

Collective Adaptation in Financial Markets: Financial Engineering, Complex Networks, and Systemic Resilience

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Abstract

Financial systems distribute risk through portfolios, contracts, funding relationships, and market infrastructures, but the same arrangements that support risk sharing can also transmit stress. This paper develops a theoretical framework that treats the financial system as a complex adaptive risk-sharing network in which heterogeneous agents, balance sheets, and contractual exposures co-evolve. Financial engineering - including derivatives, insurance, netting, collateralization, and clearing - is modeled as an endogenous layer of that network rather than as a purely institution-level risk-management tool. The framework links bounded rationality and the Adaptive Markets Hypothesis with heterogeneous-agent finance, agent-based modeling, nonlinear macrofinance, and multilayer financial-network theory. Its central implication is a micro-macro wedge: an instrument can reduce an individual institution's exposure while increasing system-wide liquidity demand, concentration, or synchronized adjustment. A parsimonious formal model makes beliefs, positions, leverage, liquidity, collateral, and risk-transfer exposures jointly state dependent and yields seven testable propositions concerning diversity, connectivity, adaptation speed, binding constraints, counterparty concentration, and policy damping. The framework also specifies resilience measures based on absorption, propagation, recovery, and reorganization. Climate risk, entrepreneurship, polycentric governance, and sustainability are treated as applications of the core financial mechanism.

JEL classification: C63; G01; G18; G21; G23

1. Introduction

Modern financial systems are designed to allocate capital and distribute risk across time, states of the world, and institutions. The same arrangements that support these functions also create interdependence. Credit contracts connect balance sheets; common asset holdings connect investors through prices; derivatives and insurance contracts connect counterparties through contingent obligations; collateral rules connect risk management to liquidity demand; and information, benchmarking, and delegated management connect behavior through common signals and incentives. These links are valuable because they permit diversification and specialization. Under stress, however, they can become channels through which losses, margin calls, fire sales, funding withdrawals, and strategy changes propagate across the system.

This paper takes the financial system itself - rather than an individual market, institution, or representative investor - as the primary object of analysis. It conceptualizes the system as a complex adaptive risk-sharing network: a population of heterogeneous agents connected by evolving financial, informational, and institutional relations. The core premise is that market outcomes are jointly produced by adaptive behavior and by the architecture through which agents share, finance, and transmit risk. Prices are therefore not only summaries of information; they are endogenous state variables that alter wealth, leverage, margins, beliefs, and network exposures and thereby influence subsequent behavior.

This framing does not require rejecting the Efficient Market Hypothesis (EMH). A more productive interpretation is to place informational efficiency within a broader adaptive framework. Lo (2004) and Lo and Zhang (2024) develop the Adaptive Markets Hypothesis (AMH), in which the degree of efficiency depends on environmental conditions, competition, learning, and adaptation. Under relatively stable conditions, competitive adaptation can generate outcomes close to an EMH benchmark. Under structural change, heterogeneous learning, institutional constraints, or shifts in market ecology, predictability and behavior can change. Equilibrium and efficiency therefore remain useful limiting cases, but they do not by themselves provide a unified mechanism for endogenous regime shifts, nonlinear feedback, liquidity spirals, and network contagion.

The paper's second organizing idea concerns financial engineering. Conventional analysis often evaluates hedging, derivatives, and insurance from the perspective of the contracting institution: does the instrument reduce the variance or tail risk of that institution's payoff? This is an important question, but it is not sufficient for systemic analysis. A hedge that lowers one institution's exposure necessarily reallocates the exposure, transforms it, or creates offsetting obligations elsewhere. Margin and collateral can reduce counterparty credit risk while increasing liquidity needs in stress. Central clearing can improve netting and transparency while concentrating operational and liquidity dependencies. Risk transfer may therefore improve micro-resilience while either improving or reducing macro-resilience. The sign of the system-level effect is an endogenous property of network topology, leverage, liquidity, agent diversity, and behavioral feedback.

A third motivation is methodological. Representative-agent and locally linearized models remain useful for many questions, but financial stress often involves heterogeneity, nonlinear constraints, endogenous feedback, and changing network structure. Heterogeneous-agent models generate endogenous transitions among market regimes (Brock and Hommes, 1998; Hommes, 2001; He, Li, and Zheng, 2019). Agent-based models (ABMs) allow institutions with different rules, balance sheets, and constraints to interact directly (Bookstaber, Paddrik, and Tivnan, 2018; Axtell and Farmer, 2025; Choi and Choi, 2026). Nonlinear macrofinance emphasizes state-dependent funding and market-liquidity constraints (Dou et al., 2023), while financial-network models show that diversification and interconnectedness can support risk sharing in some states and magnify contagion in others (Elliott, Golub, and Jackson, 2014; Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2015; Jackson and Pernoud, 2021). The contribution here is to connect these literatures through the design and endogenous evolution of risk-sharing arrangements.

The paper makes four contributions. First, it defines a multilayer representation in which funding, common asset exposures, information, and risk-transfer relations coexist and evolve. Second, it formalizes collective financial adaptation as the joint evolution of beliefs, strategies, balance sheets, and network connections. Third, it identifies a micro-macro wedge in financial engineering and derives testable propositions for the conditions under which private risk reduction improves or weakens system resilience. Fourth, it operationalizes resilience with conventional systemic-risk measures together with network, complexity, and post-shock recovery measures. The resulting framework is intended to be

modular: climate and catastrophe risk, entrepreneurship and innovation, polycentric governance, and sustainability can be added as applications without changing the core financial mechanism.

The remainder of the paper proceeds as follows. Section 2 reviews bounded rationality and adaptive markets, heterogeneous-agent and agent-based finance, financial networks, liquidity and leverage feedback, and resilience. Section 3 develops the complex adaptive risk-sharing network framework. Section 4 presents the formal model and testable propositions. Section 5 sets out empirical and computational operationalization. Section 6 develops applications and extensions. Section 7 discusses implications and limitations, and Section 8 concludes.

2. Literature Review and Theoretical Positioning

2.1 Bounded rationality, behavioral finance, and adaptive markets

The intellectual starting point is bounded rationality. Simon (1955, 1974) argued that decision makers operate with limited information-processing capacity and within organizational structures that decompose complex problems into semi-autonomous levels. In finance, the behavioral literature documents systematic departures from the frictionless rational benchmark, including reference dependence, loss aversion, biased updating, and context-sensitive choice (Kahneman and Tversky, 1979). The important implication for the present paper is not that agents are simply 'irrational.' It is that decision rules are conditioned by experience, institutions, incentives, and the information environment and may change when those conditions change.

The Adaptive Markets Hypothesis supplies a bridge between informational efficiency and behavioral adaptation. Lo (2004) interprets financial interactions through evolutionary mechanisms such as competition, adaptation, and selection. Lo and Zhang (2024) develop this idea into a broader account of financial-system dynamics. In this view, the empirical relevance of a given heuristic or trading strategy depends on the market ecology in which it operates. Efficiency can therefore be an emergent and state-dependent property rather than an all-or-nothing maintained assumption. This is useful for the present framework because it permits EMH-like behavior in tranquil states while allowing the population of strategies, constraints, and network exposures to evolve during structural change.

At the same time, empirical evidence for the AMH should be treated carefully. Time variation in predictability is not by itself proof of evolutionary adaptation, and rolling-window tests can generate multiple-testing problems. Hřebáčka (2026), for example, shows that some apparent evidence for the AMH can be sensitive to rolling-window methodology. The framework developed below therefore does not infer adaptation from time-varying returns alone. It represents adaptation structurally through changes in agents' strategy weights, balance sheets, liquidity positions, and network connections.

2.2 Heterogeneous-agent finance and agent-based modeling

Heterogeneous-agent models show how market dynamics can arise endogenously from interactions among agents using different forecasting rules. Brock and Hommes (1998) demonstrate that boundedly rational switching among forecasting strategies can generate complex and even chaotic asset-price dynamics. Lux and Marchesi (1999) show that interactions among market participants can generate scaling and volatility clustering without requiring similarly scaled exogenous news. Hommes (2001) synthesizes this literature by treating financial markets as nonlinear adaptive evolutionary systems in which prices and beliefs co-evolve. He, Li, and Zheng (2019) review how evolutionary dynamics among heterogeneous beliefs can generate stochastic switching among market states, stylized facts, bubbles, and crashes.

Agent-based modeling extends the heterogeneous-agent approach by allowing richer institutional structure, discrete rules, balance-sheet constraints, and explicit networks. Bookstaber, Paddrik, and Tivnan (2018) model funding and collateral flows and show that crisis severity can depend critically on agents' reactions to initial losses. Axtell and Farmer (2025) review the expansion of ABM across economics and finance and identify clustered volatility, market impact, systemic risk, and housing markets as areas in which the approach has generated substantial insights. Recent surveys emphasize three design dimensions that are particularly relevant here: the degree of agent heterogeneity, the fidelity of market mechanisms, and the topology of interactions (Choi and Choi, 2026). These dimensions map directly into the proposed model's population of agents, trading and collateral rules, and multilayer network structure.

The attraction of ABM for this setting is not simulation for its own sake. It is the ability to represent state-dependent behavior and constraints that are difficult to aggregate without losing the mechanism of interest. The corresponding burden is model discipline: a useful financial ABM should reproduce selected empirical regularities without being tuned to every fact, identify which mechanisms are necessary for its results, and demonstrate robustness to plausible alternative behavioral rules. Section 5 translates these requirements into a transparent calibration and validation strategy.

2.3 Financial networks, contagion, and the efficiency-stability trade-off

Financial-network research provides a second foundation. In network models, institutions are nodes and their bilateral exposures, common holdings, ownership ties, funding relationships, or contingent contracts form edges. Elliott, Golub, and Jackson (2014) show that integration and diversification can have non-monotonic effects on cascades. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) establish a related phase-transition result: greater interconnectedness can distribute sufficiently small shocks but can transmit sufficiently large shocks through the system. Jackson and Pernoud (2021) distinguish

direct network externalities, such as defaults, correlated portfolios, and fire sales, from feedback mechanisms such as runs and credit freezes.

The network view has become increasingly multilayer and time dependent. Bardoscia et al. (2021) review financial networks involving loans, common asset ownership, higher-order contracts such as credit default swaps, and multiplex links that can extend into the real economy. Franch, Nocciola, and Vouldis (2024) show that temporal and higher-order network representations can improve the identification of contagion across banks, insurers, and shadow banks. Gofman, Herskovic, and Segal (2026) emphasize an efficiency-stability trade-off: networks transmit liquidity, information, and gains from specialization while also creating channels for contagion. Their network-of-networks perspective is especially compatible with a financial system in which funding, asset, information, and risk-transfer networks interact.

This literature implies that 'connectivity' cannot be treated as a scalar good or bad. The relevant questions concern which agents are connected, through what contracts, with what direction and maturity, under which collateral and close-out rules, and how the network changes when agents respond to stress. A network that is resilient to small independent shocks may be fragile to common or correlated shocks. A diversified portfolio layer may coexist with a concentrated derivatives layer. A static network map can therefore understate risk when exposures and behavior co-evolve.

2.4 Liquidity, leverage, and endogenous amplification

The mechanism that connects balance-sheet adaptation to market dynamics is well established in the liquidity literature. Brunnermeier and Pedersen (2009) model the mutually reinforcing relationship between market liquidity and funding liquidity, showing how margins can become destabilizing and generate liquidity spirals. Adrian and Shin (2010) document procyclical leverage among market-based intermediaries, linking mark-to-market balance sheets to aggregate liquidity. Greenwood, Landier, and Thesmar (2015) show how leverage restoration through asset sales can create fire-sale spillovers across institutions holding common assets. More recent nonlinear macrofinance work emphasizes that local linear approximations can omit important state-dependent dynamics generated by funding constraints, market-liquidity frictions, and run mechanisms (Dou et al., 2023). Goldstein, Huang, and Yang (2025) similarly review mechanisms through which market prices can react disproportionately to fundamental or nonfundamental shocks.

These mechanisms are central to understanding financial engineering at the system level. Derivatives and collateral arrangements reduce some forms of counterparty exposure but may create contingent liquidity needs. The Financial Stability Board's 2024 recommendations on margin and collateral calls were motivated by episodes in which sudden margin requirements strained non-bank institutions during broad market stress. The FSB explicitly notes that margin is protective against counterparty risk while simultaneously capable of amplifying liquidity demand when calls are unexpected and widespread. Claessens (2024) places such episodes within the broader growth of nonbank financial intermediation and emphasizes the interaction among leverage, liquidity mismatch, interconnection, and procyclicality.

2.5 From stability to resilience and collective adaptation

Stability and resilience should be distinguished. Stability concerns the sensitivity of a system to perturbations around a state; resilience concerns the ability to absorb, adapt to, and recover from disturbance. Holling (1973, 2001) developed this distinction in ecological systems and emphasized persistence under changing conditions rather than return to a unique equilibrium. The original version of this research agenda adopted a related distinction between resilience that preserves system identity and resilience that involves reorganization into a new stable domain. That distinction is retained here but translated into financial-system language: a resilient system may restore intermediation and market functioning without returning to its exact pre-shock network configuration.

Brunnermeier (2024) brings resilience directly into macrofinance, arguing for a shift from managing the probability and size of shocks toward understanding adaptation after shocks and explicitly distinguishing micro- from macro-resilience. This distinction closely matches the argument developed here: actions that protect an individual balance sheet can have different effects once their general-equilibrium and network consequences are considered. Galesic et al. (2023) add a complementary concept of collective adaptation, emphasizing the dynamic interaction of social integration strategies, network structure, and the problem environment. Their emphasis on path dependence, lack of global optimization, and adaptive network change is particularly useful for financial markets, where agents jointly modify beliefs, positions, and counterparties in response to evolving stress.

In this paper, collective financial adaptation is defined as the endogenous joint evolution of agents' decision rules, balance sheets, contractual exposures, and network connections in response to realized and anticipated market states. The concept is deliberately broader than collective intelligence. Adaptation can improve resilience, but it can also be collectively maladaptive. Individually sensible actions - raising cash, reducing leverage, closing risk, demanding more collateral, or copying a strategy that recently performed well - can become destabilizing when many agents act simultaneously.

2.6 Complexity measures and early-warning indicators

Complexity science offers tools for detecting changes in system organization, including entropy, synchronization, recurrence, spectral properties, and network concentration. Earlier work proposed using statistical complexity and synchronization to characterize distance from equilibrium and impending instability. That direction remains promising, but recent evidence argues against relying on any single universal precursor. Diks, Hommes, and Wang (2019) find evidence of critical slowing down before the 1987 crash but mixed or insignificant results for several later crises. Song and Li (2024) obtain more encouraging results using multiplex recurrence networks and nonlinear indicators for U.S. and Chinese stock markets. The appropriate implication is methodological caution: complexity measures should be evaluated as complements to, rather than substitutes for, market-based and balance-sheet measures of systemic vulnerability.

This point is reinforced by Acharya, Brunnermeier, and Pierret (2025), who show that market-based systemic-risk measures contain information complementary to traditional balance-sheet metrics across a long sample of U.S. financial stress. The operationalization below therefore combines measures of systemic exposure with measures of system organization. The purpose is not deterministic crash prediction; it is to test whether changes in topology, synchronization, diversity, and liquidity constraints add explanatory or predictive information about nonlinear amplification, cascade severity, and recovery.

Table 1
Positioning of the proposed framework

Literature	Primary unit	Core mechanism	Role in this paper
Adaptive markets / behavioral finance	Investor or strategy	Learning, heuristics, evolutionary selection	Explains state-dependent beliefs and strategy adaptation
Heterogeneous-agent / ABM finance	Interacting agents	Bottom-up emergence and nonlinear feedback	Provides computational architecture for endogenous regime dynamics
Financial networks	Institutions and exposures	Diversification, contagion, fire sales, network formation	Represents the topology of funding, assets, and contracts
Liquidity and nonlinear macrofinance	Balance sheets and markets	Leverage, margins, funding and market-liquidity spirals	Links risk management to endogenous amplification
Resilience / collective adaptation	System trajectory	Absorption, adaptation, recovery, reorganization	Defines system-level outcome and post-shock dynamics
Financial engineering	Contracts and portfolios	Risk transfer, hedging, netting, collateralization	Becomes an endogenous network layer rather than an exogenous damping device

3. Financial System as a Complex Adaptive Risk-Sharing Network

3.1 Units, layers, and state variables

Consider a financial system populated by heterogeneous agents $i = 1, \dots, N$. Agents can represent banks, broker-dealers, hedge funds, pension funds, insurers, mutual funds, households, nonfinancial firms, central counterparties, and public authorities. The appropriate level of aggregation depends on the research question. Each agent has a state vector containing wealth or equity, cash and liquid assets, leverage, risk tolerance, funding maturity, collateral availability, beliefs, and strategy weights. Agents differ in objectives and constraints; importantly, the model does not require that all decision makers share a common forecasting model or horizon.

Relations among agents are represented as a multiplex network rather than a single adjacency matrix. At minimum, the framework distinguishes five interacting layers. The information and strategy layer records

observation, imitation, common signals, and delegated-management benchmarks. The market and asset layer records trading, common holdings, and price impact. The funding and balance-sheet layer records secured and unsecured credit, deposits, repo, and other financing. The risk-transfer layer records derivatives, insurance, reinsurance, guarantees, netting sets, and contingent claims. The institutional layer represents rules that condition behavior, including capital requirements, margin, collateral eligibility, central clearing, position limits, circuit breakers, and lender-of-last-resort facilities. These layers are analytically distinct but dynamically coupled.

The multilayer representation makes the micro-macro distinction explicit. A derivative contract may lower the variance of agent i 's cash flow while changing the exposures of agent j , increasing collateral dependence on a CCP, and altering the set of assets that must be sold to meet a margin call. A portfolio hedge can therefore be privately effective and systemically destabilizing, privately and systemically beneficial, or largely neutral. The relevant outcome cannot be inferred from the hedge's payoff profile alone; it depends on who bears the residual risk, how that risk is financed, and how the network responds in stress.

3.2 Collective adaptation as co-evolution

Collective adaptation occurs through several coupled channels. Agents update beliefs after observing returns, volatility, news, and the actions of others. They alter positions and hedges in response to revised beliefs and risk constraints. These trades change prices and liquidity, which feed back into measured volatility, collateral requirements, wealth, and leverage. Agents can also change counterparties, substitute between secured and unsecured funding, migrate toward or away from central clearing, or withdraw from markets altogether. Network topology is therefore partly endogenous.

This co-evolution matters because financial stability is path dependent. The same exogenous shock can have different consequences depending on the distribution of liquidity, leverage, strategy similarity, and contractual concentration at the moment the shock arrives. Conversely, a period of low volatility can change the system before any shock occurs: it can encourage leverage, compress risk premia, concentrate strategies, and make risk estimates more similar. The shock is then only one component of the eventual crisis; the pre-shock adaptive state determines amplification.

3.3 Financial engineering as endogenous risk architecture

Financial engineering is defined broadly as the design and use of contracts, portfolios, institutions, and trading rules that transform the timing, state contingency, or ownership of risk. This includes conventional derivatives, insurance and reinsurance, securitization, structured products, collateral and margin arrangements, netting, and risk-sensitive portfolio design. In the proposed framework, financial engineering changes the risk architecture of the system in three ways.

First, it changes loss allocation. A hedge transfers payoff exposure from one agent to another or embeds it in a chain of offsetting contracts. Second, it changes liquidity timing. Collateralized risk transfer converts part of counterparty risk into contingent liquidity demand. Third, it changes network topology.

Netting, central clearing, standardized contracts, and dealer intermediation can reduce the number of bilateral links while increasing concentration in particular nodes or infrastructures. These mechanisms imply that the welfare and resilience effects of financial engineering are state dependent and cannot be classified ex ante as stabilizing or destabilizing in all circumstances.

3.4 Resilience as a system-level outcome

A resilience framework should measure more than whether asset prices revert after a shock. The financial system performs multiple functions: market liquidity, payments, credit provision, insurance, savings intermediation, and risk bearing. A shock may therefore leave prices stable while impairing credit, or produce a temporary price dislocation without lasting damage to intermediation. The empirical design should distinguish at least four dimensions: absorption (maximum functional loss), propagation (cascade breadth and depth), recovery (time and path back toward a viable domain), and reorganization (the extent to which the post-shock network differs from the pre-shock configuration).

This interpretation also clarifies the role of equilibrium. A system can be resilient without returning to the exact state from which it was displaced. Institutions may exit, new intermediaries may enter, and risk may migrate across sectors. Viability in the sense of maintaining critical functions can therefore be more informative than convergence to a unique equilibrium. Aubin's (1997) viability approach provides a useful conceptual language for identifying states from which feasible policy or behavioral paths keep the system within acceptable constraints.

Table 2
Core layers and candidate observables

Layer	Examples of links	State variables / observables	Primary stress channel
Information / strategy	Common signals, imitation, benchmarking	Strategy shares, forecast dispersion, portfolio similarity	Herding and synchronized adjustment
Market / asset	Trading and common holdings	Market depth, turnover, price impact, overlap	Fire sales and price-mediated contagion
Funding / balance sheet	Loans, repo, deposits, credit lines	Leverage, maturity, cash, haircuts, funding concentration	Runs, rollover risk, deleveraging
Risk transfer	Derivatives, insurance, guarantees, netting	Gross/net exposures, margin, collateral, counterparty concentration	Contingent liquidity and counterparty losses
Institutional / governance	Clearing, capital, margin, circuit breakers	Requirements, thresholds, eligible collateral, intervention rules	Damping or amplification through common constraints

4. A Parsimonious Formal Model

The purpose of the model is to isolate the mechanisms that distinguish a complex adaptive risk-sharing network from a fixed-network or representative-agent benchmark. The model can be analyzed in restricted cases and implemented computationally as an agent-based system in the general case. Time is discrete, $t = 0, 1, 2, \dots$, and the baseline economy contains one risky asset. Additional assets, sectors, and derivative classes can be introduced without changing the core state-transition structure.

4.1 Agent states and adaptive beliefs

Agent i has equity or wealth $W(i,t)$, liquid resources $C(i,t)$, leverage $L(i,t)$, risk-tolerance parameter $\gamma(i)$, adaptation intensity $\beta(i)$, and a vector of forecasting weights $w(i,t)$. Expected next-period return is a weighted combination of a fundamental signal $F(t)$, a trend or technical signal $T(t)$, and a social/network signal $S(i,t)$:

$$E(i,t)[r(t+1)] = wF(i,t) F(t) + wT(i,t) T(t) + wS(i,t) S(i,t) \quad (1)$$

The social signal aggregates observations from information neighbors. With $G(t)$ denoting the information network and $g(i,j,t)$ its normalized weights,

$$S(i,t) = \sum_j g(i,j,t) r(j,t), \text{ or more generally, } S(i,t) = \sum_j g(i,j,t) s(j,t) \quad (2)$$

where $s(j,t)$ can represent a neighbor's trade, forecast, or risk posture. Strategy weights adapt to realized performance. A convenient specification is exponential reinforcement:

$$w_k(i,t+1) = w_k(i,t) \exp[\beta(i) \pi_k(i,t)] / \sum_k w_k(i,t) \exp[\beta(i) \pi_k(i,t)] \quad (3)$$

where $\pi_k(i,t)$ is the realized performance of strategy k . The parameter $\beta(i)$ controls adaptation speed. Low β implies persistent strategy weights; high β produces rapid switching toward recently successful rules. This structure nests relatively stable forecasting behavior as well as rapid endogenous changes in the composition of market strategies.

4.2 Portfolio demand, hedging, and constraints

Desired exposure to the risky asset reflects expected excess return, perceived risk, hedging demand, and financing constraints. A reduced-form demand equation is

$$q^*(i,t) = \{E(i,t)[r(t+1)] - r_f\} / \{\gamma(i) \sigma^2(i,t)\} + H(i,t) - \Phi[L(i,t), M(i,t), C(i,t)] \quad (4)$$

where $H(i,t)$ is the net position implied by hedging or insurance objectives and $\Phi(\cdot)$ captures the shadow cost of leverage, margin $M(i,t)$, and liquidity constraints. This formulation deliberately separates the desired risk position from the financing conditions required to carry it. Under normal conditions Φ can be small; near leverage, collateral, or liquidity thresholds it can become strongly nonlinear.

4.3 Price formation and market liquidity

Aggregate order imbalance changes prices through an endogenous price-impact coefficient λ_t :

$$\Delta p(t) = \lambda(t) \sum_i \Delta q(i,t) + \varepsilon(t), \text{ with } \lambda(t) = \lambda[\text{Depth}(t), \text{Vol}(t), \text{DealerCapacity}(t)] \quad (5)$$

Market depth is not fixed. It depends on the risk-bearing capacity of dealers and other liquidity providers, recent volatility, and funding conditions. A decline in depth raises λ_t , so a given quantity of forced selling has a larger price effect. This channel links the agent-based representation to the liquidity spiral of Brunnermeier and Pedersen (2009) and to the broader nonlinear macrofinance literature.

4.4 Risk-transfer network and collateral dynamics

Let $D(t) = [d(i,j,t)]$ denote the matrix of net contingent exposures generated by derivatives, insurance, guarantees, or other risk-transfer contracts. The cash flow from the risk-transfer layer to agent i is

$$X_{\square}(i,t+1) = \sum_j d(i,j,t) \Psi(j,t+1) \quad (6)$$

where $\Psi(j,t+1)$ represents the state-contingent payoff driver. Gross contracts can be represented separately when collateral and netting are important. Margin requirements depend on current exposures and volatility:

$$M(i,t) = m_i[|D(i,t)|, \sigma(t), p(t), \text{collateral}(i,t), \text{clearing rules}] \quad (7)$$

A rise in volatility or a deterioration in collateral value increases required cash or high-quality collateral. If available liquidity is insufficient, the agent must borrow, sell assets, unwind positions, or default. Thus, risk transfer can reduce terminal loss exposure while increasing interim liquidity sensitivity.

4.5 Balance-sheet transition and network co-evolution

After market and derivative cash flows are realized, each agent updates equity and liquidity. In reduced form,

$$W(i,t+1) = W(i,t) + q(i,t) \Delta p(t) + X_{\square}(i,t+1) - \text{funding costs}(i,t) - \text{losses}(i,t) \quad (8)$$

$$C(i,t+1) = C(i,t) + \text{cash flows}(i,t+1) - \Delta M(i,t) - \text{redemptions}(i,t) + \text{new funding}(i,t) \quad (9)$$

Agents then revise counterparties and contractual exposures. Let $G(t)$ denote the collection of network layers. Network evolution can be represented as

$$G(t+1) = \mathcal{G}[G(t), W(t+1), C(t+1), \text{performance}(t), \text{regulation}(t), \text{search costs}] \quad (10)$$

where $\mathcal{G}$ can encode relationship persistence, counterparty substitution, central-clearing rules, endogenous withdrawal, or preferential attachment. This step is essential: the model is not merely a dynamic process on a fixed network; it is a model in which the network itself can adapt.

4.6 Systemic resilience metrics

Let $Y(t)$ denote a vector of system functions, for example market depth, aggregate credit, aggregate net worth, settlement continuity, and risk-bearing capacity. Let $Y_{\square}(t)$ denote a baseline path. Rather than

collapsing resilience immediately into one number, the model records a vector of outcomes: maximum functional loss, cumulative loss relative to baseline, time to recover a chosen fraction of baseline function, default/cascade size, and structural distance between pre- and post-shock networks. A composite index may be constructed for particular policy exercises, but its weights should be transparent and application specific.

For simulation comparisons, a normalized cumulative-loss metric can be defined as

$$\text{Loss}(H) = \sum(\tau = 0 \dots H) \omega(\tau) \frac{\|Y(t_0 + \tau) - Y(t_0)\|}{\sum(\tau = 0 \dots H) \omega(\tau) \|Y(t_0 + \tau)\|} \quad (11)$$

with lower $\text{Loss}(H)$ indicating greater resilience over horizon H . This measure can be reported alongside recovery time and cascade size rather than interpreted as a universal index. The distinction between micro-resilience and macro-resilience is operationalized by comparing the distribution of institution-level losses with system-level functional loss.

4.7 Testable propositions

The model yields seven propositions that can be evaluated in simulation, laboratory settings, or empirical data when relevant exposures are observable. They are directional statements with explicit scope conditions and allow threshold or non-monotonic effects.

P1 - Diversity and resilience. Holding aggregate risk-bearing capacity constant, greater diversity in forecasting rules, funding structures, and rebalancing thresholds reduces synchronized adjustment and lowers cascade severity over a broad intermediate range. Extremely fragmented or thinly capitalized ecologies can offset this benefit, so the relationship need not be globally monotonic.

P2 - Connectivity is non-monotonic. Greater connectivity improves risk sharing for small or idiosyncratic shocks but can increase propagation once shocks are sufficiently large, correlated, or concentrated. The turning point depends on capitalization, recovery values, and the distribution of exposures.

P3 - Micro-risk reduction does not imply macro-resilience. Introducing a hedging or insurance instrument reduces the direct exposure of some agents but improves system resilience only when transferred risk is absorbed without creating larger leverage, liquidity, or concentration externalities.

P4 - Collateral and leverage create endogenous thresholds. The effect of a shock on price impact and defaults rises nonlinearly as more agents approach binding margin, haircut, leverage, or redemption constraints. Near these thresholds, small additional shocks can produce disproportionately large system responses.

P5 - Adaptation speed has an interior optimum. Very slow adaptation delays necessary adjustment, while very rapid and homogeneous adaptation increases correlated trading and endogenous volatility. System resilience is therefore highest over an intermediate, state-dependent range of adaptation speeds.

P6 - Contractual concentration increases tail dependence. Conditional on aggregate net exposure, greater concentration of derivative, insurance, or clearing exposures in a small number of counterparties raises the tail sensitivity of system outcomes unless offset by superior collateralization, loss mutualization, or liquidity capacity.

P7 - Damping mechanisms are state dependent. Circuit breakers, margin rules, capital buffers, and liquidity facilities reduce cascade losses when they relieve binding feedback loops, but poorly timed or highly procyclical constraints can shift losses across layers or intensify synchronized adjustment.

Table 3
Propositions, mechanisms, and indicative empirical signatures

Hypothesis	Mechanism	Indicative signature
P1	Strategy / balance-sheet diversity limits synchronized action	Lower co-movement of flows and smaller cascades at comparable shock size
P2	Risk sharing versus propagation	U-shaped or threshold relation between connectivity and systemic loss
P3	Risk transfer creates a micro-macro wedge	Institution-level tail exposure falls while liquidity demand or network tail risk rises in some configurations
P4	Binding constraints generate nonlinear amplification	Price impact and defaults accelerate near margin/leverage thresholds
P5	Adaptive learning can become correlated	Intermediate adaptation speed minimizes cumulative loss and recovery time
P6	Counterparty concentration creates tail dependence	System loss rises with concentration after controlling for net exposure and capital
P7	Regulatory damping interacts with state variables	Policy effectiveness varies with liquidity, leverage, shock type, and implementation timing

5. Empirical and Computational Operationalization

5.1 Nested identification strategy

A tractable implementation should identify mechanisms before adding institutional scale. The baseline specification therefore uses a small number of agent classes - for example, leveraged funds, banks or dealers, insurers or long-horizon asset owners, and a central counterparty - trading one or two risky assets. The objective is not to reproduce the full financial system in a single calibration, but to preserve the channels required to distinguish adaptive risk sharing from simple diversification or fixed-network contagion.

Three nested model variants provide an identification strategy. Model A contains heterogeneous beliefs and endogenous prices but no explicit risk-transfer network. Model B adds funding, common asset

holdings, and fire-sale channels. Model C adds derivatives or insurance, margin, and network rewiring. Comparing the variants reveals which stylized facts and resilience outcomes require each mechanism and limits the risk that a richly parameterized ABM reproduces outcomes for reasons that are difficult to interpret.

5.2 Calibration and validation

Calibration should combine institutional parameters with targeted empirical moments. Institutional parameters include leverage limits, haircut or margin schedules, capital constraints, redemption rules, and contract maturities. Market targets can include unconditional volatility, tail thickness, volatility clustering, turnover, price impact, and cross-sectional return correlation. Network targets can include degree distribution, concentration, assortativity, common-asset overlap, and persistence of relationships. The objective is not to fit every moment simultaneously but to choose a small set that identifies the mechanisms under study.

Validation should be layered. First, the model should reproduce stylized facts not directly targeted in calibration. Second, it should reproduce qualitative responses to documented stress mechanisms, such as a volatility shock that raises margin requirements and induces correlated asset sales. Third, out-of-sample or cross-episode validation should test whether parameters calibrated to one period generate plausible dynamics in another. Fourth, sensitivity analysis should identify which conclusions survive alternative behavioral rules, network-formation processes, and parameter ranges. Axtell and Farmer (2025) and Choi and Choi (2026) emphasize validation as a central challenge for financial ABMs; here it is treated as part of model identification rather than as a final diagnostic.

5.3 Data architecture

The empirical counterpart of the model is naturally multilayer. Market data provide prices, realized volatility, turnover, bid-ask spreads, and measures of market depth. Regulatory filings and balance-sheet data provide leverage, cash, maturity, and common asset exposures. Where available, supervisory or trade-repository data provide bilateral derivatives, repo, or securities-financing exposures. Public data are generally less complete than supervisory data, so early applications can infer latent network structure from common holdings, co-movement, funding exposures, or reported counterparty concentrations. Network reconstruction methods should be accompanied by uncertainty bands rather than treated as observed truth.

The research design can also exploit sector-level rather than institution-level networks. Franch, Nocciola, and Vouldis (2024), for example, analyze temporal contagion across banks, insurers, and shadow banks. Such an aggregation can be useful when granular contract data are unavailable and can serve as an empirical validation target for an agent-based model that contains the same institutional sectors.

5.4 Outcome measures

No single indicator should define systemic resilience. The preferred outcome set contains four classes of measures. Market measures include drawdowns, volatility, spreads, depth, and price impact.

Institution measures include equity losses, liquidity shortfalls, leverage, defaults, and forced sales. Network measures include centrality, concentration, component size, assortativity, spectral radius, reciprocity, and changes in multilayer overlap. Systemic-risk measures can include market-based stress measures summarized by Acharya, Brunnermeier, and Pierret (2025), while complexity measures can include entropy, synchronization, recurrence, and higher-order network indicators.

The key empirical criterion is incremental value. A complexity or network indicator is informative if it improves the explanation or prediction of amplification, cascade severity, or recovery conditional on conventional measures of volatility, leverage, and capital. This criterion avoids treating any complexity statistic as a universal crisis predictor. The mixed evidence on critical slowing down in finance (Diks, Hommes, and Wang, 2019) and the more encouraging evidence from recurrence-based methods (Song and Li, 2024) support a comparative, multivariate evaluation.

5.5 Computational experiments

The computational design varies one structural dimension at a time before examining interactions. A diversity experiment changes the dispersion of strategies and constraints while holding aggregate wealth and average leverage fixed. A connectivity experiment varies density and concentration separately. A risk-transfer experiment compares no hedge, bilateral contracts, central clearing, and insurance while holding the underlying shock fixed. A liquidity experiment varies cash buffers, haircuts, and funding maturity. An adaptation experiment varies both the speed and heterogeneity of strategy updating. Policy experiments then introduce countercyclical margin, liquidity facilities, capital buffers, or circuit breakers from the same pre-shock state.

Table 4
Computational experiment matrix

Experiment	Treatment variable	Controls	Primary outcomes
Diversity	Number / dispersion of strategies and constraints	Total wealth, mean leverage, shock size	Flow synchronization, drawdown, cascade size, recovery time
Connectivity	Density, degree dispersion, assortativity	Capital and exposure totals	Loss distribution, contagion depth, nonlinear threshold
Risk transfer	No hedge / bilateral / cleared / insured	Underlying exposure and shock	Micro loss, margin demand, systemic loss, concentration
Liquidity	Cash buffers, haircuts, funding maturity	Portfolio risk and network	Forced sales, price impact, defaults
Adaptation	β and heterogeneity of learning speeds	Information set and payoffs	Regime switching, volatility clustering, resilience
Policy	Margin, buffers, circuit breakers, facilities	Same pre-shock state	Functional loss, recovery, redistribution across layers

5.6 Falsifiability and model discipline

The framework specifies conditions under which its central claims would fail. P1 would be rejected if greater heterogeneity systematically raised cascade risk across plausible parameter regions after controlling for capital and liquidity. P2 would be rejected if connectivity had a monotonic effect across shock sizes and network structures. P3 would be weakened if risk-transfer instruments always improved system outcomes whenever institution-level exposure fell, or if they never did. P5 would be rejected if resilience were monotonic in adaptation speed. Explicit failure conditions matter because a model that can rationalize every outcome after the fact has little explanatory value.

The same discipline applies to calibration. Parameter uncertainty should be propagated into outcome uncertainty, and policy conclusions should be reported only for regions of parameter space in which they are robust. Where network data are inferred rather than observed, alternative reconstructions should be treated as competing states of knowledge. The aim is a transparent computational laboratory whose mechanisms can be inspected, disabled, and compared - not a black-box forecasting engine.

6. Applications and Extensions

6.1 Climate and catastrophe risk

Climate risk is a natural application because the probability distribution of losses is non-stationary, uncertainty is deep, and physical and transition shocks can interact with financial constraints. Battiston, Dafermos, and Monasterolo (2021) argue that nonlinearity, endogeneity, and deep uncertainty challenge conventional financial-risk methods. Roncoroni et al. (2021) demonstrate how climate transition risk can interact with a network of banks and investment funds. The Network for Greening the Financial System has continued to develop both long-horizon scenarios and, beginning in 2025, short-term scenarios designed to examine near-term macro-financial stress. These scenarios can provide exogenous shock paths for the model developed here, while the adaptive network supplies endogenous amplification channels.

The distinctive financial-engineering question is how different risk-transfer architectures handle the same climate shock. One can compare conventional insurance, reinsurance, catastrophe bonds, derivatives, public backstops, and combinations of these instruments. The system-level evaluation would ask not only who ultimately bears the insured loss but also how collateral, liquidity, asset sales, and counterparty concentration evolve before and after the loss is realized. This reframes climate finance from a problem of correctly pricing an external shock to a problem of designing an adaptive risk-sharing architecture under changing hazards.

6.2 Entrepreneurship, innovation, and reorganization

Entrepreneurship and innovation enter the framework as mechanisms of reorganization rather than as a separate theory of the entire socioeconomic system. In complex systems, new strategies and organizational forms can arise at relatively fast, local levels and later scale through selection and diffusion. In finance, analogous processes include new market-making technologies, new risk-transfer

instruments, alternative trading venues, fintech intermediaries, and organizational responses to regulation. Such innovation can increase adaptive capacity by adding new sources of risk bearing or information, but it can also create new forms of common exposure and model dependence.

This extension preserves an important insight of the original manuscript: resilience is not synonymous with returning to the old configuration. After severe stress, intermediation may migrate toward new institutions, contracts, or technologies. An empirical measure of resilience should therefore distinguish restoration of financial functions from restoration of the identical institutional network.

6.3 Polycentric governance and regulatory architecture

Financial systems are governed by overlapping authorities, private infrastructures, contractual standards, and market conventions. This resembles the polycentric governance logic associated with Ostrom and Janssen (2004): multiple centers of decision making operate at different scales and possess different information and instruments. In the financial setting, central banks, prudential regulators, securities regulators, CCPs, exchanges, standard setters, and private risk managers can all alter the constraints faced by agents.

A complex adaptive perspective cautions against assuming that more centralized control is always superior. Centralization may improve coordination and information in some settings while concentrating operational or liquidity dependencies in others. The appropriate question is which allocation of monitoring, buffers, discretion, and intervention preserves essential system functions across a wide range of shocks. The model can therefore compare regulatory architectures rather than simply compare a regulated and unregulated state.

6.4 Sustainability as a higher-level extension

The financial system is embedded in a broader socioeconomic and ecological environment. The original research agenda emphasized this nesting and the different speeds at which economic, social, and environmental variables adjust. That intuition remains valuable, but it is best treated as a higher-level extension after the financial mechanism has been made operational. Financial institutions transmit environmental and technological shocks into asset prices, credit conditions, insurance availability, and investment, while financial engineering can alter who bears those risks and when they become binding. The multilayer architecture developed here is therefore designed to connect outward to real-economy, social, or ecological networks without requiring the first model to represent them in full detail.

7. Discussion

7.1 The micro-macro wedge in financial engineering

The principal theoretical implication is a micro-macro wedge. Financial engineering is typically designed and evaluated at the contract or portfolio level, but the systemic effect depends on the equilibrium of risk transfer, financing, and adaptive response. A put option can reduce a fund's downside exposure while

increasing a dealer's hedging demand. An interest-rate hedge can stabilize cash flows while creating variation-margin needs. Insurance can absorb idiosyncratic losses while concentrating exposure in reinsurers. Central clearing can reduce bilateral counterparty chains while increasing dependence on a small set of infrastructures. None of these mechanisms implies that financial engineering is inherently destabilizing. They imply that its resilience contribution is conditional and measurable only at the network level.

This point also clarifies how the framework differs from a simple critique of financial innovation. The objective is not to argue for less risk transfer. On the contrary, a system without mechanisms for sharing risk would be fragile to many shocks. The objective is to identify designs that distribute risk without synchronizing liquidity needs, concentrating tail exposure, or creating hidden feedback loops. The central policy and engineering problem becomes one of architecture: how to preserve diversification benefits while limiting endogenous amplification.

7.2 Relation to the EMH and equilibrium modeling

The framework is complementary to rather than a replacement for equilibrium analysis. Equilibrium models remain powerful when the research question concerns pricing under stable institutions and well-characterized constraints. The present approach becomes most useful when the constraints themselves move with prices, when agent composition changes, when networks rewire, or when the system crosses thresholds that make local approximations unreliable. Lo and Zhang's (2024) adaptive framework is useful precisely because it avoids a false dichotomy between efficient and behavioral markets. Likewise, Dou et al. (2023) show that contemporary macrofinance has already moved toward nonlinear global solution methods when local linearization is insufficient.

The model therefore treats EMH-like informational efficiency as a possible emergent regime rather than defining complexity by the failure of efficiency. A market can be informationally efficient in a narrow sense and still be systemically fragile because leverage, collateral, or common exposures create nonlinear responses to shocks. Conversely, temporary predictability need not imply imminent systemic instability. Separating informational efficiency from systemic resilience is therefore essential to the framework.

7.3 Implications for regulation and risk management

For risk managers, the framework suggests supplementing position-level hedging analysis with measures of contingent liquidity and crowding. Stress tests should ask not only how the portfolio value changes under a shock but also which margin calls, collateral substitutions, and common hedging trades the shock triggers. For regulators, the framework suggests that gross and net exposures, liquidity capacity, and network concentration should be analyzed jointly. A low net exposure can coexist with large gross flows and operational demands; a well-collateralized position can still be a source of liquidity stress.

The FSB's margin and collateral recommendations illustrate this logic in practice: collateral protects against counterparty loss, yet widespread margin calls can amplify liquidity demand in a stressed market. The appropriate response is therefore not to abandon margining but to design liquidity preparedness, stress testing, collateral arrangements, and buffers that recognize system-wide synchronization. Similar reasoning applies to central clearing, capital regulation, and circuit breakers. Their effects depend on state variables and interactions, which is why the model treats regulatory mechanisms as parameters of the adaptive system rather than as external fixes.

7.4 Limitations

Several limitations should be explicit. First, detailed bilateral derivatives and funding data are often confidential, so public empirical work may require network inference or sector-level aggregation. Second, agent-based models are sensitive to behavioral specification; reproducing stylized facts does not establish uniqueness of the underlying mechanism. Third, institutional rules are jurisdiction specific and evolve over time, so calibration can become stale. Fourth, complexity indicators can generate false positives and should not be presented as deterministic crash forecasts. Fifth, a multilayer model faces a persistent trade-off between institutional realism and interpretability.

These limitations motivate a modular strategy. Each additional layer should be added only when it answers a specific research question and produces a testable implication. The framework's value lies in making the causal architecture explicit - beliefs, constraints, contracts, prices, and networks - so that mechanisms can be turned on, turned off, and compared. The goal is explanatory and experimental discipline rather than maximal complexity.

8. Conclusion

This paper develops a theoretical framework in which the financial system is treated as a complex adaptive risk-sharing network. Heterogeneous agents update beliefs and strategies, manage leverage and liquidity, and enter contracts that transfer risk across a multilayer network. Prices and volatility feed back into balance sheets and collateral; balance-sheet responses feed back into prices; and the network itself can change as agents substitute counterparties, funding sources, and risk-management strategies. Systemic outcomes therefore arise from co-evolution rather than from the aggregation of independent decisions.

The framework repositions financial engineering as an endogenous component of financial-system architecture. Hedging, insurance, derivatives, clearing, and collateralization can improve shock absorption by reallocating losses toward agents with greater risk-bearing capacity. The same mechanisms can also create liquidity spikes, concentrated dependencies, and correlated adjustments. The central research question is accordingly conditional: under what combinations of diversity, connectivity, leverage, liquidity, contract design, and adaptation does risk sharing produce resilience rather than amplification?

This formulation creates a tractable bridge among adaptive markets, heterogeneous-agent finance, agent-based modeling, financial networks, nonlinear macrofinance, and resilience theory. It yields falsifiable propositions, a nested identification strategy, and a disciplined role for complexity measures alongside conventional systemic-risk metrics. Sustainability, climate risk, entrepreneurship, and polycentric governance remain important, but they enter as applications of a financial mechanism that is first made explicit and testable.

The framework provides a concrete criterion for evaluating financial engineering at the system level: compare the reduction in institution-level exposure with the induced changes in liquidity demand, concentration, cascade loss, and recovery. This criterion makes the micro-macro wedge empirically testable and permits alternative contract and regulatory designs to be evaluated within a common adaptive-network architecture.

Declarations

Author Contribution

Rossitsa Yalamova was solely responsible for the conceptualization of the study, development of the theoretical framework and formal model, literature review, methodology, formulation of the theoretical propositions, development of the empirical and computational research design, interpretation of the theoretical implications, preparation of figures and tables, and writing, review, and editing of the manuscript. The author read and approved the final manuscript.

Data availability.

No new empirical data were created or analyzed in this theoretical study.

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Figures

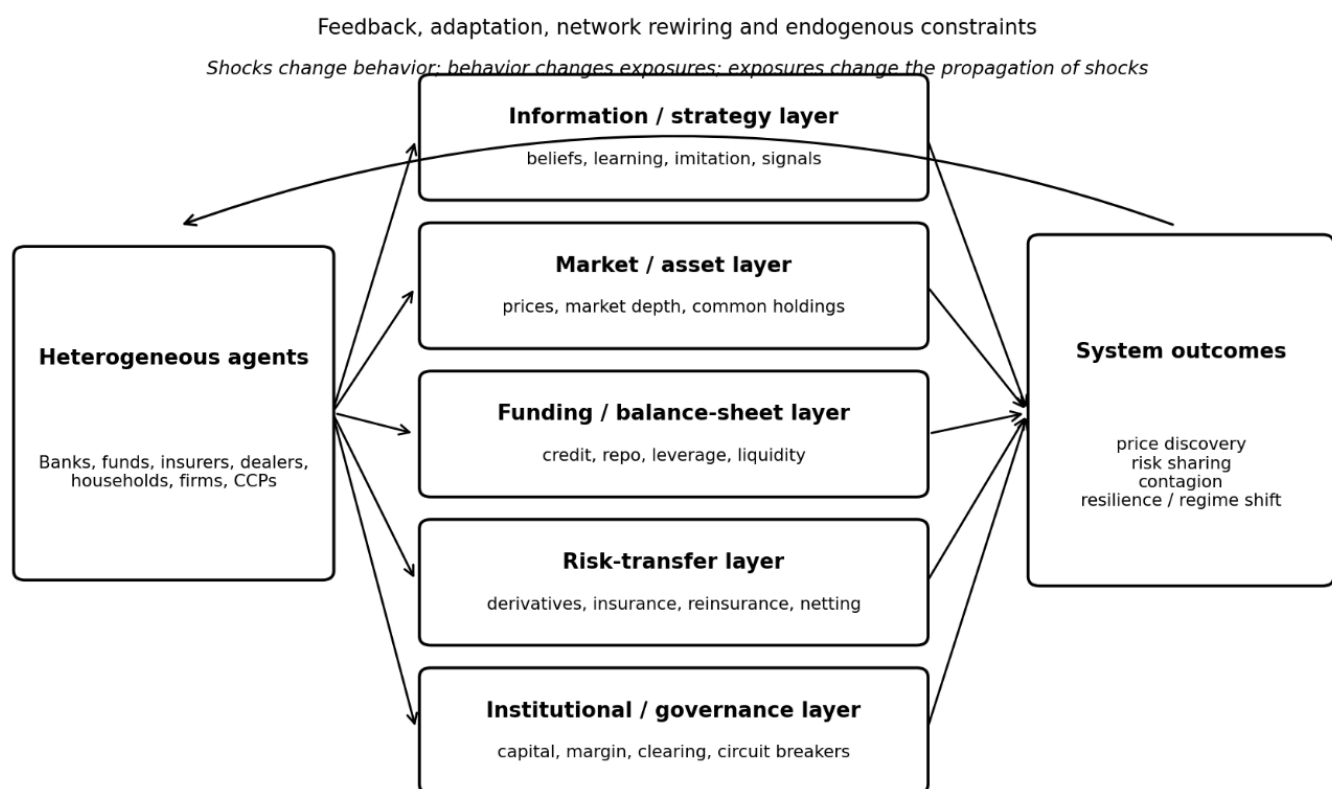


Figure 1

Financial system as a multilayer complex adaptive risk-sharing network. The key object is the feedback between heterogeneous agents, contractual/network layers, and system outcomes.

Supplementary Files

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