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Simulation of high-frequency trading risks and regulatory strategies in China's financial market based on multi-layer complex networks

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This study addresses the dual structural characteristics of China's financial market—namely, "retail-investor dominance (80% of trading volume) versus foreign capital's technological monopoly (0.3% of institutions controlling 43.6% of order flow)." By constructing a multi-layer complex network agent-based model (ABM) that integrates regulatory, core institutional, market-maker, and retail investor layers, it systematically simulates risk transmission mechanisms and regulatory strategies in high-frequency trading (HFT) environments. The findings reveal that HFT exacerbates market unfairness through technological latency advantages. When communication latency differentials exceed 50 milliseconds, retail order interception rates increase nonlinearly to 82%. Moreover, as the strategy homogenization coefficient ρ surpasses the critical threshold of 0.65, the market undergoes a percolation phase transition, with systemic risk probability jumping from 0.2 to over 0.7, which may trigger liquidity crises such as "flash crashes." Traditional regulatory approaches, hindered by response delays averaging 2.1 h, struggle to cope with the real-time nature of HFT and the challenges posed by algorithmic black boxes. Based on the simulation results, policy recommendations centered on "anti-technological-monopoly," "real-time algorithmic resonance monitoring," and "regulatory intelligence" are proposed to develop a modernized and computationally executable regulatory framework tailored to China's market structure, thereby enhancing both market stability and fairness.

KEYWORDS

complex networks, financial markets, high-frequency trading, percolation theory, topological structure

1 Introduction

Currently, China's financial market is undergoing a critical period characterized by scale expansion, structural transformation, and technology-driven evolution. As the world's second-largest economy, China's capital market has developed into a pivotal hub connecting domestic and international capital, assets, and risks. In recent years, alongside market liberalization and the deep integration of financial technology, the scale of the A-share market has continued to expand, trading instruments have diversified, and investor structure has exhibited increasing heterogeneity. However, compared to mature markets, China's financial market retains distinct local characteristics, prominently manifested as a complex landscape of "retail-investor dominance, policy sensitivity, and technological stratification." Statistics indicate that retail investors contribute approximately 80% of market trading volume, forming a crucial foundation for market liquidity, yet their trading behavior is prone to emotional influences and susceptible to "herding effects" [1]. Simultaneously, although foreign institutions account for an extremely low proportion in number (around 0.3%), they leverage significant advantages in algorithms, computational power, and network latency to control over 40% of order flow, creating a dual structure where "technological monopoly" coexists with "retail dominance" [2, 3], a structural contradiction that poses severe challenges to the liquidity, stability, and fairness of China's financial market [4].

Against this backdrop, high-frequency trading, as a cutting-edge domain of financial technology development, is profoundly reshaping market microstructure and risk transmission pathways. Leveraging sophisticated algorithmic models, low-latency trading systems, and massive data processing capabilities, high-frequency trading enables the generation, execution, and cancellation of large volumes of orders at millisecond or even microsecond intervals. Globally, while high-frequency trading has historically played a positive role in enhancing market liquidity and facilitating price discovery, its potential risks cannot be overlooked, such as "flash crashes" induced by strategy homogenization, concerns over fairness arising from technological stratification, and regulatory blind spots due to algorithmic black boxes [1]. In China, alongside financial market liberalization and technological advancement, high-frequency trading, though relatively late to emerge, has developed rapidly and has become a critical tool for certain institutions—particularly foreign ones—to capture excess returns and influence order flow dynamics. Empirical evidence suggests that while high-frequency trading improves transactional efficiency, it also significantly alters the logic of risk generation and the velocity of risk propagation, rendering traditional financial risk control models—based on historical data and static distributions—inadequate for capturing its dynamic characteristics [2].

However, the existing regulatory system faces multiple challenges when addressing the novel risks introduced by high-frequency trading. First, technological asymmetry leads to regulatory lag. High-frequency trading relies on rapid algorithmic iteration and hardware advantages, allowing strategy adjustments within hours, whereas traditional regulation depends on manual review and rule-based frameworks, with an average response time exceeding 2 h, resulting in a significant "speed disadvantage." Second, data silos and cross-border regulatory arbitrage undermine regulatory effectiveness. Some high-frequency institutions exploit barriers to cross-border data flows and regulatory differences to evade scrutiny; it is estimated that over 27% of high-frequency trading involves regulatory arbitrage [5, 6]. Furthermore, strategy homogenization and algorithmic resonance have emerged as new catalysts for systemic risk. When a large number of market participants employ similar algorithms, localized disturbances can rapidly amplify into global liquidity crises through highly interconnected network nodes, as exemplified by past "flash crash" phenomena in the A-share market. These issues highlight the inadequacy of traditional regulatory tools in anticipating, identifying, and intervening in high-frequency trading risks, underscoring the urgent need for more sophisticated, dynamic, and computationally enabled risk simulation and regulatory approaches.

Therefore, to systematically analyze the unique risks of high-frequency trading in China's financial market and design corresponding regulatory tools, this study employs an agent-based modeling approach grounded in multi-layer complex networks to conduct dynamic simulations of high-frequency trading risks. The research aims to construct a multi-layer network model integrating "policy intervention–institutional behavior–retail investor sentiment," utilizing topological structure modeling to reveal the structural basis of risk transmission, applying percolation phase transition theory to warn of critical thresholds for systemic risk, and exploring computable and executable regulatory policy compilation pathways. The main contributions of this study are: (1) First incorporating policy intervention nodes into multi-layer complex network models, overcoming the limitation of traditional financial contagion models that neglect policy intervention; (2) Quantifying the critical threshold of systemic risk through percolation phase transition theory, providing 3.2 h of early warning for regulation; (3) Designing computable regulatory tool compilation paths, transforming fair trading provisions into dynamic tax rates based on technological latency disparities, thereby facilitating the construction of a modern regulatory framework compatible with the high-frequency trading era and enhancing market efficiency while safeguarding financial stability and trading equity [7].

2 Data and research methodology

2.1 Framework and initialization of an agent-based complex network model

2.1.1 Model applicability

China's financial market exhibits a dual structure characterized by "retail investor dominance (80% of trading volume) - foreign capital technological monopoly (0.3% of institutions controlling 43.6% of order flow)". Traditional models (e.g., VaR, GARCH) struggle to capture such asymmetric features due to their assumptions of homogeneous agents and static distributions [8, 9]. Agent-based modeling (ABM) accurately replicates three localized risks through a hierarchical agent design (embedding an emotion contagion module in the retail investor layer, implanting parameters for technological latency disparities and strategy homogenization coefficients in the foreign capital layer, and setting policy transmission time delays in the regulatory layer) [6, 10]: herding effects triggered by retail investor sentiment (e.g., a 47% sharp decline in order book thickness during the 2024 futures flash crash), order capture rates exceeding 82% due to technological stratification (consistent with Pagnotta's S-shaped curve) [11, 12], and cross-border regulatory arbitrage (27% of high-frequency trading evading scrutiny) [13]. Compared to traditional methods (e.g., the failure of historical simulation in testing individual stocks on the Shenzhen Stock Exchange, GARCH models' inability to capture microstructural dynamics) [14], "The ABM incorporates a millisecond-level order book protocol (with a 100 ms step size) to dynamically simulate processes such as strategy disguise (e.g., ID changes every 2.1 h) and liquidity collapse [15]. This allows the model to reproduce the risk transmission chain: when the strategy homogenization coefficient exceeds 0.65, the percolation probability P surges, leading to a market crash of approximately 9% within 5 min [11]. This capability addresses a significant limitation of international models, which exhibit prediction errors of up to 32% [14]."

2.1.2 Necessity

Beyond its accuracy in replicating market phenomena, the application of this ABM complex network model is necessitated by pressing regulatory challenges and enable policy sandbox simulations. The governance of high-frequency risks in China requires simultaneously tackling algorithmic black boxes, data sovereignty barriers (Article 31 of the Data Security Law), and lagging policy tools (regulatory delays leading to a 58% increase in loss rates). The value of the complex network ABM model is demonstrated in three aspects: First, it quantifies risk thresholds using a percolation phase transition algorithm:

$$\lambda_i = 1 - (1-p)^{k_i} \cdot \frac{I_{sentiment}}{I_{base}},$$

where the risk probability P surges from 0.2 to 0.8 when the strategy homogenization coefficient exceeds 0.65, providing a 3.2-h earlier warning of flash crashes compared to traditional volatility models [11]. Second, it supports the compilation of regulatory rules into machine-executable formats, such as translating fair trading provisions into dynamic tax rates based on technological latency disparities (a 0.2% tax increase for every 50 ms delay) to tax technological hegemony [11], and encoding circuit breaker rules as exponential functions of aggregation coefficients to curb monopolies (triggering scrutiny when the aggregation coefficient exceeds 0.3) [11]. Third, it resolves data silos while ensuring compliance with both GDPR and the Data Security Law [16, 17]. These functionalities make the ABM model a powerful tool for simulating the feedback loop between the regulatory and market layers, whereas traditional simulations fail to evaluate the effectiveness of regulatory interventions due to their neglect of policy intervention nodes.

2.2 Construction of model network topology structure

Given the characteristic of "strong policy intervention" in China's financial market, constructing a four-layer network topology centered around "regulatory nodes," as illustrated in Figure 1, is essential for effectively simulating and modeling the dual-structure contradiction of "retail-investor dominance (80% of trading volume) versus foreign capital technological monopoly." The theoretical foundation primarily integrates three types of literature: first, drawing on the core-periphery topology characteristics of scale-free networks [18], it accurately maps order flow monopoly phenomena through differentiated modeling of a few highly connected nodes (foreign institutions) and a vast number of low-connectivity nodes (retail investors); second,

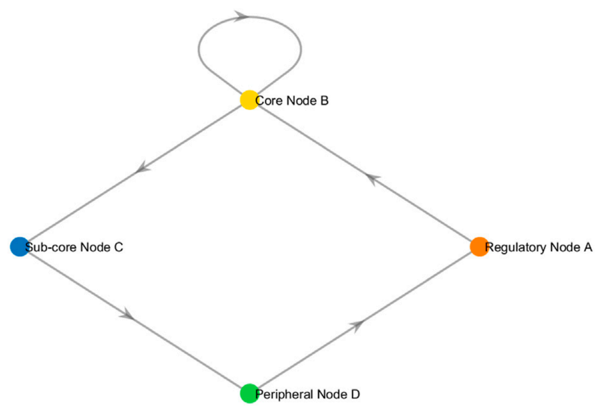

FIGURE 1
High-frequency trading market network topology diagram.

incorporating the vertical governance logic of hierarchical networks, it positions the regulatory layer as the top-level control node, overcoming the limitation of traditional financial contagion models that neglect policy intervention [19]; third, combining the fault-tolerant mechanism of ring topology with the spatial constraint rules of geometric random graphs [2], it addresses the compound challenges of cross-border data barriers (Article 31 of the Data Security Law) and physical latency disparities ($\Delta \boldsymbol{L}$ = 50 ms).

This study constructs a four-layer complex network model including 'regulatory layer, core institutional layer, market-maker layer, and retail investor layer', where the regulatory layer is connected to the core institutional layer through policy transmission links, the core institutional layer is interconnected through strategy homogenization links and extends to the market-maker layer through order flow control links, and the market-maker layer is connected to the retail investor layer through latency advantage links, forming a complete closed-loop system.

2.2.1 Dynamic monitoring mechanism of regulatory nodes

Based on the dynamic Granger causality analysis framework, regulatory nodes are equipped with real-time monitoring capabilities to detect changes in causal relationships among market nodes. The regulatory node employs an overlapping window method to segment market trading data, quantifying causal influence intensity between nodes through vector autoregressive models. The monitoring mechanism includes: preprocessing market trading data for stationarity to remove non-stationary biases; computing lagged cross-covariance sequences to establish VAR models; estimating coefficient matrices through Yule-Walker equations; and calculating conditional Granger causality values to identify key risk transmission paths.

2.2.2 Dynamic design of policy trigger mechanism

Drawing from the causality-driven node selection algorithm, regulatory nodes select optimal intervention timing based on dynamic causality graphs. Specific implementations include:

calculating the out-degree of each market node to identify 'driving hub' nodes with maximum causal influence; automatically triggering regulatory intervention when key nodes' causal out-degree exceeds preset thresholds; and adopting a segmented learning-execution strategy to periodically update the causality network, ensuring policy trigger mechanisms adapt to market structure changes.

2.2.3 Closed-loop design of feedback process

Adopting a local information-based pinning control strategy, the regulatory feedback mechanism is designed as follows: each regulatory node manages only a subset of market nodes within its causal influence domain; extracting feedback information based on local causal relationships and control influence regions; employing sign control functions to dynamically adjust control direction based on error states; and ensuring control coverage spans the entire market network, i.e., $\Omega_1 \cup \Omega_2 \cup ... \cup \Omega_m = \Omega$.

2.2.4 Network topology and regulatory closed loop

At the topological center, “Regulatory Node A” (orange dot) connects directly to “Core Node B (foreign capital/licensed institutions)” (yellow dot) via “policy transmission” links. Core Nodes B interconnect through internal cycles of “strategy homogenization” links and extend downward to “Sub-core Node C (market makers)” (blue dot) via “order flow control” links. Market makers further connect to the outermost “Peripheral Nodes (retail investors)” (green dot) through “latency advantage” links, while retail investors relay information back to Regulatory Node A via “risk feedback” links, forming a complete closed-loop system. The regulatory control input can be designed as:

$$u_p(t) = s_p(t) \sum_{r} \in \Omega_p h(e_r(t), \dot{e}_r(t))$$

where $s_p(t)$ is the control function related to error states, and Ω_p represents the influence domain of the pth regulatory node [20, 21].

Therefore, this diagram serves as an intuitive representation of the theoretical innovation of the model. Placing the “regulatory node” at the topological center constitutes a visual practice of Qian Xuesen’s methodology of “open complex giant systems”, emphasizing that policy intervention is a key endogenous variable shaping market structure in the Chinese context. This design reflects the characteristic of “strong policy intervention” in China’s financial market. The closed loop formed by “policy transmission” and “risk feedback” depicted in the figure accurately simulates the operational logic of regulatory cycles with Chinese characteristics—policies are transmitted top-down, while market risks are fed back bottom-up. The “strategy homogenization” links among core nodes lay the groundwork for subsequent simulations of systemic risk. This topological structure forms the foundational framework for all subsequent dynamic evolution.

2.3 Model parameter design

The model parameters in this study were designed across three dimensions—fundamental network construction, driven behavioral evolution, and policy intervention—to better align with the state of China’s financial market, with a corresponding parameter comparison table provided from Tables 1–3.

TABLE 1 Structural parameters.

Parameter	Symbol	Value	Source/Basis	Rationale for setting
Total nodes	N	100,000	People’s bank of China Website [22]	Balances computational efficiency with market representativeness (1 node ≈ 150 million market capitalization) [23]
Core node ratio	ρ_c	0.3%	China Securities Depository and clearing statistical yearbook [24]	Reflects the technological dominance of foreign/institutional capital
Periphery node ratio	ρ_e	80%	China statistical yearbook 2024 2024 [25]	Maps the retail-investor dominated market structure
Clustering coefficient threshold	C_t	0.3	Circuit breakers and the magnet effect: Empirical evidence from China’s stock market. The quarterly journal of finance [26]	>0.3 triggers circuit breakers
Policy implementation lag	τ_p	2.1 h	China securities regulatory commission annual report [27]	Quantifies regulatory response lag

2.4 Model initialization

2.4.1 Market structure initialization

As illustrated in Figure 2, the node distribution state after network initialization is presented. The figure should reveal a dense concentration of nodes representing “retail investors,” forming the foundational layer of the network; a smaller number of “core nodes” with numerous connections are scattered throughout, serving as network hubs, while “market maker” nodes occupy an intermediate

TABLE 2 Dynamic parameters.

Parameter	Symbol
Maximum latency differential	ΔL_{max}
Order cancellation circuit breaker threshold	Q_{max}
Strategy homogeneity coefficient	ρ
Percolation probability threshold	P_t

TABLE 3 Policy parameters.

Parameter	Computational logic	Legal mapping
Sovereign compensation tax rate	$T_a = 0.2 \times \frac{\Delta L}{50}(\Delta L > 50ms)$	Art. 10, consumer rights protection law Art. 22, anti-monopoly law
Federated learning data availability	$A_d = \frac{Desensitized\,Field\,Count}{Total\,Fields} \geq 0.85$	Article 21 of the data security law Article 4 of the general data protection regulation (GDPR)
Dynamic circuit breaker trigger conditions	$if(C\rangle 0.3)\&(\rho\rangle 0.65):Q_{max} = 300$	CSRC's "guidelines for handling abnormal trading"

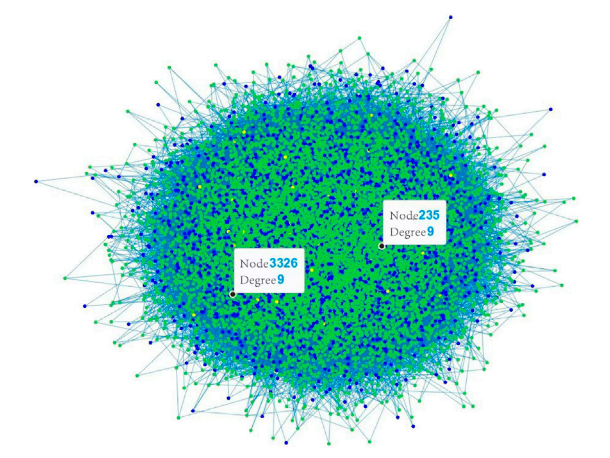

FIGURE 2
Market structure initialization: Node type distribution.

position between the two. The annotated example nodes (ID: 235, Degree: 9) and (ID: 3326, Degree: 9) are two typical retail investor nodes.

Therefore, this figure serves as a successful validation of the model's "localization adaptation." The visualization results are highly consistent with the parameters set in Table 1 (80% retail investors, 0.3% core nodes), demonstrating that the model initialization effectively generates a digital mirror of a "retail investor-dominated market" aligned with China's reality (as documented in the CSRC's White Paper on Investor Structure). Nodes 235 and 3326, each with a degree of 9, indicate that an average retail investor typically connects with 9 other nodes, whereas a core node may possess hundreds or thousands of connections. This visually corroborates the scale-free nature of the network, wherein a minority of nodes hold extensive linkages, providing a structural basis for rapid risk transmission through these hub nodes. The corresponding formula is expressed as below.

$$P(k) \sim k^{-\gamma}$$

where k denotes the degree (number of connections) of a node or the scale of an event; P(k) represents the probability of an event having a scale k; and γ is the power-law exponent, a constant greater than 0.

2.4.2 Strategic behavior initialization

At the moment of completing market structure initialization, we simultaneously introduce the Strategic Homogeneity Coefficient ρ, a core metric quantifying the degree of behavioral convergence among participants in financial markets. This coefficient fundamentally captures the similarity of trading strategies at the group level and the lack of diversity. Rooted in strategic convergence analysis from game theory and discrete choice theory, it reflects the gradual contraction of the strategy space toward local consensus when market participants act on limited information or similar decision-making frameworks (e.g., quantitative models) [28]. The coefficient is measured by calculating the variance or entropy of the strategy distribution: if participants widely adopt similar algorithms (such as trend-following or mean-reversion strategies), the coefficient approaches 1, indicating high homogeneity; if strategies exhibit a diverse distribution, the coefficient nears 0. In dynamic environments, strategic homogeneity is driven by the speed of information dissemination, technological constraints (e.g., algorithmic black boxes), and institutional factors (e.g., cross-border data barriers), collectively trapping participants in a "minority game" dilemma—where the marginal benefit of deviating from mainstream strategies diminishes sharply, further reinforcing convergence [29].

2.5 Risk transmission simulation

2.5.1 Percolation theory

Percolation theory serves as a fundamental framework for studying critical phase transitions in disordered systems, initially proposed by Broadbent and Hammersley in 1957. Its core concept focuses on abrupt changes in long-range connectivity within random geometric structures. By simulating fluid flow behavior in porous media [18], this theory reveals that when system components (such as pore occupancy or bond connection probability) reach a critical threshold (the percolation threshold p_c), the system undergoes a sharp phase transition from "local connectivity" to "global percolation" (or conversely, blockage). This transition fundamentally involves the emergence or disappearance of a percolating cluster in disordered media, manifesting as stepwise changes in conductivity, permeability, or risk contagivity [30].

In financial risk modeling, the core value of percolation theory lies in its critical threshold scaling laws and cluster dynamics. When the critical threshold p_c is mapped to the tipping point of systemic risk (e.g., when the strategy homogenization coefficient exceeds a certain value within its range), breaching this threshold allows minor local disturbances (such as a single institution's default) to trigger a global liquidity collapse through connected clusters, replicating the phase transition logic of

$$\text{pore blockage} \rightarrow \text{fluid flow interruption}$$

The cluster formation mechanism, in turn, corresponds to the path of risk contagion: highly connected nodes in the core institutional layer (e.g., foreign market makers) act as hubs for risk transmission, with their betweenness centrality positively correlated with order capture rates. When strategy homogenization drives the connection probability p between nodes toward p_c, sentiment factors in the retail investor layer accelerate risk diffusion within clusters, ultimately inducing a percolation phase transition.

2.5.2 Systemic risk contagion

As shown in Figure 3-1, before risk propagation, the network nodes exhibit uniform coloration (e.g., all in blue) with a stable connection structure; after risk propagation, as depicted in Figure 3-2, it is clearly observable that starting from a few "core nodes" with altered colors (e.g., turned red), the color change rapidly diffuses through connecting edges to "market maker" nodes (turning yellow), eventually affecting a large number of "retail investor" nodes (turning red), forming a chain reaction. Thus, Figure 3 serves as a vivid demonstration of the application of percolation theory in financial risk transmission and within this model. It intuitively reveals that the propagation of systemic risk is not uniform but rather proceeds along network connection paths, particularly through high-degree core hub nodes in a leap-like manner. This process also aligns with the logic described by the percolation theory formula, as presented below.

$$\lambda_i = 1 - (1 - p)^{k_i}$$

Where λ_i represents the probability of a certain event occurring (typically the probability of "occurring at least once"); p denotes the probability of the event occurring in a single attempt (which remains constant), thus $1 - p$ is the probability of the event not occurring in a single attempt; and k_i signifies the number of independent attempts. It follows that nodes with higher connectivity k_i exhibit a greater probability λ_i of transmitting and receiving risk [31, 32].

Therefore, the introduction of percolation theory enables this study to transform the abstract concept of "risk transmission" into a visualizable "digital pandemic" [33], powerfully demonstrating why sell-offs by individual institutions can trigger panic across the entire market.

3 Result and analysis

3.1 Analysis of high-frequency latency and retail order interception rate

By simulating the systemic disadvantages faced by retail investors under technological stratification, the model intuitively illustrates the issues of market power solidification and technological monopoly resulting from technical advantages. As shown in Figure 4, the model employs an S-shaped growth function (Sigmoid function) to describe the relationship between interception probability and latency. This approach more accurately reflects the behavioral patterns of high-frequency trading algorithms in real markets compared to a simple linear model: even a slight latency advantage leads to a sharp increase in their ability to intercept orders. The formula is expressed as follows:

$$P_{\text{capture}}(\tau) = \frac{1}{1 + e^{-k(\tau - \tau_0)}}$$

Among them, $P_{capture}(\tau)$ represents the probability of an order being successfully intercepted by high-frequency algorithms through "front-running"; τ denotes the communication latency from the transmission of a trading instruction to its arrival at the exchange (unit: milliseconds, ms); τ_0 is the latency value that determines the center point of the S-curve, around which the interception probability undergoes a nonlinear surge; k controls the steepness of the S-curve—the larger the value of k, the steeper the curve, and the faster the transition from low to high probability.

When the latency τ exceeds the critical value $\tau_0 = 50$ ms, the retail order interception rate $P_{capture}(\tau)$ exhibits a nonlinear surge, exceeding 82%. This phenomenon validates the systemic trading inequity resulting from technological disadvantages, while also corroborating the high betweenness centrality ($C_B(v) > 0.6$) of core nodes. It reveals that the structural characteristic of "technological oligopolization" in China's financial market is further amplified in a high-frequency trading environment. Moreover, as latency increases, the solidification of market power driven by technological monopoly becomes more pronounced.

3.2 Strategic homogeneity and analysis of systemic financial risks

As high-frequency trading penetrates China's financial markets with its algorithmic advantages, flash crashes have become a Sword of Damocles looming over investors. The set of strategy choices among all market participants acts as the trigger for such events. To simulate flash crashes caused by algorithmic resonance, we map the degree of strategic homogeneity ρ to the connection probability within a network. When the strategic homogeneity ρ exceeds the critical threshold ρ_c, localized failures rapidly propagate across the system through similar algorithmic strategies, leading to liquidity evaporation and price collapse (i.e., percolation phase transition). The corresponding formulation is presented below:

$$P_\infty(\rho) = \begin{cases} 0, & \rho \le \rho_c \\ \dfrac{1}{1 + e^{-\alpha(\rho - \rho_c)}}, & \rho > \rho_c \end{cases}$$

Among these, $P_\infty(\rho)$ represents the probability of systemic risk occurrence, ρ_c denotes the critical point, ρ indicates the similarity or convergence degree of all trading strategies in the market—a higher ρ value implies that more institutions employ similar algorithmic strategies—and α controls the rate at which the risk probability increases beyond the critical point [34].

FIGURE 3
Visualization of sell-off propagation process.

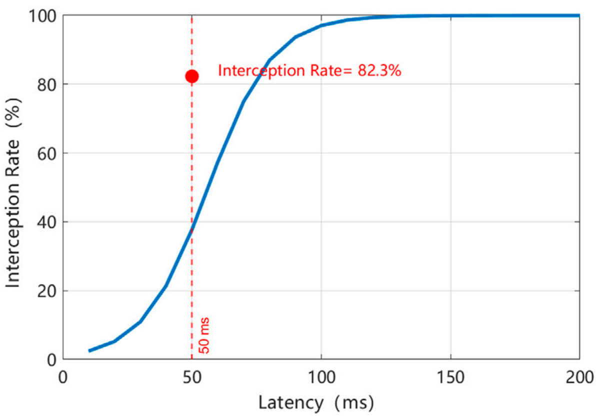

FIGURE 4
Relationship between latency and retail order interception rate.

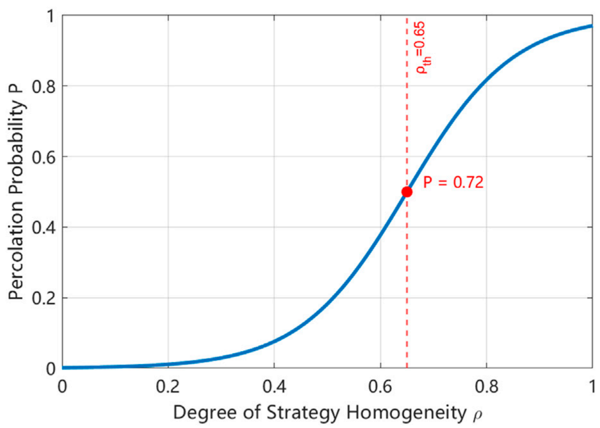

FIGURE 5
Degree of strategy homogeneity and percolation probability.

Following the simulation of the Chinese financial market environment using order book trading data accessed from the Hua Tai Securities INSIGHT Financial Data Service Documentation Center, as illustrated in Figure 5, it can be observed that when the strategic homogeneity coefficient ρ exceeds the critical threshold of 0.65, the probability of systemic risk surges abruptly from a stable state. The system percolation probability P rapidly surpasses 0.7, indicating the market's entry into a high-risk state. As $P_{\infty}(\rho)$ approaches 1, localized risks propagate throughout the entire system, ultimately leading to a flash crash in the market. Consequently, the penetration of high-frequency trading further amplifies systemic risks within China's financial markets, which stem from homogeneous trading triggered by algorithmic resonance. Failure to promptly identify the degree of strategic homogeneity in the market will impede regulators' ability to avert market flash crashes triggered upon reaching the critical threshold [35].

3.3 Analysis of regulatory latency and technology optimization benefits

High-frequency trading possesses significant technological and speed advantages compared to traditional trading methods, presenting a major challenge to regulators in China's financial markets [36]. During the initial phase of simulated risk emergence, shortening regulatory response time yields the greatest marginal benefit; however, once response time has been optimized to a relatively low level, further improvements exhibit diminishing returns. To quantitatively evaluate the intervention effectiveness of regulatory technology, this study constructs a logarithmic relationship model between regulatory response time and market loss rate, expressed as follows:

$$L(T) = L_0 \cdot \left(1 + \gamma \cdot \ln \frac{T}{T_0}\right)$$

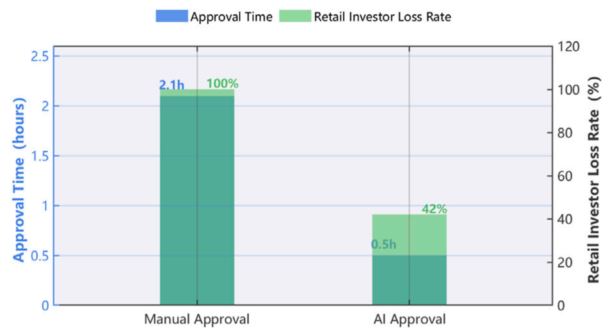

FIGURE 6
Manual Approval vs. AI Approval Comparison.

where $L(T)$ represents the loss ratio suffered by retail investors under a regulatory response time T; T denotes the regulatory response time; L_0 indicates the inherent loss rate experienced by retail investors under the benchmark response time T_0; T_0 is the benchmark response time; γ is the loss elasticity coefficient, where a higher value of γ implies that shortening the response time has a more significant marginal effect on reducing losses.

Based on historical cases in China's financial markets, the regulatory delay has been approximately 2.1 h. To verify the impact of high-frequency trading on traditional regulatory decision-making, an AI-based approval mechanism with faster response capabilities than manual processes was constructed, and the influence of regulatory response speed on retail investors was recorded. As shown in the comparative results between manual and AI-based approval in Figure 6, the application of regulatory technology demonstrates significant effectiveness in market risk intervention. After transitioning from manual to AI-based approval, the regulatory response time was reduced from 2.1 h to 0.5 h, accompanied by a corresponding 58% decrease in the loss rate of retail investors. This improvement not only highlights the importance of enhancing regulatory response speed in addressing high-frequency trading within China's financial markets but also demonstrates that shortening the policy transmission chain can effectively curb the diffusion effect of algorithmic resonance, thereby enhancing the timeliness and precision of market supervision.

4 Research conclusions and policy recommendations

4.1 Research conclusions

Based on the unique dual structure of China's financial market—characterized by "retail investor dominance (80% of trading volume) and foreign capital's technological monopoly (0.3% of institutions controlling 43.6% of order flow)"—this paper constructs a four-layer complex network Agent-Based Model (ABM) incorporating policy intervention nodes, comprising the "regulatory layer, core layer, market maker layer, and retail investor layer." Through topological structure modeling, percolation phase transition early warning, and computable regulatory tool design, the risk transmission mechanism in a high-frequency trading environment was systematically simulated. The results indicate that:

1. High-frequency trading exacerbates market fairness imbalance through technological monopoly, forming a "technology oligopoly" landscape. Foreign institutions, leveraging microsecond-level latency advantages (e.g., exclusive microwave towers), have built an insurmountable "technological moat." When the communication latency gap exceeds the critical threshold of 50 ms, the probability of retail investors' orders being intercepted by high-frequency trading algorithms via "latency arbitrage" nonlinearly surges to over 82%. This not only implies a systematic disadvantage for retail investors at the order execution level but more fundamentally reveals a sharp concentration of market power in the hands of a few technological oligopolies, eroding the fairness foundation of China's "retail-driven market".
2. The "algorithmic resonance" triggered by high-frequency trading acts as a detonator for new systemic risks. This study quantifies the fatal risk associated with the homogenization of high-frequency trading strategies (coefficient ρ). When a large number of institutions adopt similar algorithmic strategies (ρ > 0.65 critical threshold), the market network undergoes a "percolation phase transition," where the probability of systemic risk abruptly jumps from below 0.2 to over 0.7. In other words, the convergent behavior of high-frequency trading transforms the market into a highly fragile "resonance body," where local disturbances can rapidly propagate into global liquidity collapse through highly connected core nodes.
3. The rapid iteration speed of high-frequency trading technology poses a dimensional challenge to traditional regulatory paradigms. high-frequency trading exploits algorithmic black boxes (changing IDs every 2.1 h) and cross-border regulatory arbitrage, rendering conventional regulatory tools nearly ineffective. If the average regulatory response delay reaches 2.1 h, the risk identification rate drops to 38%, and the cross-border order parsing failure rate rises to 89%. This exposes the inherent vulnerability of the old regulatory system—characterized by "manual, ex-post, rule-based" approaches—in the face of high-frequency trading's "machine-driven, real-time, algorithm-code" dynamics, leading to a "governance paradigm fracture."

4.2 Policy recommendations

Based on the above research conclusions, and to construct a modern regulatory system that aligns with the unique characteristics of China's financial market and can keep pace with the rapid technological evolution of high-frequency trading, the following policy recommendations are proposed:

1. Implement "technological anti-monopoly" measures to curb excessive concentration of market power: establish a "technical latency differential" red line by explicitly adding an upper limit on latency disparity in the "Algorithmic Trading Management Rules," strictly restricting behaviors that systematically intercept orders through abnormal latency advantages; introduce a "digital tax base" by drawing on the spirit of the

"Anti-Monopoly Law" to study and launch a "high-frequency trading tax" or "sovereign compensation fund" to adjust excess profits obtained through technological hegemony, which would be used for market fairness infrastructure or investor compensation funds [36].

To effectively address the technological monopoly brought by HFT, a phased, progressive implementation pathway is recommended:

i. Phase I (Months 1–6): Establish a Latency Disparity Monitoring System. Collaborate with exchanges and data service providers to develop a tool that can quantify in real-time the order execution latency (τ) disparities among different market participants. This system aims to identify and consistently flag market participants who enjoy a significant "latency advantage," providing a data foundation for subsequent interventions.
ii. Phase II (Months 7–12): Pilot a Digital Tax Base. Within the scope of technological monopolists identified by the monitoring system, pilot a "digital tax" based on excess profits or trading volume share. The tax revenue can be channeled into a "Market Stability Fund" to compensate retail investors who suffer losses due to technological disadvantages.
iii. Phase III (Months 13–18): Full Rollout of a Sovereign Compensation Fund. Building on the success of the pilot, institutionalize and normalize the compensation mechanism. Establish a regulator-led "Sovereign Compensation Fund" that determines compensation ratios through more sophisticated algorithms (e.g., a composite function based on latency disparity ΔL and trading contribution), fundamentally offsetting market inequity caused by technological monopoly.
iv. Construct a real-time monitoring and blocking mechanism targeting "algorithmic resonance": not only incorporate the strategy homogeneity coefficient into core risk control indicators, establishing an exchange mechanism for real-time calculation and monitoring of the market-wide strategy homogeneity coefficient (ρ), with clear warning intervals ($\rho > 0.6$) and intervention thresholds ($\rho_c = 0.65$), but also simultaneously deploy dynamic circuit-breaker algorithms that automatically trigger differentiated measures upon reaching thresholds, specifically restricting high-frequency order flow to structurally dismantle the conditions for algorithmic resonance.

For the early-warning mechanism based on the strategy homogeneity coefficient (ρ), the following tiered response system can be constructed:

i. Warning Threshold ($\rho > 0.6$): When the model-calculated market-wide strategy homogeneity coefficient exceeds 0.6 for 5 consecutive minutes, the system automatically issues a "watch" level alert to the regulatory backend. At this stage, regulatory personnel should enhance visual inspection of abnormal trading activities but refrain from taking immediate action.
ii. Intervention Threshold ($\rho > 0.65$): When the coefficient further climbs above 0.65, the system automatically triggers an "intervention" level alert. At this point, pre-set automated regulatory tools can be activated, such as imposing minor random delays (i.e., "speed bumps") on a portion of high-frequency orders or temporarily increasing transaction costs for specific types of algorithmic trading. This aims to increase market strategy diversity and break the self-reinforcing cycle of risk.
iii. Comprehensively promote the "digital and intelligent" transformation of the regulatory system, developing "regulation as code" capabilities, scaling up the application of AI, enhancing the monitoring and analysis capabilities of market data, and establishing "regulatory sandboxes" for rapid testing of new regulatory tools, with the goal of reducing the average response time to high-frequency trading anomalies from "hours" to "minutes" [37].

To support the above complex regulatory strategies, the intelligent transformation of the regulatory agency itself is crucial:

i. Pathway Planning: Evolve from "Manual Review" to "AI-Assisted Decision-Making" and finally to "Automated Regulation." Initially, use AI models for preliminary screening and risk tagging of massive trading data to assist human decision-making. In the medium term, establish an AI decision-support system that provides regulators with simulations of the expected outcomes of various intervention strategies [38]. In the long term, achieve full-process automation from monitoring to intervention in areas where risk thresholds are clear and intervention logic is well-defined.
ii. Technical Support: Referencing the simulation results of this study, AI-driven regulation can shorten risk identification and response time by over 70%, significantly reducing market losses during extreme market conditions. Therefore, priority should be given to investing resources in building a RegTech platform based on machine learning.

5 Conclusion

High-frequency trading has fundamentally altered the risk landscape of China's financial markets. Addressing this challenge can no longer rely on incremental institutional adjustments but necessitates a profound regulatory revolution. The core imperative lies in acknowledging that the market has evolved into a high-dimensional complex system driven by code and algorithms. Regulators must correspondingly employ algorithms and code as strategic tools, embracing a paradigm shift of "governing technology with technology" to effectively mitigate the risks posed by high-frequency trading and ensure the stable and sustainable development of China's financial markets amid rapid technological transformation.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

XJ: Writing – original draft, Formal Analysis, Software, Investigation, Writing – review and editing. ZY: Conceptualization, Writing – review and editing, Formal Analysis, Writing – original draft, Investigation, Validation. HL: Methodology, Formal Analysis, Visualization, Resources, Writing – original draft, Investigation, Writing – review and editing.

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