Beyond the "Innovation-Imitation" Paradox:

A Study of Platform Economy Ecosystems and Strategic Evolution Based on Multi-Agent Modeling

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Abstract

This study systematically explores the evolutionary mechanisms of market strategy diversity and resilience in the context of the platform economy by constructing an agent-based interdisciplinary computational model. The research reveals that innovation and imitation behaviors jointly drive the formation of market strategy diversity, but their roles exhibit nonlinear and dynamically complementary characteristics: imitation not only serves as a channel for strategy diffusion but also generates new strategies through recombination. Market resilience (measured by the post-shock recovery speed λ) is not determined by a single factor, but rather depends on the dynamic balance between the innovation rate and the imitation rate. The study shows that there exists a universal "optimal resilience range" (innovation rate $\mu \approx$ 0.6 0.7, imitation rate $\iota \approx$ 0.2-0.4), which corresponds to a moderate level of strategy diversity, enabling the market to both respond quickly to shocks and recover robustly. This reveals a profound insight: moderate strategy homogenization, rather than maximizing diversity, is key to building collective market adaptability and coordination efficiency. The research conclusions provide an integrated theoretical framework and empirical evidence for understanding market competition, platform governance, and resilience building in the digital age.

Key words: Agent-Based Modeling; Platform Economy; Strategy Diversity; Resilience; Innovation-Imitation Dynamics; Market Evolution

Contents

1. Introduction

1.1. Opening phenomenon

In the platform economy and digital age, the exponential acceleration of technological iteration has blurred the boundaries between innovation and imitation, creating a dynamic cycle of rapid interaction and mutual reinforcement. This process has given rise to several significant phenomena that are profoundly reshaping market competition, industrial organization, and the social innovation ecosystem.

Firstly, the "fast-following" strategy has become the dominant competitive model for platform companies, leading to a market characterized by both "winner-take-all" dynamics and rapid iteration. [WM Fruin, SA Rodan] The low marginal cost of digital products, network effects, and data feedback loops mean that once a business model or technological application shows market potential, it is quickly imitated and optimized by competitors. This imitation storm in platform competition phenomenon has causes the market to transform from a blue ocean to a red ocean in a very short time. For example, in ride-hailing, short video, and community group buying sectors, the innovations of early movers often lead to a large number of similar services within months, ultimately resulting in a few dominant platforms through capital subsidies, algorithm optimization, or ecosystem integration. While this intense imitative competition accelerates service adoption and experience optimization, it may also stifle original exploration, leading to resources being skewed towards short-term iteration rather than long-term fundamental innovation.

Secondly, the open-source ecosystem and modular architecture have shifted the innovation process from closed to open, and imitation behavior has evolved from simple "copying" to "recombinative innovation." [M Gu, E Tse] In the digital technology stack, open-source code repositories (such as GitHub), standardized APIs, and cloud service infrastructure have significantly lowered the barriers to innovation. Developers can quickly recombine existing modules to achieve secondary innovation by standing on the shoulders of giants. This means that imitation is no longer simply a matter of copying products, but rather a creative integration and improvement of core components. For example, many artificial intelligence applications are developed based on open-source frameworks such as TensorFlow and PyTorch. Companies can quickly launch differentiated services by fine-tuning models or combining them with specific scenario data.

Furthermore, data-driven learning through imitation has become a core mechanism in building platform capabilities [V Fast, D Schnurr, M Wohlfarth], with the feedback loop between algorithms and data continuously reinforcing competitive dynamics. Platform companies can quickly identify market trends and effective strategies of competitors by collecting user behavior data in real time, and then precisely imitate and surpass them through A/B testing and algorithm optimization. This data-driven agile response capability shortens the innovation and imitation cycle from several years in traditional industries to weeks or even days.

In summary, the rapid cycle of innovation and imitation in the platform economy and the digital age, while promoting technological diffusion and improving consumer welfare, has also given rise to multiple challenges such as market polarization and monopolies. In the future, it will be necessary to seek a dynamic balance between encouraging open innovation and protecting original incentives, and between promoting data flow and maintaining fair competition, in order to build a sustainable digital innovation ecosystem.

1.2. Research Questions

Based on my practical experience as an operations manager in a hospitality company and my deep involvement in the company's brand strategy, I have observed that in the wave of digitalization and the platform economy, industry competition exhibits the characteristics of a high-speed cycle of innovation and imitation, as mentioned in section 1.1. How this dynamic process shapes the diversity of market behavior and ultimately affects the entire industry's resilience to shocks is a question that urgently needs to be clarified in practice. As an independent researcher, I aim to transform my past micro-level operational observations into verifiable macro-level strategic propositions using quantitative methods. The core research questions of this study are as follows:

First, I aim to explore how the frequency of innovation and imitation in dynamic environments jointly shapes the diversity of market strategies. In the hospitality industry, a successful marketing strategy or cross-industry collaboration model is often imitated by competitors in different forms within a short period. Does this innovation-imitation cycle promote strategic diversification, or does it instead lead to strategic convergence? I hypothesize that moderate imitation may increase short-term diversity through the diffusion and improvement of basic innovations; however, excessively high imitation frequency, combined with the "winner-take-all" platform logic, may squeeze out niche markets, leading to a decline in long-term diversity. This study will attempt to quantify this non-linear relationship.

Secondly, I am dedicated to examining whether market strategy diversity constitutes a key micro-foundation for industry resilience and analyzing its mechanisms.

I observed that under the impact of the COVID-19 pandemic, brands with more diversified strategies (e.g., those simultaneously offering high-end resorts, business hotels, long-term apartments, and cross-industry collaborations) often exhibited faster recovery and stronger adaptability. This study hypothesizes that strategic diversity enhances resilience through two channels: first, the risk diversification[D Jayeola, Z Ismail, SF Sufahani], where diversified strategies, like an investment portfolio, have different sensitivities to shocks, thus preventing systemic collapse; and second, the innovation seed bank, where in a crisis, certain unconventional or marginalized strategies may happen to be well-suited to the new environment, providing alternative templates for the overall evolution of the industry. Based on the market model established in the previous question, I will use a controlled variable method to examine the relationship between strategic diversity and the recovery speed of key market indicators after a shock.

Finally, this study aims to derive insights from both the brand operation (micro) and social system (macro) levels. At the micro level, the research findings are intended to provide decision-making guidance for hospitality brand operators: in today's fast paced "innovation-imitation" competitive market, how can they accurately position themselves, achieve steady and sustainable development, and contribute to the long-term healthy development of the entire industry? At the macro level, this study attempts to view the market as a complex system, and its conclusions can be discussed in conjunction with sociological theories of resilient communities and institutional diversity. A healthy socio-economic ecosystem may not depend on the unlimited replication of a few optimal strategies, but rather requires cultivating and maintaining sufficient diversity to cope with unknown future shocks. This may provide policymakers with empirical evidence from quantitative analysis on how to regulate the platform economy and encourage healthy competition rather than stifle diversity.

In summary, this study is rooted in my industry practice and attempts to connect multiple theoretical frameworks. The answers to the questions explored above are not only relevant to the specific operations of a particular brand, but also to our general understanding of a healthy market ecosystem in the digital economy era.

2. Interdisciplinary Theoretical Framework

2.1. Economics - Power Law Distribution of Market Size

In constructing the theoretical framework for this study, I view the market as a complex evolutionary system and introduce the power-law distribution as a core mathematical tool to describe market structure and scale. Numerous empirical studies have shown that many socioeconomic systems, from firm size and urban population to website traffic, follow a power-law distribution, meaning that a small number of individuals in the system account for the vast majority of the scale or resources. [P Soriano-Hernández, M del Castillo-Mussot] Its probability density function can be expressed as $P \sim x^{(-\gamma)}$, where the exponent γ (Gamma value) is a key parameter determining the distribution shape, profoundly characterizing market concentration and inequality. Therefore, the computer modeling used in this study employs a power-law distribution to simulate the initial structure of market prices, and the parameter γ controls the skewness of the distribution. A higher γ value indicates that market weight is more concentrated towards lower-priced goods, which can be mapped to the real-world scenario where consumers reduce spending on high-end non-essential items and downgrade their consumption structure during economic downturns or periods of increased uncertainty. Furthermore, the "gamma shock" (temporarily increasing the γ value) in the system resilience experiment section of this study aims to simulate the impact of such macroeconomic negative shocks on the underlying market structure, and then observe the market strategy evolution and system resilience driven by different innovation and imitation rates under this structural change.

2.2. Biology – Models of Biological Evolution

In designing brand clusters within the market and understanding the relationship between these brands and the market environment, I have drawn upon the core paradigm of evolutionary biology, viewing the market as a complex ecosystem evolving under constant selective pressure. From this perspective, brands and their strategies are considered "phenotypes" within the ecosystem, and their generation, variation, and selection processes exhibit profound isomorphism with biological evolution. Specifically, the two core evolutionary mechanisms of gene mutation and horizontal gene transfer provide a powerful analogy for understanding the dynamics of innovation and imitation in the market.

First, gene mutation corresponds to the endogenous, accidental, and often gradual process of strategic innovation within companies. In biology, gene mutation is a random error that occurs during the replication of genetic material, providing the raw material for natural selection. By analogy to the market, new strategies generated by brands through independent research and development, trial and error, or the exploitation of local knowledge can be considered a "strategic mutation." This mutation is the fundamental source of market diversity, and its frequency and intensity affect the richness of the strategic gene pool.

Second, horizontal gene transfer precisely parallels the process of strategic imitation, learning, and cross-industry borrowing in the market. In the microbial world, horizontal gene transfer allows organisms to bypass vertical inheritance and directly acquire gene fragments from the environment or other species, thereby rapidly acquiring new traits. In the market ecosystem, companies directly transplant successful strategic modules into their own organizations through reverse engineering, talent mobility, strategic alliances, open-source technologies, or observation and learning from industry best practices—this is horizontal strategic transfer. The rise of the platform economy has greatly facilitated this process, allowing business models, algorithmic models, and user experience designs to spread between organizations at an unprecedented rate. While this mechanism can quickly improve the average fitness of the industry, it may also lead to strategic convergence, weakening the overall diversity of the system.

Ultimately, whether new strategies are generated through mutation or transfer, they must be tested by market selective pressure, and their success or failure depends on their fitness. In evolutionary biology, fitness is a measure of an individual's genotype's relative contribution to the gene pool of future generations. In this research framework, the fitness of a strategy is simplified to the degree of match between its pricing and overall product quality in a given market environment (defined by power-law distribution structure, competitive intensity, etc.) – this consideration is based on my previous operational experience: although customers subconsciously prefer high-quality products at low prices, for most brands, only when the value of the product offered roughly equals its price can the brand truly survive stably in the long term.

However, the market ecosystem is not static. When the market encounters major external shocks (such as economic crises, technological disruptions, or pandemics), selective pressure and environmental preference may change dramatically. Previously optimized strategies for brand marketing in a stable environment (such as high standardization and efficiency-driven approaches) may instantly become ineffective; while some previously less adaptive marginal strategies or redundant variations (such as models based on local community trust, diversified revenue structures) may gain a selective advantage due to their robustness or fortuitous match with the new environment. This dynamic reshaping is the evolutionary core of market resilience – a market ecosystem that can survive crises and recover must pre-emptively maintain sufficient diversity of potential adaptive variations in its strategic gene pool to cope with unpredictable environmental changes.

In this research model, this is specifically manifested as an increase or decrease in the γ value of the power-law distribution in these situations. Therefore, as the market size changes, some brands that previously survived, even if their fitness values are very high, may still be eliminated due to the shrinking market size in that price range. And when the market environment recovers, different levels of market resilience will present different degrees and speeds of recovery.

2.3. Physics - The Resilience of Spring Systems

I introduce the spring model from classical physics as a core metaphor and formal tool for understanding market resilience. This model analogizes the recovery behavior of a system (such as a market) after an external shock to the process of an ideal spring returning to its equilibrium position after a brief deformation. The key to this analogy is that it captures two interconnected core dimensions of the resilience concept: the ultimate extent of recovery (whether the system can return to its original state or reach a new stable state) and the speed of recovery. Under the linear approximation of Hooke's Law, the spring's recovery process typically exhibits an exponential recovery curve, where the displacement over time follows the form $x(t) = x_0 e^{(-\lambda t)}$, where the recovery rate parameter λ is a key physical constant determining how quickly the system recovers. A higher λ value indicates a stronger intrinsic recovery force of the system and a faster recovery from the shock; conversely, it indicates a sluggish system response and a prolonged recovery period.

Mapping this physical model to market resilience research has profound implications. When the hospitality service market encounters brief but severe external shocks such as pandemic lockdowns, economic recessions, or sudden public events, the recovery trajectory of its key performance indicators (such as revenue) can, ideally, be modeled as a similar exponential recovery process. Here, the recovery strength coefficient λ is no longer a purely physical parameter, but an emergent system attribute that comprehensively reflects the collective recovery force generated by the combined effects of internal market structure, brand strategy interactions, and other factors. The magnitude of this coefficient directly relates to the total economic losses caused by the shock and the time window required for industry recovery, thus having important economic and management implications.

More importantly, the essence of the spring model lies in revealing the mechanism behind the recovery force. The spring's recovery force originates from its intrinsic elastic coefficient and structural integrity. By analogy, the market's recovery force (i.e., a high λ value) stems from its micro-foundations—namely, the diversity of market strategies, which is the core focus of this study. A diverse range of strategies forms a distributed resilience matrix: when shocks occur, companies employing different strategies are affected differently (similar to how different components in a spring system deform to varying degrees). Some strategies may be severely damaged, while others (such as those focusing on local markets, diversifying revenue streams, or possessing strong digital channels) may exhibit greater resilience. These still-viable components can provide the necessary elastic potential energy and positive feedback for the entire system to recover by filling market gaps, maintaining essential services, and quickly adapting to new demands.

However, we should not forget the complexity of the real world. The market recovery process in the real world may not be a perfect exponential curve, but will be affected by non-linear factors (such as synergistic effects between companies, threshold effects, and time lags in policy interventions). At the same time, massive shocks may cause the system to exceed its elastic limit, resulting in permanent structural changes, i.e., entering a new stable state (such as permanent changes in consumer habits or a structural increase in industry concentration), which corresponds to the plastic deformation or fracture of a spring.

2.4. Theoretical Integration

In summary, I have preliminarily constructed an interdisciplinary theoretical framework: the market can be conceptualized as a complex adaptive system, in which brands (agents) undergo strategic evolution through innovation and imitation (biological evolutionary mechanisms). Moreover, the distribution of strategic diversity shaped by this evolutionary process may contribute to the resilience characteristics of the market system when facing external shocks (which can be described using the recovery dynamics parameters of a physical spring system).

3. Research Design and Methods

3.1. Operationalization of Core Concepts

In the operationalization section of the core concepts, this study translates the key constructs in the theoretical framework into quantifiable variables and measurement models for subsequent simulation and empirical analysis.

First, the core evolutionary dynamics derived from biological analogies are operationalized as follows: The strategy innovation rate directly corresponds to the gene mutation rate μ, defined as the probability that a single brand independently generates a completely new strategy combination within a single simulation cycle. The strategy imitation rate corresponds to the horizontal gene transfer rate ι, defined as the probability that a firm successfully observes and adopts a strategy used by another firm within a single cycle. These two mechanisms jointly drive the dynamic changes in the market strategy pool. Individual fitness is operationalized as the degree of match between a firm's preferences and its "ideal consumer" preferences across two key dimensions: price and product quality. Specifically, the calculation formula is: Fitness = 1 / (1 + |Price - Quality|). This formula means that the smaller the absolute difference between the price set by the firm and the quality of the product it provides, the higher its fitness, indicating a more precise market positioning and a greater likelihood of survival and development advantages.

Secondly, market strategy diversity is operationalized as a structural indicator. It does not simply calculate the number of different firms, but rather counts the number of unique "price-quality" strategy combinations adopted by all firms in a given market (or a specific replication set in the simulation).

The calculation formula is:

Diversity = (Number of unique strategy combinations in the market) / (Total number of firms in the market)

Its mathematical expression is:

Let N be the total number of brands in the market, and S be the set of different (price, technology, design, environmental protection) strategy combinations adopted by these brands, with ‖S‖ being the number of elements (i.e., the number of unique strategies).

The formula for calculating strategy diversity D is:

$D = (||S||) / N$

This operationalization method has the following significant advantages:

Normalization: It limits the diversity value to the interval (0, 1]. When D=1, it means that every company in the market adopts a unique strategy, representing maximum diversity. When D approaches 0, it means that almost all companies adopt only a few completely identical strategies, representing extremely low diversity (high homogeneity).

Comparability: This standardized ratio eliminates the influence of different market sizes (i.e., the total number of companies N), allowing for direct comparison of diversity levels between markets operating under different parameters (such as different μ and ι

settings), or between actual markets in different industries or regions.

Finally, market resilience is quantified by drawing on the recovery process of a physical spring model. The core of this approach is estimating the recovery speed λ of key indicators (represented by price and quality levels before the shock) after the market is subjected to an external shock. At the same time, this study distinguishes between short-term recovery curves (focusing on the rapid rebound dynamics in the initial period after the shock) and long-term recovery curves (observing how long it takes for the system to recover to pre-shock levels) to comprehensively capture different dimensions of resilience. In this way, the abstract concept of "resilience" is transformed into comparable and analyzable dynamic parameters.

3.2. Computational Experiment Design

3.2.1. Overall Framework

This study first analogizes the market to an ecosystem, where each brand (company) is considered an "organism" with strategic genes (price, craftsmanship, design, environmental attributes). Market evolution is driven by the following mechanisms:

Gene Mutation: Occurs with probability mu/μ, representing spontaneous, random strategic innovation by brands.

Horizontal Gene Transfer: Occurs with probability hgt/ι, representing strategic replication between brands through imitation and learning.

Natural Selection: Based on a fitness function. Fitness is defined as 1 / (1 + |price - comprehensive quality|), where comprehensive quality is the product of craftsmanship, design, and environmental attributes. This design reflects the "value matching" idea, meaning that brands with prices closer to perceived quality have higher market fitness. In each generation, the top market_size brands with the highest fitness survive, the rest are eliminated, and new brands are added to maintain a stable total number.

Structural Constraints and Shocks: The price distribution of new brands entering the market follows a power-law distribution controlled by the parameter gamma (weight is (1/price)^gamma), simulating inherent structural characteristics of the market (such as unequal resource allocation). In the version with shocks, a temporary increase in the gamma value (e.g., +0.5) is introduced in generations 15-20 to simulate a brief external shock (e.g., policy changes, economic crisis), and then restored in generation 21, to observe the dynamic recovery process of the system after the disturbance and calculate its convergence speed (resilience λ).

3.2.2. Key Data and Parameter Settings

1) Core Parameters:

mu (μ): Strategy innovation/mutation rate, values [0.2, 0.6, 1.0].

hgt (ι): Strategy imitation/horizontal gene transfer rate, values [0.2, 0.6, 1.0].

gamma (γ): Power-law exponent of the market size distribution, initial value 0.5, temporarily increased by 0.5 during shocks.

num_brands: Total number of brands, fixed at 1000.

market_size: Number of surviving brands per generation, fixed at 800, elimination rate is 20%.

2) Key Output Data:

Average Price and Average Comprehensive Quality (of the market in each generation).

Strategy Diversity: Strategy combinations are formed by grouping prices (discretized into 100 bins) and three quality attributes (each discretized into 2 bins). The number of unique strategy combinations is calculated. In the analysis, this value is normalized as a proportion of the total number of brands to measure the degree of heterogeneity.

Recovery Speed: Market resilience is quantified by observing the convergence of the average price after the shock (from generation 21 onwards) towards the "target price" recorded before the shock (generation 15), and calculating the exponential decay coefficient λ of the recovery curve.

3.2.3. Libraries Used

The code primarily relies on three standard Python libraries:

random: Used to generate random numbers, driving probabilistic processes such as mutation, transfer, and selection.

pandas: Used for efficient processing and storage of structured data generated by the simulation (attributes and overall market statistics for each brand in each generation), and ultimately outputting it as a CSV file.

numpy: Primarily used for efficient numerical calculations, such as calculating the average price and quality of brands in each generation.

3.3. Data Analysis Methods

3.3.1. Overall Framework

Three-Dimensional Dynamic Visualization of Strategy Evolution: This section of the code generates 3D scatter plots to visually demonstrate the spatial distribution and convergence trends of market strategies over time. Price, comprehensive quality (craftsmanship × design × environmental friendliness), and time (generation) are used as the three dimensions. Color mapping (using kernel density estimation to calculate local density) is used to show the emergence and evolution of strategy clusters. All charts use a unified perspective (top-down diagonal view) to highlight whether brands converge towards the ideal equilibrium line of "price = quality". By generating separate charts for each parameter combination (μ, ι) and finally summarizing them into a grid overview, a systematic visual comparison of evolutionary patterns across the entire parameter space is achieved.

Parameter Space Mapping of Strategy Diversity: This section of the code calculates and visualizes the core variable—strategy diversity. Diversity is operationalized as a standardized indicator (number of unique strategies / total number of brands), and the average diversity value at the final generation is calculated for each parameter combination (μ, ι). A two-dimensional interpolated heatmap is used to display the pattern of change in strategy diversity across the continuous (μ, ι) parameter plane.

Quantitative Analysis of Market Resilience: This section of the code quantifies and visualizes the recovery of the spring model (market) after a shock.

1) ***Data Extraction:*** Focusing on the recovery period after the temporary gamma shock applied in the simulation (generation 21 and beyond), the dynamic values of average price and average quality are extracted.
2) ***Exponential Fitting:*** A novel approach is used to perform dual exponential fitting of the recovery trajectory for both short-term (e.g., the first 10 generations) and long term (the entire recovery period). This distinguishes between the rapid adjustment phase and the slow asymptotic phase after the shock, potentially corresponding to different recovery mechanisms.
3) ***Result Visualization:*** Detailed recovery trajectory charts are generated for each

parameter combination, comparing the actual data, short-term fitting, and long-term fitting curves. All results are then summarized into a 3x6 grid overview for global comparison.

4) ***Spatial Summary of Resilience Parameters:*** Finally, the calculated short-term and long-term recovery rates λ (for both price and quality) are mapped back to the (μ, ι) parameter space, generating four continuous interpolated heatmaps. This will directly reveal how different combinations of innovation and imitation probabilities systematically affect the speed at which the market resists shocks and recovers, i.e., market resilience.

The entire analytical framework achieves a complete, quantifiable empirical test from micro-level brand strategy distribution to meso-level market diversity characteristics and macro-level system resilience performance. II.

3.3.2. Libraries Used

The code comprehensively utilizes core libraries from the Python data science ecosystem:

pandas and numpy: As the foundation of data analysis, used for data reading, filtering, aggregation, and calculation.

matplotlib: As the core plotting library, responsible for generating all 2D and 3D static charts, and providing high levels of customization.

mpl_toolkits.mplot3d: Used to create 3D scatter plots, showing the spatiotemporal distribution of strategy evolution.

scipy: The \`griddata\` function in its \`interpolate\` module is used to generate smooth continuous heatmaps; the \`curve_fit\` function in its \`optimize\` module is used to perform key exponential curve fitting to quantify the recovery speed λ.

scikit-learn: Its \`KernelDensity\` is used to estimate the local density of data points in the 3D plot to enhance visualization.

seaborn: Although indirectly used in the main plotting process, its aesthetic style is partially borrowed to improve the visual appeal of the charts.

glob and os: Used to automatically find, manage, and read generated image files, enabling batch processing and summarization.

4. Research Findings

4.1. Macro-level Patterns of Strategy Evolution

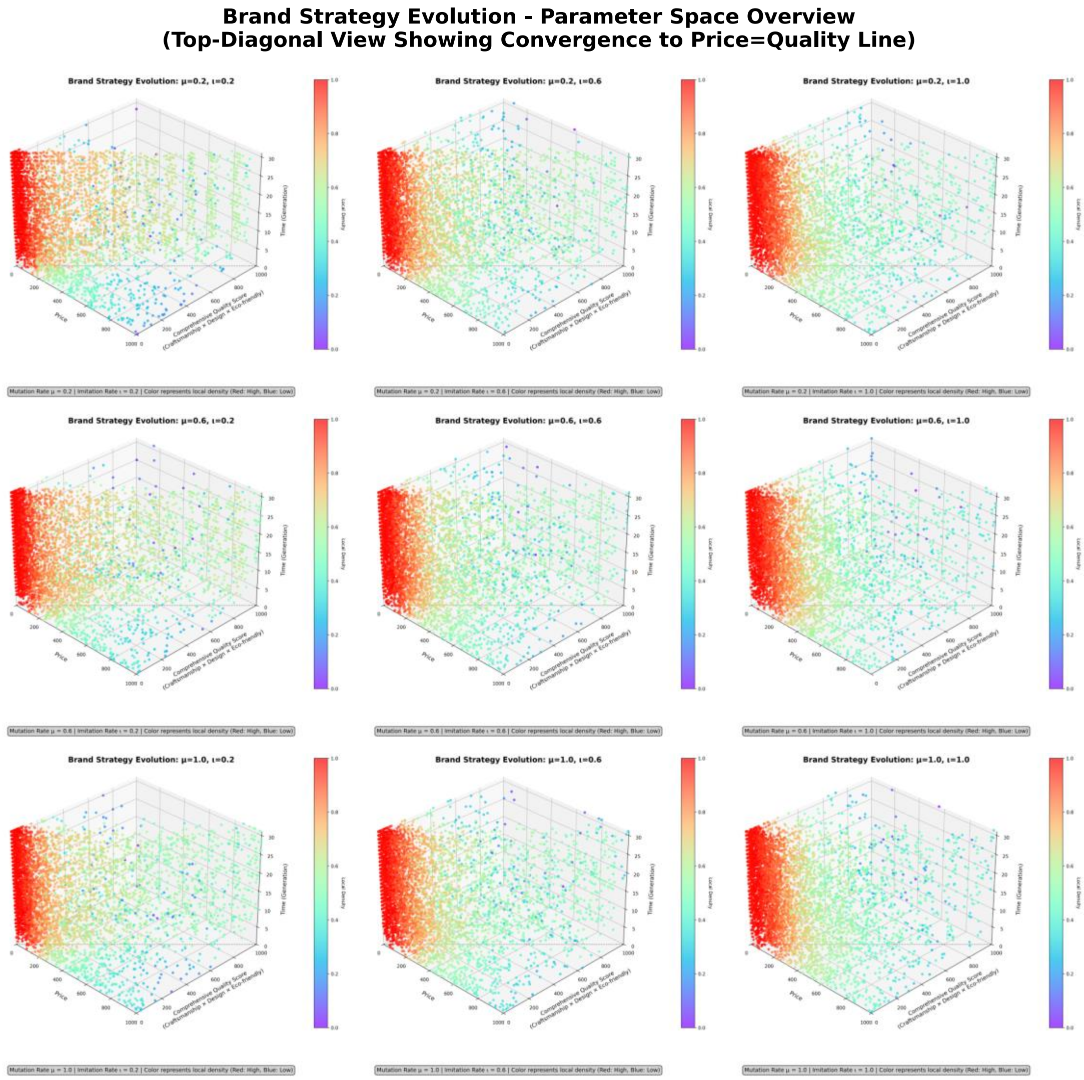

Figure 1.

Based on the first visualization results of this study (Figure 1), market evolution dynamics exhibit asymmetric sensitivity to the probabilities of innovation and imitation (represented by μ and ι, respectively), revealing the dominant role of imitation behavior in shaping the overall market structure. With the probability of imitation (ι) fixed, regardless of whether ι is 0.2, 0.6, or 1.0, the macroscopic evolutionary trajectory of market strategies shows high stability; that is, the overall convergence direction and the distribution pattern of strategy clusters are primarily determined by the value of ι. This finding indicates that imitation intensity is the "order parameter" of market structure evolution; once set, it can dominate the macroscopic evolutionary path of the system, while changes in the innovation rate (μ) can only trigger local adjustments within the system under this constraint.

However, an increase in the innovation rate (μ) triggers a "polarization" effect in the strategy distribution within the market structure. As the value of μ increases, independent innovation behavior expands the exploration range of the strategy space, leading to the diversification of brand strategies. Specifically, the number of "middle-market" brands with medium quality and medium prices significantly decreases, while the number of high-quality, high-price brands shows differentiated responses under different ι values—when imitation intensity is high (ι=0.6 or 1.0), their number remains basically stable; but when imitation intensity is low (ι=0.2), their number even increases. This suggests that in a low-imitation environment, innovation not only brings diversity but may also, through niche creation, provide high-quality brands with a survival space protected from large-scale imitation.

On the other hand, when the innovation rate (μ) remains constant, an increase in the probability of imitation (ι) systematically drives the market structure downwards. High ι values (such as 1.0) lead to rapid strategy convergence, and because low-quality, low-price strategies dominate the original market distribution, the brand cluster ultimately becomes highly concentrated in the low quality-low-price range. This reveals a potential risk of imitation-driven markets: even with a certain level of innovation activity, if the imitation intensity is too high, the market will still converge to a low-level equilibrium trap dominated by low end, homogeneous competition.

In summary, the visualization in Figure 1 depicts the following picture: the imitation rate (ι) dominates the macroscopic direction and convergence speed of market evolution, while the innovation rate (μ) mainly influences the strategic distribution and diversity level within the market. Different combinations of imitation and innovation probabilities give rise to vastly different market ecosystems—from low-end, homogeneous "red ocean markets" to polarized "M shaped markets."

4.2. Heatmap of Strategy Diversity

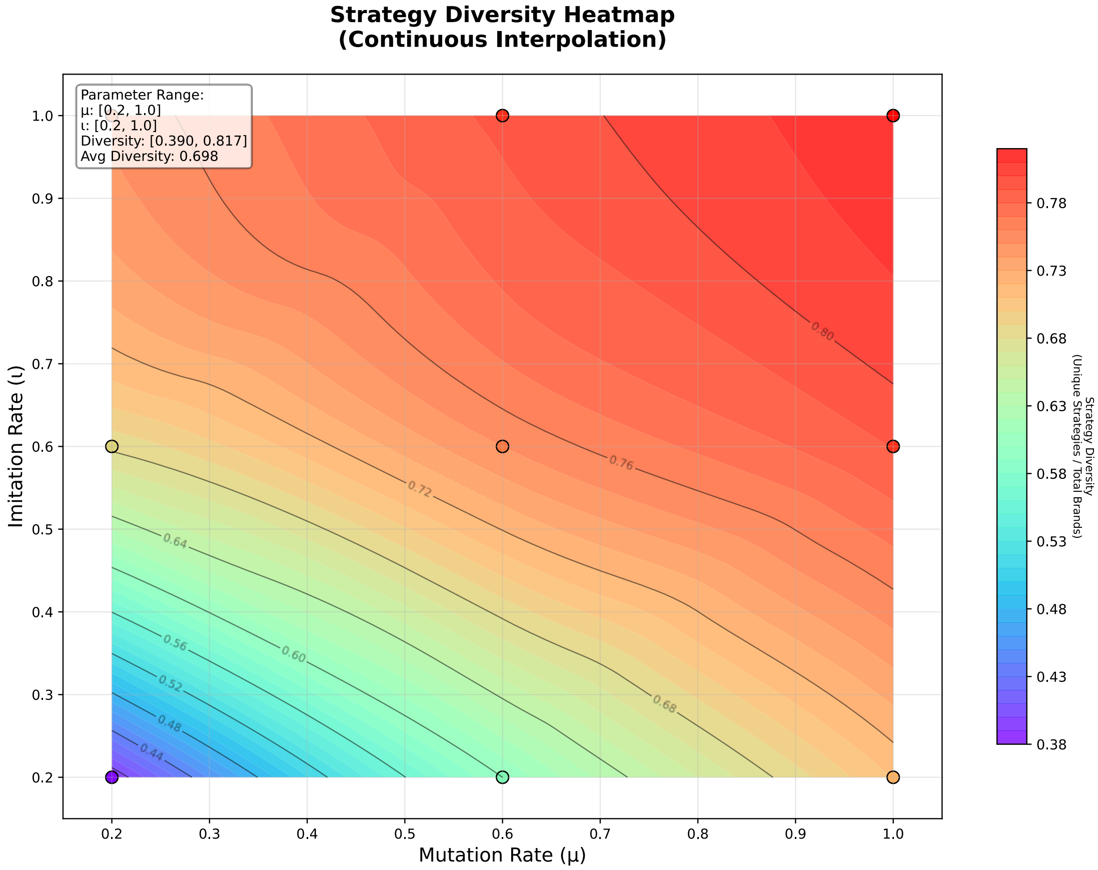

Figure 2.

As shown in the simulation visualization results in Figure 2, market strategy diversity is significantly and positively influenced by both the innovation rate (μ) and the imitation rate (ι), but their influence mechanisms also exhibit nonlinear and dynamic characteristics. Overall, an increase in either μ or ι leads to an increase in strategy diversity. This finding is partly consistent with expectations, but partly counterintuitive: under a fixed ι value, an increase in μ enhances diversity by generating more novel strategies, consistent with the classic understanding of "innovation-driven differentiation"[MK Maingi, NS Kamau]. However, under a fixed μ value, an increase in ι also leads to increased diversity, which seems to contradict the common perception that imitation leads to convergence. This seemingly contradictory phenomenon reveals the complex duality of imitation behavior: in a dynamic evolutionary environment, imitation (horizontal gene transfer) not only spreads existing strategies but also generates new hybrid strategies through a re-combinative innovation mechanism, combining strategy modules from different sources. Especially in a multidimensional strategy space with separable attributes, high-frequency imitation promotes the extensive exchange and recombination of strategy genes, thus becoming an important engine for generating diversity.

Further analysis reveals a significant marginal increasing relationship between diversity enhancement and the growth of innovation and imitation parameters. The data shows that to achieve the same increase in diversity (e.g., 0.04 units), a smaller increase in μ or ι is required in the low-diversity range; while in the high-diversity range, a much larger increase in parameters is needed. For example, to increase diversity from 0.56 to 0.60, μ only needs to increase by 0.1, and ι only needs to increase by approximately 0.05; while to increase diversity from 0.68 to 0.72, μ needs to increase by approximately 0.15, and ι needs to increase by approximately 0.13. This phenomenon of increasing marginal cost indicates that the generation of strategy diversity is not a linear process. When diversity is low, there are many "empty ecological niches" in the market, and a small amount of innovation or imitation can quickly fill them, resulting in high efficiency. As diversity increases, the strategy space gradually becomes saturated. Generating new strategies not only requires avoiding duplication with existing strategies but also surviving in fierce competition, leading to a significant increase in the difficulty of enhancing diversity, exhibiting evolutionary pressure similar to the "Red Queen effect".

More critically, the dominant influence of parameters on diversity dynamically shifts with the level of diversity. Analysis of the slope changes of diversity contour lines on the (μ, ι) parameter plane reveals that in low-diversity regions, the contour lines are relatively flat, indicating that increases in μ have a greater marginal contribution to diversity enhancement, with innovation playing a dominant role. In high-diversity regions, the contour lines become steeper, meaning that increases in ι have a relatively stronger marginal contribution to diversity enhancement, and imitation gradually becomes the key driving force for maintaining and further increasing diversity. This shift reveals a phased division of labor between innovation and imitation in market evolution: in the early stages of diversity building, exploratory innovation is the core driving force for opening up new directions and breaking down homogenization; while after the market has achieved considerable diversity, exploitative imitation (through recombination and diffusion) becomes the main mechanism for connecting different strategies, consolidating the ecological structure, and deriving new variants. This finding challenges the traditional view that simply opposes innovation and imitation or regards imitation as a purely homogenizing force, emphasizing that in a complex market ecosystem, the two are essentially complementary and dynamically synergistic in the diversity generation system.

4.3. Recovery Curve after the Shock

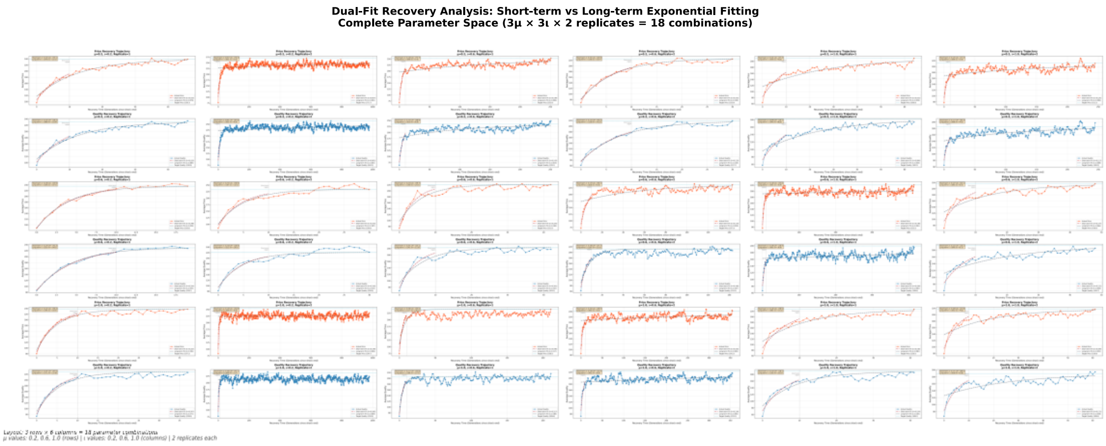

Figure 3.

Based on the simulation results of the recovery process after a market shock, system resilience—represented in Figure 3 as the time required to recover to the target equilibrium state—exhibits significantly different "reproducibility" or stability under different combinations of innovation rate (μ) and imitation rate (ι). The results show that not all parameter combinations produce stable and predictable recovery trajectories; instead, the fluctuations in recovery time reveal significant differences in the sensitivity of system dynamics to random initial conditions and evolutionary paths. Specifically, when the imitation rate is at its lowest level (ι=0.2) and the innovation rate is at extreme values (μ=0.2 or 1.0), the system's recovery behavior exhibits extremely high uncertainty. Two replicate simulations under the same parameters can show recovery times differing by as much as 1.5 orders of magnitude, for example, one taking as long as 1000 generations, and the other only about 40 generations, a 50-fold difference. This indicates that in an environment of low imitation and extreme innovation, market evolution is highly path-dependent, and small initial disturbances or random events can lead the system into completely different recovery trajectories, or even into a kind of stagnation or slow adaptation metastable state. This high volatility reflects that, in the absence of effective imitation mechanisms to diffuse and coordinate adaptive strategies, the system's recovery process is highly dependent on accidental innovative breakthroughs, making the results difficult to predict.

However, as the imitation rate (ι) increases, the reproducibility of the recovery time significantly improves. When the value of ι increases, even though there are still differences in recovery times between two replicate simulations (e.g., one 200-400 generations, the other around 50 generations), the magnitude of the difference and the range of fluctuations are significantly reduced, no longer showing orders of magnitude differences. This highlights the important role of imitation behavior in coordinating system behavior and enhancing the convergence of evolutionary paths. A high imitation rate promotes the rapid spread of adaptive strategies within the population, weakening the decisive influence of single random innovations, thus making the system's macroscopic recovery dynamics more robust and predictable. It is worth noting that certain specific parameter combinations exhibited highly consistent recovery times. For example, when (μ=0.6, ι=0.2), the average recovery time was approximately 20 generations; when (μ=0.6, ι=0.6), it was approximately 100 generations; when (μ=1.0, ι=0.6), it was approximately 300 generations; and when (μ=1.0, ι=1.0), it was approximately 50 generations. These "stable points" indicate that when innovation and imitation work together in specific proportions, a balanced evolutionary mechanism can be formed: innovation provides the necessary adaptive variations, while imitation ensures that beneficial variations are effectively selected and disseminated. Together, they drive the system back to equilibrium at a predictable rate.

4.4. Resilience Topography of Parameter Space

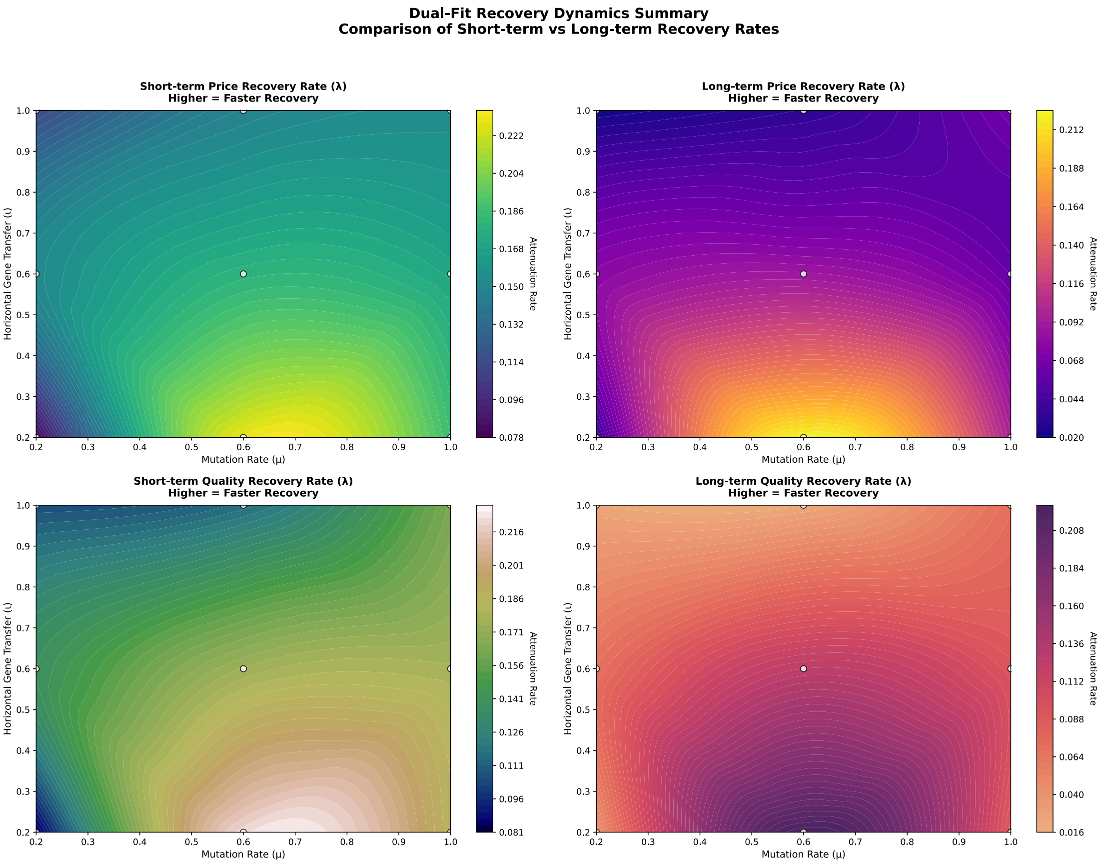

Figure 4.

Based on a systematic analysis of the phase diagrams of market recovery rates after shocks (Figure 4), a key and interesting finding is that, regardless of whether it concerns price or quality, and whether it is a short-term or long-term recovery process, the recovery rate (λ) exhibits a highly consistent spatial distribution pattern in the parameter space defined by the innovation rate (μ) and the imitation rate (ι). This indicates the existence of a universal "resilience structure" that governs the market system's ability to recover from shocks across different dimensions.

Specifically, the contour lines of the four recovery rate phase diagrams (short-term price λ, long-term price λ, short-term quality λ, long-term quality λ) show remarkable similarity. They all center around an elliptical or semi-circular "fastest recovery zone," with the recovery rate decreasing gradually outwards from this peak region. This reveals a core principle: optimal market resilience is not randomly distributed, but is stably anchored in a specific region of the parameter space. For short-term recovery, the fastest recovery zone is located in the range of $\mu = 0.6 - 0.8$ and $\iota = 0.2 - 0.4$, with a corresponding peak recovery rate of approximately 0.22. For long-term recovery, the optimal region shifts slightly towards lower innovation rates, located at $\mu = 0.5 - 0.7$ and $\iota = 0.2 - 0.4$, with a peak rate of approximately 0.21.

This subtle difference has important implications: immediate rapid rebound after a shock requires a slightly higher level of innovative activity as a "starter" to quickly generate adaptive strategies; while achieving lasting and stable complete recovery requires a slightly lower but more balanced level of innovation to avoid strategic fluctuations caused by excessive exploration, thus combining with moderate imitation to achieve robust convergence. Notably, both optimal ranges clearly point to a combination of "medium-to-high innovation rate" and "low imitation rate." This contradicts the intuition that high imitation promotes rapid learning and thus accelerates recovery, but aligns with a key point in complex adaptive systems theory: the balance between exploration (innovation) and exploitation (imitation), two components both contribute to organizational adaptability. [J Uotila] Excessive imitation ($\iota > 0.4$) can lead to strategies converging prematurely to a "local consensus" that may not be optimal, thus delaying the search for a new equilibrium.

In stark contrast, the locations of the "slowest recovery zones" in the four phase diagrams also highly overlap, mainly concentrated in two "resilience valleys": one is the "stagnation corner" with low innovation and low imitation ($\mu = 0.2 - 0.3$, $\iota = 0.2 - 0.4$), and the other is the "imitation trap" with low innovation and high imitation ($\mu = 0.2 - 0.5$, $\iota = 0.9 - 1.0$). In the first region, due to insufficient exploration and exploitation, the system lacks the motivation and direction for change, resulting in slow recovery. The second region reveals the dangers of over-reliance on imitation: in the absence of sufficient innovation, extremely high imitation rates (ι close to 1.0) can cause the population to rapidly converge to the dominant strategy that may no longer be suitable after a shock, forming a strong inertia or get locked-in, thereby severely hindering the system from making necessary structural adjustments. This explains why in some platform economies, despite extremely rapid information flow (high ι), if there is a lack of substantive innovation (low μ), the entire industry exhibits surprising fragility and delayed recovery when faced with disruptive shocks.

5. Discussion

5.1. Theoretical Contributions

The theoretical contribution of this study lies in constructing and validating a novel dynamic analytical framework of "innovation-imitation-diversity-resilience" for complex systems by integrating theories from economics, evolutionary biology, and physics. This framework deepens our understanding of market evolution and adaptability in the platform economy era. First, this study breaks through the traditional perspective that simply opposes innovation and imitation, revealing their non-linear complementary relationship in shaping market strategy diversity through multi-agent simulation. The research finds that imitation is not merely a simple reducer of diversity; under conditions where strategic attributes are recombinable, high-frequency imitation, through a "horizontal gene transfer" mechanism, can become a key driving force for generating new strategic combinations and thus enhancing diversity. This finding corrects the assumption in classical industrial economics that imitation leads to convergence, echoing and extending the concept of "recombinative innovation". [G Faïz]

Secondly, this study operationalizes market resilience as a quantifiable dynamic parameter (recovery speed λ) and systematically reveals its micro-evolutionary basis. The results show that market resilience is not determined by a single factor of innovation or imitation, but rather depends on an "optimal ratio" between the two. Importantly, the study identifies a universal "optimal resilience zone" ($\mu \approx 0.6\text{-}0.7$, $\iota \approx 0.2\text{-}0.4$), within which the market can achieve the fastest and most stable recovery. This finding provides specific, quantitative empirical support for the "exploration exploitation balance" in complex adaptive systems theory and anchors the abstract concept of resilience to observable and adjustable market evolutionary mechanisms.

Finally, this study constructs a multi-level theoretical bridge connecting micro-level strategic behavior with macro-level system performance, clearly illustrating how micro level brand innovation and imitation decisions influence meso-level market strategy diversity and shape macro-level market resilience. This "micro-meso-macro" transmission mechanism provides an integrated analytical framework for understanding the robustness of market ecosystems.

5.2. Policy Implications

The findings of this study provide valuable insights, both theoretical and practical, for policymakers, platform managers, and business operators. At the policy and platform governance level, regulatory focus should shift from simply preventing monopolies or encouraging innovation to cultivating and maintaining market resilience. The study reveals that the most resilient market regions correspond to a combination of "moderate innovation and limited imitation" ($\mu \approx 0.6\text{-}0.7$, $\iota \approx 0.2\text{-}0.4$). This suggests that regulatory agencies should carefully assess the "imitation" effects of platform algorithms—for example, overly homogenized recommendation mechanisms may suppress diversity and weaken ecosystem resilience. Policies can focus on designing dynamic and inclusive rules that both protect original incentives (ensuring a certain μ value) and promote the moderate openness and interoperability of knowledge, modules, or interfaces (guiding the formation of beneficial ι values), thereby guiding the market towards a high-resilience range.

However, the region with the strongest market resilience ($\mu \approx 0.6\text{-}0.7$, $\iota \approx 0.2\text{-}0.4$) corresponds to a strategy diversity of only about 0.6. This also reminds us that moderate strategy repetition and brand homogenization competition are not entirely without benefit. A certain degree of strategic convergence and brand homogenization competition may be precisely the micro-foundation for building efficient coordination and rapid collective response. Limited imitation (ι) ensures that a sufficient number of companies in the market master and implement mainstream adaptive strategies, forming a "consensus-based action foundation" to cope with shocks, thus avoiding coordination failures and slow responses caused by excessive strategy differentiation.

At the level of business operations and brand management, managers need to re-evaluate the balance between innovation and imitation in their competitive strategies. This study finds that simply pursuing high-frequency imitation (high ι value) easily leads brand clusters into a low-quality, low-price "red ocean," while a combination of "moderate innovation supplemented by limited imitation" is most conducive to building a stable and resilient market position. Therefore, companies should strive to develop "composite capabilities" that are difficult to simply replicate (such as unique brand narratives, diversified experience integration, or community trust), rather than merely engaging in rapid functional or price imitation. At the same time, companies with richer strategic reserves (diversity) are more likely to survive and lead the recovery when shocks occur, which emphasizes the strategic value of investing in exploratory, even marginal, innovations during stable periods. From a broader sociological perspective, a healthy socio-economic system is like a highly resilient market, whose robustness depends on the diversity of its subsystems (such as businesses and communities) and moderate mutual learning among them. This study warns that overemphasizing optimal efficiency and standardization (equivalent to extremely high levels of imitation), while potentially increasing overall output in the short term, erodes the system's "adaptive gene pool," making it exceptionally vulnerable to unforeseen shocks. Therefore, encouraging social innovation, protecting cultural diversity, and establishing mechanisms that support trial and error and knowledge sharing are not only economic issues but also fundamental building blocks for a resilient society.

5.3. Research Limitations and Future Directions

Although this study presents the macroscopic dynamics of market strategy evolution through Figure 1, it has not yet delved into the micro-level tracking of individual brands or specific strategies. Future research could focus on the life cycle trajectories of individual brands, detailing their strategic changes, fitness fluctuations, and survival status transitions under the pressures of innovation and imitation; simultaneously, it could also track the diffusion network of a single strategy, analyzing its diffusion path and ultimate impact range, thereby revealing the heterogeneous mechanisms and complex diffusion processes in market evolution in more detail.

Regarding the shock setting, this study only examined the specific scenario where the Gamma value temporarily increased from 0.5 to 1.0. To enhance the generalizability of the conclusions, subsequent work could systematically expand the parameter space: for example, setting different initial Gamma values (such as 0.3, 0.7, 1.2, etc.), and applying shocks of varying magnitudes and directions (such as a sudden drop in Gamma value, or an initial increase followed by a decrease), to test whether the optimal range of market resilience remains stable under different structural conditions, thus extracting more universal structural-resilience correlation laws.

Under the same parameter settings, the recovery time after a system shock showed significant differences across different replicate experiments, indicating that the recovery trajectory is highly path-dependent. However, this study has not yet been able to deeply analyze the specific micro-mechanisms and key influencing factors that lead to this difference. Future research could use more refined tracking and measurement methods to systematically observe the dynamic changes of various potential variables during the recovery period—for example, the diffusion path of individual strategies, the emergence time of adaptive mutations, and the instantaneous structure of strategy distribution within the population. Through this process tracking analysis, it is expected to identify key events or critical states that, while not significantly changing the long-term equilibrium, can profoundly affect the recovery speed and path, thus more completely revealing the micro-determinants of market resilience in dynamic evolution.

6. Conclusion

This study systematically explores the evolutionary mechanisms of market strategy diversity and resilience in the platform economy era by constructing a complex systems multi-agent simulation model integrating economics, evolutionary biology, and physics. The core findings indicate that market strategy diversity is positively driven by both innovation (μ) and imitation (ι) behaviors, but their mechanisms differ: innovation directly increases diversity by generating new strategies, while imitation indirectly contributes to diversity through "strategy recombination." More importantly, market resilience (measured by the exponential recovery rate λ after a shock) is not determined by a single factor, but rather depends on the dynamic balance between innovation and imitation. The study identifies a universal "optimal resilience range" ($\mu \approx 0.6\text{-}0.7$, $\iota \approx 0.2\text{-}0.4$), within which the market achieves the fastest and most robust recovery. The strategy diversity corresponding to this range is approximately 0.6, suggesting that moderate strategy homogenization helps form a consensus basis for coordinated action, which is an indispensable component of resilience. Conversely, excessively high imitation rates ($\iota > 0.6$) can lead the market into a low-quality, low-price "lock-in" state, resulting in slow and unstable recovery; while excessively high innovation rates may increase the unpredictability of the recovery path. Therefore, this study theoretically constructs a multi-level analytical framework connecting micro-level strategic behavior, meso-level market structure, and macro-level system resilience; and practically provides key insights for platform governance and corporate competitive strategies: cultivating a resilient and healthy market ecosystem is crucial, and this requires maintaining an environment conducive to the synergistic coexistence of "moderate innovation" and "limited imitation" through rules and incentive mechanisms, thereby achieving lasting adaptability and stability in a dynamic equilibrium.

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