Two Layers of Bank Interconnectedness and Aggregate Dynamics

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Motivation

- Financial stability is a structural property: it depends not only on individual banks but on how they are interconnected.
  A bank sound in isolation can be a source of systemic stress if it sits at a central node ('too-connected-to-fail').

- A large theory literature shows network architecture shapes whether shocks are absorbed or amplified.
  Diversification-contagion trade-off: dense networks diversify/stabilize small shocks but can propagate large ones (e.g., Allen & Gale 2000; Acemoglu et al. 2015; Elliott et al. 2014).

- But there is little empirical evidence on how banking-network structure evolves with aggregate conditions.
  Interconnectedness is treated as a single object and most data reveal only one layer of it.

Interconnectedness is not one object. We distinguish two layers.

- **Contractual layer** (W_t^{phys}). The recorded network of bilateral obligations.
  The layer supervisors naturally monitor (explicit channels for transmitting distress): Interbank funding, repos, derivatives.

- **Behavioral layer** ($\hat{W}_t^{\text{beh}}$): It captures strategic interdependence.
  Even without direct claims, banks adjust liquidity in response to peers' actions and balance sheets. Not directly recorded.

- The key idea is that the relationship between the two layers (not just each one) carries information about systemic vulnerability: Do they align under stress? That alignment could itself be a fragility signal.

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In this paper

Using administrative data from the Chilean banking system, we ask:

How does the architecture of bank interconnectedness evolve with aggregate conditions, and does the alignment between the two layers reveal a distinct dimension of systemic fragility?

- We first recover the behavioral network from balance sheets with no prior knowledge of ties (de Paula, Rasul & Souza, 2025, *Restud*).

  Baseline outcome: the liquidity-asset share $\Rightarrow$ strategic interdependence in liquidity management.

- We also build the contractual network (physical) from confidential administrative records of bilateral interbank obligations.

  Baseline: total debt at the end of the month.

- Then we trace network topology over the cycle and after monetary-policy surprises, and we ask whether the layers converge under stress.

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Why should we care? (contributions)

- **Two layers, one system, same frequency.**
  Most studies observe direct exposures *or* market-based correlations, rarely both for a direct comparison.

- **A dynamic macro-financial view of network topology.**
  We relate density, reciprocity, and concentration to the cycle and to policy shocks — how the ‘‘robust-yet-fragile’’ structure reconfigures across states.

- **Macroprudential implications of layer divergence.**
  Does monitoring contractual exposures alone, the current standard, miss a behaviorally driven channel of shock propagation?

- **Method.** We bring latent-network recovery (de Paula et al. 2025) to a financial setting, validated against a simultaneously observed administrative exposure network.

What we find (Three takeaways; preliminary, staged by data coverage)

1. **Tightening fragments mutual liquidity support.**
   On the long panel, unanticipated tightening lowers the **reciprocity** of behavioral liquidity ties. The sign recurs across local projections, event regressions, and BVARs — recovered with **no exposure data**.

2. **The behavioral layer is non-redundant, yet grounded.**
   Where both layers are observed: contractual ties do **not** predict behavioral ties edge-by-edge. But the two layers identify the **same central banks**, and this survives controlling for size.

3. **Do the layers converge under stress? Not yet answerable.**
   The current overlap is too short. This is the bridge to the next stage.

Related literature

- **Financial networks and systemic risk: structure governs amplification**
  (e.g., Allen & Gale 2000; Acemoglu et al. 2015; Elliott et al. 2014; Glasserman & Young 2016)
  We ask whether contractual exposures alone are enough to characterize banks' systemic footprint.

- **Multilayer financial networks: a single exposure layer can miss systemic risk**
  (e.g., Brunetti et al. 2019; Aldasoro & Alves 2018; Poledna et al. 2015).
  We compare an observed contractual layer with a *recovered behavioral* layer, not just the observed.

- **Strategic liquidity interaction**, (e.g., Denbee et al. 2021; Li & Li 2026).
  Motivates the liquidity-asset share as the outcome, because liquidity management is where funding stress and peer responses should appear.

- **Peer effects, network recovery, and monetary transmission**
  (e.g., Manski 1993; de Paula et al. 2025; Bassett et al. 2014; Ciccarelli et al. 2015).
  We study whether policy surprises reorganize the topology of latent liquidity interdependence.

Data: two supervisory sources, rarely available together

1. **Contractual network (CMF File C18).**
   Confidential administrative bilateral interbank obligations. Allowed to accessed a limited sample.
   We build the row-normalized, time-varying W_t^{phys} across instruments and maturities.

2. **Bank balance sheets and income statements (CMF).**
   Monthly outcomes and covariates for latent-network recovery; baseline outcome is the liquidity-asset share.

3. **Macro-financial series (Central Bank of Chile).**
   IMACEC activity, the policy rate (TPM), inflation; monetary-policy surprises (EEE; three-month swap; Bloomberg), EMBI, others.

Window	Behavioral	Contractual	Overlap
Sample	2010m01–2017m10	2016m04–2017m12	2016m04–2017m10
Months	94	21	19

Notes: The asymmetry in coverage drives the paper's staged design: the behavioral layer carries the heavy lifting; the cross-layer dynamic test awaits a longer C18 panel.

Recovering the behavioral network without observing ties

- Canonical linear-in-means model for the liquidity outcome y_{it}:

$$y_{it} = \rho_0 \sum_{j \neq i} w_{0,ij}^{\text{beh}} y_{jt} + \boldsymbol{x}_{it}' \boldsymbol{\beta}_0 + \sum_{j \neq i} w_{0,ij}^{\text{beh}} \boldsymbol{x}_{jt}' \boldsymbol{\gamma}_0 + \alpha_i + \tau_t + \varepsilon_{it}$$

where the latent adjacency W_0^{beh} matrix is the object of interest (the who-influences-whom).

- **Identification (de Paula, Rasul & Souza 2025, *Restud*):** W_0^{beh} is globally identified from the reduced form

$$\Pi_0 = (I - \rho_0 W_0^{\text{beh}})^{-1}(\beta_0 I + \gamma_0 W_0^{\text{beh}})$$

under mild conditions (e.g., the non-cancellation condition $\beta_0\rho_0 + \gamma_0 \neq 0$).

- Estimated by **Adaptive Elastic Net GMM**; tracked over time with **Gaussian kernel weighting**.
This yields a directed, weighted, structurally interpretable network; not a correlation matrix.

(more details)

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Why this is not just a correlation network

Manski (1993) reflection problem: hard to separate endogenous peer effects from contextual and correlated effects.

The approach mitigates it through structure and rich data (not classical instruments):

- **Contextual effects:** peers' characteristics $\boldsymbol{x}_{jt}$ enter the model explicitly.
- **Correlated effects:** time effects τ_t absorb common macro/regulatory shocks; row-normalization permits global demeaning.
- **Endogenous effect** (ρ_0) **and the ties:** identification exploits the structure of the reduced form across the implied powers $I, W, W^2, \ldots$
- **Validation:** the recovered behavioral network is compared against a *simultaneously observed* administrative exposure network (Part II).

Comparing the layers: topology, edges, nodes, alignment

- **Contractual network**: row-normalized obligations, $w_{ij,t}^{\text{phys}} = \text{TotalObligations}_{i\to j,t} / \sum_{k\neq i} \text{TotalObligations}_{i\to k,t}$.
- **Topology statistics** for each layer, each month: density, reciprocity, concentration (HHI of in-strength, top-3 share).
- **Cross-layer comparison** at three levels: edge (does W^{phys} predict a behavioral tie?), node (do they rank the same banks central?), and **alignment**:

$$\text{Convergence}_t = \frac{\boldsymbol{w}_t^{\text{beh}} \cdot \boldsymbol{w}_t^{\text{phys}}}{\|\boldsymbol{w}_t^{\text{beh}}\| \, \|\boldsymbol{w}_t^{\text{phys}}\|}$$

Benchmarked against permutation nulls that relabel bank identities.

(more details)

Empirical strategy: a staged design

- **Part I — the result this version delivers** (long behavioral panel, 94 months)
  How the behavioral liquidity network responds to the cycle and to MP surprises, via local projections, event regressions, and BVAR/BVARX checks reported *together*.

- **Part II — grounding the behavioral layer** (19-month overlap)
  Is the recovered network economically grounded in observed contractual exposures? Edge-level and node-level comparisons.

- **Part III — the central two-layer question, scoped** (19-month overlap)
  The Stress Alignment Hypothesis, the convergence pilot, and a power analysis quantifying the data needed to test it.

We report the full set of methods so that recurring patterns (not any single specification) carry the interpretation.

(more details)

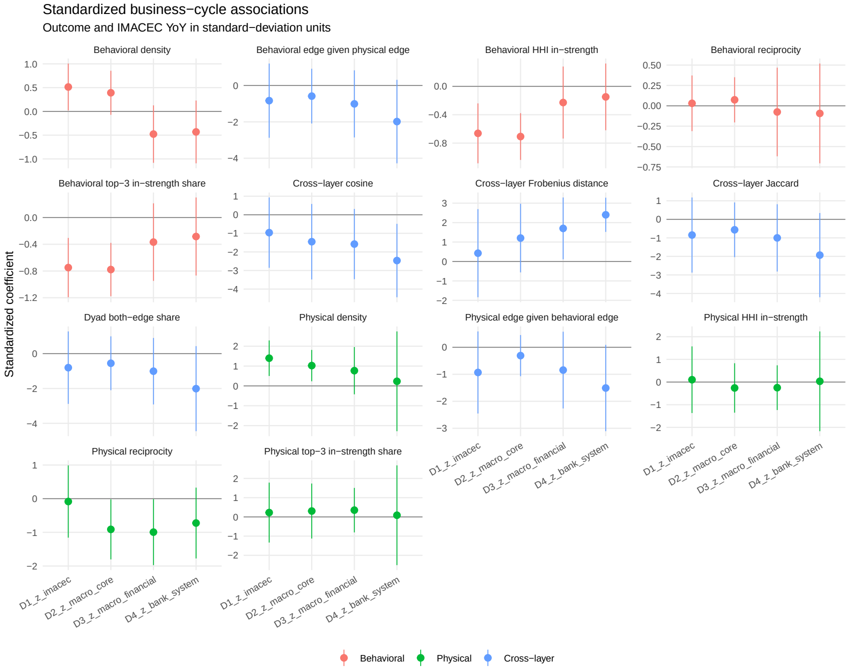
Part I. Business cycle:

In parsimonious specifications: behavioral **density** is positively associated with growth; **concentration** negatively.

Both **vanish** under the saturated controls. Unconditional cyclicality is partly absorbed by macro-financial and banking-system controls.

Outcome	IMACEC only	Macro core	Macro financial	Bank system
HHI in-strength	-0.005^{***}	-0.005^{***}	-0.002	-0.001
	(0.002)	(0.001)	(0.002)	(0.002)
Density	0.002^{**}	0.002^{*}	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Reciprocity	0.001	0.001	-0.001	-0.002
	(0.003)	(0.003)	(0.005)	(0.006)
Top-three in-strength share	-0.015^{***}	-0.016^{***}	-0.007	-0.006
	(0.005)	(0.004)	(0.006)	(0.006)

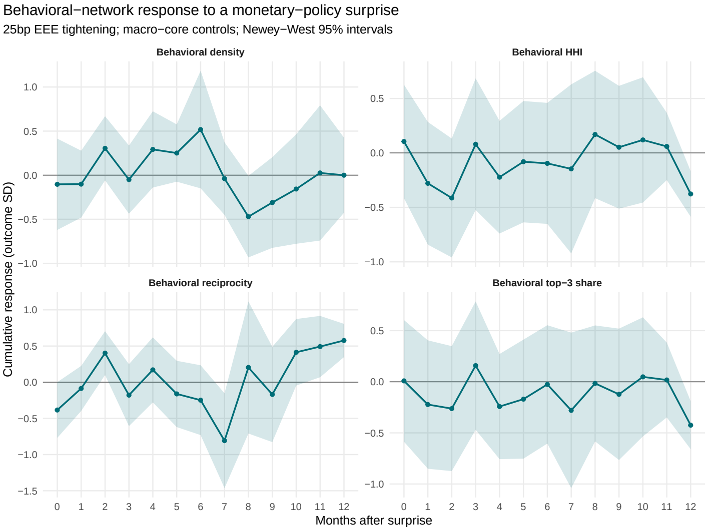
Notes: The table reports the coefficient on year-on-year IMACEC growth from the business-cycle regression in the paper. The behavioral sample covers 2010m01–2017m10 and contains 94 monthly observations. HAC/Newey–West standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.



Standardized business−cycle associations
Outcome and IMACEC YoY in standard−deviation units
Behavioral density
Behavioral edge given physical edge
Behavioral HHI in−strength
Behavioral reciprocity
Behavioral top−3 in−strength share
Cross−layer cosine
Cross−layer Frobenius distance
Cross−layer Jaccard
Dyad both−edge share
Physical density
Physical edge given behavioral edge
Physical HHI in−strength
Physical reciprocity
Physical top−3 in−strength share
Standardized coefficient
D1_z_imacec
D2_z_macro_core
D3_z_macro_financial
D4_z_bank_system
Behavioral
Physical
Cross−layer

Part I. After tightening, reciprocity falls; concentration falls slowly

Local projections to a 25 bp EEE tightening (macro-core controls, Newey–West 95% bands)



- **Reciprocity:** -0.38 SD on **impact** ($p \approx 0.05$).
- **Concentration:** HHI and top-3 **decline at 12 months** (-0.38, -0.43).
- **Density:** no stable response (CIs contain zero).
- The h=12 reciprocity reversal carries an anomalously small SE, a symptom of sample attrition at long horizons; it is not interpreted.

Part I. Reciprocity drops after tightening (suggestive after multiplicity)

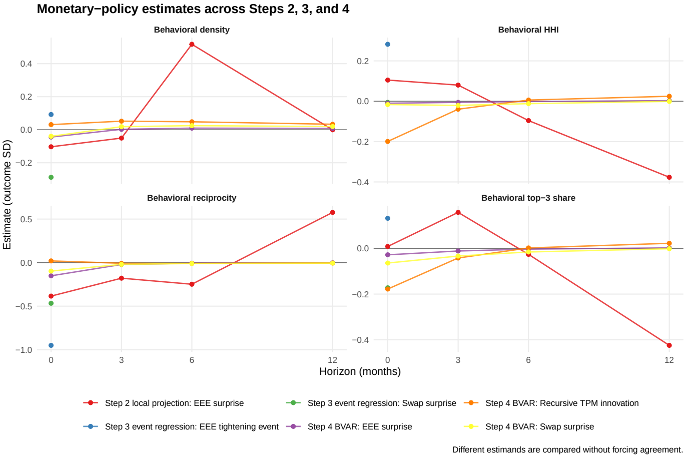
Monthly event regressions; effects in outcome-SD units; credibility comes from agreement across methods, not one coefficient

Behavioral reciprocity	Estimate	Inference	
EEE tightening (event)	**-0.95** *	(i) Paw $p = 0.072$; (ii) Romano-Wolf $p = 0.946$	(i) Primary hypothesis (ii) not family-wise significant
3-month swap (signed)	**-0.47** **	raw $p \approx 0.02$; HAC(3)	richer support (84 nonzero months)
Local projection (impact)	$\boxed{\textbf{-0.38}^{*}}$	$p \approx 0.05$	
BVARX impact (swap / EEE)	**-0.10 / -0.15**	90% CI incl. 0	sign-consistent
Leave-one-event-out: sign stable (-1.16 to -0.47).			

HAC/Newey–West and HAC(3) inference. Romano–Wolf adjusts the pre-specified EEE event family; the EEE coefficient does not survive that correction. The *recurring negative sign* across methods is the result.

Part I. The negative reciprocity sign recurs across four methods

Local projections, EEE and swap event regressions, and surprise-augmented BVARX agree in sign; the recursive BVAR marks the identification boundary



- **Reciprocity:** negative short-run sign in LP, both event regressions, and BVARX.
  Recursive BVAR ≈ 0 on impact $\Rightarrow$ impact sign is identification-dependent.
- **Concentration:** negative; LP places it at 12m, recursive BVAR near impact.
- **Density:** least stable; not interpreted.
- **Takeaway:** tightening $\Rightarrow$ fragmentation of *mutual* liquidity support.

Part I. The channel is real in sign, but modest in magnitude

- The reciprocity **sign** is robust across methods and shock measures.
- But policy innovations explain only a **modest share** of behavioral-network forecast-error variance.
  At 18 months, the TPM-shock share is $\approx 1\%$ (reciprocity) to 2% (HHI); own-network shocks dominate.
- Concentration's **timing** is identification-dependent (12m in LP vs. impact in recursive BVAR); density does not respond.
- We therefore frame Part I as a **network-topology channel of monetary transmission**, a clear qualitative reorganization rather than a large quantitative effect.

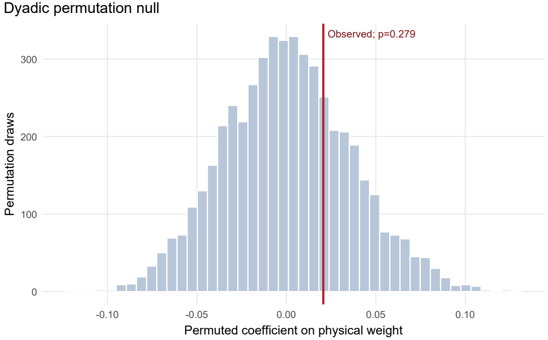
Part II. Contractual exposure does not predict where behavioral ties form

Overlap 2016m04–2017m10: 15 banks, 210 directed dyads, 3,990 dyad-months

Dyadic linear-probability model; physical-weight coefficient across specifications:

	Bivariate	+ pair controls	+ FE
Physical weight	0.0506	0.0264	0.0156
(Wild-cluster p)	(0.376)	(0.698)	(0.817)
(Permutation p)	(0.078)	(0.226)	(0.333)

Physical-tie indicator: -0.0745 in Column 1 (cluster $p = 0.012$), attenuating with controls and FE.



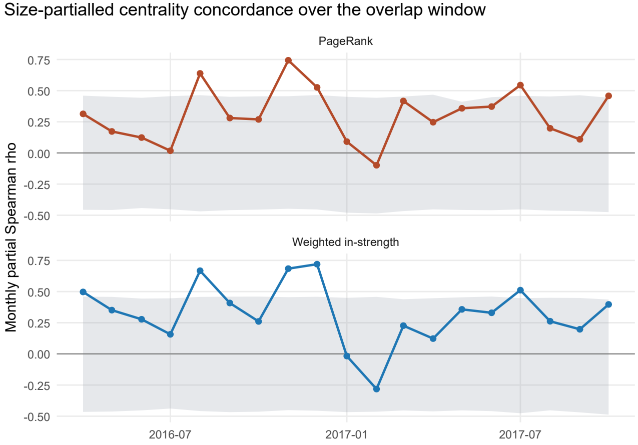
Permutation-null distribution for the physical-exposure coefficient; the observed value lies inside the null.

$\Rightarrow$ **Behavioral ties are not a relabeling** of contractual exposures: **non-redundancy**.

(more details)

Part II. Yet both layers rank the same banks central, beyond size

Node-level rank concordance; in-strength and PageRank; partialling out bank size



Size-partialled mean Spearman ρ:

	$\bar{\rho}$	Months +	Perm. / block p
Weighted in-strength	**0.322**	17/19	< 0.001
PageRank	**0.304**	18/19	< 0.001
Raw contr. in-strength	**0.299**	18/19	< 0.001

- Concordance **strengthens** after partialling out size $\Rightarrow$ **not** a common size factor.
- $\rho \approx 0.30$ is **moderate**: the largest banks dominate *contractual* centrality, while the behavioral layer also elevates others.

$\Rightarrow$ **Distinct wiring, same central banks:** the behavioral layer is **non-redundant but grounded**.

Part III. Do the layers converge under stress? The Stress Alignment Hypothesis

Hypothesis: in good times banks manage liquidity loosely relative to contractual counterparties; as conditions tighten, obligations bind and $\hat{W}^{\text{beh}}$ **converges** toward W^{phys}.
The degree of convergence could itself be a macroprudential early-warning signal.

- **Baseline level:** the layers are related but far from identical (i.e., Cosine or Jaccard ≈ 0.10).
- **Short-overlap pilot** (swap shock, 19 months): estimates are statistically indistinguishable from zero. Point estimates carry large standardized magnitudes that reflect noisy scaling.

The available overlap gives **no reliable evidence** on convergence in either direction. So, working on

- Extending C18 toward the start of the behavioral sample brings **sub-**σ_C effects within reach.
- The Stress Alignment Hypothesis becomes **testable once the administrative exposure panel is extended**.

(power analysis)

Summary and agenda

- Bank interconnectedness has two layers; we recover the behavioral one from balance sheets and observe the contractual one in administrative data.
- **Part I:** unanticipated tightening lowers behavioral **reciprocity**, a fragmentation of mutual liquidity support, recurring across LP, event regressions, and BVARs; magnitude modest.
- **Part II:** the behavioral layer is non-redundant at the edge level yet grounded at the node level (size-partialled concordance, $\rho \approx 0.30$).
- **Part III:** cross-layer convergence, the macroprudential question, needs a longer panel.
- **Next:** extend the C18 panel; test whether the substitution lean persists; estimate convergence with adequate support; **Eisenberg–Noe vs. strategic-multiplier** contagion; a tight-window policy surprise/shock.

Thanks! Comments very welcome.

Appendix

Additional material

- Identification of the latent network (de Paula et al. 2025)
- Adaptive Elastic Net GMM and kernel-weighted networks
- Behavioral-layer variables
- Contractual network and topology statistics
- Monetary-policy surprises and dynamic specifications; BVAR/BVARX
- Dyadic LPM and centrality concordance: full results and inference
- Power analysis and planned contagion comparison

Appendix: identification of the latent network

Reduced form. Stacking the linear-in-means model, $\boldsymbol{y}_t = \Pi_0 \boldsymbol{x}_t + \boldsymbol{\nu}_t$, with

$$\Pi_0 = (I - \rho_0 W_0^{\text{beh}})^{-1}(\beta_0 I + \gamma_0 W_0^{\text{beh}}).$$

De Paula et al. (2025) give conditions under which the high-dimensional θ_0 — all $N(N-1)$ ties — is **globally identified** from Π_0.

Maintained assumptions in our setting:

- No self-links ($w_{ii} = 0$) and stability ($|\rho_0| < 1$).
- Non-cancellation: $\beta_0\rho_0 + \gamma_0 \neq 0$ (endogenous and exogenous effects do not offset).
- Row-sum normalization ($\sum_j w_{ij} = 1$): permits global demeaning of common macro shocks; we expect a heterogeneous diagonal of $(W_0^{\text{beh}})^2$ (verified post-estimation).

Outcome. Baseline $y_{it}^{(L)}$ = liquidity-asset share $\Rightarrow$ the recovered network is an *outcome-specific* latent network for liquidity management.

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Appendix: Adaptive Elastic Net GMM and kernel-weighted networks

Estimation. Penalized GMM (Caner & Zhang 2014; de Paula et al. 2025):

$$G_{NT}(\theta, p) = g_{NT}(\theta)' M_T \, g_{NT}(\theta) + p_1 \sum_{i \neq j} |w_{ij}^{\text{beh}}| + p_2 \sum_{i \neq j} (w_{ij}^{\text{beh}})^2.$$

L_1 (Lasso) selects ties; L_2 (Ridge) handles collinearity. Three stages: Elastic-Net selection $\rightarrow$ unpenalized Post-GMM for asymptotically normal SEs.

Time variation. Recover a sequence $\{\hat{W}_t^{\text{beh}}\}$ on **Gaussian kernel**-weighted windows (bandwidth $h = 12$ months, boundary bandwidth 10). Kernel weights are renormalized at sample edges (zeroth-order boundary correction); the effective number of periods comfortably exceeds the parameter count.

Post-selection inference, bandwidth ($h \in \{6, 12, 18, 24\}$), and penalty-path sensitivity are documented as estimator-robustness; sharpening them is part of the extended-sample agenda.

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Appendix: behavioral-layer variables

Role	Variable
Baseline outcome	Liquidity-asset share $y^{(L)}$
Alternative outcomes	Consumer / housing / commercial lending shares (checks)
Controls $\boldsymbol{x}_{it}$	Size, capitalization, ROAA, operating efficiency, deposit funding, NPLs, loan-to-assets, funding costs
Stress proxies	Total/segment NPL ratios, provisioning coverage, profitability stress (forward-looking; appendix template)

Liquidity management is the balance-sheet channel most directly connected to funding stress, precautionary hoarding, and the binding nature of contractual interbank obligations — hence the baseline outcome. Lending-share networks test whether the recovered structure is liquidity-specific or extends to portfolio allocation.

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Appendix: contractual network and topology statistics

Contractual layer (C18). Aggregate monthly obligations across maturity, currency, and instrument for each ordered pair; row-normalize:

$$w_{ij,t}^{\text{phys}} = \frac{\text{TotalObligations}_{i\to j,t}}{\sum_{k\neq i}\text{TotalObligations}_{i\to k,t}}.$$

Raw exposures retained for the extensive-margin tie indicator and raw-basis centrality. Alternative layers (unsecured, derivatives, settlement-inclusive, by maturity/currency) used as robustness.

Topology statistics (per layer, per month):

- **Density**; **reciprocity** (mutuality of directed ties).
- **Concentration:** HHI of weighted in-strength; top-3 in-strength share.
- **Cross-layer:** cosine convergence, edge Jaccard, Frobenius alignment, in-strength rank alignment.

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Appendix: monetary-policy surprises and dynamic specifications

Surprises. Baseline EEE survey-expectations series (12 nonzero behavioral months); robustness with three-month swap (84 nonzero) and Bloomberg (9 nonzero). Each normalized to an unexpected 25 bp tightening.

Caveat: EEE is survey-based, the swap is a curve object; neither isolates the global financial cycle for a small open economy. A tight-window OIS/one-day-swap surprise is on the agenda.

Local projections.

$$y_{t+h} - y_{t-1} = \alpha_h + \beta_h MP_t + \rho_h y_{t-1} + \phi_h MP_{t-1} + \boldsymbol{\Gamma}_h' \boldsymbol{X}_{t-1} + \varepsilon_{t+h}.$$

Event regressions.

$$\Delta y_t = \alpha + \beta_T \mathbb{1}\{\text{tightening}_t\} + \beta_E \mathbb{1}\{\text{easing}_t\} + \boldsymbol{\Gamma}' \boldsymbol{X}_{t-1} + u_t.$$

Notes: Newey–West / HAC(3) inference; Romano–Wolf family-wise adjustment for the pre-specified EEE event family.

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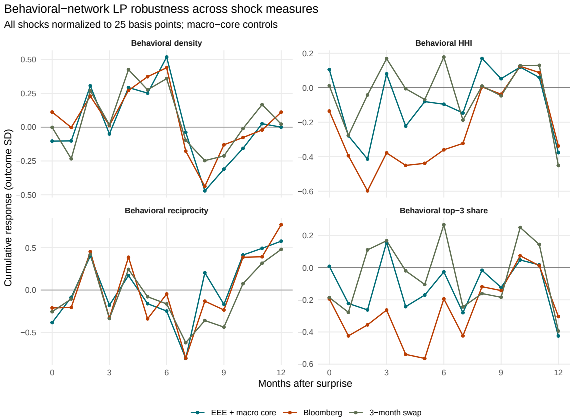
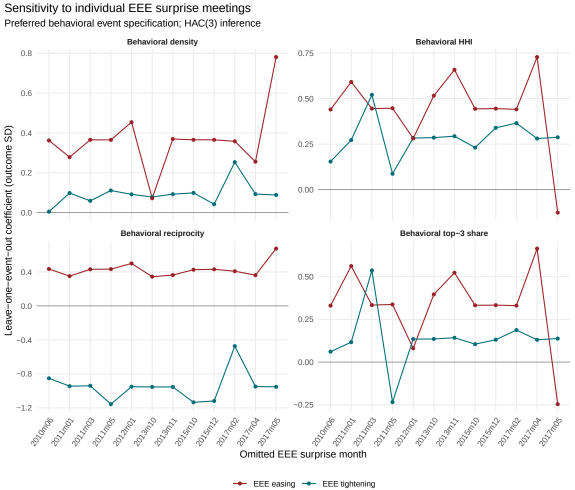
Appendix: LP robustness and event sensitivity

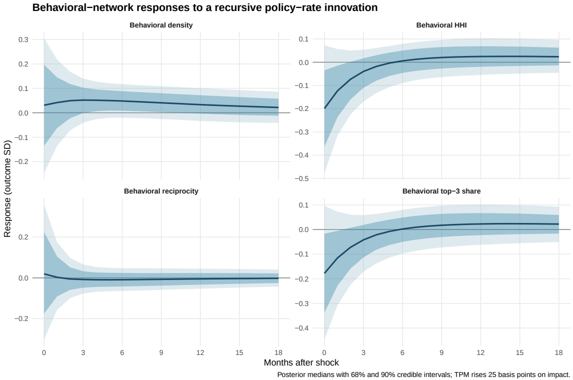


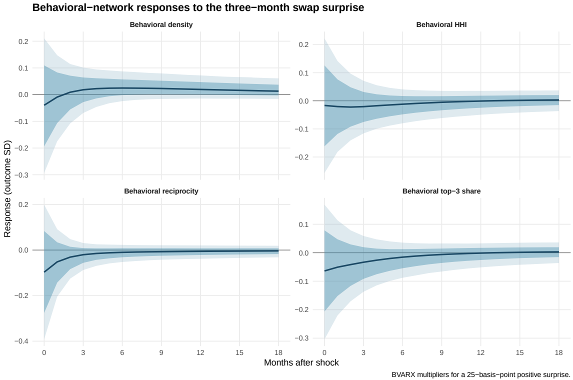
LP responses across EEE, Bloomberg, and three-month swap surprises (25 bp; macro-core).



Leave-one-event-out: the reciprocity tightening sign is stable to omitting any single EEE meeting.

Appendix: BVAR / BVARX dynamic evidence





Recursive 25 bp TPM innovation; posterior medians with 68/90% credible intervals.

Three-month swap-surprise BVARX; surprise normalized to 25 bp tightening.

Minnesota-style shrinkage, 10,000 stable draws. Reciprocity median negative after tightening in the surprise systems; concentration most negative near impact in the recursive system; density small and unstable. Policy shocks explain a modest FEV share (≈ 0.7–1.7% at 18m).

Appendix: dyadic LPM and centrality concordance

Dyadic LPM. $\mathbf{1}[\hat{w}_{ij,t}^{\text{beh}} > 0]$ on the physical weight and an extensive-margin contractual-tie indicator (from raw exposures), plus pair controls (size difference, capitalization similarity, portfolio overlap) and month/obligor FE. Inference: two-way (pair, month) clustering, wild-cluster bootstrap, and a bank-relabeling permutation null — the latter is the primary device given 19 month clusters.

Centrality concordance. Monthly Spearman correlations of behavioral vs. physical centrality (raw in-strength and PageRank primary; raw-basis eigenvector secondary; normalized-basis eigenvector is degenerate on row-stochastic matrices and kept only as a diagnostic). **Size-partialled** correlation removes a within-month bank-size rank before comparison; benchmarked against a permutation null and a block bootstrap.

Edge: $P(\text{beh}|\text{phys}) = 0.061$ vs. base 0.086 vs. $P(\text{beh}|\text{no phys}) = 0.130$; full-model physical weight 0.0156 with permutation $p = 0.333$. Node (size-partialled): weighted in-strength $\rho = 0.322$, PageRank $\rho = 0.304$, both clear the null.

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Appendix: power analysis and planned contagion comparison

MDE. For a mean-shift design contrasting k surprise months against $T-k$ controls with convergence residual SD σ_C,

$$\text{MDE} \approx (z_{1-\alpha/2} + z_{1-\beta})\,\sigma_C\,\sqrt{\tfrac{1}{k} + \tfrac{1}{T-k}}.$$

At $T = 19, k = 3$: $\approx 1.8\,\sigma_C$; at $T \approx 96, k \approx 12$: $< 0.9\,\sigma_C$. A simulation re-running the convergence LP under the historical serial-correlation structure complements the closed form.

Planned contagion comparison. Contrast an EisenbergNoe2001 default cascade on W^{phys} (raw liability matrix, outside assets, equity) with a strategic-multiplier shock $(I - \rho\hat{W}^{\text{beh}})^{-1}$ on the behavioral layer — which banks each layer identifies as propagators, and how each transmits a common shock. Feasible in static form on current snapshots; central to the macroprudential argument.

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