# The Puzzling Effects of Monetary Policy in VARs:

Invalid Identification or Missing Information?

Mark Kerssenfischer<sup>1</sup>

<sup>1</sup>Deutsche Bundesbank

August 2018

The views expressed in this paper do not necessarily reflect those of the Deutsche Bundesbank.



due to invalid identification scheme?

#### Motivation

### Contractionary monetary policy shocks

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

imposes invalid timing restrictions

due to invalid identification scheme?

#### Motivation

Method

### Results

Conclus

#### Dobusto

110003111

### Detail

Dynamic Facto Model Identification

### 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

due to invalid identification scheme?

#### Motivation

Empirio

Results

Conclus

Dobusto

Tiobastin

Dynamic Facti Model

Identification Nonfundamenta ness

## 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

or due to missing information?

#### Motivation

Method

ricoun

Corrolasi

Robustne

### Detail

Dynamic Factor Model Identification Nonfundamentalness

### 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

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

or due to missing information?

#### Motivation

Method

Result

Conclusi

Pobuetne

Details

Dynamic Fact Model

Identification Nonfundamenta ness

### 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

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

or due to missing information?

#### Motivation

Method

Result

Conclus

Robustn

Dynamic Fact Model

Identification Nonfundamenta ness

### 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

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

or due to missing information?

#### Motivation

Methods

----

----

Robustne

Details

Dynamic Factor

Model

Identification

### 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

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

#### Motivation

Method

Resul

Conclusi

Robustne

----

Detail

Dynamic Facto Model

Identification Nonfundamenta ness My research question: what explains puzzling VAR results?

- invalid identification?
- or missing information?

Approach: start with basic Cholesky VAR and

- apply external instrument identification
- expand information set via factors
- → check which puzzles these methods are able to solve

Result: missing information is key

#### Motivation

Method

Resul

Conclusio

Robustne

Dynamic Factor
Model

Model Identification Nonfundamenta ness My research question: what explains puzzling VAR results?

- invalid identification?
- or missing information?

Approach: start with basic Cholesky VAR and

- apply external instrument identification
- expand information set via factors
- ightarrow check which puzzles these methods are able to solve

Result: missing information is key

#### Motivation

Method

Result

001101001

Robustne

Details

Dynamic Fact

Model
Identification
Nonfundamenta

My research question: what explains puzzling VAR results?

- invalid identification?
- or missing information?

Approach: start with basic Cholesky VAR and

- apply external instrument identification
- expand information set via factors
- $\rightarrow$  check which puzzles these methods are able to solve

Result: missing information is key

Models

#### Empirical Methods

 $N \times T$   $N \times r$   $r \times T$   $N \times T$ 

 $X = \Lambda F + e$  and  $\Phi(L) F = u$  $r \times r \quad r \times T \qquad r \times T$ 

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

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

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

Models

#### Empirical Methods

 $N \times T$   $N \times r$   $r \times T$   $N \times T$ 

 $X = \Lambda F + e$  and  $\Phi(L) F = u$  $r \times r \quad r \times T \qquad r \times T$ 

### 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)

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

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



### Models

Motivation

Empirical

Methods

Conclus

Debuston

----

Details

Dynamic F

Model Pac

Identification Nonfundamenta

$$X = \bigwedge_{N \times T} F + e$$
 and  $\Phi(L) F = u$ 

### VAR:

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

### FAVAR:

- N >> r,  $F = (IP, CPI, 1y rate, <math>F^*)$ ,  $F^*$ : 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)



### Models

Motivation

Empirical Methods

Resul

Conclusi

Robustne

. . .

Dynamic Fa

Model

Identification Nonfundamenta ness

$$X = \bigwedge_{N \times T} F + e$$
 and  $\Phi(L) F = u$ 

### VAR:

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

### FAVAR:

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

## DFM (dynamic factor model):

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

### Models

Motivation

Empirical Methods

Result

Conclusi

Robustne

Date 1

Dynamic Fa

Identification Nonfundamenta

$$X = \bigwedge_{N \times T} F + e$$
 and  $\Phi(L) F = u$ 

### 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,  $F = (IP, CPI, 1y rate, <math>F^*)$ ,  $F^*$ : 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)



### Identification

Motivation

### Empirical Methods

### Dogulto

Conclus

Debustes

Tiobustile

### Detail

Model
Identification
Nonfundamental

reduced-form structural u = H 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

### Identification

Motivatio

Empirical Methods

Resul

Conclusi

Dobustos

Dota

Model Pacti

Identification

Nonfundament

reduced-form structural 
$$u = H e$$

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



### Identification

Motivatio

Empirical Methods

Resul

Conclusio

Robustne

\_

Dynamic Facto Model

Nonfundament ness u = H e structural

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

# Results: Output and Prices

Motivation

## Results

Conclusio

Robustne

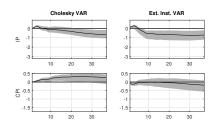
Details

Dynamic Factor

Model

Identification
Nonfundamenta

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

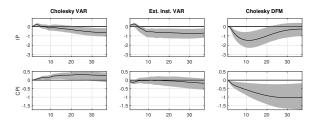


- recursive VAR yields puzzling results
- ext. inst. VAR solves IP puzzle (Gertler and Karadi, AEJ 2015)
- → but CPI response remains muted

# Results: Output and Prices

Results

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



- dynamic factor model yields intuitive results
- → even with Cholesky identification (Forni and Gambetti, JME 2010)

# Results: Output and Prices

Motivation

Results

Conclusio

Robustne

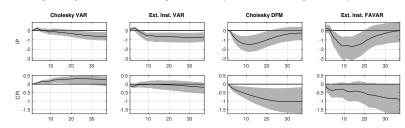
Details

Dynamic Fac

Model

Identification
Nonfundamenta

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



- ext. inst. FAVAR yields broadly similar results
- → difference b/w VAR and DFM due to info sets

# Results: Corporate Bond Spreads

Motivation

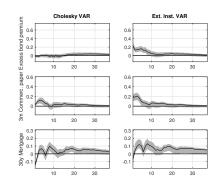
Empirical Methods

### Results

Conclusio

Robustne

Dynamic Factor Model Identification Nonfundamental



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

# Results: Corporate Bond Spreads

Motivation

Danish

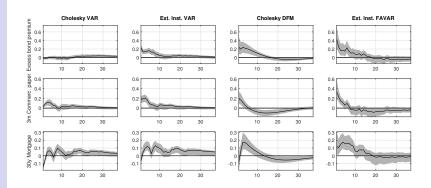
Results

Conclusion

Robustne

. . .

Details
Dynamic Factor
Model
Identification



- DFM and FAVAR find somewhat larger effects
- → largely confirm each other



# Results: Real Exchange Rates

Motivation

\_ . . . . .

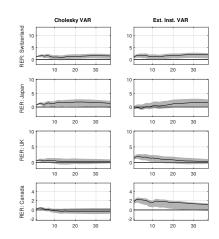
Results

Conclusio

Robustne

Dynamic Fa

Identification Nonfundamenta ness



- recursive VAR yields puzzling results
- ext. inst. VAR as well



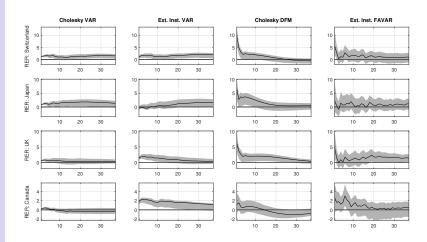
# Results: Real Exchange Rates



Robustne

Detelle

Dynamic Factor Model Identification Nonfundamenta



- DFM and FAVAR yield intuitive results
- $\,\rightarrow\,$  immediate appreciation of US dollar across the board



### Motivation

Method

### Results

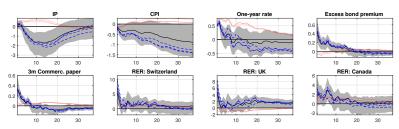
Conclusio

Robustne

Details

Dynamic Factor Model Identification Nonfundamenta

### FAVAR results for different numbers of princ. components

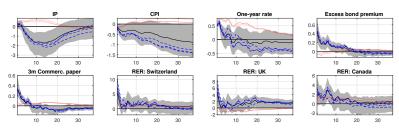


Black line and shaded area: benchmark results with 9 principal components; red dotted lines: 1-3 princ. comp.; dashed blue lines: 7, 11, 13 princ. comp.

- with too few factors, puzzling VAR results re-emerge
- robust results when increasing number of factors
- ightarrow sufficient information is key

### 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

Motivation Empirical

### Results

Conclusio

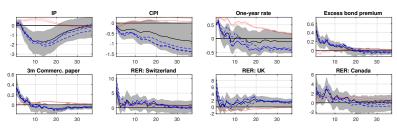
Robustne

Details

Dynamic Fact
Model

Identification

### FAVAR results for different numbers of princ. components

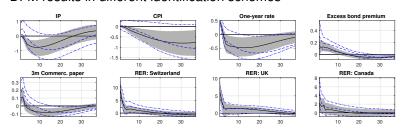


Black line and shaded area: benchmark results with 9 principal components; red dotted lines: 1-3 princ. comp.; dashed blue lines: 7, 11, 13 princ. comp.

- with too few factors, puzzling VAR results re-emerge
- robust results when increasing number of factors
- → sufficient information is key

### Results

### DFM results in different identification schemes



Black line and shaded area: benchmark results with recursive Cholesky scheme; blue dashed lines: external instrument scheme. Figure refers to pre-crisis sample (ending June 2008), estimates noisier for full sample.



### Motivation

Empirica Methods

### Results

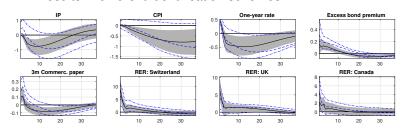
Conclusio

Robustne

### Dotaile

Dynamic Factor Model Identification Nonfundamenta

### DFM results in different identification schemes



Black line and shaded area: benchmark results with recursive Cholesky scheme; blue dashed lines: external instrument scheme. Figure refers to pre-crisis sample (ending June 2008), estimates noisier for full sample.

- dynamic factor model results broadly similar
- irrespective of identification scheme
- → Cholesky scheme might not be invalid per se



Motivation

Empirica Methods

### Results

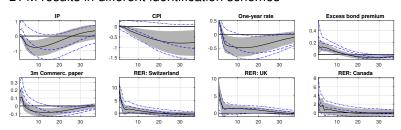
Conclusio

Robustne

Details

Dynamic Factor Model Identification Nonfundamental ness

### DFM results in different identification schemes



Black line and shaded area: benchmark results with recursive Cholesky scheme; blue dashed lines: external instrument scheme. Figure refers to pre-crisis sample (ending June 2008), estimates noisier for full sample.

- dynamic factor model results broadly similar
- irrespective of identification scheme
- → Cholesky scheme might not be invalid per se



# Further Results: Euro area

#### Motivation

#### wouvation

### Results

#### Conclusi

Dobustos

#### ----

Dynamic Fact

Identification
Nonfundamenta

### In a joint paper with Lucia Alessi, we show

- even with high-frequency instrument, puzzling VAR results :
  - IP & CPI expand after contractionary shock
  - Stocks & credit spreads barely react (or exhibit wrong sign) as in Jarocinski & Karadi, ECB WP 2018
- using same instrument in factor model yields intuitive results
  - solves IP & CPI puzzle
  - yields stronger & more rapid asset price effects

See "The Response of Asset Prices to Monetary Policy Shocks: Stronger Than Thought", Alessi & Kerssenfischer (2018)

# Further Results: Euro area

Motivation

Methods

Results

Corrolasio

Robustne

Details

Model Lacto

Identification Nonfundamenta ness

### In a joint paper with Lucia Alessi, we show

- even with high-frequency instrument, puzzling VAR results :
  - IP & CPI expand after contractionary shock
  - Stocks & credit spreads barely react (or exhibit wrong sign) as in Jarocinski & Karadi, ECB WP 2018
- using same instrument in factor model yields intuitive results
  - solves IP & CPI puzzle
  - yields stronger & more rapid asset price effects

See "The Response of Asset Prices to Monetary Policy Shocks: Stronger Than Thought", Alessi & Kerssenfischer (2018)

# Further Results: Euro area

Motivation

Metho

## Results

----

Hobusine

Details

Identification
Nonfundamenta

### In a joint paper with Lucia Alessi, we show

- even with high-frequency instrument, puzzling VAR results :
  - IP & CPI expand after contractionary shock
  - Stocks & credit spreads barely react (or exhibit wrong sign) as in Jarocinski & Karadi, ECB WP 2018
- using same instrument in factor model yields intuitive results
  - solves IP & CPI puzzle
  - yields stronger & more rapid asset price effects

See "The Response of Asset Prices to Monetary Policy Shocks: Stronger Than Thought", Alessi & Kerssenfischer (2018)

# Conclusion

#### Motivation

**Empirica**Methods

Result

### Conclusion

Date of the

#### Hobustne

Dynamic Factor Model Identification Nonfundamental

- Recursive small-scale VARs produce puzzling results
- External high-frequency instrument solves some puzzles
- A recursive dynamic factor model solves all puzzles
- Remaining discrepancies are due to limited info set of VAR
- → ext. inst. FAVAR similar to recursive DFM
- ⇒ Cholesky scheme not invalid per se, invalid only in conjunction with small-scale VARs
- Overall comforting news: Two leading empirical advances (external instruments and DFMs) cross-verify each other



- Recursive small-scale VARs produce puzzling results
- External high-frequency instrument solves some puzzles



- Recursive small-scale VARs produce puzzling results
- External high-frequency instrument solves some puzzles
- A recursive dynamic factor model solves all puzzles



- Recursive small-scale VARs produce puzzling results
- External high-frequency instrument solves some puzzles
- A recursive dynamic factor model solves all puzzles
- Remaining discrepancies are due to limited info set of VAR
- → ext. inst. FAVAR similar to recursive DFM.



- Recursive small-scale VARs produce puzzling results.
- External high-frequency instrument solves some puzzles
- A recursive dynamic factor model solves all puzzles
- Remaining discrepancies are due to limited info set of VAR
- → ext. inst. FAVAR similar to recursive DFM.
- ⇒ Cholesky scheme not invalid per se, invalid only in conjunction with small-scale VARs



- Recursive small-scale VARs produce puzzling results.
- External high-frequency instrument solves some puzzles
- A recursive dynamic factor model solves all puzzles
- Remaining discrepancies are due to limited info set of VAR
- → ext. inst. FAVAR similar to recursive DFM.
- ⇒ Cholesky scheme not invalid per se, invalid only in conjunction with small-scale VARs
- ⇒ Overall comforting news: Two leading empirical advances (external instruments and DFMs) cross-verify each other



### Motivation

Methods

riesuits

### Conclusion

Robustnes

Details

Model Pactor

Identification

Nonfundamen

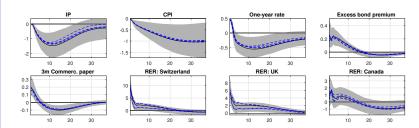
# Thank you for your attention!

Any questions?

## Cholesky DFM: static factors

### Robustness

Model

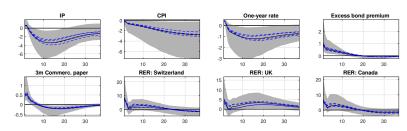


- black/shaded: r = 16 (benchmark)
- blue:  $r = \{14, 15, 17, 18\}$

## Ext. Inst. DFM: static factors

## Robustness

Model



- black/shaded: r = 16 (benchmark)
- blue:  $r = \{14, 15, 17, 18\}$

# Cholesky DFM: dynamic factors

Motivation

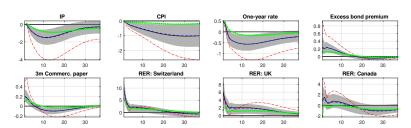
iviotivatioi

\_

Conclusio

## Robustness

Dynamic Factor Model Identification



- black/shaded: q = 4 (benchmark)
- red: *q* = 3
- blue: *q* = 5
- green: *q* = 6

# Ext. Inst. DFM: dynamic factors

Motivation

\_ .. .

Regulto

Conclusio

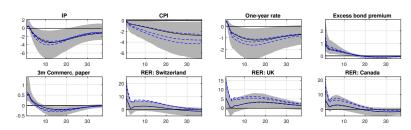
Robustness

Details

Dynamic Fact

Model

Model Identification Nonfundamentalness



- black/shaded: q = 4 (benchmark)
- blue:  $q = \{3, 5, 6\}$

# Subsample Analysis: Macro aggregates

Motivation

\_ .

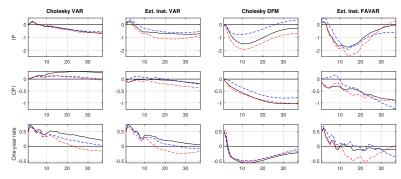
Result

Conclusio

### Robustness

Details

Model Identification Nonfundamental ness



- black: 1973m4-2016m9 (benchmark)
- blue: 1973m4-2008m6 (pre-crisis)
- red: 1979m7-2012m6 (Gertler and Karadi, AEJ 2015)

# Subsample Analysis: Credit Spreads

Motivation

Method

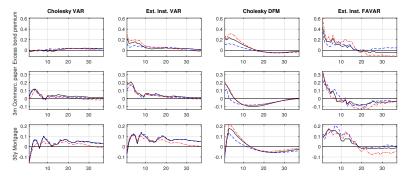
Results

Conclusio

### Robustness

Details Dynamic

Model Identification Nonfundamentalness



- black: 1973m4-2016m9 (benchmark)
- blue: 1973m4-2008m6 (pre-crisis)
- red: 1979m7-2012m6 (Gertler and Karadi, AEJ 2015)

## Subsample Analysis: FX rates



Empirical Methods

Result

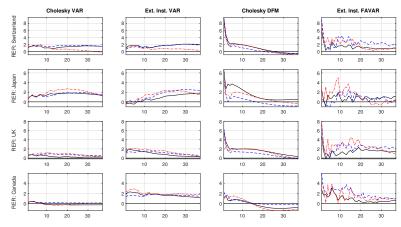
Conclusio

### Robustness

. . .

Dynamic Fact Model

Identification Nonfundament ness



- black: 1973m4-2016m9 (benchmark)
- blue: 1973m4-2008m6 (pre-crisis)
- red: 1979m7-2012m6 (Gertler and Karadi, AEJ 2015)



idio. comp.

Forni and Gambetti (2010)

Dynamic Factor

Model

component

variables N×1

Forni and Gambetti (2010)

Dynamic Factor

Model

variables 
$$_{N imes 1}^{\text{variables}}$$
 idio. comp.  $X_t = \chi_t + e_t$   $_{\text{common component}}^{\text{common component}}$   $\chi_t = \Lambda \cdot F_t$   $_{r ext{ static factors}}^{\text{component}}$ 

Forni and Gambetti (2010)

Dynamic Factor Model

variables 
$$N \times 1$$
 idio. comp.  $X_t = \chi_t + e_t$   $e_t$   $common component$   $component$   $com$ 

VAR
$$(p)$$
 matrix  $r \times q$   $\Phi(L)$   $F_t = G \cdot \underbrace{u_t}_{q \text{ reduced-form shocks}} q \le r$ 

Forni and Gambetti (2010)

Motivation

Method

Result

Conclus

Robustne

Detail

Dynamic Factor Model

Nonfundamenta

variables Nx1 idio. comp. 
$$X_t = \chi_t + e_t$$
 common component 
$$\chi_t = \Lambda \cdot F_t$$
  $r \leqslant N$   $r \ll N$ 

$$\Phi(L) \ F_t = G \ \cdot \ \underbrace{u_t}_{q \ \text{reduced-form shocks}} q \le r$$

$$u_t = H$$
  $\epsilon_t$   $q$  structural shocks

Forni and Gambetti (2010)

Motivation

Methods

Result

Conclus

Robustne

Detail

Dynamic Factor Model

Nonfundamenta

variables 
$$N \times 1$$
 idio. comp.  $X_t = \chi_t + e_t$   $e_t$   $e_t$   $\chi_t = \Lambda \cdot F_t$   $\chi_t = \Lambda \cdot F_t$   $r \leqslant N$ 

$$VAR(p)$$
  $matrix \\ r imes q$   $\Phi(L)$   $F_t = G \cdot \underbrace{u_t}_{q \text{ reduced-form shocks}} q imes r$ 

$$u_t = H$$
  $\epsilon_t$ 
 $q \text{ structural shocks}$ 

→ Challenge: identify matrix *H* (or column thereof)



Gertler and Karadi (2015)

Motivation

Motivatio

....

Resul

Conclus

Robustne

Dyna

Model

### Identification

Nonfundamen

## Rewrite

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

and w.l.g. pick  $\epsilon_{1t}$  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:  $E(\epsilon_{jt}Z_t) = 0, j = 2, \dots, q$

we get

$$\begin{bmatrix} E(u_{1t}Z_t) \\ E(u_{\bullet t}Z_t) \end{bmatrix} = E(u_tZ_t) = E(H\epsilon_tZ_t) = [H_1H_{\bullet}] \begin{bmatrix} E(\epsilon_{1t}Z_t) \\ E(\epsilon_{\bullet t}Z_t) \end{bmatrix} = \mathbf{H}_1\alpha$$

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

Gertler and Karadi (2015)

Motivation

Method

Resul

Conclusi

Robustna

Duna

Model

Identification

Nonfundame

## Rewrite

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

and w.l.g. pick  $\epsilon_{1t}$  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:  $E(\epsilon_{it}Z_t) = 0, j = 2, ..., q$

we get

$$\begin{bmatrix} E(u_{1t}Z_t) \\ E(u_{\bullet t}Z_t) \end{bmatrix} = E(u_tZ_t) = E(H\epsilon_tZ_t) = [H_1H_{\bullet}] \begin{bmatrix} E(\epsilon_{1t}Z_t) \\ E(\epsilon_{\bullet t}Z_t) \end{bmatrix} = H_1\alpha$$

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

Gertler and Karadi (2015)

Identification

### Rewrite

$$u_t = H\epsilon_t = [H_1 \dots H_q] egin{pmatrix} \epsilon_{1t} \ dots \ \epsilon_{qt} \end{pmatrix}$$
 and w.l.g. pick  $\epsilon_{1t}$  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:  $E(\epsilon_{it}Z_t) = 0, j = 2, \dots, q$

we get

$$\begin{bmatrix} E(u_{1t}Z_t) \\ E(u_{\bullet t}Z_t) \end{bmatrix} = E(u_tZ_t) = E(H\epsilon_tZ_t) = [H_1H_{\bullet}] \begin{bmatrix} E(\epsilon_{1t}Z_t) \\ E(\epsilon_{\bullet t}Z_t) \end{bmatrix} = H_1\alpha$$

Gertler and Karadi (2015)

Identification

Rewrite

$$u_t = H\epsilon_t = [H_1 \dots H_q] \begin{pmatrix} \epsilon_{1t} \\ \vdots \\ \epsilon_{qt} \end{pmatrix}$$
 and w.l.g. pick  $\epsilon_{1t}$  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:  $E(\epsilon_{it}Z_t) = 0, j = 2, \dots, q$

we get

$$\begin{bmatrix} E(u_{1t}Z_t) \\ E(u_{\bullet t}Z_t) \end{bmatrix} = E(u_tZ_t) = E(H\epsilon_tZ_t) = [H_1H_{\bullet}] \begin{bmatrix} E(\epsilon_{1t}Z_t) \\ E(\epsilon_{\bullet t}Z_t) \end{bmatrix} = H_1\alpha$$

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

VAR models: a quick recap

Motivation

Empirica Methods

Results

Corrolasi

Robustne

Detail

Dynamic Facto Model

Identification

Nonfundamentalness  $Y_t$ : economic variables (production, prices, interest rates, ...)

 $\epsilon_t$ : Shocks (technology, fiscal and monetary policy, ...)

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

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

- estimate reduced form VAR:  $A(L)Y_t = u_t$
- obtain  $u_t$  and  $A_i$  by OLS (equation by equation)
- $\bigcirc$  apply identification restrictions  $B_0$  (Cholesky, signs, long-run, ...)
- $\rightarrow$  structural shocks  $\epsilon_t = B_0^{-1} u_t$
- $\rightarrow$  structural IRFs  $B(L) = \tilde{A}(L)^{-1}B_0$

VAR models: a quick recap

Motivation

Method

Conclusi

Dobustos

. . . . . .

Detail

ynamic Facto lodel

Nonfundamentalness *Y<sub>t</sub>*: economic variables (production, prices, interest rates, ...)

 $\epsilon_t$ : Shocks (technology, fiscal and monetary policy, ...)

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

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

- estimate reduced form VAR:  $A(L)Y_t = u_t$
- $\bigcirc$  obtain  $u_t$  and  $A_i$  by OLS (equation by equation)
- $\bigcirc$  apply identification restrictions  $B_0$  (Cholesky, signs, long-run, ...)
- $\rightarrow$  structural shocks  $\epsilon_t = B_0^{-1} u_t$
- $\rightarrow$  structural IRFs  $B(L) = \mathring{A}(L)^{-1}B_0$

VAR models: a quick recap

Motivation

Result

Conclusi

Robustne

Details

Dynamic Facto Model

Nonfundamentalness

- $Y_t$ : economic variables (production, prices, interest rates, ...)
- $\epsilon_t$ : Shocks (technology, fiscal and monetary policy, ...)

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

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

- estimate reduced form VAR:  $A(L)Y_t = u_t$
- **2** obtain  $u_t$  and  $A_i$  by OLS (equation by equation)
- **apply identification restrictions**  $B_0$  (Cholesky, signs, long-run, ...)
- $\rightarrow$  structural shocks  $\epsilon_t = B_0^{-1} u_t$
- $\rightarrow$  structural IRFs  $B(L) = A(L)^{-1}B_0$

VAR models: the problem

Motivation

iviotivatio

Pocul

Conclusion

Date of the

Dynamic Fa

Model

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

- Economic agents incorporate large information sets
  - ightarrow ECB e.g. monitors more variables than just GDP & HICP
- VARs typically capture only a few variables
- $\Rightarrow$  agent's information set > econometrician's information set

⇒ Nonfundamentalness

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

<u>Technically</u>: structural moving average representation is not invertible



VAR models: the problem

Motivation

Results

\_ .

Robustne

Details

Dynamic Facti
Model

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

- Economic agents incorporate large information sets
  - ightarrow 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

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

<u>Technically</u>: structural moving average representation is not invertible



VAR models: the problem

Motivatio

Result

Conclusio

Robustne

Details

Dynamic Facto Model

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

- Economic agents incorporate large information sets
  - ightarrow 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

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

<u>Technically</u>: structural moving average representation is not invertible



# Nonfundamentalness ←⇒ missing information

Nonfundamental-

The problem with VARs:

include only few selected variables

hundreds of other potentially important variables neglected

**Economic agents** real activity GDP, industrial production, **VARs** exports.... **GDP** asset prices **FONIA** stocks, bonds, real estate. HICP commodities.... vields short/long-term, safe/risky, ...

イロト イ団ト イヨト イヨト ヨー 夕久へ

# Nonfundamentalness ←⇒ missing information

Nonfundamental-

Basic idea of factor models:

expand the information space (drastically)

usually >100 variables vs. 4-8 in VARs

## **Economic agents** real activity GDP, industrial production. exports.... Factor asset prices stocks, bonds, real estate. models commodities, ... vields short/long-term safe/risky, ...

