Identifying sectoral shocks with a modicum of economic theory:

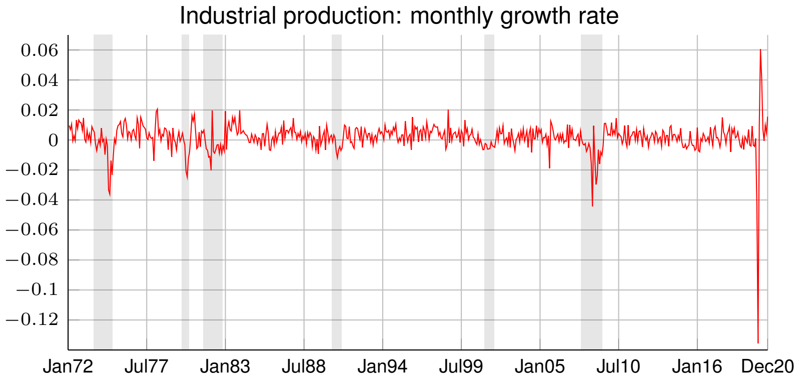
from the 1970s to the pandemic

Ferre De Graeve
KU Leuven

Jan David Schneider
KU Leuven

ASSA 2022 Annual Meeting: SCE Session

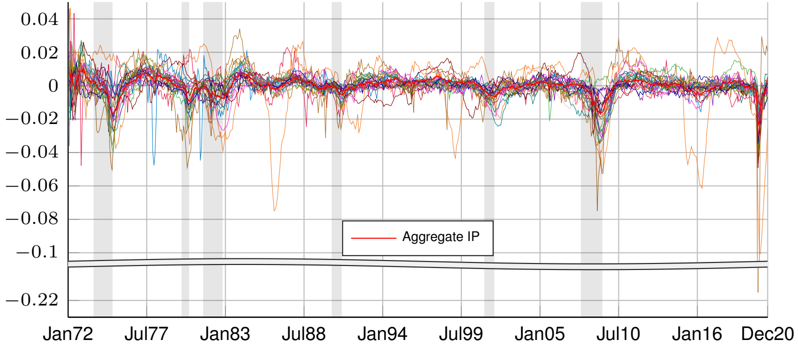
Motivation



- IP volatility decreased in mid-1980s (Great Moderation)
- More recently: intermittent periods of extreme fluctuations (Great Recession, Pandemic)
- **What are the sources of aggr. business-cycle fluctuations?**

Motivation

Aggr. & sectoral IP: smoothed demeaned growth rates (one-sided HP-filter)



- Breaking down IP into 25 sectors
- Sectors co-move and correlated with aggregate growth
  - Average correlation btw. sectoral and aggr. growth: 0.53
- **What drives sectoral co-movement?**

Motivation

Questions

- **What are the sources of aggr. business-cycle fluctuations?**
- **What drives sectoral co-movement?**

Potential drivers

- Macro (aggr.) shocks: demand, supply, fiscal, mp, etc.
- Micro to macro: sectoral shocks with aggregate consequences

Challenge

- **Fundamental identification problem**: sectoral co-movement from sectoral or aggr. shocks?
- Most quantifications rely on theoretical models
    - Misspecification concerns

Approach

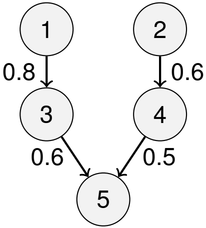
Method

- Need theory-consistent restrictions to solve identification problem
- **Identification not from time domain but using additional cross-sectional data**

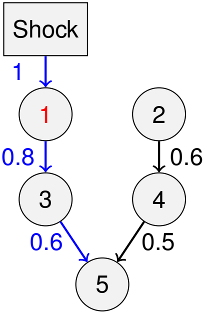
Identification idea

- Theory: Shocks propagate through network in particular pattern
- Summarize pattern using network measures, s.a. Leontief inverse: input-output data
- Rank connectedness and implement as heterogeneity restrictions in a FAVAR

Stylized identification example: 3 shocks, 3 rankings



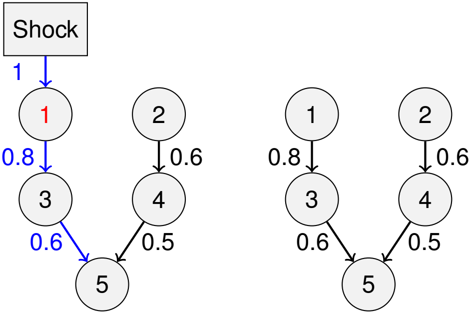
Stylized identification example: 3 shocks, 3 rankings



Ranking (value):

1 (1)
3 (0.8)
5 (0.6)
2 (0)
4 (0)

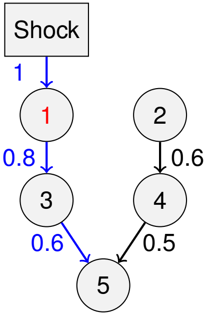
Stylized identification example: 3 shocks, 3 rankings



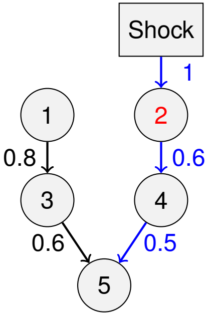
Ranking (value):

1 (1)
3 (0.8)
5 (0.6)
2 (0)
4 (0)

Stylized identification example: 3 shocks, 3 rankings

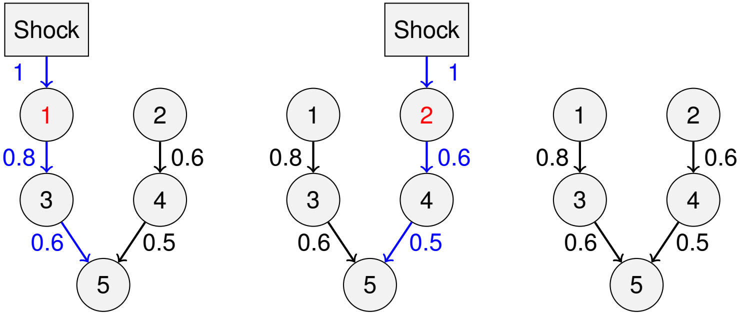


Ranking (value):
1 (1)
3 (0.8)
5 (0.6)
2 (0)
4 (0)



Ranking (value):
2 (1)
4 (0.6)
5 (0.5)
1 (0)
3 (0)

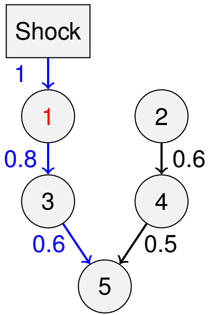
Stylized identification example: 3 shocks, 3 rankings



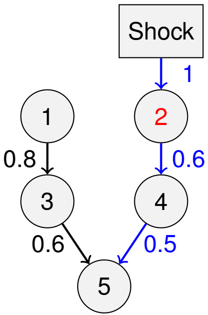
Ranking (value):
1 (1)
3 (0.8)
5 (0.6)
2 (0)
4 (0)

Ranking (value):
2 (1)
4 (0.6)
5 (0.5)
1 (0)
3 (0)

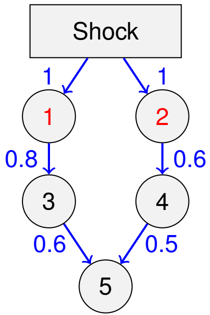
Stylized identification example: 3 shocks, 3 rankings



Ranking (value):
1 (1)
3 (0.8)
5 (0.6)
2 (0)
4 (0)



Ranking (value):
2 (1)
4 (0.6)
5 (0.5)
1 (0)
3 (0)



Ranking (value):
5 (1.1)
1 (1)
2 (1)
3 (0.8)
4 (0.6)

Identification strategy

Sectoral shocks in multi-sector RBC models

- e.g. Carvalho (2008) or Horvath-Dupor model
- **Leontief inverse $\approx$ sufficient statistic for sectoral shock transmission through network**
  - Rankings of theoretical IRFs $\approx$ rankings of Leontief inverse

Sectoral vs. aggregate shocks

- Aggregate shocks propagate differently through network
  - Rankings for aggregate shocks $\neq$ rankings for sectoral shocks

Identification strategy

Rankings of a sectoral and aggr. tech. shock

Rank	u_{13}: Leontief	u_{13}: $IRF_{t=0}$
1.	13	13
2.	3	3
3.	2	2
4.	14	14
5.	1	1
6.	26	26
⋮	⋮	⋮
20.	9	4
21.	4	23
22.	23	9
23.	24	24
24.	5	5
25.	25	25
26.	20	20

- 26-sector Carvalho (2008) model

Identification strategy

Rankings of a sectoral and aggr. tech. shock

Rank	u_{13}: Leontief	u_{13}: $IRF_{t=0}$
1.	13	13
2.	3	3
3.	2	2
4.	14	14
5.	1	1
6.	26	26
$\vdots$	$\vdots$	$\vdots$
20.	9	4
21.	4	23
22.	23	9
23.	24	24
24.	5	5
25.	25	25
26.	20	20

- 26-sector Carvalho (2008) model
- Direct correspondence btw. IRF rankings and Leontief inverse

Identification strategy

Rankings of a sectoral and aggr. tech. shock

Rank	u_{13}: Leontief	u_{13}: $IRF_{t=0}$	v_{agg}: $IRF_{t=0}$
1.	13	13	13
2.	3	3	22
3.	2	2	6
4.	14	14	17
5.	1	1	7
6.	26	26	8
$\vdots$	$\vdots$	$\vdots$	$\vdots$
20.	9	4	1
21.	4	23	2
22.	23	9	24
23.	24	24	16
24.	5	5	3
25.	25	25	26
26.	20	20	25

- 26-sector Carvalho (2008) model
- Direct correspondence btw. IRF rankings and Leontief inverse

Identification strategy

Rankings of a sectoral and aggr. tech. shock

Rank	u_{13}: Leontief	u_{13}: $IRF_{t=0}$	v_{agg}: $IRF_{t=0}$
1.	13	13	13
2.	3	3	22
3.	2	2	6
4.	14	14	17
5.	1	1	7
6.	26	26	8
⋮	⋮	⋮	⋮
20.	9	4	1
21.	4	23	2
22.	23	9	24
23.	24	24	16
24.	5	5	3
25.	25	25	26
26.	20	20	25

- 26-sector Carvalho (2008) model
- Direct correspondence btw. IRF rankings and Leontief inverse
- Aggregate shock different ranking/ network propagation

Literature

Production networks (input-output data)

Long & Plosser (1983), Horvath (1998, 2000), Dupor (1999), Acemoglu et al. (2012), Bouakez, Cardia & Ruge-Murcia (2014), Baqaee & Farhi (2019, 2020), Bigio & La'O (2020), Pasten, Schoenle & Weber (2020, 2021)

Empirical prod. networks but calibrated on specific theory

Foerster et al. (2011), Acemoglu, Akcigit & Kerr (2016), Atalay (2017), vom Lehn & Winberry (2021)

- **Contribution: Minimal theory**

Identification using cross-sectional information

De Graeve & Karas (2014), Amir-Ahmadi & Drautzburg (2021), Matthes & Schwartzman (2021)

- **Contribution: Using I-O data to identify sectoral shocks**

Outline

- Reduced-form model
- Additional identification details
- 4 main results
- DGP exercise

Reduced-form FAVAR model

$$X_t = \Lambda F_t + E_t$$
$$F_t = \Phi F_{t-1} + U_t$$

- FAVAR companion form
- X_t: sector and aggr. output growth rates
- F_t: factors with loadings Λ
- E_t: includes measurement errors, $\epsilon_t \sim \mathcal{N}(0, R_\epsilon)$
  - R_ϵ diagonal
- U_t: includes reduced-form shocks, $u_t \sim \mathcal{N}(0, Q_u)$

Distinguish up- and downstream propagation

- Downstream propagation of shocks:

$$H = (I - A)^{-1} \quad \text{with} \quad a_{ij} = \frac{\text{Sales of } j \text{ to } i}{\text{Total Sales of } i}$$

- Upstream propagation of shocks:

$$\widetilde{H} = \left(I - \widetilde{A}\right)^{-1} \quad \text{with} \quad \widetilde{a}_{ij} = \frac{\text{Sales of } i \text{ to } j}{\text{Total Sales of } i}$$

- Rank columns of H and $\widetilde{H}$; use for identification

Parametrisation

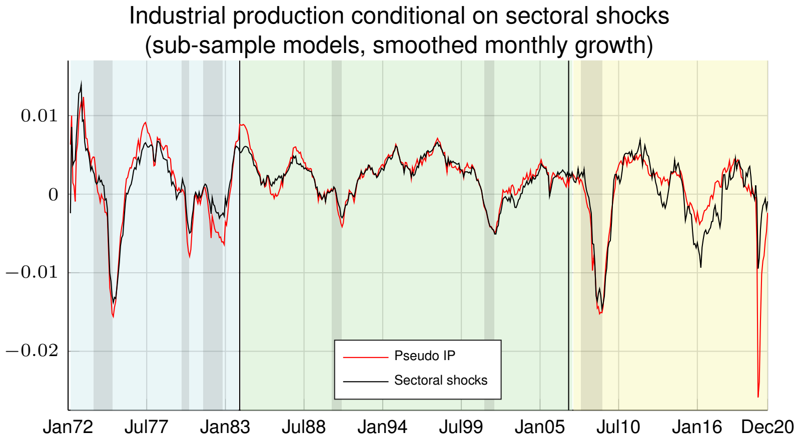
Sub-sample dependent model parametrisation

Parameters	Feb72 – Dec20	Feb72 – Dec83	Jan84 – Nov07	Jan07 – Dec20
M	1	1	1	1
K	12	12	15	8
P	3	1	1	4
s	0	0	0	0
r	1	1	1	1

More details

- 1997 I-O accounts including materials *and* capital flows
- Derive rankings for 64 GDP sectors and only rank subset of 25 industrial production sectors
- Partial identification of single sectoral shocks; all sectoral shock contributions aggregated afterwards
- Use standard sign restriction algorithms (Uhlig 2005 or Rubio-Ramírez et al. 2010)
- Identify sectoral shocks only in somewhat connected sectors with sufficient heterogeneity of connections
- Implement rankings in clusters: allows for small deviations from strict rankings
- Regress historical decomp. on sectoral output: Account for individually identified shocks not being orthogonal to each other
- Models for different sub-samples to account for heteroskedasticity, structural breaks, etc.

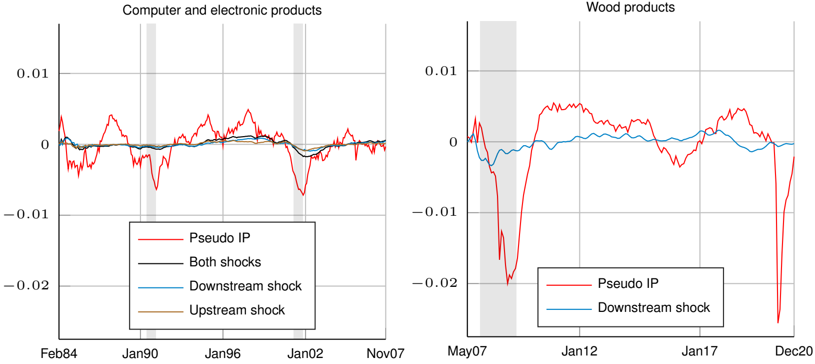
1. Sectoral shocks major source of aggr. fluctuations



- Sectoral shocks explain major part of aggr. fluctuations
- Exception: Pandemic

2. Sector examples match typical macro narratives

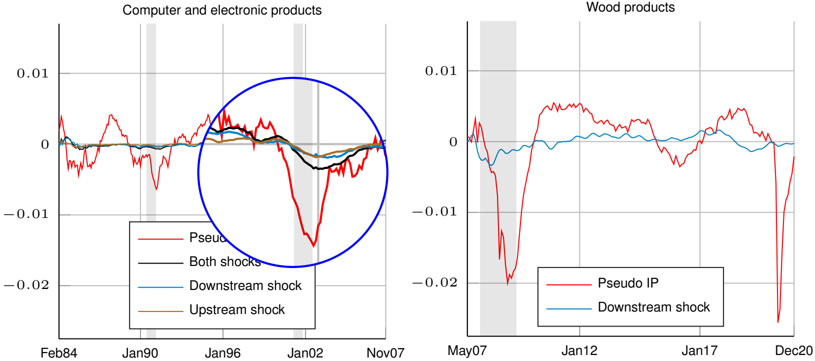
Individual contributions of sectoral shocks to IP (smoothed monthly growth)



- Tech boom (mid-1990s) and bust (early-2000s)
- GR: Wood products supplies construction (outside dataset)
- Pandemic: Wood products no major source of shocks

2. Sector examples match typical macro narratives

Individual contributions of sectoral shocks to IP (smoothed monthly growth)

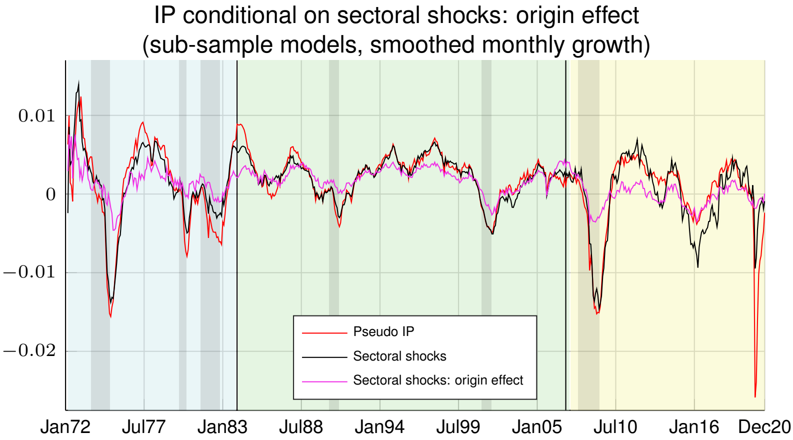


- Tech boom (mid-1990s) and bust (early-2000s)
- GR: Wood products supplies construction (outside dataset)
- Pandemic: Wood products no major source of shocks

3. No single sector dominates (all of the time)

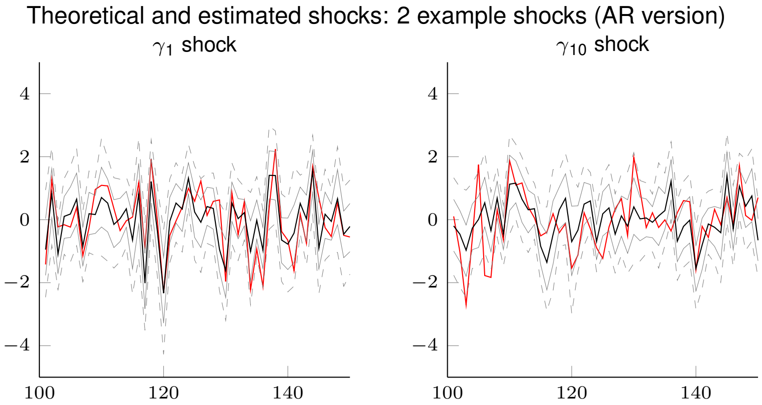
- Previous sector examples: Some sectors important sources of aggr. fluctuations *at certain points in time*
- No sectors with shocks that exhibit large aggr. consequences *all of the time*

4. Networks important for sectoral-shock propagation



- Business cycles: sectoral shocks – many or a few important?
- Network amplifies sectoral shocks; generate co-movement
- Degree of network amplification varies through time

DGP exercise using Carvalho (2008) model



- Theor. shocks (red); FAVAR estimated (black & conf. bands)
- Single small-sample simulation
- Series track each other fairly well

DGP exercise using Carvalho (2008) model

Sectors	AR shocks	RW shocks
1.	0.73	0.79
2.	0.61	0.68
3.	0.56	0.64
4.	0.66	0.73
5.	0.58	0.66
6.	0.69	0.75
7.	na	na
8.	0.35	na
9.	0.54	na
10.	0.45	na
11.	0.63	na
12.	0.63	na
13.	0.47	na
14.	0.71	0.8
15.	na	na
16.	0.47	0.56
17.	0.51	0.65
18.	0.47	na
19.	0.55	0.63
20.	0.61	0.68
21.	0.5	0.54
22.	0.42	0.45
23.	0.56	0.57
24.	0.52	0.59
25.	0.66	0.75
26.	0.53	0.6
Average	0.56	0.65

- Correlation between simul./theor. shocks and median sectoral shocks estimated by FAVAR
- Relatively high correlation considering the small simulation sample

Conclusion

- Sectoral disturbances major source of aggregate volatility
- Network amplifies sectoral shocks; generate co-movement
- Pandemic is different to most other recessions
- Source sectors of major recessions plausible
- These results do not hinge on specific theoretical model

Conclusion (*continued*)

- DGP exercise: Method works in canonical multi-sector DSGE models
- Method can be extended in the following way:
  - Can incorporate different data, e.g. prices
  - Can use methodology in different settings, e.g. financial networks, different degrees of price stickiness,. . .
  - Broadly applicable: macro equivalence/ micro dissonance