

Coupling and redundancy shape shock persistence in a computational model of social coordination

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Research Article

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Abstract

Strong coordination can concentrate responses to a disruption, but the consequences depend on coupling strength and shock direction. We examine this dependence in an equation-based, five-dimensional recurrent model with matched shock and control trajectories. A factorial experiment crosses six topology families, five coupling levels, stochastic-input conditions, shock magnitudes, directions, and energy-matched durations, producing 43,200 paired simulations from 120 independent base matrices. Normalized effective rank and mean absolute correlation describe baseline dimensionality and dependence; their combination defines a redundancy index. The outcome is normalized counterfactual-distance area from the end of forcing onward. Mean persistence rises from 0.761 to 2.769 as recurrent spectral radius increases from 0.20 to 0.80. The near-rank-one to diagonal persistence ratio rises from 1.014 to 1.554. A positive redundancy-by-coupling interaction remains under clustering by base matrix ($\beta = 0.0288$, 95% CI 0.0245–0.0331). Cross-validation holding out every coupling level of each matrix gives $R^2 = 0.821$ for organization features, compared with 0.774 for shock and coupling and 0.843 for family labels. Organization-feature performance falls to 0.678 when entire families are held out. These results identify a conditional persistence mechanism within the specified model and delimit its structural generalization. They motivate empirical tests of common-mode exposure in social and economic networks without establishing a universal resilience principle.

1 Introduction

Comparable disruptions can leave different recovery tails because coupled systems differ in their response modes and in the direction of the disturbance. Formal computational models can make these mechanisms explicit and expose the limits of a verbal claim about coordination. The present study examines how baseline dependence and dimensionality relate to shock persistence in a bounded recurrent system [1, 2, 3, 4, 5, 6].

This question also arises in economics. Financial links can diversify exposure or amplify contagion; production links can transmit local disturbances to aggregate outcomes. Such findings motivate a conditional account of connectedness rather than a universal benefit of integration [7, 8, 9, 10, 11, 12].

Resilience research distinguishes resistance, recovery, adaptability, transformation, and retained function [13, 14, 15, 16, 17, 18]. Here the measured outcome is narrower: the duration and shape of deviation from a matched unshocked trajectory. Rapid return does not establish social welfare, useful coordination, or beneficial adaptation.

Social influence models likewise distinguish consensus, polarization, and persistent disagreement under different interaction and communication rules [19, 20, 21, 22, 23, 24]. These studies motivate attention to common responses, but the present model does not instantiate their agents or institutions. Its contribution is a controlled state-space experiment relevant to hypotheses about social coordination.

A generative model is a formal argument whose validity depends on its stated purpose, transparent implementation, and discriminating tests [25, 26, 27]. This model is intended for mechanism exploration, not direct forecasting. It asks whether baseline organization adds predictive information beyond coupling and shock characteristics, and whether that information transfers to previously unseen structures.

The study distinguishes normalized effective rank E from dependence C , and uses the derived descriptors $R = C(1 - E)$ and $Q = CE$. R and Q are algebraic transformations of E and C , not independent state variables. Matched counterfactual trajectories separate persistence from ongoing exposure. Validation holds out complete base matrices and, separately, complete topology families. Table 1 summarizes the constructs and model-specific hypotheses.

Table 1
Conceptual constructs, hypotheses, and falsifiable implications

Construct / hypothesis	Operational definition	Falsifiable implication	Interpretive boundary
Differentiation (E)	Entropy-based effective rank divided by five.	Higher E preserves multiple dynamic modes; it need not imply coordination.	A structural descriptor, not social pluralism measured in people.
Dependence (C)	Mean absolute pairwise correlation of baseline state dimensions.	Dependence may have different associations with persistence across coupling levels.	Correlation within the simulated state, not interpersonal causation.
Redundancy (R)	$R = C(1 - E)$.	At sufficiently high coupling, greater R increases post-forcing persistence.	A conditional mechanism; no universal claim that redundancy is harmful.
Coordinated differentiation (Q)	$Q = CE$.	Combines dimensionality and dependence; functional benefit is not measured.	Return to baseline is not necessarily adaptation or welfare improvement.
H1: coupling effect	Persistence increases with recurrent spectral radius ρ .	Mean post-forcing AUC rises monotonically across ρ levels.	Model-internal causal effect under the factorial design.
H2: conditional redundancy trap	The R effect becomes more adverse as ρ increases.	Positive $\rho \times R$ interaction and a sign-change threshold.	Threshold is model-specific until externally replicated.
H3: directional susceptibility	Dominant-mode shocks persist more than weak-mode shocks.	Ordered mean persistence: dominant > random > weak.	Direction is defined from baseline covariance, not substantive policy content.
H4–H5: predictive scope	Structure improves prediction within known families but may not transport to unseen families.	Organization features exceed shock-only prediction; structural transfer is tested separately.	Predictive validity is computational, not empirical.

2 Theoretical Framework

2.1 Structurally embedded response

Bounded rationality places the structure of a response process within the explanation of behavior [28, 29]. Our narrower question is dynamical: how do coupled response channels sustain a deviation after a perturbation? No choice rule, utility function, or behavioral-economic regularity is estimated here.

Work on cognitive-affective processes and belief systems motivates multivariate representations of social response [30, 31, 32, 33]. The five illustrative labels are emotional state, social conformity, critical reasoning, prosocial orientation, and susceptibility to external influence. The equations are invariant to relabeling these channels; the labels therefore provide interpretation rather than validated psychological content.

2.2 Differentiation, integration, and redundancy

The mathematical distinction rests on information-theoretic and dynamical concepts. Entropy summarizes the distribution of variance across modes; total correlation captures multivariate dependence; effective rank converts an eigenvalue spectrum into an interpretable dimensionality; and classic stability theory shows that size, connectance, and interaction strength jointly shape the behavior of complex systems [34, 35, 36, 37, 38, 39]. No single metric is sufficient. A system can have high correlation because coordinated components retain complementary modes, or because all components have collapsed onto one mode.

The organization plane places E on the vertical axis and C on the horizontal axis. R is large when high dependence coincides with low effective dimensionality; Q combines dependence with retained dimensionality. Because both originate in the same covariance structure, E and C are constrained and their entire rectangular plotting domain need not be attainable. Figure 1 shows only the algebra of the derived indices. Neither index directly measures useful coordination or social performance.

2.3 Resilience as a directional, counterfactual process

Disturbance direction can matter when different state-space modes recover at different rates. Stability landscapes, multivariate early-warning methods, and critical-transition analysis motivate comparing response directions [40, 41, 42, 43, 44]. We apply shocks along the dominant and weakest baseline covariance modes and along a reproducibly drawn random direction.

The term redundancy trap is used here for a conditional persistence penalty, not an absorbing state or a demonstrated social failure. Broader resilience research considers the restoration of vulnerable configurations and trade-offs between recovery and transformation [45, 46, 47, 48]. In this experiment, the proposed trap is an interaction between redundancy and coupling; a regression-implied sign change is not evidence of a bifurcation.

2.4 Economic networks, common-mode exposure, and the proposed mechanism

Network stability and contagion research shows how connectivity, interaction strength, and common exposure shape disruption propagation [49, 50, 51, 52, 53, 54]. Similar suppliers, correlated exposures, or shared control channels are possible empirical analogues of low-dimensional response. This analogy does not identify the simulated coefficients with economic quantities.

The proposed mechanism is specific: strong recurrent coupling can lengthen the relaxation of a shared response mode. Redundancy is a baseline descriptor of that organization, rather than an independently randomized treatment. The factorial experiment varies the generating topology and coupling; regression associations with R must be interpreted within that design.

3 Model and Methods

3.1 Modelling purpose and epistemic status

The model is a virtual laboratory for generative explanation. Its purpose is to identify sufficient conditions under which a seemingly integrated system develops persistent counterfactual deviation after a shock. It is not calibrated to a population, market, institution, or country. This separation of explanatory, predictive, and policy purposes follows established guidance that simulation claims must be judged relative to the purpose for which the model was built [3, 6, 27]. The simulated object is one mesoscopic five-dimensional state system rather than a population of interacting agents; accordingly, the manuscript tests a minimal social-coordination mechanism and not an artificial society in miniature.

Causal interpretations are restricted to interventions in the specified simulation. Associations involving derived baseline metrics do not establish an independent causal effect of redundancy in real social systems.

3.2 State variables and update equations

Let $x_t \in [-1, 1]^5$ denote the five-dimensional state at time t , m_t a latent memory vector, and u_t a five-dimensional stochastic input. Matrices W_{in} , W_{rec} , and W_{self} govern input perception, recurrent coupling, and memory coupling. The update is:

$$\begin{aligned} p_t &= W_{in} u_t \\ m_t &= \tanh(W_{self} m_{t-1} + 0.1 x_{t-1}) \\ x_t &= \tanh(W_{rec} x_{t-1} + p_t + 0.2 m_t) \end{aligned}$$

The hyperbolic tangent bounds the state. At an active forcing step, $\tilde{x} = x_{t-1} + (M/\sqrt{d})v$ replaces x_{t-1} in both the memory and state updates; otherwise $\tilde{x} = x_{t-1}$. The five channels are latent response coordinates rather than psychometric scales. Online Resource 1 gives the full update order and an explanatory schematic (Fig. S2).

3.3 Topology families and coupling intensity

Six 5×5 matrix families were generated: diagonal, dense heterogeneous, modular, hub, chain, and near-rank-one. Twenty base matrices per family were normalized to spectral radius one, giving 120 independent base matrices. Each A was reused at all five values $\rho \in \{0.20, 0.35, 0.50, 0.65, 0.80\}$. Thus $W_{rec} = \rho A$, $W_{in} = 0.50A$, and $W_{self} = 0.25A$ define 600 matrix-coupling units, not 600 independent matrix

draws. Shared topology makes the geometric comparison explicit but limits separation of input, memory, and recurrence effects.

3.4 Stochastic inputs, shocks, and matched counterfactuals

Inputs followed either white noise ($\varphi = 0$) or an AR(1) process ($\varphi = 0.70$), with two innovations seeds per condition. After 130 baseline steps, shocks were applied along the dominant covariance eigenvector, the weakest eigenvector, or a reproducibly generated random unit vector. Magnitudes were 0.50, 1.50, and 3.00. Durations were one or eight steps; amplitude was scaled by $1/\sqrt{\text{duration}}$ so that shock energy was matched.

Each shocked trajectory shared its matrix, input stream, and pre-shock state with its unshocked control. Counterfactual distance was $D_k = \|x_k^{\text{shock}} - x_k^{\text{control}}\|_2$, with $k = 0$ at shock onset. For duration d , the outcome used $D_{d-1}, \dots, D_{129}$: the first value is the state after the last forcing update. This remaining curve was divided by its maximum and integrated by the trapezoidal rule with unit time spacing; a zero curve had zero AUC. There are 130 observations for $d = 1$ and 123 for $d = 8$. The endpoint convention and horizon difference are fixed by the implementation (Online Resource 1, Fig. S1).

3.5 Factorial experiment

The complete design is shown in Fig. 2 and enumerated in Table 2. The factorial product comprised 6 topology families $\times$ 5 coupling levels $\times$ 20 topology seeds $\times$ 2 input seeds $\times$ 2 input autocorrelation states $\times$ 3 magnitudes $\times$ 3 directions $\times$ 2 durations = 43,200 paired shock/no-shock simulations. There were 2,400 unique baselines and 18 shock configurations per baseline.

Table 2
Factorial design and units of observation

Component	Levels	Count contribution	Purpose
Topology family	Diagonal; dense heterogeneous; modular; hub; chain; near-rank-one	6	Span distinct organizational geometries.
Recurrent coupling ρ	0.20, 0.35, 0.50, 0.65, 0.80	5	Test nonlinear intensity effects and thresholds.
Topology seed	20 independent matrices per family	20	Each matrix is reused at all five ρ levels.
Input process	2 seeds $\times \varphi \in \{0, 0.70\}$	4	Test stochastic-input robustness.
Shock magnitude	0.50, 1.50, 3.00	3	Test perturbation scale.
Shock direction	Dominant, random, weak	3	Test anisotropic susceptibility.
Shock duration	1 or 8 steps; energy matched	2	Separate duration from energy.
Total paired simulations	$6 \times 5 \times 20 \times 4 \times 3 \times 3 \times 2$	43,200	Run-level dataset.
Matrix–coupling units	Family $\times$ seed $\times \rho$	600	Repeated conditions, not independent matrices.
Independent base matrices	Family $\times$ topology seed	120	Regression clusters, bootstrap blocks and grouped-CV units.
Baselines	Topology unit $\times$ input condition	2,400	Matched counterfactual starting points.

3.6 Structural metrics

Baseline covariance was estimated from steps 55–129 with a scale-adjusted ridge. If λ_i are covariance eigenvalues and $p_i = \lambda_i / \sum \lambda_i$, effective rank is $\exp[-\sum p_i \ln p_i]$, and E is effective rank divided by five. C is the mean absolute off-diagonal correlation. $R = C(1 - E)$ and $Q = CE$. Additional descriptors included participation ratio, regularized total correlation, matrix density, Frobenius norm, non-normality, baseline variance, and saturation fraction.

The organization plane was evaluated against family labels and raw matrix descriptors to determine whether interpretable state-space metrics captured predictive information beyond nominal topology classes. Figure 3 later displays the realized E – C geometry across all 600 topology units.

3.7 Statistical analysis and validation

Bootstrap intervals resampled independent base matrices. For summaries across coupling levels, each family-by-seed block retained all five values of ρ . Cluster-robust ordinary least squares used $\log(1 + \text{persistence})$ and 120 family-by-seed clusters. The conditional model included standardized coupling and magnitude, duration, input autocorrelation, shock direction, family, standardized R , $\rho \times R$, and $R \times \text{direction}$. These are conditional model associations, not separately identified interventions on R .

Five-fold GroupKFold validation held out complete family-by-seed blocks, so all coupling levels and conditions of a base matrix remained in the same fold. Histogram gradient boosting compared shock plus coupling, matrix descriptors, organization features, and family labels. The organization feature set adds E , C , R , and Q to the shock and matrix descriptors; it is not an E – C -only model. Leave-one-family-out validation trained on five families and predicted the sixth. Model verification and computational validation are distinguished from external empirical validation [55, 56, 57].

Continuous regression predictors were standardized using experiment-wide means and population standard deviations. Bootstrap resampling used seed 20260810, with 2,000 resamples for condition and family-by-coupling summaries and 3,000 for family-wide means and ratio contrasts. Grouped prediction used $\log(1 + \text{persistence})$, learning rate 0.06, 300 iterations, 31 leaf nodes, minimum leaf size 50, and L2 regularization 1.5. Predictions were inverse-transformed for R^2 , MAE, and RMSE. Leave-one-family-out models used 350 iterations and L2 regularization 2.0; consequently, the comparison across validation schemes also changes these settings. No nested hyperparameter optimization or independent tuning set was used.

3.8 Model documentation and reproducibility

Online Resource 1 documents the model using an ODD-style structure [58, 59, 26, 60]. Online Resource 2 contains simulation and analysis code, all 43,200 run-level records, normalized curves, exact tables, figure sources, software versions, and verification results. Rerunning the simulation reproduced the archived numeric data and curves exactly in the documented environment. The analysis groups base matrices across coupling levels. ChatGPT (OpenAI) assisted with language editing, code and documentation work, reference-metadata checking, and preparation of the submission files. The author retains responsibility for the design, interpretation, and submitted content.

4 Results

4.1 The organization plane separates dimensional richness from dependence

The six families occupied distinct regions of the E – C plane (Fig. 3). Diagonal systems retained the highest mean normalized effective rank ($E = 0.849$) and the lowest mean dependence ($C = 0.154$), yielding $R = 0.027$. Near-rank-one systems collapsed to $E = 0.201$ with near-perfect dependence ($C = 1.000$), yielding $R = 0.799$. Intermediate families did not fall on a single integration continuum: hub systems had lower E but higher C than modular or chain systems, demonstrating why topology labels

and a one-dimensional connectedness score are insufficient. Table 3 reports the topology-bootstrap summaries.

Table 3
Family summaries with bootstrap intervals over 20 base matrices per family

Family	Base matrices	Mean AUC	95% CI	Mean E	Mean C	Mean R
Diagonal	20	1.382	1.353 to 1.409	0.849	0.154	0.027
Dense heterogeneous	20	1.453	1.408 to 1.500	0.526	0.439	0.216
Modular	20	1.524	1.493 to 1.556	0.379	0.569	0.357
Chain	20	1.602	1.575 to 1.629	0.559	0.473	0.221
Hub	20	1.433	1.398 to 1.468	0.358	0.778	0.505
Near-rank-one	20	1.806	1.770 to 1.840	0.201	1.000	0.799

4.2 Coupling intensity dominates and topology separates at high coupling

Mean persistence increased monotonically from 0.761 at $\rho = 0.20$ to 2.769 at $\rho = 0.80$ (Table 4). Family curves diverged as coupling increased (Fig. 4). The near-rank-one to diagonal ratio was 1.014, 1.088, 1.172, 1.325, and 1.554 across the five coupling levels. The low-coupling interval includes one, whereas the high-coupling contrast is pronounced. This comparison varies an entire topology family rather than redundancy alone.

Table 4
Coupling intensity, overall persistence, and the near-rank-one penalty

ρ	Mean AUC	95% CI	Recovery steps	Ratio	Ratio 95% CI
0.20	0.761	0.756 to 0.765	2.49	1.014	0.997 to 1.031
0.35	0.978	0.968 to 0.988	3.24	1.088	1.062 to 1.115
0.50	1.316	1.298 to 1.334	4.33	1.172	1.136 to 1.210
0.65	1.843	1.806 to 1.880	6.00	1.325	1.287 to 1.362
0.80	2.769	2.684 to 2.857	8.89	1.554	1.496 to 1.618

4.3 Shock direction and duration modify persistence

Dominant-mode shocks produced mean persistence of 1.710 (95% base-matrix bootstrap CI 1.684 to 1.737), followed by random shocks (1.545; 1.517 to 1.576) and weak-mode shocks (1.345; 1.300 to 1.395). Eight-step shocks had greater mean post-forcing AUC than one-step shocks (1.609 versus 1.457). AUC varied little across magnitudes, while autocorrelated inputs modestly reduced it. Duration comparisons use the endpoint convention and available horizons specified in Section 3.4.

Figure 5 compares normalized decay curves for upper- and lower-quartile redundancy groups. The displayed envelopes describe run-to-run variation, not confidence intervals. The grouping combines different topologies and coupling values; this plot therefore illustrates a marginal association rather than an isolated redundancy effect.

4.4 Cluster-robust inference identifies a conditional redundancy trap

The conditional redundancy regression explained 81.2% of variation in log-transformed persistence, compared with 80.3% for the base model. At mean coupling and for dominant-mode shocks, the standardized R coefficient was -0.0260 (95% CI -0.0484 to -0.0035), while the coupling-by-R interaction was positive (0.0288 , 0.0245 to 0.0331 ; Table 5). Standard errors cluster all coupling levels within each of the 120 base matrices. The estimated marginal association crosses zero near $\rho = 0.691$ for dominant-mode shocks, 0.697 for random shocks, and 0.779 for weak-mode shocks. These are point estimates, not confidence bounds or demonstrated dynamical critical points.

The near-rank-one to diagonal comparison in Fig. 6 complements the regression and supports the conditional version of H2. The positive interaction survives grouping by independent base matrix. However, the additional weak-mode interaction is not statistically distinguishable from zero with this clustering ($p = 0.171$); the different fitted sign-crossing locations should therefore not be read as established differences between directions.

Table 5
Key cluster-robust coefficients for the conditional redundancy model

Term	β	Cluster SE	95% CI	p
Coupling $z(\rho)$	0.2599	0.0029	0.2542 to 0.2657	< 0.001
Magnitude $z(M)$	-0.0037	0.0002	-0.0041 to -0.0033	< 0.001
Eight-step duration	0.0545	0.0031	0.0484 to 0.0605	< 0.001
Input autocorrelation ϕ	-0.0340	0.0068	-0.0474 to -0.0206	< 0.001
Redundancy $z(R)$	-0.0260	0.0114	-0.0484 to -0.0035	0.023
$z(\rho) \times z(R)$	0.0288	0.0022	0.0245 to 0.0331	< 0.001
$z(R) \times \text{weak-mode shock}$	-0.0119	0.0087	-0.0290 to 0.0051	0.171

4.5 Organization features add information beyond shock and coupling

When all conditions of a base matrix were held out together, the organization-feature model achieved mean $R^2 = 0.821$, MAE = 0.211, and RMSE = 0.361. It exceeded shock plus coupling ($R^2 = 0.774$) and slightly exceeded matrix descriptors (0.816), but family labels performed better (0.843; Table 6). Figure 7 aggregates out-of-fold predictions into 600 matrix–coupling means ($R^2 = 0.961$; MAE = 0.090). This aggregate display score is distinct from mean fold-level run prediction performance.

4.6 External structural generalization remains limited

The stricter leave-one-family-out test changed the ranking. For histogram gradient boosting, shock plus coupling achieved mean $R^2 = 0.739$, whereas the organization plane achieved 0.678 and matrix descriptors 0.652. Figure 8 shows family-specific variation: organization metrics transferred reasonably to hub, modular, chain, and diagonal families, but less well to dense heterogeneous and near-rank-one structures. This result supports H5 and prevents an overbroad claim that E, C, R, and Q universally identify unseen structural classes.

Table 6
Predictive validation at two levels of structural novelty

Feature set	Grouped R^2	Grouped MAE	Grouped RMSE	LOFO R^2	LOFO MAE	LOFO RMSE
Shock + coupling intensity	0.774	0.245	0.408	0.739	0.259	0.421
Matrix descriptors	0.816	0.217	0.367	0.652	0.299	0.482
Organization plane	0.821	0.211	0.361	0.678	0.286	0.472
Family labels	0.843	0.200	0.339	—	—	—

4.7 Hypothesis-level synthesis

The experiment supports increasing persistence with coupling, an interaction between coupling and redundancy, and direction-dependent mean persistence. Organization features improve prediction over shock and coupling alone but do not outperform family labels within these ensembles. Transfer to an unseen family remains limited. Table 7 distinguishes these computational findings from proposed empirical analogies.

Table 7
Claim–evidence–boundary matrix

Claim	Primary evidence	Status	Boundary
Coupling intensity increases endogenous persistence.	Table 4; Fig. 4; β for $z(\rho)$ = 0.260.	Supported in model.	Not a calibrated real-world elasticity.
Redundancy creates a conditional trap.	Table 5; Fig. 6; positive $\rho \times R$ interaction.	Supported conditionally.	Sign and threshold depend on model specification.
Dominant-mode shocks persist longer.	Direction means; Fig. 5.	Supported.	Directions derive from simulated baseline covariance.
The organization plane adds within-family predictive information.	Table 6; Fig. 7.	Supported.	Below family-label prediction; modest increment over matrix descriptors.
Structure does not transport uniformly to unseen families.	Table 6; Fig. 8.	Supported limitation.	Additional topology ensembles and external systems are required.
Economic systems may exhibit analogous common-mode fragility.	Mechanistic correspondence with network and resilience theory.	Research hypothesis.	Requires empirical production, financial, institutional, or infrastructure data.

5 Discussion

5.1 Conditional redundancy and the contribution of the experiment

Slow relaxation in strongly coupled systems is not itself a new principle. The contribution is the joint operational comparison of baseline organization, matched post-forcing response, and two levels of structural prediction in a reproducible factorial design. The redundancy descriptor captures one aspect of that organization. Because it is derived from baseline covariance and the same A governs input, memory, and recurrence, the experiment does not separately identify dimensional collapse as the unique cause of persistent deviation.

The result is consistent with work on resilience trade-offs in social-ecological and infrastructure systems [61, 62, 45, 47, 63, 48]. Its more limited contribution is testable within a stated model: the association of R with persistence depends on coupling, and its predictive use has structural boundaries.

5.2 Interpreting response organization

High E and low C describe differentiated, weakly dependent response, whereas low E and high C describe concentration around shared modes. Intermediate configurations retain several modes while

remaining dependent. Terms such as coordinated differentiation are descriptive shorthand: the model has no task, reward, or functional performance criterion. It cannot show that independence impairs social coordination or that an intermediate organization is socially optimal.

The mechanisms also clarify why a single recovery time can mislead. A system may have a small initial deviation but a long normalized tail, or a large impact followed by rapid decay. By starting the primary outcome after forcing ends and normalizing the endogenous curve, the analysis focuses on persistence geometry. This complements resilience metrics based on performance trajectories, distributional identification, recovery scheduling, and multiscale robustness [64, 65, 66, 67, 68, 69, 63, 70, 17, 71].

5.3 Implications for economic science

Possible empirical analogues include correlated financial exposures, production networks with common suppliers, and institutions relying on shared information channels. These are proposals for measurement rather than applications already demonstrated by the simulation. One would need to distinguish useful functional redundancy from correlated vulnerability and measure how each affects outcomes.

Complexity economics provides a setting for such tests through heterogeneous interactions, nonlinear response, and emergent aggregate patterns [72, 73, 74, 75, 76]. The present descriptors could be estimated from multivariate observations, provided the observation scale, covariance window, and measured notion of dependence are justified.

An empirical design could estimate baseline E and C, construct a matched or synthetic counterfactual, and test whether R interacts with measured coupling or common exposure to explain recovery tails. Production-network shock studies offer one concrete starting point [77, 78]. The outcomes should also include retained function or welfare, so that rapid return is not mistaken for successful adaptation.

5.4 Implications for computational social science

The grouping correction is substantively informative. A matrix used at several coupling levels is one structural draw, so splitting its conditions between training and testing would assess interpolation across conditions of partly familiar structures. Holding out the complete matrix provides a clearer test of structural prediction. Under that test, family labels outperform organization features, narrowing the original interpretation of the organization plane.

Likewise, a high score after averaging predictions over conditions is not equivalent to accurate run-level prediction. Reporting the grouping rule, aggregation level, feature composition, and held-out target makes the computational evidence easier to reuse. The model can serve as a compact benchmark for these distinctions, while its interpretation as social coordination remains a hypothesis about application.

5.5 Limitations

First, the model contains one stylized five-dimensional unit rather than a population of interacting agents. Interpersonal influence, institutions, prices, strategic behavior, learning, entry, exit, and

endogenous network formation are absent. Second, dimension labels are interpretive and unvalidated. Third, the same topology was used for input, recurrence, and memory, which sharpens organizational contrast but may exaggerate common-mode alignment. Fourth, only six constructed topology families and five coupling levels were studied. Fifth, tanh dynamics and fixed coefficients constrain the functional class.

Sixth, the primary outcome measures return toward a counterfactual trajectory, not retained task performance, social welfare, distributional justice, adaptation, or beneficial transformation. Seventh, grouped cross-validation shows strong interpolation among known families, whereas leave-one-family-out results reveal limited extrapolation. Eighth, the experiment is computational and contains no empirical identification strategy. These limits preclude claims about specific economies, communities, or persons.

Intervals and predictive scores are conditional on the six chosen topology families, two input-innovation seeds, fixed coefficients, and finite observation window. They do not exhaust uncertainty over model form or stochastic environments. The bibliography is a contextual synthesis rather than a systematic review.

5.6 Falsification and extension agenda

The next research stage should try to disconfirm, not merely illustrate, the mechanism. The conditional redundancy trap would be weakened if R adds no predictive information after exposure and coupling are measured, if its interaction sign is unstable across plausible dynamics, if alternative dimensionality metrics reverse conclusions, or if high- R economic networks do not display longer post-shock tails in external data.

Useful extensions include independent reimplementations, broader dimensionality, alternative activation functions, independently varied input and memory topologies, endogenous network formation, adaptive rewiring, and richer signed interactions. Global sensitivity analysis could test coefficients held fixed here [79, 80, 81, 82].

Empirical work should specify the measurement and counterfactual strategy before testing the mechanism across independent settings. Retrospective shock studies and prospective validation could assess whether the interaction adds useful information beyond established network measures. No general economic or social law follows from the present experiment.

6 Conclusion

In this model, coupling is the dominant driver of counterfactual shock persistence, while baseline organization and disturbance direction qualify that relationship. Near-rank-one and diagonal systems respond similarly at weak coupling and diverge at strong coupling. The positive redundancy-by-coupling interaction persists when inference respects the 120 independent base matrices.

Organization features add predictive information beyond shock and coupling, but family labels perform better within known ensembles and transfer to entirely new families remains weaker. The experiment therefore supports a conditional, model-specific persistence mechanism. It does not establish coordinated differentiation as necessary or sufficient for real-world resilience.

Statements and Declarations

Ethics approval and consent

Not applicable. This computational study used no human participants, identifiable personal data, animals, or biological materials. Consent to participate and consent for publication are not applicable.

Data and code availability

All simulation-generated data and code supporting this study are provided in Online Resource 2 (ESM_2.zip), including the 43,200-row dataset, normalized post-forcing curves, simulation and analysis scripts, statistical tables, figure sources, software requirements, and verification results. The model protocol is provided in Online Resource 1 (ESM_1.pdf). No external empirical dataset was used.

Competing interests

The author declares no competing interests.

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Author contributions

Anderson Díaz Pérez: conceptualization, methodology, software, validation, formal analysis, investigation, data curation, visualization, writing—original draft, and writing—review and editing. The author is responsible for the content of the manuscript.

Generative AI assistance

ChatGPT (OpenAI) assisted with language editing, code and documentation work, reference-metadata checking, and manuscript preparation, as described in Section 3.8. It is not listed as an author. Responsibility for verification, interpretation, and the final submitted version rests with the author.

References

1. Anzola D, Barbrook-Johnson P, Cano JI (2017) Self-organization and social science. *Comput Math Organ Theory* 23(2):221–257. <https://doi.org/10.1007/s10588-016-9224-2>

2. Castellano C, Fortunato S, Loreto V (2009) Statistical physics of social dynamics. *Rev Mod Phys* 81(2):591–646. <https://doi.org/10.1103/revmodphys.81.591>
3. Cioffi-Revilla C (2010) A Methodology for Complex Social Simulations. *J Artif Soc Soc Simul* 13(1):7. <https://doi.org/10.18564/jasss.1528>
4. Polhill JG, Ge J, Hare MP, Matthews KB, Gimona A, Salt D, Yeluripati J (2019) Crossing the chasm: a ‘tube-map’ for agent-based social simulation of policy scenarios in spatially-distributed systems. *Geoinformatica* 23(2):169–199. <https://doi.org/10.1007/s10707-018-00340-z>
5. Schelling TC (1971) Dynamic models of segregation†. *J Math Sociol* 1(2):143–186. <https://doi.org/10.1080/0022250x.1971.9989794>
6. Epstein JM (2008) Why model? *J Artif Soc Soc Simul* 11(4):12. <https://www.jasss.org/11/4/12.html>
7. Haldane AG, May RM (2011) Systemic risk in banking ecosystems. *Nature* 469(7330):351–355. <https://doi.org/10.1038/nature09659>
8. Allen F, Gale D (2000) Financial Contagion. *J Polit Econ* 108(1):1–33. <https://doi.org/10.1086/262109>
9. Acemoglu D, Carvalho VM, Ozdaglar A, Tahbaz-Salehi A (2012) The Network Origins of Aggregate Fluctuations. *Econometrica* 80(5):1977–2016. <https://doi.org/10.3982/ecta9623>
10. Acemoglu D, Ozdaglar A, Tahbaz-Salehi A (2015) Systemic Risk and Stability in Financial Networks. *Am Econ Rev* 105(2):564–608. <https://doi.org/10.1257/aer.20130456>
11. Elliott M, Golub B, Jackson MO (2014) Financial Networks and Contagion. *Am Econ Rev* 104(10):3115–3153. <https://doi.org/10.1257/aer.104.10.3115>
12. Carvalho VM, Tahbaz-Salehi A (2019) Production Networks: A Primer. *Annual Rev Econ* 11(1):635–663. <https://doi.org/10.1146/annurev-economics-080218-030212>
13. Holling CS (1973) Resilience and Stability of Ecological Systems. *Annu Rev Ecol Syst* 4(1):1–23. <https://doi.org/10.1146/annurev.es.04.110173.000245>
14. Carpenter S, Walker B, Anderies JM, Abel N (2001) From Metaphor to Measurement: Resilience of What to What? *Ecosystems* 4(8):765–781. <https://doi.org/10.1007/s10021-001-0045-9>
15. Walker B, Holling CS, Carpenter SR, Kinzig AP (2004) Resilience, Adaptability and Transformability in Social-ecological Systems. *Ecol Soc* 9(2):art5. <https://doi.org/10.5751/es-00650-090205>
16. Folke C (2006) Resilience: The emergence of a perspective for social–ecological systems analyses. *Glob Environ Change* 16(3):253–267. <https://doi.org/10.1016/j.gloenvcha.2006.04.002>
17. Hosseini S, Barker K, Ramirez-Marquez JE (2016) A review of definitions and measures of system resilience. *Reliab Eng Syst Saf* 145:47–61. <https://doi.org/10.1016/j.ress.2015.08.006>
18. Martin R, Sunley P (2015) On the notion of regional economic resilience: conceptualization and explanation. *J Econ Geogr* 15(1):1–42. <https://doi.org/10.1093/jeg/lbu015>
19. Gavrillets S, Tverskoi D, Sánchez A (2024) Modelling social norms: an integration of the norm-utility approach with beliefs dynamics. *Philosophical Trans Royal Soc B: Biol Sci* 379(1897):20230027. <https://doi.org/10.1098/rstb.2023.0027>

20. Giardini F, Vilone D (2021) Opinion Dynamics and Collective Risk Perception: An Agent-Based Model of Institutional and Media Communication About Disasters. *J Artif Soc Soc Simul* 24(1):4. <https://doi.org/10.18564/jasss.4479>
21. Pansanella V, Sîrbu A, Kertesz J, Rossetti G (2023) Mass media impact on opinion evolution in biased digital environments: a bounded confidence model. *Sci Rep* 13(1):14600. <https://doi.org/10.1038/s41598-023-39725-y>
22. Quante L, Stechemesser A, Hödtke D, Levermann A (2024) Convolution of individual and group identity: self-reliance increases polarisation in basic opinion model. *Humanit Social Sci Commun* 11(1):838. <https://doi.org/10.1057/s41599-024-03359-w>
23. Peralta AF, Ramaciotti P, Kertész J, Iñiguez G (2024) Multidimensional political polarization in online social networks. *Phys Rev Res* 6(1):013170. <https://doi.org/10.1103/physrevresearch.6.013170>
24. Tump AN, Wolf M, Romanczuk P, Kurvers RHJM (2022) Avoiding costly mistakes in groups: The evolution of error management in collective decision making. *PLoS Comput Biol* 18(8):e1010442. <https://doi.org/10.1371/journal.pcbi.1010442>
25. Macy MW, Willer R (2002) From Factors to Actors: Computational Sociology and Agent-Based Modeling. *Ann Rev Sociol* 28(1):143–166. <https://doi.org/10.1146/annurev.soc.28.110601.141117>
26. Grimm V, Railsback SF, Vincenot CE, Berger U, Gallagher C, DeAngelis DL, Edmonds B, Ge J, Giske J, Groeneveld J, Johnston ASA, Milles A, Nabe-Nielsen J, Polhill JG, Radchuk V, Rohwäder MS, Stillman RA, Thiele JC, Ayllón D (2020) The ODD Protocol for Describing Agent-Based and Other Simulation Models: A Second Update to Improve Clarity, Replication, and Structural Realism. *J Artif Soc Soc Simul* 23(2):7. <https://doi.org/10.18564/jasss.4259>
27. Edmonds B, Le Page C, Bithell M, Chattoe-Brown E, Grimm V, Meyer R, Montañola-Sales C, Ormerod P, Root H, Squazzoni F (2019) Different Modelling Purposes. *J Artif Soc Soc Simul* 22(3):6. <https://doi.org/10.18564/jasss.3993>
28. Simon HA (1955) A Behavioral Model of Rational Choice. *Q J Econ* 69(1):99. <https://doi.org/10.2307/1884852>
29. Simon HA (1956) Rational choice and the structure of the environment. *Psychol Rev* 63(2):129–138. <https://doi.org/10.1037/h0042769>
30. Bourgaïs M, Taillandier P, Vercouter L, Adam C (2018) Emotion Modeling in Social Simulation: A Survey. *J Artif Soc Soc Simul* 21(2):5. <https://doi.org/10.18564/jasss.3681>
31. Bourgaïs M, Taillandier P, Vercouter L (2020) BEN: An Architecture for the Behavior of Social Agents. *J Artif Soc Soc Simul* 23(4):12. <https://doi.org/10.18564/jasss.4437>
32. Schröder T, Homer-Dixon T, Maynard JL, Mildenerger M, Milkoreit M, Mock SJ, Quilley S, Thagard P (2013) A Complex Systems Approach to the Study of Ideology: Cognitive-Affective Structures and the Dynamics of Belief Systems. *J Social Political Psychol* 1(1):337–363. <https://doi.org/10.5964/jspp.v1i1.36>
33. Melnyk A, Edmonds B, Ghorbani A, van de Poel I (2024) Editorial: Modelling Values in Social, Technical, and Ecological Systems. *J Artif Soc Soc Simul* 27(1):20.

- <https://doi.org/10.18564/jasss.5361>
34. Shannon CE (1948) A Mathematical Theory of Communication. *Bell Syst Tech J* 27(3):379–423. <https://doi.org/10.1002/j.1538-7305.1948.tb01338.x>
 35. Watanabe S (1960) Information Theoretical Analysis of Multivariate Correlation. *IBM J Res Dev* 4(1):66–82. <https://doi.org/10.1147/rd.41.0066>
 36. Tononi G, Sporns O, Edelman GM (1994) A measure for brain complexity: relating functional segregation and integration in the nervous system. *Proceedings of the National Academy of Sciences*, 91(11), 5033–5037. <https://doi.org/10.1073/pnas.91.11.5033>
 37. Roy O, Vetterli M (2007) The effective rank: A measure of effective dimensionality. In *Proceedings of the 15th European Signal Processing Conference* (pp. 606–610). EURASIP. <https://www.eurasip.org/Proceedings/Eusipco/Eusipco2007/Papers/a5p-h05.pdf>
 38. MAY RM (1972) Will a Large Complex System be Stable? *Nature* 238(5364):413–414. <https://doi.org/10.1038/238413a0>
 39. GARDNER MR, ASHBY WR (1970) Connectance of Large Dynamic (Cybernetic) Systems: Critical Values for Stability. *Nature* 228(5273):784–784. <https://doi.org/10.1038/228784a0>
 40. Bitterman P, Bennett DA (2016) Constructing stability landscapes to identify alternative states in coupled social-ecological agent-based models. *Ecol Soc* 21(3):art21. <https://doi.org/10.5751/es-08677-210321>
 41. Morr A, Kuehn C, Datseris G (2026) Computing resilience measures in dynamical systems. *Chaos: Interdisciplinary J Nonlinear Sci* 36(2):023102. <https://doi.org/10.1063/5.0303938>
 42. Scheffer M, Carpenter SR, Lenton TM, Bascompte J, Brock W, Dakos V, van de Koppel J, van de Leemput IA, Levin SA, van Nes EH, Pascual M, Vandermeer J (2012) Anticipating Crit Transitions *Science* 338(6105):344–348. <https://doi.org/10.1126/science.1225244>
 43. Weinans E, Lever JJ, Bathiany S, Quax R, Bascompte J, van Nes EH, Scheffer M, van de Leemput IA (2019) Finding the direction of lowest resilience in multivariate complex systems. *J Royal Soc Interface* 16(159):20190629. <https://doi.org/10.1098/rsif.2019.0629>
 44. Kuehn C (2011) A mathematical framework for critical transitions: Bifurcations, fast–slow systems and stochastic dynamics. *Physica D* 240(12):1020–1035. <https://doi.org/10.1016/j.physd.2011.02.012>
 45. Rachunok B, Nateghi R (2021) Overemphasis on recovery inhibits community transformation and creates resilience traps. *Nat Commun* 12(1):7331. <https://doi.org/10.1038/s41467-021-27359-5>
 46. Rasoulkhani K, Mostafavi A (2018) Resilience as an emergent property of human-infrastructure dynamics: A multi-agent simulation model for characterizing regime shifts and tipping point behaviors in infrastructure systems. *PLoS ONE* 13(11):e0207674. <https://doi.org/10.1371/journal.pone.0207674>
 47. Homayounfar M, Muneeppeerakul R, Anderies JM (2022) Resilience-performance trade-offs in managing social-ecological systems. *Ecol Soc* 27(1):art7. <https://doi.org/10.5751/es-12892-270107>

48. Tenza A, Pérez I, Martínez-Fernández J, Giménez A (2017) Understanding the decline and resilience loss of a long-lived social-ecological system: insights from system dynamics. *Ecol Soc* 22(2):art15. <https://doi.org/10.5751/es-09176-220215>
49. Newman MEJ (2003) The Structure and Function of Complex Networks. *SIAM Rev* 45(2):167–256. <https://doi.org/10.1137/s003614450342480>
50. Albert R, Jeong H, Barabási AL (2000) Error and attack tolerance of complex networks. *Nature* 406(6794):378–382. <https://doi.org/10.1038/35019019>
51. Buldyrev SV, Parshani R, Paul G, Stanley HE, Havlin S (2010) Catastrophic cascade of failures in interdependent networks. *Nature* 464(7291):1025–1028. <https://doi.org/10.1038/nature08932>
52. Gao J, Barzel B, Barabási AL (2016) Universal resilience patterns in complex networks. *Nature* 530(7590):307–312. <https://doi.org/10.1038/nature16948>
53. Gai P, Kapadia S (2010) Contagion in financial networks. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 466(2120), 2401–2423. <https://doi.org/10.1098/rspa.2009.0410>
54. Glasserman P, Young HP (2016) Contagion in Financial Networks. *J Econ Lit* 54(3):779–831. <https://doi.org/10.1257/jel.20151228>
55. Sargent RG (2013) Verification and validation of simulation models. *J Simul* 7(1):12–24. <https://doi.org/10.1057/jos.2012.20>
56. Peng RD (2011) Reproducible Research in Computational Science. *Science* 334(6060):1226–1227. <https://doi.org/10.1126/science.1213847>
57. Wilkinson MD, Dumontier M, Aalbersberg IJ, Appleton G, Axton M, Baak A, Blomberg N, Boiten JW, da Silva Santos LB, Bourne PE, Bouwman J, Brookes AJ, Clark T, Crosas M, Dillo I, Dumon O, Edmunds S, Evelo CT, Finkers R, Mons B (2016) The FAIR Guiding Principles for scientific data management and stewardship. *Sci Data* 3(1):160018. <https://doi.org/10.1038/sdata.2016.18>
58. Grimm V, Berger U, Bastiansen F, Eliassen S, Ginot V, Giske J, Goss-Custard J, Grand T, Heinz SK, Huse G, Huth A, Jepsen JU, Jørgensen C, Mooij WM, Müller B, Pe'er G, Piou C, Railsback SF, Robbins AM, DeAngelis DL (2006) A standard protocol for describing individual-based and agent-based models. *Ecol Model* 198(1–2):115–126. <https://doi.org/10.1016/j.ecolmodel.2006.04.023>
59. Grimm V, Berger U, DeAngelis DL, Polhill JG, Giske J, Railsback SF (2010) The ODD protocol: A review and first update. *Ecol Model* 221(23):2760–2768. <https://doi.org/10.1016/j.ecolmodel.2010.08.019>
60. Müller B, Bohn F, Dreßler G, Groeneveld J, Klassert C, Martin R, Schlüter M, Schulze J, Weise H, Schwarz N (2013) Describing human decisions in agent-based models – ODD + D, an extension of the ODD protocol. *Environ Model Softw* 48:37–48. <https://doi.org/10.1016/j.envsoft.2013.06.003>
61. Fonteijn H, van Oort P, Hengeveld G (2024) DARTS: Evolving Resilience of the Global Food System to Production and Trade Shocks. *J Artif Soc Soc Simul* 27(2):1. <https://doi.org/10.18564/jasss.5307>
62. Kou C, Yang X (2023) Improving social resilience amid the COVID-19 epidemic: A system dynamics model. *PLoS ONE* 18(11):e0294108. <https://doi.org/10.1371/journal.pone.0294108>

63. Naylor LA, Brady U, Quinn T, Brown K, Anderies JM (2019) A multiscale analysis of social-ecological system robustness and vulnerability in Cornwall, UK. *Reg Environ Chang* 19(7):1835–1848. <https://doi.org/10.1007/s10113-019-01530-7>
64. Steinmann P, Tobi H, van Voorn GAK (2024) Resilience Metrics for Socio-Ecological and Socio-Technical Systems: A Scoping Review. *Systems* 12(9):357. <https://doi.org/10.3390/systems12090357>
65. Jesse BJ, Kramer GJ, Koning V (2024) Characterization of necessary elements for a definition of resilience for the energy system. *Energy Sustain Soc* 14(1):46. <https://doi.org/10.1186/s13705-024-00478-9>
66. Yang Z, Barroca B, Laffr  chine K, Weppe A, Bony-Dandrieux A, Daclin N (2023) A multi-criteria framework for critical infrastructure systems resilience. *Int J Crit Infrastruct Prot* 42:100616. <https://doi.org/10.1016/j.ijcip.2023.100616>
67. An X, Yin Z, Tong Q, Fang Y, Yang M, Yang Q, Meng H (2023) An integrated resilience assessment methodology for emergency response systems based on multi-stage STAMP and dynamic Bayesian networks. *Reliab Eng Syst Saf* 238:109445. <https://doi.org/10.1016/j.ress.2023.109445>
68. Song Y, Li R (2022) System resilience distribution identification and analysis based on performance processes after disruptions. *PLoS ONE* 17(11):e0276908. <https://doi.org/10.1371/journal.pone.0276908>
69. Fang YP, Fang C, Zio E, Xie M (2021) Resilient Critical Infrastructure Planning Under Disruptions Considering Recovery Scheduling. *IEEE Trans Eng Manage* 68(2):452–466. <https://doi.org/10.1109/tem.2019.2902916>
70. Arora V, Ventresca M (2018) Modeling topologically resilient supply chain networks. *Appl Netw Sci* 3(1):19. <https://doi.org/10.1007/s41109-018-0070-7>
71. Bruneau M, Chang SE, Eguchi RT, Lee GC, O'Rourke TD, Reinhorn AM, Shinozuka M, Tierney K, Wallace WA, von Winterfeldt D (2003) A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities. *Earthq Spectra* 19(4):733–752. <https://doi.org/10.1193/1.1623497>
72. Kirman A (1993) Ants, Rationality, and Recruitment. *Q J Econ* 108(1):137–156. <https://doi.org/10.2307/2118498>
73. Arthur WB (1989) Competing Technologies, Increasing Returns, and Lock-In by Historical Events. *Econ J* 99(394):116. <https://doi.org/10.2307/2234208>
74. Arthur WB (1999) Complexity and the Economy. *Science* 284(5411):107–109. <https://doi.org/10.1126/science.284.5411.107>
75. Farmer JD, Foley D (2009) The economy needs agent-based modelling. *Nature* 460(7256):685–686. <https://doi.org/10.1038/460685a>
76. Axtell RL (2001) Zipf Distribution of U.S. Firm Sizes. *Science* 293(5536):1818–1820. <https://doi.org/10.1126/science.1062081>

77. Barrot JN, Sauvagnat J (2016) Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks *. Q J Econ 131(3):1543–1592. <https://doi.org/10.1093/qje/qjw018>

78. Inoue H, Todo Y (2019) Firm-level propagation of shocks through supply-chain networks. Nat Sustain 2(9):841–847. <https://doi.org/10.1038/s41893-019-0351-x>

79. Saltelli A, Annoni P, Azzini I, Campolongo F, Ratto M, Tarantola S (2010) Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index. Comput Phys Commun 181(2):259–270. <https://doi.org/10.1016/j.cpc.2009.09.018>

80. Sobol' IM (2001) Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. Math Comput Simul 55(1–3):271–280. [https://doi.org/10.1016/s0378-4754\(00\)00270-6](https://doi.org/10.1016/s0378-4754(00)00270-6)

81. Morris MD (1991) Factorial Sampling Plans for Preliminary Computational Experiments. Technometrics 33(2):161–174. <https://doi.org/10.1080/00401706.1991.10484804>

82. Helton JC, Johnson JD, Sallaberry CJ, Storlie CB (2006) Survey of sampling-based methods for uncertainty and sensitivity analysis. Reliab Eng Syst Saf 91(10–11):1175–1209. <https://doi.org/10.1016/j.ress.2005.11.017>

Figures

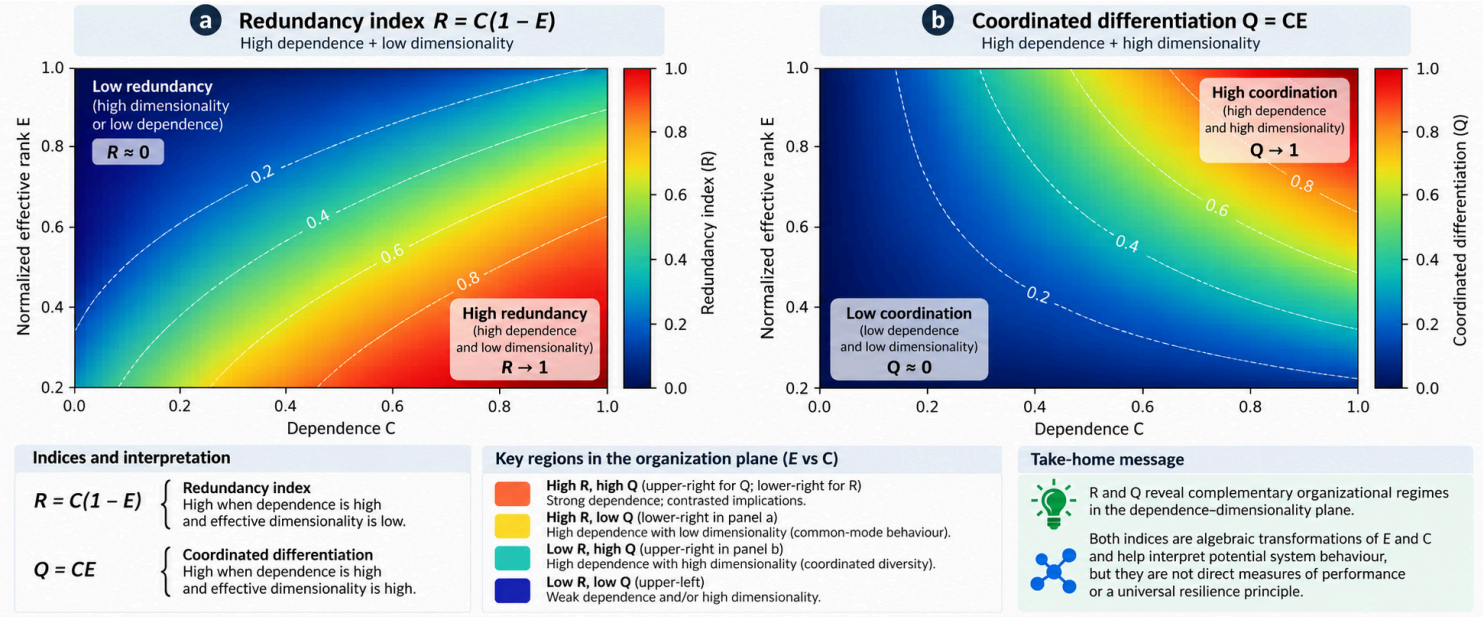


Figure 1

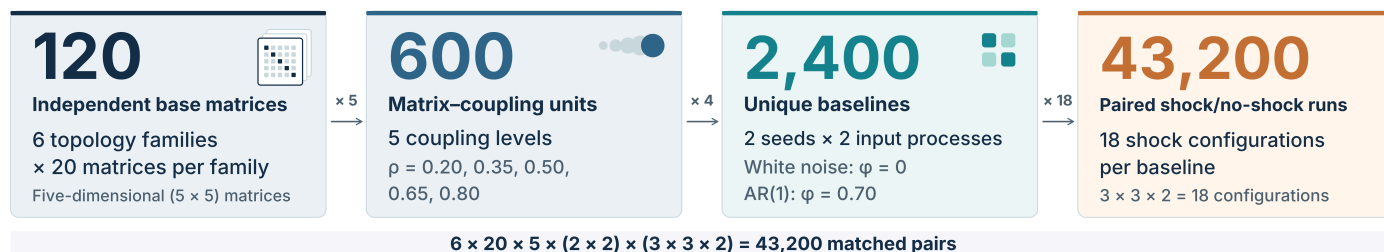
Algebraic organization plane. Color shows $R = C(1 - E)$ in panel a and $Q = CE$ in panel b. This schematic is not simulation evidence and does not imply that every E–C combination is feasible for a five-dimensional covariance matrix

Factorial experiment and structural validation

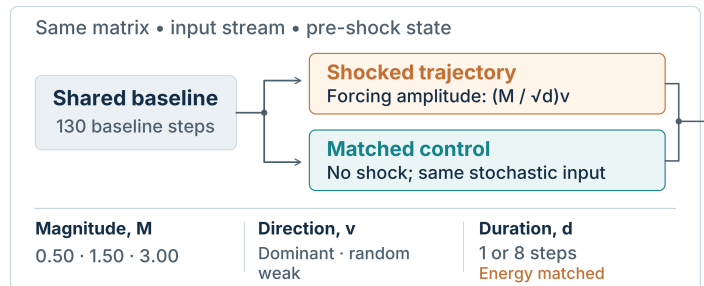
Matched counterfactual design in a five-dimensional recurrent state model

a Full-factorial experiment

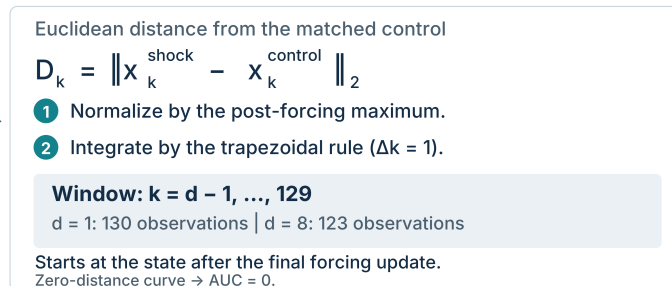
DESIGN EXPANSION



b Matched shock and control

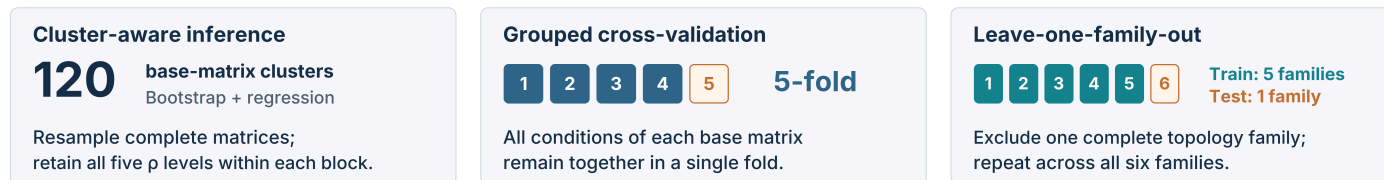


c Persistence: normalized post-forcing AUC



d Inference and structural validation

INDEPENDENT UNIT: FAMILY × BASE-MATRIX SEED



43,200 paired runs arise from 120 independent base matrices.

Computational validation—not external empirical validation.

FIGURE 2

Figure 2

Factorial experiment and validation. Matched shocked and unshocked trajectories share their matrix, stochastic input, and initial state. Inference and grouped prediction account for the reuse of each base matrix across five coupling levels

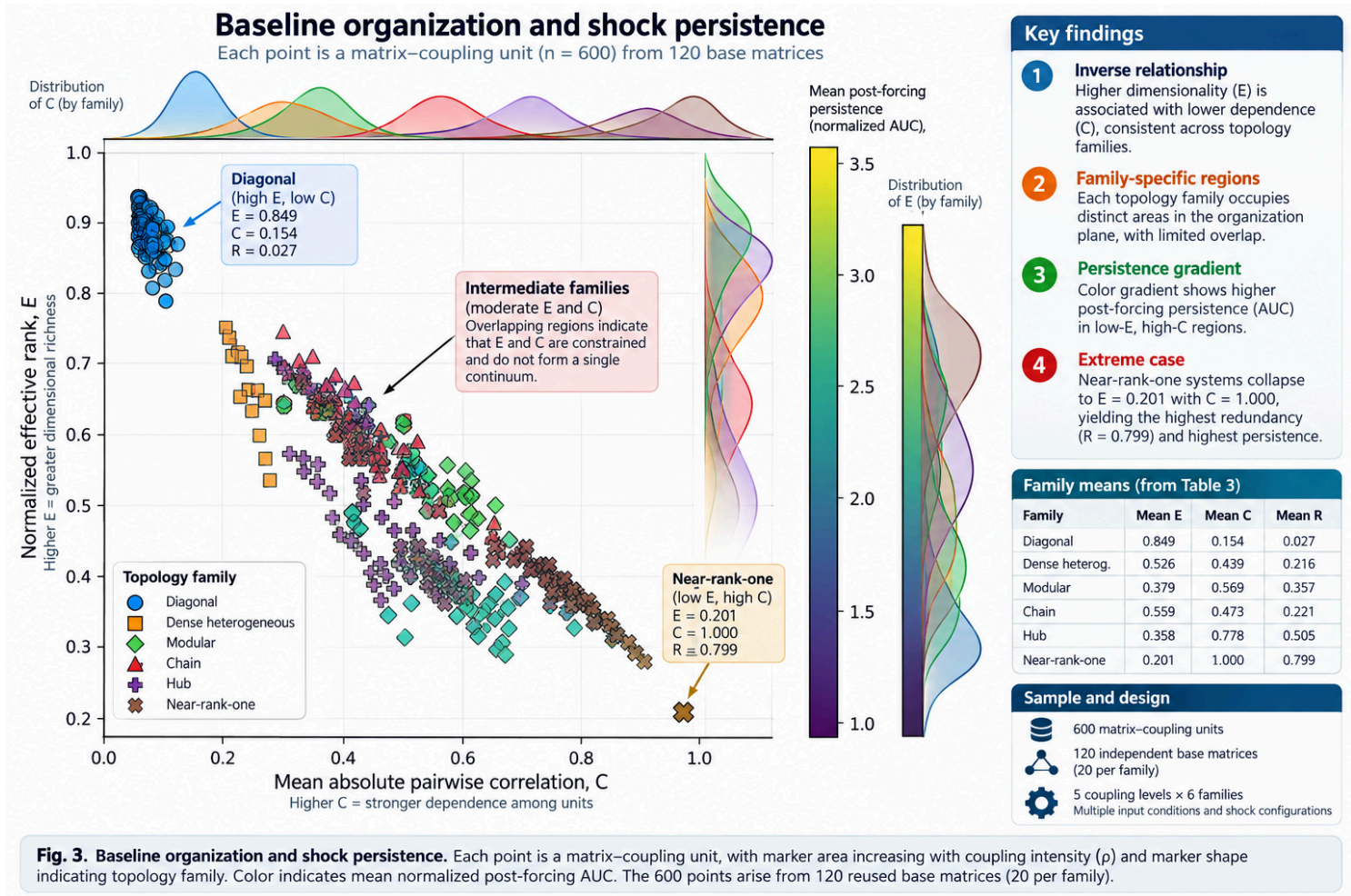
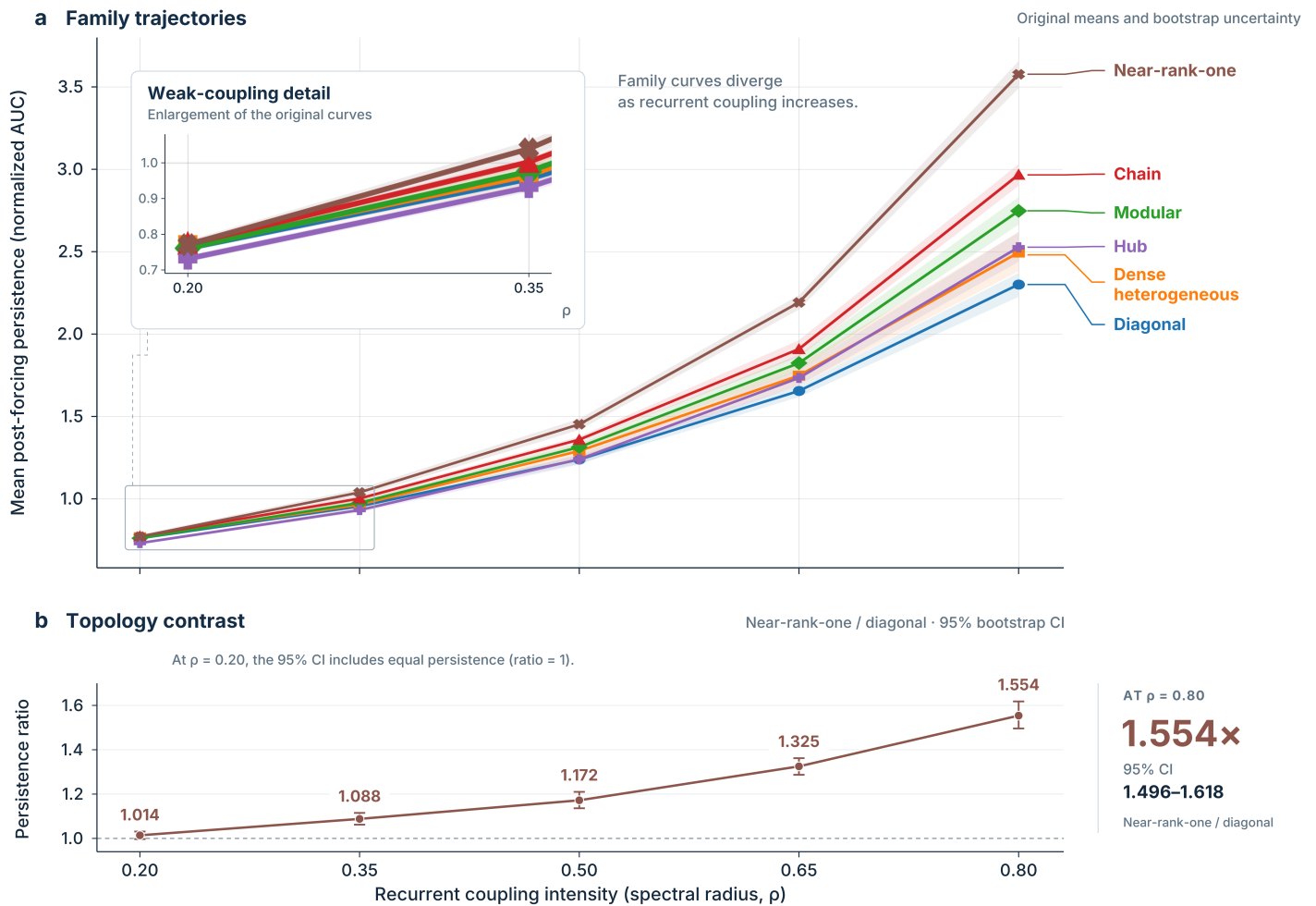


Figure 3

Baseline organization and shock persistence. Each point is a matrix-coupling unit, with marker area increasing with ρ and marker shape indicating family. Color indicates mean normalized AUC. The 600 points arise from 120 reused base matrices

Coupling separates topology-specific persistence

Matched counterfactual simulation in a five-dimensional recurrent model



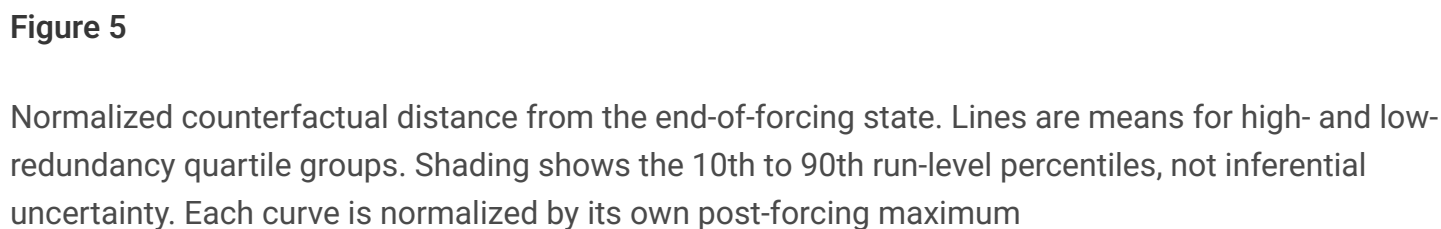
120 independent base matrices · 20 per family · Five coupling levels

Curves: Fig. 4 | Contrasts: Table 4

Figure 4

Mean normalized post-forcing persistence by topology family and recurrent coupling intensity. Shaded intervals represent topology-bootstrap uncertainty. Topological separation becomes pronounced as ρ approaches 0.80

Normalized post-forcing decay across three shock directions



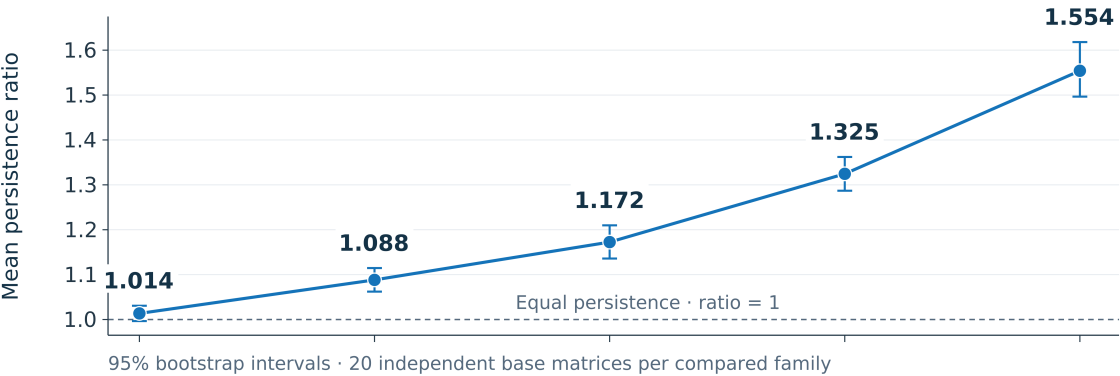
Topology contrast and conditional redundancy

Increasing persistence ratios and a distinct regression-implied sign change

a Family-level persistence ratio

Near-rank-one / diagonal · mean normalized post-forcing AUC

TOPOLOGY CONTRAST



AT $\rho = 0.80$

1.554x

Mean persistence ratio

95% BOOTSTRAP CI

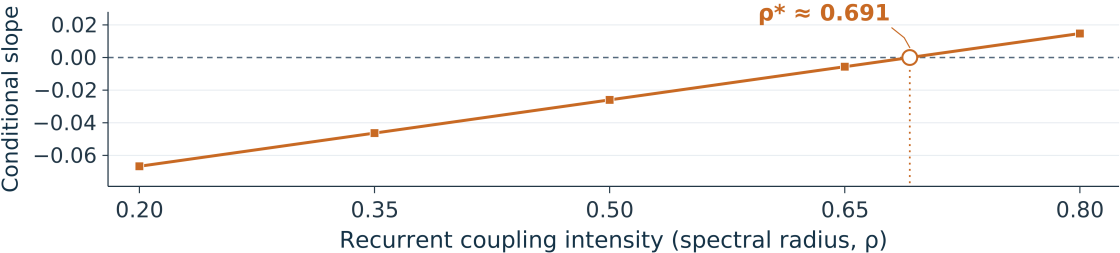
1.496-1.618

+55.4%

Relative to diagonal

b Conditional association of redundancy

Slope of $\log(1 + \text{AUC})$ per one-SD increase in R · dominant-mode shocks



REGRESSION REFERENCE

$\rho^* \approx 0.691$

Estimated sign change;
not a bifurcation.

Point estimate only.

Different quantities: a topology-family ratio (a) versus a conditional regression slope (b).

The sign change in b is not the crossing of ratio = 1 in a. Slope uncertainty is not shown.

Source: exact archived summaries · Table 4 · Section 4.4

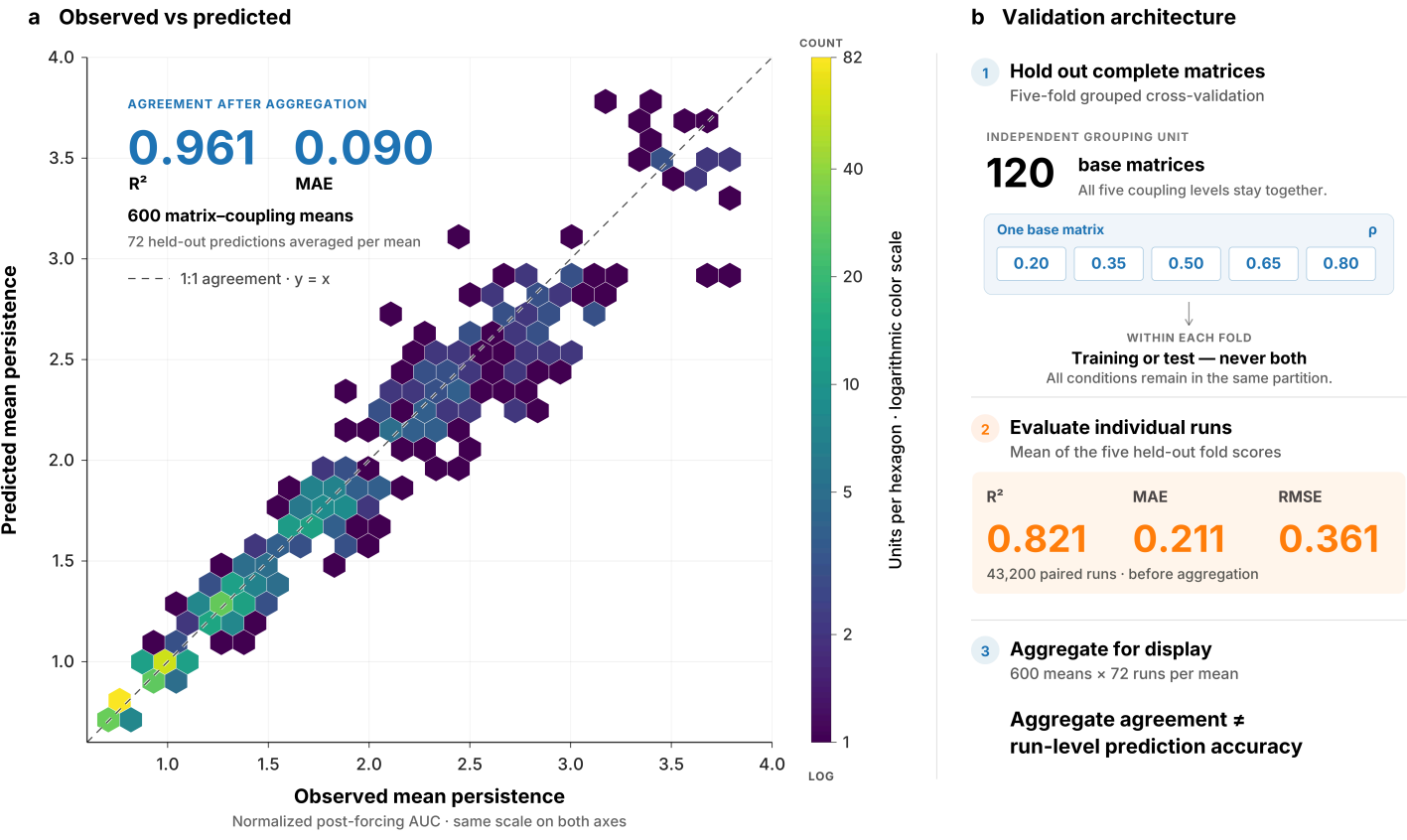
Regression: 120 base-matrix clusters

Figure 6

Near-rank-one to diagonal persistence ratio across coupling levels. Error bars are 95% bootstrap intervals from base matrices within each family. The dotted line indicates the fitted redundancy sign change for dominant-mode shocks; it is not a bifurcation estimate

Predicting shock persistence

Organization-feature model / out-of-fold predictions



Computational validation within known topology families; not external empirical validation.

Figure 7

Out-of-fold predictions aggregated to matrix-coupling means. Entire base matrices, including all five coupling levels, were held out. Displayed R² and MAE describe 600 aggregates from 120 base matrices, not the run-level cross-validation scores in Table 6

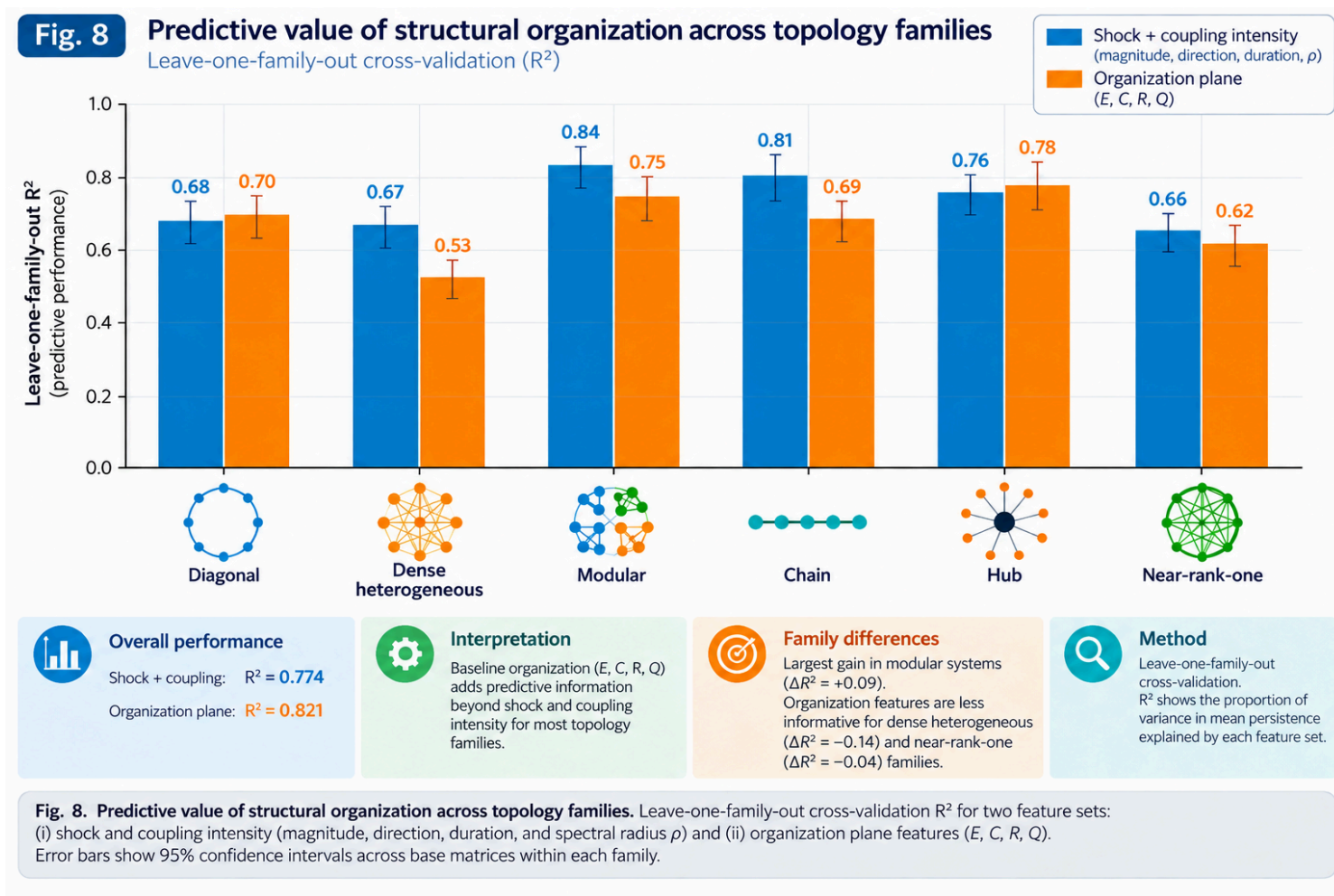


Figure 8

Leave-one-family-out R^2 for histogram gradient boosting. The organization plane improves interpretation but does not universally outperform shock and coupling intensity when an entirely new topology family is excluded from training

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

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- [ESM2.zip](#)