Network Spillovers versus Common Factors: A Joint-Estimation Approach

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Motivation

- Research on networks in economics (macro/trade) has exploded recently
  - Relevant networks in the literature: input-output linkages, investment linkages, trade credit linkages, banking linkages, cross-country trade/financial linkages

- Two main approaches to studying the role of networks
  1. **Empirical**: VAR-like methods to describe/decompose/forecast
     - Diebold and Yilmaz (2014), Mlikota (2023), Barigozzi et al (2023)
  2. **Structural**: Multisector business cycle models to understand sources of macro fluctuations
     - Horvath (1998, 2000), Foerester, Sarte and Watson (2011), Atalay (2017), Herskovic (2018), Pasten, Schoenle, and Weber (2020), vom lehn and Winberry (2022)

This paper

We propose a semi-structural approach to jointly estimate spillovers (from observed networks) and unobserved common factor(s).

What We Do

- **Estimate the following model:**

$$y_{i,t} = \sum_{s=1}^{P} \sum_{j=1}^{N} A_{s,ij} y_{j,t-s} + \Lambda_i \mathbf{F}_t + u_{i,t},$$

  using observed network(s) to guide the estimation of spillovers $\mathbf{A}_{s,ij}$ and factors $\mathbf{F}_t$

- **Applications and findings**:
  - Sectoral output growth: input-output network falls short in accounting for spillovers
  - Commodity price comovement: important overestimation of the role of global factors
  - Drivers of inflation: Important role of trade linkages

Literature

- **Methodological**: Factor models (Geweke, 1977; and Sargent and Sims, 1977), Vector Autoregression (VAR) models (Sims, 1980), Factor-VAR (Bernanke, Boivin, and Eliasz, 2005), Panel Models with Interactive FE (Moon and Weidner, 2023), High-dimensional VAR with factors (Mlikota, 2023; Barigozzi et al., 2023)
  - Our approach uses network information to our disposal to study spillovers while accounting for common factors
- **Semi-structural applications**: Causes of the Great Recession (Altinoglu, 2019; Li and Martin, 2019); Reduction in comovement post-1984 (Foerster, Sarte, and Watson, 2011, Garin et al., 2019, vom Lehm and Wimberry, 2022)
  - Our approach can accommodate many networks and freely estimate their relative importance

A motivating example

A Well-Known Structural Model: Long and Plosser (1983)

Let

$$d\ln \mathbf{Y}_t = \mathbf{A}^T d\ln \mathbf{Y}_{t-1} + \epsilon_t,$$

the underlying DGP for sectoral output growth. For **A**, we use the US input-output structure (BEA 71 sectors in 2014). We assume that

$$\epsilon_{it} = \underbrace{\Pi_t}_{\text{aggregate shock}} + \underbrace{u_{it}}_{\text{idiosyncratic shock}}$$

.

Then, simulate long series of $d\ln Y_t$.

How well Factor Models (FM) estimate the structure of ϵ_t: aggregate vs. idiosyncratic shocks?

Factor Models when Units are Highly Connected

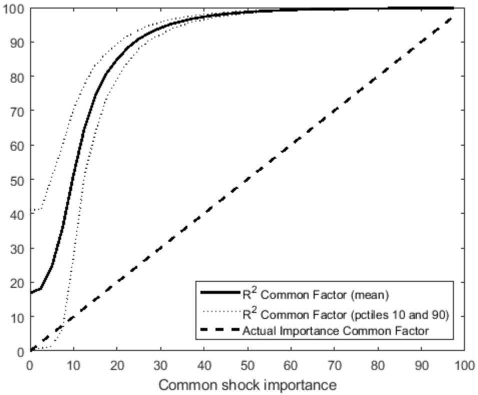


Figure: Error in detecting a true common factor

Therefore, using factor models (e.g., granular IV approach) can largely understate the role of idiosyncratic shocks in propagating/amplifying shocks within the network

Our approach

Model

Let the dynamics of unit i at time t (e.g., firm i's output growth or country i's inflation rate) be expressed as

$$y_{i,t} = \sum_s \sum_j A_{s,ij} y_{j,t-s} + \Pi_t + u_{i,t},$$

$$\Pi_{it} = \Lambda_i \mathbf{F}_t$$

- $\sum_s \sum_j A_{s,ij} y_{j,t-s}$ accounts for spillovers between *units*
- $\Pi_{it} = \Lambda_i \mathbf{F}_t$ is the unobserved common factor structure
- u_{it} are unit-specific idiosyncratic *errors*, which are orthogonal to $y_{j,t-s}$ and Π_t

Estimating Network Spillovers and Common Factors - Low Dimensional

Moon and Weidner (2023) estimator applies when $\mathbf{A}$ is known up to a fixed number of unknown constants (e.g., $\mathbf{A} = \beta\mathbf{B}$) where β captures the intensity of spillovers.

Minimize the convex objective function with respect to β and Π,

$$
\mathit{argmin}_{\beta,\Pi}\left(\underbrace{\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{i,t}-\sum_{s=1}^{P}\sum_{j=1}^{N}\mathbf{A}_{\mathbf{s},\mathbf{ij}}y_{j,t-s}-\Pi_{it}\right)^{2}}_{OLS}+\underbrace{\lambda p(\Pi)}_{Rank}\right),
$$

$$
A_{s,ij}=\sum_{k=1}^{K}\sum_{l=1}^{K}\mathbf{1}(k(i)=k)\mathbf{1}(k(j)=l)\quad\underbrace{\beta_{kl}}_{Unobserved}\cdot\underbrace{B_{s,ij}}_{Observed},
$$

where $\lambda \geq 0$ is a tuning parameter selected in a data driven manner and $p(\Pi)$ is the sum of the singular values of Π. Moon and Weidner (2023) establish $\sqrt{NT}$ consistency of β.

Application I

Linkages in US sectoral output data

Data

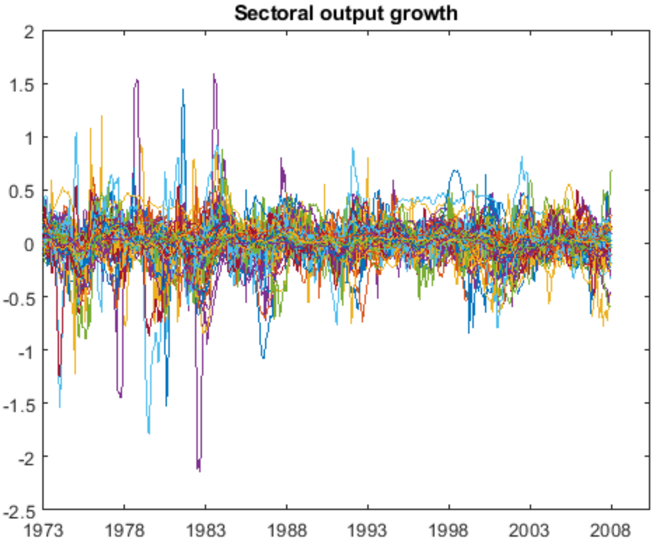
- $\mathbf{Y}_t$: Monthly industrial production (IP) indices for $N = 138$ US sectors for $T = 421$ months from January 1973 to April 2008 (from Foerster, Sarte, and Watson, 2011)
- $N \times N$ IO matrix
- Assume a Long and Plosser (1983) structure

$$d\ln Y_t = \mathbf{A}^T d\ln Y_{t-1} + \Pi_t + \mathbf{U}_t,$$

Do input-output linkages account well for comovement?

More general model

US sectoral output growth over time



Low dimensional estimator (Moon and Weidner, 2023)

- Assume $\mathbf{A} = \beta \mathbf{B}^\top$ where $\mathbf{B}$ is the observed IO matrix.

$$d \ln Y_t = \beta \mathbf{B}^\top d \ln Y_{t-1} + \Pi_t + \mathbf{U}_t,$$

- Estimates of β (obtain three common factors.)

	OLS	M+W
β	1.9763	1.7304
	(0.0321)	(0.0566)
Obs	57,960	57,960

- Mean column sum of $\mathbf{B}$ is 0.3987. So, for the mean sector, a 1pp increase in the growth of each supplying sector leads to a $0.3987 \times 1.7792 = 0.7094$pp increase in growth

- By omitting factors, OLS overestimates the role of spillovers and idiosyncratic shocks

- Still results suggest that empirical linkages are 70% stronger than what implied by the IO network

Application II:

Common factor vs linkages in commodity prices

Commodity price comovement

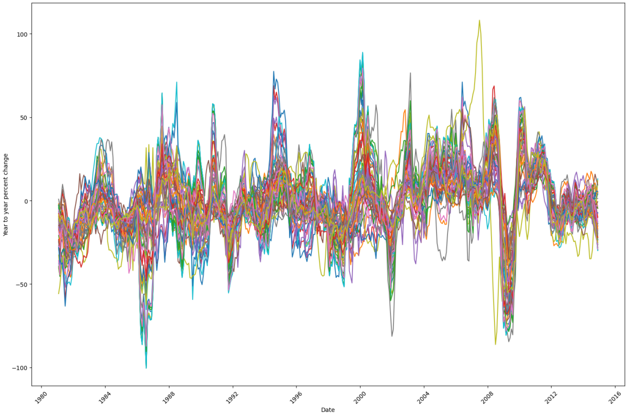


Figure: Monthly real commodity price index for 60 EMEs, Fernández, González, and Rodriguez (2018)

Algeria, Argentina, Australia, Austria, Belarus, Bolivia, Botswana, Brazil, Bulgaria, Cameroon, Canada, Chile, Colombia, Costa Rica, Ivory Coast (Côte d'Ivoire), Croatia, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Gabon, Georgia, Ghana, Guatemala, Honduras, India, Indonesia, Iran, Jamaica, Jordan, Kazakhstan, Kuwait, Lithuania, Malaysia, Mexico, Mongolia, Morocco, New Zealand, Niger, Nigeria, Norway, Oman, Pakistan, Panama, Paraguay, Peru, Philippines, Russia, Saudi Arabia, South Africa, Thailand, Trinidad and Tobago, Tunisia, Ukraine, United Arab Emirates, Uruguay, Venezuela, Vietnam.

Spillovers in commodity price fluctuations

Use three versions of observed linkages based on bilateral trade linkages from the Direction of Trade Statistics (DOTS)

Table: Importance of common factors in cross-country commodity price indexes

Model	**Factors**	**Idiosync.**	**Spillovers**
PCA	77%	23%	NA
MW using M_1	49%	23%	28%
MW using M_2	49%	23%	28%
MW using M_3	42%	16%	42%

Note: M_1 uses trade linkages between country i and country j as follows. M_{ij} represents the observed links between country i and country j. In particular, $M_{1_{ij}}$ is the ratio of the sum between exports from i to j and imports of i from j ($\text{exports}_{ij} + \text{imports}_{ij}$) and total trade of countries i and j. $M_{2_{ij}}$ is the ratio of the sum between exports from i to j and imports of i from j ($\text{exports}_{ij} + \text{imports}_{ij}$) and the GDP of country i. $M_{3_{ij}}$ is the ratio of the sum between exports from i to j and imports of i from j ($\text{exports}_{ij} + \text{imports}_{ij}$) and the GDP of country j.

Application III:
Drivers of global inflation

Drivers of global inflation

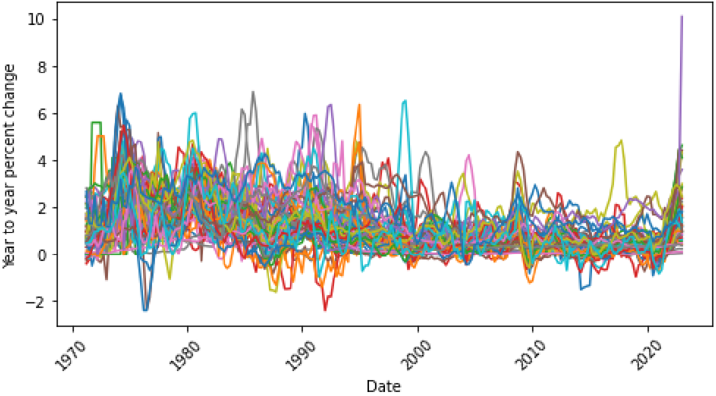


Figure: Quarterly headline CPI inflation 60 countries from Ha, Kose, and Ohnsorge. (2023)

Countries: Argentina, Australia, Austria, Burundi, Belgium, Burkina Faso, Bahamas, Bolivia, Canada, Switzerland, China, Ivory Coast (Côte d'Ivoire), Cameroon, Colombia, Cyprus, Germany, Denmark, Dominican Republic, Ecuador, Egypt, Spain, Finland, Fiji, France, Gabon, United Kingdom, Greece, Guatemala, Honduras, Haiti, Indonesia, India, Ireland, Iceland, Italy, Jamaica, Japan, South Korea, Luxembourg, Morocco, Mauritius, Malaysia, Niger, Netherlands, Norway, New Zealand, Pakistan, Peru, Philippines, Portugal, Paraguay, Singapore, El Salvador, Sweden, Thailand, Tunisia, Turkey, Tanzania, Uruguay, United States of America, Samoa, and South Africa.

Results with homogeneous spillovers: the UK

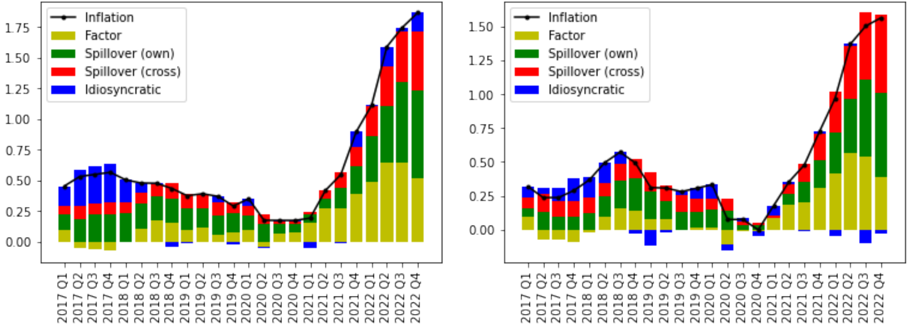


Figure: Decomposition of UK (left) and France (right) inflation

Estimate heterogeneous spillovers: USA-Europe-ROW

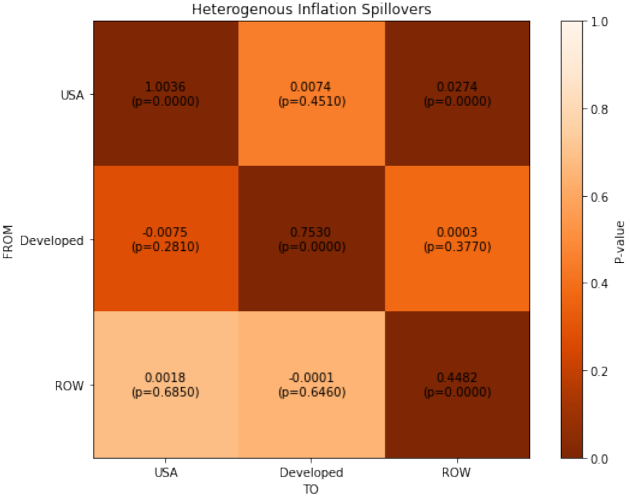


Figure: Heterogeneous spillovers

Results with heterogeneous spillovers: the case of Korea

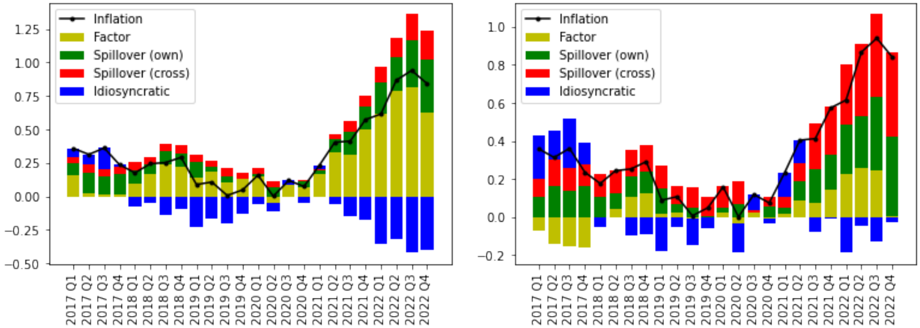


Figure: Decomposition of Korea's inflation. Homogeneous (left) and heterogeneous (right) spillovers

Additional decompositions

Suppose we have our estimated model

$$\mathbf{y_t} = \widehat{\mathbf{A}}\mathbf{y_{t-1}} + \hat{\Pi}_t + \hat{\mathbf{U}}_t,$$

We define the following alternative model

$$\tilde{\mathbf{y}}_t = \widetilde{\mathbf{A}}\mathbf{y}_{t-1} + \widetilde{\Pi}_t + \widetilde{\mathbf{U}}_t,$$

in which

- $\widetilde{\mathbf{A}}$ is another network structure that could prevail
- Suppose we are interested in the propagation of an idiosyncratic shock (e.g., wildfires in Canada) or a common shock (e.g., COVID-19). In this case we could use $\widehat{\mathbf{A}}$ to construct impulse response functions arising from some counterfactual shocks $\widetilde{\mathbf{U}}_t, \ldots, \widetilde{\mathbf{U}}_s$

.

Conclusion

- We propose an econometric approach that separately identifies general spillovers, using observed networks, from unobserved common factor(s)
- Useful to understand the sources of macroeconomic fluctuations from disaggregated and high-dimensional data
- Applied to US sectoral output/commodity prices/inflation, our approach highlights the relevance of linkages and spillovers

Appendix

A Well-Known Structural Model: Carvalho (2007)

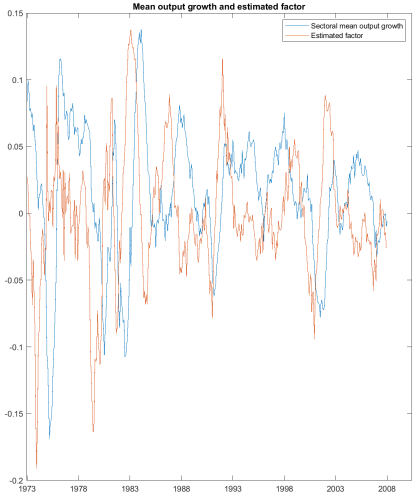
There is labor, capital, and intermediate inputs. Capital depreciates in one period and is produced using same sector's output. We have

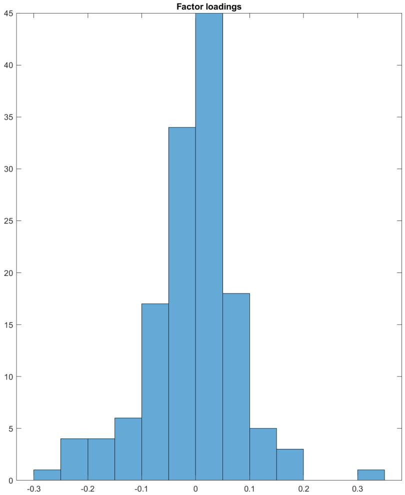
$$d \ln Y_t = (I - \mathbf{A})^{-1} \alpha_d \ln Y_{t-1} + (I - \mathbf{A})^{-1} \epsilon_t,$$

where α_d is a matrix with sectoral capital shares in its diagonal and zero otherwise.

Back

Moon and Weidner (2023): First estimated factor and loadings





Estimating Unobserved Networks and Common Factors - High Dimensional

If **A** is not known up to a fixed number of unknown constants we have a high dimensional problem.

Propose to minimize a convex objective function such as the following with respect to $(A_s)_{s=1,\dots,P}$ and Π,

$$argmin_{A,\Pi}\left(\underbrace{\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{i,t}-\sum_{s=1}^{P}\sum_{j=1}^{N}A_{s,ij}y_{j,t-s}-\Pi_{it}\right)^2}_{OLS}+\lambda_1\underbrace{\sum_{i=1}^{N}\sum_{j=1}^{N}p_1(i,j)}_{Sparsity}+\underbrace{\lambda_2 p_2(\Pi)}_{Rank}\right),$$

where $\lambda_1 \geq 0, \lambda_2 \geq 0$ are tuning parameters.

The sparsity function is $p_1(i,j) = \left(\sum_{s=1}^{P}\left(A_{s,ij} - A_{0,ij}\right)^2\right)^{1/2}$. The matrix $\mathbf{A}_0$ could be zeros or a prior network up to a fixed number of constants. Additional convex restrictions can be added to **A**.

More complex economy

Assume VARMA (1,1) structure in Foerster, Sarte, and Watson (2011)

$$d \ln \mathbf{Y}_t = \varrho d \ln \mathbf{Y}_{t-1} + \Theta \mathbf{U}_{t-1} + \Pi_a \mathbf{U}_t,$$

where ϱ, Θ, and Π_a are functions of IO, investment network, factor shares, and consumption-capital policy rules. Assume that capital fully depreciates after a period to get

$$d \ln \mathbf{Y}_t = (I - \mathbf{A}^T)^{-1} \alpha_d \tilde{\Theta} d \ln \mathbf{Y}_{t-1} + (I - \mathbf{A}^T)^{-1} \epsilon_t,$$

More generally, we could express a VARMA(1,1) as a $VAR(\infty)$ in which

$$d \ln \mathbf{Y}_t = \sum_{l}^{\infty} \Xi_i d \ln \mathbf{Y}_{t-l} + \mathbf{U}_t,$$

Back