Factor Augmented Network Vector Autoregression (FANVAR)

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Motivation

- Many important economic questions depend on **dynamic spillovers through economic networks**:
  - Sources of macro volatility, comovement, persistence of shocks, occurrence-magnitude of sudden stops
  - Propagation of oil price shocks, U.S. monetary policy shocks, productivity shocks in key sectors (e.g., semiconductors)
- **Challenge:** Identifying network spillovers is difficult when they coexist with pervasive aggregate shocks.
- Existing approaches face a trade-off:
  - **Structural models:** Economic interpretation, but impose restrictions on propagation mechanisms. Horvath (1998, 2000), Foerester, Sarte and Watson (2011), Atalay (2017), Herskovic (2018), Pasten, Schoenle, and Weber (2020), vom Lehn and Winberry (2022)
  - **Empirical models:** Greater flexibility, but limited structural interpretation of spillovers and subject to biases. Diebold and Yilmaz (2014), Mlikota (2023), Barigozzi et al. (2023), Grant and Yung (2024), Miao et al. (2023)

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This paper: A semi-structural approach that jointly estimates spillovers, through observed networks, and unobserved common factors.

What We Do

- **Would like to estimate the following model:**

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

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Solution: guided by theory, use observed/constructed networks ($B_{s,ij}$) to guide the estimation of spillovers $A_{s,ij}$. Specifically, define $A_{s,ij} = \beta B_{s,ij}$. Estimate β (could be scalar or a vector) using observed $B_{s,ij}$.

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Applications: Today: Sectoral price dynamics and the role of input-output networks. In progress, role of financial linkages and/or trade linkages in cross-country GDP dynamics.

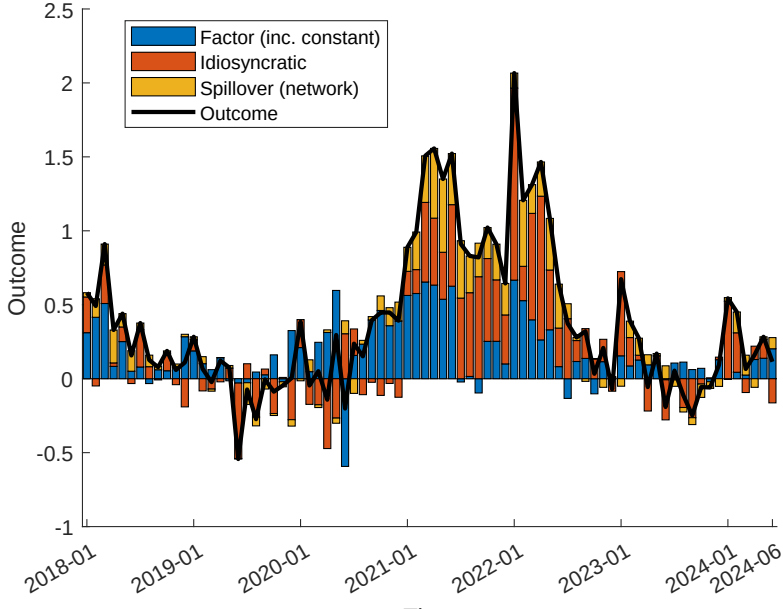
What We Find

- From Monte Carlo simulations, FANVAR provides a substantial improvement with respect to VAR and Factor models
  - VAR models, omitting factors, overstate the role of spillovers
  - Factor models overstate the role of common factors in the presence of networks

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  - VAR models, omitting factors, overstate the role of spillovers
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- Application to US PPI inflation. Compare FANVAR to implications from Boivin, Giannoni, and Mihov (2009)
  - Sectoral inflation comoves because industries face common shocks and because price changes propagate through production linkages. They imply different transmission mechanisms for shocks (e.g. monetary policy).
  - What Boivin et al. (2009) characterized as sluggish response to aggregate shocks, in our approach are sluggish sectoral spillovers in addition to aggregate shocks
  - Using more recent sample, we show that spillovers played a key role during COVID-19 in 2021-2022.

Average PPI change during 2018-2024: FANVAR-based decomposition



Contribution to the 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, Maio, Phillips, Su, 2023)
  - Our approach uses network information at 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 (or models) and estimate their relative importance

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

$$y_{i,t} = \sum_s \sum_j A_{s,ij} y_{j,t-s} + \Lambda_i \mathbf{F}_t + u_{i,t},$$

- $\sum_s \sum_j A_{s,ij} y_{j,t-s}$ accounts for dynamic spillovers between *units*
- $\Lambda_i \mathbf{F}_t$ is the unobserved common factor structure
- u_{it} are unit-specific idiosyncratic *errors*; can be mildly correlated across units.

Estimating Network Spillovers and Common Factors

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 $\Pi_{i,t} = \Lambda_i \mathbf{F}_t$,

$$argmin_{\beta,\Lambda,\mathbf{F}} \left(\underbrace{\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{i,t} - \sum_{s=1}^{P}\sum_{j=1}^{N} A_{s,ij} y_{j,t-s} - \Pi_{i,t}\right)^2}_{LS} + \lambda \underbrace{p(\Pi)}_{\text{Nuclear norm}} \right),$$

$$A_{s,ij} = \underbrace{\beta}_{Unobserved} \cdot \underbrace{B_{s,ij}}_{Observed},$$

where $\lambda \geq 0$ is a tuning (penalty) parameter selected in a data driven manner and $p(\Pi)$ is the sum of the singular values of Π.

Nuclear norm replaces **rank** to make the objective convex (LASSO analogy).

Key assumptions

1. **Connectivity and cross-sectional variation.** Network-weighted lag $X_{it} = \sum_j B_{ijt} y_{j,t1}$ is not itself well approximated by a low rank factor structure
2. **Weak dependence:** Weak cross-sectional and temporal correlation of errors
3. **Exogeneity:** Spillover term $\sum_j B_{ijt} y_{j,t1}$ and idiosyncratic error μ_{it}
4. **Strong factor condition:** Pervasive effect of common factor across units

Practical implementation

1. **Convex pilot.** Obtain an initial estimate $\widehat{\beta}^{(0)}$ using the nuclear-norm estimator.
2. **Factor dimension.** Form the network-filtered residual matrix
$$\widehat{E}^{(0)} = Y - \widehat{\beta}^{(0)} X,$$
and estimate the number of factors R by singular-value thresholding (data-driven).
3. **Factor spaces.** Given R, estimate the factors and loadings from the leading principal components of $Y - \widehat{\beta}^{(s)} X$.
4. **Coefficient update.** Re-estimate β after projecting Y and X off the estimated factor and loading spaces, and repeat.

Asymptotic result

Under the conditions in Moon and Weidner (2026), two or more post-estimation updates yield a $\sqrt{NT}$-consistent estimator that is asymptotically equivalent to the local interactive-effects least-squares estimator.

Monte Carlo Simulations

The Monte Carlo Simulations

The data-generating process follows

$$y_{i,t} = \sum_j A_{ij} y_{j,t-1} + \Lambda_i \mathbf{F}_t + u_{i,t},$$

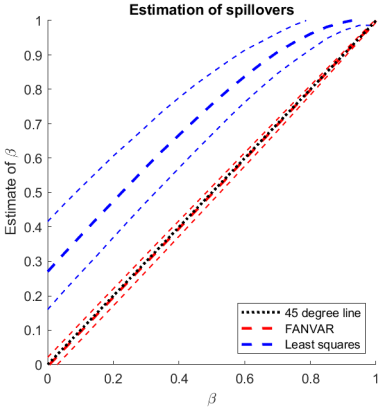
where the true network $A = \beta B$ in which B is drawn from a Bernoulli distribution (Erdos-Renyi graph) with $p = log(N)/N$ and then row-normalized.

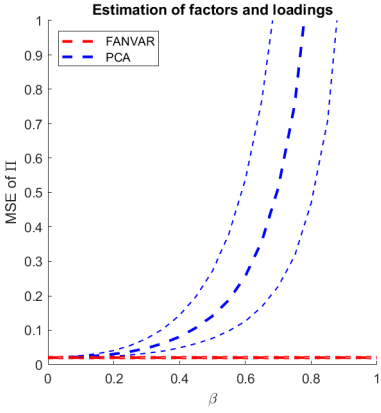
We assume one common factor $F_t = 0.9F_{t-1} + v_t$, with v_t iid standard normal. The factor loadings Λ_i are drawn from a normal distribution with mean 0.5 and standard deviation 1. We set $N = 100$, $T = 100$.

We vary β – the intensity with which the observed network B generates spillovers. Then, using B, we estimate β and $\Pi_t = \Lambda_i \mathbf{F}_t$.

True vs Estimated Spillover

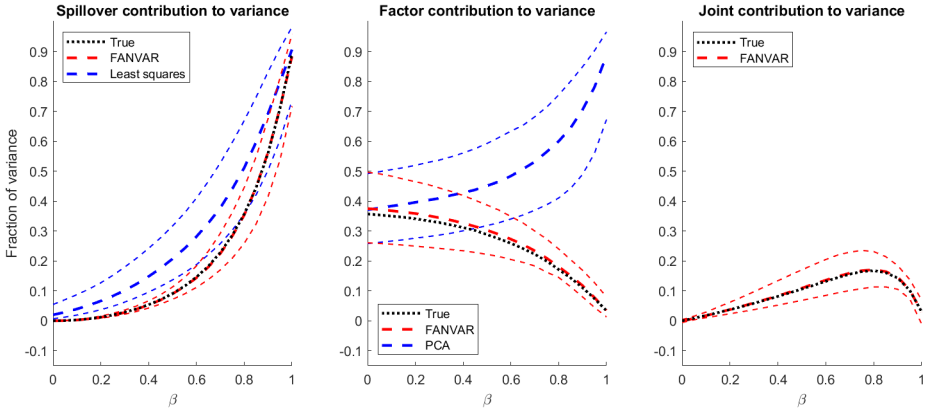
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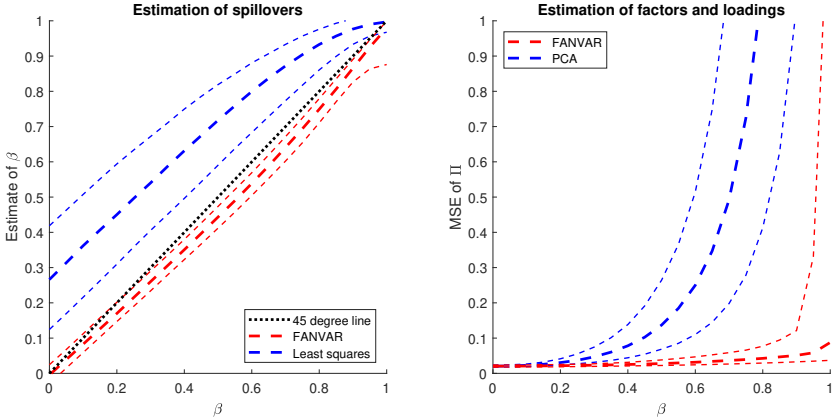


Decomposing the sources of fluctuations

$$y_{i,t} = \sum_j \beta B_{1,ij} y_{j,t-1} + \Pi_t + u_{i,t},$$



True vs Estimated Spillover if B not fully observed (only 90 % of links)



Two more checks: i) a fraction of the true links are measured with significant error; ii) modify the DGP to include a star supplier, but then perform the estimation omitting that unit from the data.

Impulse Responses

Impulse Response Analysis

Provide more structure to the factors

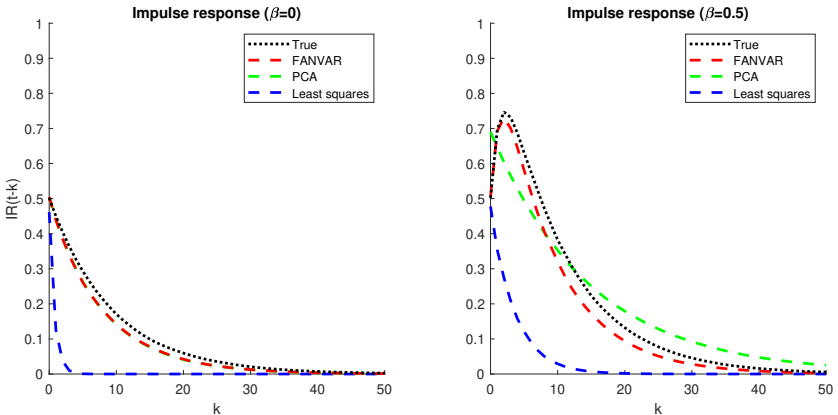
$$
\begin{aligned}
Y_t &= \beta \mathbf{B} Y_{t-1} + \Lambda F_t + v_t, \\
F_t &= \psi F_{t-1} + \omega W_t + u_t,
\end{aligned}
$$

where W_t is a set of observable macro controls (observed factors). Now we can obtain the IRFs from aggregate shocks to W, which are observed factors such as US monetary policy, oil prices or global financial conditions.

$$
\frac{\partial Y_t}{\partial W_{it-K}} = \left(\sum_{j=0}^{K} (\beta \mathbf{B})^{K-j} \Lambda \psi^j \right) \omega_i.
$$

IRF to an aggregate shock W

Figure: Impulse Response to aggregate shock: different underlying network



Baseline simulation: N=100,T=100, 1 factor, Erdos-Renyi with $p = log(N)/N$, with persistence $\psi = 0.9$.

Application to sectoral inflation dynamics

Theoretical Motivation: Sticky-Price Production Networks

Sticky prices generate delayed propagation of shocks through production linkages (e.g., Pasten et al. (2020) and Rubbo (2023))

$$dp_t = \underbrace{\mathcal{L}^{-1}(I-\Delta)dp_{t-1}}_{\text{Dynamic network spillovers}} + \underbrace{\mathcal{L}^{-1}\Delta\alpha dw_t}_{\text{Aggregate shocks}} + \underbrace{\left(-\mathcal{L}^{-1}\Delta dz_t + \mathcal{L}^{-1}\rho(I-\Delta)dE\pi_{t+1}\right)}_{\text{Sector-specific disturbances}},$$

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where $\mathcal{L} = (I - \Delta\Omega)$.

- Ω: observed input-output network
- Δ: sectoral price flexibility (frequency of price adjustment)
- $\mathcal{L}^{-1} = (I - \Delta\Omega)^{-1}$ captures equilibrium network amplification
- The implied propagation matrix is $B = (I - \Delta\Omega)^{-1}(I - \Delta)$

From Structural Networks to the Semi-structural Form

The sticky-price production network model implies

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Motivates the following semi-structural specification:

$$Y_t = \underbrace{\beta B Y_{t-1}}_{\text{Dynamic network spillovers}} + \underbrace{\Lambda F_t}_{\text{Aggregate shocks}} + \underbrace{u_t}_{\text{Sector-specific disturbances}}$$

with $B = (I - \Delta\Omega)^{-1}(I - \Delta)$.

- B determines the *structure* of propagation
- β determines the *strength* of propagation in the data

Data

- 154 sectoral PPI series for the US
  - Sample 1: 1970m1-2005m6 (original Boivin et al., 2009)
  - Sample 2: 1990m1-2024m6 (our new data)
- Match these series to IO tables to obtain our measure of observed linkages
- Note that we are omitting several sectors and links (more sectors coming soon). Factors will then capture part of these omitted spillovers.

Spillover estimates

	Pasten et al. Average $\bar{\delta}$	Pasten et al. Heterogeneous Δ	Estimated $\hat{\delta} = 0.63$
Network coefficient β, OLS	0.254	0.263	0.419
	(0.004)	(0.005)	(0.007)
Network coefficient β, FANVAR	0.204	0.203	0.347
	(0.004)	(0.005)	(0.007)
Serial correlation	-0.015	0.008	-0.017
	(0.004)	(0.004)	(0.004)
OLS R^2	0.049	0.039	0.053
MW R^2	0.149	0.144	0.151
Selected factors	1	1	1
Observations	63448	63448	63448

E.g, A 1 percentage point increase in inflation in the iron and steel pipe at $t \rightarrow$ a 0.38 percentage point increase in inflation in the concrete block and brick manufacturing industry at time $t+1$.

Sources of variation in Sectoral Inflation: Factor Models vs FANVAR

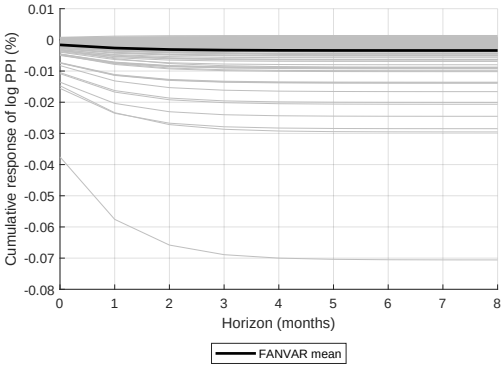
Standard deviation (in percent)

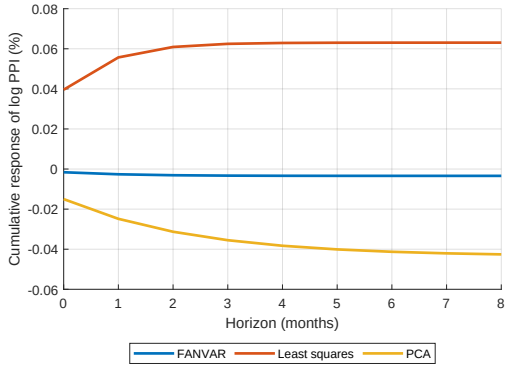
	Inflation	Common factors	Sector specific	Spillovers
FAVAR (Boivin et al.), updated sample, $R = 5$				
PPI Mean	1.28	0.51	1.08	–
Median	0.94	0.23	0.84	–
Std. dev.	1.00	0.87	0.68	–
FANVAR baseline, $R = 1$				
PPI Mean	1.28	0.20	1.21	0.25
Median	0.94	0.06	0.89	0.19
Std. dev.	1.00	0.47	0.88	0.18

What Boivin et al. (2009) interpreted as persistent aggregate shocks, we uncovered as delayed network spillovers

Sectoral IRFs from Monetary Policy

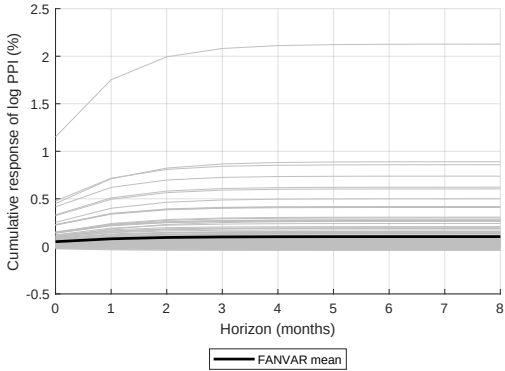
Using externally identified shocks to monetary policy Jarociński and Karadi (2020)
(10 basis points increase in US Fed rate)

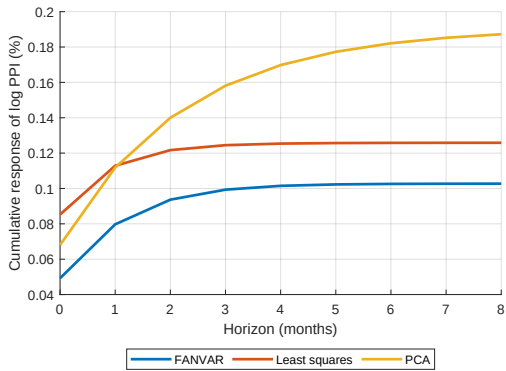




Sectoral IRFs from Oil price shock

Oil prices shocks form Känzig (2021) (10% increase in oil prices)





Conclusion

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

Thank you