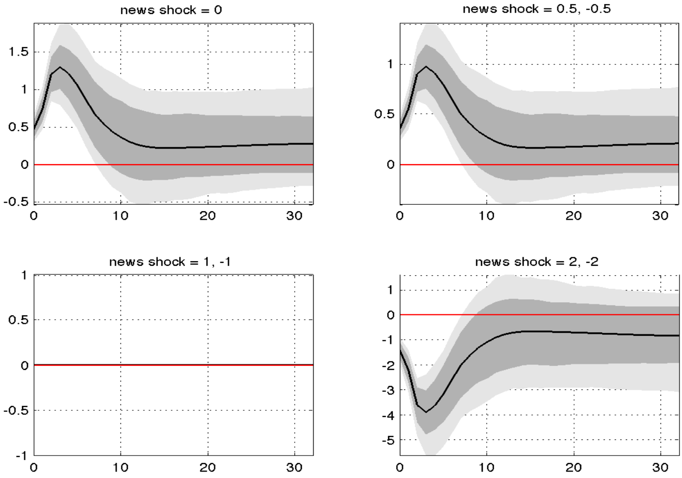


Variance decomposition

Variable	Horizon				
	Impact	1-Year	2-Years	4-Years	10-Years
	Squared news shock				
Squared News Shock	100.0	89.5	86.8	83.8	82.4
News Shock	8.0	8.9	8.9	8.9	8.9
Output	8.4	17.9	11.7	7.4	5.3
non durables and services	5.6	6.4	3.0	1.3	0.6
Investment	9.1	14.9	8.4	5.5	4.4
Hours Worked	5.8	21.3	18.0	13.1	9.9
	News shock				
Squared News Shock	0.0	3.3	4.7	5.0	5.1
News Shock	92.0	89.6	89.5	89.2	89.1
Output	0.9	20.5	32.2	40.9	47.3
non durables and services	19.6	46.3	53.8	58.1	62.0
Investment	0.0	19.5	29.6	35.2	41.1
Hours Worked	0.8	17.4	31.3	40.2	32.7

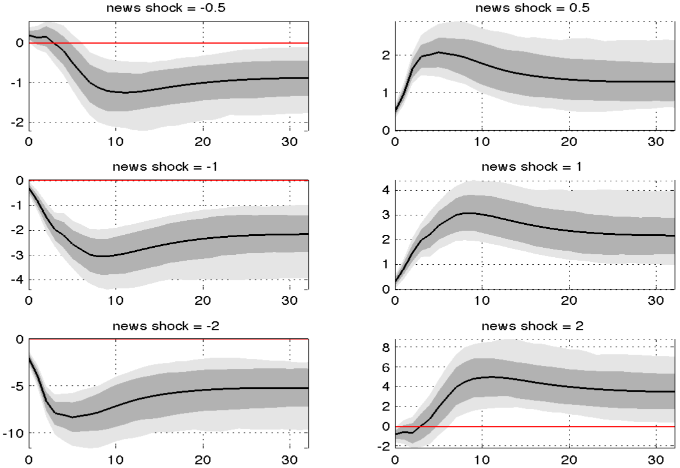
Table: Variance decomposition for VAR 2. The entries are the percentage of the forecast error variance explained by the shocks.

Uncertainty effects different size of news



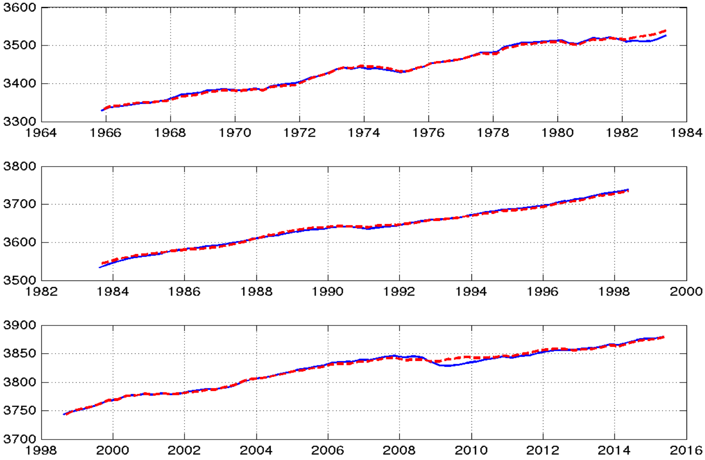
$$\hat{f}(L)(s_t^2 - 1)/\hat{\sigma}_{s^2},$$

Non-linear effects of news on GDP

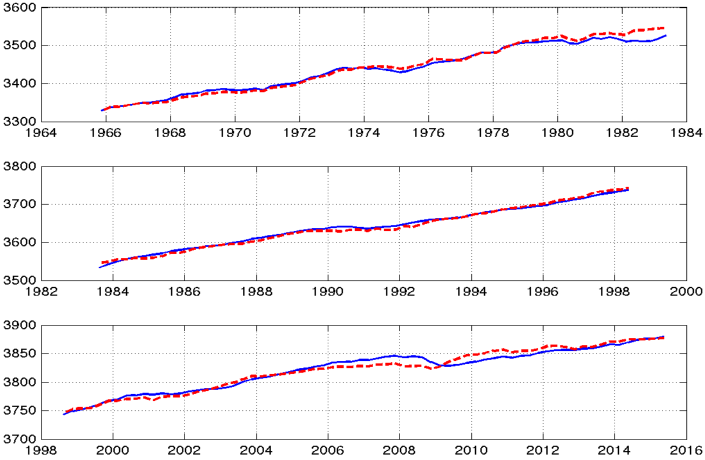


$$\hat{f}(L)s_t + \hat{f}(L)(s_t^2 - 1)/\hat{\sigma}_{s^2}$$

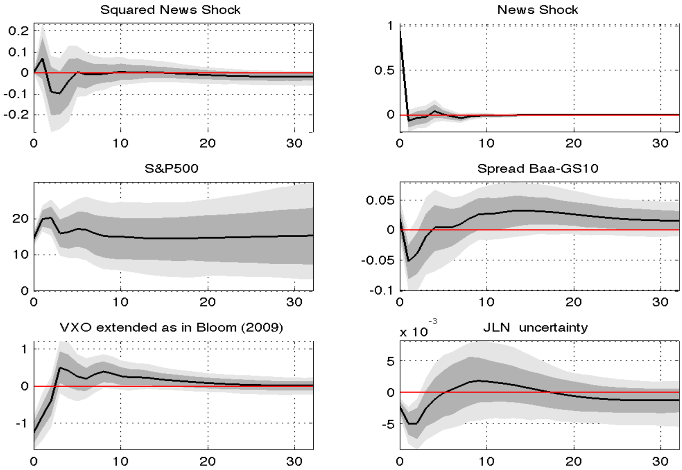
Historical decomposition (no uncertainty)



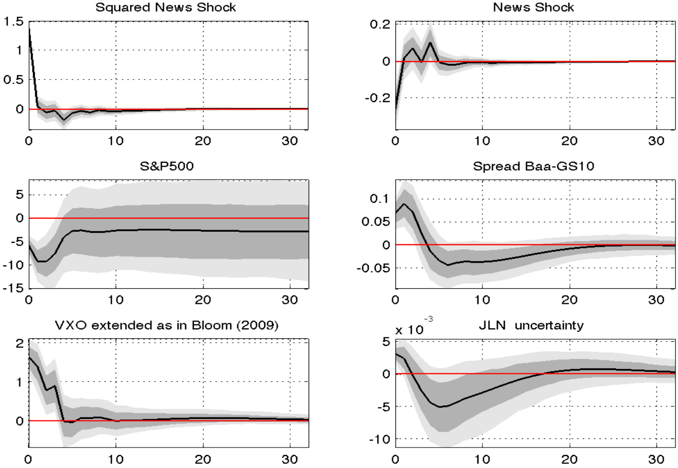
Historical decomposition (no uncertainty, no news)



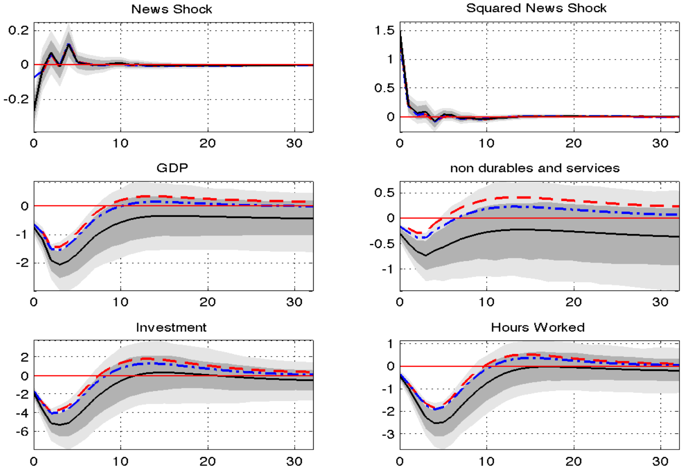
IRF to news in VAR 3



IRF to uncertainty in VAR 3



Robustness 1



Robustness 2