Generative Network Simulation: A Framework for Shock Propagation and Evolutionary Process

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Abstract. Macroeconomic frameworks relying on representative agents frequently struggle to map the heavy-tailed distribution of systemic risk. This study develops a generative simulation synthesizing spectral graph theory, Bayesian game theory, and input-output accounting to model endogenous network formation under bounded rationality. Evaluating the model across a Latin Hypercube parameter space isolates a phase transition. When market concentration approaches an HHI of approximately 0.6, the failure of an apex node triggers cascading Leontief multiplier expansions, supporting the Granular Hypothesis [6]. Concurrently, correlated policy shocks bypass routing redundancies, indicating that network density provides limited defense against simultaneous multi-node failures. The findings suggest an evolutionary trade-off where the behavioral preference for reliable hubs increases short-term efficiency while generating structural vulnerability.

Keywords: Granular Hypothesis · Macroeconomic Networks · Agent-Based Modeling · Latin Hypercube Sampling · Systemic Risk · Bounded Rationality

1 Introduction

Macroeconomic analysis built upon the representative agent framework confront structural limitations when applied to highly interconnected, heterogeneous economies. In environments defined by complex input-output linkages, idiosyncratic micro-shocks rarely cancel out in the aggregate. The Granular Hypothesis [6] suggests that shocks originating in large hub nodes propagate asymmetrically, driving aggregate macroeconomic fluctuations. Recent literature utilizes network-based models to map supply chain dependencies [1,4]. Nevertheless, the majority of these frameworks operate on static topologies, omitting the endogenous evolution of industrial networks under conditions of incomplete information and friction.

This paper addresses this gap through a generative macroeconomic simulation that integrates spectral graph theory with Bayesian evolutionary game theory. The model abandons spatial, undirected topologies in favor of scale-free, directed production networks initialized across varying levels of market

concentration. Firms in this environment operate under strict bounded rationality. They observe noisy market signals regarding partner reliability and utilize Bayesian inference to update their beliefs [5]. The physical wiring of the network evolves continuously via replicator dynamics, strengthening successful supply chain alliances while pruning inefficient ties.

Following the establishment of an evolutionary metastable state, the study measures systemic resilience by injecting empirically grounded idiosyncratic shocks, including transient infrastructure degradation, single-hub bankruptcy, and correlated batch policy removals. A spectral radius normalization algorithm enforces $\rho(A) < 1$, guaranteeing the mathematical stability of the Leontief inverse expansion and permitting the measurement of output losses via Domar weights.

The model is evaluated using Latin Hypercube Sampling across 150 unique parameter configurations to mitigate localized stochastic variance. The multidimensional analysis isolates distinct topological phase transitions. Distributed networks dissipate transient infrastructure frictions effectively. However, single-hub bankruptcies trigger severe structural collapse when the system crosses a concentration threshold of approximately HHI > 0.6, resulting in Leontief multiplier explosions. Correlated policy shocks completely bypass endogenous routing redundancies, and vulnerability to batch failures scales linearly with network size. The results indicate that endogenous evolution naturally drifts toward centralized equilibrium states, wherein agents trade long-term systemic resilience for short-term search-cost efficiency.

2 Literature Review

Current research increasingly connects standard macroeconomic models with complexity economics. Historically, real business cycle models relied on the law of large numbers, assuming that the standard deviation of aggregate GDP growth relative to firm-level volatility scales inversely with the square root of the number of firms in the economy [7].

Gabaix [6] challenged this assumption, demonstrating that when the firm size distribution follows a heavy-tailed property, the law of large numbers breaks down. Aggregate economic volatility in highly centralized environments becomes a function of firm-level volatility multiplied by the Herfindahl-Hirschman Index. Acemoglu et al. [1] formalized this mechanic, proving that macroeconomic tail risks are linked to the network topology of input-output connections. A highly asymmetric eigenvector centrality distribution ensures that shocks to apex nodes are amplified rather than dissipated. Empirical studies on localized disasters validate that supply chain disruptions propagate powerfully across multiple degrees of separation [4]. Baqaee and Farhi [2] establish that misallocations in general equilibrium possess significant non-linear magnification effects.

This framework extends the existing literature by evaluating dynamic input-output measurements. Permitting the Leontief inverse to emerge as an output of an evolutionary process provides a mechanism to test how market concentration structurally predetermines the intensity of a shock multiplier.

Although standard Agent-Based Models utilize continuous composite utility functions to balance local constraints, their reliance on rigid spatial grids restricts their applicability to scale-free industrial supply chains. Interactions in modern economies are directed by technological dependencies and capital accumulations rather than Euclidean proximity [7].

To map this dynamic, the methodology applies behavioral game theory and the mechanics of decision-making under incomplete information [3]. Integrating Bayesian learning mechanisms [5] allows firms to dynamically attempt to discern the true hidden strategic orientations of their partners.

The physical structure of the macroeconomy becomes endogenous as edge weights within the adjacency matrix adjust according to replicator dynamics. This behavioral approach captures the institutional reality of bounded rationality. Faced with high market noise, agents rely on highly visible hubs to minimize search costs. This organic clustering breeds centralized topologies that render the aggregate economy exceptionally fragile to targeted idiosyncratic shocks.

3 Methodology: Mathematical Framework and Computational Dynamics

The simulation architecture requires a fully vectorized, object-oriented framework to capture non-linear macroeconomic fluctuations. This section formalizes the three sequential phases of the model and derives the computational mechanics from first-principles economic theory.

3.1 Phase I: Topological Initialization and Spectral Constraints

The simulated economy operates as a directed, weighted adjacency matrix $A \in \mathbb{R}^{N \times N}$, where the vertex set represents N heterogeneous firms. The element A_{ij} denotes the intensity of the supply chain linkage from node i to node j. The initial degree distribution is generated via a preferential attachment algorithm calibrated to an emergent Herfindahl-Hirschman Index (HHI). Initial edge weights are drawn from a uniform distribution $A_{ij} \sim U(0.5, 0.8)$, representing a generic contracting phase prior to endogenous learning.

The macroeconomic accounting identity dictates that a firm's total output vector $\mathbf{x}$ is the sum of intermediate industrial demand $A\mathbf{x}$ and final consumer demand $\mathbf{y}$:

$$\mathbf{x} = A\mathbf{x} + \mathbf{y} \implies (I - A)\mathbf{x} = \mathbf{y} \implies \mathbf{x} = (I - A)^{-1}\mathbf{y} \tag{1}$$

where $L = (I - A)^{-1}$ is the Leontief inverse. The Leontief inverse can be expressed as an infinite Neumann power series:

$$L = \sum_{k=0}^{\infty} A^k = I + A + A^2 + A^3 + \dots \tag{2}$$

For this series to converge to a finite macroeconomic equilibrium, the dominant eigenvalue of the adjacency matrix, $\rho(A) = \max |\lambda_i(A)|$, must satisfy $\rho(A) < 1$. The formation of massive apex hubs in concentrated networks frequently drives $\rho(A) \geq 1$, rendering shock propagation mathematically undefined.

A spectral normalization algorithm resolves this structural vulnerability. The scaled matrix is defined as $A_{spectral} = A/(\rho(A) + \epsilon)$, where $\epsilon = 0.05$ provides a mathematical margin of safety. An asymmetric normalization approximates column stochasticity:

$$A_{stable} = A_{spectral} \oslash (\mathbf{s}^T \cdot 1.05) \tag{3}$$

where $\mathbf{s} = \mathbf{1}^T A$ is the vector of column sums, and $\oslash$ denotes element-wise division. The scalar 1.05 acts as a computational dampener, maintaining $\rho(A_{stable}) < 1$.

Algorithm 1 Network Normalization Module

Require: Adjacency matrix $A \in \mathbb{R}^{N \times N}$, Margin of safety $\epsilon = 0.05$

```
procedure ENFORCE_SPECTRAL_RADIUS(A)
    if N > 1000 then
        Compute dominant eigenvalue ρ(A) using sparse solver
    else
        Compute all eigenvalues using dense solver, find ρ(A)
    end if
    if ρ(A) ≥ 1.0 then
        A ← A × 1/(ρ(A)+ε)
    end if
    return A
end procedure

procedure ENFORCE_COLUMN_STOCHASTICITY(A)
    s ← sum(A, axis = 0)
    s[s == 0] ← 1.0                    ▷ Prevent zero-division for sink nodes
    A ← A/(s^T × 1.05)
    return A
end procedure
```

3.2 Phase II: Incomplete Information and Bayesian Replicator

Each firm possesses a hidden binary orientation $\theta_i \in \{0, 1\}$, where 1 denotes a reliable technological innovator and 0 denotes an opportunistic rent-seeker. Firm i holds a prior belief regarding the reliability of firm j, denoted $B_{ij} \in (0, 1)$.

At discrete time step t, firm i extracts a noisy performance signal S_{ij} generated via a Gaussian channel:

$$S_{ij,t} = \theta_j + \mathcal{N}(0, \sigma^2) \tag{4}$$

Firm i updates its belief using Bayes' rule. The likelihood function is symmetrically bounded to $[10^{-6}, 1 - 10^{-6}]$ to enforce Cromwell's Rule, reflecting the statistical axiom that absolute certainty is empirically impossible due to market friction.

Let $\pi_{ij,t} = A_{ij,t}B_{ij,t}$ represent the expected payoff of the interaction. Derived from the continuous-time replicator equation, the topological evolution of the edge weight ΔW_{ij} is discretized as:

$$\Delta W_{ij} = \alpha A_{ij,t}(\pi_{ij,t} - \tau) \tag{5}$$

where α is the structural learning rate and τ is the Schumpeterian survival threshold. When $A_{ij} < \tau_{min} = 10^{-4}$, the edge is held at an infinitesimal limit rather than annihilated. This preserves latent institutional memory capable of future supply chain reactivation. The resulting topological structure is visualized in Figure 1.

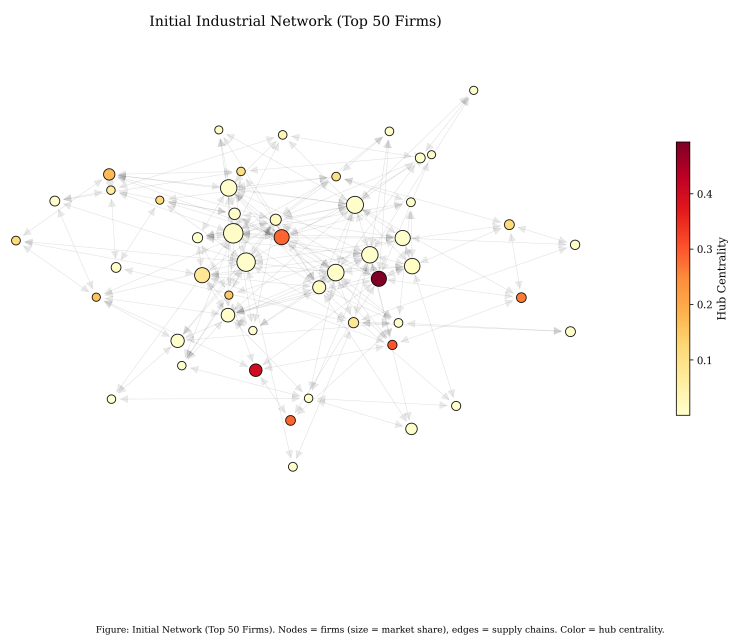

Fig. 1. Topological visualization of the top 50 nodes following the endogenous evolution phase, demonstrating the centralization of capital around apex hubs prior to shock injection.

Algorithm 2 Evolutionary Engine Module

Require: Network size N, Learning rate α, Survival threshold τ

Initialize uniform prior belief matrix $B \in \mathbb{R}^{N \times N} \leftarrow 0.5$
Set diagonal of $B \leftarrow 0$
procedure STEP_EVOLUTION(A_t, true_types, σ^2)
  $\epsilon \sim \mathcal{N}(0, \sqrt{\sigma^2}, (N, N))$
  $S \leftarrow$ true_types $+ \epsilon$
  $L \leftarrow \text{clip}(S, 10^{-6}, 1 - 10^{-6})$ ▷ Enforce Cromwell's Rule
  $M \leftarrow L \times B + (1 - L) \times (1 - B)$
  $B \leftarrow (L \times B)/M$
  $B \leftarrow \text{clip}(B, 10^{-6}, 1 - 10^{-6})$
  $\Delta W \leftarrow \alpha \times A_t \times (A_t \times B - \tau)$
  $A_{t+1} \leftarrow \text{clip}(A_t + \Delta W, 0, 1)$
  $A_{t+1}[A_{t+1} < 10^{-4}] \leftarrow 10^{-6}$ ▷ Enforce Structural Dormancy
  return A_{t+1}
end procedure

3.3 Phase III: Shock Propagation and Block Matrix Inversion

Exogenous shocks are injected once the evolutionary phase converges to a metastable state. The aggregate macroeconomic response relies on the regularized Leontief inverse:

$$L = (I - A_{stable} + 10^{-6} I)^{-1} \tag{6}$$

For Correlated Policy Shocks, naive additive demand vectors are mathematically invalid due to non-linear network superposition. Partitioning the identity $\mathbf{x} = L\mathbf{y}$ into the target set S and non-target set T, and assuming no direct final demand shock to the surviving network ($\Delta \mathbf{y}_T = 0$), the indirect output loss of the surviving nodes $\Delta \mathbf{x}_T$ due solely to the supply chain failure of nodes S is derived using block matrix inversion:

$$\Delta \mathbf{x}_T = L_{TS} L_{SS}^{-1} \Delta \mathbf{x}_S \tag{7}$$

This derivation dictates that simultaneous multi-node failures violently bypass dormant routing redundancies.

Algorithm 3 Shock Injection Engine Module

Require: Evolved adjacency matrix A
Normalize A using Algorithm 1
Compute regularized Leontief inverse $L = (I - A + 10^{-6}I)^{-1}$
procedure CORRELATED_POLICY_SHOCK(targets S, magnitude γ)
  $T \leftarrow \text{setdiff}(\text{arange}(N), S)$
  $L_{SS} \leftarrow L[S, :][:, S]$
  $L_{TS} \leftarrow L[T, :][:, S]$
  $\text{inv_}L_{SS} \leftarrow \text{inv}(L_{SS} + 10^{-6} \cdot I)$
  $\Delta\mathbf{x}_T \leftarrow -L_{TS} \times \text{inv_}L_{SS} \times \text{ones}(|S|) \times \gamma$ ▷ Derived indirect impact
  $\Delta\mathbf{x}_S \leftarrow -\text{ones}(|S|) \times \gamma$ ▷ Direct targeted impact
  Construct full vector $\mathbf{v}$ from $\Delta\mathbf{x}_S$ and $\Delta\mathbf{x}_T$
  return v
end procedure

4 Quantitative Results: Latin Hypercube Sampling Analysis

Evaluating the structural resilience of the endogenous network topologies involves Latin Hypercube Sampling across a high-dimensional parameter space. The simulated economy runs across 150 distinct parameter vectors spanning five boundary conditions: Network Size (N), Market Concentration (HHI), Learning Rate (α), Survival Threshold (τ), and Market Noise Variance (σ^2). Table 1 presents the core descriptive statistics of macroeconomic output loss across the three idiosyncratic shock vectors.

Table 1. Descriptive Statistics of Macroeconomic Loss Across Shock Scenarios

	Total Output Loss			**Severe Loss Nodes**		
Statistic (by scenarios)	**A**	**B**	**C**	**A**	**B**	**C**
Mean	3.19	4.26	435.61	1.06	1.36	309.00
Median	1.55	2.05	386.54	1.00	1.00	302.50
Minimum	0.80	1.00	13.10	1.00	1.00	10.00
Maximum	16.95	34.61	1320.22	4.00	10.00	798.00
Standard Deviation	3.27	4.89	298.73			

Notes: Scenario A represents Transient Infrastructure Degradation; Scenario B represents Lehman Bankruptcy (Hub Annihilation); Scenario C represents Correlated Policy Shock. Severe Loss Nodes defined as firms experiencing $> 50\%$ output reduction. Sample size $n = 150$ LHS iterations per scenario.

The baseline evaluation injects a transient capacity reduction into an infrastructure hub. The macroeconomic response is highly resilient, with an aggregate output median loss of 1.55 units and an average of 1.06 severe node-level defaults per iteration. Transient capacity reductions degrade node efficiency without permanently severing topological edges, preserving the structural integrity of the Neumann series expansion.

Modeling the permanent bankruptcy of the most central eigenvector hub results in a heavily right-skewed loss distribution. The median loss sits at 2.05, while the variance expands significantly, generating a maximum systemic loss of 34.61.

This output tracks a topological phase transition governed primarily by Market Concentration (HHI). Dispersed networks ($HHI < 0.2$) absorb the hub loss. As HHI approaches 0.99, the endogenous evolution collapses the network into a centralized star graph. When the threshold of approximately $HHI > 0.6$ is breached, the Leontief multiplier for the apex hub expands exponentially. The bankruptcy severs input-output pathways simultaneously, initiating secondary default cascades.

Subjecting the network to simultaneous batch failures introduces systemic fragmentation (Figure 2), generating an average aggregate loss of 435.61 and averaging 309 severe node-level defaults per iteration.

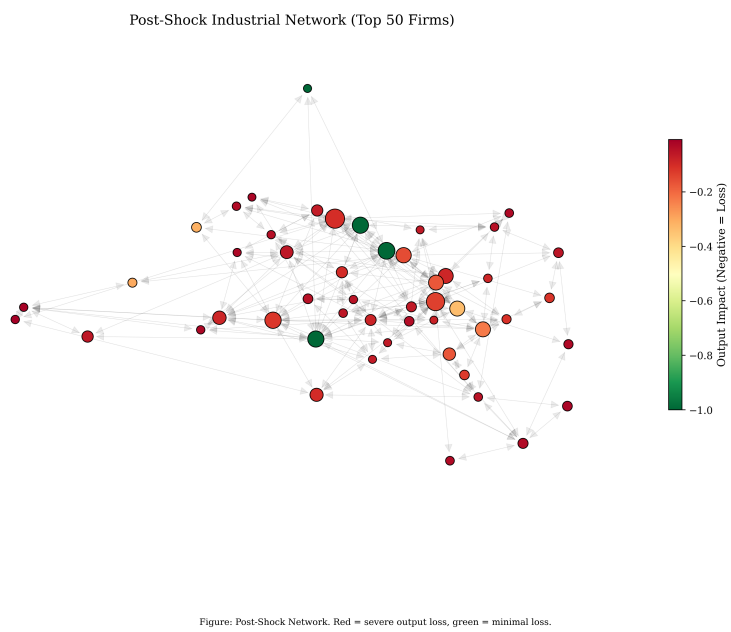

Fig. 2. Network topology of the top 50 nodes following a correlated policy shock. The visualization captures the structural fragmentation and bypassing of endogenous routing redundancies.

Vulnerability in this scenario isolates from market concentration, exhibiting a linear correlation with Network Size (N). Highly granular networks produce significant aggregate losses. Block matrix inversion mechanics dictate that the simultaneous removal of a node subset bypasses endogenous routing redundancies, suggesting that scale and density offer little structural resilience against correlated batch blockages.

5 Discussion, Limitations, and Future Recommendations

The simulation results highlight an evolutionary trade-off within industrial networks. Behavior driven by bounded rationality drifts toward centralized states. This dynamic minimizes search frictions during periods of stability while organically breeding topologies that are vulnerable to targeted disruptions.

The baseline resilience demonstrated in Scenario A confirms that central banks do not need to aggressively intervene during transient operational failures. The endogenous learning mechanism of the market identifies these events as high-variance market noise rather than indicators of permanent rent-seeking. Conversely, the collapse observed in Scenario B supports the Granular Hypothesis. When market concentration breaches approximately HHI > 0.6, the failure of an apex hub triggers exponential multiplier explosions. Current antitrust frameworks evaluate market power primarily through horizontal consumer market share. These findings suggest that macro-prudential regulators must also track eigenvector centrality within supply chains to prevent the formation of highly asymmetric apex structures.

Scenario C indicates that density provides limited defense against correlated batch failures. In events such as targeted trade sanctions or coordinated cyberattacks, the simultaneous removal of a node subset bypasses routing redundancies. Policies that promote intense industrial clustering may inadvertently maximize vulnerability to correlated policy shocks. Governments subsidizing structural redundancies and maintaining dormant alternative supply pathways can provide topological circuit breakers during batch failure events.

These findings are subject to specific computational and theoretical limitations. The simulation initializes Bayesian beliefs using a maximum entropy uniform prior ($B_{ij} = 0.5$). Real-world industrial organization features prior beliefs skewed by institutional signaling, historical market dominance, and observable capital endowments. The findings regarding learning convergence are limited to environments where signal noise follows a Gaussian distribution, and further research is needed to confirm if alternative noise distributions alter the evolutionary trajectory. Additionally, holding pruned edge weights at an infinitesimal limit preserves the stability of the Leontief inverse but may understate the economic friction of re-establishing severed supply chains. Empirical supply chain data indicates that destroyed capital carries significant reactivation costs that simple topological adjustments do not fully capture.

To transition this framework from descriptive analysis to prescriptive policy intervention, future research should integrate Markov Decision Processes. By

defining the state space as the real-time topological matrix and the action space as targeted regulatory interventions, reinforcement learning algorithms could compute mathematically optimal bailout strategies. This extension would allow regulators to maximize aggregate post-shock output while minimizing the fiscal cost of the intervention.

A Computational Architecture and Execution Pipeline

The mandate to execute this multi-phase simulation across high-dimensional parameter spaces necessitates a robust, enterprise-grade computational architecture. The transition from simplistic spatial grids to fully connected, Bayesian-updating directed graphs exponentially increases computational complexity. The simulation environment is built upon a modern scientific Python stack, explicitly leveraging `NumPy` for tensor mathematics, `SciPy` for sparse linear algebra, `NetworkX` for topological analytics, and `Pandas` for cross-sectional data aggregation. This appendix details the software engineering optimizations required to render the simulation mathematically stable, computationally feasible, and highly reproducible.

A.1 Vectorization and Matrix Regularization

For an industry comprising thousands of firms ($N \leq 5000$), the adjacency matrix contains millions of potential directed edges. Executing the Bayesian posterior updates and replicator dynamics via standard procedural loops incurs catastrophic execution overhead and severe Python Global Interpreter Lock (GIL) contention.

To resolve this, the computational `EvolutionaryEngine` entirely eliminates sequential iteration over individual agents. All signal processing, marginal probability evaluations, and belief updates are mathematically vectorized utilizing the highly optimized C-backends of the `NumPy` and `SciPy` libraries. For instance, Cromwell's Rule is enforced simultaneously across the entire network via tensor clipping (`np.clip`), preventing floating-point underflow and division-by-zero anomalies natively within the C-compiled layer.

Furthermore, calculating the Leontief inverse $L = (I - A)^{-1}$ poses significant mathematical instability risks during automated parameter sweeps. Stochastically generated high-concentration topologies occasionally approach mathematical singularity when subjected to simulated bankruptcy scenarios. The `ShockEngine` mitigates this via Tikhonov regularization, systematically injecting a micro-scalar identity matrix ($10^{-6}I$) prior to the linear algebraic inversion (`np.linalg.inv`). This programmatic compromise guarantees continuous execution during unsupervised sampling without meaningfully distorting the macroscopic shock multipliers.

A.2 Computational Complexity and Graph Analytics

To guarantee that the simulation scales efficiently up to $N = 5000$, algorithmic complexity bounds must be strictly managed. The initialization phase, which utilizes preferential attachment and Pareto distribution sampling, resolves in $\mathcal{O}(N^2)$ time. The evolutionary loop, involving element-wise matrix multiplications without requiring computationally expensive dot products, operates in $\mathcal{O}(T \cdot N^2)$ time, where T represents the number of discrete evolutionary epochs.

The primary computational bottleneck occurs during Phase III (Shock Propagation) and network evaluation. The calculation of Eigenvector Centrality and the extraction of the dominant spectral radius $\rho(A)$ required for matrix normalization are fundamentally $\mathcal{O}(N^3)$ operations if solved densely. To optimize this, the `NetworkNormalizer` and `NetworkGraphAnalyzer` conditionally deploy the Implicitly Restarted Arnoldi Method (ARPACK) via `scipy.sparse.linalg.eigs` when $N > 1000$. This reduces the complexity of extracting the largest magnitude eigenvalue ($k = 1$) to approximately $\mathcal{O}(I \cdot N^2)$, where I represents the iterations to convergence.

To ensure the automated pipeline does not fatally crash if the ARPACK algorithm fails to converge within the allotted iterations, a known risk in highly fragmented or symmetric graphs lacking a distinct spectral gap, a robust fallback mechanism is implemented. If an `ArpackError` exception is raised during centrality calculation, the engine automatically defaults to standard Degree Centrality, preserving the analytic pipeline at the cost of minor precision.

A.3 Latin Hypercube Sampling (LHS) Engine

To rigorously map the response surface of the simulation without the exponential explosion of combinatorial states inherent in a naive grid search, the architecture integrates a Quasi-Monte Carlo Latin Hypercube Sampler (`scipy.stats.qmc`).

The `LatinHypercubeSensitivityAnalyzer` stratifies the five-dimensional parameter space: Network Size ($N \in [10, 5000]$), Market Concentration ($HHI \in [0.01, 0.99]$), Learning Rate ($\alpha \in [0.01, 0.50]$), Survival Threshold ($\tau \in [0.01, 0.20]$), and Market Noise Variance ($\sigma^2 \in [0.001, 0.10]$). The unit-hypercube samples $[0, 1)^5$ are mapped orthogonally and subsequently translated to exact operational bounds utilizing the `qmc.scale` function prior to injection into the generative simulator.

Crucially, the execution sweep is encapsulated within a robust error-handling pipeline. If a specific parameter vector generates a mathematically invalid topology, the engine logs the failure trace and continues execution. This ensures absolute continuity during the automated generation of the 150-sample dataset utilized in the econometric regressions.

The orchestrating logic binding the LHS generator, the evolutionary adapter, and the data logging mechanisms is detailed in Algorithm 4.

Algorithm 4 LHS Execution Pipeline and Adapter Logic

Require: Dimensionality $D = 5$, Sample Size $M = 150$, Target Scenario S

```
procedure EXECUTE_LHS_SWEEP(D, M, S)
    Sampler ← qmc.LatinHypercube(d = D, seed = 42)
    Unit_Samples ← Sampler.random(n = M)
    Scaled_Samples ← qmc.scale(Unit_Samples, Bounds)
    Results_Log ← []
    for each param_vector in Scaled_Samples do
        N, HHI, α, τ, σ^2 ← param_vector
        try:
            // Phase 1 & 2: Initialization and Evolution
            Sim ← GenerativeMacroeconomicSimulator(N, HHI, α, τ)
            Sim.run_evolution(steps = 50, noise_var = σ^2)
            // Phase 3: Scenario-Specific Shock Injection
            kwargs ← Map_Scenario_Parameters(S, N)
            v_shock, origin ← Sim.apply_shock(S, kwargs)
            // Phase 4: Macroscopic Evaluation
            Loss_total ← Σ |v_shock|
            Loss_severe ← count(v_shock < −0.50)
            Density ← Calculate_Network_Density(Sim.A)
            Append {param_vector, Loss_total, Loss_severe, Density} to Results_Log
        except Exception as e:
            Append {param_vector, Status: Failed, Trace : e} to Results_Log
    end for
    Export_To_CSV(Results_Log, S)
end procedure
```

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References

1. Acemoglu, D., Carvalho, V.M., Ozdaglar, A., Tahbaz-Salehi, A.: The Network Origins of Aggregate Fluctuations. Econometrica **80**(5), 1977–2016 (2012). https://doi.org/10.3982/ECTA9623
2. Baqaee, D.R., Farhi, E.: Productivity and Misallocation in General Equilibrium. The Quarterly Journal of Economics **135**(1), 105–163 (2020). https://doi.org/10.1093/qje/qjz030
3. Camerer, C.F.: Behavioral Game Theory: Experiments in Strategic Interaction. Princeton University Press, Princeton (2003). ISBN 978-0-691-09039-9
4. Carvalho, V.M., Nirei, M., Saito, Y.U., Tahbaz-Salehi, A.: Supply Chain Disruptions: Evidence from the Great East Japan Earthquake. The Quarterly Journal of Economics **136**(2), 1255–1321 (2021). https://doi.org/10.1093/qje/qjaa044

5. Fudenberg, D., Levine, D.K.: The Theory of Learning in Games. MIT Press, Cambridge, MA (1998). https://api.semanticscholar.org/CorpusID:153837092
6. Gabaix, X.: The Granular Origins of Aggregate Fluctuations. Econometrica **79**(3), 733–772 (2011). https://doi.org/10.3982/ECTA8769
7. Sargent, T.J., Stachurski, J.: Economic Networks: Theory and Computation. Cambridge University Press, Cambridge (2024). ISBN 978-1-009-45636-4