The Puzzling Effects of Monetary Policy in VARs:

Invalid Identification or Missing Information?

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Puzzling Effects of Monetary VARs

due to invalid identification scheme?

Contractionary monetary policy shocks

- increase prices ('price puzzle')
- have hump-shaped effect on FX rates ('delayed overshooting')
- do not affect credit spreads

Main suspected culprit: Recursive (Cholesky) identification

- imposes invalid timing restrictions

Solution: external instruments (*Gertler and Karadi, 2015*)

- high-frequency futures around FOMC decisions
- no restrictions on contemporaneous shock effects

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or due to missing information?

But...
Puzzling VAR results may also be due to **Missing Information**

- VARs suffer curse of dimensionality
  inevitable proliferation of unknown parameters as further variables (or lags) are added
- may lead to nonfundamentalness

⇒ invalidates results, **regardless of identification scheme**

Solution: enlarge information set

- FAVAR: add factors to observable variables
- DFM: assume all factors are unobservable

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My research question: what explains puzzling VAR results?

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Approach: start with basic Cholesky VAR and

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- expand information set via factors

→ check which puzzles these methods are able to solve

Result: missing information is key

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Empirical Methods

Models

$$\underset{N\times T}{X} = \underset{N\times r}{\Lambda}\ \underset{r\times T}{F} + \underset{N\times T}{e} \quad \text{and} \quad \underset{r\times r}{\Phi(L)}\ \underset{r\times T}{F} = \underset{r\times T}{u}$$

VAR:

- $N = r = 4$: log IP, log CPI, 1-year rate + variable of interest
- $X = F = Y^{\text{VAR}}$, $e = 0$ (all factors perfectly observable)

FAVAR:

- $N >> r$, $F =$(IP, CPI, 1y rate, F^*), F^*: 9 princ. comp.
- idiosyncratic (e.g. measurement) errors e

DFM (dynamic factor model):

- $N >> r > q$ (dynamic factors), $F = F^*$

dataset X covers $N = 132$ US series from 1973 to 2016 ($T = 522$)

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Identification

$$\underset{\text{reduced-form}}{u} = \underset{r \times r}{H} \underset{\text{structural}}{e}$$

Recursive Cholesky identification: mon. policy shock

- increases 1-year rate
- has no immediate effect on CPI or IP

External instrument identification:
fed funds future movements around FOMC announcements

- due to policy shocks
- not any other structural shock

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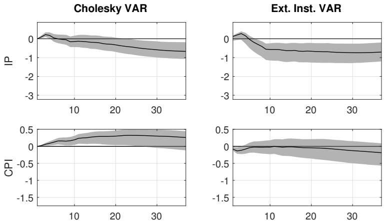
Results: Output and Prices

Study 50bp increase in 1-year rate (contractionary shock)



- recursive VAR yields puzzling results
- ext. inst. VAR solves IP puzzle (*Gertler and Karadi, AEJ 2015*)

→ but CPI response remains muted

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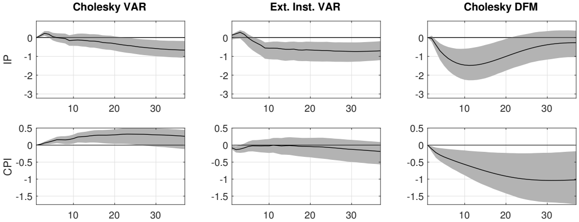

- dynamic factor model yields intuitive results

$\rightarrow$ even with Cholesky identification (*Forni and Gambetti, JME 2010*)

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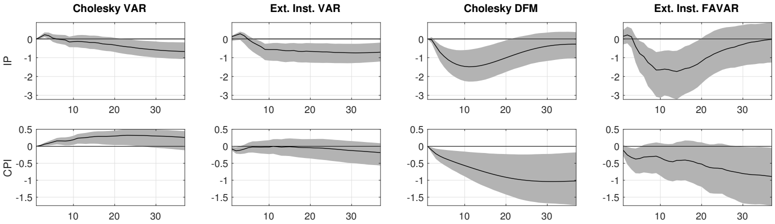
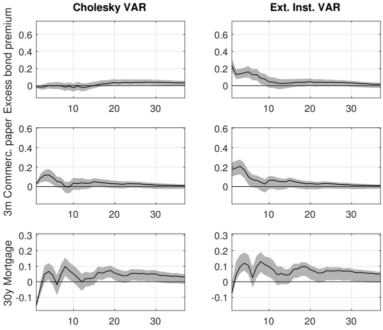


- ext. inst. **FA**VAR yields broadly similar results

→ difference b/w VAR and DFM due to info sets

Results: Corporate Bond Spreads



- recursive VAR yields puzzling results
- ext. inst. VAR solves most puzzles (*Gertler and Karadi, AEJ 2015*)

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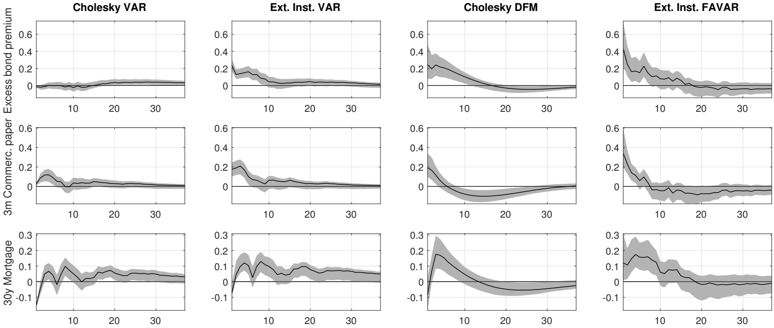
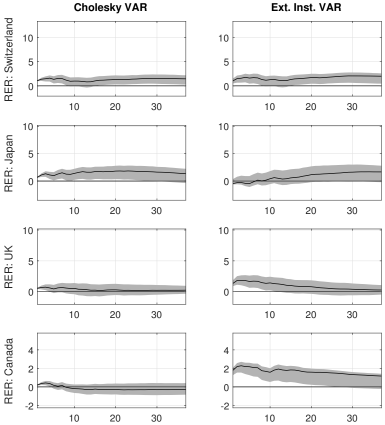


- DFM and FAVAR find somewhat larger effects

$\rightarrow$ largely confirm each other

Results: Real Exchange Rates



- recursive VAR yields puzzling results
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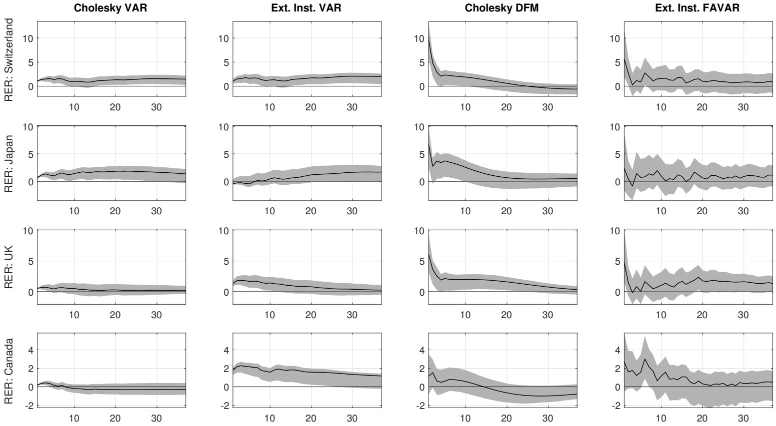
Results: Real Exchange Rates

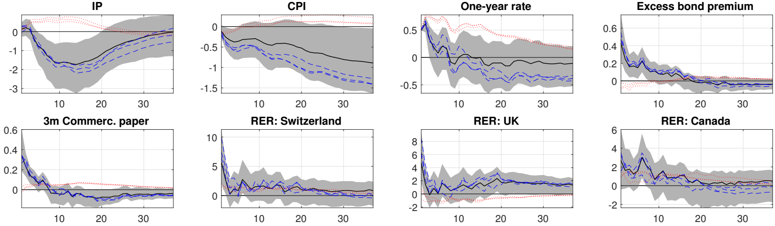


- DFM and FAVAR yield intuitive results

$\rightarrow$ immediate appreciation of US dollar across the board

Further Results

FAVAR results for different numbers of princ. components



Black line and shaded area: benchmark results with 9 principal components; red dotted lines: 1-3 princ. comp.; dashed blue lines: 7, 11, 13 princ. comp.

- with too few factors, puzzling VAR results re-emerge
- robust results when increasing number of factors

→ sufficient information is key

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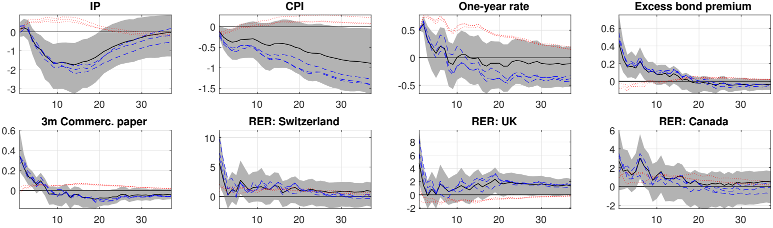

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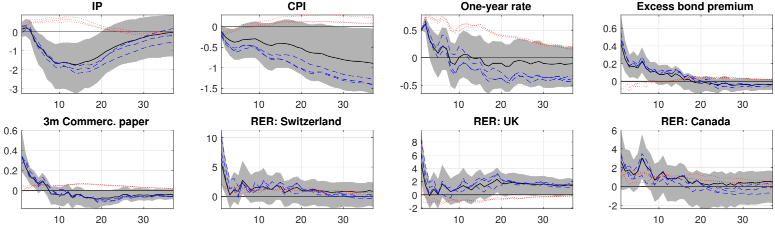

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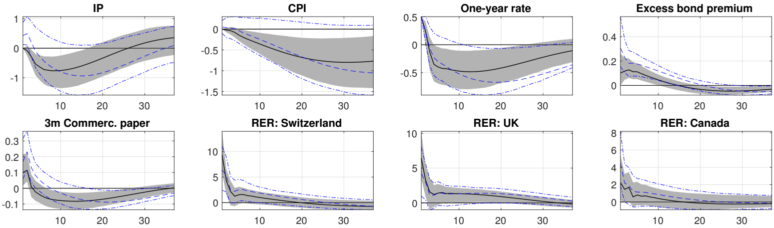
DFM results in different identification schemes



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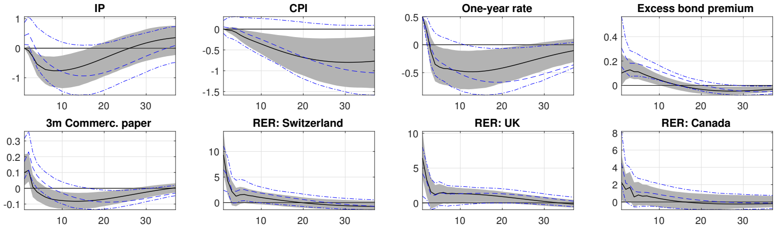

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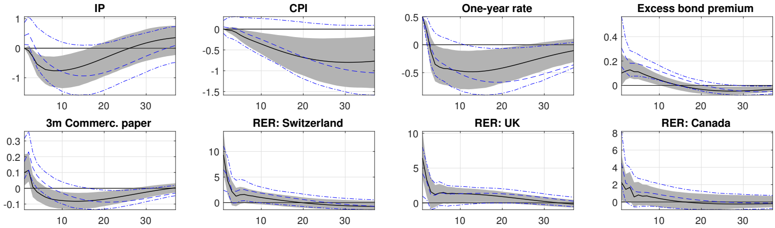

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In a joint paper with Lucia Alessi, we show

- even with high-frequency instrument, puzzling VAR results :
  - IP & CPI expand after contractionary shock
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  as in Jarocinski & Karadi, ECB WP 2018

- using same instrument in factor model yields intuitive results
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Conclusion

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2. External high-frequency instrument solves *some* puzzles
3. A recursive dynamic factor model solves *all* puzzles
4. Remaining discrepancies are due to limited info set of VAR

$\rightarrow$ ext. inst. FAVAR similar to recursive DFM

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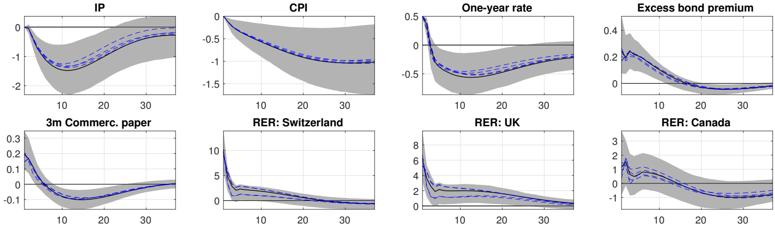
Thank you for your attention!

Any questions?

Cholesky DFM: static factors



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- blue: $r = \in \{14, 15, 17, 18\}$

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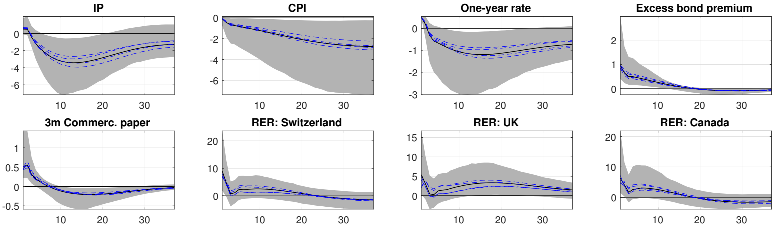

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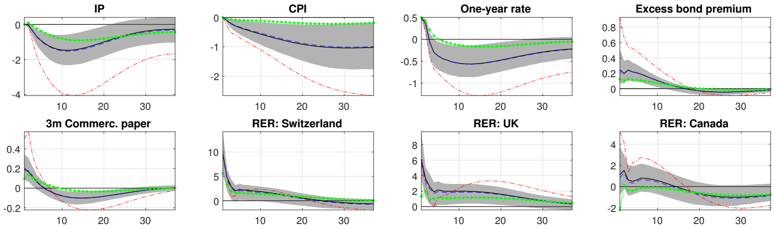
Cholesky DFM: dynamic factors

- Motivation
- Empirical Methods
- Results
- Conclusion
- **Robustness**
- Details
  - Dynamic Factor Model
  - Identification
  - Nonfundamentalness



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- blue: $q = 5$
- green: $q = 6$

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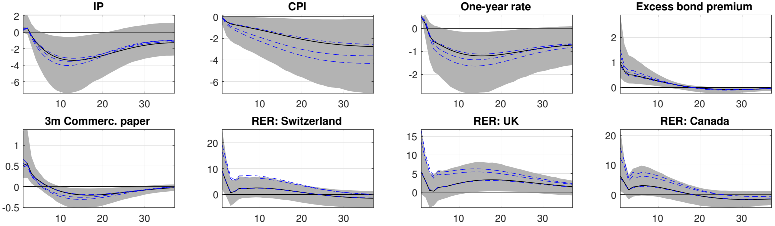

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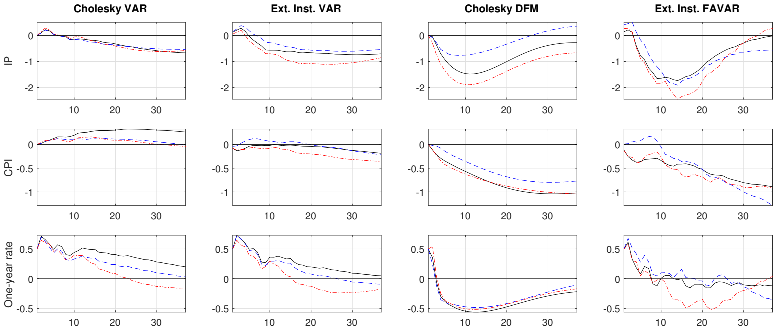
Subsample Analysis: Macro aggregates



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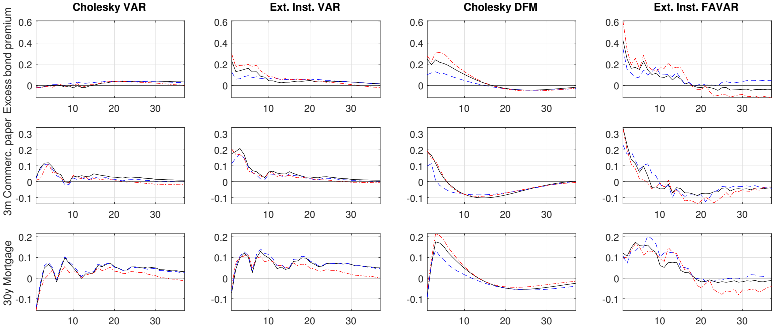
Subsample Analysis: Credit Spreads



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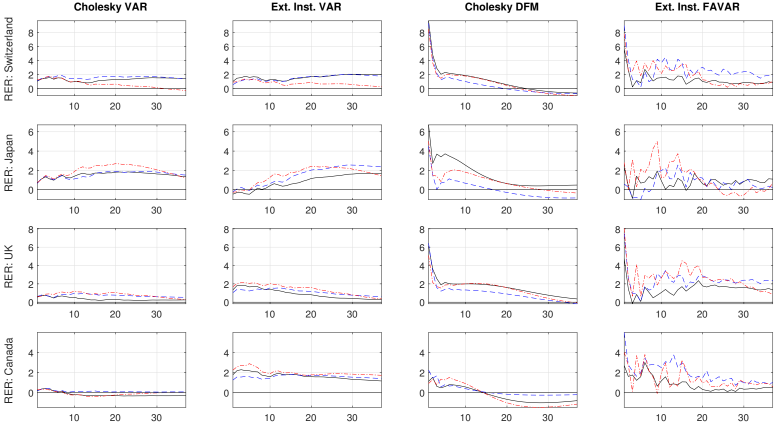

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Forni and Gambetti (2010)

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$\rightarrow$ Challenge: identify matrix H (or column thereof)

External instrument identification

Gertler and Karadi (2015)

Rewrite

$$u_t = H\epsilon_t = [H_1 \ldots H_q] \begin{pmatrix} \epsilon_{1t} \\ \vdots \\ \epsilon_{qt} \end{pmatrix}$$

and w.l.g. pick ϵ_{1t} as the mon.pol. shock

Given an instrumental variable Z_t that meets

- relevance condition: $E(\epsilon_{1t} Z_t) = \alpha \neq 0$
- and exogeneity condition: $E(\epsilon_{jt} Z_t) = 0, j = 2, \ldots, q$

we get

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$\rightarrow$ In practice: estimate H_1 by regressing instrument Z_t on reduced form shocks u_t

External instrument identification

Gertler and Karadi (2015)

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Nonfundamentalness in small-scale VARs

VAR models: a quick recap

Y_t: economic variables (production, prices, interest rates, ...)
ϵ_t: shocks (technology, fiscal and monetary policy, ...)

$$\Rightarrow Y_t = B(L)\epsilon_t$$

Intuition: the economy is driven by exogenous structural shocks and agent's reaction to them (households, firms, ...)

1. estimate reduced form VAR: $A(L)Y_t = u_t$
2. obtain u_t and A_j by OLS (equation by equation)
3. apply identification restrictions B_0 (Cholesky, signs, long-run, ...)

$\rightarrow$ structural shocks $\epsilon_t = B_0^{-1} u_t$
$\rightarrow$ structural IRFs $B(L) = A(L)^{-1} B_0$

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Assumption (implicit): structural shocks can be recovered using present and past values of economic time series. But:

- Economic agents incorporate large information sets
  - → ECB e.g. monitors more variables than just GDP & HICP
- VARs typically capture only a few variables

⇒ agent's information set > econometrician's information set

⇒ **Nonfundamentalness**

Intuitively: VAR variables Y_t do not contain enough information to recover structural shocks u_t and IRFs $B(L)$

Technically: structural moving average representation is not invertible

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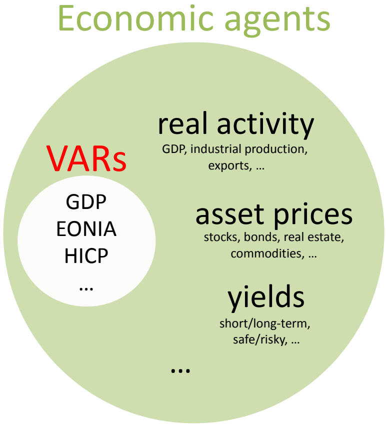
Nonfundamentalness $\Longleftrightarrow$ missing information

The problem with VARs:

- include only few selected variables
- hundreds of other potentially important variables neglected



Nonfundamentalness $\Longleftrightarrow$ missing information

Basic idea of factor models:

- expand the information space (drastically)
- usually >100 variables vs. 4-8 in VARs