Discussion of "Noisy News in Business Cycle" by Forni, Gambetti, Lippi, and Sala

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IV International Conference in memory of Carlo Giannini

My understanding of the paper

Great contribution in the **literature of NEWS and NOISE shocks**: Barsky and Sims (2011, JME) and Blanchard, L'Huillier, and Lorenzoni (2013, AER)

> "... **news shocks** are the **permanent productivity shocks** that because of their gradual effect on productivity, are largely information about future productivity rather than changes in current productivity. **Noise shocks**, by contrast, are **shocks to the signal that are unrelated to changes in productivity**. Ideally agents would ignore the noise shocks, but they are unable to fully distinguish between noise and news." [Krusell and Mckay, Economic Quarterly, 2010]

My understanding of the paper

- The paper proposes to achieve **identification using dynamic rotations (dynamic identification) of the reduced form residuals in case of non-fundamentalness**
- **A contemporaneous linear combination of the VAR residuals cannot deliver the structural shock, but a dynamic combination (i.e. a combination of present and future residuals) can**
- The structural shock are recovered as function of future reduced form ones, not current ones
- **MAIN RESULTS:** the "**noisy news**" (the real and the noise shocks together) explain more than half fluctuations of GDP, consumption and investment

Real shock, Noise, Signal ...

We assume that the potential output

$$a_t = a_{t-1} + \varepsilon_{t-1} \quad (1)$$

where ε_t (**REAL SHOCK**) is a Gaussian, serially uncorrelated process affecting the output with a one-period delay
Consumers observe a noisy signal of ε_t (**REAL or NEWS SHOCK**), the **SIGNAL** s_t :

$$s_t = \varepsilon_t + v_t \quad (2)$$

where v_t (**NOISE SHOCK**)

... Learning ...

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} L & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix} \quad (3)$$

we can rewrite as:

$$\begin{pmatrix} \Delta a_t \\ s_t \end{pmatrix} = \begin{pmatrix} 1 & L\sigma_\varepsilon^2/\sigma_s^2 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} u_t \\ s_t \end{pmatrix} \quad (4)$$

where

$$\begin{pmatrix} u_t \\ s_t \end{pmatrix} = \begin{pmatrix} L\frac{\sigma_v^2}{\sigma_s^2} & -L\frac{\sigma_\varepsilon^2}{\sigma_s^2} \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix} \quad (5)$$

u_t is the **LEARNING SHOCK** which represents the new information about past structural shocks

What I like ...

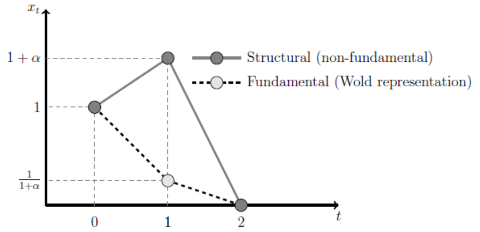
- Different names for shocks: **noise, news, real, noisy news, signal, learning**, ... :-)
- Focus on **MA representation in shocks** and fundamentalness test :-)
- An **identification strategy ad-hoc** to use VAR in this topic :-)

$\Longrightarrow$ Future applications to **medium scale DSGE models with a VARMA representation** :-)))

What I like ...

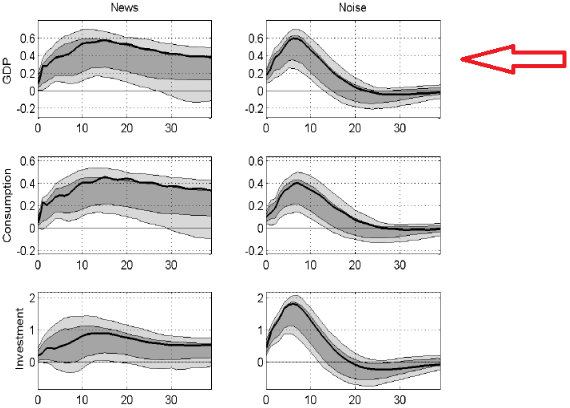
Focus on **MA representation in shocks** and fundamentalness test :-)
In Beaudry and Portier (2013)

Figure 6: A structural nonfundamental news-rich MA(1) process and its fundamental representation



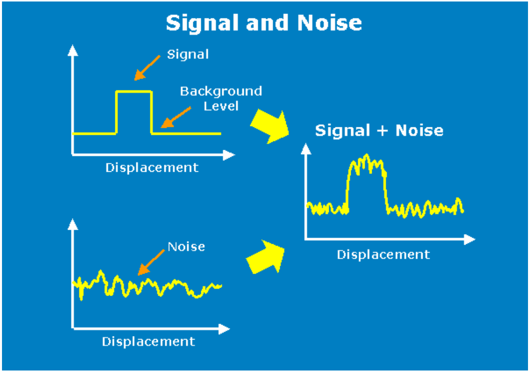
Note: This Figure displays the impulse response functions to a unit shock for the structural non-fundamental process (18) and its Wold representation (19).

What I like ...


News
Noise
GDP
Consumption
Investment
0.6
0.4
0.2
0
-0.2
2
1
0
10
20
30

What I like less ...

Different names for shocks: **noise, news, real, noisy news, signal, learning**, ... :-(



What I like less ...

Variable	Horizon				
	Impact	1-Year	2-Years	4-Years	10-Years
	Learning				
GDPPOT	100.0	91.5	78.8	62.6	49.6
E12M	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				
GDPPOT	0.0	2.9	12.5	23.0	15.2
E12M	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
	Real				
GDPPOT	0.0	87.4	87.6	81.4	63.1
E12M	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				
GDPPOT	0.0	4.6	2.1	3.1	1.1
E12M	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
	Real+Noise				
GDPPOT	0.0	92.0	89.7	84.5	64.1
E12M	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

Table 3: Variance decomposition in the 5-variable VAR, E12M ordered second. The entries are the percentage of variance explained by the shocks.

My Comments

Maybe we can identify ONLY the noise shock ... NOT a NOISY NEWS ...

how?

Masolo and Paccagnini (2013)

- **We combine the identification of noise shock with real-time data, using different vintages**
- We focus on the economic implications using a simple VAR and the **Impulse Responses**
- We assume that **early vintages of data are a NOISY version of the final release**
- **MAIN RESULTS**: Significant Responses of Output, Unemployment and Investment to a **NOISE SHOCK** suggest that revisions are important in the behavior of macro variables

Cholesky Identification Scheme in Data

$$x_t^0 = x_t^f + v_t \tag{6}$$

x_t^0 is the **EARLY RELEASE,** x_t^f is the **FINAL RELEASE,** $v_t = x_t^0 - x_t^f$ is a **NOISE SHOCK**
We include two vintages of GDP growth and unemployment in a VAR and identify the noise shock as that shock which *contemporaneously* affects the early release of data but not the latest.
Our baseline specification:

$$\begin{bmatrix} \Delta y_t^f \\ u_t^f \\ \Delta y_t^0 \end{bmatrix} = \beta_0 + \beta_1 \begin{bmatrix} \Delta y_{t-1}^f \\ u_{t-1}^f \\ \Delta y_{t-1}^0 \end{bmatrix} + C \begin{bmatrix} \nu_t^1 \\ \nu_t^2 \\ \nu_t^3 \end{bmatrix} \tag{7}$$

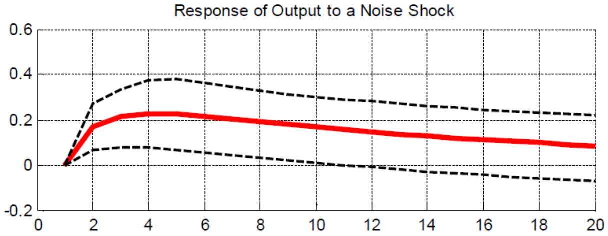
Cholesky Identification Scheme in Data

Our identification strategy identifies ν_t^3 as the noise or revision shock.

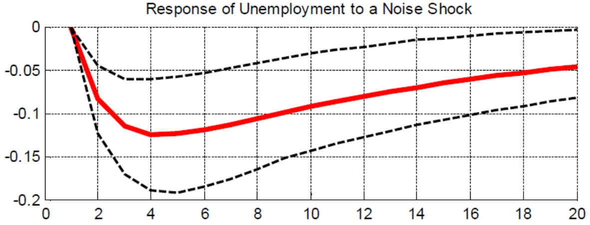
$$C = \begin{bmatrix} \dots & 0 \\ & 0 \\ \dots & C_{33} \end{bmatrix} \tag{8}$$

Noise shocks are identified by the fact that they contemporaneously affect **only the early release of data**
As a result:
$\nu_t^3 \perp \Delta y_{t-1}^f,\ u_{t-1}^f,\ \Delta y_{t-1}^0,\ \Delta y_t^f,\ u_t^f$

Impulse Response Functions



Impulse Response Functions



Conclusions

The paper is a FANTASTIC contribution !!!!

Noise vs News

Mankiw and Shapiro (1986) and Aruoba (2008)

- **Noise**: *the initial announcement is an observation of the final series, measured with error. The revision is uncorrelated with the final value but correlated with the data available when estimate is made*
- **News**: *the initial announcement is an efficient forecast which depends on all information. The revision is correlated with the final value but uncorrelated with the data available when estimate is made*

Setup

Proposed state equation for a model with dispersed information (i.e. one in which additional information about the past is still relevant):

$$x_t^f = A(L)x_{t-1}^f + B(L)v_{t-1} + \varepsilon_t \tag{9}$$

- The final release is assumed to be the variable set by agents in the model
- With the benefit of hindsight the information set of the econometrician is richer than that of model agents
- Main assumption: **the early release for the current period is not available when agents make their decisions (hence v_t does not show up in the law of motion)**

Classical Noise

$$x_t^0 = A(L)x_{t-1}^f + B(L)v_{t-1} + \varepsilon_t + v_t \quad (10)$$

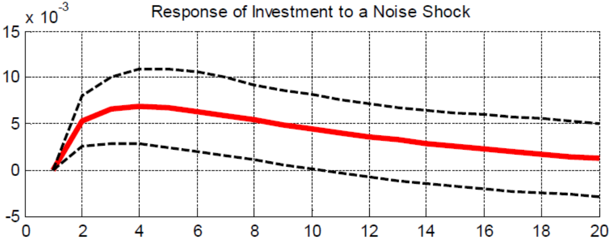
The revision is orthogonal to the final release

Identification Assumption: *the noise shock contemporaneously affects the early but not the final release*

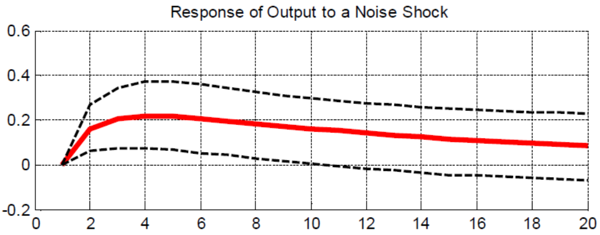
Data

- Quarterly vintages and quarterly observations of the **Real GNP/GDP** (ROUTPUT). We take the first difference logarithmic transformation, considering it as a quarterly (annualized) growth rate $\longrightarrow$ **Early and final vintages**
- Quarterly vintages and monthly observations of the **Unemployment Rate** (RUC). We transform our data from monthly to quarterly frequency considering the first observation of the quarter
- All the series are taken **from 1966:1 to 2006:4**, considering **the latest revision of 2011:3**
- Source: FED of Philadelphia

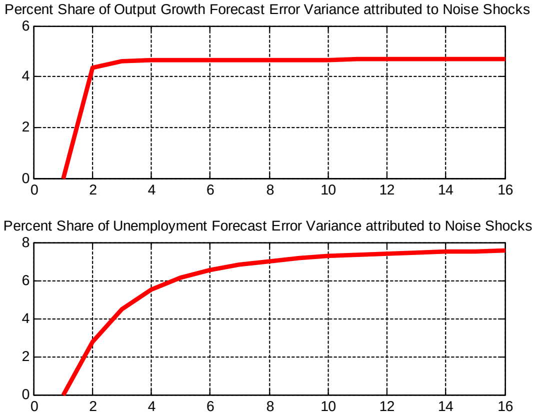
Impulse Response Functions



Impulse Response Functions



Variance Decomposition



Variance Decomposition: Comparison

	Output Growth		Unemployment	
	BQ	SDN	BQ	SDN
Supply	43.48	41.23	2.08	1.11
Demand	56.52	54.04	97.92	91.16
Noise	n.a.	4.73	n.a.	7.73