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The Diffusion of Competitive Platform-Based Products with Network Effects

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Abstract: The existence of network effects not only changes traditional product diffusion patterns but also has significant impacts on individuals' decision behaviors. Previous studies on competitive product diffusion have focused on macro-level diffusion speed and effects while neglecting the micro-level impacts of individual heterogeneity and social interaction on product diffusion. This paper introduces the individual heterogeneities and social interactions of consumers into the competitive product diffusion model on the basis of a two-sided market framework and complex network theory. We proposed a small world network model and behavioral game theory. Specifically, the small world network model was used to build interactions between users, and behavioral game theory was utilized to describe the interactions between users. In our model, the direct network effect was distinguished from the indirect network effect on the basis of the synergy of multiple complementary products. The results show that the final distribution often presented a situation wherein two products coexisted, but the market share was very different. In an asymmetric first-mover situation, the direct network effect dominated the indirect network effect. Moreover, the dominant position of one product at present can be changed by the other under certain conditions. Finally, when the switching and learning costs were high, the market maintained its concentration, and the prior platform was unable to dominate the market. A decrease in the costs raised the prior platform's market share and the speed of market occupation.

Keywords: platform-based products; diffusion; network effect; complex networks

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1. Introduction

With the revolution of the internet and information technologies, a great many products are designed as platform based as they are structured as systems comprising platforms and complementary products [1,2]. Examples of platforms and complements include video game consoles and video games (e.g., Sony's PlayStation, Microsoft's Xbox One), operating system platforms, and software applications (e.g., Google's Android, Windows). These systems are "two-sided" in the sense that both types of end users need to gain access to the same platform to be able to interact with users on the other side. Hence, according to the two-sided platform theory [3–5], the platform-based products exhibit network effects.

A network effect refers to a phenomenon whereby the utility of a consumer's consumption of a product increases as the number of other end users who use the same product increases. Katz and Shapiro [6] classify network effects into two categories on the basis of the source of network effects. The first is the direct network effect, whose externality is generated by size of the same consumer type. For instance, an individual game player of Xbox One gets a higher utility when they can play games with more of their friends who also get access to the platform. The second is the indirect network effect, which is generated indirectly from a distinct type of user. For example, an individual mobile device consumer gets higher utility when they can download diverse applications supplied by a larger number of third-party developers.

Under the influence of network effects, the diffusion of products, which is key to the success of a company, exhibits completely different characteristics from that observed in traditional industries. For example, the empirical results on product diffusion with network effects show that the diffusion model is much more complex than the common S-type trajectory, e.g., double-peaked and saddle-type diffusion patterns [7,8]. On the other hand, product diffusion is also related to the competitive environment in which a product is located. The spread of competitive products also affects the interactions between consumers [9]. In this paper, we investigated the diffusion dynamics and outcomes of network industries to understand the mechanisms of product growth and competition with network characteristics.

With the network effects, the benefits of consumers are related to the number of users who use the same product. However, it is obvious that no consumer can interact with all other consumers. Each consumer has their own social network or neighbors, and network effects are related to that neighborhood. As complex network theory shows, the social communication structure of economic agents is neither regular nor completely random [10,11]. In many cases, it should have some statistical characteristics of complex networks such as "small world effects" [12,13]. Therefore, the nature of this interaction network will have an important influence on the diffusion process under network externalities.

The externalities and social characteristics of network effects described above imply that the utility of consumers depends not only on the products that they use but also on the number of users in the neighborhood who use the same products; the sellers' profit depends not only on the number of users on the platform but also on the number of sellers who provide complementary products on the same platform [5]. Therefore, it can be concluded that when deciding whether to adopt a product, consumers should interact with their neighbors (the nature of complex networks) and surrounding environment (in the case of indirect network effect, this mainly refers to the number of complementary products) and adjust their strategies through learning by doing. Learning by doing refers to the fact that learning should be relevant and practical, and not just passive and theoretical [14,15]. On the other side, a similar conclusion can be derived for sellers. It is such a complex interaction system that constitutes the characteristics of product diffusion. Therefore, we consider product diffusion in such a system as a typical complex evolution system including the complexities of individual adaptive learning behavior and individual interaction structure complexity.

During product diffusion, users decide whether to adopt a platform according to the strategies of other individuals in their neighborhood and on the basis of the number of products that can be used in the platform to maximize their benefits. Similarly, the sellers make decisions through the game with other sellers and depend on the number of users attached to the platform. Here, the actions of the micro-individuals will determine global variables (the supply of complementary products and the number users on a particular platform under various circumstances), creating two-way interactions between micro and macro variables during product diffusion. Such interactions promote the evolution of the entire system and ultimately determine the outcomes of product diffusion, market shares, or the distribution of products.

Specifically, we introduced the individual heterogeneity and social interactions of consumers into the competitive product diffusion model with network effects based on a two-sided market framework. In our model, the direct network effect was distinguished from the indirect network effect on the basis of the synergy of multiple complementary products, and thus the competitiveness of products was not only reflected in differences in product quality but also in the development of related complementary product markets. Both the user and seller sides will choose between two competitive platforms on the basis of the current platform states and expected states in the next period, which are recursively impacted by their decisions.

Our main results and insights were derived from simulating the diffusion process with different settings. We show that the diffusion of competing products showed explosive growth when users and sellers reached a certain critical mass. The final distribution often

presents a situation wherein two products coexist, but the market share is very different. The effects of direct and indirect networks are essentially different in terms of product diffusion. The direct network effect dominates the indirect network effect in an asymmetric first-mover situation when one product has an advantage on the user side, while the other product has an advantage on the seller side. The dominant position of one product at present can be changed by the other under certain conditions. Finally, the switching and learning costs have significant impacts on market concentration.

The rest of this paper is organized as follows. Section 2 reviews the related literature; Section 3 presents a general model of two-sided markets that captures dynamic strategic interactions between two distinct groups of participants; and in Section 4, we describe the simulation method and parameter settings. In Section 5, we present our computing results, and Section 6 concludes the paper.

2. Literature Review

Our work is related to three streams of literature, namely, research on the (1) network effects, (2) two-sided platforms, and (3) product diffusion.

2.1. Research on Network Effects

The ongoing theoretical and empirical research on network effects has achieved fruitful results [16–23], while few of such studies have comprehensively examined the diffusion of competitive products under network effects, especially the indirect network effect. A feature of past research is the use of the assumption of the rational "economic man" where market equilibrium is achieved automatically. Under the economic man assumption, agents' expectations are rational in the sense that expectations are fulfilled in equilibrium.

Furthermore, the existing studies above use representative consumer models in which all agents of the same type are identical, thus disregarding the heterogeneity of agents to facilitate analysis, while neglecting local interactions between market participants and those between market participants and market environments, while it is these interactions that constitute the competition and diffusion processes of products. In addition, from the perspective of research methods, the existing research focuses on the diffusion process from a macro-perspective [24,25], while disregarding consumers' personalities and social interactions at the micro-level. Traditional aggregate diffusion models aim at making empirical generalizations and hence describe the parsimonious spread of new products at the market level, such as the Bass model [26].

2.2. Research on Two-Sided Platforms

Our key contribution is to develop a diffusion model for the products built around two-sided platforms with micro foundations. Accordingly, this paper contributes to the growing strategy and economics literature on two-sided platforms [3,4,27–31]. Rysman [32] provides a general review of the literature of this field. These theoretical analyses have sought to explain the existence of direct and indirect network effects in diverse settings and subsequent effects on the decisions of participants and market structures. However, these studies investigate the mechanisms of network effects on the basis of an assumption that network effects are derived through a general function of the quantity of relative agents, for example, network effects are represented by a linear function of the total number of users involved, thus disregarding interactions between agents and their individual decision-making process. We present a general model of two-sided markets that captures dynamic strategic interactions between two distinct groups of participants.

2.3. Research on Product Diffusion

Our work is related to efforts to study product diffusion with network effects. The impact of network effects on product diffusion has received considerable attention [9,33]. The conventional view suggests that rapid market growth may derived from network effects due to the bandwagon effect [34–36]. However, network effects may also have

the opposite effects, such as the "chilling effect" labeled by Goldenberg et al. [37]. In the early stages of the product life cycle, diffusion may be very slow and occur mainly in a small number of consumers because of the small size of adopters. Overall, product diffusion under network effects can be characterized by distinct dynamic processes, i.e., an initial slow growth and followed by an explosive growth [38]. Many articles have empirically studied the diffusion of products in various settings [39–43]. Goldenberg et al. [37] investigated the effect of direct network externalities on dynamic diffusion rate by separating the network effect and imitation effects, finding that network externalities have a "chilling" effect on initial growth of a new product. Yu et al. [44] studied the diffusion of electric vehicles on the basis of a two-sided framework, mainly focusing on the equilibrium outcomes between the consumers and charging station investor, but not the diffusion pattern under various market structures, as we studied in this paper. Moreover, we considered the diffusion dynamics in a competitive environment. On the basis of both direct and indirect network effects, we present an agent-based simulation model that extends the traditional economic network perspective by incorporating individual decision making under realistic information assumptions. We enriched and deepened the theory of competitive product diffusion from a micro-perspective to help understand the diffusion mechanisms of products under an agent-based environment.

Our paper also builds on previous work on product diffusion based on a complex network structure. Delre et al. [45] proposed an agent-based diffusion model based on a small world network structure and studied how different network structures affect diffusion. Choi et al. [46] also demonstrated the effect of network topology on the dynamics of diffusion. Katona et al. [47] studied the diffusion of an online social network with a direct network effect and found that the network structure together with specific characteristics of adopted users and potential adopters can be good predictors of diffusion. These works do not focus on platform-based products. We believe that it is necessary to study standard diffusion by using an analytical method that can include heterogeneous individuals in the model. In this respect, complexity theory and agent-based model serve as a good tool for us to analyze the interaction of heterogeneous agents and the impacts of heterogeneous individuals on diffusion. On the basis of network effects, we modeled and analyzed the diffusion of competitive products from the individual micro-level.

There are several innovations in this paper. First, both direct and indirect network effects were investigated for two aspects: the influence of individual consumers, and the synergistic effects of multiple complementary products. Second, according to the expected benefit satisfaction decision-making mechanism, individual social interaction is carried out. Under the effects of agent distribution and individual heterogeneity, an evolutionary model of individual decision making was constructed. Third, the diffusion process of competitive products was simulated, and the effects of network and individual characteristics on the diffusion of competitive products are discussed.

3. The Model

3.1. Consumer Decisions

We assume that there are two incompatible platform-based products $k \in \{A, B\}$. We refer to complementary product providers as sellers and consumer agents as users. Users are interested in accessing a variety of sellers so that value derived from joining a platform increases with the number of sellers. Conversely, sellers' profits from joining a platform increase with the number of users on the same platform. The platform controls access on both sides of the market. We regard the bottleneck feature of this platform as exogenous. In fact, it may be the result of many micro-foundations [48]. The competitiveness of the platforms is reflected in the number of users and complementary products in the market. For example, competition for telecommunications products is reflected not only in the user but also in corresponding content and terminal equipment.

Suppose that there are N users in the market where each user $i(i = 1, 2, \ldots N)$ can select only one platform to join in one period or choose not to join either platform. We assume that there is an initially installed base with both platforms represented by N_{A0} and N_{B0}. In each period t, each consumer can interact with k_i other consumers, $(k_i = 1, 2 \ldots, N-1)$, which is referred to as consumer $i's$ degree in complex network theory; we adopt a small world model proposed by Newman and Watts [49] to depict the user's network structure. After adopting a hardware platform k, a consumer purchases an assortment of compatible products in each period, $x_{ikt}(x_{ik1t}, \ldots, x_{ikM_{kt}t})$. In sum, the utility of user i at time t when the user joins the platform k is given by

$$u_{ikt} = v_{0k} + v_{1k}(d_{ikt}) + v_{2k}\left(\left(\Sigma_{j\in\{1,\ldots M_{ik}\}} x_{ikjt}^{\sigma}\right)^{1/\sigma}\right), \tag{1}$$

where v_{0k} is the intrinsic value derived from the basic content of platform k. Function $v_{1k}(\cdot)$ is the utility derived from direct network effect resulting from interactions with the user's "neighbors" (e.g., friends and family network), and d_{ikt} is the number of neighbor(s) who also join the same platform at time t. Unlike most previous studies where a user's decision is globally affected by all other users' adoption of decision making in the market, we model the direct network effect in a local sense. That is, d_{ikt} represents the number of adopters in user i's local network or "neighbors" at time t. The third item represents the benefit brought by the indirect network effect. We distinguish between the utility of consuming complementary products and the utility of indirect network effects. Of course, the utility that consumers derive from complementary products is related to the direct quantity of products, but it is also related to other factors such as opportunities and accessibility levels, e.g., in taxi-haling industries, and consumer utility related to the geographical locations of taxis and the number of taxis. M_{kt} denotes the number of complementary products on platform k at time t. $(\sum_{j\in\{1,\ldots,M_k\}} x_{ikjt}^{\sigma})^{1/\sigma}$ represents the constant elasticity of substitution (CES) utility of consume complementary products, where $0 < \sigma < 1$ denotes the degree of product substitution. $v_{1k}(\cdot)$ and $v_{2k}(\cdot)$ are assumed to be convex according to the principle of diminishing marginal returns. More precisely, the function forms are assumed to be

$$v_{1k}(d_{ikt}) = \alpha_{1k}(d_{ikt})^{1/\beta_1}, \tag{2}$$

and

$$v_{2k}\left(\left(\sum_{j\in\{1,\ldots,M_k\}} x_{ijkt}^{\sigma}\right)^{1/\sigma}\right) = \alpha_{2k}\left(\left(\sum_{j\in\{1,\ldots,M_k\}} x_{ijkt}^{\sigma}\right)^{1/\sigma}\right)^{1/\beta_2}, \tag{3}$$

where α_{1k} and α_{2k} represent the strengths of direct and indirect network effects, respectively, and β_1 and β_2 are the network effect indexes. We assume that the cost of a consumer switching across two platforms is a portion of the total utility derived from the original platform in period t, and so the cost of consumer i switching from platform k to the other platform is

$$s_{ikz} = \lambda\left(v_{0k} + v_{1k}(d_{ikt}) + v_{2k}(\sum_{j\in\{1,\ldots,M_k\}} x_{ikjt}^{\sigma})^{1/\sigma}\right) \tag{4}$$

$\lambda \in [0, 1]$ is the coefficient of the switching cost, where a higher value of λ indicates a larger switching cost. This cost is incurred only if the consumer switches from platform k to the other. Suppose that the price of the platform k at time t is p_{kt}, and the price of the complementary product is p_{jkt}. In our model, we do not regard the price as a decision variable of platforms, as we rather examine the evolution of industries under the assumption of exogenous prices. Consumers select platforms on the basis of the current and expected

next states of platforms. The surplus of users under different conditions is described as follows:

$$\pi_{it}(a_{it}|a_{-it}, a_{Jt}, \delta_t) = \begin{cases} 0 & if\ \delta_t = 0, a_t = 0 \\ u_{ikt} - p_{kt} & if\ \delta_t = 0, a_t = k \\ -s_{kt} & if\ \delta_t = k, a_t = 0 \\ u_{ikt} - p_{kt} - s_{kt} & if\ \delta_t = k, a_t = k' \\ u_{ikt} & if\ \delta_t = k, a_t = k \end{cases} \tag{5}$$

where $a_{it}, a_{-it}, a_{Jt} \in \{0, A, B\}$ represent the decision of user i, other users except for i, and sellers on which platform to join, and $\delta_{it} \in \{0, A, B\}$ represents the state of user i in terms of whether they use a platform and which platform they are attached to.

In a complex learning system, the agent has adaptability and learning ability. They can adjust their current strategy according to past strategies and expectations for the future. We define the evolution of the behaviors of players on the basis of behavioral game theory on the learning behaviors of players. During product diffusion, past experience or reinforcement learning has a certain role, while faith learning also plays an important role in decision making. The experience-weighted attraction (*EWA*) learning algorithm combines these two main learning processes—intensive and belief learning [50]. Therefore, we use the *EWA* algorithm as the basis of the agent learning algorithm. The *EWA* assumes that each strategy has a numerical attractiveness index, and the probability of choosing each strategy is determined by certain rules. It should be noted that this is a very general rule such that the interpretation and use of the attractiveness index can be very flexible (e.g., introducing expectation factors). In the model, we set different expectation parameters for different platforms. Higher expectations represent more preferences for platforms.

We modify the EWA as follows: First, we introduce the user's expectations on their neighbors' and the sellers' adoption decision as

$$\begin{cases} d^E_{ikt} = d^E_{ikt-1} + \gamma(d_{kt-1} - d^E_{ikt-1}) \\ M^E_{ikt} = M^E_{ikt-1} + \gamma(M_{kt-1} - M^E_{ikt-1}) \end{cases} \tag{6}$$

where d^E_{ikt} and d^E_{ikt-1} are the expected number of their neighbors who will join platform k at time t and $t-1$, respectively; d_{kt-1} is the actual number of their neighbors who have joined platform k at time $t-1$; and γ is the learning rate coefficient. Similarly, M^E_{ikt} and M^E_{ikt-1} are the expected number of sellers providing complementary products for platform k.

Attractions start at $A^k_i(0)$ and are updated according to

$$A^k_i(t) = \frac{\phi N(t-1) A^j_i(t) + [\tau + (1-\tau)\delta_t]\pi_{it}(s^k_i, d^E_{ikt}, M^E_{ikt} \Big| \delta_t)}{N(t)} \tag{7}$$

where $N(t)$ represents the empirical weight, which starts at an initial value $N(0)$ and is updated according to $N(t) = \phi(1-\kappa)N(t-1) + 1$; ϕ represents the discount factor of past experience; and τ indicates the degree of the "imitation effect" or the discount factor for the payment of unselected strategies or opportunity costs. The larger the value is, the more the users pay attention to the strategy that they used in the last period or the higher the expectation payment of the selected strategy. In the *EWA* algorithm, each strategy is randomly chosen. The attractiveness index determines the probability of each strategy being adopted accordingly. Therefore, the strategy with the larger attractiveness index is more likely to be selected. To reflect the effects of expectations, we multiply each attractiveness index by a corresponding expectation factor ρ_k. On the basis of the commonly used Logit decision model, then the probability of a consumer joining platform k is

$$p_{ikt} = \frac{\exp(\rho_k A_{ik}(t))}{\Sigma_{l \in \{0,A,B\}} \exp(\rho_l A_{il}(t))} \tag{8}$$

3.2. Seller Decisions

Under the indirect network effect, the number of sellers that a platform can afford is endogenous and dynamic. This number is directly related to the number of users who used the platform in the previous period. We take a structural model of constant elasticity of substitution (*CES*) demand in the complementary product market to identify the decisions of sellers. After joining a platform k, a user i purchases an assortment of complementary products in each period by maximizing her utility subject to budget constraints:

$$\begin{cases} \max_{\{x_{i1kt},\ldots,x_{iM_{kt}kt}\}} \left(\Sigma_{j\in\{1,\ldots,M_{kt}\}} x_{ijkt}^{\sigma}\right)^{1/\sigma} \\ s.t.\ \Sigma_{j\in\{1,\ldots,M_k\}} p_{jkt} x_{ijkt} = I_{it} \end{cases} \tag{9}$$

The term I_{it} is the budget constraint of user i at time t, which when assumed obeys an identical independent normal distribution $N(E(I_{it}), Var(I_{it}))$.

Then, the corresponding individual Marshallian demand for product j on platform k is

$$x_{ijkt}^{*} = \frac{I_{it}}{p_{jkt}^{1/(1-\sigma)} \Sigma_{j\in M_k} p_{jkt}^{-\sigma/(1-\sigma)}} \tag{10}$$

Then, on the seller side, the profit function for a seller j on platform k in period t is

$$\pi_{jkt} = (p_{jkt} - c) \sum_{i\in\{1,\ldots,n_k\}} x_{ijkt}^{*} \tag{11}$$

where c is the marginal cost consisting of both production costs and royalties to the platform. We assume that the sellers are ex ante identical and then there is a symmetric price equilibrium in which each firm sets prices as follows:

$$p_{jkt}^{*} = \frac{\sigma(M_{kt} - 1)}{M_{kt} - \sigma} c \tag{12}$$

Thus, the profit is

$$\pi_{jkt}(n_k, M_{kt}) = \frac{\sigma - 1}{\sigma(M_{kt} - 1)} \Sigma_{i\in\{1,\ldots,n_k\}} I_{it} \tag{13}$$

Sellers choose to join a platform on the basis of the expected quantity of users and sellers on each platform, and like the users, the adaptive expectations of seller j on the number of users and sellers are

$$\begin{cases} n_{ikt}^{E} = n_{ikt-1}^{E} + \gamma_s (d_{kt} - n_{ikt-1}^{E}) \\ M_{ikt}^{E} = M_{ikt-1}^{E} + \gamma_s (M_{kt-1} - M_{ikt-1}^{E}) \end{cases} \tag{14}$$

the seller's profit function for different cases is summarized as follows:

(1) The sellers who has not joined any platform and who will continue to do so will gain no profit; if the sellers choose to join platform k, they will gain net profits $\pi_{jkt}(n_{kt}^{E}, M_{kt}^{E}) - lc_j$, where lc_j is the learning cost incurred from preparing to produce a compatible product or service, which is assumed to be a normally distributed random variable, $N(E(lc_j), Var(lc_j))$.

(2) A seller on platform k will gain $\pi_{jkt}(n_{kt}^{E}, M_{kt}^{E})$ when continuing to stay on; if sellers withdraws from platform k and will not join any platform, they will gain no profit; if they join the other platform, then the net profits are $\pi_{jk't}(n_{k't}^{E}, M_{k't}^{E}) - lc_j$.

Then, the probability of a seller joining platform k is

$$p_{jkt} = \frac{\exp(\rho_k \pi_{jk}^{E})}{\Sigma_{l\in\{0,A,B\}} \exp(\rho_l \pi_{jl}^{E})} \tag{15}$$

3.3. Complex User Network Construction

The complex network used in the users' interaction network is based on the small world network model proposed by Newman and Watts [49], where the connection topology is assumed to be either completely regular or completely random. The specific steps involved in constructing the network are as follows:

(1) Start with order: Construct a ring-shaped network consisting of N nodes, where each node i is adjacent to its neighboring nodes, $i = 1, 2, \ldots, K/2$, with K being even. Here, the nodes represent users.
(2) Randomization: Add shortcuts between randomly chosen pairs of nodes with probability p.

We adopted the simulation method for the following two reasons: First, by explicating the micro-foundations of user decision making, one can discern the decision-making mechanism that underlies the transformation of user scale and comprehensively examine the rationales behind the impact of distinct parameters on the outcomes of the model. This enables a more nuanced comprehension of the two-sided platform's operations, which remains elusive through big data analytics alone. Second, the extant body of literature pertaining to user simulation models exhibits a dearth of scholarship that focuses on two-sided platforms, with an even more conspicuous absence of research on competitive two-sided platforms. Consequently, the present study significantly supplements the current corpus of simulation model research by addressing this research gap.

4. Computing Settings

Under the above model settings, a large number of repeated computer simulation experiments were carried out to investigate the influence of various factors or parameters on product diffusion by adjusting the relevant parameter values. We applied our model as an agent-based model. Here, we present a simulation for a population of 200 users with each user having eight neighbors on average $(k = 4)$ and with 20 sellers in total. We simulated the evolution of market structures 30 periods, as we found that almost all results tended to be convergent over 30 periods. Each set of simulations included 50 runs. We report the average of the runs and standard deviations.

We assumed that in the initial stage, the number of sellers and users was exogenously given. The platform software product was incompatible. At each time t, everyone calculated the expected total return of each strategy. The EWA algorithm was used to calculate the attractiveness index of each strategy and then to adopt a certain strategy of a certain probability on the basis of the attractiveness index. The platforms' market shares of users and sellers evolve according to each agents' decisions.

The main parameters of the model are the intrinsic value v_{0k}, the strength of the direct network effect α_{1k} and indirect network effect α_{2k}, and the degree of switching costs λ. We used $v_{0A} = v_{0B} = 5$ as the baseline, which represents a case in which no user joins the platform without network effects. The lower bound for λ is zero and corresponds to an unrealistic case in which switching to another platform never incurs costs. On the other hand, if λ is sufficiently high then the few users will choose to switch. We considered $\lambda \in \{0.01, 0.1, 0.5\}$ and made a distinction between two platforms. We considered the strength of network effect $\alpha_{1k}, \alpha_{2k} \in \{1, 2, 3\}$ and $\beta_1 = 1.5$, $\beta_2 = 2$ to render the effects of direct and indirect network roughly equal. The remaining benchmark parameters were set as follows (Table 1):

Table 1. Benchmark parameters.

Parameter		Value	
		A	**B**
N	Size of consumer population	200	
M	Size of seller population	20	

Table 1. *Cont.*

Parameter		Value	
		A	**B**
N_{k0}	Initial install bases of users	20	20
M_{k0}	Initial install bases of users	2	2
α_{1k}	Strength of direct network effect	2	2
α_{2k}	Strength of indirect network effect	2	2
β_1	Index of direct networks	1.5	
β_2	Index of indirect network effect	2	
σ	Index of CES utility	0.5	
v_{0k}	Intrinsic value of platforms	5	5
K	Average number of neighbors of user	8	
λ	Switching costs	0.5	0.5
p_{kt}	Price of platforms	15	15
γ_b	Adaptive expectation coefficient of users	0.5	
γ_s	Adaptive expectation coefficient of sellers	0.5	
$E(I_{it})$	Users' budget expectations	10	
$Var(I_{it})$	Users' budget variance	4	
c	Marginal cost of sellers	10	
$E(lc_{jt})$	Sellers' expected learning costs	100	
$Var(lc_{jt})$	Variance in learning costs	16	
ρ_{uk}	Expectation factors of users	1	1
ρ_{sk}	Expectation factors of sellers	0.1	0.1
ρ	Probability of randomly added shortcuts	0.2	

5. Results Analysis

5.1. Properties of Platform Diffusion with Direct and Indirect Network Effects

First, simulations were performed on the basis of the benchmark parameters. Here, the two platforms had exactly the same initial conditions. It can be observed from the experimental results (Figure 1) that the platform's diffusion under the indirect network effect and small-world networks among users was significant, where the diffusion rate was very fast and increased significantly when the number of users using the platform reached a certain threshold, which was also the case for the seller side. The nature of diffusion was determined by network effects and the average shortest path of the "small world" model. We also observed that the consequences of diffusion were directly related to the initial state and especially to the distribution of the individual on the users' network structure. The dominating platform was random under the same simulation conditions. Due to network externalities, there were obvious nonlinear and positive feedback properties of the diffusion of competitive platforms. Slight differences in initial states may generate completely different results from the diffusion process. The platform that reaches the threshold number of users first can certainly occupy a large share of the market. This conclusion partly confirms the results in Kretschmer et al. [51].

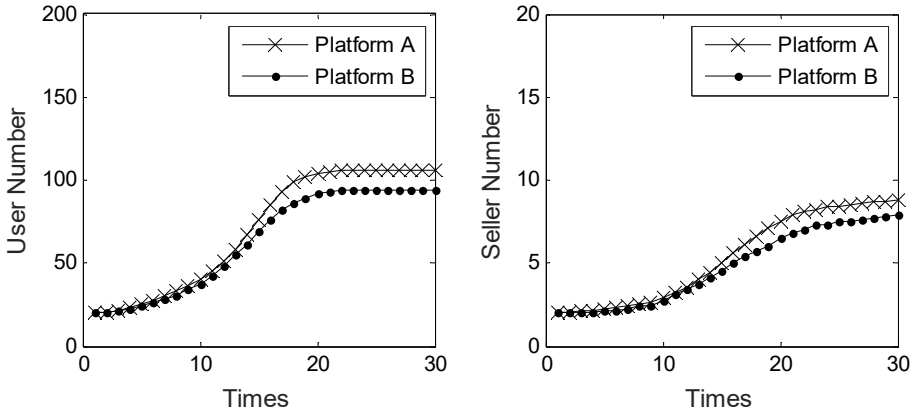


Figure 1. Competitive platform diffusion on the user and seller sides with the same initial conditions.

In addition, due to local properties of the small-world network structure, the coexistence of multiple platforms in the market was prevalent but with a fair degree of asymmetry in market shares rather than only one platform dominating the entire market. To ensure the robustness of this conclusion, we simulated 50 times under the same initial conditions and collected statistics on the market shares of platforms for the user and seller sides. As is shown in Figure 2, the market share of both platforms was distributed at 0.2–0.8, and most of the time their shares were asymmetric. On the user side, the mean value market share of platform A was 0.54, and the standard deviation was 0.36. This was the case because the user's utility under the direct network effect was determined by the number of neighboring individuals who used the same platform rather than the entire quantity. Therefore, even from a global perspective, the number of users using the other platform was greater, and using the original platform was still optimal from a local perspective, which often leads to formation of a variety of platforms. The coexistence of multiple platforms is also a phenomenon that people often observe in the competitive market. For example, in the operating system market, although Microsoft occupies the main market, Microsoft Windows, Linux, and MacOS operating systems have coexisted for a long time, and it appears that they will continue to exist. This conclusion can also be seen in the works of Zhu and Iansiti [30] and Farronato et al. [52].

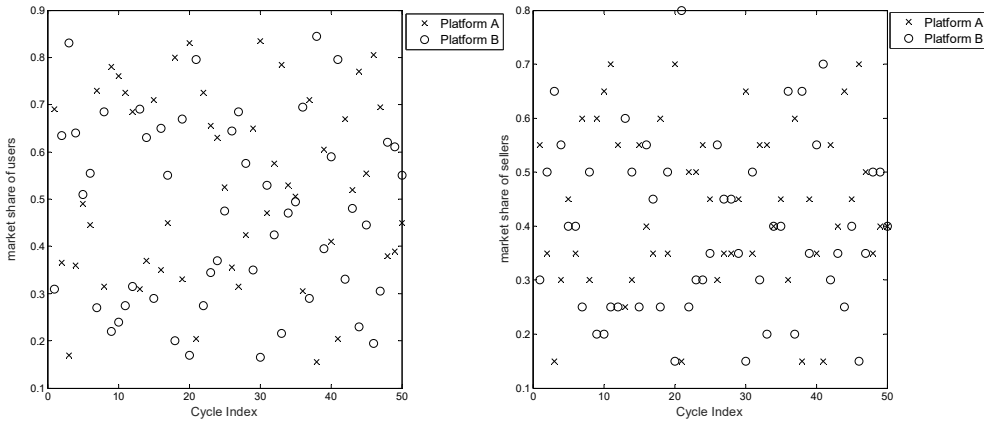


Figure 2. Simulation robustness test.

Conclusion 1. Under the indirect network effect and a small-world network, the diffusion of platforms shows explosive growth when users and sellers reached a certain critical mass. In addition, the final distribution of platform diffusion often creates a situation where two platforms coexist, while the market share is asymmetric.

5.2. First-Mover Advantage—The Number of Users and Available Complementary Products

The first-mover advantage of product diffusion and the resulting path dependence and even lock-in effects are often mentioned in the platform diffusion and competition literature [53,54]. Under the indirect network effect, the two main factors that may lead to a first-mover advantage are the number of users and the number of complementary products that can be used in the initial stage, but as we show above, these two factors impact the diffusion process through different mechanisms. In simulations, when the number of users in the initial stage of platform A was larger than that of platform B we set $n_{A0} = 40$ and $n_{B0} = 20$), the results (Figure 3) show that this initial advantage can overcome the randomness of diffusion such that the advantage platform (which had more users at the beginning) can occupy most of the market share on both sides, even when there were no advantages on the seller side. The randomness of diffusion refers to uncertainty in market structures under symmetrical initial conditions. The first-mover advantage can overcome this uncertainty and cause the market to present a stable trend. The average market share of platform A on the user side was roughly 85.96% and was 72.30% on seller side. This conclusion enriches the traditional theory of first-mover advantage [53,54].

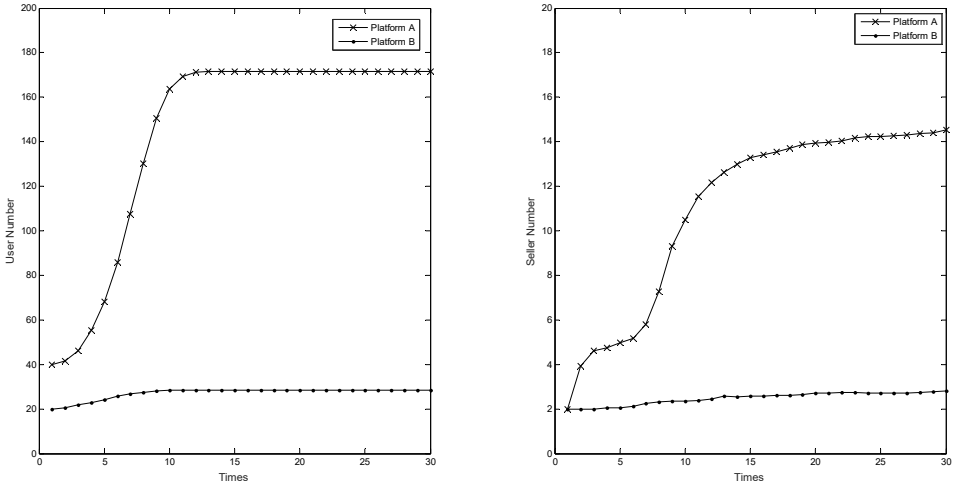


Figure 3. Platform diffusion with a first-mover advantage on the user side.

When repeated 50 times, the platform with a first-mover advantage for users presented obvious steady-going advantages, as shown in Figure 4. Variances in differences between market shares of platforms A and B on the user and seller sides were 0.0417 and 0.075, respectively, which means that platform A maintained a higher degree of market occupation with remote fluctuations.

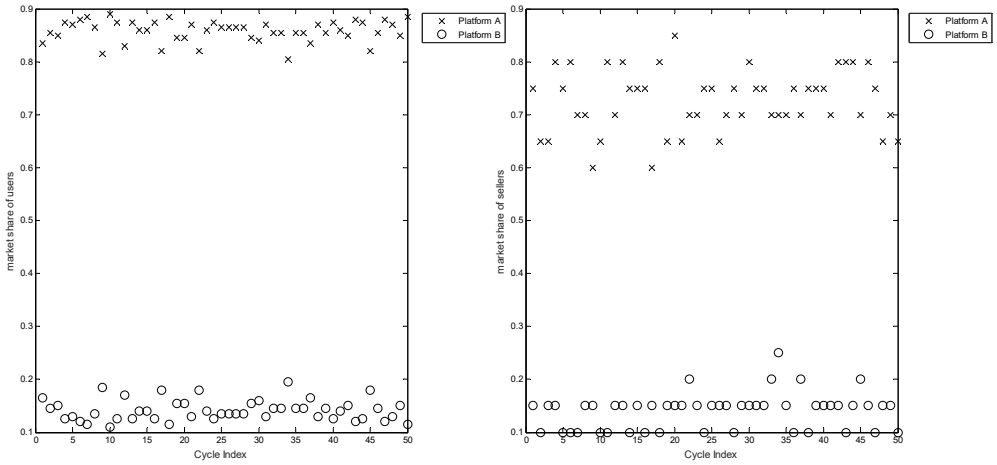


Figure 4. Robustness test conducted under a first-mover advantage on the user side.

Under the indirect network effect, a larger number of sellers that can be provided on one platform can also form a first-mover advantage. If one platform offers more complementary products than the other in initial stages, users endow that platform with a higher value, forming a positive feedback mechanism. We now consider the impact of the first-mover advantage of the seller side on diffusion. The number of sellers providing complementary products for platform B under the above settings was changed to 4 with the same number of users ($n_{A0} = n_{B0} = 20$). The simulation results are shown in Figure 5. The first-mover platform of the seller side occupied roughly 73.67% of the market share of the user side and 61.5% of that of the seller side. With 50 repetitions, the robustness results are shown in Figure 6. Platform B here always occupied a larger market share on both sides than platform A. It can be observed that first-mover advantages of the user and seller sides can help create a considerable competitive advantage over the lagging one. When combined with the emerging properties of diffusion shown in the previous section, it was also found that the first-mover advantage can only be obtained after a critical point. As an example of a first-mover advantage on the seller side, we can refer to competition between Microsoft and Apple's operating systems. Although Microsoft is behind in the initial

stage, it provides a more convenient development tool for supporting the faster growth of third-party software. This is one reason why Microsoft can dominate the competition.

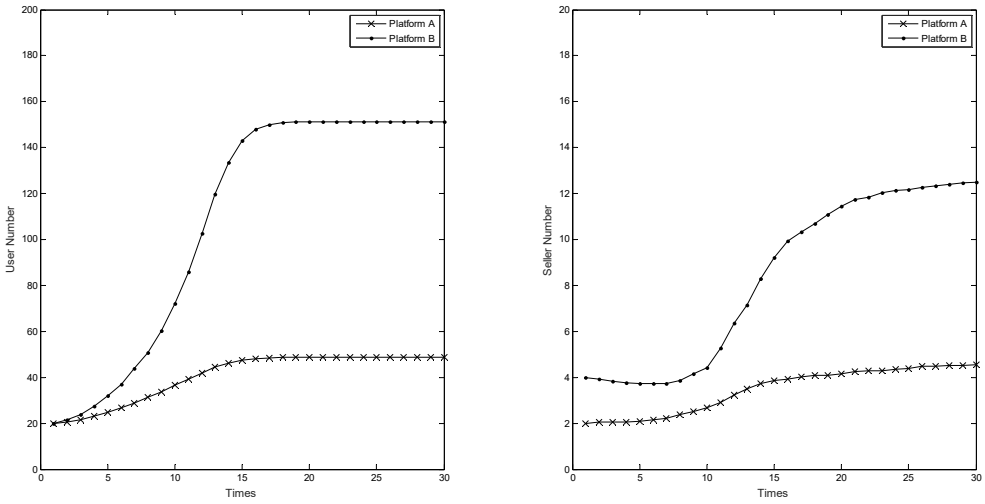


Figure 5. Platform diffusion with first-mover advantages on the seller side.

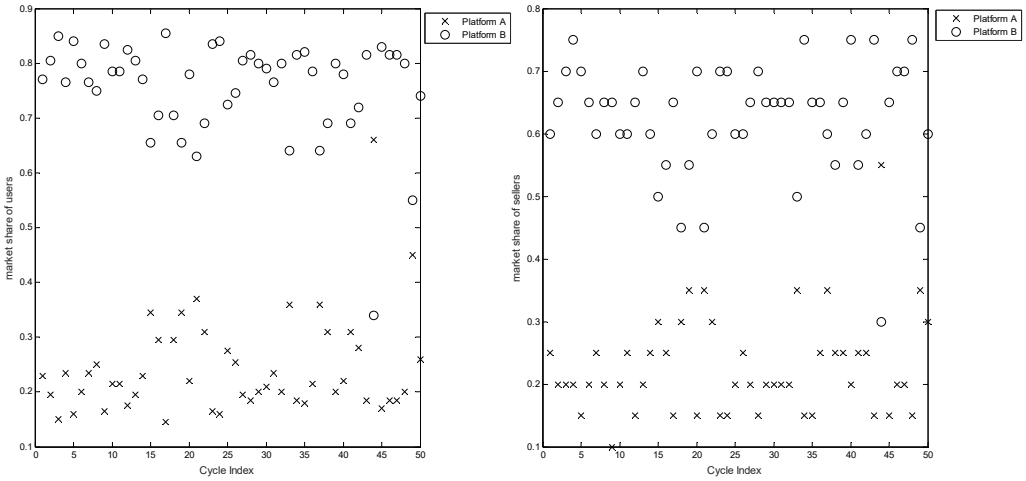


Figure 6. Robustness test conducted with first-mover advantages on the seller side.

We then investigated what will occur when one platform presents an advantage on the user side, while the other presents an advantage on the seller side. We set the number of platform users as $n_{A0} = 40, n_{B0} = 20$ and the number of sellers as $M_{A0} = 2, M_{B0} = 4$. As the advantages applied were the same as those used previously, we were able to compare them with the cases involving a one-sided advantage. The results given in Figure 7 show that platform A with advantages for users showed more occupation on both sides. Although platform B offered more complementary product providers initially, soon this advantage dissipated, and the direct network effect dominated the indirect network effect in this case. This was a novel result, as most previous studies have modeled indirect network effect by only considering quantity effects and equating direct and indirect network effect as of the same position. We found the mechanisms of these two factors to be quite different. Due to substitute effects among sellers, more sellers on one platform results in more intensive competition among them. Thus, if a platform gains a first-mover advantage on the seller side but falls behind on the other side, then they will lose the original advantage. As can be observed from Figure 7, even though platform A had no first-mover advantage on the seller side, they still achieved a considerable advantage in terms of product proliferation due to the faster increase on the seller side. The robustness results are shown in Figure 8.

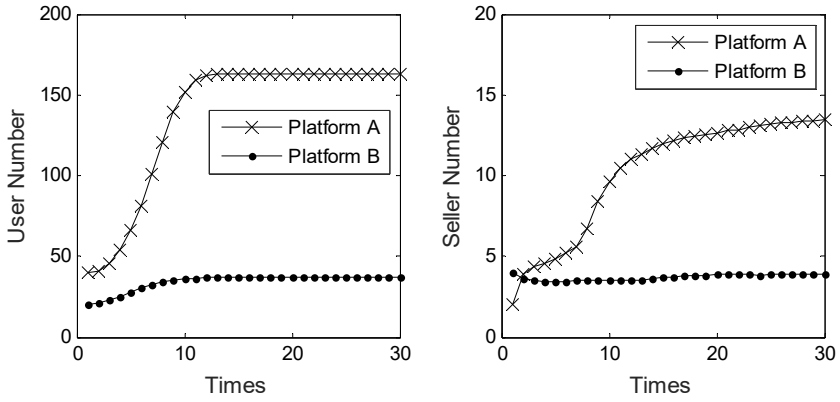


Figure 7. Platform diffusion with first-mover advantages on different sides.

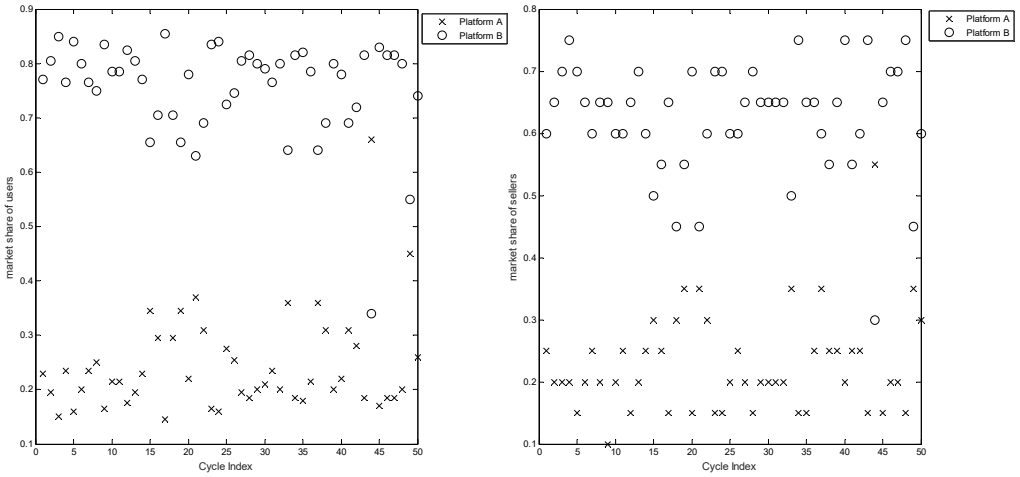


Figure 8. Robustness test conducted with first-mover advantages on different sides.

Conclusion 2. The impacts of direct and indirect network effects on platform diffusion and on their mechanisms are essentially different. Both the number of users and the number of sellers can form a first-mover advantage under indirect network effect. The direct network effect dominates the indirect network effect in an asymmetric situation when one platform offers an advantage on the user side, while the other platform offers an advantage on the seller side.

5.3. Iteration of Platforms and Consumer Heterogeneity

The iteration between new and old platforms under a strong network effect is an interesting issue to explore. The users of old platforms will not adopt new platforms unless they switch to a new one, as the utility of adopting a new platform is certainly not as strong as it is when switching does not occur under strong network effects. In fact, platform iteration is not a fast-moving process and is rather a process of gradual evolution from part to whole.

In this case, we introduced the heterogeneity of users by adjusting the expectations of different platforms under conditions of old platform dominance. The intrinsic value of a new platform and new platform expectation factors were improved, and the price of a new platform slightly declined. The simulation results showed that even when an old platform is far superior in terms of its market share on both the user and seller sides, the new platform can still replace the old one and realize a complete reversal of previous technologies.

In our setting, platform A occupied 75% of the market share on both sides in initial stages, and a new platform B was characterized by higher intrinsic value ($v_{0B} = 20$), stronger user expectations of future utility ($\rho_{uB} = 2$), and stronger network effects ($\alpha_{1A} = \alpha_{2A} = 1, \alpha_{1B} = \alpha_{2B} = 3$) of market entry with an initial 25% market share on both

sides. In addition, we set a slightly reduced price to the new entrant in the initial stage ($p_{B0} = 12$). Under these settings, the simulation results (Figure 9) show that the iteration of new and old platforms can be realized. And the robustness results are shown in Figure 10.

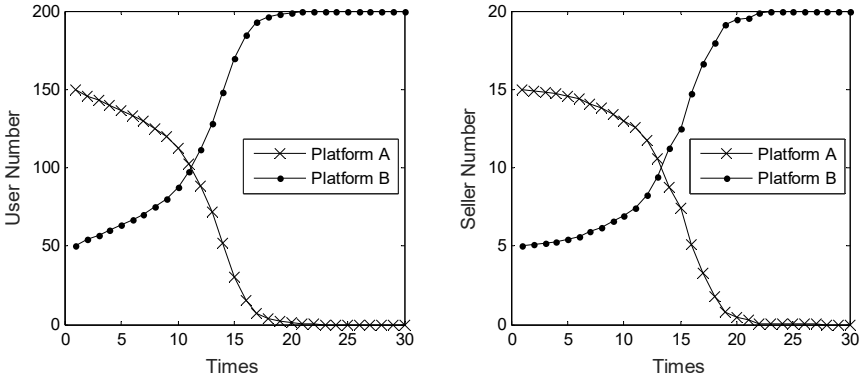


Figure 9. Iteration of new and old platforms.

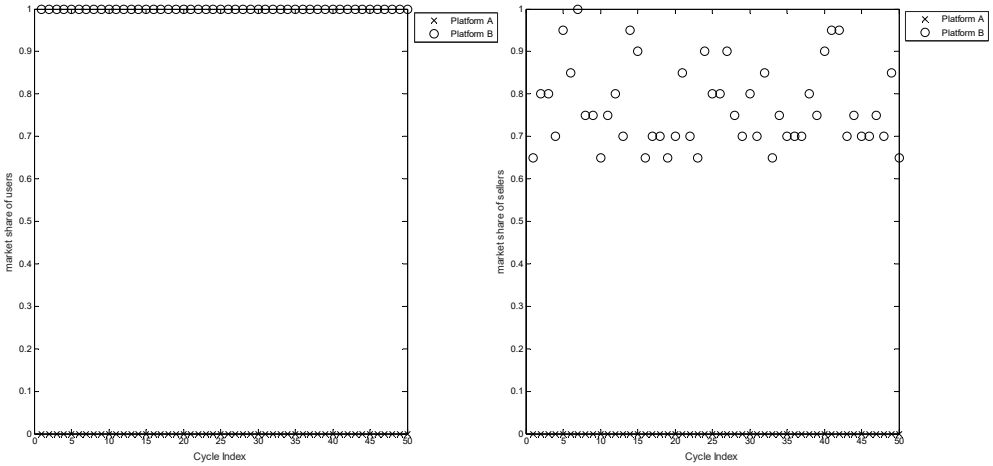


Figure 10. Robustness test of new and old platform diffusion.

As an interesting phenomenon, we found that the evolution of the seller number lags that of the user side. Since the seller's only concern is the total number of users on the platform, the sellers will not change their places until the install base of the other platform is large enough to conquer their learning costs of switching to the other platform. From a strategic perspective, the role of direct network effect should be emphasized in the early stages of platform launch. Enterprises should understand the preferences of their target customers and try their best to increase the number of initial users through the use of various marketing strategies. After launching, enterprises should also pay attention to the development of complementary markets, constantly enriching and expanding the development of supporting products as much as possible to enhance the role of indirect network effects and realize sustainable development.

Conclusion 3. Iteration between new and old platforms will occur when a user's expectations of future utility from a new platform and of the intrinsic value of a new platform are higher, as well as when the new platform provides a slightly lower price in an initial stage.

5.4. Effects of Switching and Learning Costs on Platform Competition

Industries with network effects are often characterized by finite switching and learning costs: consumers and sellers can switch between platforms, but it is costly for them to do so in terms of money and/or effort. Asymmetries in switching and learning costs also have significant implications for platforms competing across differentiated market

structures. In the absence of switching costs, network effects tend to lead to high market concentration: the platform with larger network size is more attractive to consumers, forming positive feedback to stimulate the platform to continue to grow. The existence of switching costs change this situation. Switching costs will increase the growth resistance of large-scale platforms, thereby expanding the survival space of smaller platforms. When this influence dominates the network effect, the larger platforms tends to "harvest" its lock-in users with a higher price, and in turn, the market will not evolve into a structure of "winner-take-most". We examined market structures that apply under different switching and learning costs when one platform has prior quality but a lower market share. We set $n_{A0} = 150, n_{B0} = 50, M_{A0} = 15, M_{B0} = 5, v_{0A} = 5, v_{0B} = 20$. As is shown in Figure 11, when switching and learning costs are relatively high ($\lambda = 0.5, E(lc) = 100$), platform A of lower quality but with a higher market share keeps its leading position unchanged; as switching and learning costs decrease, platform B of higher quality but with a lower market share will overturn the market on both sides, and the more costs decrement, the faster platform B dominates on both sides.

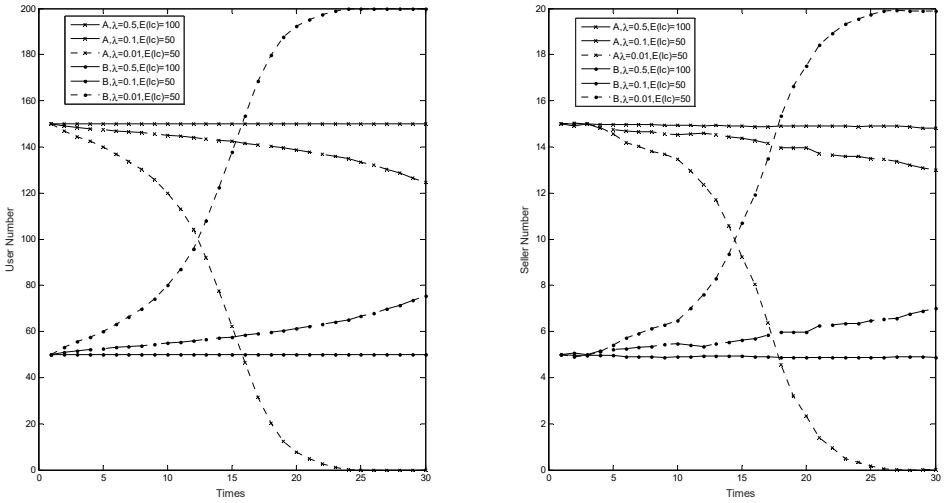


Figure 11. The impacts of switching and learning costs on platform competition.

Conclusion 4. The switching costs of users and learning costs of sellers have significant impacts on market concentration. When these costs are high, the market maintains its concentration and the prior platform cannot dominate the market. A decrease in switching and learning costs raises the prior platform's market share and the speed of market occupation.

6. Conclusions and Discussion

This paper explores competitive platform diffusion occurring under network effects and in complex networks. We distinguish the direct network effect from the indirect network effect by constructing different individual decision-making models and interaction mechanisms to investigate complex two-way interactions between micro-individuals (user and seller decision making) and macro-phenomena (platform diffusion). The diffusion of new platforms should be regarded as a systematic process, and the role of different network effects in different stages of platform diffusion should be fully understood. We analyzed "emergence" phenomena of platform diffusion; the impact of first-mover advantages, expectations, switching costs, and learning costs on platform diffusion; and the renewal of new and old platforms through the simulation of users' and sellers' choice behaviors.

6.1. Theoretical Implications

Our results demonstrate that competition and diffusion occurring in platforms depend on a variety of factors that are often ignored to obtain closed-form solutions. Our findings highlight that the diffusion of platform-based products with a network effect hinges on the nature of competition. We reveal that when the diffusion of platforms shows explosive

growth when users and sellers reach a certain critical mass, the final distribution of platform diffusion often creates a situation in which two platforms coexist, while the market share is asymmetric. Platforms can form a first-mover advantage on both the user side and seller side under indirect network effect, and when one platform has an advantage on the user side while the other platform has an advantage on the seller side, the direct network effect always dominates the indirect network effect due to competition effects among sellers. Iteration between new and old platforms will occur, provided that when a user's expectations of future utility from a new platform and of the intrinsic value of a new platform are higher, and when the new platform provides a slightly lower price in an initial stage. Finally, the switching costs of users and the learning costs of sellers have significant impacts on market concentrations. When these costs are high, the market maintains its concentration, and the prior platform cannot dominate the market. A decrease in switching and learning costs raises the prior platform's market share and the speed of market occupation.

6.2. Practical Implications

The results of this paper show that there is a significant and positive relationship between the growth of a platform's installed base and market share in long run. This synergistic growth path indicates that the network effects still play a very important role in competition. Therefore, for platform sponsors, the most important thing is to formulate a reasonable product release strategy that combines the quality and installed base according to the characteristics of the market, especially to enhance the quality of product attributes related to the network effects. Our research shows that when the intrinsic value and network value of the platform coexist, the market tends to be highly centralized. This does not mean that the platform with the first-mover advantage or the quality advantage will inevitably become the last incumbent. With different industrial characteristics, a platform's market position can be turned by using appropriate strategies.

6.3. Limitations

This study also has some limitations that leave room for future research. First, parameters such as network effect were set to constant. Actually, the network effect can be modeled as a function of the user quantity that the strength of the effect varies with different user scales, and such a change may lead to different results. Second, in our model, we kept the price unchanged in most situations, incorporating the pricing strategy into the model will help derive insights about how to make the price decision under different diffusion stages, but it will undoubtedly increase the difficulty of solving and calculating the model. Third, we assumed that both consumer and seller are single-homing, and there may be more meaningful results if the multi-homing of users is considered. Moreover, we only considered sellers' learning cost for each product and ignored their transfer costs. In addition, strengthening the robustness of conclusions through statistical methods will be a meaningful extension in the future.

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