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This paper seeks to answer three questions. First, which drives the success of a platform, installed base, platform quality or consumer expectations? Second, when does a monopoly emerge in a platform-based market? Finally, when is a platform-based market socially efficient? We analyze a dynamic model where an entrant with superior quality competes with an incumbent platform, and examine long-run market outcomes. We find that the answers to these questions depend critically on two parameters: the strength of indirect network effects and consumers' discount factor of future applications. In addition, contrary to the popular belief that indirect network effects protect incumbents and are the source of market inefficiency, we find that under certain conditions, indirect network effects could enhance entrants' quality advantage and market outcomes hence could be more efficient with stronger indirect network effects. We empirically examine the competition between the Xbox and PlayStation 2 consoles. We find that Xbox has a small quality advantage over PlayStation 2. In addition, the strength of indirect network effects and consumers' discount factor in this market are within the range in which platform success is driven by quality advantage and the market is potentially efficient. Counterfactual experiments suggest that PlayStation 2 could have driven Xbox out of the market had the strength of indirect network effects more than doubled or had consumers' discount factor increased by fifty percent.

Key words: platform competition; two-sided markets; indirect network effects; video game industry

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1 Introduction

Many high-technology markets are mediated by platforms.¹ These markets are often viewed as two-sided, since platform providers must get both consumers and developers of complementary applications on board in order to succeed (e.g., Evans 2003; Parker and Alstyne 2005). For instance, the markets for personal computers, personal digital assistants, and mobile phones are built around operating systems such as Windows and Linux. An operating system provider serves two parties: on one side, consumers need an operating system in order to access software applications, while on the other side, independent software vendors need to access the programming interface of the operating system in order to develop software applications. Other examples of such markets include intermediation services like online auction houses and sponsored search engines. Table 1 provides additional examples.

This paper seeks to answer three questions. First, which drives the success of a platform, installed base, platform quality or consumer expectations? Second, when does a monopoly emerge in a platform-based market? Finally, when is a platform-based market socially efficient? We consider a platform-based market to be socially efficient if it allows new platforms with superior quality to survive.

Researchers disagree widely on the answers to these questions. Some scholars argue that the success of a platform is driven by its installed-base advantage. Platform-based markets are often characterized by significant indirect network effects because of an inter-dependence between demands for platforms and demands for their associated applications: having more applications on a platform leads to greater demand for that platform; at the same time, a larger installed base of consumers leads to a larger supply of applications. As a result of indirect network effects, a platform that has a small lead on both sides of the market is likely to take over the entire market even if its quality is inferior to its rivals', thereby leading to an inefficient outcome (e.g., Shapiro and Varian 1999).² Consistent with this argument, in the Microsoft trial, the government claimed that indirect network effects materially strengthened Microsoft's monopoly power (Bresnahan 2002).

¹A platform is a system with well-defined access points and rules on which other parties can build applications or services (Iansiti and Levien 2004; Eisenmann et al. 2006).

²The QWERTY keyboard and the VHS video-recording format are two examples of allegedly inferior standards that won the battles over the Dvorak keyboard and the Betamax format because of indirect network effects (David 1985; Cusumano et al. 1992).

Park (2004) points out that if an incumbent has a big advantage due to a wide variety of available applications, a potential rival even with a significant cost or quality advantage should nevertheless not enter the market since the incumbent's installed-base advantage outweighs the cost and quality advantage of the potential entrant.

Some scholars argue that consumer expectations are the most critical factor in determining market domination. This expectation-driven view is largely supported by static models of indirect network effects (e.g., Katz and Shapiro 1994). In these models, consumers often form rational, or self-fulfilled, expectations regarding the market size of each platform. Expectations are important as each consumer prefers to adopt the platform that will be adopted by the majority of other consumers to maximize his benefit from application provision. When two platforms compete with each other, there often exist "monopoly equilibria" in which all consumers and application developers adopt one platform, and an "oligopolistic equilibrium" in which the two platforms share the market on each side. The monopoly outcome occurs when consumers and developers hold favorable expectations of one platform—they believe everyone else will adopt the same platform. As entrants lack installed bases, consumers tend to hold favorable expectations of the established platforms. Therefore this view also implies first-mover advantages and predicts that incumbents are likely to dominate the markets.

Other scholars challenge the installed-base driven and the expectation driven views. Evans (2003) finds that many early entrants in platform-based markets, such as Apple in personal computers, Netscape in browsers, and Diners Club in credit cards, did not retain their leadership positions. Srinivasan et al. (2004) finds that network effects actually have a negative effect on the survival duration of pioneers. Liebowitz and Margolis (1994, 1999) and MacCormack and Iansiti (forthcoming) argue that platform quality is the key to success and that Microsoft was successful because it produced a superior operating system. Rangan and Adner (2001) point out that there is no guarantee that the benefits from network effects will go to the first mover and emphasize the importance of being the best. Liebowitz (2002) argues that even in cases where the winner takes all, having the highest quality matters more than being first to market.³

³In addition, quality has been found to be have a significant positive influence on market share (e.g., Jacobson and Aaker 1985; Sethi 2000) and stock market returns (e.g., Aaker and Jacobson 1994; Johnson and Tellis forthcoming).

The three views outlined above would lead to distinct implications. The installed-base driven view emphasizes the importance of early leads and suggests that platform providers should rush to the market even if their products are premature. The expectation-driven view emphasizes the importance of expectation management. Entrants could shape expectations through aggressive advertising and credible commitments such as contractual agreements with application developers. Both the installed-base driven view and the expectation-driven view suggest that a potential entrant, even with a superior technology, may not succeed in the market given that indirect network effects protect the incumbent. Thus the market outcome could be socially inefficient and government intervention may be necessary. On the other hand, the quality-driven view suggests that the market is potentially efficient. According to this view, platform providers should invest heavily in R&D to improve their quality and only enter the market when their products are superior. Therefore, understanding the drivers of platform success has profound implications. Platform providers could make more informed decisions regarding time-to-market, quality update and pricing strategies. Policy makers could use this information to determine the likelihood that a society is locked into inferior technologies and decide whether to intervene.

To address the debate, we analyze a dynamic model in which an entrant with superior quality competes with an incumbent platform, and examine the long-run market outcomes. We find that the driver of platform success, long-run market structure and market efficiency depend critically on two parameters: the strength of indirect network effects and consumers' discount factor of future applications.

We empirically examine the competition between the Xbox and PlayStation 2 consoles. We find that Xbox has a small quality advantage over PlayStation 2, and that the strength of indirect network effects and the discount factor in this market are within the range in which platform success is quality driven. Counterfactual experiments suggest that PlayStation 2 could have driven Xbox out of the market had the strength of indirect network effects more than doubled or had consumers' discount factor increased by fifty percent. These results help explain the successful entry of Xbox into the home video game market and provide support for our theoretical model.

Our study makes several contributions. First, we present a dynamic model on platform com-

petition.⁴ Platforms have been studied extensively, mostly in the context of static models (e.g., Caillaud and Jullien 2003; Rochet and Tirole 2003; Armstrong 2007).⁵ The static models often lead to multiple equilibria as a result of the increasing return to demand in these markets. In many cases, the equilibrium market structure can either be monopolistic or oligopolistic in equilibrium. As industries characterized by indirect network effects are among the most dynamic industries, there is a need to develop dynamic models to address the equilibrium selection problem.

Second, the results from our dynamic model provide a positive reconciliation of the mixed views and suggest that one cannot make an *a priori* statement for market outcomes without empirical investigations. In addition, contrary to the popular belief that indirect network effects protect incumbents and are the source of market inefficiency, our results indicate that under certain conditions, indirect network effects could enhance entrants' quality advantage and market outcomes could actually be more efficient with stronger indirect network effects.

Our work also contributes to the empirical literature on indirect network effects. Researchers have examined indirect network effects in the context of digital televisions, home video cassette recorders, DVD and Divx players, yellow pages, personal digital assistants and home video games. Table 2 summarizes these earlier empirical studies. All of these studies, with the exception of Gandal et al. (2000) and Park (2004), reply on static frameworks. An implicit assumption of these static approaches is that both consumers and application developers act myopically. Gandal et al. (2000) analyze dynamic demand for a market with a homogeneous product (DVD players), while we study a market with two competing products. Park (2004) analyzes the competition between VHS and Betamax. As Park does not have data on the number of movie titles available for each technology, he essentially models indirect network effects as if they were direct: consumer utility is a function of the installed base of consumers rather than movie variety. Our study extends the

⁴There have been a handful of dynamic models on direct network effects, in which consumers benefit directly from the existence of other consumers, rather than from application provision (e.g., Cabral 2007; Driskill 2007). In these models consumers are often assumed to be myopic (Kandori and Rob 1998; Auriol and Benaïm 2000; Drinea et al. 2002), or only live for a single period (Skrzypacz and Mitchell 2006; Economides et al. 2005). As most network effects arise in indirect manner (Rochet and Tirole 2003), we examine indirect network effects, and allow both consumers and application developers to forward-look and live for many periods.

⁵One exception is Sun and Tse (2007) in which they use a differential game framework to analyze two competing platforms and find that one platform will dominate the market when each agent only adopts one platform. We show that market outcome also depends on the strength of indirect network effects and consumers' discount factor of future applications.

approaches in Gandal et al. (2000) and Park (2004), and considers forward-looking behavior in a market with differentiated products.

In addition, most existing empirical studies focus on detecting the presence of indirect network effects in specific markets. The relative importance of installed base, platform quality and consumer expectations in the evolution of platform-based markets has not been explored sufficiently. Our primary interest in conducting the empirical analysis is to find empirical support for our theoretical model. Policy makers and platform providers could apply the same approach to new situations to gain insights into market outcomes, and design optimal strategies accordingly.

The rest of the paper is organized as follows. Section 2 describes the model. Section 3 provides long-run equilibrium analysis. Section 4 generalizes our model to incorporate forward-looking consumer behavior. Section 5 discusses empirical strategies and reports results. Section 6 concludes by discussing the implications of our findings.

2 The Model

We consider two competing platforms, an entrant E and an incumbent I. Each platform is associated with a group of consumers and application developers on each side of the market. The two platform technologies are incompatible with each other: applications developed for one platform cannot be used on the other platform. Each application developer supplies one application. Each consumer is assumed to single-home: each adopts one platform only.

Timing is as follows. In each period, (1) a group of new consumers choose platforms and purchase available applications, (2) a group of new application developers choose the platforms, incur fixed costs and sell their applications to the installed base of consumers.⁶ The two actions occur simultaneously. When we go to the next period, the same set of actions is repeated. We assume, for simplicity, that each consumer allocates a fixed budget, y, to purchase applications in each period.

We assume that the two platforms are priced at the same level. While platform providers

⁶It is possible that the fixed costs are incurred at a different time or over a long period. In such cases, we evaluate the total fixed costs at the time of entry.

could strategically use prices to differentiate their platforms, this assumption allows us to focus on the interactions of installed base, platform quality and consumer expectations. Such intentional simplification is a time-honored approach and is used frequently in laboratory experiments and simulations (e.g., Nelson and Winter 1982; Burton and Obel 1995). In addition, this assumption is valid for many platforms that are based on non-proprietary technologies or sponsored by advertisers. Even for platforms based on proprietary technologies, as we will show in our empirical application, platform providers may choose to match each other's price.

We first consider the interaction between the two sides of the market within each period. Our objective is to characterize how consumer demand of a platform changes with application availability, and how application supply of a platform changes with its installed base of consumers. As the single-period analysis is well established in the literature (e.g., Church and Gandal 1992; Gandal et al. 2000; Park 2002; Nair et al. 2004), we present them here in abbreviated form.

2.1 Consumer Adoption

In this section, we focus on the myopic case in which a consumer's utility from adopting platform j is derived from the number of applications associated with the platform at the time of adoption. We relax this assumption in Section 4. We use b_{jt} and d_{jt} to denote the installed base of consumers and the total number of applications (equivalently, the total number of developers) associated with platform $j \in \{E, I\}$ at the beginning of period t. We use Q_j to denote the quality of platform j and assume that Q_j is constant over the life-cycle of the platform.⁷

Following the approaches in the literature (e.g., Church and Gandal 1992; Nair et al. 2004), we

⁷Consumers may also take application quality into consideration. We do not use a separate measure for application quality for two reasons. First, platform quality is often more important. The purchase experience on an auction site depends critically on the design and security protection of the site. Second, platform quality is often highly correlated with application quality. For example, applications written for a more powerful platform tend to run faster. Therefore, we use a single measure Q_j to capture the overall quality. When a platform is upgraded, we consider it as a new platform. Major platforms are often upgraded infrequently. For example, major upgrades to operating systems and Web browsers happen every few years, and new generations of video game consoles are released every six years on average. Therefore, we assume Q_j does not change over time and leave the competitive dynamics over multiple generations for future research.

obtain the utility a consumer receives from adopting platform j in period t, V_{jt} , as⁸

$$V_{jt} = \ln y + \ln Q_j / \rho_j + e \ln d_{jt}, \tag{1}$$

where ρ_j is the application price⁹ and e > 0 is a constant. Equation (1) suggests that the consumer's utility increases with the total budget he has for the applications, the (application price-adjusted) quality of the platform, and the amount of applications associated with the platform. The functional form has been used in empirical studies of indirect network effects such as Ohashi (2003).

Following the literature (e.g., Nair et al. 2004; Clements and Ohashi 2005), we use the standard logit model to capture heterogeneity in consumer tastes in platforms: We assume that the unobserved random portion of a consumer's utility independently and identically follows a Type-I extreme-value (Gumbel) distribution. Hence, the percentage of consumers choosing platform j in period t, s_{jt} , is (McFadden 1973):

$$s_{jt} = \frac{\exp(V_{jt})}{\exp(V_{Et}) + \exp(V_{It})}.$$
(2)

Simplifying equation (2), we have

$$s_{Et} = \frac{Q \cdot d_{Et}^e}{Q \cdot d_{Et}^e + d_{It}^e} \text{ and } s_{It} = \frac{d_{It}^e}{Q \cdot d_{Et}^e + d_{It}^e},$$
(3)

where $Q = \frac{Q_E/\rho_E}{Q_I/\rho_I}$. We refer to Q as the (application price-adjusted) quality ratio of the two platforms on the consumer side. It measures the quality advantage of the entrant over the incumbent.

From equation (3), we have:

$$\frac{s_{Et}}{s_{It}} = Q(\frac{d_{Et}}{d_{It}})^e. \tag{4}$$

As e > 0, the expression suggests that a platform becomes more attractive to consumers when its quality advantage increases, and when the number of associated applications increases. We use e as our measure for the strength of indirect network effects as it measures how much platform

⁸We include the detailed derivation in Appendix A.

⁹There exists a symmetric equilibrium in which application prices are the same for each platform. See Appendix B for details.

demand at time t responds to the change in the ratio of the numbers of associated applications. 10

2.2 Developer Entry

We follow the approach due to Gandal et al. (2000) to analyze the dynamics on the developer side. Developers choose platforms to maximize total profits over the life-cycle of their applications. Using the free-entry condition on the developer side, we could obtain the number of new developers supporting platform j in period t, Δd_{jt} , as:¹¹

$$\Delta d_{jt} = \alpha_t \cdot \frac{b_{jt}}{F_{jt}},\tag{5}$$

where α_t is a function of t and F_{jt} is the fixed cost of supporting platform j in period t. The equation suggests that an exogenous reduction in the fixed cost (F_{jt}) , and an increase in the installed base of consumers (b_{jt}) could induce more application developers to enter the market.

We assume that the fixed cost drops at the same rate for both platforms and let $F = F_{It}/F_{Et}$ be the ratio of the two fixed costs. As F_{It} and F_{Et} drop at the same rate, F does not vary over time. F measures the cost advantage of platform E over platform I on the developer side.

We now proceed to illustrate how successive adoption choices made by consumers and developers in each period eventually aggregate into a collective choice.

3 Long-Run Equilibrium Analysis

We now extend the one-period model into multiple periods. As consumers may cease to use platforms or switch to other ones and application popularity tends to decrease over time, it is important to take into consideration the decay in the installed base of consumers and applications.

We use $\delta_b \in (0,1)$ and $\delta_d \in (0,1)$ to denote the "rate of decay" (or "death rate") of the installed base and associated applications. Let M_t be the total number of new consumers at time t. The

¹⁰There is no standard measure of the strength of indirect network effects. One appeal of our measure is that it is unitless, thus allowing comparisons across different markets.

¹¹We include the detailed derivation in Appendix B.

change of the installed base of platform E is

$$\dot{b}_{Et} = \Delta b_{Et} - \delta_b b_{Et} = M_t \cdot s_{Et} - \delta_b b_{Et} = M_t \cdot \frac{Q \cdot d_{Et}^e}{Q \cdot d_{Et}^e + d_{It}^e} - \delta_b b_{Et}. \tag{6}$$

Equation (6) is intuitive: the change of the installed base of platform E is the number of new consumers adopting platform E less the number of existing consumers who exit the installed base in a given period. By incorporating δ_b , we essentially allow consumers to re-enter the potential market and re-consider their platform choices. We expect δ_b to decrease with switching cost: the more costly it is to switch, the lower is the rate of decay of the installed base.

We apply the same approach to the developer side and obtain a system of four equations:

$$\dot{b}_{Et} = M_t \cdot \frac{Q \cdot d_{Et}^e}{Q \cdot d_{Et}^e + d_{It}^e} - \delta_b b_{Et}, \qquad \dot{b}_{It} = M_t \cdot \frac{d_{It}^e}{Q \cdot d_{Et}^e + d_{It}^e} - \delta_b b_{It},$$

$$\dot{d}_{Et} = \alpha_t \cdot \frac{b_{Et}}{F_{Et}} - \delta_d d_{Et}, \qquad \dot{d}_{It} = \alpha_t \cdot \frac{b_{It}}{F_{It}} - \delta_d d_{It}.$$

We could then take t from 0 to infinity to understand the evolution of market. We summarize the long-run market structure in the proposition below.

Proposition 1. The long-run market structure depends on the strength of indirect network effects, e:

- (a) When e > 1, the market evolves towards a monopoly. That is, one platform eventually dominates the market.
- (b) When e < 1, the market evolves towards an oligopoly. That is, both platforms co-exist in the long run. In the long-run equilibrium, the ratio between the number of consumers in the two platforms is $Q^{\frac{1}{1-e}}F^{\frac{e}{1-e}}$, and the ratio between the number of developers is $(QF)^{\frac{1}{1-e}}$.
- (c) When e = 1,
 - (c.1) If QF > 1, the market evolves towards a monopoly and platform E eventually dominates the market.

- (c.2) If QF < 1, the market evolves towards a monopoly and platform I eventually dominates the market.
- (c.3) If QF = 1, the market evolves towards an oligopoly. The equilibrium market shares on both sides depend on initial installed bases and the two ratios, Q and F.

Proof. See Appendix D.

Proposition 1 suggests that the market may evolve toward either one of two regimes: a monopoly regime and an oligopoly regime. The market structure transits from one regime to the other at e=1. The intuition is that for a monopoly regime to emerge, indirect network effects have to be strong enough so that the market share advantage increases over time. When indirect network effects are not sufficiently strong, the initial installed-base advantage of the incumbent will actually diminish over time and the market eventually reaches a steady state.

We are particularly interested in the relative impact of installed-base advantage and quality advantage on the dynamics and efficiency of the market when a later platform enters with superior quality. Therefore, in the following discussion, we assume $Q \ge 1$ and $F \ge 1$, and $b_{E,0} < b_{I,0}$ and $d_{E,0} < d_{I,0}$. That is, the new entrant, E, has quality and cost advantages but the incumbent, I, has installed-base advantage. Based on Proposition 1, we have the following corollary:

Corollary 1. When e < 1, as e increases, the market share of platform E in the long-run equilibrium increases. The equilibrium market shares on both sides are independent of the initial installed bases.

Corollary 1 shows that the effects may actually enhance quality advantage of the entrant. When e approaches 1, the entrant's market share approaches 100% on each side even if its quality advantage is small. The intuition is that since indirect network effects are not sufficiently strong, the installed-base advantage of the incumbent diminishes. Because of the presence of indirect network effects, however, more consumers will take the same action and buy the higher quality platform. Therefore,

 $^{^{12}}$ The cost of developing a given application is often lower for a platform with higher quality (e.g., due to better development toolkits provided the platform). Hence Q and F are often positively correlated. We use quality advantage to refer to both quality and cost advantages in the following discussions.

the market shares of the entrant become larger on both sides due to indirect network effects. Furthermore, Corollary 1 indicates that initial installed bases have no effects on the market outcome in the long run. This result is striking as it contrasts with predictions of static models: it suggests that in the oligopoly regime, the installed-base advantage may not present barriers to entry, and that platform success can be entirely driven by quality advantage.

Although we have derived a closed-form solution for the long-run market share in the oligopoly regime, we do not have a closed-form solution to determine which platform would become the monopoly in the monopoly regime. We use numerical simulations to obtain insights.

Figure 1 shows simulation results for equilibrium market shares of platform E for different levels of indirect network effects. We assume $b_{E,0} = d_{E,0} = 10$, $M_0 = 5$ and $\delta_b = \delta_d = 10^{-3}$ in all simulations. As we are primarily interested in the growth stage of the market, we set the number of adopters to increase by 5% in each period.¹³

In Figure 1.A and 1.B, we let $b_{I,0} = d_{I,0} = 20$ and allow quality advantages Q and F to vary. We plot the long-run market share of platform E.¹⁴ Consistent with our theoretical prediction, when e < 1, both platforms co-exist in the long run and market shares of platform E increase with e. When e > 1, if the platforms are of the same quality, the incumbent platform I will be the monopoly platform. When the entrant's quality is higher, there exists a threshold, e^* , under which platform E will be the monopoly. Otherwise, platform E will be the monopoly. The threshold, e^* , increases with quality advantage: it increases from 1.65 for Q = F = 1.2 to 5.42 for Q = F = 2.0.

In Figure 2.A and 2.B, we fix the quality advantage at Q = F = 1.2 but allow the installed-base advantage to vary. Figure A shows the market share over time of platform E on the consumer side for e = 0.6 (the pattern for the developer side is similar and is thus omitted). We find that indeed the installed-base advantage does not affect the long-run market structure when e < 1. Figure B shows the value of e^* as the installed-base advantage of platform I increases. We find that e^* decreases with the installed-base advantage.

We summarize these results in the following proposition:

¹³Alternatively, one may use diffusion models (Bass 1969) to generate the number of adopters in each period. The results are not qualitatively different.

¹⁴Our algorithm stops if the market share does not change more than 10⁻⁵ on each side of the market.

Proposition 2. There exists a threshold e^* such that when $1 < e < e^*$, platform E will be the monopoly; when $e > e^*$, platform I will be the monopoly. e^* increases with the quality advantage of platform E and decreases with the installed-base advantage of platform I.

Hence when $e < e^*$, indirect network effects enhance quality advantage. The market outcome is efficient as the platform with superior quality has a larger market share on each side. When $e > e^*$, the platform with inferior quality may dominate the market.

4 Forward-looking Consumers

In our previous analysis, consumers are myopic—they make their decisions based on current state variables and do not consider utility from future applications. Such an assumption is frequently used in dynamic models on technology adoptions to yield analytically tractable solutions (see, for example, Auriol and Benaïm 2000; Casadesus-Masanell and Ghemawat 2006). In markets where switching costs are low or technology obsoletes fast, this assumption provides a good approximation.¹⁵

When consumers need to incur large fixed costs for access to platforms, they may take into account not only the current utility but also the expected future utilities from new applications. Consumer expectations in these contexts could play an important role in shaping the market dynamics. We extend our model to a setting in which consumers are forward-looking.

Studies on network effects have generally accepted the assumption of fulfilled consumer expectations (e.g., Katz and Shapiro 1985; Park 2004). Following this convention, we assume that consumers form rational expectations of the number of new applications in future periods. Let T be the life-expectancy of the platform.¹⁶ When a consumer adopts platform j in period t, his utility from the current applications is $V_{jt} = \ln y + \ln Q_j/\rho_j + e \ln d_{jt}$ and his utility from new applications

¹⁵For example, Internet surfers often choose video sharing sites based on the current number of clips each site offers.

¹⁶The model can be easily extended to the case where consumers plan to use the platform forever (i.e., $T \to \infty$).

released in period $s, s = t + 1, \dots, T$, is¹⁷:

$$V_{js} = \ln y - \ln \rho_j + e \ln \Delta d_{js}. \tag{7}$$

Hence the total utility a consumer derives from platform j is:

$$V_{jt}^{Total} = \sum_{s=t}^{T} \varphi^{s-t} V_{js} = \beta_y + \ln Q_j / \rho_j + e \ln N_{jt},$$

where $\beta_y = \ln y + \sum_{s=t+1}^T \varphi^{s-t} (\ln y - \ln \rho_j)$ and $N_{jt} = \exp\left(\ln d_{jt} + \sum_{s=t+1}^T \varphi^{s-t} \ln \Delta d_{js}\right)$. $\varphi \in [0,1]$ is the discount factor of future utility for consumers. When $\varphi = 0$, consumers place no value on future applications and we are back to the myopic case. As φ approaches 1, consumers are patient and value future applications as much as those currently available.

Following the same approach as in the myopic case, we derive a system of four equations:

$$\dot{b}_{Et} = M_t \cdot \frac{Q \cdot N_{Et}^e}{Q \cdot N_{Et}^e + N_{It}^e} - \delta_b b_{Et}, \qquad \dot{b}_{It} = M_t \cdot \frac{N_{It}^e}{Q \cdot N_{Et}^e + N_{It}^e} - \delta_b b_{It},$$

$$\dot{d}_{Et} = \alpha_t \cdot \frac{b_{Et}}{F_{Et}} - \delta_d d_{Et}, \qquad \dot{d}_{It} = \alpha_t \cdot \frac{b_{It}}{F_{It}} - \delta_d d_{It}.$$

An important feature of this system is that the adoption behavior influences and at the same time is influenced by application provision in the future.¹⁸ To understand the evolution of the market, we need to search for self-consistent equilibrium paths of the four variables, $(\dot{b}_{Et}, \dot{b}_{It}, \dot{d}_{Et}, \dot{d}_{It})$, to the above system. As do other structural models of network effects (e.g., Ackerberg and Gowrisankaran forthcoming; Rysman 2004), we must confront the issue of multiple equilibria.¹⁹ Different equilibrium paths reflect the fact that in each period, new consumers could hold different expectations. The following proposition indicates that multiple equilibria could occur only when consumers are sufficiently patient.

Proposition 3. There exists a threshold φ^* such that when $\varphi < \varphi^*$, there is a unique equilibrium

¹⁷See Appendix C for details.

¹⁸Mathematically, as the choice of \dot{b}_{jt} affects b_{js} for s > t and N_{jt} is a function of $b_{j,s}$, N_{jt} is a function of $\dot{b}_{j,t}$.

¹⁹As the right hand side of each equation is a continuous function, it is immediate from Brouwer's fixed point theorem that there must exist one fixed point (i.e., at least one solution for \dot{b}_{jt} and \dot{d}_{jt}).

path to the system.

Proof. See Appendix D.

Proposition 3 suggests that when consumers are not patient enough, there is a unique selfconsistent set of expectations of future application provision and hence a unique trajectory of market evolution.

While it is theoretically possible to compute all equilibria when $\varphi > \varphi^*$, this approach can take a prohibitive amount of time when the number of periods is large. For example, if every period involves two solutions (i.e., two possible paths along which the market could evolve) and the life expectancy of the platforms is 100 periods, there could be a maximum of 2^{100} paths or approximately 10^{30} possible paths. To tackle this problem of dimensionality, researchers often impose additional constraints to limit the number of possible equilibria.²⁰

In our analysis, we assume that consumers in all periods hold favorable expectations of one platform. As consumers hold favorable expectations of platform j, when there are multiple solutions, we pick the solution that maximizes \dot{b}_{jt} and \dot{d}_{jt} . This assumption is likely to hold when consumers coordinate with each other about their expectations. Equivalently, one may think that we are examining two polar cases. As we illustrate below, these two polar cases provide sufficient insights as to when consumer expectations matter.

The complexity of the model makes analytical solutions intractable, and we solve the model numerically. We outline our fixed-point iteration algorithm for computing equilibrium paths in Appendix E. Figure 3 provides simulation results for the case where T = 300, Q = F = 1.2 and $b_{I,0} = d_{I,0} = 20$. For different levels of e, we plot the equilibrium market share of platform E on the consumer side as the discount factor, φ , increases from 0 to 1. When $\varphi = 0$, we have the myopic outcome. The plots for the developer side are similar and are thus omitted. Figure 3.A and

²⁰For example, researchers often pose restrictions on the order of entry in empirical models related to entry (e.g., Berry 1992). In addition to imposing constraints, researchers often calibrate computational results with data from a real-world market. For example, Ackerberg and Gowrisankaran (forthcoming) and Rysman (2004) compute a limited set of equilibria and select one by matching them to the data. Ryan and Tucker (2007) use the two-step approach proposed in Bajari et al. (forthcoming) which recovers reduced-formed policy functions as a function of state variables in the first step and projects these functions into the dynamic model in the second step.

3.B show the results in which all consumers hold favorable expectations for the incumbent and the entrant respectively.

Comparing the two plots, we find that the market outcomes are different only when φ is above a threshold for a given e. The market tips the platform of which consumers hold favorable expectations. As e increases, the threshold decreases. We summarize these results in the next proposition:

Proposition 4. When $\varphi > \varphi^*$, multiple equilibrium paths exist and the platform with favorable expectations will be the monopoly. The threshold φ^* decreases with e.

Proposition 4 suggests that consumer expectations affect market outcome only when consumers are sufficiently patient. In this case, the success of a platform is entirely driven by consumer expectations. Intuitively, when φ is large, consumers place large value on future applications. Hence their utilities become similar to the utilities of future adopters, and they are more likely to take the same actions as future adopters. As a result, the market tips one platform.

We also find that when φ ad e are low, consumers' forward-looking behavior further enhances quality advantage: the market share of platform E increases as φ increases. In addition, as in the myopic case, simulation results show that equilibrium market shares are independent of the initial installed-base advantage. We summarize these results in the following proposition:

Proposition 5. When $\varphi < \varphi^{**}$ and $e < e^*$, both indirect network effects and forward-looking behavior enhance quality advantage. In particular, when 0 < e < 1 and $\varphi < \varphi^{**}$, the two platforms will co-exist in the long run; when $1 < e < e^*$ and $\varphi < \varphi^{**}$, platform E will be the monopoly. The equilibrium market shares are independent of the initial installed-base advantage. The threshold φ^{**} decreases with e.

Both the strength of indirect network effects (e) and consumers' discount factor of future applications (φ) determine the extent to which consumers value future applications. When consumers place a relatively small value on future applications (i.e., small e and φ), their beliefs about the evolution of the market have little impact on their adoption decisions and hence their pattern of adoption is close to that of the myopic case.

When e and φ become larger, we find that the market starts to tip the incumbent. In this case,

future application provision becomes an important factor in consumers' adoption decisions. When φ is not very large, consumers only value applications in the near future and are not patient enough to wait for the entrant to take over the leadership. Hence, the only self-consistent equilibrium path is the one in which the market tips the incumbent. When e increases, the installed-base advantage becomes more pronounced. Therefore, the range of φ for the market to tip the incumbent enlarges. To summarize, we have:

Proposition 6. When $e > e^*$ and $\varphi^{**} < \varphi < \varphi^*$, platform I will be the monopoly. φ^{**} decreases with e, and φ^* increases with e.

We summarize market outcomes for different values of e and φ in Figure 4. Our results indicate that the success of a platform can be driven by different factors under different circumstances. When the values of e and φ lie in region A of Figure 4, the success is driven by quality advantage. In particular, when e > 1, the platform with superior quality will be the monopoly. In region B, platform success is driven by installed-base advantage, and the platform with such advantage will become the monopoly. In region C, the success is driven by consumer expectations. The platform with the favorable expectations will become the monopoly.

Our results also suggest that the long-run market structure can be either oligopolistic or monopolistic. The two platforms co-exist if the market is quality driven and e < 1 (the shaded region). Otherwise, we have the "winner-takes-all" outcome.

Figure 5 illustrates the evolution of the market for different scenarios. We set e = 0.9 and allow φ to vary. As φ increases from 0.1 to 0.9, the driver of platform success changes from quality to installed base and then to consumer expectations. Figure 5.A shows the (cumulative) market share of platform E on the consumer side and 5.B shows the percentage of new consumers adopting platform E in each period. The two figures suggest the following result.

Proposition 7. When market dynamics are driven by consumer expectations or installed base, a monopoly emerges rapidly; when market dynamics are driven by quality, an oligopoly emerges gradually.

In sum, our results indicate that market dynamics can be driven by different factors and one

cannot make an a priori statement on the outcome. To understand the evolution of a market, it is essential to conduct empirical analysis to estimate the strength of indirect network effects (e) and consumers' discount factor (φ) .

5 Empirical Analysis

We apply the insights from our theoretical model to the setting of the video game console market. This market is two-sided in that console providers need to attract both game players and game publishers. Previous research has shown that the market exhibits significant indirect network effects (e.g., Shankar and Bayus 2003; Clements and Ohashi 2005). Schilling (2003) provides an excellent overview of this market.

5.1 Competition between PlayStation 2 and Xbox

We study the competition between Sony's PlayStation 2 and Microsoft's Xbox consoles between November 2001 and October 2005. PlayStation 2 was introduced in October 2000 and is backward compatible with PlayStation 1. Xbox was introduced a year later. While previous entrants to this market often came with next generation technology (e.g., Nintendo in 1986 and Sega in 1989), Xbox technology belongs to the same generation as PlayStation 2 (128 bits generation).²¹ Table 3 compares the features of the two consoles. The only differences are in the clock speed and the amount of memory. PlayStation 2 had a significant lead in installed base and availability of games: By the time Xbox was introduced, more than 4.5 million PlayStation 2 consoles had been sold in the United States and more than 1000 compatible game titles were available for PlayStation 2.

Although many industry experts and scholars cast doubt on Xbox's ability to seize a significant market share, Xbox made successful entry to this market. Table 4 shows the market shares of the installed base, the total number of games, the new console sales and the number of new game releases for each console over time. We compute these market shares by dividing the number for each console by the sum of the two consoles in each year.²² As the numbers indicate, Xbox has

²¹The bit-value refers to the word length of a console's processor and is often considered the most important measure of the graphical performance of a console. As a result, the number of bits is used to classify different generations of consoles.

 $^{^{22}}$ In our dataset, the monthly sales data in units for games vary from 1 to 1.2 million. As game players are likely

been very successful in growing its market shares on both sides. Its shares of installed base and associated games increased over years. In 2004, Xbox had more than 40% shares in both new console sales and new game releases. While the share of its new game releases increased to 45% in 2005, Xbox sales slowed down in 2005, most likely due to the anticipated release of the next generation system, Xbox 360.²³ We also compute the percentage of PlayStation 2 games provided by Sony and the percentage of Xbox games supplied by Microsoft. The data suggest that console providers only produced a very small number of game titles and third party game publishers are the major supplies of games.

The competition between the two consoles provides an ideal setting for our empirical analysis for two reasons. First, as both consoles target adults between 18 and 34, they position themselves in direct competition with each other. While several other consoles were also available on the market during this period, they were either targeted at different demographics (such as Nintendo's GameCube) or were obsolete (such as Nintendo's N64 and Sega's DreamCast). PlayStation 2 and Xbox together accounted for more than 80% of new console sales in 2005.

Second, our theoretical model assumes that platforms are priced at the same level. The pricing strategies of Microsoft and Sony fit this assumption well. Figure 6 shows price differences between Xbox and PlayStation 2 consoles since the entry of Xbox in November 2001. PlayStation 2 had been priced at \$299 before the release of Xbox. Since the release of Xbox, both console providers have dropped console prices over time. The price differences are less than ten dollars in all months except March 2004 and April 2004. This pattern suggests that the two console providers quickly matched each other's price over time. For example, in May 2002 Microsoft was forced to cut the price of Xbox by \$100 in response to a similar price reduction of PlayStation 2. As the consoles were offered at similar prices in each period, we expect that consumers made their purchase decisions based on the quality of the consoles and the variety of associated games.²⁴

to pay attention only to games with significant sales, we only count games that have more than 15,000 copies sold in each month (about 10 games in each state per day). On average, these games account for more than 60% total game sales in each month for both consoles.

²³Xbox 360 was released in November 2005. Microsoft officially announced its release date in May 2005.

²⁴In our theoretical model (Appendix B), we have implicitly assumed that the marginal cost of each application does not change over time for each platform. In the video game industry, console providers charge royalties for games sold for their consoles. While we do not directly observe royalties, as our theoretical model suggests that application prices are linear functions of marginal costs, we could test the changes in application prices to detect changes in royalties. We focus on prices of new games released in each period as game prices usually declines with their ages.

In the video game market, consumer utility may also depend on the size of the installed base if direct network effects are significant. As Xbox and PlayStation 2 consoles both have online capability, direct network effects could exist. However, online console-based games did not take off until 2006.²⁵ In addition, only 5.2% games released for the two consoles could be played online and even games with heralded online features are often played alone. Thus we believe that the indirect effects are of far greater significance for the period we are studying.

Our theoretical model predicts that under two scenarios an entrant with superior quality could be successful: 1) the strength of indirect network effects and consumers' discount factor are within the range where the market dynamics are quality driven, and 2) the discount factor is sufficiently large and consumers hold favorable expectations toward the entrant. In the video game console market, the equilibrium did not emerge rapidly. Thus, the second scenario is less likely. We therefore hypothesize that in this market, market dynamics are driven by platform quality.

5.2 Data

Data on console and game sales are from the NPD Group, a leading market research firm that tracks this industry. NPD collects data from approximately 17 leading US retail chains that account for 80% of the U.S. market. From these data, NPD formulates estimates of sales figures for the entire U.S. market. We obtain monthly sales and price data for PlayStation 2 and Xbox consoles and their associated games from October 2000 to October 2005. For each console, we compute the average monthly price by dividing the monthly revenue by the volume of units sold. Game publishers continued to release new games for the two consoles after October 2005. We collect data on the number of new games released for each console in each month after October 2005 from GameSpot.com (also known as VideoGames.com). According to Ranking.com, GameSpot.com is the 172th most visited site among all Web domains and is the most visited one on video games.²⁶

Regression analysis suggests that prices of new games do not change significantly over time. This result provides indirect evidence that royalties charged by each console provider may not change significantly over time. One may think that console providers would charge a low royalty fee in the early stage of its life cycle to attract more game developers. Hagiu (2006) shows that as console providers decide console prices after games are developed and there could be a hold-up problem, to address this hold-up problem it is optimal for console providers to charge a high loyalty fee.

²⁵Kemp Powers, "Xbox Live challenge is to reach masses," December 21, 2006, http://news.yahoo.com/s/nm/20061221/tc_nm/gaming_microsoft_dc_1, accessed December 2006.

²⁶http://www.ranking.com, accessed April 2006. Ranking.com tracks the popularity of the top one million Web domains.

5.3 Empirical Specifications

Our objective here is to measure the strength of indirect network effects, e, the discount factor, φ , and the two quality ratios, Q and F. As Q and F are ratios, we use console dummies in regressions to estimate them instead of developing metrics to explicitly measure them.

We transform equation (4) to yield the following specification (Berry 1994):

$$\ln s_{Et} - \ln s_{It} = \beta_Q + e(\ln N_{Et} - \ln N_{It}) + \beta_{2005} Dummy_{2005} + \xi_t, \tag{8}$$

where the entrant, E, is Xbox and the incumbent, I, is PlayStation 2. β_Q captures the quality advantage of Xbox over PlayStation 2. The quality ratio, Q, can be obtained as $\exp(\beta_Q)$. While the log-difference specification takes away time-specific effects that are common to both consoles, we include a dummy for year 2005 to control for potential cannibalization effects from the planned release of Xbox 360.²⁷ N_{jt} measures game variety, which includes both available games at time t and discounted games from future releases. Similar to other empirical work related to forward-looking consumers, we adopt the "errors-in-variables" approach (e.g., Wickens 1982). That is, as we assume consumer expectations are fulfilled, we use the actual game release data in the future and express N_{jt} as a function of φ .

We now consider the developer side. Using equation (5), we obtain the following specification:

$$\ln \Delta d_{jt} = \beta_0 + \beta_1 \ln b_{jt} + \beta_2 Dummy_E + \sum_{i=3}^{5} \beta_i Dummy_{2000+i} + \beta_6 Dummy_{Holiday} + \xi_{jt}, \quad (9)$$

where the dependent variable, $\ln \Delta d_{jt}$, is the logarithm of the number of new games released for console j at time t, and b_{jt} is the installed base of console j in period t. The size of the installed base by console and by month is obtained from cumulative console sales up to the current month, subject to a constant rate of decay. We experiment with different decay rates and compare our data on the console market share with survey results from other sources. We find that the annual decay rate of 10%, which corresponds to a monthly decay rate of 0.87%, provides the best match. According to our theoretical model, we expect β_1 to be 1. The quality ratio, F, can be obtained as

 $^{^{27}}$ While Microsoft announced the official release date in May 2005, the release had been widely expected since early 2005.

 $\exp(-\beta_2)$. As we do not observe y and F_{jt} in each period, we include year dummies and a holiday dummy (which equals 1 when the month is November or December and 0 otherwise) to control for their variations over time.²⁸

5.4 Results

Table 5 presents our regression results. Panel A reports results for console adoption on the consumer side. In Model I, we estimate equation (8), assuming myopic consumers (i.e., $\varphi = 0$). In Model II, we relax this myopia assumption and use non-linear least square (NLS) estimation. The time period starts from the introduction of Xbox into the US market, November 2001, to October 2005. Our results indicate significant indirect network effects in this market. The estimated strength of indirect network effects is 0.69 and 0.62 in the two models, suggesting that myopic models may overestimate the strength. We also find that the discount factor is small (0.31). In addition, we find a small quality advantage of Xbox over PlayStation 2. The quality ratio Q is $\exp(\beta_Q) = 1.35$. Finally, the significant negative coefficients of the dummy for year 2005 suggests that the anticipated release of Xbox 360 significantly slowed down the adoption of Xbox.

We conduct several robustness checks. First, we include the price difference between the two consoles as an additional control variable to test our assumption that price difference does not have a significant impact on the relative console sales.²⁹ The results from Model III suggest that price difference indeed does not affect consumer choices and is consistent with the observation that two console providers matched each other's price quickly.

We are also concerned that game players may only value games with high quality when making

²⁸Although we have monthly observations, we could not obtain meaningful estimates by including dummies for each month largely due to the lack of cross-sectional variation with only two consoles.

²⁹Console prices, however, are likely to be correlated with changes in unobserved attributes. For example, an improvement in brand image as a result of an increase in advertising expenditure may induce greater willingness to pay and thus lead to a higher price. To alleviate the endogeneity of the US console prices, we use console retail prices in Japan and the exchange rates between Japanese Yen and US dollar as instrument variables. The console retail prices in Japan are from GfK Marketing Services Japan. Prices in Japan are correlated with US prices as both depend on production costs. Japanese prices, however, would not be correlated with unobserved console attributes in the US market if Japanese game players have different tastes in consoles. Numerous news articles suggest that such taste difference does exist. The different pattern of console prices in the Japanese market also indicates a taste difference. The Xbox price was about ¥7,000 (equivalent to US\$59) higher than the PlayStation 2 consoles at its introduction but dropped more rapidly. Since mid-2002, its price has been lower than PlayStation 2 in Japan. Similar instruments have been used in other studies (e.g., Nevo 2001; Clements and Ohashi 2005). We have fewer observations in the regression as Xbox entered the Japanese market in February 2002.

purchase decisions. We therefore collect professional ratings for games from GameSpot.com. We only count games with ratings greater than 7.0 on a 10.0 point scale. Games with scores above 7.0 are considered good according to GameSpot's rating system. We repeat our analysis and obtain similar results (Model IV).

Panel B reports results for game supply on the developer side. We use equation (9) as the empirical specification and report the results in Model II. In Model III, we estimate equation (9) without the holiday dummy. In Model III, we add an interaction variable between the dummy for Xbox and the dummy for year 2005 to control for potential negative effects from the release of Xbox 360. In Model IV, we only count games with ratings greater than 7.0 on a 10.0 scale at GameSpot.com. Results are similar in all four models. We find that the coefficients of $\ln b_{jt}$, β_1 , are above 0.80 in all models. T-tests cannot reject the hypothesis that β_1 is 1 in any model and thus the result supports our theoretical model. We also find that the difference in development costs between the two consoles is statistically indistinguishable from zero. The negative coefficients of the year dummies and positive coefficients of the holiday dummy suggest that game players allocate smaller budgets for game purchases over time and larger budgets during holiday seasons. Finally, we do not detect significant negative impact from the release of Xbox 360 on Xbox game supply. This result is most likely due to the fact that Xbox 360 is backward compatible and can be used to play Xbox games.

To sum up, our empirical results show that Xbox has a small quality advantage (Q = 1.35 and F = 1), the strength of indirect network effects, e, is 0.62 and consumers' discount factor, φ , is 0.31 in this market. We substitute these results into our dynamic model and find that the values of e and φ are such that the market dynamics are driven by quality advantage.

5.5 Counterfactual Experiments

We use our dynamic model and empirical estimates to conduct three counterfactual experiments.

These experiments provide additional support for our theoretical model and could help platform providers understand market evolution in different environments.

First, we estimate the long-run market outcome assuming that neither console provider chooses

to upgrade its console technology. We use January 2005 as the initial period. As data on the number of new adopters after January 2005 are affected by the release of Xbox 360, we use the data from the corresponding month in 2004.³⁰ We use the results from Model II of Table 5.A and Model III of Table 5.B in our simulation. We find that the market share on each side would be greater had Xbox 360 not been released. By the end of 2007, Xbox could have had 40.6% market share on the consumer side and 46.4% on the developer side. The two market shares asymptotically approach 72% and 75% respectively.

We then consider what changes to e and φ are needed for PlayStation 2 to drive Xbox out of the market. We use January 2002 as the initial period and simulate the market dynamics by holding one factor at the estimated level and changing the other factor. We find that given $\varphi=0.31$, e needs to be greater than 1.49 for PlayStation 2 to drive Xbox out of the market. Figure 7.A shows the actual market share trajectory, the fitted market share trajectory based on our regression results and the market share trajectory for e=1.60 for the consumer side (the pattern for the developer side is similar and is thus omitted). We find that when e=1.60, the market share of Xbox would drop from 16% in January 2002 to less than 10% in October 2005. We also find that given e=0.62, the market dynamics are driven by installed base when φ is between 0.47 and 0.87. In this case, the market share of Xbox would decrease over time. The market dynamics are driven by consumer expectations when φ is greater than 0.87. Figure 7.B shows the market share trajectories for $\varphi=0.45$, $\varphi=0.75$ and $\varphi=0.90$. These results are consistent with our theoretical predictions summarized in Figure 4.

Finally, we consider the hypothetical situation in which Microsoft delays the release of Xbox for a year. We assume that as a result of the delay, Microsoft could improve the quality advantage of Xbox by another 35% (i.e., $Q = 1.35 \times 1.35 = 1.82$). We consider two scenarios. In the first one, we assume that Sony does not drop the price for PlayStation 2 before the release of Xbox. In this case, we assume that the number of PlayStation 2 consoles sold between November 2001 and October 2002 is the same as in the year before. In the second case, we assume that Sony drops PlayStation 2 price following the pattern observed in the dataset. In this case, more PlayStation

 $^{^{30}}$ Alternatively, we allow the number of new adopters decreases by 5% per year and the results do not vary significantly.

2 consoles are sold between November 2001 and October 2002. Figure 8 shows the trajectories of Xbox market shares on the consumer side for both cases, and compare them to the actual one. We find that if Sony chooses not to cut console prices before the release of Xbox, Xbox will have a larger market share in October 2005 with a delayed release. However, if Sony cuts console prices, it is optimal for Microsoft not to delay the release.

6 Discussion and Conclusion

In this paper, we develop a dynamic model to examine the evolution of platform-based markets. We find that market dynamics depend critically on the strength of indirect network effects and consumers' discount factor of future applications. Using data from the video game industry, we analyze the competition between Xbox and PlayStation 2. We find that Xbox has a small quality advantage and the market dynamics are quality driven. These results help explain the successful entry of the Xbox console into this market and provide support for our theoretical model.

While we do not have data to test other model predictions, our empirical analysis serves as a benchmark to understand other industries. In the video game industry, each console owner buys only eight games on average (Eisenmann et al. 2006). Therefore, we expect game players to place relatively small value on game variety. In the case of the home video cassette recorder (VCR) market, users on average watch several movie titles in a month.³¹ We expect movie watchers to be more sensitive to the current and future movie titles associated with each standard. Therefore, we expect both the strength of indirect network effects and consumers' discount factor of future applications to be higher in the VCR market. Indeed, empirical findings in Ohashi (2003) support our reasoning. Ohashi studies user adoption of the VHS and Betamax standards in this market. While he does not consider forward-looking behavior and hence might overestimate the strength of indirect network effects, we compute our measure, e, from his regression results (Table IV, Ohashi 2003) to be above 3 during 1978-1982.³² It is thus not surprising that the VCR market tipped and that VHS quickly emerged as the de facto standard.

³¹For example, it has been reported that on average consumers watch almost six movies a month on DVD. Jennifer Netherby, "DVD holds share of leisure time," July 12, 2006, http://www.videobusiness.com/article/CA6352215. html?industryid=43291&industry=Retail, accessed February 2007.

³²The indirect network effects were mostly driven by the video rental business. Video rental shops began to expand in the early 1980s and grew exponentially. Therefore, the strength of indirect network effects increased over years.

6.1 Implications

Understanding the driver of platform success, long-run market structure and market efficiency is of critical importance for both policy makers and managers. The conventional wisdom (e.g., Schilling 2003) suggests that if a new platform is unable to make its technology compatible with the incumbent, for it to be successful its technical advantage must offer so much value to consumers that it exceeds the combination of functionality, installed base, and complementary goods value offered by the incumbent. Our results indicate that a huge quality advantage may not be necessary for success. When market dynamics are driven by quality, a platform with a small quality advantage can also be successful, as in this case both indirect network effects and forward-looking behavior enhance quality advantage. Installed-base advantages thus do not necessarily provide a safety shield for the incumbent. To defend its leadership position, the incumbent needs to constantly enhance its quality.

We also show that in the quality driven scenario, a market with indirect network effects could be more efficient than it would be without indirect network effects. Government intervention may be counter-productive in this case. On the other hand, when a market is installed-base driven, an inefficient outcome will occur. In this case, government intervention such as enforcing standardization and interoperability can help rescue the market from an inefficient outcome. Finally, in the expectations driven scenario, government support of the superior platform may help it gain favorable expectations and hence market dominance.

6.2 Future Research

In our study, we treat the strength of indirect network effects (e) and consumers' discount factor (φ) as exogenous. Future research could examine the determinants of these two parameters. For example, e is likely to correlate with the degree of differentiation between the two platforms. When the two platforms have little differentiation, e should be very large as adoption decisions will be strongly influenced by application variety. Therefore, platform providers could strategically design and position their products to change e.

In addition, we assume that platform prices are the same in each period. While this assumption

applies to many markets, in some markets prices could significantly influence market evolution. For example, as the number of applications increases, the incumbent might find it optimal to increase the price of its platform. In this case, the entrant may be more likely to survive. In addition, while platform providers can use the insights from our model to decide whether and when to upgrade platforms, our model does not explicitly consider quality upgrade. An account of how firms dynamically set their prices and adjust platform quality, and how consumers' forward-looking behavior is transmitted into these endogenized price and quality decisions is an empirical challenge even for markets without indirect network effects (e.g., Melnikov 2001; Song and Chintagunta 2003; Gowrisankaran and Rysman 2007). We leave these topics for future research.

Appendix A: Details for Deriving Equation (1)

Following the literature (e.g., Spence 1976; Dixit and Stiglitz 1977; Chou and Shy 1990; Church and Gandal 1992, 1993; Nair et al. 2004), we use a representative consumer approach and model the consumer preferences of the applications using a modified CES (Constant Elasticity of Substitution) utility function. The representative consumer approach provides an aggregate description of an underlying consumer population characterized by discrete choices at the individual level—while an individual consumer often purchases only a few of the available applications, the representative consumer typically buys some of every application.³³ While this approach abstracts away some dynamics of application demand, it retains the fundamental interdependence between platform demand and application supply.

The utility a representative consumer receives from adopting platform j in period t is:

$$u_{it} = \ln(Q_i z_{it}),\tag{A-1}$$

where $z_{jt} = (\sum_{k=1}^{d_{jt}} x_{kjt}^{1/\beta})^{\beta}$ and x_{kjt} is the amount of applications the representative consumer purchases from developer k at time t. Q_j is the platform quality. $\beta > 1$ is a constant and measures elasticity of substitution across applications.³⁴ Thus z_{jt} captures indirect network effects resulting from consumer preference for application variety. Our functional form of u_{jt} allows both quality effect and indirect network effects to occur simultaneously. We use logarithm transformation so that the utility function is concave in the application variety and platform quality.³⁵

The representative consumer maximizes his utility subject to the budget constraint $\sum_{k=1}^{d_{jt}} \rho_{kjt} x_{kjt} \le y$, where ρ_{kjt} is the price of the application sold by developer k and y is the total budget.

As
$$u_{jt} = \ln(Q_j z_{jt}) = \ln Q_j + \ln z_{jt}$$
, essentially the consumer is maximizing $\sum_{k=1}^{d_{jt}} x_{kjt}^{1/\beta}$ s.t. $\sum_{k=1}^{d_{jt}} \rho_{kjt} x_{kjt} \leq y$.

Let
$$G = \sum_{k=1}^{d_{jt}} x_{kjt}^{1/\beta} + \lambda (y - \sum_{k=1}^{d_{jt}} \rho_{kjt} x_{kjt})$$
, where λ is the Lagrange multiplier. The first order

³³Anderson et al. (1992) show that CES models can be constructed as being representative of a population of consumers making discrete choices.

³⁴In particular, when $\beta \to 1$, the applications become perfect substitutes of each other.

³⁵Similar transformations have been used in other research. For example, Nair et al. (2004) use $g(z_{jt}) = z_{jt}^{\frac{1}{\alpha\beta}}$, $(\alpha \ge 1)$, to ensure concavity. We choose the log-transformation to derive a more analytically tractable form.

condition with respect to x_{kjt} yields:

$$x_{kjt} = (\lambda \beta \rho_{kjt})^{\frac{\beta}{1-\beta}}.$$

Hence $y = \sum_{k=1}^{d_{jt}} \rho_{kjt} x_{kjt} = \sum_{k=1}^{d_{jt}} \rho_{kjt} (\lambda \beta \rho_{kjt})^{\frac{\beta}{1-\beta}}$. Therefore $(\lambda \beta)^{\frac{\beta}{1-\beta}} = \frac{y}{\sum_{k=1}^{d_{jt}} \rho_{kjt}^{1/(1-\beta)}}$. The consumer's optimal demand for each application can be derived as:

$$x_{kjt}^* = \frac{y \cdot \rho_{kjt}^{\beta/(1-\beta)}}{\sum_{k=1}^{d_{jt}} \rho_{kjt}^{1/(1-\beta)}} = \frac{y \cdot \phi_{jt}^{1/(\beta-1)}}{\rho_{kjt}^{\beta/(\beta-1)}},$$
(A-2)

where $\phi_{jt} = (\sum_{k=1}^{d_{jt}} \rho_{kjt}^{\frac{1}{1-\beta}})^{1-\beta}$ is often referred to as the price index for the applications.

A developer maximizes his total profit. Assume the marginal cost of each application developed for platform j, mc_j , is the same. There exists a symmetric equilibrium in which the prices of applications for each platform are the same, i.e., $\rho_{kjt} = \rho_j = \beta mc_j$ (see Appendix B). While the marginal cost of producing many digital goods is close to zero, platform providers often charge developers for applications sold. For instance, game console providers charge royalty fees for each game sold for their consoles. Auction houses also charge each seller a listing fee.

The demand for each application thus becomes $x_{kjt}^* = \frac{y}{d_{jt}\rho_j}$. Therefore, the demand for each application increases with the amount of budget each consumer allocates, and decreases with the total number of applications and application price. Substituting this demand expression into equation (A-1), we obtain the indirect utility function of the consumer as:

$$V_{jt} = \ln y + \ln Q_j / \rho_j + e \ln d_{jt}.$$

where Q_j/ρ_j is the platform quality adjusted by the application price and $e = \beta - 1 > 0$.

Appendix B: Details for Deriving Equation (5)

According to equation (A-2), each existing consumer purchases $x_{jt}^* = \frac{y \cdot \phi_{jt}^{1/(\beta-1)}}{\rho_{jt}^{\beta/(\beta-1)}}$ amount of applications from each new developer in period t.

Therefore, each new developer in period t pays a fixed cost of F_{jt} and earns

$$\pi_{jt} = b_{jt} \cdot x_{jt}^* \cdot (\rho_{jt} - mc_j).$$

Developers choose application prices, ρ_{jt} , to maximize their profits. Given the concavity of the profit function, the first-order condition requires that each developer set the price such that his marginal revenue equals his marginal cost. Following the literature (e.g., Nair et al. 2004), we assume that, given the large number of applications available in the market, the effect of a single application's price on the aggregate price index, ϕ_{jt} , is negligible and can be ignored. The price elasticity of game demand, η_j , can then be obtained as $\beta/(\beta-1)$. Therefore, the marginal revenue of the developer is $\rho_{jt}(1-\eta_{jt})/\eta_{jt} = \rho_{jt}/\beta$. We solve for the optimal price by equating the marginal revenue to the marginal cost and have $\rho_j = \beta mc_j$.

Hence the maximal profit is

$$\pi_{jt} = \frac{y \cdot b_{jt} \cdot (\beta - 1)}{\Delta d_{jt} \beta},$$

where Δd_{jt} is the equilibrium number of new developers supporting platform j at time t. Thereafter, new consumers purchase applications from each developer, and similarly, $\pi_{js} = \frac{y \cdot \Delta b_{js} \cdot (\beta - 1)}{d_{js}\beta}$ for s > t, where Δb_{js} is the number of new consumers adopting platform j at time s.³⁶

Each new developer in period t sells his application to the installed base of consumers in period t and then sells the application to new consumers in future periods. Therefore, each developers pays a fixed cost of F_{jt} and earns a total profit of

$$-F_{jt} + \pi_{jt} + \varphi_d \pi_{j,t+1} + \varphi_d^2 \pi_{j,t+2} + \cdots, \qquad (B-1)$$

where φ_d is the discount factor of future earnings for the developers.

If the developer enters in period t+1, he earns a discounted profit evaluated at period t of

$$-\varphi_d F_{j,t+1} + \varphi_d \pi'_{j,t+1} + \varphi_d^2 \pi'_{j,t+2} + \cdots,$$
 (B-2)

³⁶Interestingly, mc_j does not affect π_{jt} . This is because an increase in mc_j leads to a high application price as $\rho_j = \beta mc_j$ and hence a higher profit per application. On the other hand, an increase in mc_j leads to a decrease in application demand according to equation (A-2). The two effects offset each other in the profit function.

where $\pi'_{j,t+1} = \frac{y \cdot b_{j,t+1} \cdot (\beta-1)}{\Delta d_{j,t+1}\beta}$ and $\pi'_{j,t+i} = \pi_{j,t+i}$ for $i \geq 2$. A free-entry condition requires that developers are indifferent between the two options. This implies

$$F_{jt} - \varphi_d F_{j,t+1} = \pi_{j,t} + \varphi_d \pi_{j,t+1} - \varphi_d \pi'_{j,t+1}. \tag{B-3}$$

Given the large installed base of consumers and applications, and relatively small number of new consumers and new applications in each period, we have $\frac{b_{j,t+1}}{\Delta d_{j,t+1}} \gg \frac{\Delta b_{j,t+1}}{d_{j,t+1}}$ and $\pi_{j,t} \approx \pi'_{j,t+1}$. Therefore, we can simplify equation (B-3) as:

$$F_{jt} - \varphi_d F_{j,t+1} = \frac{(1 - \varphi_d) \cdot y \cdot (\beta - 1)}{\Delta d_{jt} \beta} \cdot b_{jt}.$$
 (B-4)

We assume that the fixed cost drops at the same rate for both platforms: $F_{j,t+1}/F_{j,t} = \gamma_t$, where $0 < \gamma_t < 1$. Therefore, we have:

$$\Delta d_j = \alpha_t \frac{b_{jt}}{F_{jt}}. (B-5)$$

where $\alpha_t = \frac{(1-\varphi_d) \cdot y \cdot (\beta-1)}{\beta(1-\varphi_d \gamma_t)}$.

The analysis above assumes that each application lives for many periods. In some platform-based markets, the popularity of applications declines rapidly after their releases. As a result, application developers may focus on the installed bases of platforms rather than future consumers. For example, in the video game industry, a typical game title makes more than 50%, sometimes as much as 80%, of its total sales in the first three months after its release. Although the sales of popular games may last longer, game publishers often regularly release their sequels (e.g., Halo vs. Halo 2; NFL 2003 vs. NFL 2004), which reduces demand for older versions. As a result, game developers could make decisions based on the current installed bases of the consoles and heavily discount their revenues from future game players. Similarly, new listings on online auction houses (e.g., eBay) or sites of classified advertisements (e.g., Craigslist) expire in a few days and sellers may choose the sites based on the current number of users of these sites. Indeed, many empirical studies on indirect network effects assume that application developers care only about current installed

bases (e.g., Nair et al. 2004; Clements and Ohashi 2005; Prieger and Hu 2006).

In this case, the total profit of a new developer adopting platform j at time t is:

$$\pi_{it} = b_i \cdot x_{it}^* \cdot (\rho_{it} - mc_i) - F_{it},$$

where
$$x_{jt}^* = \frac{y \cdot \phi_{jt}^{1/(\beta-1)}}{\rho_{jt}^{\beta/(\beta-1)}}$$
.

Maximizing the profit function, we again have $\rho_{jt} = \beta mc_j$. Therefore, $\frac{y \cdot b_{jt} \cdot (\beta - 1)}{\Delta d_{jt} \beta} = F_{jt}$.

Hence,

$$\Delta d_j = \alpha_t \frac{b_{jt}}{F_{jt}}. (B-6)$$

where $\alpha_t = y \frac{\beta - 1}{\beta}$. Equation (B-6) is the same as equation (B-5) except for the definition of α_t .

Appendix C: Details for Deriving Equation (7)

The total utility a consumer adopting in period t receives is $u_{jt} = \ln Q_j + \sum_{s=t}^T \ln z_{js}$, where z_{jt} captures utility from current associated applications and z_{js} captures utility from new applications released in period s. As the consumer maximize his utility subject to his budget constraint, following the approach in Appendix A, we have $V_{js} = \ln y - \ln \rho_j + e \ln \Delta d_{js}$ for s > t.

Appendix D: Proofs of Proposition 1 and Proposition 3

Proof of Proposition 1. It is convenient to consider a heuristic approach using $\frac{db_j}{dt} = \dot{b}_{jt}$ and $\frac{dd_j}{dt} = \dot{d}_{jt}$. Similar approaches have been used frequently in understanding long-run market trajectories (see, for example, Auriol and Benaïm 2000). We first rewrite the differential equations and then use phase diagrams to illustrate the trajectories of the market. Define the ratio of the number of developers in the two networks as $r_d = d_E/d_I$ and the ratio of the number of consumers as $r_b = b_E/b_I$.

Then

$$\frac{dr_d}{dt} = \frac{(d_I)(dd_E/dt) - (d_E)(dd_I/dt)}{d_I^2} = \frac{\alpha_t b_I}{d_I F_I} \cdot (Fr_b - r_d),$$

and similarly,

$$\frac{dr_b}{dt} = \frac{M_t d_I^e}{b_I(Q \cdot d_{Et}^e + d_{It}^e)} \cdot (Qr_d^e - r_b).$$

The directions of the trajectories are determined by the signs of $\frac{dr_d}{dt}$ and $\frac{dr_b}{dt}$, which are in turn determined by $Fr_b - r_d$ and $Qr_d^e - r_b$. By examining the signs of $\frac{dr_d}{dt}$ and $\frac{dr_b}{dt}$, we obtain the phase diagrams in Figure 9. We use arrows to indicate the directions of the trajectories for states in each region. In the cases of e > 1 and e < 1, the two curves intersect at point H, $(r_d = (QF)^{\frac{1}{1-e}}, r_b = Q^{\frac{1}{1-e}}F^{\frac{e}{1-e}})$.

Case (a): e > 1. We have three fixed points: (0,0), H and (∞,∞) . It is easy to see that H is an unstable fixed point. Therefore, the trajectories naturally converge to (∞,∞) or (0,0). That is, a monopoly emerges.

Case (b): e < 1. In this case, only H is a stable fixed point. The trajectories naturally converge to H so that the system eventually reaches a state where both platforms exist and have fixed market shares on the two sides. The market shares are determined by F and Q. In the case where F = Q = 1, the system converges to a state in which the number of consumers and the number of developers are equal for both platforms.

Case (c): e = 1. We have three scenarios depending on the size of FQ. When FQ > 1, only (∞, ∞) is the stable fixed point and platform E eventually has 100% of the market shares on both sides. When FQ < 1, only (0,0) is the stable fixed point and platform I will eventually dominate the market. When FQ = 1, the two curves coincide. All points on the curve are stable fixed points and the deterministic system eventually hits one. In this case, both platforms exist in the long run.

Proof of Proposition 3. We use mathematical induction to prove the existence of φ^* . Clearly, the statement is true for T=1. We assume that it is true for $T=n\geq 1$ and then show that it is true for T=n+1.

Consider the case where T=n+1. As $b_{E,1}=b_{E,0}+\dot{b}_{E,0}$ and $\dot{b}_{E,0}\in[0,M_0]$, we have $b_{E,1}\in[b_{E,0},b_{E,0}+M_0]$. Our assumption suggests that for any given $b_{E,1}$ (equivalently, any state $\{b_{E,1},b_{I,1},d_{E,1},d_{I,1}\}$), there exists a threshold such that there is a unique equilibrium path from t=1 to t=T. Let φ_n denote the smallest threshold for all possible $b_{E,1}$'s. Hence when $\varphi < \varphi_n$, there is a unique equilibrium path from t=1 to t=T for any $\dot{b}_{E,0}$.

Consider the scenario where $\varphi < \varphi_n$. We need to find a threshold such that there is a unique $\dot{b}_{E,0}$. We first re-write the expression for $\dot{b}_{E,0}$ as:

$$\dot{b}_{E,0} = M_0 \frac{\exp(e \ln N_{E,0} + \ln Q)}{\exp(e \ln N_{E,0} + \ln Q) + \exp(e \ln N_{L,0})} - \delta_b b_{E,0}.$$

 $N_{E,0}$ is a function of $\dot{b}_{E,0}$. Let $g = (e \ln N_{E,0} + \ln Q) + (e \ln N_{I,0})$ and $h = (e \ln N_{E,0} + \ln Q) - (e \ln N_{I,0})$. We have:

$$\dot{b}_{E,0} = M_0 \frac{\exp(\frac{g+h}{2})}{\exp(\frac{g+h}{2}) + \exp(\frac{g-h}{2})} - \delta_b b_{E,0} = M_0 \frac{\exp(h/2)}{\exp(h/2) + \exp(-h/2)} - \delta_b b_{E,0}.$$

Hence,

$$2(\dot{b}_{E,0} + \delta_b b_{E,0})/M_0 - 1 = \frac{\exp(h/2) - \exp(-h/2)}{\exp(h/2) + \exp(-h/2)} = \tanh(h/2).$$

$$\tan\left(2(\dot{b}_{E,0} + \delta_b b_{E,0})/M_0 - 1\right) = h/2. \tag{D-1}$$

h is an increasing function of $\dot{b}_{E,0}$. We can plot the curves for the LHS and RHS of Equation (D-1) with $\dot{b}_{E,0}$ as the x-axis . It is easy to see that given e, there exists a threshold φ_0 such that when $\varphi < \varphi_0$ (i.e., the curve for h is sufficiently flat), the two curves can only have one intersection and hence have one solution. Therefore, for T = n + 1, when $\varphi < \varphi_{n+1} = \min\{\varphi_0, \varphi_n\}$, we have a unique equilibrium path. This completes the proof.

Appendix E: Numerical Computation of Equilibrium Paths

When consumers are forward-looking, we solve for the equilibrium path numerically using fixed point iteration, given the initial states $(b_{E,0}, b_{I,0}, d_{E,0}, d_{I,0})$. We outline the steps for the case in which platform E is considered favorably. The case in which platform I has favorable expectations

proceeds similarly.

- i. Choose target horizon T, adjustment factor λ (a small positive number), and convergence criterion $\epsilon > 0$. Compute b_{Et} using $b_{Et} = (1 \delta_b) \cdot b_{E,t-1} + M_{t-1}$ for $t = 1, \dots, T$. This gives a path in which b_{Et} is maximized in each step. Denote this path as $(b_{Et}^0)_{t=0}^T$ and use this as the initial guess.
- ii. Given the guess $(b_{Et}^i)_{t=0}^T$ $(i \ge 0)$, compute $(b_{It}^i)_{t=0}^T$ using the fact that $b_{It}^i = (1 \delta_b) \cdot (b_{E,t-1}^i + b_{I,t-1}^i) + M_t b_{Et}^i$ for $t = 1, \dots, T$.
- iii. Given $(b_{Et}^i)_{t=0}^T$ and $(b_{It}^i)_{t=0}^T$, compute $(d_{Et}^i)_{t=0}^T$ and $(d_{It}^i)_{t=0}^T$ using the fact that $d_{Et}^i = (1 \delta_d) \cdot d_{E,t-1}^i + \frac{\alpha_{t-1}}{F_{E,t-1}} \cdot b_{E,t-1}^i$, and $d_{It}^i = (1 \delta_d) \cdot d_{I,t-1}^i + \frac{\alpha_{t-1}}{F_{I,t-1}} \cdot b_{I,t-1}^i$ for $t = 1, \dots, T$.
- iv. Given $(d_{Et}^i)_{t=0}^T$ and $(d_{It}^i)_{t=0}^T$, compute $(b_{Et}^+)_{t=0}^T$ and $(b_{It}^+)_{t=0}^T$.
- v. If each component of $(b_{Et}^+ b_{It}^i)_{t=0}^T$ has magnitude less than ϵ , stop.³⁷ Else, go to (vi).
- vi. Compute a new path $(b_{Et}^{i+1})_{t=0}^T$. For each $t=1,\cdots,T$, $b_{Et}^{i+1}=b_{Et}^i+\lambda(b_{Et}^+-b_{Et}^i)$. Go back to (ii) with $(b_{Et}^{i+1})_{t=0}^T$ as the initial guess.

References

- Aaker, David, Robert Jacobson. 1994. The financial information content of perceived quality. *Journal of Marketing Research* **31**(2) 191–201.
- Ackerberg, Daniel A., Gautam Gowrisankaran. forthcoming. Quantifying equilibrium network externalities in the ACH banking industry. $RAND\ Journal\ of\ Economics$.
- Anderson, Simon P., André de Palma, Jacques-François Thisse. 1992. Discrete Choice Theory of Product Differentiation. The MIT Press, Cambridge, Massachusetts.
- Armstrong, Mark. 2007. Competition in two-sided markets. Rand Journal of Economics 37(3) 668-691.
- Auriol, Emmanuelle, Michel Benaïm. 2000. Standardization in decentralized economics. *American Economic Review* **90**(3) 550–570.
- Bajari, Patrick, C. Lanier Benkard, Jonathan Levin. forthcoming. Estimating dynamic models of imperfect competition. *Econometrica* .
- Bass, Frank M. 1969. A new product growth model for consumer durables. *Management Science* **15**(5) 215–227.

³⁷To ensure the path found is stable, we create small derivations to the path and use it as the initial guess. We re-run the algorithm and check whether the algorithm converges to the same path.

- Basu, Amiya, Tridib Mazumdar, S. P. Raj. 2003. Indirect network externality effects on product attributes.

 *Marketing Science 22(2) 209–221.
- Berry, Steve. 1994. Estimating discrete-choice models of product differentiation. *RAND Journal of Economics* **25**(2) 242–262.
- Berry, Steven T. 1992. Estimation of a model of entry in the airline industry. Econometrica 60(4) 889–917.
- Bresnahan, Timothy F. 2002. The economics of the Microsoft case. Stanford Law and Economics Olin Working Paper No. 232.
- Burton, Richard M., Børge Obel. 1995. The validity of computational models in organization science: From model realism to purpose of the model. *Computational and Mathematical Organization Theory* 1(1) 57–71.
- Cabral, Luís. 2007. Dynamic price competition with network effects. Working Paper, New York University and CEPR.
- Caillaud, Bernard, Bruno Jullien. 2003. Chicken & egg: Competition among intermediation service providers. RAND Journal of Economics 34(2) 309–328.
- Casadesus-Masanell, Ramon, Pankaj Ghemawat. 2006. Dynamic mixed duopoly: A model motivated by Linux vs. Windows. *Management Science* **52**(7) 1072–1084.
- Chou, Chien-fu, Oz Shy. 1990. Network effects without network externalities. *International Journal of Industrial Organization* 8(2) 259–270.
- Church, Jeffrey, Neil Gandal. 1992. Network effects, software provision and standardization. *Journal of Industrial Economics* **40**(1) 85–104.
- Church, Jeffrey, Neil Gandal. 1993. Complementary network externalities and technological adoption. *International Journal of Industrial Organization* 11(2) 239–260.
- Clements, Matthew T., Hiroshi Ohashi. 2005. Indirect network effects and the product cycle: Video games in the U.S., 1994-2002. *Journal of Industrial Economics* **53**(4) 515–542.
- Cottrell, Tom, Ken Koput. 1998. Software variety and hardware value: A case study of complementary network externalities in the microcomputer software industry. *Journal of Engineering and Technology Management* 15(4) 309–338.
- Cusumano, Michael A., Yiorgos Mylonadis, Richard S. Rosenbloom. 1992. Strategic maneuvering and mass-market dynamics: The triumph of VHS over Beta. *Business History Review* **66**(1) 51–94.
- David, Paul A. 1985. Clio and the economics of QWERTY. American Economic Review, Papers and Proceedings 75(2) 332–337.
- Dixit, Avinash K., Joseph E. Stiglitz. 1977. Monopolistic competition and optimum product diversity. American Economic Review 67(3) 297–308.
- Dranove, David, Neil Gandal. 2003. The DVD vs. DVIX standard war: Network effects and empirical evidence of preannouncement effects. *Journal of Economics and Management Strategy* **12**(3) 363–386.
- Drinea, Eleni, Alan Frieze, Michael Mitzenmacher. 2002. Balls in bins processes with feedback. *Proceedings of the 11th Annual ACM-SIAM Symposium on Discrete Algorithms* 308–315.
- Driskill, Robert. 2007. Monopoly and oligopoly supply of a good with dynamic network externalities. Working Paper, Vanderbilt University.
- Economides, Nicholas, Matthew F. Mitchell, Andrzej Skrzypacz. 2005. Dynamic oligopoly with network effects. Working paper, New York University.

- Eisenmann, Thomas R., Geoffrey Parker, Marshall W. Van Alstyne. 2006. Strategies for two-sided markets. Harvard Business Review 84(10) 92–101.
- Evans, David S. 2003. Some empirical aspects of multi-sided platform industries. Review of Network Economics 2(3) 191–209.
- Gandal, Neil, Shane Greenstein, David Salant. 1999. Adoptions and orphans in the early microcomputer market. *Journal of Industrial Economics* 47(1) 87–105.
- Gandal, Neil, Michael Kende, Rafael Rob. 2000. The dynamics of technological adoption in hard-ware/software systems: The case of compact disc players. RAND Journal of Economics 31(1) 43–61.
- Gowrisankaran, Gautam, Marc Rysman. 2007. Dynamics of consumer demand for new durable goods. Working paper, Washington University of St. Louis.
- Gupta, Sachin, Dipak C. Jain, Mohanbir S. Sawhney. 1999. Modeling the evolution of markets with indirect network externalities: An application to digital television. *Marketing Science* **18**(3) 396–416.
- Hagiu, Andrei. 2006. Pricing and commitment by two-sided platforms. Rand Journal of Economics 37(3) 720–737.
- Iansiti, Marco, Roy Levien. 2004. The Keystone Advantage: What the New Dynamics of Business Ecosystems Mean for Strategy, Innovation, and Sustainability. Harvard Business School Press.
- Jacobson, Robert, David Aaker. 1985. Is market share all that it's cracked up to be? *Journal of Marketing* **49**(4) 11–22.
- Johnson, Joseph, Gerard J. Tellis. forthcoming. The value of quality: Stock market returns to published quality reviews. *Marketing Science*.
- Kandori, Michihiro, Rafael Rob. 1998. Bandwagon effects and long-run technology choice. *Games and Economic Behavior* **22**(1) 30–60.
- Katz, Michael L., Carl Shapiro. 1985. Network externalities, competition, and compatibility. *American Economic Review* **75**(3) 424–440.
- Katz, Michael L., Carl Shapiro. 1994. Systems competition and network effects. Journal of Economic Perspectives 8(2) 93–115.
- Liebowitz, Stan. 2002. Re-Thinking the Network Economy: The True Forces That Drive the Digital Market-place. New York: Amacom.
- Liebowitz, Stan J., Stephen E. Margolis. 1994. Network externality: An uncommon tragedy. *Journal of Economic Perspectives* 8(2) 133–150.
- Liebowitz, Stanley J., Stephen E. Margolis. 1999. Winners, Losers & Microsoft: Competition and Antitrust in High Technology. Independent Institute.
- MacCormack, Alan David, Marco Iansiti. forthcoming. Intellectual property, architecture, and the management of technological transitions: Evidence from Microsoft Corporation. *Journal of Product Innovation Management*.
- McFadden, Daniel S. 1973. Conditional logit analysis of qualitative choice behavior. Paul Zarembka, ed., Frontiers in Econometrics. Academic Press.
- Melnikov, Oleg. 2001. Demand for differentiated durable products: The case of the US printer market. Working paper, Cornell University.
- Nair, Harikesh, Pradeep Chintagunta, Jean-Pierre Dubé. 2004. Empirical analysis of indirect network effects in the market for personal digital assistants. Quantitative Marketing and Economics 2(1) 23–58.

- Nelson, Richard R., Sidney G. Winter. 1982. An evolutionary theory of economic change. Cambridge, MA: Harvard University Press.
- Nevo, Aviv. 2001. Measuring market power in the ready-to-eat cereal industry. Econometrica 69(2) 307–342.
- Ohashi, Hiroshi. 2003. The role of network effects in the U.S. VCR market, 1978-1986. *Journal of Economics and Management Strategy* **12**(4) 447–496.
- Park, Sangin. 2002. Network benefit function in the presence of indirect network externalities. Working paper, Department of Economics, SUNY at Stony Brook.
- Park, Sangin. 2004. Quantitative analysis of network externalities in competing technologies: The VCR case. Review of Economics and Statistics 86(4) 937–945.
- Parker, Geoffrey G., Marshall W. Van Alstyne. 2005. Two-sided network effects: A theory of information product design. *Management Science* **51**(10) 1494–1504.
- Prieger, James E., Wei-Min Hu. 2006. An empirical analysis of indirect network effects in the home video game market. NET Institute Working Paper No. 06-25.
- Rangan, Subramanian, Ron Adner. 2001. Profits and the Internet: Seven misconceptions. *MIT Sloan Management Review* (Summer) 44–53.
- Rochet, Jean-Charles, Jean Tirole. 2003. Platform competition in two-sided markets. *Journal of European Economic Association* 1(4) 990–1029.
- Ryan, Stephen, Catherine Tucker. 2007. Heterogeneity and the dynamics of technology adoption. NET Institute Working Paper No. 06-26.
- Rysman, Marc. 2004. Competition between networks: A study of the market for yellow pages. *Review of Economic Studies* **71**(2) 483–512.
- Schilling, Melissa A. 2003. Technological leapfrogging: Lessons from the U.S. video game console industry. California Management Review 45(3) 6–33.
- Sethi, Rajesh. 2000. New product quality and product development teams. *Journal of Marketing* **64**(2) 1–14.
- Shankar, Venkatesh, Barry L. Bayus. 2003. Network effects and competition: An empirical analysis of the home video game industry. *Strategic Management Journal* **24**(4) 375–384.
- Shapiro, Carl, Hal R. Varian. 1999. Information Rules: A Strategic Guide to the Network Economy. Boston, MA: Harvard Business School Press.
- Shurmer, Mark. 1993. An investigation into sources of network externalities in the packaged PC software market. *Information Economics and Policy* **5**(1) 231–51.
- Skrzypacz, Andrzej, Matthew F. Mitchell. 2006. Network externalities and long-run market shares. *Economic Theory* **29**(3) 621–648.
- Song, Inseong, Pradeep K. Chintagunta. 2003. A micromodel of new product adoption with heterogeneous and forward-looking consumers: Application to the digital camera category. *Quantitative Marketing and Economics* 1(4) 371–403.
- Spence, Michael. 1976. Product selection, fixed costs, and monopolistic competition. *Review of Economic Studies* 43(2) 217–235.
- Srinivasan, Raji, Gary L. Lilien, Arvind Rangaswamy. 2004. First in, first out? The effects of network externalities on pioneer survival. *Journal of Marketing* **68**(1) 41–58.

- Stremersch, Stefan, Gerard J. Tellis, Philip Hans Franses, Jeroen L. G. Binken. 2007. Indirect network effects in new product growth. *Journal of Marketing* **71**(3) 52–74.
- Sun, Mingchun, Edison Tse. 2007. When does the winner take all in two-sided markets? Review of Network Economics **6**(1) 16–40.
- Wickens, M. R. 1982. The efficient estimation of econometric models with rational expectations. Review of Economic Studies $\bf 49(1)$ 55–67.

Table 1. Examples of Platform-based Markets

Market	Side 1	Platform(s)	Side 2
PC operating systems	Computer users	Windows, Macintosh, Linux	Application developers
Web browsers	Internet surfers	Internet Explorer, Firefox	Plugin developers
Portable documents	Document readers	Adobe	Document writers
Online auction houses	Buyers	eBay.com	Sellers
Video sharing	Clip makers	YouTube.com	Clip watchers
Online dating clubs	Men	Match.com, AmericanSingles.com	Women
Credit cards	Cardholders	Visa, Mastercard	Merchants
Streaming audio/video	Content users	Windows media player, Real audio	Content creators
Sponsored search	Searchers	Google, MSN, Yahoo	Advertisers
Stock exchanges	Equity purchasers	NYSE, NASDAQ	Listed companies
Home video games	Game players	Xbox, PlayStation, WII	Game developers
Recruitment sites	Job seekers	Monster.com, Hotjobs.com	Employers

Table 2. Overview of Empirical Studies on Indirect Network Effects

	Markets	Demand or Supply Side	Dynamic Model
Shurmer (1993)	PC software	Demand	No
Basu et al. (2003)	$^{\mathrm{CD}}$	Demand	No
Clements and Ohashi (2005)	Video game console	Both	No
Cottrell and Koput (1998)	Micro-computer	Demand	No
Dranove and Gandal (2003)	DVD and Divx players	Demand	No
Gandal et al. (1999)	CP/M and DOS	Both	No
Gandal et al. (2000)	$^{ m CD}$	Both	Yes
Gupta et al. (1999)	Digital television	Both	No
Nair et al. (2004)	PDA	Both	No
Ohashi (2003)	VCR	Demand	No
Park (2004)	VCR	Demand	Yes
Prieger and Hu (2006)	Video game console	Both	No
Rysman (2004)	Yellow page	Both	No
Shankar and Bayus (2003)	Video game console	Demand	No
Stremersch et al. (2007)	9 different markets	Both	No

Table 3. Features of PlayStation 2 and Xbox Consoles

We compare the features of PlayStation 2 and Xbox consoles. The only major differences between the two consoles are in the clock speed and the amount of memory.

Platform	Platform	Launch Date	Price on the	Mai	n Characte	eristics
Name	Provider	in the US	Launch Date	Bits	MHZ	RAM
PlayStation 2	Sony	October 2000	\$299	128	300	38
Xbox	Microsoft	November 2001	\$299	128	733	64

Table 4. Summary Statistics of PlayStation 2 and Xbox Consoles

We present summary statistics on console sales and game releases.

	PlayStation 2			Xbox				
	2002	2003	2004	2005	2002	2003	2004	2005
% of Installed Base	0.81	0.76	0.72	0.69	0.19	0.24	0.28	0.31
% of Total Games	0.84	0.80	0.71	0.65	0.16	0.20	0.29	0.35
% of New Console Units Sold	0.73	0.67	0.53	0.68	0.27	0.33	0.47	0.32
% of New Games Released	0.68	0.60	0.60	0.55	0.32	0.40	0.40	0.45
% of New Games by Console Provider	0.09	0.09	0.07	0.08	0.08	0.10	0.07	0.05

Table 5. Regression Results for Both Console Adoption and Game Supply

Panel A reports regression results for console adoption on the consumer side. Equation (8) is the regression specification. Model I uses OLS estimation and Model II, III and IV use non-linear least square estimation. In Model III, we use console retail prices in Japan and the exchange rates between Japanese Yen and US dollar as instruments for console prices in the United States. Panel B reports regression results for game supply on the developer side. Equation (9) is the empirical specification. All models use OLS estimation. Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.

Panel A: Console Adoption

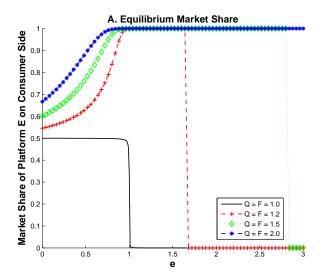
Model	I	II	III	IV
$\overline{eta_Q}$	0.28*	0.30**	0.32	0.28**
	[0.14]	[0.14]	[0.26]	[0.13]
$\ln N_{Et} - \ln N_{It}$	0.69***	0.62***	0.64^{***}	0.59***
	[0.10]	[0.11]	[0.12]	[0.11]
arphi		0.31^*	0.34^{*}	0.36**
		[0.18]	[0.18]	[0.16]
$Dummy_{2005}$	-0.60^{***}	-0.61^{***}	-0.62^{***}	-0.60^{***}
	[0.12]	[0.12]	[0.12]	[0.11]
$p_{Et} - p_{It}$			-0.00	
			[0.04]	
Observations	47	47	45	47
R-squared	0.53	0.54	0.53	0.57

Panel B: Game Supply

Model	I	II	III	IV
$\ln b_{jt}$	0.81***	0.87***	0.83***	0.87***
•	[0.25]	[0.30]	[0.28]	[0.32]
$Dummy_E$	0.49	0.56	0.53	0.55
	[0.31]	[0.36]	[0.36]	[0.40]
$Dummy_{Holiday}$	0.33^{*}		0.33^{*}	0.31^{*}
	[0.20]		[0.20]	[0.19]
$Dummy_E \times Dummy_{2005}$			-0.06	-0.04
			[0.33]	[0.36]
$Dummy_{2003}$	-0.56**	-0.63**	-0.58*	-0.74**
	[0.28]	[0.29]	[0.30]	[0.31]
$Dummy_{2004}$	-0.93^{**}	-1.03**	-0.96**	-1.04**
	[0.36]	[0.39]	[0.39]	[0.40]
$Dummy_{2005}$	-1.08**	-1.25^{***}	-1.08**	-1.26^{***}
	[0.42]	[0.47]	[0.42]	[0.47]
Observations	94	94	94	94
R-squared	0.26	0.22	0.26	0.25

Figure 1. Equilibrium Market Share with Different Quality Advantages

We let $b_{I,0} = d_{I,0} = 20$ and allow quality advantages Q and F to vary. We use $b_{E,0} = d_{E,0} = 10$, $M_0 = 5$, $\delta_b = \delta_d = 10^{-3}$, $\varphi_d = 0.95$, $\gamma_t = 1 - 0.1^t$ (so that the fixed costs do not converge to zero over time) and $\frac{(1-\delta_d)\cdot y\cdot(\beta-1)}{\beta} = 0.1$ in all of our simulations.



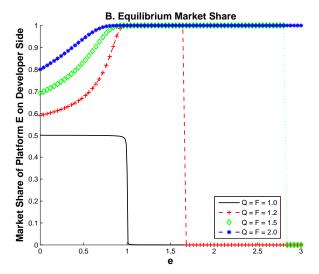
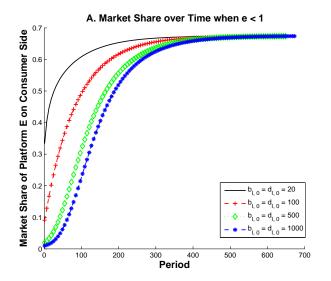


Figure 2. Equilibrium Market Share with Different Installed-Base Advantages

We fix the quality advantage at Q = F = 1.2 but allow the installed-base advantage to vary. Figure A shows the market share over time of platform E on the consumer side for e = 0.6. Figure B shows the value of e^* as the installed-base advantage of platform I increases.



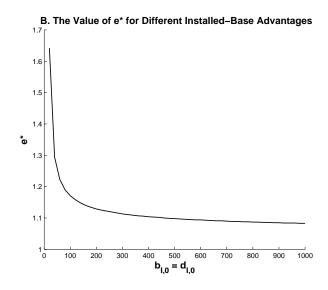
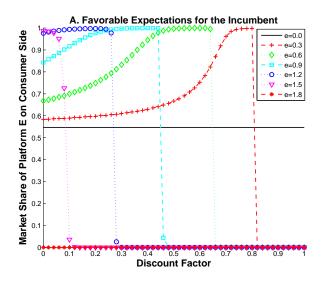


Figure 3. Equilibrium Market Share with Different Consumer Expectations

For different levels of e, we plot the equilibrium market share of platform E on the consumer side as the discount factor, φ , increases from 0 to 1. Figure A and B show the results in which all consumers hold favorable expectations for the incumbent and the entrant respectively. We use $T=300,\ Q=F=1.2$ and $b_{I,0}=d_{I,0}=20$ in our simulations.



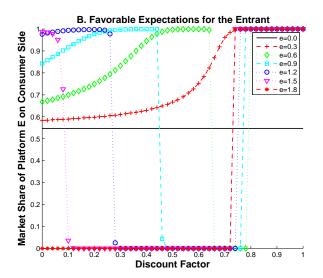


Figure 4. Summary of Theoretical Results

We identify drivers of market dynamics for different values of e and φ . We use straight lines to segment the area for simplicity.

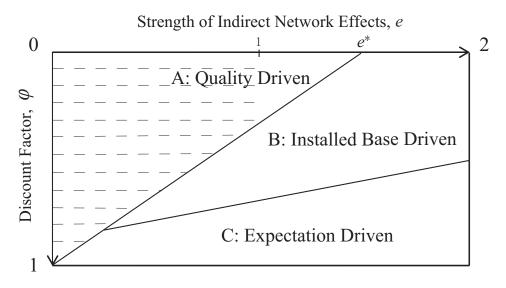
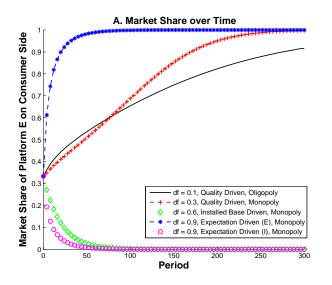


Figure 5. Market Evolution for Different Scenarios

We let e = 0.9 and allow φ to vary. Figure A shows the market share of platform E on the consumer side and B shows the percentage of new consumers adopting platform E in each period. When $\varphi = 0.9$, two equilibria exist depending on consumer expectations. We illustrate both cases.



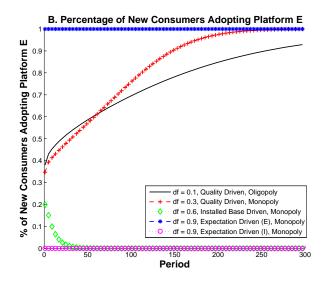


Figure 6. Price Difference between Xbox and PlayStation 2 Consoles

Console prices are computed by dividing the monthly dollar value of the sales by the volume of units sold for each console.

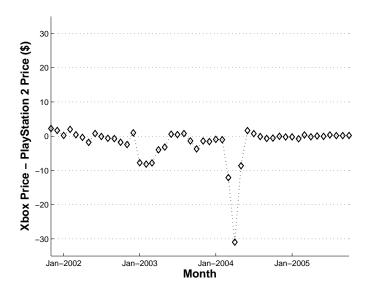
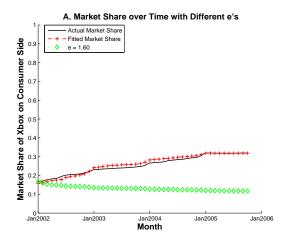


Figure 7. Counterfactual Analysis: Market Evolution with Different Values of e and φ

We use January 2002 as the initial period and simulate the market dynamics. Figure A illustrates the market share trajectory for e=1.60, given $\varphi=0.31$, for the consumer side and compares it to the actual one and fitted one from our regression results. Figure B shows the market share trajectories for $\varphi=0.45$, $\varphi=0.75$ and $\varphi=0.90$ (we show the case in which Xbox has favorable expectations), given e=0.62, compares them to the actual one.



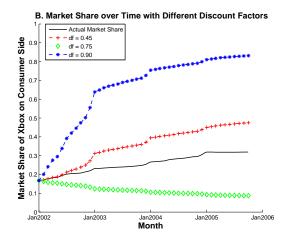


Figure 8. Counterfactual Analysis: Delayed Release of Xbox

We assume that Microsoft could improve the quality advantage of Xbox by another 35% (i.e., Q=1.82). We consider two scenarios. In the first one, we assume that Sony does not drop the price for PlayStation 2 before the release of Xbox. In the second case, we assume that Sony drops PlayStation 2 price following the pattern observed in the dataset. We illustrate the trajectories of Xbox market shares on the consumer side for both cases, and compare them to the actual one.

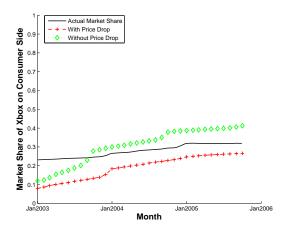


Figure 9. Phase Diagrams for Different Values of e

Arrows are used to indicate the directions of trajectories for states in each region, as determined by signs of $\frac{dr_d}{dt}$ and $\frac{dr_b}{dt}$.

