# Comments to Gimme a Break!, by Bacchiocchi, Castelnuovo and Fanelli 

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Main object of the paper: to say new and exciting things by using non-recursive identification SVAR scheme.

## Main points: <br> (a Identification through heteroskedasticity à la Rigobon (2003) and Bacchiocchi (2010); <br> (2) deep parameter estimation via IRF (minimum-distance) matching; <br> B nice story about how the 1984q1 break modified the cost channel hope I haven't forgotten anything.

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## Trivial stuff

(1) Perhaps some exogenous variable (commodity prices?) could have helped.
(2) Some robustness check as to the timing of the break would have been nice.
(3) Policy relevance in a post-Lehman world?

## The economic rationale of triangular identification

Triangular identification: $\varepsilon_{t}=C u_{t}$

$$
\left[\begin{array}{c}
\vdots \\
\varepsilon_{F F} \\
\vdots
\end{array}\right]=\left[\begin{array}{lll}
* & & \\
* & * & \\
* & * & *
\end{array}\right]\left[\begin{array}{c}
\vdots \\
u_{m p} \\
\vdots
\end{array}\right]
$$

In words: the structural monetary policy shock is identified via the fact that it doesn't affect instantaneously stuff above FF but hits stuff below. for the ordering of the columns of $C$; more generally, $\varepsilon_{t}=\left(C P^{\prime}\right)\left(P u_{t}\right)$, where $P$ is a permutation matrix.

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In words: the structural monetary policy shock is identified via the fact that it doesn't affect instantaneously stuff above FF but hits stuff below. If you reverse the ordering of the elements of $u_{t}$ nothing changes, except for the ordering of the columns of $C$; more generally, $\varepsilon_{t}=\left(C P^{\prime}\right)\left(P u_{t}\right)$, where $P$ is a permutation matrix.

This is normally justified via

- Institutional features (eg price stickiness)
- Technology
- Information asymmetries

Having 2 (or more) regimes for the deep parameters is irrelevant, as long as the above continues being true.

## What the authors do

Break-based identification: $\varepsilon_{t}=\left[C+Q_{t}\right] u_{t}$, where $Q_{t}=0$ for $t<B$ and $Q$ is diagonal for $t \geq B$ ( $C$ is unconstrained)

$$
\begin{aligned}
& {\left[\begin{array}{c}
\vdots \\
\varepsilon_{F F} \\
\vdots
\end{array}\right]=\left[\begin{array}{ccc}
* & * & * \\
* & * & * \\
* & * & *
\end{array}\right]\left[\begin{array}{c}
\vdots \\
u_{m p} \\
\vdots
\end{array}\right] \quad \text { regime } 0} \\
& {\left[\begin{array}{c}
\vdots \\
\varepsilon_{F F} \\
\vdots
\end{array}\right]=\left[\begin{array}{ccc}
\star & * & * \\
* & \star & * \\
* & * & \star
\end{array}\right]\left[\begin{array}{c}
\vdots \\
u_{m p} \\
\vdots
\end{array}\right] \quad \text { regime } 1}
\end{aligned}
$$

The structural monetary policy shock is identified via it being the only structural shock whose impact on the one-step-ahead prediction error for the fedfunds changes after the break.

Unless I'm missing something, the implicit hypothesis for this is:

- Traditional (frictional) arguments for identification don't apply.
- Deep parameters change from regime 0 to regime 1 in such a way that the relationship between structural shocks and reduced-form disturbances is unaffacted, except for a one-to-one correspondence between prediction errors and structural shocks.
- The "monetary policy shock" is then defined as the one associated with the prediction error for the FED funds rate.
And the economic rationale for this is. . . what?
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Note: this could be rephrased as "why is $Q_{t}$ diagonal?" (as opposed to weirder arrangements, as long as there's only one non-zero entry per row and per column). That would simply exchange the ordering of the structural shocks $u_{t}$, which is of course conventional. Note: this doesn't apply to similar application, such as, eg, Rigobon(2003, 2004).


## Questions

As a consequence:

- Are we sure that what we're seeing are the IRFs to a policy shock and not something else?
- But if they're not, what are they?
- Hence, minimum-distance IRFs calibration gives us. . . what?

On nearly the same data, I found that the six largest eigenvalues of the companion matrix are

$$
\lambda=\left[\begin{array}{llllll}
0.9939 & 0.9669 & 0.9669 & 0.9587 & 0.9587 & 0.9307
\end{array}\right]
$$

| Rank | Trace | pvalue |
| ---: | ---: | ---: |
| 0 | 188.59 | $[0.0000]$ |
| 1 | 135.60 | $[0.0000]$ |
| 2 | 89.894 | $[0.0011]$ |
| 3 | 53.694 | $[0.0180]$ |
| 4 | 29.739 | $[0.0601]$ |
| 5 | 14.345 | $[0.0789]$ |
| 6 | 0.33760 | $[0.5690]$ |

If you're lucky, you may have that you have no fewer than 3 permanent shocks; if you assume policy shocks are transitory you can call unit roots to the rescue and use a KPSW-style strategy to help.

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