경영학석사학위논문

The Impact of Competition on Pricing in a Two-sided Market

양면 시장에서 플랫폼 간 경쟁이 가격에 미치는 영향에 대한 연구

2013년 2월

서울대학교 대학원

경영학과 경영학 전공

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Abstract

Today, many high-tech products function as intermediaries in two-sided markets and a thorough understanding of the distinguished market mechanism is considered to be a key to success. The hardware manufacturers battle for getting the initial advantage, reinforcing their own networks and ultimately dominating the market. Although an extensive empirical research focuses on the relationship between competition and indirect network effects, accounting for market dominance due to the unique price mechanism, little empirical studies have addressed the extent to which the distinguished price structure in two-sided markets depends on the market structure among platforms. The reverse causality of the commonly investigated relationship in durable goods industry is a particularly interesting avenue for research.

This paper develops an empirical model to investigate the impact of competition on optimal pricing of durable products under indirect network effects by extending the framework in Dubé, Hitsch and Chintagunta(2010). This study differs from theirs in the following ways: First, I modify the framework in the supply side to incorporate the hypothetical market structure (i.e. monopoly) as well as the observed market structure (i.e. oligopoly). Second, they focus on the endogenous market dominance of one platform whereas my analysis explains the impact of exogenously determined market structure. I estimate demand that accounts for consumers' forward-looking behaviors and solve for the Markov Perfect Nash Equilibrium through numerical dynamic programming techniques. The research entails comparing the expected price in the oligopoly market to the hypothetical expected price in the absence of competition and examines the impact of exogenously determined competition among intermediaries. The monopoly case consists of two scenarios: 1) one of the existing firms in the oligopoly market produces and sells a single product and 2) the existing firms are merged into one firm which offers several kinds of hardware products at different prices. This research investigates the second scenario and compares the price levels in oligopoly market to those in monopoly market.

I apply my model to the U.S. video game console market, a canonical example of a two-sided market. The empirical estimation and simulation results indicate that the manufacturers price skim over time regardless of market structure. The price level differentiates the two markets. The merged firm sets higher prices by 12.6% for Sony PlayStation and 14.1% for Nintendo 64 on average than the different firms do for their single platforms respectively since the merged firm does not get engaged in the standard war. The measure of difference between the price levels reveals the impact of exogenously determined competition on two-sided dynamic pricing for customers.

Keywords: two-sided market, indirect network effect, competition, dynamic programming, high technology

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1. Introduction

Shoppers want shopping malls in which a lot of retailers are running their shops and retailers pick platforms that are or will be frequently visited by consumers. Smartphone users decide to buy a carrier that is compatible with many applications and application developers are motivated to launch an application for a platform that is popular among users. That is, in certain industries, two types of agents interact via platforms and affect each other's decision about whether to join the market or not. Such indirect network effect is a distinguished property of two-sided markets. Two-sided market, demonstrated by shopping malls, video game consoles and credit cards, is largely analyzed in economic and marketing literature because its participants follow distinguished processes to establish pricing and other managerial strategies from agents in one-sided market. Today, many information technology products function as intermediaries in two-sided market and a thorough understanding of the unique market mechanism is considered to be a key to success.

While some two-sided market studies assume that participants make static decisions to join the market, durable goods market studies that incorporate network externalities tend to get better data-fitting results by taking account of forward-looking consumers and firms. Participants' dynamic optimal decisions are mainly analyzed by dynamic structural models that assume conditional independence among state variables and estimated by numerical dynamic programming techniques. The dynamic approaches reflect the desire to verify and measure behavioral theories with empirical data, and to utilize recent technical developments for estimation of these models. There is a large literature in econometrics, industrial organization and marketing that explains such decisions. An extensive empirical research focuses on the relationship between competition and indirect network effects in durable product markets, accounting for market evolution in two-sided markets by constructing dynamic structural models ([Markovich and Moenius(2009), Dubé, Hitsch and Chintagunta(2010)]. However, to my best knowledge, the empirical literature has not addressed the extent to which a distinguished price structure in two-sided market depends on market structure. The reverse causality of the commonly investigated relationship in durable goods industry is a particularly interesting avenue for research.

The empirical application of the key idea to durable product market can empirically measure the degree of differences between the competitive equilibrium prices under oligopolistic competition and the counterfactual prices assuming no competition among firms. The equilibrium is derived from the model that accounts for consumers' forward-looking behaviors in the demand side and for competitive dynamics in the supply side.

I estimate structural parameters in the demand side by using two-stage estimation of conditional choice probabilities as suggested in Hotz and Miller(1993) which overcomes the curse of dimensionality. I numerically solve for the pricing strategies as Markov Perfect Equilibrium by adopting value function iteration algorithm and compare the results with hypothetical expected pricing policies that would arise in the absence of competition between standards. The monopoly case consists of the scenario that only one of the existing platforms in the oligopoly market offers the product and the scenario that the firms under oligopolistic competition are merged into one firm and the merged firm offers various hardware products. I quantify the difference in prices in the oligopoly market and those in the monopoly market to reveal the impact of competition on dynamic pricing for customers.

The results indicate that the merged firm in the monopoly market is more likely to set higher prices than competing firms in the duopoly market from the introduction stage. This is because the merged firm does not need to care about the initial advantage as much as the competing firms do. The competing firms in the duopoly market set lower prices to capture initial advantages so that they can benefit from indirect network effects, finally to dominate the market.

The rest of this paper is organized as follows. In Section 2, I discuss the previous studies that explore the research problems on the market with indirect network effects and dynamic structural models. Section 3 contains the framework that incorporates customers' and firms' forward-looking behaviors to solve for equilibrium and to analyze the impact of competition on market outcomes. Section 4 briefly describes video game console industry data used in the study. Section 5 covers the parameter estimation procedure, numerical simulation to compute the equilibrium and discusses results. I summarize this research and suggest future research direction in Section 6.

2. Literature Review

The related literature to this study can be characterized along two dimensions: two-sided market and forward-looking behaviors. Since Katz and Shapiro(1985), there has been an extensive theoretical literature that has studied two-sided markets to incorporate indirect network effects. Early theoretical studies [Caillaud and Jullien(2003), Rochet and Tirole(2003)] are mainly interested in identifying and modeling the network effect that distinguishes the market from one-sided market to unveil the determinants of equilibrium prices. Rochet and Tirole(2006) identify a two-sided market in terms of price structure and externalities as one of pioneering theoretical studies on the market. In terms of price structure, a market is two-sided if the relative level of buyer market price and seller market price matters in deciding market size. It is one-sided when only aggregate price matters. Coase theorem does not apply to the transactions in two-sided markets, since platform restricts negotiations between different sides of the market through transaction cost or membership fee. In terms of externalities, a two-sided market is distinguished from a traditional market in that the number of customers in one side of a market is decided not only by price level for the side, but also by the number of participants on the other side of the market. This research contributes to establish the definitions of two-sided markets. Armstrong(2006) investigates the market outcome - the equilibrium prices of a monopoly platform, a competing platform that consumers single-home and a competing platform to which the competitive bottleneck model is applied - depending on the three different strategies in a two-sided market - the relative size of cross-group externalities, whether the platform charges fixed fees or per-transaction fees and whether consumers single-home or multi-home the platform. The literature extends to cover many economic topics in the market such as product strategies [Sun, Xie and Cao(2004)], market leadership determinants [Nair, Chintagunta and Dubé(2004), Argentesi and Filistrucchi(2007), Tellis, Yin and Niraj(2009)], market evolution [Gupta, Jain and Sawhney(1999), Markovich and Moenius(2009), Dubé, Hitsch and Chintagunta(2010)] and pricing [Park(2004), Kaiser and Wright(2006), Liu(2010)]. Kaiser and Wright(2006) take a framework from Armstrong(2006) and demonstrate that magazines set cover prices below marginal cost and set advertising prices over marginal cost. They differentiate two platforms based on the Hotelling model and apply the theory to magazine industry where a platform maximizes its total profits by choosing cover price, advertising price and the amount of contents. Also the literature extends to analyze a specific type of markets under the indirect network effect. Some studies [Tellis, Yin and Niraj(2009), Godes, Ofek and Sarvary(2009)] develop a theoretical model that applies to a certain market. Godes, Ofek and Sarvary(2009) are closely related to the current study since they explore the impact of competition among platforms on media firm profits and actions by developing a theoretical framework that is applied to the specific type of industry. They examine the extent to which the unbalanced pricing strategy in media industry varies across the competition intensity. The paper compares the duopoly cases to the monopoly case to investigate how the competition affects media firm strategies in a two-sided context. Others provide empirical results from market data [Nair, Chintagunta and Dubé(2004), Park(2004), Kaiser and Song(2006), Dubé, Hitsch and Chintagunta(2010), Liu(2010)] or field experiment data [Tucker and Zhang(2010)]. The markets are categorized into durable product market and non-durable product market. The two types of markets differ in whether consumers make forward-looking decisions or not to get on board for the platforms. Table 1 summarizes the types of industries and the economic topics that each research explores.

There is a large literature that assumes economic agents' dynamic behaviors and presents dynamic decision models. The studies focus on considering the role of consumers' and firms' beliefs theoretically and empirically and assessing their relevance to purchase and marketing decisions. Chintagunta, Erdem, Rossi and Wedel(2006) indicate that dynamic structural models contain three common components: 1) time and

Table 1. Two-sided Market Research

Industry	Topics	References
General	platform competition	Katz and Shapiro(1985), Caillaud and Jullien(2003), Rochet and Tirole(2003), Armstrong(2006)
	product strategy	Sun,Xie and Cao(2004)
	market identification	Rochet and Tirole(2006)
Durable Products	market evolution	Gupta, Jain and Sawhney(1999), Markovich and Moenius(2009)[1c], Dubé, Hitsch and Chintagunta(2010)[1a, 1c], Nair, Chintagunta and Dubé(2004)[1a], Tellis, Yin and Niraj(2009)[1a]
	pricing	Park(2004)[1a,1c], Liu(2010)[1a, 1c]
Non-durable Products[1b]	platform competition	Godes, Sarvary and Ofek(2009)
	pricing	Kaiser and Wright(2006)
	market evolution	Argentesi and Filistrucchi(2007)
	advertisement effect	Kaiser and Song(2006), Tucker and Zhang(2010)

1a. empirically measures the size of indirect network effects compared to quality effects

1b. mostly includes advertising-supported media industries

1c : incorporates consumers' and /or firms' forward-looking behaviors

uncertainty, 2) decision makers' objective functions and current information available, and 3) multi-period objective functions to be maximized. That is, economic agents get the information on the current choice set and maximize their expected utilities to make decisions. Rust(1987) develops a nested fixed point algorithm to solve a stochastic discrete choice dynamic programming problem and describes a replacement behavior of bus engines. The algorithm is free from constraints in model specifications to derive closed-form solutions. The article contributes to develop a numerical dynamic programming method that is applied in many studies ex post. A curse of dimensionality is raised as a limitation of the procedure and addressed in other methodological literature. I do not implement nested-fixed point algorithm due to the limitation and adopt two-stage estimation of conditional choice probabilities suggested in Hotz and Miller(1993). They establish the existence of a one-to-one mapping between the conditional valuation functions for the dynamic problem and their associated conditional choice probabilities. The empirical studies on forward-looking behaviors in

Table 2. Forward-looking Behavior Research : Topics

Topic	References
Advertising effect	Erdem and Keane(1996)[2a], Ackerberg(2003)[2a],
Role of search cost	Mehta, Rajiv and Srinivasan(2003)[2a]
Purchase incidence	Gönül and Srinivasan(1996)[2a]
Purchase timing	Sun(2005)[2a]
Brand choice/switch	Sun, Neslin and Srinivasan(2003)[2a], Erdem, Keane and Strebel(2005)[2a], Sun(2005)
Product Diffusion	Song and Chintagunta(2003)[2a]
R&D, Product Innovation	Goettler and Gordon(2011)[2b]
Product Replacement	Rust(1987)[2a], Gordon(2009)[2a]
Product Launch and Exit	Hitsch(2006)[2c]
Inventory behavior	Erdem, Imai and Keane(2003)[2a], Hendel and Nevo(2006)[2a]
Pricing	Nair(2007)[2b], Liu(2010)[2c]
Market evolution	Markovich and Moenius(2009)[2a] , Dubé, Hitsch and Chintagunta(2010)[2b]

2a : builds dynamic structural demand models

2b : builds dynamic structural models of demand and firm behavior

2c : builds dynamic structural supply models marketing field cover various topics as summarized in Table 2 and incorporate expectations with regard to several forward-looking components as shown in Table 3. Some of them build dynamic structural demand models to explain consumers' forward-looking behaviors and others account for both consumers' and firms' dynamic behaviors and solve for market equilibrium.

Table 3. Forward-looking Behavior Research : Components

Expectation components	References
Promotion expectation	Gönül and Srinivasan(1996), Sun, Neslin and Srinivasan(2003), Sun(2005),
Price expectation	Erdem, Imai and Keane(2003), Nair(2007) Mehta, Rajiv and Srinivasan(2003), Hendel and Nevo(2006)
Quality expectation	Rust(1987), Erdem and Keane(1996), Ackerberg(2003), Markovich and Moenius(2009), Goettler and Gordon(2011)
Price and Quality expectation	Song and Chintagunta(2003), Erdem, Keane and Strebel(2005), Gordon(2009)
Demand expectation	Hitsch(2006), Markovich and Moenius(2009), Liu(2010), Goettler and Gordon(2011)
Price and Demand expectation	Dubé, Hitsch and Chintagunta(2010)

Song and Chintagunta(2003) formulate an optimal stopping problem to describe consumers' adoption behaviors of a durable product. They apply the framework to digital camera category data and analyze heterogeneous and forward-looking consumers' strategies. They simulate data for the same values of parameters to show that the model is able to recover consumer heterogeneity structure from market-level data with information on heterogeneity distribution. This framework demonstrates that aggregate data is sufficient to estimate parameters from the individual-level model and that consumer heterogeneity and dynamic decisions explain consumer behaviors in durable product market. Nair(2007) presents a framework to determine the optimal pricing of durable goods in a market with forward-looking customers and a forward-looking monopoly firm. The author applies the model to video game console market data and contributes to empirically analyze dynamic demand estimates and dynamic pricing structure of a durable product. The framework presents a two-step approach to solve for Markov Perfect Nash Equilibrium. The first step is demand parameter estimation and the second step takes demand parameters as given and numerically solve for forward-looking firm's optimal pricing. The results indicate that a durable product seller follows skimming pricing pattern and no consideration on forward-looking behaviors leads to potential biases. Gordon(2009) provides a dynamic structural model to estimate forward-looking consumers' replacement decisions under the uncertainty on future price and quality and applies the framework to PC processor industry. This study solves value function through the nested fixed-point algorithm that outer iterations lead to produce the value that minimizes Generalized Method of Moments objective function and that inner loops compute corresponding value functions. The author simulates individual-level data to estimate a model and to assess the validity of prior estimates from aggregate data. Unique to this research is that replacement decision is indirectly inferred from the combination of sales volume and the accumulated installed base in aggregate data. The author uncovers the patterns of ownership and compares it to sales performance of each period to separate adoption and replacement behaviors. The combination of data on product availability and changes in the installed base provides information on endogenously determined consumer heterogeneity. This article contributes not only to recover estimated parameters in panel data from aggregate data, but also to investigate the role of price and quality expectations and endogenous consumer heterogeneity on replacement decisions in terms of forward-looking behavior research.

Closely related to my research, Liu(2010) and Dubé, Hitsch and Chintagunta(2010) integrate these two research streams and explore marketing issues in a two-sided market by formulating dynamic structural models. Liu(2010) analyzes whether video game console firms have incentives for price skimming or price penetration by studying a dynamic pricing game between firms under indirect network effects, consumer heterogeneity and oligopolistic competition between platforms. The author estimates empirical parameters and uses the results to numerically solve for the Markov Perfect Equilibrium. The study simulates market evolution by using the obtained equilibrium on two firms' pricing policies and concludes that video game console industry follows the skimming price pattern. This article computes the biases when either network effects or consumer heterogeneity or dynamic pricing decision is not incorporated into the model and assesses the impact of key components in the framework. The research also measures the degree of indirect network effects relative to that of price-quality effects and provides various policy simulations.

My research mainly extends Dubé, Hitsch and Chintagunta(2010) by modifying the framework used in the study. They measure tipping or market dominance caused by indirect network effects in a durable product market where forward-looking consumers and firms play a dynamic game and applies the framework to video game console market data. Tipping is measured by comparing the expected market share of a platform to the well-defined counterfactual fraction of market that each standard gains when underlying factors related to indirect network effects are changed. They estimate the structural parameters following the two-stage algorithm claimed by Hotz and Miller(1993) since traditional nested-fixed point algorithm suffers from the curse of dimensionality. They do not compute the choice-specific value functions but simulate consumer choice rules from pooling market data and estimate consumers' structural parameters by minimizing the distance between simulated choice strategies and observed decisions. The first step investigates how strategic variables are related to state variables and the second stage is replicated in alternative model specifications. The study solves for Markov Perfect Bayesian Equilibrium by multiple-agent policy iteration algorithm that iterates discounted values of software, choice-specific value functions, no-purchase value functions and new pricing policies until pricing strategies converge. They measure tipping in cases of symmetric and asymmetric competitions and conclude that market concentration increases if indirect network effect is present. This study not only quantifies the degree of tipping for the first time but also provides an elaborate quantitative framework to analyze forward-looking agents' behaviors in a two-sided market. I extend their study in the following ways: First, I modify the framework in the supply side to incorporate the hypothetical market structure (i.e. monopoly) as well as the observed market structure (i.e. duopoly). Second, they focus on the endogenous market dominance of one platform whereas my analysis investigates the impact of exogenously determined market structure.

3. Model

3.1. Software Provision

The game titles compatible with platform j at time t+1 target customers who have purchased the platform j up to period t. Therefore, software provision is determined by the number of customers who own the corresponding hardware. The equation (1) captures the indirect network effect between game provision and hardware demand. The relationship is specified as a log-linear function that is derived from constant elasticity of substitution (CES) software demand in the software market and free-entry equilibrium following Nair, Chintagunta and Dubé(2004). The model takes software provision into account only in terms of their variety since their quality or contents are hard to measure.

$$\ln(n_{jt}) = \kappa_j - \varphi_j \ln(y_{jt}) + \upsilon_{jt} \tag{1}$$

Here, n_{jt} is the number of software titles that are compatible with platform j at time t and y_{jt} is the market share of platform j's installed hardware base at time t. Positive φ_j indicates that software manufacturers are expected to develop more various games at time t when there are more customers who have adopted the corresponding platform up to the beginning of the period.

3.2. Customers

Customers derive their utility from their benefit from hardware model and their benefit from available software in the market. In choosing the hardware, forward-looking customers consider not only current software availability but also the present value of future software purchases compatible with the platform that they plan to adopt. Forward-looking customers make expectations on the evolution of state space to make adoptions. The installed hardware base is anticipated to evolve as

$$y_{t+1} = f^e(y_t, \xi_t) \tag{2}$$

where ξ_{jt} is the platform-specific demand shock at time t, which is not known to its competitors until its sales is realized, independent and identically distributed across time and has the probability density function of $\phi_j(\cdot)$.

Customers expect that firms set prices according to

$$p_{jt} = \sigma_j^e(y_t, \xi_{jt}) \tag{3}$$

Since the software provision is a function of installed hardware base, the software value is denoted as

$$\omega_j(y_{t+1}) = E\left[\sum_{k=0}^{\infty} \beta^k u_j(y_{j,t+k+1}) | y_{t+1}\right] \tag{4}$$

where β is the discount factor for consumers.

The value is computed recursively as

$$\omega_j(y_{t+1}) = u_j(y_{j,t+1}) + \beta \int \omega_j\left(f^e(y_{t+1}, \xi)\right)\phi(\xi)d\xi \tag{5}$$

Customers compare the choice-specific value of purchase and value of waiting to make adoption decisions. The value of purchasing platform j at time t is given by

$$\nu_j(y_t, \xi_t, p_t) = \delta_j + \omega_j\left(f^e(y_t, \xi_t)\right) - \alpha p_{jt} + \xi_{jt} \tag{6}$$

where δ_j is the intrinsic preference for platform j and α is marginal disutility from price.

The value of delaying the purchase is denoted as

$$\nu_0(y_t, \xi_t) = \beta \int \max\Big\{\nu_0(y_{t+1}, \xi_t) + \epsilon_0, \max\Big\{\nu_j\left(y_{t+1}, \xi, \sigma^e\left(y_{t+1}, \xi_{jt}\right)\right) + \epsilon_j\Big\}\Big\} \phi_\epsilon(\epsilon)\phi(\xi)d(\epsilon, \xi) \tag{7}$$

where ϵ_j is random utility component for platform j which follows type I extreme value distribution and independent and identically distributed across platforms.

The market share of platform j given the distributional property of error terms is

$$s_j(y_t, \xi_t, p_t) = \frac{\exp(v_j(y_t, \xi_t, p_t))}{\exp(v_0(y_t, \xi_t)) + \sum_{k=1}^{J} \exp(v_k(y_t, \xi_t, p_t))} \tag{8}$$

The installed hardware base is expected to evolve as the equation (9) which is used as law of motion in the estimation part.

$$y_{j,t+1} = y_{jt} + \left(1 - \sum_{k=1}^{J} y_{kt}\right) s_j(y_t, \xi_t, p_t) = f_j(y_t, \xi_t, p_t) \tag{9}$$

3.3. Firms

3.3.1. Oligopoly

Let J platforms compete in the market and customers single-home, or choose at most one product in the whole period. Customers are assumed to make rational expectations on the firms' policy function so that firms set prices as the customers expected:

$$p_j = \sigma_j\left(y, \xi_j\right) \tag{10}$$

Here, the strategy follow Markov process, or depends solely on the firms' present state. Firms are also assumed to expect rationally, so they anticipate that customers' behaviors and market state will be realized according to the equations (6)~(9).

Firms' per-period profit function is given by

$$\pi_j(\mathrm{y}, \xi_j, p_j) = (p_j - c_j) \cdot \left(1 - \sum_{k=1}^{J} y_{kt}\right) \cdot \int s_j\left(y, \xi_j, \xi_{-j}, p_j, \sigma_{-j}(y, \xi_{-j})\right) \phi_j(\xi_{-j}) d\xi_{-j}$$
$$+ r_j \int q_j\left(f_j\left(y, \xi_j, \xi_{-j}, p_j, \sigma_{-j}(y, \xi_{-j})\right)\right) \phi_j(\xi_{-j}) d\xi_{-j} \qquad (11)$$

where c_j is the marginal production cost, r_j is the royalty rate from software suppliers, $q_j(y_{t+1})$ is the number of software titles sold at time t and $\sigma_{-j}(y, \xi_{-j})$ is the policy function of firms other than firm j. Note that the hardware manufacturer's profit consists of the sales profit from end-users and the royalty fees from game developers.

The expected present value of profit for platform j is written by

$$V_j(y_t, \xi_t | \sigma) = E\left\{\sum_{k=0}^{\infty} {\beta_f}^k \pi_j\left(\mathrm{y}_{t+k+1}, \xi_{j,t+k+1}, \sigma_j(\mathrm{y}_{t+k+1}, \xi_{j,t+k+1})\right) | y_t, \xi_t, \sigma\right\} \qquad (12)$$

where β_f is the discount factor of hardware firms and σ is the vector of price strategies of J firms. Firm j will choose the policy function that maximizes the equation (12) and the maximization problem is specified as the Bellman equation (13).

$$\mathrm{V_j}(\mathrm{y}, \xi_\mathrm{j}) = \sup\left\{\pi_\mathrm{j}(\mathrm{y}, \xi_\mathrm{j}, \mathrm{p_j})\right.$$
$$\left. + \beta_\mathrm{f} \int \mathrm{V_j}\left(\mathrm{f}\left(\mathrm{y}, \xi_\mathrm{j}, \xi_{-\mathrm{j}}, \mathrm{p_j}, \sigma_{-\mathrm{j}}(\mathrm{y}, \xi_{-\mathrm{j}})\right), \xi_\mathrm{j}'\right) \phi(\xi_{-\mathrm{j}}) \phi(\xi_\mathrm{j}') \mathrm{d}(\xi_{-\mathrm{j}}, \xi_\mathrm{j}')\right\} \qquad (13)$$

3.3.2. Monopoly

The value to be maximized is specified in the modified way when only one firm offers the product in the market. The monopoly case is categorized into two cases: the first case is when one of the existing firms in the oligopoly market produces and sells a single product and the other case is when the existing firms are merged into one firm which offers J kinds of hardware products at different prices. The J kinds of platforms are manufactured by J different firms in the oligopoly market.

If only one of the platform manufacturers runs its business, the per-period profit function is denoted as

$$\pi(\mathrm{y}, \xi, p) = (p - c) \cdot (1 - y) \cdot s(y, \xi, p) + r \cdot q\big(f(y, \xi, p)\big) \tag{14}$$

The optimal policy which is the solution of the Bellman equation given by

$$\mathrm{V}(\mathrm{y}, \xi) = \sup\{\pi(\mathrm{y}, \xi, p) + \beta_{\mathrm{f}} \int \mathrm{V}(\mathrm{f}(\mathrm{y}, \xi, \mathrm{p}), \xi')\phi(\xi')\mathrm{d}(\xi')\} \tag{15}$$

will maximize the monopolist's value of profit.

The merged firm collects the profit

$$\pi(\mathrm{y}, \xi, p) = \sum_{k=1}^{J}\left[(p_k - c_k) \cdot \left(1 - \sum_{k=1}^{J} y_{kt}\right) \cdot s_k\big(y, \xi_k, p_1, p_2, \dots, p_J\big) + r_k \cdot q_k\left(f_k\big(y, \xi, p_1, p_2, \dots, p_J\big)\right)\right] \tag{16}$$

where ξ_k is the demand shock specific for platform k. Note that the firm sets different prices for the different platforms which are offered by different firms in the oligopoly market. The Bellman equation is given as

$$\mathrm{V}(\mathrm{y}, \xi) = \sup\left\{\pi(\mathrm{y}, \xi, p) + \beta_{\mathrm{f}} \int \mathrm{V}\big(\mathrm{f}\big(\mathrm{y}, \xi, p_1, p_2, \dots, p_J\big), \xi'\big)\phi(\xi')\mathrm{d}(\xi')\right\} \tag{17}$$

3.4. Equilibrium

Given the behaviors of software suppliers, customers and firms, I solve for Markov Perfect Equilibrium which seeks the strategies that have the Markov property of memorylessness, or depend only on the payoff-relevant information. Consumers and firms are assumed to expect and act rationally so that their expectations and realized actions are mutually consistent.

4. Data

Video game console industry is a canonical example of a two-sided market. I estimate the parameters using data[1] from the U.S. 32/64-bit video game console market obtained from NPD Techworld's point of sales database. The data consists of price, hardware unit sales and the number of compatible software titles at monthly level for Sony PlayStation and Nintendo 64 from September 1996 to August 2002. I provide the descriptive statistics in Table 4.

Table 4. Descriptive Statistics

	Sony PlayStation		Nintendo 64	
	Mean	Std. dev.	Mean	Std. dev.
HW Price	273,103.1	285,365.4	102,891.3	198,917
HW Sales	121	31.3	118.7	34.8
SW Variety	704.1	335.3	158	104.3

Nintendo 64 was launched at the time period from which the data is available and Sony PlayStation was released in the market one year before. The standard war between the two platforms changed the market leader from Nintendo to Sony since Nintendo had dominated the video game console market for the two previous generations before Sony started to dominate the market with PlayStation.

The empirical model includes time trend as an exogenous variable to control for declining marginal production costs[2] for platforms. Also I include the producer price indices (PPIs) from the U.S. Bureau of Labor Statistics for computers, computer storage

[1] Professor Pradeep Chintagunta at the University of Chicago and Professor Hongju Liu at the University of Connecticut provided the data.

[2] I estimate the declining marginal cost in the appendix to estimate structural parameters in the demand side and to simulate the equilibrium prices under the different assumption on the cost. The results are robust to the cost specification.

devices, and audio/video equipment to control for technology costs and the exchange rate (JPY per USD) to control for the costs associated with the import of console parts. The final exogenous variable to be included in the empirical model is monthly fixed effects that enable the framework to control for seasonal demand and price peaks. Here, time trend and monthly fixed effects are considered to drive the demand variation and included in demand models and all the exogenous variables - time trend, monthly fixed effects, PPIs and exchange rates - are considered to affect costs or to drive the price policies and included in price functions.

5. Estimation and Simulation

5.1. Demand Estimation

The empirical model has several concerns in parameter identification. Since there is potential price endogeneity that price might be correlated with demand shocks, I adopt control function approach. The approach derives a proxy variable that conditions on the part of price that depends on the demand shock. The remaining variation in the endogenous variable after the control is independent of the unobservable variable and standard estimation approaches are consistent.

Also demand might have dependence over time and interdependence in the outcome variables thus I might not be able to separately identify intrinsic preferences of the specific platform and the indirect network effect coefficients. I include cost-shift variables that do not affect demand or software provision but affect prices to address this concern.

A dynamic structural model incorporates customers' belief on the evolution of state variables and the beliefs are mostly estimated by nested fixed point approach suggested in Rust(1987), nesting the solution to the consumers' dynamic adoption decision into the demand estimation procedure. However, since this methodology suffers from the curse of dimensionality, I calibrate the model with two-stage estimation of conditional choice probabilities suggested in Hotz and Miller(1993). The approach estimates parameters following two steps, first of which uncovers the relationship between state variables and market outcome variables and the second stage simulates choice-specific value functions based on the assumption that customers make rational beliefs and constructs moment conditions which match the observed log-odds of market shares with the simulated ones.

5.1.1. First Stage

First, I estimate the software provision, firms' pricing policies and consumers' purchase decision with respect to installed hardware base of platforms and demand shocks in the market. The software provision function is specified as

$$\ln(n_{jt}) = \Delta(y_{j,t+1}; \theta_n) + \eta_{jt} \tag{18}$$

where $y_{j,t+1}$ is the platform j's installed base at the beginning of time t+1 and η_{jt} is the random error which follows normal distribution as $\eta_{jt} \sim \mathrm{N}(0, \sigma_\eta^2)$

The firms' pricing policies are denoted as

$$\ln(p_{jt}) = \Psi(y_{jt}, y_{-jt}, z_t^p; \theta_p) + \xi_{jt} \tag{19}$$

where y_{-jt} is the competitors' installed base at the beginning of time t, z_t^p is the exogenous variables including time trend, monthly dummy variables, PPIs and exchange rates. The random error ξ_{jt} follows normal distribution as $\xi_{jt} \sim \mathrm{N}(0, \sigma_\xi^2)$. The function Ψ can take various forms and here I choose the quadratic specification that fits data best[3].

I estimate the consumers' purchase decision by estimating log-odds of market shares. The function is derived from equation (8) as follows:

[3] Dubé, Hitsch and Chintagunta(2010) use various specifications for price policy functions by modifying the number of cost-shift variables, adding two-mixture components and taking linear functional forms and conclude that the model used in my study has the highest likelihood based on the BIC predictive fit criterion.

$$
\begin{aligned}
\mu_{jt} &= \ln(s_{jt}) - \ln(s_{0t}) \\
&= \ln\left(\frac{\exp\left(v_j(y_t, \xi_t, p_t)\right)}{\exp\left(v_0(y_t, \xi_t)\right) + \sum_{k=1}^{J}\exp\left(v_k(y_t, \xi_t, p_t)\right)}\right) \\
&\quad - \ln\left(\frac{\exp\left(v_0(y_t, \xi_t, p_t)\right)}{\exp\left(v_0(y_t, \xi_t)\right) + \sum_{k=1}^{J}\exp\left(v_k(y_t, \xi_t, p_t)\right)}\right) + \varsigma_{jt} \\
&= v_j(y_t, \xi_t, p_t) - v_0(y_t, \xi_t, p_t) + \varsigma_{jt} \\
&= \mathrm{T}\left(y_{jt}, y_{-jt}, \xi_{jt}, \xi_{-jt}, z_t^d; \theta_\mu\right) + \varsigma_{jt}
\end{aligned} \tag{20}
$$

Here, z_t^d is the exogenous variable that affects consumers' purchase decisions including time trend and monthly fixed effects and the random measurement error ς_{jt} follows normal distribution as $\varsigma_{jt} \sim \mathrm{N}(0, \sigma_\varsigma^2)$. I include the control function to handle endogeneity in the model between the demand shock and the pricing strategies as outcome variable. Control function approach is an alternative to Two Stage Least Squares (2SLS) which is generally used to identify endogenous variables in econometric models. I derive a proxy function $\xi_{jt} = \mathrm{H}\left(y_{jt}, p_{jt}, z_t^p\right)$ that makes the error term depend on the part of endogenous variable. Control function correction resolves endogeneity bias by making the remaining variation in the endogenous variable independent of the error term.

Table 5. Software Provision

	Sony PlayStation		Nintendo 64	
	Estimate	Std. error	Estimate	Std. error
Intercept	8.0549	0.0067	8.8035	0.0076
y_j	0.7396	0.0028	1.6578	0.0028
σ_i	-1.8607	0.0069	-1.8607	0.0069

Table 6. Pricing Policies

	Sony PlayStation		Nintendo 64	
	Estimate	Std. error	Estimate	Std. error
Intercept	7.0557	0.0222	6.4912	0.0216
y_{Sony}	0.5255	0.3520	-4.3989	0.3176
$y_{Nintendo}$	-13.8021	0.5584	14.4230	0.6705
y_{Sony}^2	-1.8074	1.8098	-4.1352	2.6410
$y_{Nintendo}^2$	-2.1695	3.8213	-0.9662	5.7801
Time	0.0348	0.0000	-0.0131	0.0001
January	-0.2185	0.0044	0.0875	0.0038
February	-0.1879	0.0041	0.0952	0.0034
March	-0.1805	0.0040	-0.0093	0.0043
April	-0.1720	0.0036	0.1189	0.0038
May	-0.1418	0.0029	0.0854	0.0045
June	-0.1721	0.0028	0.0807	0.0041
July	-0.1230	0.0032	0.0733	0.0041
August	-0.2256	0.0036	0.0026	0.0039
September	-0.2279	0.0039	-0.0597	0.0040
October	-0.2533	0.0060	-0.0376	0.0041
November	-0.1467	0.0042	-0.0051	0.0026
PPI1[6e]	0.1968	0.0530	-0.1403	0.0621
PPI2[6b]	2.6621	0.0481	2.8525	0.0596
PPI3[6c]	-4.3662	0.0295	-3.5104	0.0353
Exchange rate 1[6d]	0.1194	0.0194	-0.0869	0.0213
Exchange rate 2[6e]	-0.1791	0.0091	-0.6672	0.0143
σ_i	-1.9652	0.0125	-1.9652	0.0125

Note. Producer Price Index for computers (**6a**), for computer storage devices (**6b**) and for audio/video equipment (**6c**)

Note. JPY per USD exchange rates with 3-month lags (**6d**) and with 7-month lags (**6e**)

Table 7. Log-odds of Market Shares

	Sony PlayStation		Nintendo 64	
	Estimate	Std. error	Estimate	Std. error
Intercept	-3.5242	0.0153	-3.4584	0.0232
y_{Sony}	11.8477	0.7056	3.4502	1.0409
$y_{Nintendo}$	4.3025	1.2197	5.4781	1.9147
y_{Sony}^2	-6.2032	3.3483	1.5997	5.6435
$y_{Nintendo}^2$	-1.2868	7.7446	0.7488	13.5826
Time	-0.0108	0.0009	0.0053	0.0011
January	-0.3448	0.0092	-0.5244	0.0138
February	-0.2866	0.0083	-0.4403	0.0125
March	-0.2914	0.0082	-0.4578	0.0129
April	-0.2181	0.0072	-0.3155	0.0101
May	-0.1421	0.0051	-0.2785	0.0078
June	-0.1699	0.0052	-0.3162	0.0082
July	-0.0866	0.0054	-0.1662	0.0087
August	-0.0899	0.0066	-0.1994	0.0099
September	-0.0046	0.0076	-0.1470	0.0107
October	-0.0260	0.0112	-0.1476	0.0162
November	0.0381	0.0065	-0.0201	0.0084
ξ_{Sony}	0.2030	0.0040	0.2853	0.0056
$\xi_{Nintendo}$	-0.0338	0.0034	-0.0523	0.0067
ξ_{Sony}^2	0.0899	0.0023	0.1243	0.0033
$\xi_{Nintendo}^2$	-0.0112	0.0028	-0.2278	0.0053
σ_i	-3.2036	0.0015		

Using the distributional properties of random measurement errors, I estimate parameters $\Theta = (\theta_n, \theta_p, \theta_\mu, \sigma_\eta, \sigma_\xi, \sigma_\varsigma)$ by maximizing likelihood function. The likelihood function to be maximized is as follows.

$$\ln(L) \propto \sum_{\substack{i=\eta,\xi,\varsigma \\ \mathrm{j=n,p,\mu}}} -2\ln(\sigma_i) - \frac{1}{2}((\frac{\theta_j}{\sigma_i})^2 + (\frac{\theta_j}{\sigma_i})^2) \tag{21}$$

The estimation results from software supply function, pricing function and market share function are provided in Table 5, Table 6 and Table 7, respectively. The maximum likelihood estimation in the first stage reveals a significant and positive relationship between the software variety and the installed base of each platform. In the same manner, I estimate the empirical distribution of state variables including price and log-odds of market share. I include a control function to resolve price endogeneity with demand shocks when estimating log-odds of market share.

5.1.2. Second Stage

I simulate outcome variables in the second stage based on the relationship estimated in the first stage. In detail, I draw random numbers for $\xi_{jt}^{(r)}$, demand shocks of platform j at period t from standard normal distributions. Here, $\mathrm{r} = 1,2,\ldots,\mathrm{R}$ and R denotes the number of draws used in the simulation. I simulate outcome variables by iterating on the following equations:

$$\ln(n_{jt}^{(r)}) = \Delta\left(y_{j,t+1}; \widehat{\theta_n}\right) \tag{22}$$

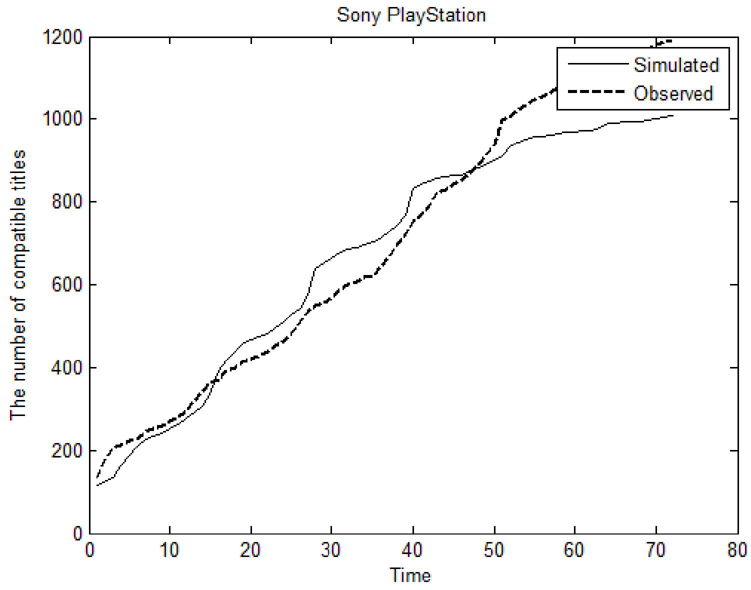
$$\ln\left(p_{jt}^{(r)}\right) = \Psi\left(y_{jt}, y_{-jt}, z_t^p; \widehat{\theta_p}\right) \tag{23}$$

$$\mu_{jt}^{(r)} = \mathrm{T}\left(y_{jt}, y_{-jt}, \xi_{jt}, z_t^d; \widehat{\theta_\mu}\right) \tag{24}$$

$$s_{jt}^{(r)} = \frac{\exp(\mu_{jt}^{(r)})}{1+\sum_{k=1}^{J} exp(\mu_{kt}^{(r)})} \tag{25}$$

$$y_{j,t+1}^{(r)} = y_{jt}^{(r)} + (1 - \sum_{j=1}^{J} y_{jt}^{(r)}) \cdot s_{jt}^{(r)} \tag{26}$$

Figure 1. In-Sample Fit : Game Provision



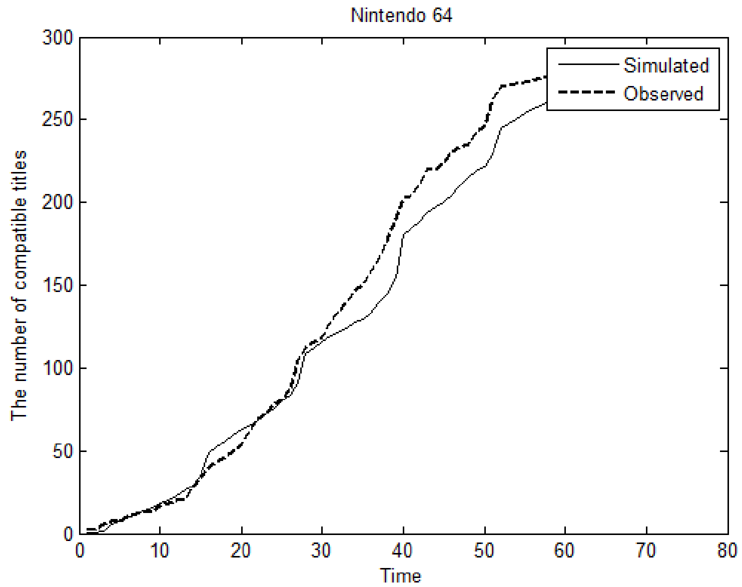


Figure 2. In-Sample Fit : Price

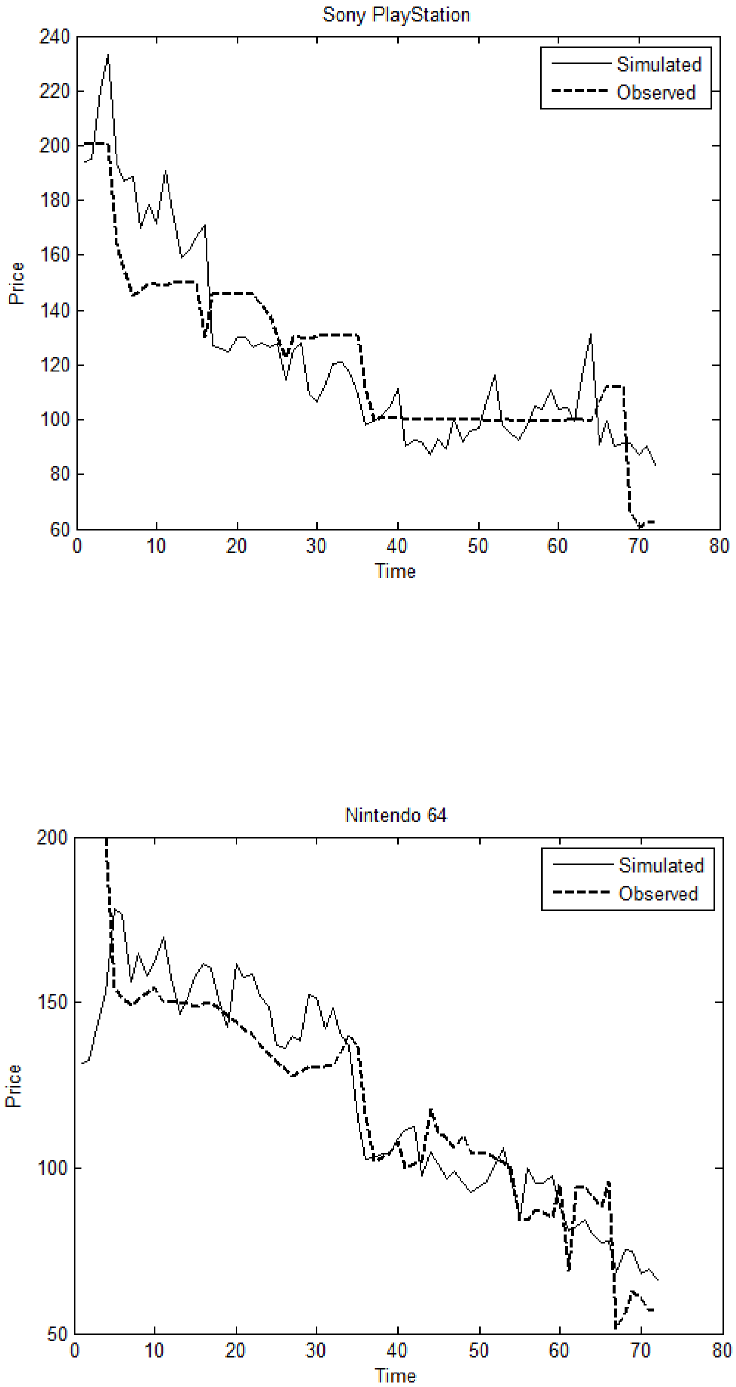
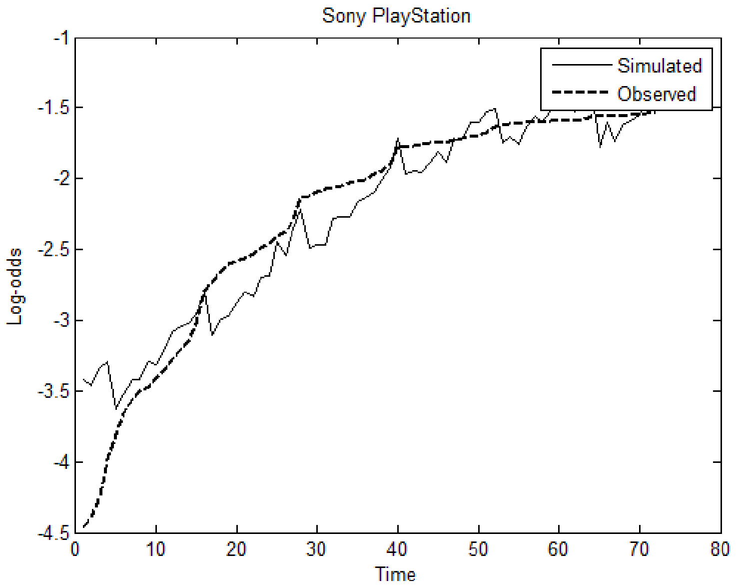
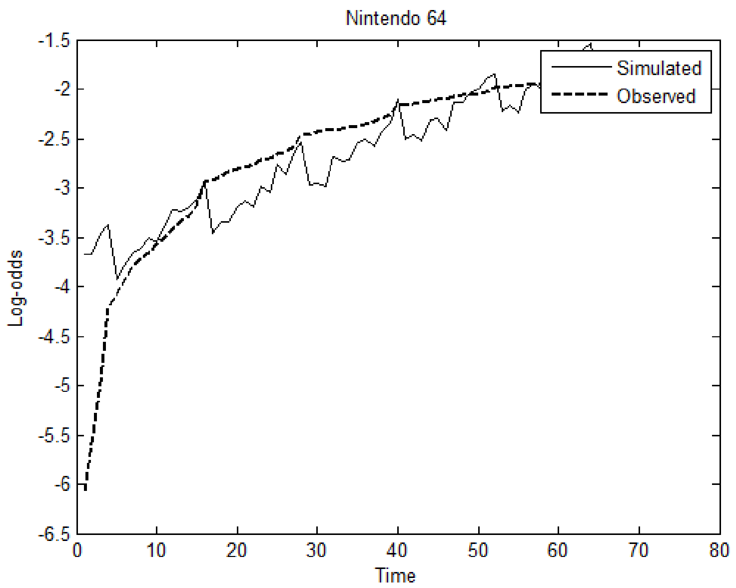


Figure 3. In-Sample Fit : Log-odds of Market Share





The simulation results provided in Figure 1, Figure 2 and Figure 3 exhibit that the simulated market outcome follows the similar pattern with the observed market outcome. Thus, the model captures the relationship between outcome variables and state variables.

I then simulate choice-specific values and value of waiting to match the observed market share to the simulated one. I simulate the values by iterating on the equations as follows:

$$v_j\left(y, \xi, p; \Lambda, \widehat{\Theta}\right) = \delta_j + w_j\left(f(y, \xi); \Lambda, \widehat{\Theta}\right) - \alpha p_j + \sigma_\xi \xi_j \tag{27}$$

where $\Lambda = (\delta_{\text{Sony}}, \delta_{\text{Nintendo}}, \alpha, \gamma, \sigma_\xi)$ is the structural parameters to be estimated in the second stage. $w_j\left(f(y, \xi); \Lambda, \widehat{\Theta}\right)$ is the expected present value of software which is simulated as

$$w_j\left(f(y, \xi); \Lambda, \widehat{\Theta}\right) = \frac{1}{R}\sum_{r=1}^{R}\sum_{t=0}^{T}\beta^t u_{jt}^{(r)}(y_{j,t+1}^{(r)}) \tag{28}$$

where $u_{jt}^{(r)}\left(y_{j,t+1}^{(r)}\right) = \gamma \exp\left(\Delta\left(y_{j,t+1}; \widehat{\theta_n}\right)\right) = \gamma n_{jt}^{(r)}$ is the per-period software utility which is assumed to be proportional to the simulated per-period number of available software.

The simulated value of waiting is the average expected present value of waiting over R draws.

$$v_0\left(y, \xi; \Lambda, \widehat{\Theta}\right) = \frac{1}{R}\sum_{r=1}^{R} Z^{(r)} \tag{29}$$

The expected discounted value of waiting for each draw is denoted as

$$Z^{(r)} = \sum_{t=1}^{T}\beta^t (p_{ot}^{(r)} \tau\left(y_t^{(r)}, \xi_t^{(r)}\right) + \sum_{j=1}^{J} p_{jt}^{(r)} \cdot u_{jt}^{(r)}\left(y_{j,t+1}^{(r)}\right) \tag{30}$$

where $p_{ot}^{(r)} = s_{0,t-1}^{(r)} \cdot p_{0,t-1}^{(r)}$ is the probability that a customer has not purchased any platform up to time t and $p_{jt}^{(r)} = p_{j,t-1}^{(r)} + s_{j,t-1}^{(r)} \cdot p_{0,t-1}^{(r)}$ is the probability that a customer has purchased platform j up to time t.

$$\tau\left(y_t^{(r)}, \xi_t^{(r)}\right) = s_{0t}^{(r)} \cdot E(\epsilon_{0t}) + \sum_{j=1}^{J} s_{jt}^{(r)} \cdot \left(\delta_j + u_{jt}^{(r)}\left(y_{j,t+1}^{(r)}\right) - \alpha p_{jt} + \sigma_\xi \xi_{jt} + E(\epsilon_{jt})\right) \tag{31}$$

is the per-period utility of waiting at time t. The expected present discounted value of waiting is the discounted sum of the per-period utility of waiting given that a customer has not entered the hardware market and the per-period utility of software given that a customer has adopted one of the platforms prior to time t. I estimate the results based on 0.9 of discount factor and 60 simulations.

Then I minimize the distance between the simulated log-odds of market shares and the observed ones to estimate structural parameters $\Lambda = (\delta_{\text{Sony}}, \delta_{\text{Nintendo}}, \alpha, \gamma, \sigma_\xi)$ which is a vector containing intrinsic preferences for each platform, marginal disutility of price, marginal utility of software titles and standard deviation of demand shocks. The distance between the observed log-odds of market shares and the simulated ones should be equal to zero theoretically. The distance is given as

$$Q_{jt}\left(\Lambda_0, \widehat{\Theta}\right) = \mu_{jt} - \left(v_j\left(y, \xi, p; \Lambda_0, \widehat{\Theta}\right) - v_0\left(y, \xi; \Lambda_0, \widehat{\Theta}\right)\right) \tag{32}$$

where Λ_0 is the true parameter values. I solve the minimization problem by minimizing the Generalized Method of Moments objective function specified by Λ_{GMM}.

$$\Lambda_{GMM} = Q(\Lambda, \widehat{\Theta})' W Q(\Lambda, \widehat{\Theta}) \tag{33}$$

where W is a weight matrix that is positive semi-definite according to GMM estimation properties. Here, I assume W to be an identity matrix for empirical estimation. The parameter estimation result provided in Table 5 indicates that the coefficient which captures indirect network effect is estimated to be positive.

Table 8. Structural Parameters

	Estimate	Standard error
δ_{Sony}	-0.4972	6.9260
δ_{Nintendo}	-0.4454	0.4989
α	0.0192	0.0005
γ	0.0061	0.1090
σ_{ξ}	0.0511	0.0548

5.2. Price Simulation

I numerically simulate hardware prices through value function iteration algorithm which relies on the contraction mapping property of the Bellman equation. The algorithm iterates expected software value, choice-specific value, value of waiting and new pricing policies until value functions change little. The pricing strategy that corresponds to the converged value function is the optimized policy function. The detailed computation procedure is as follows:

Step 1. I discretize installed hardware base, demand shocks and pricing policies of each firm. Installed hardware base in the state space is discretized in Y grids and each grid consists of two elements, each of which is Sony PlayStation's installed base and Nintendo 64's installed base. The sum of the installed hardware base on each grid is smaller than 1 by definition. Demand shocks are discretized based on N-point Gauss-Hermite quadrature rule. I integrate out demand shocks in the subsequent steps by evaluating the integrand at the quadrature nodes. Pricing policies of each firm are discretized into P uniformly spaced grids, respectively.

Step 2. The algorithm takes initial guesses on the consumers' expectations on the evolution of the installed hardware base $f^{e}(y_t, \xi_t)$ and pricing policies $\sigma_j^{e}(y_t, \xi_{jt})$. I assume reasonable initial values by reflecting the relationship between the outcome variables to be evolved and the state variables from the data. Note that the initial guesses should be one of the discretized grids. I take the discretized values which have the minimum distances from the expected outcomes from the data as initial values.

Step 3. I compute $\omega_j(y_{t+1})$, the expected present value of software titles using equation (5) given $f^e(y_t, \xi)$. The per-period utility of software $u_j(y_{j,t+1}) = \gamma \cdot \exp(\Delta(y_{j,t+1}))$ is calculated using discretized state grids, the estimated relationship between installed hardware base and software variety provided in Table 2 and the estimated structural parameters provided in Table 5. Note that the integral over ξ space is the weighted average of the integrand over the discretized quadrature nodes. I iterate $\omega_j(y_{t+1})$ on the contraction mapping until both $\omega_{Sony}(y_{t+1})$ and $\omega_{Nintendo}(y_{t+1})$ converge.

Step 4. Based on $\omega_j(y_{t+1})$ computed in step 3 and structural parameters provided in Table 5, I calculate $\nu_j(y_t, \xi_t, p_t)$, choice-specific values from the equation (6).

Step 5. I calculate $\nu_0(y_t, \xi_t)$, value of waiting from the equation (7) by iterating the value on the contraction mapping. The equation is equal to

$$\nu_0(y_t, \xi_t) = \beta \int \ln(\exp(\nu_0(y_{t+1}, \xi_t)) + \sum_{j=1}^{J} \exp\left(\nu_j\left(y_{t+1}, \xi, \sigma^e(y_{t+1}, \xi_{jt})\right)\right))\phi(\xi)d(\xi) \tag{34}$$

since ϵ, the econometric error term follows type I extreme value distribution. Note that the integrand consists of value of waiting and choice-specific values evaluated at time t+1, not at time t. I iterate $\nu_0(y_t, \xi_t)$ on the contraction mapping until the value converges.

Step 6. I calculate and update the market share from the equation (8) based on the updated values from step 4 and 5. The equation (9), the law of motion then allows the installed hardware base to be evolved. I take the value on the discretized space as the new installed base which has the minimum distance from the updated installed hardware base.

Step 7. I compute the per-period profit function and the corresponding Bellman equation from the equation (11) and (12) for the oligopoly case and (16) and (17) for the monopoly case on each value of discretized pricing policies. Thus the Bellman equation computed has dimensions that are P times greater than the dimensions of the values and Bellman equations calculated in the previous steps. Note that $q_j(y_{j,t+1})$ is estimated from the data[4]. Since I control for falling marginal costs by including exogenous variables, I assume constant marginal costs[5] in the empirical model.

Step 8. I find new pricing policies $\sigma_j(y, \xi_j)$ that maximize the Bellman equation converged in step 7 on each state space grid and compute the maximized Bellman equation corresponding to the pricing policies of each standard from the equation (16) for the oligopoly case and (17) for the monopoly case.

Step 9. I update pricing policies as $p_j = \sigma_j(y, \xi_j)$ and consumers' expectations about the installed hardware base as $y = f(y, \xi)$. I iterate from step 3 to step 7 until the policy function converges. Here, I use the modified Newton-Raphson method[6], one of the damping schemes to facilitate convergence since the multi-agent iteration algorithms have multiple equilibria and some of them do not converge but oscillate.

---

[4] Dubé, Hitsch and Chintagunta(2010) estimate the relationship between the installed hardware base and the number of software titles sold as $\log(q_{jt}) = \varrho + \varphi_j \log(y_{j,t+1})$ from CES preference model. I use the parameters reported to estimate the software sales.

[5] Marginal production costs are set to be $147 (Sony PlayStation) and $122 (Nintendo 64) and royalty fees are assumed to be $9 (Sony PlayStation) and $18 (Nintendo 64) based on Liu(2010) and Dubé, Hitsch and Chintagunta(2010). I test the robustness of the results with a different cost specification in the appendix.

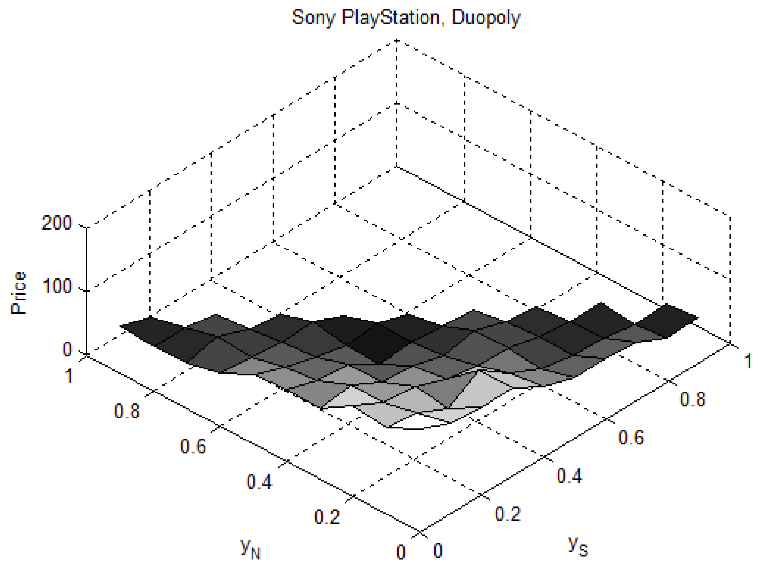
[6] $\sigma_j^{(k+1)}(y, \xi_j) = a \cdot \sigma_j^{(k+1)}(y, \xi_j) + (1 - a) \cdot \sigma_j^{(k)}(y, \xi_j)$ where $a \in [0,1]$ and the closer a is to 0, the more likely the function is to converge.

I assume that firms and consumers use the discount factor of 0.9 and normalize the market size to be 1. I examine a symmetric competition case where Sony and Nintendo launch their products at the same time at the beginning period of this analysis and they share the same demand functions. I examine the equilibrium market outcomes for both standards with and without competition among manufacturers. Dubé, Hitsch and Chintagunta(2010) examine equilibrium market outcomes in the general case where firms are asymmetric ex ante as well as in the symmetric case.

The result from the oligopoly market can be compared to the three monopoly cases in the empirical model: 1) when only Sony sells PlayStation in the market, 2) when Nintendo is the monopolist to sell Nintendo 64 and 3) when Sony and Nintendo are merged in one firm which still separately manufactures and sells PlayStation and Nintendo 64 while the prices are set simultaneously and the firm maximizes the joint profit from two standards. Here I investigate the third scenario and compare the price policies, price patterns and price levels in oligopoly market to those in monopoly market. I apply the different profit function and Bellman equation as shown in equation (16) and (17) but hold all other functions, parameters and assumptions constant at their values in the observed duopoly market. The equilibrium policies and expected paths are anticipated to be realized in the different way in the oligopoly and three monopoly cases.

The simulation results are displayed in the following figures. In the monopoly case where I assume one merged firm sells two differentiated platforms, Sony PlayStation denotes the standard originally manufactured and sold by Sony and Nintendo 64 refers to that of Nintendo. Figure 4 and Figure 5 exhibit equilibrium pricing policies at each discretized point of hardware installed base in duopoly and monopoly market, respectively. Here y_S stands for installed hardware base of Sony PlayStation and y_N represents that of Nintendo 64.

Figure 4. Equilibrium Pricing Policies in Duopoly Market



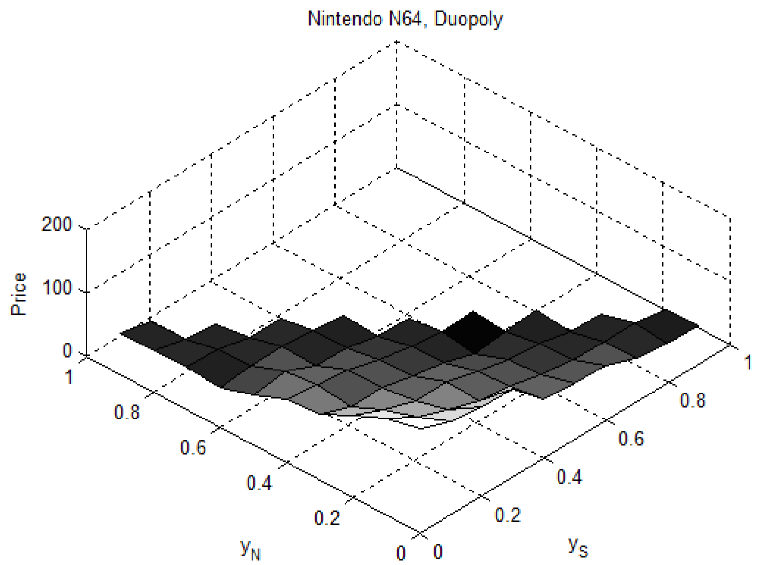
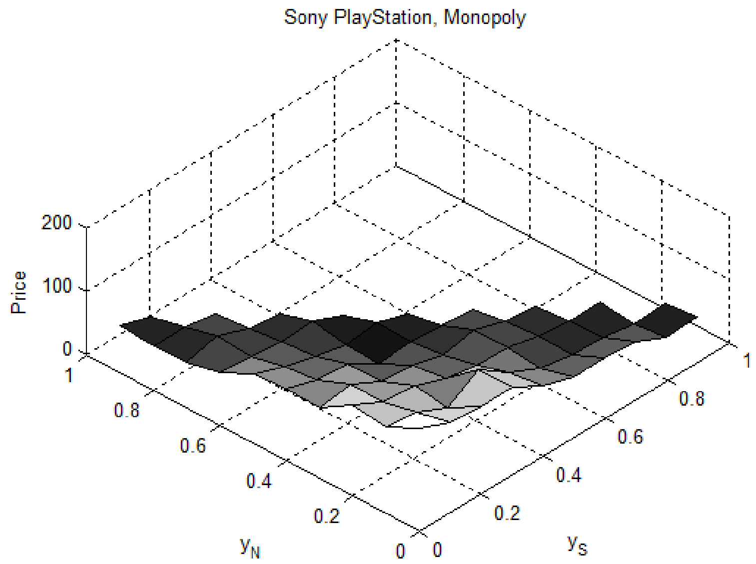


Figure 5. Equilibrium Pricing Policies in Monopoly Market



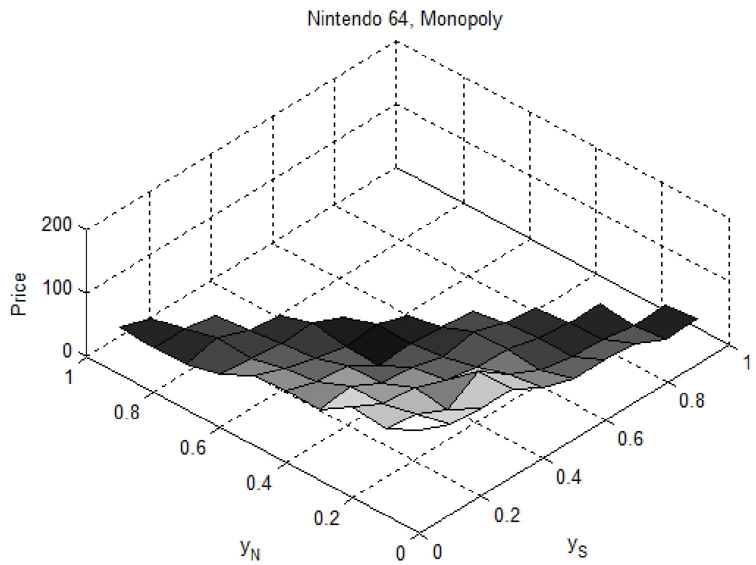
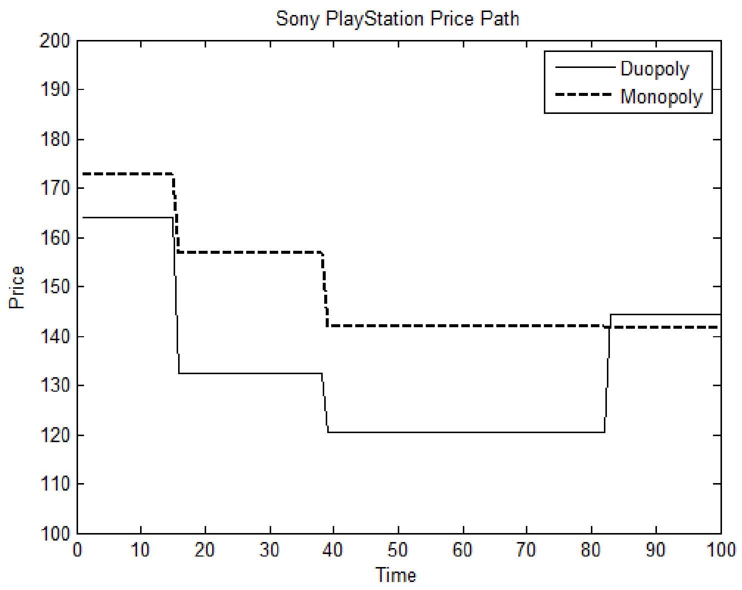
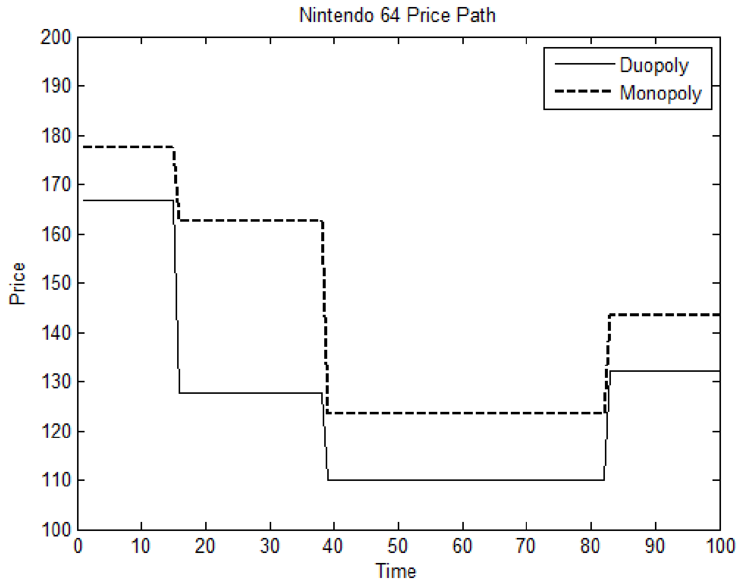


Figure 6 displays the expected price paths in duopoly and monopoly market for each standard. The paths are conditional on cases where customers and firms make decisions at the monthly level, both standards sell as many products as their observed sales by the end of T=72 and the rates of increase in their installed base remain constant afterwards. I simulate the prices for 100 months. The expected pricing policies are functions of installed hardware base and demand shocks which are private information and not known to researchers. Here I generate 80 simulations of the random transitions of demand shocks and average the realized prices from the simulations. In addition, I generate simulations of the market evolution at the same time. The evolution of the market needs to be simulated since the software provision function, the no-purchase value function and the Bellman equations in the supply side depend on the installed hardware base in the subsequent period.

The patterns are similar for both standards regardless of the number of firms. The manufacturers bring down their product prices over time. The price levels differentiate duopoly and monopoly markets. The firms offer lower prices when they do not have competition in the platform market. The competing firms focus on capturing initial advantage and enticing more customers to join their networks by setting lower prices. Note that a two-sided market is distinguished from a traditional market since customers' adoption decisions are affected by indirect network effects. That is, a standard with initial advantage gets positive feedbacks from its customers and its software suppliers. The initial advantage leads to more software variety for the standard than its competitors. Hence, more consumers will purchase the platform than other standards in the subsequent period. This asymmetric adoption rate reinforces the leadership of the standard, helps the platform's network to create a virtuous cycle and finally leads to market concentration in favor of the standard. Customers who have already joined one of the networks are reluctant to switch to other networks since they are not willing to give up their accumulated resources such as game titles compatible with the platform

Figure 6. Expected Price Paths





that they own. However, the merged firm in the monopoly market does not have to take account of the initial advantage or the risks that customers might prefer other standards over its product at the introduction stage. If one of the differentiated product offered by the merged firm fails to gain initial advantage and does not sell well in the market, the firm can give up producing and selling the platform and focus on the standard with a higher market share. This result is robust to a different cost specification and the marginal costs are simulated in the appendix. Note that my model abstracts from consumer heterogeneity and assumes that all customers share similar tastes.

I now quantify the impact of competition on dynamic pricing of platforms as the average percentage changes in prices and in consumers' values from duopoly to monopoly market for each standard. The percentage change is computed by the ratio of the difference between the values in duopoly market and those in monopoly market to the values in duopoly market. The result is shown in Table 9. The prices go up by 12.6% for Sony PlayStation and by 14.1% for Nintendo 64 on average when I eliminate the competition among platforms exogenously. The merged manufacturer increases Nintendo 64's price more than Sony PlayStation's price in terms of percentage because the supplier of Nintendo 64 in the duopoly market sets relatively lower prices to capture initial advantage so that it can benefit from higher royalty fees from game developers.

Table 9. Percentage Change in Price and Customer Value

	Sony PlayStation			Nintendo 64		
	Min	Max	Mean	Min	Max	Mean
Price (%)	-17.7	18.3	12.6	6.5	27.3	14.1
CV (%)	-33.1	3.5	-21.8	-47.5	-14.8	-23.9

Note that Nintendo 64 collects higher royalty fee for each software title sold than Sony PlayStation does in the empirical model. The competing firms in the duopoly market focus on different competitive advantages. The customer values decrease by 21.8% for Sony PlayStation and by 23.9% for Nintendo 64. The increase in price and the consequent decrease in the variety of software titles in the market lead to lower consumers' surplus.

6. Conclusion

This article provides a framework to examine firms' optimal pricing strategies in a two-sided market with or without competition among platforms. I calibrate the demand model that incorporates indirect network effects, consumers' forward-looking behaviors and manufacturers' dynamic competition by estimating parameters that minimize the distance between simulated log-odds of market share and observed ones. The supply model is specified in the different way depending on the existence of competition among firms.

I simulate how the number of hardware firms in the market affects the pricing using the parameters estimated in the demand side through value function iteration algorithm, one of the numerical dynamic programming techniques. The impact of exogenously determined competition on pricing is quantified as the percent changes in prices and customer values for each platform. The empirical application of the model to the U.S. 32/64 bit video game console category reveals that firms set higher prices in the absence of competition by 12.6% and 14.1% for Sony PlayStation and Nintendo 64, respectively. This result is attributed to the distinguished property of a two-sided market that competing firms tend to set low prices particularly at the initial period to attract customers at the introductory stage and to reinforce their own networks, finally dominating the market. Tipping, or the tendency of one system to dominate the market once it holds an initial advantage, is actually observed in many two-sided markets and the firms in two-sided markets follow penetration pricing strategies to battle for the market dominance.

Future research in various directions to relax the assumptions in this research will help shed light on the related topics. First, I here do not take account of first-mover advantage. Sony entered the video game console market with the new generation of PlayStation one year earlier than Nintendo did. Since I intend to analyze the effect of firms' dynamic decisions under various market structures, I only consider the periods when both firms sell the products in the market. If the first-mover advantage is taken into account in the model, the standard that pioneers the market will have the initial installed base advantage. This initial advantage causes more software developers to supply game titles compatible with the standard. Thus more customers will engage in the standard and the positive feedback will strengthen the market leadership of the pioneering platform. This leadership is due to indirect network effects since customers prefer to lock in the platform's network. Such initial advantage in a two-sided market will make potential entrants reluctant to set high prices in the market and the impact of exogenously determined competition in the market will differ from the results in the symmetric market investigated in my research.

Another area for future research is to capture indirect network effects in terms of software contents or quality. For instance, there are killer applications in smartphone industry that induces customers to purchase the specific carriers. I here only consider the software variety to explain the source of indirect network effects since the contents is difficult to measure and incorporate in the model. However, if some of the applications or software titles take a lot of fractions in the market and have a great impact on customers' purchase decisions, the model can provide the analysis on the role of game contents and the different values on the impact of competition among platforms in the market.

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Appendix

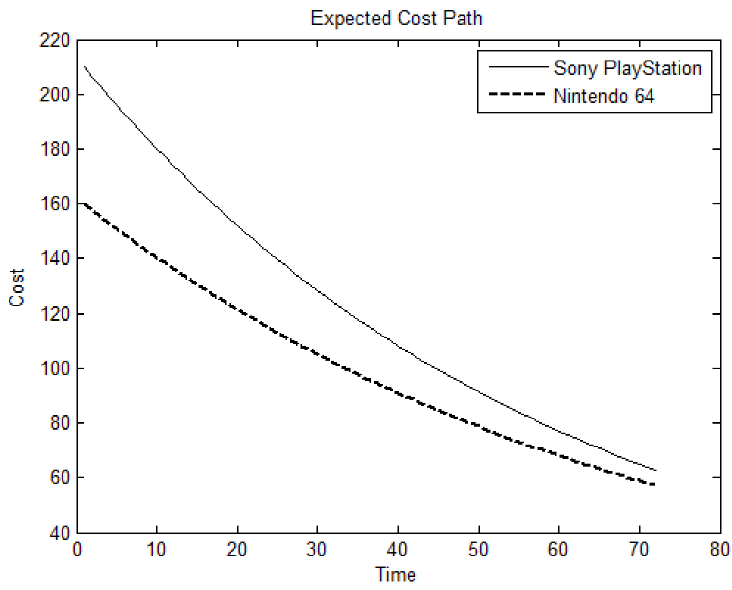
I control for declining costs with exogenous cost-shift variables and assume constant marginal costs in price simulation. Here I estimate parameters for declining costs to verify the robustness of the result. Liu(2010) specifies the cost function as

$$C_{jt}(Q_{jt}) = c_{jt}Q_{jt} + F_{jt} \tag{A.1}$$

where Q_{jt} is hardware sales for standard j, c_{jt} is marginal cost and F_{jt} is fixed cost. I assume that video game console manufacturers do not incur fixed costs and marginal costs decrease exogenously over time. Following Liu(2010), the marginal costs are assumed to decline exponentially over time which is denoted as

$$c_{jt} = a_j \exp(-b_j t) \tag{A.2}$$

Figure A.1. Expected Cost Path



Industry reports on video game console market make comments on marginal costs at a few time periods. I use the available data to compute the expected cost path throughout the observed periods and display the result in Figure A.1. I estimate demand parameters and simulate price paths again using the estimated costs. Although I do not report the full analyses here, the merged firm sets higher prices than each manufacturer does in the duopoly market. That is, the results are robust to the cost specification.

국 문 초 록

최근 많은 하이테크 제품 시장에서 간접 네트워크 효과(indirect network effects)가 일어나는 양면 시장의 특징을 관찰할 수 있다. 양면 시장의 특수한 시장 매커니즘을 이해한 플랫폼 제조업체들은 초기 고객 선점을 통해 자사 제품의 네트워크를 강화하고 궁극적으로는 시장 우위를 점하기 위해 경쟁한다. 이제까지 실증 연구를 통해 간접 네트워크 효과와 경쟁의 관계가 입증되었지만 대부분 양면 시장의 특징적인 가격 구조에 기인한 시장 지배를 분석하는 데 초점이 맞추어져 왔고 양면 시장의 특수한 가격 구조가 플랫폼 간 경쟁 상황에 따라 달라질 수 있다는 점은 연구되지 않았다.

본 연구에서는 Dubé, Hitsch and Chintagunta(2010)의 모형을 확장하여 간접 네트워크 효과 하에서 하드웨어 제품 간의 경쟁이 최적 가격에 미치는 영향을 분석한다. 본 연구가 Dubé, Hitsch and Chintagunta(2010)와 구별되는 점은 먼저 공급 측면의 모형을 수정하여 실제 시장 구조뿐만 아니라 가상적인 시장 구조에도 적용될 수 있도록 한다. 또한 Dubé, Hitsch and Chintagunta(2010)가 한 가지 플랫폼의 내생적인 시장 우위를 분석한 반면 본 연구는 외생적인 시장 구조의 영향을 연구한다. 본 연구에서는 미래지향적으로 행동하는 수요자의 모수를 추정하고 동적 계획법(dynamic programming)을 이용하여 마르코프 완전 균형(Markov Perfect Nash Equilibrium)을 수치적으로 계산한다. 다음으로 과점 시장에서 도출된 예상 가격을 독점 시장에서 도출된 예상 가격과 비교하여 외생적으로 주어진 플랫폼 간 경쟁의 효과를 측정한다. 독점 시장은 기존의 과점 시장 내 제조업체 중 한 회사만이 시장에 남아 한 가지 제품을 생산하는 경우와 기존의 과점 시장 내 제조업체들이 합병하여 한 개의 회사가 되어 기존의 다양한 제품을 다른 가격에 제공하는 경우, 두 가지 경우가 가능하다. 본 연구에서는 두 번째 경우만을 가정하여 과점 시장의 가격과 독점 시장의 가격을 비교한다.

본 연구의 모형은 양면 시장의 대표적인 예인 미국 비디오 게임 콘솔 시장에

적용된다. 본 연구의 모형에 대한 모수 추정과 수치 시뮬레이션 결과에 따르면 플랫폼의 가격은 시장 구조와 관계없이 시간에 따라 감소하며 가격 수준은 경쟁 상황에 따라 차이를 보인다. 합병된 회사는 과점 시장 내에서 경쟁하는 각 회사들에 비해 제품의 가격을 높게 설정하며 그 차이는 소니 플레이스테이션의 경우 12.6%, 닌텐도 64의 경우 14.1%로 나타난다. 가격 수준에 차이가 나타나는 이유는 합병된 회사는 과점 시장에서 경쟁하는 업체들에 비해 상대적으로 고객 선점을 통한 네트워크 구축을 위해 노력할 필요가 적기 때문이다. 과점 시장과 독점 시장에서의 최적 가격의 차이는 양면 시장에서 외생적으로 주어진 플랫폼 간 경쟁이 동적으로 계획된 플랫폼의 가격에 미치는 영향을 보여준다.

주요어: 양면 시장, 간접 네트워크 효과, 경쟁, 동적 계획법
학번: 2011-20498