News, Uncertainty and Economic Fluctuations

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Astana University, May 12th 2017
Motivation

- Two separate streams of literature on the sources of economic fluctuations.


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- In this paper:
  - news and uncertainty are closely connected
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  - uncertainty arises from news
Motivation

▶ Two separate streams of literature on the sources of economic fluctuations.


▶ 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

- Question A.6 of the Michigan Consumers Survey questionnaire:
  “During the last few months, have you heard of any favorable or unfavorable changes in business conditions?”
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- Answers: Favorable News, Unfavorable News, No Mentions
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  “During the last few months, have you heard of any favorable or unfavorable changes in business conditions?”
- Answers: Favorable News, Unfavorable News, No Mentions
- We construct a single “news” variable as the difference
  \[
  \text{News} = \% \text{ Favorable News} - \% \text{ Unfavorable News}
  \]
- Then we construct a “Big News” variable as the square of this News variable
Squared Michigan News and JLN3 Uncertainty

![Graphs of Consumer Surveys and JLN Uncertainty](image-url)
Some preliminary evidence

<table>
<thead>
<tr>
<th></th>
<th>VXO</th>
<th>VIX</th>
<th>JLN 3-month</th>
<th>JLN 1-month</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Mention</td>
<td>-0.30</td>
<td>-0.38</td>
<td>-0.53</td>
<td>-0.54</td>
</tr>
<tr>
<td>Squared News</td>
<td>0.62</td>
<td>0.67</td>
<td>0.67</td>
<td>0.69</td>
</tr>
<tr>
<td>Squared centered News</td>
<td>0.61</td>
<td>0.69</td>
<td>0.48</td>
<td>0.50</td>
</tr>
<tr>
<td>Absolute News</td>
<td>0.55</td>
<td>0.58</td>
<td>0.68</td>
<td>0.69</td>
</tr>
</tbody>
</table>

Table: Contemporaneous correlation coefficients.

Big news are associated with high uncertainty. Why?
Contribution

- Simple model of limited information where uncertainty arises from news
  - 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.
Contribution

- Simple model of limited information where uncertainty arises from news

- Simple method to estimate non-linear effects of shocks
Contribution

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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

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

where $\epsilon_t$ reflects news occurring at time $t$, but having its effect only at time $t + 1$. 
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- Agents see the news behind $\epsilon_t$, which is qualitative in nature, but are unable to quantify its effect. They form an expectation $E_t \epsilon_t = s_t$.
- The percentage error
  \[ v_t = \frac{\epsilon_t - s_t}{s_t} \]  \[ (2) \]
  is zero mean iid, independent of agents’ information set.
Implications

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

$$E_t a_{t+1} - a_{t+1} = \epsilon_t - s_t = s_t v_t$$ (3)
Implications

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$$E_t a_{t+1} - a_{t+1} = \epsilon_t - s_t = s_t v_t$$

- 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 $\epsilon_t$ and $s_t$ are small and the error $\epsilon_t - s_t$ is small.
  - If important events take place, both $\epsilon_t$ and $s_t$ are generally large and the error is potentially large.
Uncertainty

Uncertainty is the conditional variance of the prediction error

\[ E_t s_t^2 v_t^2 = s_t^2 \sigma_v^2 \]
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- Implication: big (small) news about future events generate large (little) uncertainty.
Uncertainty

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- Implication: big (small) news about future events generate large (little) uncertainty.

- In a more general setup, uncertainty is still a function of \( s_t^2 \).
More general model

- TFP

\[ \Delta a_t = \mu + c(L)\epsilon_t = \sum_{k=1}^{\infty} c_k \epsilon_{t-k}, \]  

(4)
More general model

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\Delta a_t = \mu + c(L)\epsilon_t = \sum_{k=1}^{\infty} c_k \epsilon_{t-k},
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- Presence of other shocks, \( w_t \).
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- Output is given by

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\Delta y_t = \Delta a_t + \Delta c_t
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\[ \Delta y_t = \Delta a_t + \Delta c_t \]  

(5)

- Stationary cycle

\[ \Delta c_t = f(L)(s_t^2 - \sigma_s^2)/\sigma_s^2 + g(L)s_t/\sigma_s + h(L)w_t. \]  

(6)
More general model

- **TFP**

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- Uncertainty

\[
U_t^k = \sigma_v^2 \sum_{h=0}^{\infty} (R_k^{k+h})^2 (s_{t-h}^2 - 1) + \sigma_v^2 \sum_{h=0}^{k-1} (R_h^k)^2 + \sum_{h=0}^{k-1} C_h^2.
\]
Econometric approach

- Two stage procedure.
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  - Second stage: we feed the estimated news shock and its squared values in a new VAR and we identify the uncertainty shock.
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▶ Two stage procedure.

▶ First stage: the news shocks is estimated.

▶ Second stage: we feed the estimated news shock and its squared values in a new VAR and we identify the uncertainty shock.

▶ Two linear VARs yielding nonlinear IRF.
Estimation: step 1

- $s_t$ is not observed by the econometrician.
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- Observable variables, $z_t$, which reveal $s_t$. 

Estimate (8) with structural VAR (VAR 1).

News shock identification: (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)
Estimation: step 1

- $s_t$ is not observed by the econometrician.
- Observable variables, $z_t$, which reveal $s_t$.
- Joint representation of $\Delta a_t$ and $z_t$ as

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

(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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- Having an estimate of $s_t$, we compute $s_t^2$ and the related uncertainty $U_t^k$. 
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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

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

(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:

\[
\begin{pmatrix}
\Delta a_t \\
z_{1t} \\
z_{2t}
\end{pmatrix} =
\begin{pmatrix}
1 & L & 0 \\
1 + m_1 L & 1 + n_1 L & 0 \\
1 + m_2 L & 1 + n_2 L & 1 + p_2 L
\end{pmatrix}
\begin{pmatrix}
u_t / \sigma_u \\
\frac{s_t}{s_t^2 - 1} \\
\frac{s_t^2 - 1}{\sigma_s^2}
\end{pmatrix}.
\]

(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 \(\Delta y_t\) 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

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

**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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Squared news shock</th>
<th>1-Year</th>
<th>2-Years</th>
<th>4-Years</th>
<th>10-Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Squared News Shock</td>
<td>100.0</td>
<td>89.5</td>
<td>86.8</td>
<td>83.8</td>
<td>82.4</td>
</tr>
<tr>
<td>News Shock</td>
<td>8.0</td>
<td>8.9</td>
<td>8.9</td>
<td>8.9</td>
<td>8.9</td>
</tr>
<tr>
<td>Output</td>
<td>8.4</td>
<td>17.9</td>
<td>11.7</td>
<td>7.4</td>
<td>5.3</td>
</tr>
<tr>
<td>non durables and services</td>
<td>5.6</td>
<td>6.4</td>
<td>3.0</td>
<td>1.3</td>
<td>0.6</td>
</tr>
<tr>
<td>Investment</td>
<td>9.1</td>
<td>14.9</td>
<td>8.4</td>
<td>5.5</td>
<td>4.4</td>
</tr>
<tr>
<td>Hours Worked</td>
<td>5.8</td>
<td>21.3</td>
<td>18.0</td>
<td>13.1</td>
<td>9.9</td>
</tr>
</tbody>
</table>

| 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

\[ \hat{f}(L) \left( s_t^2 - 1 \right) / \hat{\sigma}_{s^2}, \]
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

Squared News Shock

S&P500

News Shock

Spread Baa-GS10

VXO extended as in Bloom (2009)

JLN uncertainty
IRF to uncertainty in VAR 3
Robustness 1
Robustness 2

Squared News Shock

News Shock

GDP

non durables and services

Investment

Hours Worked