Noisy News in Business Cycles

Mario Forni[1] Luca Gambetti[2] Marco Lippi[3] Luca Sala[4]

[1]Università di Modena e Reggio Emilia and CEPR

[2]Universitat Autonoma de Barcelona and Barcelona GSE

[3]EIEF and CEPR

[4]Università Bocconi, IGIER and Centro Baffi

IV conference in memory of Prof. Carlo Giannini

Pavia, 25-26 March 2014

The stripped down model: preview

- We have news and noise

The stripped down model: preview

- We have news and noise
- News shocks.

  Fundamental: $a_t = a_{t-1} + \varepsilon_{t-1}$

  Agents know $\varepsilon_t \rightarrow$ Agents' decisions depend on ε_t.

The stripped down model: preview

- We have news and noise

- News shocks.

  Fundamental: $a_t = a_{t-1} + \varepsilon_{t-1}$

  Agents know $\varepsilon_t \rightarrow$ Agents' decisions depend on ε_t.

- What if agents (and econometrician) face a signal extraction problem?

  Signal: $s_t = \varepsilon_t + v_t$

The stripped down model: preview

- We have news and noise
- News shocks.

  Fundamental: $a_t = a_{t-1} + \varepsilon_{t-1}$

  Agents know $\varepsilon_t \rightarrow$ Agents' decisions depend on ε_t.

- What if agents (and econometrician) face a signal extraction problem?

  Signal: $s_t = \varepsilon_t + v_t$

- Consumption: $c_t = \lim_{j \to \infty} E(a_{t+j} | \mathcal{I}_t)$

The stripped down model: preview

- We have news and noise
- News shocks.

  Fundamental: $a_t = a_{t-1} + \varepsilon_{t-1}$

  Agents know $\varepsilon_t \rightarrow$ Agents' decisions depend on ε_t.

- What if agents (and econometrician) face a signal extraction problem?

  Signal: $s_t = \varepsilon_t + v_t$

- Consumption: $c_t = \lim_{j \to \infty} E(a_{t+j} | \mathcal{I}_t)$
- What happens if one tries to identify shocks ε_t and v_t?

In this paper

Two contributions:

- New VAR approach: identify economic shocks in a situation where agents can only observe a noisy signal.
- Investigate the role of noise (v_t) and news (ε_t) as sources of business cycle fluctuations.

In this paper

Two contributions:

- New VAR approach: identify economic shocks in a situation where agents can only observe a noisy signal.
- Investigate the role of noise (v_t) and news (ε_t) as sources of business cycle fluctuations.

Main results:

1. Noise (v_t) and news (ε_t) together explain more than half of the fluctuations of GDP, consumption and investment.
2. One third of fluctuations is due to noise (v_t) shocks.

Motivation (1/2)

Renewed interest in the idea (Pigou, 1927) that news about future changes in fundamentals can generate business cycles through changes in expectations.

Motivation (1/2)

Renewed interest in the idea (Pigou, 1927) that news about future changes in fundamentals can generate business cycles through changes in expectations.

- Many papers assume perfect information (Beaudry and Portier, 2006): agents observe ε_t (but maybe not the econometrician...).

Motivation (1/2)

Renewed interest in the idea (Pigou, 1927) that news about future changes in fundamentals can generate business cycles through changes in expectations.

- Many papers assume perfect information (Beaudry and Portier, 2006): agents observe ε_t (but maybe not the econometrician...).
- Economic fluctuations are generated by expected changes in future economic conditions which always materialize.

Motivation (2/2)

- Few works have relaxed the assumption of perfect observability.

Motivation (2/2)

- Few works have relaxed the assumption of perfect observability.
- Imperfect information: agents receive imperfect signals about economic fundamentals (among others, Lorenzoni, 2009, Angeletos and La'O, 2010, Blanchard, Lorenzoni and L'Huillier, 2012, BLLH, Barsky and Sims, BS, 2011).

Motivation (2/2)

- Few works have relaxed the assumption of perfect observability.
- Imperfect information: agents receive imperfect signals about economic fundamentals (among others, Lorenzoni, 2009, Angeletos and La'O, 2010, Blanchard, Lorenzoni and L'Huillier, 2012, BLLH, Barsky and Sims, BS, 2011).
- Business cycles can be driven by expected changes in future economic conditions which do not materialize.

Implications (1/3)

- Imperfect shocks' observability very intriguing and realistic idea but...

Implications (1/3)

- Imperfect shocks' observability very intriguing and realistic idea but...
- ... has dramatic implications for empirical analysis based on VAR models.

Let's see why.

Implications (2/3)

- In a VAR, the innovation e_t is function of present and past Y:

$$e_t = Y_t - \text{proj}(Y_t | Y_{t-1}, Y_{t-2}, ...)$$

Implications (2/3)

- In a VAR, the innovation e_t is function of present and past Y:

$$e_t = Y_t - \text{proj}(Y_t | Y_{t-1}, Y_{t-2}, ...)$$

- If agents do not observe the shocks, current and past realizations of the data cannot provide enough information to estimate the shocks (non-fundamentalness). (More)

Implications (2/3)

- In a VAR, the innovation e_t is function of present and past Y:

$$e_t = Y_t - \text{proj}(Y_t | Y_{t-1}, Y_{t-2}, ...)$$

- If agents do not observe the shocks, current and past realizations of the data cannot provide enough information to estimate the shocks (non-fundamentalness). (More)

- Structural shocks ε_t do not "contemporaneously live" in the agents' innovations:

$$\varepsilon_t \neq K e_t$$

Implications (2/3)

- In a VAR, the innovation e_t is function of present and past Y:

$$e_t = Y_t - \text{proj}(Y_t | Y_{t-1}, Y_{t-2}, ...)$$

- If agents do not observe the shocks, current and past realizations of the data cannot provide enough information to estimate the shocks (non-fundamentalness). (More)

- Structural shocks ε_t do not "contemporaneously live" in the agents' innovations:

$$\varepsilon_t \neq K e_t$$

- Implication: standard VAR analysis will fail.

Implications (3/3)

- Question: shall we dismiss VAR models under the assumption of imperfect information?

Implications (3/3)

- Question: shall we dismiss VAR models under the assumption of imperfect information?
- YES: BLLH (2013), BS (2012).

Implications (3/3)

- Question: shall we dismiss VAR models under the assumption of imperfect information?
- YES: BLLH (2013), BS (2012).
- Our answer is NO.

A simple model (1/3)

- Fundamental:

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

where ε_t is white noise.

A simple model (1/3)

- Fundamental:

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

where ε_t is white noise.

- Agents observe a noisy signal:

$$s_t = \varepsilon_t + v_t$$

v_t, the noise shock, is a white noise, uncorrelated with ε_t.

A simple model (1/3)

- Fundamental:

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

where ε_t is white noise.

- Agents observe a noisy signal:

$$s_t = \varepsilon_t + v_t$$

v_t, the noise shock, is a white noise, uncorrelated with ε_t.

- Agents' information set: $\mathcal{I}_t = \text{span}(a_{t-k}, s_{t-k}, k \geq 0)$.

A simple model (1/3)

- Fundamental:

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

where ε_t is white noise.

- Agents observe a noisy signal:

$$s_t = \varepsilon_t + v_t$$

v_t, the noise shock, is a white noise, uncorrelated with ε_t.

- Agents' information set: $\mathcal{I}_t = \text{span}(a_{t-k}, s_{t-k}, k \geq 0)$.

- Consumption is set on the basis of expected long-run fundamentals

$$c_t = \lim_{j \to \infty} E(a_{t+j} | \mathcal{I}_t)$$

A simple model (2/3)

Given the process for a_t:

$$E(a_{t+j}|\mathcal{I}_t) = a_t + E(\varepsilon_t|\mathcal{I}_t) = a_t + \gamma s_t$$

where $E(\varepsilon_t|\mathcal{I}_t) = \gamma s_t$ is the projection of ε_t on s_t ($\gamma = \sigma_\varepsilon^2/\sigma_s^2$).

A simple model (2/3)

Given the process for a_t:

$$E(a_{t+j}|\mathcal{I}_t) = a_t + E(\varepsilon_t|\mathcal{I}_t) = a_t + \gamma s_t$$

where $E(\varepsilon_t|\mathcal{I}_t) = \gamma s_t$ is the projection of ε_t on s_t ($\gamma = \sigma_\varepsilon^2/\sigma_s^2$).

Consumption:

$$c_t = a_t + \gamma(\varepsilon_t + v_t)$$

A simple model (2/3)

Given the process for a_t:

$$E(a_{t+j}|\mathcal{I}_t) = a_t + E(\varepsilon_t|\mathcal{I}_t) = a_t + \gamma s_t$$

where $E(\varepsilon_t|\mathcal{I}_t) = \gamma s_t$ is the projection of ε_t on s_t ($\gamma = \sigma_\varepsilon^2/\sigma_s^2$).

Consumption:

$$c_t = a_t + \gamma(\varepsilon_t + v_t)$$

Change in consumption:

$$\begin{aligned}\Delta c_t &= \Delta a_t + \gamma \Delta s_t \\ &= \gamma \varepsilon_t + (1-\gamma)\varepsilon_{t-1} + \gamma v_t - \gamma v_{t-1}\end{aligned}$$

A simple model (3/3)

$$\Delta c_t = \Delta a_t + \gamma \Delta s_t = \gamma \varepsilon_t + (1-\gamma)\varepsilon_{t-1} + \gamma v_t - \gamma v_{t-1}$$

Remarks:

- Noise v_t can generate temporary fluctuations in consumption.

A simple model (3/3)

$$\Delta c_t = \Delta a_t + \gamma \Delta s_t = \gamma \varepsilon_t + (1-\gamma)\varepsilon_{t-1} + \gamma v_t - \gamma v_{t-1}$$

Remarks:

- Noise v_t can generate temporary fluctuations in consumption.
- Business cycles can be driven by expected changes in fundamentals which never materialize.

The failure of standard structural VAR methods

Interesting econometric implications. Model solution is:

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} L & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix}$$

The polynomial matrix has rank $= 1$ when $L = 0$.

The failure of standard structural VAR methods

Interesting econometric implications. Model solution is:

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} L & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix}$$

The polynomial matrix has rank $= 1$ when $L = 0$.

$\Rightarrow$ the MA is non-invertible

The failure of standard structural VAR methods

Interesting econometric implications. Model solution is:

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} L & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix}$$

The polynomial matrix has rank $= 1$ when $L = 0$.

$\Rightarrow$ the MA is non-invertible

$\Rightarrow$ A VAR representation in the structural shocks does not exist

What does a VAR do?

Rewrite the structural representation:

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} L & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix}$$

as the Wold representation (estimated with VAR):

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} 1 & L\sigma_\varepsilon^2/\sigma_s^2 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} u_t \\ s_t \end{pmatrix}$$

where:

$$\begin{pmatrix} u_t \\ s_t \end{pmatrix} = \begin{pmatrix} L\frac{\sigma_v^2}{\sigma_s^2} & -L\frac{\sigma_\varepsilon^2}{\sigma_s^2} \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix},$$

The innovations $(u_t \; s_t)'$ are combinations of present and past values of the structural shocks (recall: $\varepsilon_t \neq K e_t$).

The existing solution

- Estimate directly the model with the Kalman filter as in BLLH or BS.

The existing solution

- Estimate directly the model with the Kalman filter as in BLLH or BS.
- Problem: tight restrictions.

The existing solution

- Estimate directly the model with the Kalman filter as in BLLH or BS.
- Problem: tight restrictions.
- BLLH and BS find opposite results. (BLLH and BS)

A solution: intuition

The mapping between structural and fundamental shocks:

A solution: intuition

The mapping between structural and fundamental shocks:

$$\begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix} = \begin{pmatrix} L^{-1} & \frac{\sigma_\varepsilon^2}{\sigma_s^2} \\ -L^{-1} & \frac{\sigma_v^2}{\sigma_s^2} \end{pmatrix} \begin{pmatrix} u_t \\ s_t \end{pmatrix}$$

A solution: intuition

The mapping between structural and fundamental shocks:

$$\begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix} = \begin{pmatrix} L^{-1} & \frac{\sigma_\varepsilon^2}{\sigma_s^2} \\ -L^{-1} & \frac{\sigma_v^2}{\sigma_s^2} \end{pmatrix} \begin{pmatrix} u_t \\ s_t \end{pmatrix}$$

The structural shocks can be obtained as a combination of future and present values of the fundamental innovations.

A solution: intuition

The mapping between structural and fundamental shocks:

$$\begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix} = \begin{pmatrix} L^{-1} & \frac{\sigma_\varepsilon^2}{\sigma_s^2} \\ -L^{-1} & \frac{\sigma_v^2}{\sigma_s^2} \end{pmatrix} \begin{pmatrix} u_t \\ s_t \end{pmatrix}$$

The structural shocks can be obtained as a combination of future and present values of the fundamental innovations.

Intuition: at time $t+1$ agents look back and understand whether it was noise or news at time t.

Econometric model (1/3)

General process for a_t:

$$\Delta a_t = c(L)\varepsilon_t,$$

where $c(0) = 0$ (news shock).

Econometric model (1/3)

General process for a_t:

$$\Delta a_t = c(L)\varepsilon_t,$$

where $c(0) = 0$ (news shock).

The structural non-fundamental representation

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} c(L) & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix},$$

Econometric model (2/3)

The fundamental representation is

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} \frac{c(L)}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s^2} \\ 0 & 1 \end{pmatrix} \begin{pmatrix} u_t \\ s_t \end{pmatrix},$$

where

$$\begin{pmatrix} u_t \\ s_t \end{pmatrix} = \begin{pmatrix} b(L)\frac{\sigma_v^2}{\sigma_s^2} & -b(L)\frac{\sigma_\varepsilon^2}{\sigma_s^2} \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix}$$

and the Blaschke factor:

$$b(L) = \prod_{j=1}^{n} \frac{L - r_j}{1 - \bar{r}_j L}$$

where r_j, $j = 1, \ldots, n$, are the roots of $c(L)$ which are smaller than one in modulus and $\bar{r}_j$ is the complex conjugate of r_j.

Econometric model (3/3)

Assume that the signal is not observable to the econometrician. There is an observable variable, z_t, which reveals the signal:

$$z_t = d(L)u_t + f(L)s_t$$

Econometric model (3/3)

Assume that the signal is not observable to the econometrician. There is an observable variable, z_t, which reveals the signal:

$$z_t = d(L)u_t + f(L)s_t$$

Therefore,

$$\begin{pmatrix} \Delta a_t \\ z_t \end{pmatrix} = \begin{pmatrix} \frac{c(L)\sigma_u}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} \\ d(L)\sigma_u & f(L)\sigma_s \end{pmatrix} \begin{pmatrix} u_t/\sigma_u \\ s_t/\sigma_s \end{pmatrix}$$

Econometric model (3/3)

Assume that the signal is not observable to the econometrician. There is an observable variable, z_t, which reveals the signal:

$$z_t = d(L)u_t + f(L)s_t$$

Therefore,

$$\begin{aligned}\begin{pmatrix}\Delta a_t \\ z_t\end{pmatrix} &= \begin{pmatrix}\frac{c(L)\sigma_u}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} \\ d(L)\sigma_u & f(L)\sigma_s\end{pmatrix}\begin{pmatrix}u_t/\sigma_u \\ s_t/\sigma_s\end{pmatrix} \\ &= \begin{pmatrix}\frac{c(L)\sigma_u}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} \\ d(L)\sigma_u & f(L)\sigma_s\end{pmatrix}\begin{pmatrix}\frac{b(L)\sigma_v}{\sigma_s} & -\frac{b(L)\sigma_\varepsilon}{\sigma_s} \\ \frac{\sigma_\varepsilon}{\sigma_s} & \frac{\sigma_v}{\sigma_s}\end{pmatrix}\begin{pmatrix}\varepsilon_t/\sigma_\varepsilon \\ v_t/\sigma_v\end{pmatrix}\end{aligned}$$

Econometric model (3/3)

The signal is not observable to the econometrician. There is an observable variable, z_t, which reveals the signal:

$$z_t = d(L)u_t + f(L)s_t$$

Therefore,

$$\begin{aligned}
\begin{pmatrix} \Delta a_t \\ z_t \end{pmatrix} &= \begin{pmatrix} \frac{c(L)\sigma_u}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} \\ d(L)\sigma_u & f(L)\sigma_s \end{pmatrix} \begin{pmatrix} u_t/\sigma_u \\ s_t/\sigma_s \end{pmatrix} \\
&= \underbrace{\begin{pmatrix} \frac{c(L)\sigma_u}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} \\ d(L)\sigma_u & f(L)\sigma_s \end{pmatrix}}_{\text{Step 1}} \begin{pmatrix} \frac{b(L)\sigma_v}{\sigma_s} & -\frac{b(L)\sigma_\varepsilon}{\sigma_s} \\ \frac{\sigma_\varepsilon}{\sigma_s} & \frac{\sigma_v}{\sigma_s} \end{pmatrix} \begin{pmatrix} \varepsilon_t/\sigma_\varepsilon \\ v_t/\sigma_v \end{pmatrix}
\end{aligned}$$

Econometric model (3/3)

The signal is not observable to the econometrician. There is an observable variable, z_t, which reveals the signal:

$$z_t = d(L)u_t + f(L)s_t$$

Therefore,

$$\begin{aligned}
\begin{pmatrix} \Delta a_t \\ z_t \end{pmatrix} &= \begin{pmatrix} \frac{c(L)\sigma_u}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} \\ d(L)\sigma_u & f(L)\sigma_s \end{pmatrix} \begin{pmatrix} u_t/\sigma_u \\ s_t/\sigma_s \end{pmatrix} \\
&= \underbrace{\begin{pmatrix} \frac{c(L)\sigma_u}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} \\ d(L)\sigma_u & f(L)\sigma_s \end{pmatrix}}_{\text{Step 1}} \underbrace{\begin{pmatrix} \frac{b(L)\sigma_v}{\sigma_s} & -\frac{b(L)\sigma_\varepsilon}{\sigma_s} \\ \frac{\sigma_\varepsilon}{\sigma_s} & \frac{\sigma_v}{\sigma_s} \end{pmatrix}}_{\text{Step 2}} \begin{pmatrix} \varepsilon_t/\sigma_\varepsilon \\ v_t/\sigma_v \end{pmatrix}
\end{aligned}$$

Dynamic identification

Dynamic identification

1. Estimate an unrestricted VAR for Δa_t and z_t and identify with a Cholesky scheme ($c(0) = 0$).

Dynamic identification

1. Estimate an unrestricted VAR for Δa_t and z_t and identify with a Cholesky scheme ($c(0) = 0$).

$$\begin{pmatrix} \Delta a_t \\ z_t \end{pmatrix} = \begin{pmatrix} \frac{c(L)\sigma_u}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} \\ d(L)\sigma_u & f(L)\sigma_s \end{pmatrix} \begin{pmatrix} \frac{b(L)\sigma_v}{\sigma_s} & -\frac{b(L)\sigma_\varepsilon}{\sigma_s} \\ \frac{\sigma_\varepsilon}{\sigma_s} & \frac{\sigma_v}{\sigma_s} \end{pmatrix} \begin{pmatrix} \varepsilon_t/\sigma_\varepsilon \\ v_t/\sigma_v \end{pmatrix}$$

Dynamic identification

1. Estimate an unrestricted VAR for Δa_t and z_t and identify with a Cholesky scheme ($c(0) = 0$).

$$\begin{pmatrix} \Delta a_t \\ z_t \end{pmatrix} = \begin{pmatrix} \frac{c(L)\sigma_u}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} \\ d(L)\sigma_u & f(L)\sigma_s \end{pmatrix} \begin{pmatrix} \frac{b(L)\sigma_v}{\sigma_s} & -\frac{b(L)\sigma_\varepsilon}{\sigma_s} \\ \frac{\sigma_\varepsilon}{\sigma_s} & \frac{\sigma_v}{\sigma_s} \end{pmatrix} \begin{pmatrix} \varepsilon_t/\sigma_\varepsilon \\ v_t/\sigma_v \end{pmatrix}$$

2. Estimate $b(L)$ by computing the roots of $c(L)\frac{\sigma_\varepsilon^2}{\sigma_s}$ and selecting the roots which are smaller than one in modulus.

$$\begin{pmatrix} \Delta a_t \\ z_t \end{pmatrix} = \begin{pmatrix} \frac{c(L)\sigma_u}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} \\ d(L)\sigma_u & f(L)\sigma_s \end{pmatrix} \begin{pmatrix} \frac{b(L)\sigma_v}{\sigma_s} & -\frac{b(L)\sigma_\varepsilon}{\sigma_s} \\ \frac{\sigma_\varepsilon}{\sigma_s} & \frac{\sigma_v}{\sigma_s} \end{pmatrix} \begin{pmatrix} \varepsilon_t/\sigma_\varepsilon \\ v_t/\sigma_v \end{pmatrix}$$

Dynamic identification

1. Estimate an unrestricted VAR for Δa_t and z_t and identify with a Cholesky scheme ($c(0) = 0$).

$$\begin{pmatrix} \Delta a_t \\ z_t \end{pmatrix} = \begin{pmatrix} \frac{c(L)\sigma_u}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} \\ d(L)\sigma_u & f(L)\sigma_s \end{pmatrix} \begin{pmatrix} \frac{b(L)\sigma_v}{\sigma_s} & -\frac{b(L)\sigma_\varepsilon}{\sigma_s} \\ \frac{\sigma_\varepsilon}{\sigma_s} & \frac{\sigma_v}{\sigma_s} \end{pmatrix} \begin{pmatrix} \varepsilon_t/\sigma_\varepsilon \\ v_t/\sigma_v \end{pmatrix}$$

2. Estimate $b(L)$ by computing the roots of $c(L)\frac{\sigma_\varepsilon^2}{\sigma_s}$ and selecting the roots which are smaller than one in modulus.

$$\begin{pmatrix} \Delta a_t \\ z_t \end{pmatrix} = \begin{pmatrix} \frac{c(L)\sigma_u}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} \\ d(L)\sigma_u & f(L)\sigma_s \end{pmatrix} \begin{pmatrix} \frac{b(L)\sigma_v}{\sigma_s} & -\frac{b(L)\sigma_\varepsilon}{\sigma_s} \\ \frac{\sigma_\varepsilon}{\sigma_s} & \frac{\sigma_v}{\sigma_s} \end{pmatrix} \begin{pmatrix} \varepsilon_t/\sigma_\varepsilon \\ v_t/\sigma_v \end{pmatrix}$$

3. $\frac{\sigma_\varepsilon}{\sigma_v} = \frac{c(1)\sigma_\varepsilon^2}{\sigma_s} / \frac{c(1)\sigma_u}{b(1)}$. $\frac{\sigma_\varepsilon}{\sigma_s} = \sin(\arctan(\frac{\sigma_\varepsilon}{\sigma_v}))$. $\frac{\sigma_v}{\sigma_s} = \cos(\arctan(\frac{\sigma_\varepsilon}{\sigma_v}))$.

$$\begin{pmatrix} \Delta a_t \\ z_t \end{pmatrix} = \begin{pmatrix} \frac{c(L)\sigma_u}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} \\ d(L)\sigma_u & f(L)\sigma_s \end{pmatrix} \begin{pmatrix} \frac{b(L)\sigma_v}{\sigma_s} & -\frac{b(L)\sigma_\varepsilon}{\sigma_s} \\ \frac{\sigma_\varepsilon}{\sigma_s} & \frac{\sigma_v}{\sigma_s} \end{pmatrix} \begin{pmatrix} \varepsilon_t/\sigma_\varepsilon \\ v_t/\sigma_v \end{pmatrix}$$

Empirical specification

VAR model for:

Empirical specification

VAR model for:

- a_t: log of US per-capita potential GDP from the CBO.

Empirical specification

VAR model for:

- a_t: log of US per-capita potential GDP from the CBO.
- z_t, the variable that reveals the signal s_t: expected business conditions within the next 12 months (Michigan Consumer Survey).

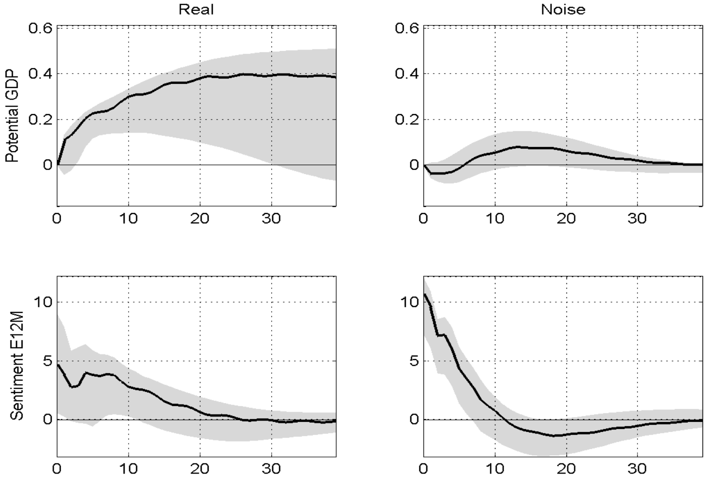
Empirical specification

VAR model for:

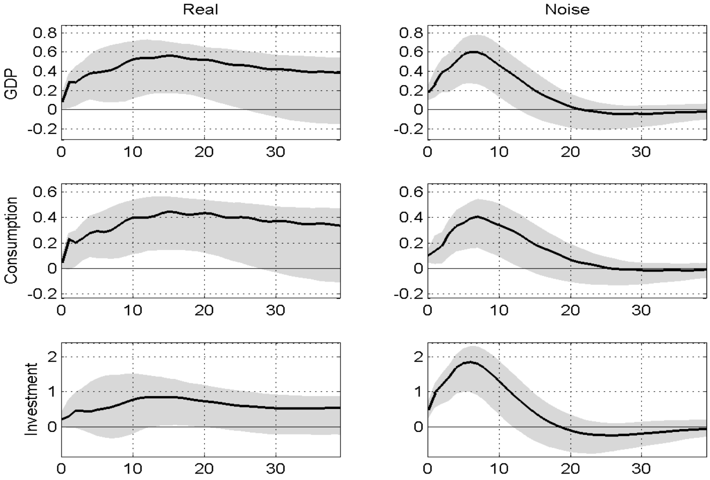
- a_t: log of US per-capita potential GDP from the CBO.
- z_t, the variable that reveals the signal s_t: expected business conditions within the next 12 months (Michigan Consumer Survey).
- Add log real per-capita GDP, consumption, and investment.

(Multivariate model)

IRF: news (real) ε_t - noise v_t (1/2)



IRF: news (real) ε_t - noise v_t (2/2)

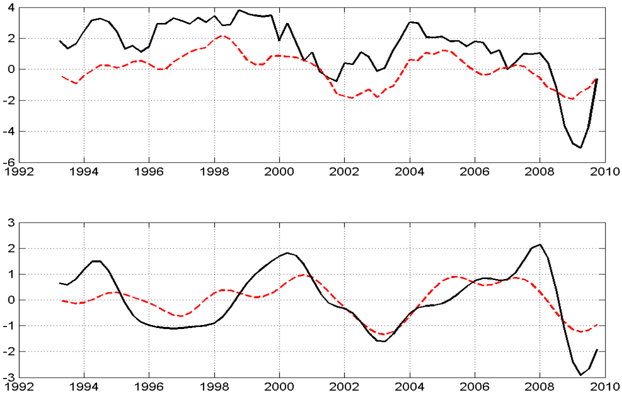


Variance decomposition

Variable	Impact	1-Year	2-Years	4-Years	10-Years
	News (Real) ε_t				
Potential	0.0	87.4	87.6	81.4	63.1
Sentiment	16.3	15.1	21.2	23.3	21.2
GDP	1.4	15.7	22.2	39.3	44.3
CONS	1.0	18.7	23.9	41.6	48.9
INV	1.3	3.3	4.6	11.8	18.5
	Noise v_t				
Potential	0.0	4.6	2.1	3.1	1.1
Sentiment	83.7	75.1	63.0	51.1	47.1
GDP	7.3	24.6	40.0	33.5	16.2
CONS	5.5	19.3	32.4	29.6	13.1
INV	6.5	33.5	45.0	39.3	29.0
	News (Real) + Noise				
Potential	0.0	92.0	89.7	84.5	64.1
Sentiment	100.0	90.2	84.2	74.4	68.3
GDP	8.7	40.2	62.2	72.8	60.4
CONS	6.5	38.0	56.3	71.2	62.0
INV	7.8	36.8	49.7	51.1	47.5
	Learning u_t				
Potential	100.0	91.5	78.8	62.6	49.6
Sentiment	0.1	1.5	5.0	8.1	8.8
GDP	6.4	3.4	4.7	16.3	29.0
CONS	15.3	6.5	7.0	17.7	32.3
INV	0.5	0.9	0.7	4.0	12.3
	Signal s_t				
Potential	0.0	2.9	12.5	23.0	15.2
Sentiment	99.9	**88.9**	**79.4**	**65.6**	59.4
GDP	8.2	**37.2**	**58.1**	**57.2**	31.7
CONS	5.5	**32.3**	**50.2**	**54.3**	30.0
INV	7.7	**36.1**	**49.0**	**47.5**	35.3

Historical decomposition of GDP

Top: GDP y-to-y growth rate (solid); noise (dashed)

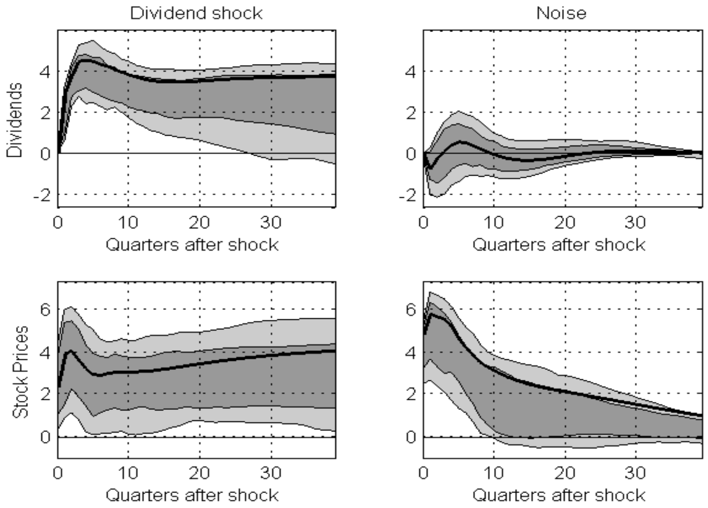


Bottom: Business cycle GDP y-to-y growth rate (solid); noise (dashed)

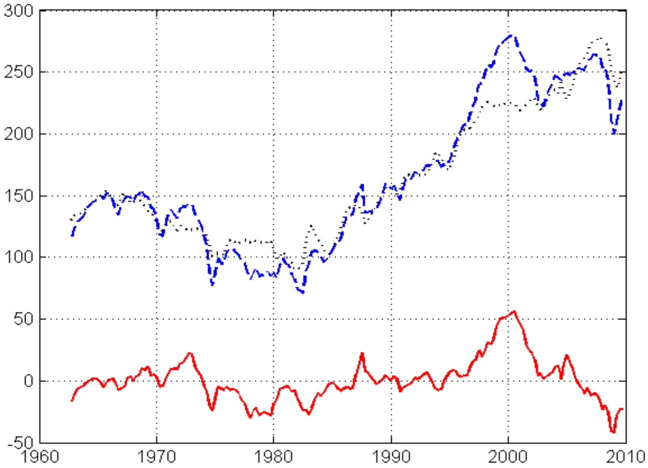
A companion paper: Noise Bubbles

- Price equation: $p_t = \frac{k}{1-\rho} + \frac{1-\rho}{\rho} \sum_{j=1}^{\infty} \rho^j E_t d_{t+j}$
  - d_t: (log) dividends.
  - p_t: (log) prices.
- Dividends process: $d_t = d_{t-1} + a_{t-1}$
  - a_t: real (news) shock.
- Signal: $s_t = a_t + e_t$
  - e_t: "noise" shock.
- Price equation solution: $p_t = \frac{k}{1-\rho} + d_t + E_t a_t$
- Price growth solution: $\Delta p_t = \frac{\sigma_a^2}{\sigma_s^2} \left(a_t + \frac{\sigma_e^2}{\sigma_a^2} a_{t-1} \right) + \frac{\sigma_a^2}{\sigma_s^2} (e_t - e_{t-1})$

Impulse response functions



Historical decomposition of S&P500



Dashed: S&P500 - Solid: noise comp. - Dotted: S&P500-noise

Conclusions

1. Expectations of future changes in economic fundamentals, which in part do not eventually materialize should be considered a major source of business cycle fluctuations.

Conclusions

1. Expectations of future changes in economic fundamentals, which in part do not eventually materialize should be considered a major source of business cycle fluctuations.

2. VAR can be successfully employed under the assumption of imperfect information.

Conclusions

1. Expectations of future changes in economic fundamentals, which in part do not eventually materialize should be considered a major source of business cycle fluctuations.

2. VAR can be successfully employed under the assumption of imperfect information.

3. Quite general identification procedure. Requirement: a variable clean of noise.

Conclusions

1. Expectations of future changes in economic fundamentals, which in part do not eventually materialize should be considered a major source of business cycle fluctuations.

2. VAR can be successfully employed under the assumption of imperfect information.

3. Quite general identification procedure. Requirement: a variable clean of noise.

4. Companion paper on stock prices. We show noise can generate stock prices fluctuations independent on economic fundamentals.

Additional slides (1)

Fundamentalness (1/2)

a) Econometrician and agents have the same information but they cannot uncover shocks (as in this paper).

(Back)

Fundamentalness (2/2)

b) Econometrician has less info than agents: more info might help.

Fundamentalness (2/2)

b) Econometrician has less info than agents: more info might help.

Forni, Gambetti, Sala (2013): Lucas tree model. TFP:

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

Agents maximize $E_t \sum_{t=0}^{\infty} \beta^t c_t$, observe ε_t and η_t at time t.

Fundamentalness (2/2)

b) Econometrician has less info than agents: more info might help.

Forni, Gambetti, Sala (2013): Lucas tree model. TFP:

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

Agents maximize $E_t \sum_{t=0}^{\infty} \beta^t c_t$, observe ε_t and η_t at time t.

The equilibrium value for asset prices is:

$$p_t = \sum_{j=1}^{\infty} \beta^j E_t a_{t+j}$$

Fundamentalness (2/2)

b) Econometrician has less info than agents: more info might help.

Forni, Gambetti, Sala (2013): Lucas tree model. TFP:

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

Agents maximize $E_t \sum_{t=0}^{\infty} \beta^t c_t$, observe ε_t and η_t at time t.

The equilibrium value for asset prices is:

$$p_t = \sum_{j=1}^{\infty} \beta^j E_t a_{t+j}$$

The structural MA:

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

det(.) $= 0$ 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.

The econometrician observing productivity and stock prices cannot recover ε_t by estimating a VAR on Δa_t and Δp_t.

(Back)

Blanchard, Lorenzoni and L'Huillier

Fundamental driven by 2 components, transitory and temporary:

$$\begin{aligned} a_t &= x_t + z_t \\ \Delta x_t &= \rho \Delta x_{t-1} + \varepsilon_t \\ z_t &= \rho z_{t-1} + \eta_t \\ s_t &= x_t + v_t \end{aligned}$$

The structural non-fundamental representation:

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} (1-\rho L)^{-1} & 0 & (1-L)(1-\rho L)^{-1} \\ 1 & 1 & 0 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ v_t \\ \eta_t \end{pmatrix}$$

2 variables, 3 shocks: no way to recover 3 shocks with 2 variables!

(Back)

Barsky and Sims

Fundamental driven by 2 components:

$$\begin{aligned} a_t &= a_{t-1} + g_{t-1} + \varepsilon_{a,t} \\ g_t &= (1-\rho)g^* + \rho g_{t-1} + \varepsilon_{g_a,t} \\ s_t &= g_t + \varepsilon_{s,t} \end{aligned}$$

Again, 2 variables (a_t and s_t), 3 shocks: no way to recover 3 shocks with 2 variables!

(Back)

Multivariate specification

$$\Delta a_t = c(L)\varepsilon_t + g(L)e_t,$$

The innovation representations is

$$\begin{pmatrix} \Delta a_t \\ z_t \\ \Delta w_t \end{pmatrix} = \begin{pmatrix} \frac{c(L)\sigma_u}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} & g(L) \\ d(L)\sigma_u & f(L)\sigma_s & p(L) \\ q(L) & h(L) & m(L) \end{pmatrix} \begin{pmatrix} u_t/\sigma_u \\ s_t/\sigma_s \\ e_t \end{pmatrix}$$

where $g(0) = p(0) = 0$ and $c(0) = 0$.

From fundamental to structural (non-fundamental) shocks:

$$\begin{pmatrix} u_t/\sigma_u \\ s_t/\sigma_s \\ e_t \end{pmatrix} = \begin{pmatrix} \frac{b(L)\sigma_v}{\sigma_s} & -\frac{b(L)\sigma_\varepsilon}{\sigma_s} & 0' \\ \frac{\sigma_\varepsilon}{\sigma_s} & \frac{\sigma_v}{\sigma_s} & 0' \\ 0 & 0 & I \end{pmatrix} \begin{pmatrix} \varepsilon_t/\sigma_\varepsilon \\ v_t/\sigma_v \\ e_t \end{pmatrix}$$

(Back)

Testing for fundamentalness

A VAR is fundamental if the shocks are orthogonal to past information (econometrician fundamentalness)

Testing for fundamentalness

A VAR is fundamental if the shocks are orthogonal to past information (econometrician fundamentalness)

VAR for 5 variables above is fundamental.

Testing for fundamentalness

A VAR is fundamental if the shocks are orthogonal to past information (econometrician fundamentalness)

VAR for 5 variables above is fundamental.

Signal (s_t) and learning (u_t) shocks are orthogonal to past information (summarized in PC)

On impact,

Identification 1:

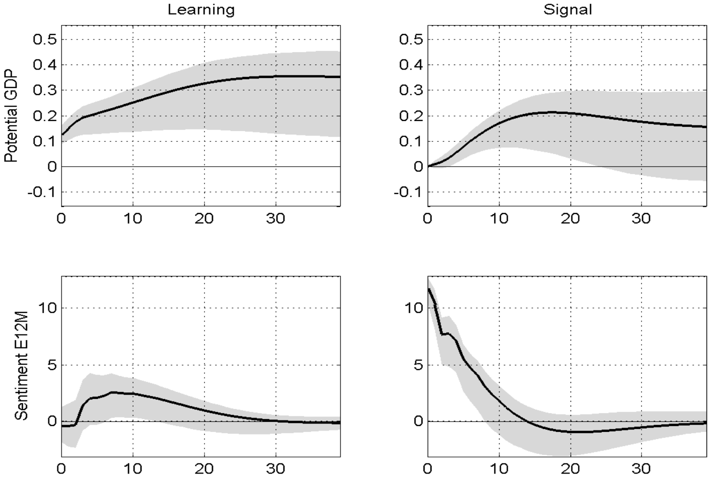
$$\begin{bmatrix} \Delta a_t \\ z_t \\ \Delta w_t \end{bmatrix} = \begin{bmatrix} k \cdot c(0) & \underline{0} & 0 \\ X & X & 0 \\ X & X & X \end{bmatrix} \begin{bmatrix} \varepsilon_t/\sigma_\varepsilon \\ v_t/\sigma_v \\ e_t \end{bmatrix}$$

Identification 2:

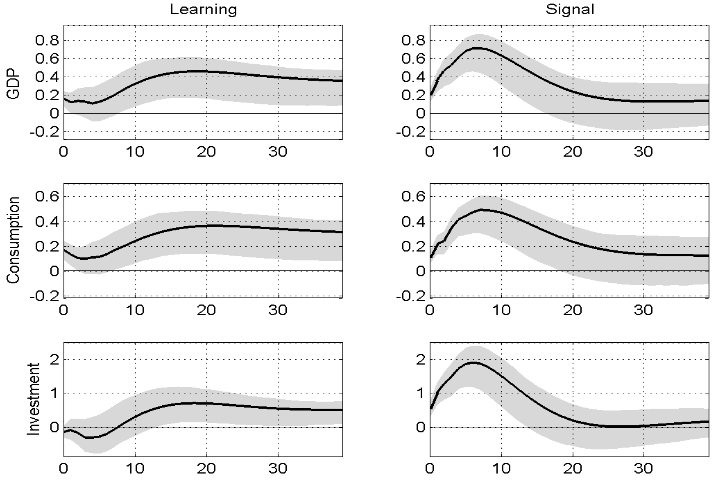
$$\begin{bmatrix} \Delta w_t \\ \Delta a_t \\ z_t \end{bmatrix} = \begin{bmatrix} X & 0 & 0 \\ X & k \cdot c(0) & \underline{0} \\ X & X & X \end{bmatrix} \begin{bmatrix} e_t \\ \varepsilon_t/\sigma_\varepsilon \\ v_t/\sigma_v \end{bmatrix}$$

(Back)

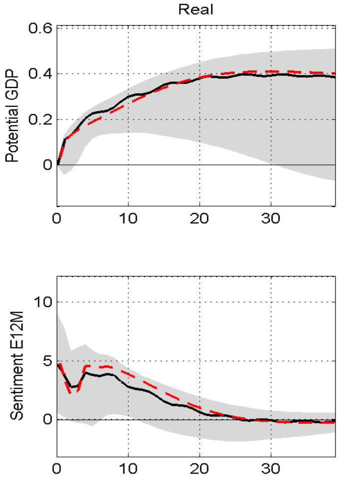
IRF: learning u_t - signal s_t (1/2)



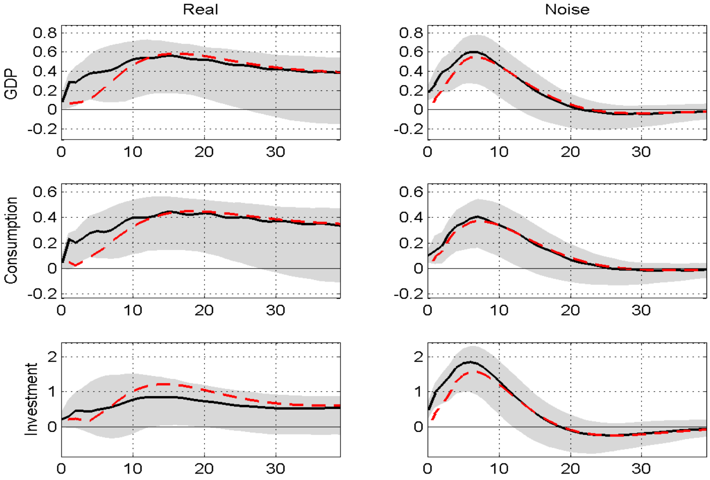
IRF: learning u_t - signal s_t (2/2)



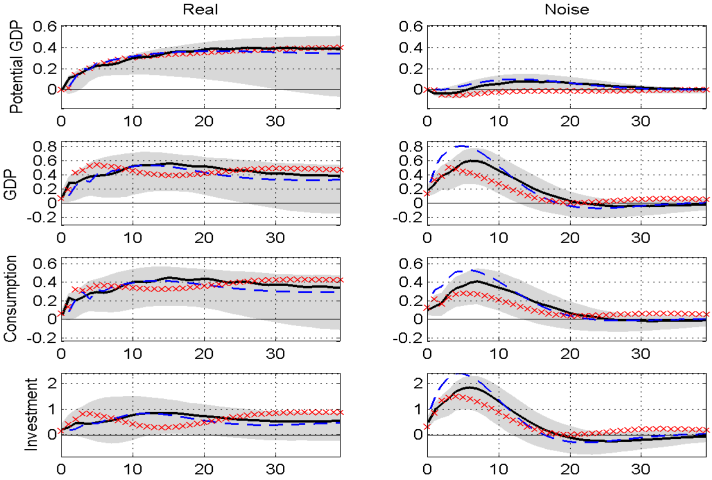
IRF: z_t ordered last



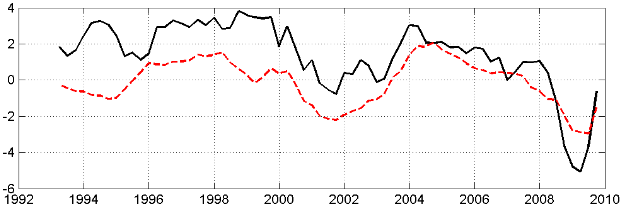
IRF: z_t ordered last

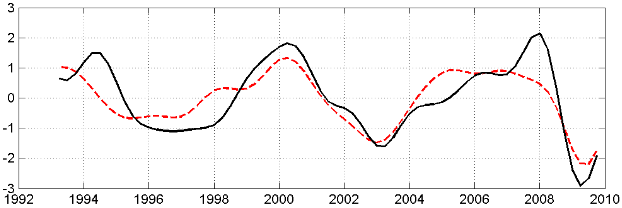


IRF: 3 leading variables



Historical decomposition of GDP (with S&P500)





Historical decomposition of GDP (with leading indicator)