Monetary Policy Spillovers

Transmission Through Networks

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Introduction

- Effects of US monetary policy shocks on stock returns using Input-Output networks (Ozdagli and Weber 2017; Di Giovanni and Hale 2022)

$$y_t = \alpha + \rho W y_t + X_t \beta + \varepsilon_t$$

Does the choice of network matter?

- Pure trade weights for all variables outperformed in model fit or predictive accuracy by other linkages in GVAR setting (Eickmeier and Ng 2015; Feldkircher and Huber 2016; Martin and Crespo Cuaresma 2017)

Network Visuals

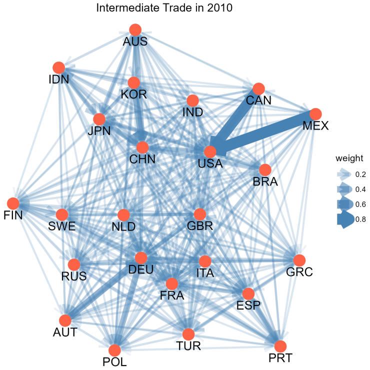


Figure 1: Intermediate Trade

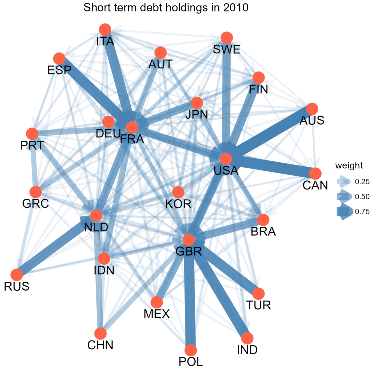


Figure 2: Short-term debt

Outline

Which networks are important for the transmission of US monetary policy shocks?

- Evaluate spillovers of US monetary policy shocks to international stock returns using SAR model
- Estimate convex combinations of time-varying networks
- BMA for uncertainty wrt. number of networks

Dynamic setting with multiple variables

Deal with endogeneity of networks

Introduction

Model uncertainty in linear regression model

(Fernández, Ley, and Steel 2001)

$\downarrow$

Model uncertainty wrt. X in SAR model

(LeSage and Parent 2007)

$\downarrow$

Uncertainty wrt. W

(LeSage and Fischer 2008; Piribauer and Crespo Cuaresma 2016)

$\downarrow$

Estimate convex combination $W_c = \sum_{\ell=1}^{L} \gamma_\ell W_\ell$

(Debarsy and LeSage 2018; Debarsy and LeSage 2022)

Introduction

Table 1: Comparison of Di Giovanni and Hale (2022), Debarsy and LeSage (2022) and this project.

	DGH22	DL22	Here
HETSAR	✓		
Panel	✓		✓
Time-varying W			✓
Estimate $W_c(\Gamma)$		✓	✓
BMA		✓	✓

Setup

$$y = \rho W_c(\Gamma) y + X\beta + \varepsilon, \quad \varepsilon \sim N(0, \sigma^2 I_{NT})$$

$$W_c(\Gamma) = \sum_{\ell=1}^{L} \gamma_\ell W_\ell, \quad 0 \leq \gamma_\ell \leq 1, \quad \sum_{\ell=1}^{L} \gamma_\ell = 1, \quad \Gamma = (\gamma_1, \ldots, \gamma_L)'$$

$$W_\ell = \begin{pmatrix} W_{\ell,1} & 0 & \ldots & 0 \\ 0 & W_{\ell,2} & \ldots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \ldots & \ldots & W_{\ell,T} \end{pmatrix}$$

- $W_{\ell,t}$ connectivity matrix:
  - Main diagonal = 0
  - Row-sums = 1
  - *NxN* number of cross-sectional observations

Setup

▸ Effects

Computationally efficient expression:

$$\tilde{y}\omega = X\beta + \varepsilon$$

$$\tilde{y} = (y, W_1 y, W_2 y, \ldots, W_L y)$$

$$\omega = (1, -\rho\Gamma')'$$

$$W_\ell y = \begin{bmatrix} W_{\ell,1} & 0 & \cdots & 0 \\ 0 & W_{\ell,2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & W_{\ell,T} \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_T \end{bmatrix} = \begin{bmatrix} W_{\ell,1} y_1 \\ W_{\ell,2} y_2 \\ \vdots \\ W_{\ell,T} y_T \end{bmatrix}$$

Likelihood

Standard Notation

$$
\begin{aligned}
y &= \rho W_c y + X\beta + \varepsilon \\
(I - \rho W_c)y &= X\beta + \varepsilon \\
Ry &= X\beta + \varepsilon \\
\varepsilon &= Ry - X\beta
\end{aligned}
$$

Computationally Efficient

$$
\begin{aligned}
\tilde{y}\omega &= X\beta + \varepsilon \\
\varepsilon &= \tilde{y}\omega - X\beta
\end{aligned}
$$

$$
\begin{aligned}
f_Y(y) &= \left| \frac{\partial \varepsilon}{\partial y} \right| f_\varepsilon(Ry - X\beta) \\
&= |R| \frac{1}{(2\pi\sigma^2)^{n/2}} \exp\left(-\frac{1}{2\sigma^2} (Ry - X\beta)^\top (Ry - X\beta) \right)
\end{aligned}
$$

$$
f\left(y \mid X, \mathcal{W}; \rho, \Gamma, \sigma^2, \beta\right) = |R(\omega)| \left(2\pi\sigma^2\right)^{-n/2} \exp\left(-\frac{e'e}{2\sigma^2} \right)
$$

Priors and Joint Posterior

Size of parameter space:

$$\Omega := \Omega_\rho \times \Omega_\Gamma \times \Omega_\beta \times \Omega_\sigma = (-1,1)x[0,1]^L x R^k x(0,\infty)$$

Flat or uniform priors for $\rho, \Gamma, \beta, log(\sigma^2)$:

$$p(\rho) \sim U(-1,1), \quad p(\Gamma) \sim U(0,1), \quad p(\beta) \propto 1, \quad p(\sigma^2) \propto \frac{1}{\sigma^2}$$

Joint Posterior

$$p\left(\rho, \Gamma, \sigma^2, \beta \mid y, X, \mathcal{W}\right) \propto |R(\omega)| \left(\sigma^2\right)^{-\frac{(n+2)}{2}} \exp\left(-\frac{1}{2\sigma^2} e'e\right)$$

MCMC Summary

- Draw β conditional on ω and σ^2
  $p\left(\beta \mid \sigma^2, \omega, \tilde{y}, X\right) \sim N$
- Draw σ^2 conditional on ω and β
  $p\left(\sigma^2 \mid \beta, \omega, \tilde{y}, X\right) \sim IG$

Metropolis–Hastings to sample ω from $p(\omega \mid \tilde{y}, X, \mathcal{W})$:

- Sample ρ conditional on Γ
- Block-sample Γ conditional on ρ

Joint Posterior for ω

β and σ^2 can be integrated out analytically from the joint posterior:[1]

$$p(\omega \mid \tilde{y}, X, \mathcal{W}) \propto |R(\omega)| \left|X'X\right|^{-1/2} \left(\omega' F \omega\right)^{-(n-k)/2}$$
$$\ln p(\omega \mid \tilde{y}, X, \mathcal{W}) \propto ln|R(\omega)| - \frac{n-k}{2} \ln \left(\omega' F \omega\right)$$

- Condition this expression on Γ to sample ρ and vice versa
- Numerically integrate this expression to arrive at the log marginal likelihood

[1] $F = U'U, \quad U = M\tilde{y}, \quad M = I_n - X\left(X'X\right)^{-1} X'$

Sampling ρ

Initial value: $\rho = 0.7$

1. Draw $\rho^p = \rho^c + cN(0,1)$
   - If $\rho^p \in (-1,1)$, continue
   - Else set $\rho^c = \rho^p$ and repeat
2. Decide acceptance: If $\alpha \geq U \sim U(0,1)$ accept ρ^p and set $\rho^c = \rho^p$. Else stay at ρ^c

$$\alpha(\rho^c, \rho^p) = \min\left(1,\ \exp\left[\ln p(\rho^p \mid \Gamma) - \ln p(\rho^c \mid \Gamma)\right]\right)$$

3. Tuned random walk:
   - If acceptance ratio $< 0.4 \implies c = c/1.1$
   - If acceptance ratio $> 0.6 \implies c = c * 1.1$

Block Sampling for Γ

Initial values: $\gamma_\ell = 1/L, \quad \forall \ell$

1. Draw $\Gamma^p = (\gamma_1^p, \dots, \gamma_L^p)$
   - For $\ell \in \{1, ..., L-1\}$ draw $V \sim U(0,1)$. [2]

Condition,	Propose	$N \leq 1000$	$N > 1000$
$V \leq 1/3$	$\gamma_\ell^p \in$	$[0,\ \gamma_\ell^c]$	$[\gamma_\ell^c - d\sigma_{\gamma_\ell}, \gamma_\ell^c]$
$V > 2/3$	$\gamma_\ell^p \in$	$(\gamma_\ell^c,\ 1]$	$(\gamma_\ell^c,\ \gamma_\ell^c + d\sigma_{\gamma_\ell}]$
else	$\gamma_\ell^p =$	γ_ℓ^c	γ_ℓ^c

   - Set $\gamma_L = 1 - \sum_{\ell=1}^{L-1} \gamma_\ell$, if $\gamma_L < 0$ repeat.
2. Decide acceptance: If $\alpha \geq U \sim U(0,1)$ accept Γ^p and set $\Gamma^c = \Gamma^p$, else stay at Γ^c

$$\alpha(\Gamma^c, \Gamma^p) = \min\left(1,\ \exp\left[\ln p(\Gamma^p \mid \rho) - \ln p(\Gamma^c \mid \rho)\right]\right)$$

3. Tuned random walk ($N > 1000$):
   - If acceptance ratio $< 0.1 \implies d = d/1.1$
   - If acceptance ratio $> 0.4 \implies d = d * 1.1$

[2] σ_{γ_ℓ} is computed using rolling window interval of 1000 draws of γ_ℓ

Calculating Average Effects ▸ Model

Effects decomposition akin to LeSage and Pace (2009)

$$\frac{\partial y}{\partial X^r} = S_r = (I_n - \rho W_c(\Gamma))^{-1}\beta_r$$

$$\bar{M}(r)_{\text{direct}} = \frac{1}{NT}\,\mathrm{tr}(S_r)$$

$$\bar{M}(r)_{\text{total}} = \frac{\beta_r}{1-\rho}$$

$$\bar{M}(r)_{\text{indirect}} = \bar{M}(r)_{\text{total}} - \bar{M}(r)_{\text{direct}}$$

These capture how changes in a covariate affect outcomes locally and across the spatial network.

Marginal Likelihood and Model Averaging

- MH-MC integration of $p(\omega \mid \tilde{y}, X, \mathcal{W})$ to arrive at the marginal likelihood
- Uniform prior over the model space
  - Posterior model probability boils down to marginal likelihood
- Debarsy and LeSage (2022) write their BMA estimation for combinations of 2 or more networks
  - We additionally estimate single network models in Appendix
  - Low marginal likelihood $\implies$ posterior probability ≈ 0
- With 5 candidates for connectivity matrices, there are 26 potential combinations of 2 or more matrices

Data: Stock Returns and Monetary Policy Shocks

Stock returns based on monthly closing prices of national stock market indices:

- 24 countries from 2001-2014
- US: SP500, Germany: DAX, ...

Identification of monetary policy shocks following Jarociński and Karadi (2020):

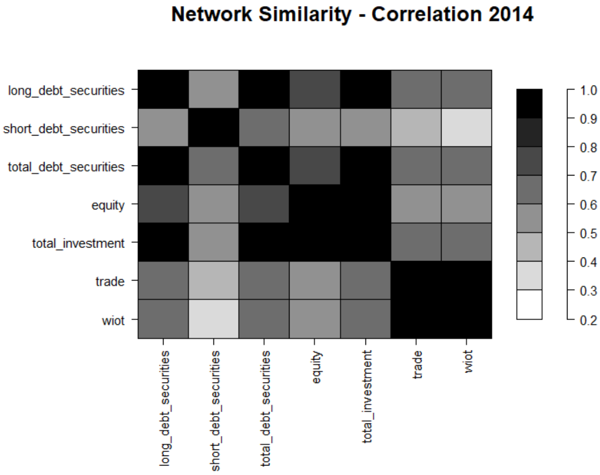
- MP shock = interest rate surprise
- Change in the three-month Federal Funds futures rate
- 30-minute window around FOMC announcements

Data: Transmission Networks

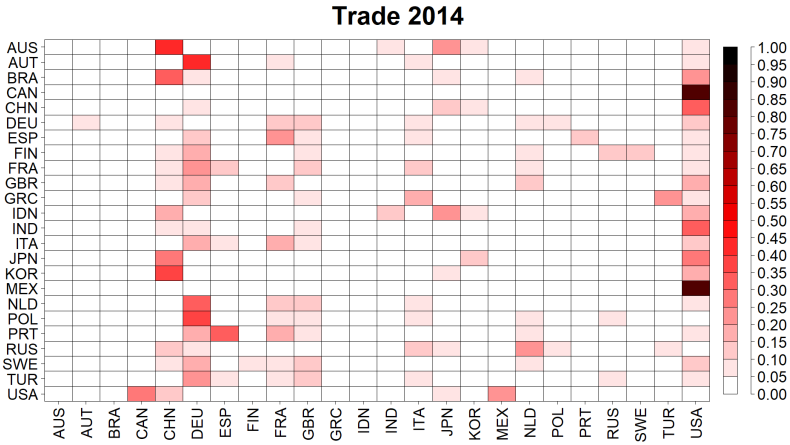
Quadratic network matrices of directed, bilateral links between countries.

- Short-term debt securities: with original maturity <1 year
- Long-term debt securities: with original maturity >1 year
- Equity holdings: Equity titles
- Trade in intermediates: input-output matrix at country-level
- Total trade: import and export flows

Network Similarity 2001-2014 (Link)



Network Evolution 2001-2014 (Link)



Results BMA 2001-2014

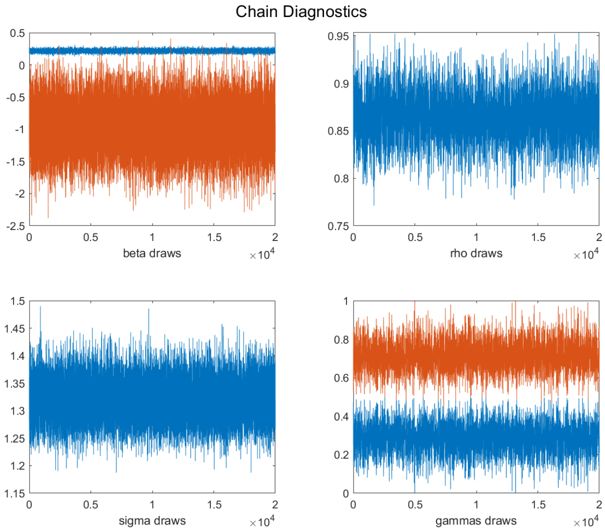
Table 2: Top 5 Models by Posterior Probability

Rank	LogLik	PostProb	ρ	W1	W2	W3	W4	W5
1	-5330.3	0.91	0.87	0.29	-	-	-	0.71
2	-5333.7	0.03	0.87	0.24	0.05	-	-	0.71
3	-5333.9	0.02	0.86	0.28	-	-	0.13	0.59
4	-5334.1	0.02	0.87	0.26	-	0.03	-	0.71
5	-5334.6	0.01	0.85	-	0.14	-	-	0.86
BMA	-5330.7	0.99	0.87	0.28	0.00	0.00	0.01	0.71

W1 Long Debt Securities
W2 Short Debt Securities
W3 Equity
W4 Trade
W5 Wiot

Trace Plot Best Model

▸ Full model



Chain Diagnostics Best Model

Full model

Table 3: MCMC Diagnostics (ndraws = 20000)

	Mode	Mean	MC Error	IACT	ESS	Geweke
α	0.2166	0.2173	0.0002	1.3722	14579	0.9995
β	-0.9534	-0.9595	0.0031	1.0179	19648	0.9863
ρ	0.8665	0.8649	0.0005	5.7472	3481	0.9996
γ_1	0.2842	0.2860	0.0017	7.5656	2644	0.9952
γ_2	0.7158	0.7140	0.0017	7.5656	2644	0.9981

Results BMA 2001-2014

Table 4: Averaged Posterior Estimates

Variable	**0.01**	**Median**	**0.99**
α	0.16	0.22	0.27
x	-1.81	-0.96	-0.10
ρ	0.80	0.86	0.93
γ_1	0.11	0.28	0.45
γ_2	0.00	0.00	0.01
γ_3	0.00	0.00	0.00
γ_4	0.00	0.00	0.02
γ_5	0.54	0.71	0.88

Table 5: Posterior Estimates for Effect Decomposition

Effect	**0.01**	**Median**	**0.99**
Direct	-2.31	-1.21	-0.13
Indirect	-14.99	-5.89	-0.66
Total	-17.13	-7.13	-0.80

Results Subsample 2001-2006

Table 6: Top 5 Models by Posterior Probability

Rank	LogLik	PostProb	ρ	W1	W2	W3	W4	W5
1	-2424.7	0.58	0.68	0.57	0.00	0.00	0.00	0.43
2	-2425.8	0.18	0.68	0.66	0.00	0.00	0.34	0.00
3	-2427.4	0.04	0.69	0.89	0.11	0.00	0.00	0.00
4	-2427.6	0.03	0.69	0.47	0.00	0.13	0.00	0.40
5	-2427.5	0.03	0.68	0.48	0.10	0.00	0.00	0.42
BMA	-2425.7	1.00	0.68	0.58	0.01	0.02	0.08	0.31

W1 Long Debt Securities
W2 Short Debt Securities
W3 Equity
W4 Trade
W5 Wiot

Results Subsample 2001-2006

Table 7: Averaged Posterior Estimates

Variable	**0.01**	**Median**	**0.99**
α	0.31	0.38	0.44
x	-2.45	-1.54	-0.66
ρ	0.60	0.68	0.76
γ_1	0.30	0.58	0.82
γ_2	0.00	0.01	0.03
γ_3	0.01	0.02	0.04
γ_4	0.02	0.08	0.16
γ_5	0.08	0.31	0.58

Table 8: Posterior Estimates for Effect Decomposition

Effect	**0.01**	**Median**	**0.99**
Direct	-2.61	-1.66	-0.72
Indirect	-5.93	-3.24	-1.41
Total	-8.36	-4.91	-2.15

Conclusion

- We analyze importance of individual networks for spillovers of US monetary policy to international stock returns
- We use panel SAR with convex combinations of time-varying networks
- Spillovers more pronounced through intermediate input trade and long-term debt linkages
- The effect sizes and the importance of individual networks change for a sub-sample before GFC

Next steps:

- Reconcile results with absolute sizes of links
- Dynamic setting with multiple variables

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Posteriors for β and σ^2

$$
\begin{aligned}
p\left(\beta \mid \sigma^2, \omega, \tilde{y}, X\right) &\sim N\left(\tilde{\beta}, \tilde{\Sigma}_\beta\right) \\
\tilde{\beta} &= \left(X'X\right)^{-1}\left(X'\tilde{y}\omega\right) \\
\tilde{\Sigma}_\beta &= \sigma^2\left(X'X\right)^{-1}
\end{aligned}
$$

$$
\begin{aligned}
p\left(\sigma^2 \mid \beta, \omega, \tilde{y}, X\right) &\propto \left(\sigma^2\right)^{-\left(\frac{n}{2}\right)} \exp\left(-\frac{e'e}{2\sigma^2}\right) \\
&\sim IG(\tilde{a}, \tilde{b}) \\
\tilde{a} &= n/2 \\
\tilde{b} &= \left(e'e\right)/2 \\
e &= \tilde{y}\omega - X\beta
\end{aligned}
$$

MH-MC Integration and Marginal Likelihood

Marginal likelihood by Metropolis-Hastings guided MC Integration:

$$\log p(data) = \log \int p(data \mid \omega)\, p(\omega)\, d\omega$$
$$\approx \log \left(\frac{1}{S} \sum_{s=1}^{S} p(data \mid \omega^{(s)})\, p(\omega^{(s)}) \right)$$

In the code:

$$\frac{1}{S} \sum_{s=1}^{S} \log p(\omega^{(s)} \mid \text{data}) + \log C$$

MH-MC Integration and Marginal Likelihood

DL22: Monte Carlo integration estimate of $p(\omega \mid \tilde{y}, X, \mathcal{W})$ is its mean. Add constants of integration to produce log marginal likelihood.

$$\frac{1}{S}\sum_{s=1}^{S} \log p(\omega^{(s)} \mid \text{data}) + \log C$$

```
results.logmarginal = mean(logp) + logC_sar;
```

Normalized nonlog joint posterior:

$$\exp[\log p(\omega) - \max(\log p(\omega))]$$

MATLAB Code

In the code:

$$\frac{1}{S}\sum_{s=1}^{S}\log p(\omega^{(s)} \mid \text{data}) + \log C$$

```
% calculate log-marginal likelihood (using Mh-MC integration)
logp = results.drawpost;
rho_gamma = results.rho_gamma;
[adj,mind] = max(logp);
results.rho_mode = rho_gamma(mind,1);
results.beta_mode = betapost(mind,:);
results.sig_mode = sigpost(mind,1);
results.gamma_mode = rho_gamma(mind,2:end);
isum = exp(logp -adj);
lndetx_sar = log(det(xpx));

% constant terms
dof = (n - m)/2; % we must include the # of weight matrices
D = (1 - 1/rmin); % from uniform prior on rho
logC_sar = -log(D) + gammaln(dof)
           - dof*log(2*pi)  -0.5*lndetx_sar;

results.logmarginal = mean(logp) + logC_sar;
results.logC_sar = logC_sar; % return constants
results.logm_profile = [rho_gamma betapost sigpost isum];
```

Log-Determinants Based on Trace Approximations

Approximation based on 4-th order Taylor series expansion:

$$\begin{aligned}
\ln |I_n - \rho W_c(\Gamma)| &= -\sum_{i=1}^{\infty} \rho^i \operatorname{tr}\left(W_c^i(\Gamma)\right)/i \\
&\simeq -\sum_{j=2}^{q} \rho^j \operatorname{tr}\left(W_c^j(\Gamma)\right)/j
\end{aligned}$$

Log-Determinants Based on Trace Approximations

Traces can be separated and precomputed. Example for j=2

$$\begin{aligned}
\operatorname{tr}\left(W_c^2(\Gamma)\right) &= \sum_{i=1}^{L}\sum_{j=1}^{L}\gamma_i\gamma_j \operatorname{tr}\left(W_i W_j\right) \\
&= \Gamma' Q \Gamma \\
&= (\Gamma \otimes \Gamma)' vec(Q),
\end{aligned}$$

$$Q = \begin{pmatrix}
\operatorname{tr}\left(W_1^2\right) & \operatorname{tr}\left(W_1 W_2\right) & \dots & \operatorname{tr}\left(W_1 W_L\right) \\
\operatorname{tr}\left(W_2 W_1\right) & \operatorname{tr}\left(W_2^2\right) & \dots & \operatorname{tr}\left(W_2 W_L\right) \\
\vdots & & \ddots & \\
\operatorname{tr}\left(W_L W_1\right) & \operatorname{tr}\left(W_L W_2\right) & \dots & \operatorname{tr}\left(W_L^2\right)
\end{pmatrix}$$

Preliminary Analysis of Individual Networks

Table 9: Marginal log-likelihood and simplified effects of Individual Networks (2001–2014)

	LogLik	Total	Direct	Indirect (%)
W1 Long Debt Securities	-5382.0	-7.1	-1.4	80
W2 Short Debt Securities	-5454.4	-6.0	-1.6	73
W3 Equity	-5453.2	-6.5	-1.5	77
W4 Trade	-5365.5	-4.6	-1.3	72
W5 Wiot	-5358.1	-4.6	-1.2	73

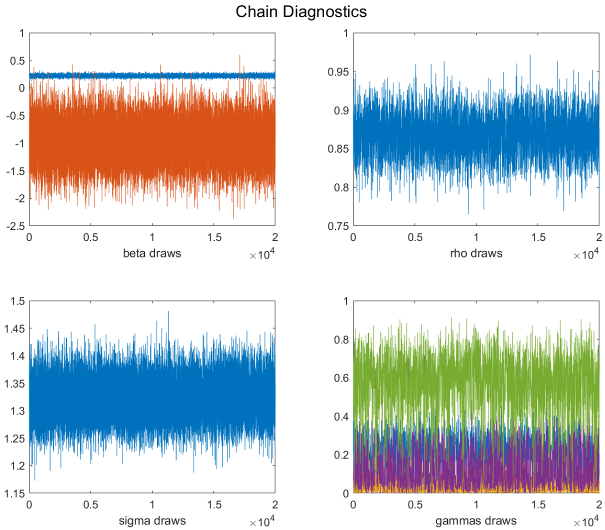
Preliminary Analysis of Individual Networks

Table 10: Marginal log-likelihood and effects of individual networks (2001–2006)

	LogLik	Total	Direct	Indirect (%)
W1 Long Debt Securities	-2430.8	-5.1	-1.8	65
W2 Short Debt Securities	-2451.5	-4.4	-1.9	57
W3 Equity	-2440.9	-4.4	-1.5	66
W4 Trade	-2435.8	-4.1	-1.7	59
W5 Wiot	-2432.9	-4.2	-1.7	59

Trace Plot Full Model

Back



Chain Diagnostics Full Model

Back

Table 11: MCMC Diagnostics (ndraws = 20000)

	Mode	Mean	MC error	Tau	ESS	Geweke
α	0.2146	0.2194	0.0001	1.4656	13643	0.9962
β	-0.9505	-0.9568	0.0019	1.0327	19368	0.9828
ρ	0.8649	0.8684	0.0004	6.5876	3036	0.9986
γ_1	0.2476	0.2135	0.0025	14.5898	1371	0.9804
γ_2	0.0071	0.0495	0.0015	15.5361	1287	0.8318
γ_3	0.0024	0.0310	0.0006	18.3683	1089	0.9731
γ_4	0.0130	0.1268	0.0036	16.2311	1233	0.9108
γ_5	0.7299	0.5792	0.0038	14.4792	1381	0.9871

Results Full Model

Back

Table 12: Posterior Estimates

	0.01	0.05	Median	0.95	0.99
α	0.1566	0.1718	0.2195	0.2677	0.2828
β	-1.9042	-1.6881	-0.9571	-0.2342	-0.0140
ρ	0.8013	0.8167	0.8686	0.9184	0.9365
γ_1	0.0138	0.0513	0.2165	0.3659	0.4111
γ_2	0.0006	0.0016	0.0413	0.1428	0.1815
γ_3	0.0002	0.0010	0.0222	0.1083	0.1437
γ_4	0.0011	0.0036	0.0946	0.4136	0.5609
γ_5	0.1608	0.2887	0.5942	0.7880	0.8388

Table 13: Posterior Estimates for Effect Decomposition

Effect	0.01	0.05	Median	0.95	0.99
Direct	-2.4862	-2.1555	-1.2152	-0.2994	-0.0178
Indirect	-16.5870	-12.8793	-6.0382	-1.5054	-0.0955
Total	-18.7172	-14.8541	-7.2596	-1.8194	-0.1133

Results Best Model

▸ Full model

Table 14: Posterior Estimates

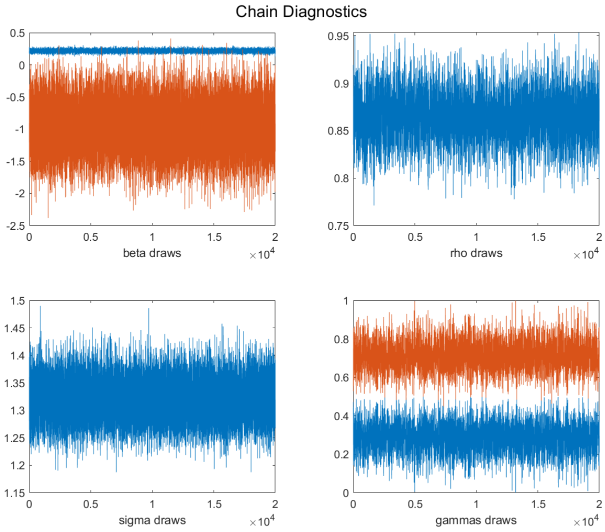
	0.01	**0.05**	**Median**	**0.95**	**0.99**
α	0.1553	0.1705	0.2172	0.2648	0.2790
β	-1.9155	-1.6953	-0.9572	-0.2307	-0.0100
ρ	0.7963	0.8144	0.8658	0.9127	0.9289
γ_1	0.0797	0.1343	0.2853	0.4385	0.4859
γ_2	0.5141	0.5615	0.7147	0.8657	0.9203

Table 15: Posterior Estimates for Effect Decomposition

Effect	**0.01**	**0.05**	**Median**	**0.95**	**0.99**
Direct	-2.4566	-2.1559	-1.2136	-0.2937	-0.0125
Indirect	-15.4240	-12.3373	-5.8572	-1.4261	-0.0583
Total	-17.6290	-14.3625	-7.0904	-1.7293	-0.0707

Trace Plot Best Model

▸ Full model



Theoretical Model of Di Giovanni and Hale 2022

Di Giovanni and Hale (2022) setup: N countries, J sectors

$$\underbrace{R_{mi}}_{\substack{\text{Sales of goods}\\ \text{produced by}\\ \text{country-sector}\\ mi}} = \underbrace{C_{mi}}_{\substack{\text{Final goods}\\ \text{expenditure on}\\ \text{good } mi \text{ across}\\ N \text{ countries}}} + \underbrace{\sum_{j=1}^{J}\sum_{n=1}^{N}\omega_{mi,nj}R_{nj}}_{\substack{\text{Intermediate}\\ \text{input}\\ \text{expenditure}}}$$

$\omega_{mi,nj}$ IO coefficient for country-sector nj purchases of the intermediate good from country-sector mi (as share of total purchases)

Theoretical Model of Di Giovanni and Hale 2022

R sales, C final goods expenditures, Ω IO matrix

$$\underset{NJ\times 1}{R} = \underset{NJ\times 1}{C} + \underset{NJ\times NJ}{\Omega} R,$$
$$R = (I-\Omega)^{-1} C,$$
$$\hat{R} = (I-\Omega)^{-1} \phi_R \circ \hat{C},$$
$$\hat{q} = (I-\Omega)^{-1} \beta \hat{M},$$

Assumptions:
$\hat{R} = \hat{\pi} = \hat{q}$, Domestic firms owned by domestic HH.
Deviations in expenditures on final consumption $\hat{C}$ are proportional to the monetary policy shocks $\hat{M}$.