Tipping and Concentration in Markets with Indirect Network Effects*

Jean-Pierre Dubé
Graduate School of Business
University of Chicago

Günter J. Hitsch
Graduate School of Business
University of Chicago

1 Introduction

We study the diffusion of competing durable goods in a market exhibiting indirect network effects due to the classic hardware/software structure (Katz and Shapiro 1985). Of particular interest is whether such markets are prone to *tipping*: "the tendency of one system to pull away from its rivals in popularity once it has gained an initial edge" (Katz and Shapiro 1994) and, our work, Jenkins, Liu, Matzkin, and McFadden (2004) allow for forward-looking hardware manufacturers. But, both papers treat consumers as myopic. In contrast, our paper allows for forward-looking consumer behavior and solves for an equilibrium in which consumers' and concentration that would arise if the sources of indirect network effects were reduced or eliminated. The key insight is that tipping generally needs to be measured relative to a well-defined, counter-factual market outcome. For an empirical implementation of this measure, we need a model that captures indirect network effects, can be calibrated from actual data, and allows us to make predictions about the equilibrium adoption of the competing standards under various different parameter values capturing the strength of indirect network effects.

To implement the proposed measure of tipping, we build a dynamic model that captures indirect network effects and gives consumer expectations a central role. Our model involves three types of players: consumers, hardware manufacturers, and software developers. The demand side of our model extends the framework of Nair et al. (2004) and allows for dynamic adoption decisions. Consumers are assumed to "single-home," meaning they adopt at most one of the competing hardware standards.

similar approach has recently been employed by Ryan and Tucker (2007).[7]

The calibrated model reveals that the 32/64 bit video game console market can exhibit economically significant tipping effects, given our model assumptions and the estimated parameter values. The market concentration, as measured by the 1-firm concentration ratio in the installed based after 25 periods, increases by at least 23 percentage points due to indirect network effects. We confirm the importance of consumer expectations as an important source of indirect network effects; in particular, we find that tipping occurs at a (monthly) discount factor of 0.9, but not for smaller discount factors. Our model also predicts *penetration pricing* (for small levels of the installed base) if indirect network effects are sufficiently strong. In markets with strong network effects, firms literally price below cost during the initial periods of the diffusion to invest in network growth.

2 Model

We consider a market with competing hardware platforms. A consumer who has adopted one of the available technologies derives utility from the available software for that platform. Software titles are incompatible across platforms. Consumers are assumed to choose at most one of the competing hardware platforms and to purchase software compatible with the chosen hardware, a behavior Rochet and Tirole (2003) term "single-homing." There are indirect network effects in this market, which are due to the dependence of the number of available software titles for a given platform on that platform's installed based. The consumers in this market have expectations about the evolution of hardware prices and the future availability of software when making their adoption decisions. Correspondingly, the hardware manufacturers anticipate the consumer's adoption decisions, and set prices for their platforms accordingly. The software market is monopolistically competitive, and the supply of software titles for any given platform is increasing in the platform's installed base.

Time is discrete, $t = 0, 1, \ldots$ The market is populated by a mass $M = 1$ of consumers. There are $J = 2$ competing firms, each offering one distinct hardware platform. $y_{jt} \in [0, 1]$ denotes the installed base of platform j in period t; i.e., the fraction of consumers who have adopted j in any period previous to t. $y_t = (y_{1t}, y_{2t})$ describes the state of the market.

In each period, platform-specific demand shocks $_{jt}$ are realized. $_{jt}$ is private information to firm j, i.e., firm j learns the value of $_{jt}$ before setting its price, but learns the demand shock of its competitor only once sales are realized. As we shall see later, $_{jt}$ can strongly influence the final distribution of shares in the installed base. In particular, the realizations of $_{jt}$ in the

[7] An interesting difference is that Ryan and Tucker (2007) use individual level adoption data, which enables them to accommodate a richer treatment of 'observed' consumer heterogeneity. The trade-off from incorporating more heterogeneity is that they are unable to solve the corresponding dynamic hardware pricing game on the supply side.

end of a period, we can denote this utility as $u_j(y_{j,t+1}) = n_{jt} = h_j(y_{j,t+1}).$ The present discounted software value is then defined as

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

This value follows the recursion

$$\omega_j(y_{t+1}) = u_j(y_{j,t+1}) + \int \omega_j(f^e(y_{t+1}, \,)) \, (\,) d \, .$$

Consumers who have not yet adopted either buy one of the hardware platforms or delay adoption. The choice-specific value of adopting hardware platform j is given by

$v_j(y_t$

2. The firm's value functions $V_1, \ldots, V_J$ satisfy the Bellman equations (5).

3. $p_j = \ _j(y; \ _j)$ maximizes the right-hand side of the Bellman equation (5) for each $j = 1, \ldots, J.$

4. The consumer's expectations are rational: $\ ^e_j \equiv \ _j$ for $j = 1, \ldots, J,$ and $f^e(y; \ ) = f(y; \ ; \ (y; \ )),$ where f is as defined by equation (4).

In the Markov perfect equilibrium, all players—firms and consumers—act rationally given their expectations about the strategies of the other market participants. Furthermore, expectations and actually realized actions are consistent.

3 Estimation

To make our computational results more realistic, we calibrate them with data from the video game console market. While demand estimation per se is not the main objective of the paper, it is nevertheless helpful to discuss briefly some of the challenges involved in estimating preference parameters for a dynamic discrete choice model. The main difficulty arises from the incorporation of consumer beliefs, a crucial element for durable goods demand in general (Horsky 1990, Melnikov 2000, Song and Chintagunta 2003, Nair 2005, Prince 2005, Carranza 2006, Gowrisankaran and Rysman 2006, and Gordon 2006). Once we include consumer beliefs in our console demand function, the derivation of the market shares, equation (3), requires us to compute the choice-specific value functions. Nesting the corresponding dynamic programming problem into the estimation problem is prohibitive due to the high

Stage 1

In the first stage, we estimate the consumer choice strategies along with the firms' pricing strategies and the software supply function. The supply function of software variety is specified as follows

$$\log(n_{jt}) = \mathcal{H}_j(y_{j,t+1}; \quad _n) + \quad _{jt}. \tag{6}$$

where $\quad _{jt} \sim N \quad 0, \quad ^2$ captures random measurement. This specification is consistent with the equilibrium software supply function derived in the Appendix, equation (9). The pricing strategies are specified as follows

$$\log(p_{jt}) = \mathcal{P}_j(y_t, z_t^p; \quad _p) + \quad _{jt}, \tag{7}$$

where $\quad _{jt} \sim N(0,1)$. In equation (7) we let $\mathcal{P}_j$ be a flexible functional form of the state variables. For the empirical model, we include exogenous state variables, z_t^p, that are observed by console firms in addition to y_t and $\quad _t,$ the state variables in the model of Section 2. These additional states are discussed in Section 4. In equation (7), we assume that the video game console manufacturers use only payoff-relevant information to set their prices. But we do not assume that their pricing strategies are necessarily optimal. This specification has the advantage that it is consistent with the Bayesian Markov perfect equilibrium concept used in our model, but does not explicitly impose it.

Conditional on the model parameters, there is a deterministic relationship between the price and installed base data and the demand unobservable, $\quad _{jt} = \mathcal{X}_j(y_{jt}, p_{jt}, z_t^p)$[12]. Then, conditional on y_t and $p_t,$ we can estimate the consumers' optimal choice strategy in log-odds:

$$\begin{aligned} \quad _{jt} &\equiv \log(s_{jt}) - \log(s_{0t}) \\ &= v_j \quad y_t, \quad _t, p_t, z_t^d \quad - v_0 \quad y_t, \quad _t, z_t^d \quad + \quad _{jt} \\ &= \mathcal{L}_j \quad y_t, \mathcal{X}(y_t, p_t, z_t^p), z_t^d; \qquad + \quad _{jt}, \end{aligned} \tag{8}$$

where $\quad _{jt} \sim N(0, \quad ^2)$ is random measurement error and z_t^ddenotes exogenous state variables observed by the consumer. By including the *control function* $\mathcal{X}(y_t, p_t, z_t^p)$ in the demand equation, we also resolve any potential endogeneity bias that would arise due to the correlation between prices and demand shocks (this is the control function approach used in . The first stage consists then of estimating the vector of parameters $\quad = (\quad _n, \quad _p, \quad , \quad)$ via maximum likelihood using the equations (6), (7), and (8).

[12] We can trivially invert out of the price equation because of the additivity assumption in (7). This is a stronger condition than in BBL, but it is analogous to other previous work such as Villas-Boas and Winer (1999) and Petrin and Train (2005).

Stage 2

In the second stage, we estimate the consumers' structural taste parameters, , by constructing a minimum distance procedure that matches the simulated optimal choice rule for the consumers to the observed choices in the data. The idea is to use the estimated consumer choice strategies, (8) and the laws of motion for prices and software variety, (7) and (6), to forward-simulate the consumers' choice-specific value functions, $\mathcal{V}_j\ \ y_t;\ _t;p_t;\ \ ;\hat{}$ and $\mathcal{V}_0(y;\ ;\ ;\hat{})$. The details for the forward-simulation are provided in the Appendix. Note that while our two-step approach does not require us to assume that firms play the Markov Perfect equilibrium strategies explicitly, we do need to assume that consumers maximize the net present value of their utilities.

The minimum distance procedure forces the following moment condition to hold approximately:

$$Q_{jt}(\ _0;\hat{}) \equiv \ _{jt} - \ \mathcal{V}_j(y;\ ;p;\ _0;\hat{}) - \mathcal{V}_0(y;\ ;\ _0;\hat{})\ = 0.$$

That is, at the true parameter values, $_0$; and given a consistent estimate of ; the simulated log-odds ratios should be approximately equal to the observed log-odds ratios for each of the observed states in the data. The minimum distance estimator, ^{MD}, is obtained by solving the following minimization problem:

$$^{MD} = \min_{\Lambda} \left\{ Q(\ ;\hat{})' W Q(\ ;\hat{}) \right\};$$

where W is a positive semi-definite weight matrix.[13] Wooldridge (2002) shows that the minimum distance estimator has an asymptotically normal distribution with the covariance matrix

$$Avar(\ ^{MD}) = \ \nabla_{\Lambda}Q'W\nabla_{\Lambda}Q\ ^{-1}\nabla_{\Lambda}Q'W\nabla_{\Theta}Q\hat{}\nabla_{\Theta}Q'W\nabla_{\Lambda}Q\ \ \nabla_{\Lambda}Q'W\nabla_{\Lambda}Q\ ^{-1};$$

where $\hat{} = Avar(\hat{});$ and $\nabla_{\Lambda}Q$ and $\nabla_{\Theta}Q$ denote gradients of Q with respect to and respectively.

The approach is closest to PS-D. But, our implementation differs in two ways. First, we

4 Data

For our calibration, we use data from the 32/64-bit generation of video game consoles, one of the canonical examples of indirect network effects. To understand the relevance of this case study to our model and our more general point about tipping in two-sided markets, we briefly outline some of the institutional details of the industry. We then discuss the data.

The US Videogame Console Industry

The market for home video game systems has exhibited a two-sided structure since the launch of Atari's popular 2600 VCS console in 1977 (Williams 2002). Much like the systems today, the VCS consisted of a console capable of playing multiple games, each on interchangeable cartridges. While Atari initially developed its own proprietary games, ultimately more than 100 independent developers produced games for Atari and more than 1,000 games were released for Atari 2600 VCS (Coughlan 2001A). This same two-sided market structure has characterized all subsequent console generations, including the 32/64-bit generation we study herein.

The 32/64-bit generation was novel in several ways. None of the consoles were backward-compatible, eliminating concerns about a previously-existing installed base of consumers which might have given a firm an advantage. This was also the first generation to adopt CD-ROM technology; although early entrants, Philips and 3DO, failed due to their high console prices of $1000 and $700 respectively. In contrast, the September 1995 US launch of Sony's 32-bit CD-ROM console, Playstation, was an instant success. So much so, that its competitors, Sega's 32-bit Saturn console and later, Nintendo's 64-bit N64 cartridge console, Saturn by three-to-one. By 1998, more than 400 Playstation titles were available in the US. In addition, Sony engaged in aggressive penetration pricing of the console early on, hoping to make its money back on game royalties (Cobb 2003).

series creates several generic identification concerns for durable goods demand estimation in general[17]. The first and most critical concern is the potential for sales diusion data to exhibit dependence over time as well as inter-dependence in the outcome variables. In addition, the di usion implies that any given state is observed at most once, a property that could complicate the estimation of beliefs. Finally, we also face the usual potential for price endogeneity to bias demand parameters if prices are correlated with the demand shocks, (Berry 1994). We now briefly discuss the intuition of our empirical identification strategy.

Di usion data may naturally exhibit dependence over time in prices, p

between prices and could introduce endogeneity bias. Our joint-likelihood approach to the first stage does provide a parametric solution to the endogeneity problem through functional form assumptions. We have imposed a structure on the joint-distribution of the data which provides us with the relationship between prices and demand shocks, . However, we can relax this strong parametric condition by using our console cost-shifters. Both the exchange rate and the PPI's provide sources of exogenous variation in prices that are excluded from demand and that are unlikely to be correlated with consumer tastes for video game consoles, i.e. . In essence, the endogeneity is resolved by including the control function, $X(y_{jt}; p_{jt}; z_t^p)$, in the log-odds of choices, equation (8) (e.g. Villas-Boas and Winer 1999 and Petrin and Train

The mean R^2 of a regression of log-odds on the observed states and the simulated is 0.95. Overall, the first-stage model appears to fit the data well.

A critical aspect of the 2-step method is that the first-stage model captures the relationship between the outcome variables and the state variables. To assess the fit of the first-stage estimates, in Tables 3, 4, and 5, we report all the first-stage estimates and their standard errors. Most of the estimates are found to be significant at the 95% level. In Table 5, we find a positive relationship between software variety and the installed base of each standard. Analogous findings are reported in Clements and O'Hashi (2005).

In the Figures 1, 2, and 3, we plot the true prices, log-odds and games under each standard. In each case, we plot the outcome variable for a standard against its own installed base (reported as a fraction of the total potential market, $M = 97,000,000$). In addition, we report a 95% prediction interval for each outcome variables based on a parametric bootstrap from the asymptotic distribution of our parameter estimates[19]. In several instances, the observed outcome variable lies slightly outside the prediction interval. But, overall, our first-stage estimates appear to do a reasonably good job preserving the relationship between the outcome variables and the installed base.

5.2 Second Stage

We report the structural parameters from the second-stage in Table 6. Results are reported for two specifications: models 3 and 7 from the previous section. Recall that model 3 does not have any exclusion restrictions across equations in the first stage. Model 7, the best-fitting model overall in stage 1, includes PPI's and exchange rates in the price equations. To estimate the second stage of the model, we maintain the assumption that consumers do not observe realizations of these costs. Instead, we assume they observe prices each period and can integrate the innovations to prices out of their expected value functions[20]. The results are based on an assumed consumer discount factor of $= 0.9$ and 60 simulated histories[21] industry observers who noted that the improvements from 32 to 64 bit technology were much

We now provide a formal definition of our tipping measure. Let ${}_{jt}$ be the share of standard j in the installed base t periods after product launch:

$$ {}_{jt} \equiv \frac{y_{j,t+1}}{y_{1,t+1} + y_{2,t+1}}. $$

Here, remember that $y_{j,t+1}$ is the installed base of standard j at the end of period t and thus includes the sales of j during period t. The cumulative 1-firm concentration ratio after T periods is then given by

$$ \mathcal{C}(y_T) = \max\{ \ {}_{1T}, \ {}_{2T}\}. $$

The realization of $\mathcal{C}(y_T)$ depends on the model parameters, $\ $; an equilibrium that exists for these parameters, $\mathcal{E}(\ )$; and a sequence of demand shocks, ${}_{t}$. Given $\ $ and $\mathcal{E}(\ )$, the distribution of $(y_t)_{t=0}^{T}$ is well defined, and we can thus calculate the expected cumulative 1-firm concentration ratio

$$ C_1(\ ,\mathcal{E}(\ )) \equiv \mathrm{E}\left(\mathcal{C}(y_T)|\ ,\mathcal{E}(\ )\right). $$

Let $\ '$ be a variation of the model where one or more parameters that govern the strength of indirect network effects are changed compared to the model described by $\ $, and let $\mathcal{E}(\ ')$ be a corresponding equilibrium. We can thus measure tipping, the increase in market concentration due to indirect network effects, as

$$ \ C_1 = C_1(\ ,\mathcal{E}(\ )) - C_1(\ ',\mathcal{E}(\ ')). $$

If we knew that the market under investigation was symmetric, then C_1 t 0.5 in the absence of indirect network effects, and we could measure tipping by $\ C_1 = C_1(\ ,\mathcal{E}(\ )) - 0.5$.

To implement the tipping measure, we calibrate the model developed in Section 2 and use it to predict the evolution of the market. The parameters consist of the demand estimates and software supply function estimates presented in section 5, along with industry estimates of hardware console production costs and royalty fees.[23] For a given set of parameter values, we solve for a Markov perfect Bayesian equilibrium of the model, and then simulate the resulting equilibrium price and adoption paths.

situation, the difference between the cumulative 1-firm concentration ratio and 50% would not provide a meaningful measure of tipping even in the symmetric case.

[23]Cost and royalty data are reported in Liu (2007) and based on various industry reports. The marginal production costs are $147 (Sony) and $122 (Nintendo), and correspond to Liu's cost estimates 20 months after the launch of Nintendo 64. The royalty fees per game sold are $9 (Sony) and $18 (Nintendo).

Preliminaries

We first summarize specific aspects of the model solutions and simulations. Firms and consumers make decisions at the monthly level. Throughout, we assume that firms discount future profits using the factor $= 0.99$[24]. However, we will consider various consumer discount factors across the different simulations. To simplify the analysis, we also normalize the market size to $M = 1$[25].

We summarize the firms' equilibrium pricing strategies by the expected pricing policies $E(p_{jt}|y_t) = E_{j}(\ _j(y_t;\ _j)|y_t)$. Here, the expectation is taken over the firm's private information, the transitory demand component $_j$. The equilibrium evolution of the state vector is summarized by a vector field, where each state is associated with the expected state in the next period.[26] Thus, for a given current state y_t, we calculate (and plot) a vector describing the expected movement of the state between periods:

$$\overrightarrow{\ }_t = E(y_{t+1}|y_t) - y_t$$

4.636 Td1t
j)| t) − yj
4.636 Td.515 0 Td [(E)]TJ/F15 10.9091 Tf 7.f9 0 Td [(y)]TJ/F35 7.9791 Tf 6.58Td.515 0 Td [(E

$T = 25; y_{T1} \geq y_{T2}.$ The marginal production costs are indicated by horizontal lines. Figure 5 shows the vector field describing the expected evolution of the state, and the distribution of shares in the installed base, $_{jt}, T = 25$ months after both standards were launched.[27]

For the scale factors 0.25, 0.5, and 0.75, the results are similar. Prices rise over time, as firms compete more aggressively when they have not yet obtained a substantial share of the market. After 25 months, both firms have an approximately equal share of all adopters. Hence, market outcomes are approximately symmetric.

Now compare these results to the model solution obtained for the estimated software utility coefficient (scale factor equals 1), indicating a larger indirect network effect than in the previous three model variations. Now, the equilibrium changes not only quantitatively but also qualitatively. First, unlike in the previous cases, we are no longer able to find a symmetric equilibrium in pure strategies. However, there are at least two asymmetric pure strategy equilibria. The graphs at the bottom of Figure 5 display one of these equilibria, which "favors" Standard 1. In this equilibrium, before any consoles have been sold ($y_0 = (0, 0)$), consumers expect that Standard 1 will obtain a larger market share than Standard 2 (note the direction of the arrow at the origin). These expectations are self-fulfilling, and due to the impact of the expected future value of software on adoption decisions, Standard 1 will, on average, achieve a larger share of the installed base than Standard 2. If, on the other hand, Standard 2 ever obtains a share of the installed base that is sufficiently larger than the share of Standard 1 (due to a sequence of favorable demand shocks, for example), then consumers' expectations flip and Standard 2 is expected to win. The advantage due to self-fulfilling expectations is increasing in the difference of shares in the installed base, $y_{jt} - y_{-j,t}.$

As a consequence of this equilibrium behavior, the market becomes concentrated, even though the standards are identical *ex ante*. The expected cumulative one-firm concentration ratio increases from $C_1 = 0.502$ for the scale factor 0.25 to $C_1 = 0.833$ for the scale factor 1 discount factor,

significantly more concentrated, $C_1 = 0.827.$

generations of game consoles become increasingly targeted (e.g. Nintendo Wii appeals to

References

[1] Augereau, Angelique, Shane Greenstein and Marc Rysman (2006), "Coordination versus Differentiation in a Standards War: 56K Modems," *The Rand Journal of Economics*, 37, 887-909.

[2] Basu, Amiya, Tridib Mazumdar and S.P. Raj (2003), "Indirect Network Externality Effects on Product Attributes," *Marketing Science*, 22, 209-221.

[15] Coughlan, Peter J. (2001c), "Competitive Dynamics in Home Video Games (K): Playstation vs. Nintendo64," *Harvard Case,* HBS 9-701-101.

[16] Coughlan, Peter J. (2001), "Competitive Dynamics in Home Video Games (I): The Sony Playstation," *Harvard Case,* HBS 9-701-099.

[17] Erdem, Tulin, Susumu Imai and Michael Keane (2003), "A Model of Consumer Brand and Quantity Choice Dynamics under Price Uncertainty," *Quantitative Marketing and Economics,* 1, 5-64.

[18] Evans, David S. (2003), "The Antitrust Economics of Multi-Sided Platform Markets," *Yale Journal on Regulation*, 20, 325-381.

[19] Evans, David S. and Richard Schmalenesee (2007), "The Industrial Organization of Markets with Two-Sided Platforms," *Competition Policy International*, 3, 151-179.

[20] Farrell, Joseph, and Paul Klemperer (2006), "Coordination and Lock-In: Competition with Switching Costs and Network E ects," Handbook of Industrial Organization, Vol. III (forthcoming).

[21] Farrel J. and Saloner G. (1986), "Installed Base and Compatibility," American Economic Review, Vol. 76, 940-955.

[22] Gandal, Neil, M. Kende and R. Rob (2000), "The Dynamics of Technological Adoption in Hardware/Software Systems: The Case of Compact Disc Players," *Rand Journal of Economics*, 31-1.

[23] Gallagher, Dan (2007) "Video game sales blow away forecasts," *MarketWatch*, October 18, 2007 SAN FRANCISCO

[24] Gordon, Brett R. (2006), "A Dynamic Model of Consumer Replacement Cycles in the PC Processor Industry," Working Paper, Carnegie Mellon.

[25] Gowrisankaran, Gautam and Marc Rysman (2006), "Dynamics of Consumer Demand for New Durable Goods," Working Paper, Washington University, St. Louis.

[26] Gupta, Sachin, Dipak C. Jain and Mohanbir S. Sawhney (1999), "Modeling the Evolution of Markets with Indirect Network Externalities: An Application to Digital Television," *Marketing Science*, 18, 396-416.

[27] Horsky, Dan (1990), "A Di usion Model Incorporating Product Benefits, Price, Income, and Information," *Marketing Science*, 9, 342-365.

[28] Jenkins, Mark, Paul Liu, Rosa L. Matzkin and Daniel L. Mcfadden (2004), "The Browser War – Econometric Analysis of Markov Perfect Equilibrium in Markets with Network E ects," Working Paper, Stanford University.

[29] Karaca-Mandic, Pinar (2004), "Estimation and Evaluation of Externalities and Complementarities," Ph.D. dissertation, University of California, Berkeley.

[30] Katz, Michael L., and Carl Shapiro (1985), "Systems Competition and Network E ects," *Journal of Economic Perspectives*, 8 (2), 93-115.

[31] Katz, Michael L., and Carl Shapiro (1986a), "Technology Adoption in the Presence of Network Externalities," *The Journal of Political Economy*, 94, 822-841.

[32] Katz, Michael L., and Carl Shapiro (1986b), "Product Market Compatibility Choice in a Market with Technological Progress" *Oxford Economic Papers, Special Issue on the New Industrial Economics*, 38, 146-165.

[33] Katz, Michael L., and Carl Shapiro (1992), "Product Introduction with Network Externalities," *The Journal of Industrial Economics*, 94, 822-841.

[34] Koski, Heli and Tobias Kretschmer (2004), "Survey on Competing in Network Industries: Firm Strategies, Market Outcomes, and Policy Implications," *Journal of Industry, Competition and Trade*, Bank Papers, 5-31.

[35] Kunii, Irene (1998), "The Games Sony Plays; can it use Playstation to win mastery of cyberspace?" Business Week, New York: June 15, 1998, Iss. 3582, 34.

[36] Liu, Hongju (2007), "Dynamics of Pricing in the Video Game Console Market: Skimming or Penetration?" Working Paper, University of Chicago.

[37] Nair, Harikesh (2006), "Intertemporal Price Discrimination with Forward-looking Consumers: Application to the US Market for Console Video-Games," forthcoming *Quantitative Marketing and Economics*.

[38] Nair, Harikesh, Pradeep Chintagunta and J.P. Dube (2004), "Empirical Analysis of Indirect Network E ects in the Market for Personal Digital Assistants," *Quantitative Marketing and Economics*, 2, 23-58.

[39] Meese, Richard A. and Kenneth Rogo (1982), "Empirical Exchange Rate Models of the Seventies, do they fit out of sample?" *Journal of International Economics*, 14, 3-24.

[40] Pesendorfer, Martin and Phillip Schmidt-Dengler (2006), "Asymptotic Least Squares Estimators for Dynamic Games," Working Paper, London School of Economics

[41] Petrin, Amil and Kenneth Train (2007), "Control Function Corrections for Omitted Attributes in Di erentiated Product Models," Working Paper, University of Minnesota.

[42] Rigdon, Joana (1996), "Nintendo 64 revitalizes slumping video-game market,"

[43] Rogoff, Kenneth (2007), "Comment on Exchange Rate Models Are Not as Bad as You Think by Charles Engel, Nelson C. Mark, and Kenneth D. West," For NBER Macroeconomics Annual 2007, Daron Acemoglu, Kenneth Rogoff and Michael Woodford, eds.

[44] Ryan, Stephen and Catherine Tucker (2007), "Heterogeneity and the Dynamics of Technology Adoption," Working Paper, MIT.

[45] Rust, John (1987), "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher," *Econometrica*, 55 (5), 999-1033.

[46] Rysman, Marc (2004), "Competition Between Networks: A Study of the Market for Yellow Pages," *Review of Economic Studies*, 71, 483-512.

[47] Rysman, Marc (2004), "Empirics of Antitrust in Two-Sided Markets," *Competition Policy*

Appendix A: Equilibrium Provision of Software

In this appendix, we illustrate how we can derive the hardware demand model based on tastes for variety of software. We use a CES model of preferences for software and assume a spot market of monopolistically competitive software suppliers.

After purchasing a hardware platform j, a consumer i purchases an assortment of compatible software each period, $x_{it} = \ x_{i1t}; :::; x_{in}$

base as follows:

$$\log(Q_{jt}) = \quad + \quad \log(y_{jt+1}) .$$

Appendix B: Forward-Simulation of the Consumers' Choice-Specific Value Functions

We outline the procedure for using the first-stage estimates of the consumers's choice strategy, (8), the console firms' pricing strategies, (7), and the software supply, (6), to forward-simulate the consumers' choice-specific value functions.

Conditional on the first-stage estimates and some initial state, y_0, we can simulate histories of all variables affecting the consumers' payoffs. For any period t with beginning-of-period installed base y_t, we draw recursively as follows:

$$
\begin{aligned}
{}_{jt} &\sim N(0;1); \qquad\qquad (j = 1;:::;J) \\
p_{jt}|y_t; {}_t &= \exp(\mathcal{P}_j(y_t;\hat{}_p) + \hat{}\ {}_{jt}); \\
{}_{jt}|y_t; {}_t &= \mathcal{L}_j(y_t; {}_t;\hat{}\ ); \\
s_{jt}| {}_t &= \frac{\exp({}_{jt})}{1+\sum_{k=1}^{J}\exp({}_{kt})};
\end{aligned}
$$

$y_{j;t+1}|y_t$

Value of waiting First, we define the expected per-period utility of a consumer who has not adopted at the beginning of period $t;$ conditional on $y_t; p_t;$ and $\ _t$:

$$\mathcal{U}(y_t; \ _t) = s_{0t}\mathrm{E}(\ _{0t}|0) + \sum_{j=1}^{J} s_{jt}(\ _j + \ n_{jt} - \ p_{jt} + \ _{jt} + \mathrm{E}(\ _{jt}|j)):$$

In this equation, $s_t; p_t;$ and n_t are the choice probabilities, prices, and number of software titles as implied by the first-stage estimates, conditional on the current states y_t and $\ _t:$ Furthermore, $\mathrm{E}(\ _{jt}|j) = -\log(s_{jt})$ is the expected value of the Type I Extreme Value random utility component, given that choice j is optimal.

Next, we define m_{0t} as the probability that a consumer has not adopted one of the hardware standards prior to period $t:$ Note that $m_{01} = 1;$ because we want to calculate the value of waiting in period $t = 0:$ Thereafter ($t > 1$), m_{0t} evolves according to

$$m_0$$

Table 1: Descriptive Statistics

	Console	Mean	SD	Min	Max
Sales	Playstation	275,409	288,675	26,938	1,608,967
	Nintendo	192,488	201,669	1,795	1,005,166
Price	Playstation	119.9	30.3	55.7	200.6
	Nintendo	117.6	33.9	50.3	199.9
Game Titles	Playstation	594.2	381.1	3	1,095
	Nintendo	151.2	109.9	1	281

Table 2: Model Fit for Different Specifications

Model	Log-Likelihood	BIC
1) Linear, , 1-comp	-187.88	679.40
2) Linear, time ($t < 60$), 1-comp	-150.11	620.97
3) Quadratic, time ($t < 60$), 1-comp	-79.38	514.01
4) Quadratic, time ($t < 60$), 2-comp	-79.38	522.28
5) Quadratic, time ($t < 60$), 1-comp, PPIs in prices	-63.54	507.69
6) Quadratic, time ($t < 60$), 1-comp, exchange rate in prices	-25.43	422.94
7) Quadratic, time ($t < 60$), 1-comp, exchange rate and PPI's in prices	-7.53	412.79

Table 3: First Stage Estimates: Pricing Policies $\mathcal{P}_j$

Table 4: First Stage Estimates: Log-odds of Market Shares, $\mathcal{L}_j$

	Sony		Nintendo	
	Estimate	SE	Estimate	SE
Intercept	-13.826	2.539	-1.141	0.744
y_{Sony}	1.456	4.669	0.065	0.012
y_{N64}	-7.670	5.884	-1.740	0.196
y^2_{Sony}	-0.334	0.432	-1.304	0.305
y^2_{N64}	-0.684	0.571	-1.820	0.335
Time (< 64)	-0.003	0.008	-2.176	0.469
Jan	-1.367	0.154	-1.950	0.528
Feb	-1.345	0.159	-1.625	0.495
Mar	-1.813	0.475	-1.682	0.525
Apr	-2.442	0.351	-1.674	0.397
May	-2.596	0.463	-1.268	0.402
Jun	-1.947	0.395	-1.713	0.215
Jul	-1.805	0.470	-0.789	0.335
Aug	-1.871	0.392	-0.288	0.070
Sep	-1.496	0.426	0.085	0.135
Oct	-1.644	0.199	-0.406	0.150
Nov	-0.781	0.120	0.084	0.173
$_{Sony}$	-27.656	5.216	0.103	0.061
$_{N64}$	0.844	4.936	-0.220	0.083
$^2_{Sony}$	-13.383	7.554	0.547	0.107
$^2_{N64}$	-0.660	0.416	-0.545	0.119

Table 5: First Stage Estimates: Equilibrium Game Provision, $\mathcal{H}_j$

	Estimate	SE
$_{Sony}$	-16.220	2.042
$_{Nintendo}$	-24.349	1.992
$_{Sony}$	1.369	0.126
$_{Nintendo}$	1.810	0.126

Table 6: Second Stage Parameter Estimates

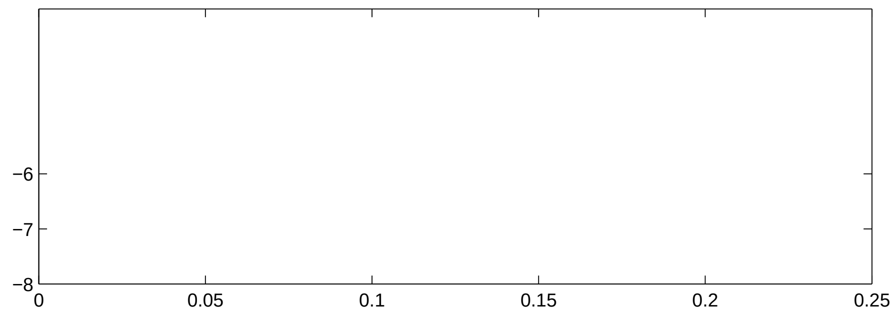

Figure 2: In-Sample Fit: Log-Odds Ratios

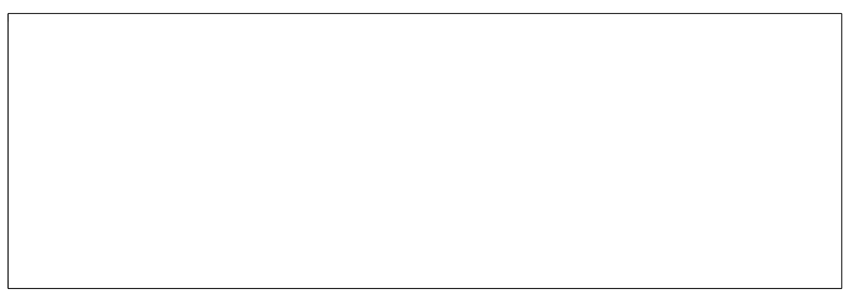

Figure 3: In-Sample Fit: Provision of Games

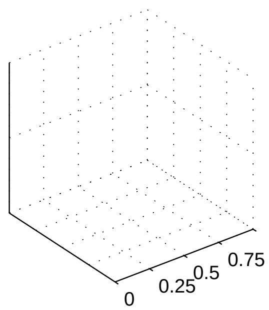

Figure 4: Symmetric competition: Equilibrium pricing policies and price paths. Consumer's software utility coefficient is scaled by different factors. The expected price paths are shown conditional on $y_{T1} \geq y_{T2}$ at the end of period $T = 25$: Marginal production costs are indicated by horizontal lines.

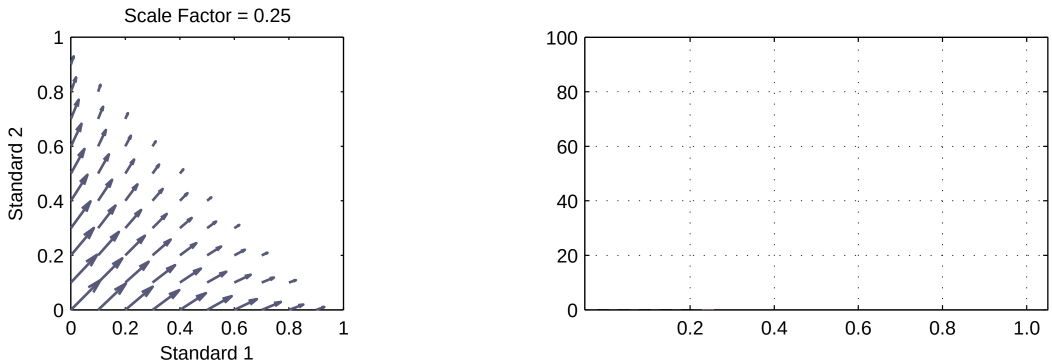

Figure 5: Symmetric competition: Expected state evolution and distribution of shares in the installed base after 25 months. Consumer's software coe□cient is scaled by di□erent factors.

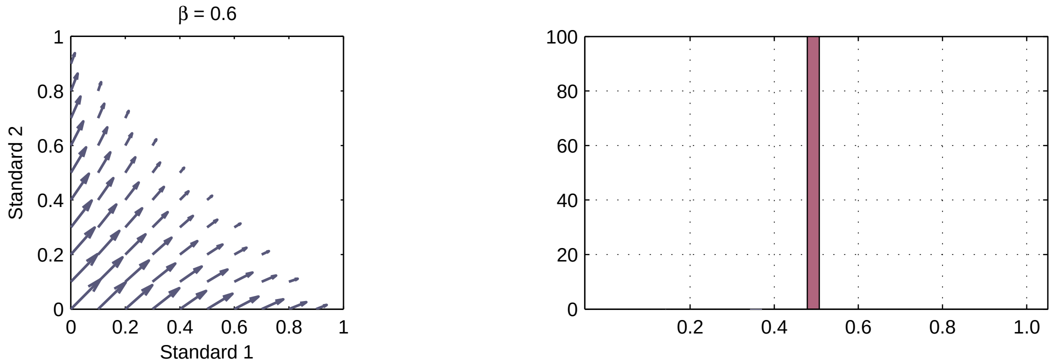

Figure 6: Symmetric competition: Equilibrium pricing policies and price paths for different consumer discount factors ( ).

Figure 7: Predictions from estimated parameter values: Expected state evolution and distribution of shares in the installed base after 25 months. Consumer's software coefficient is scaled by different factors.

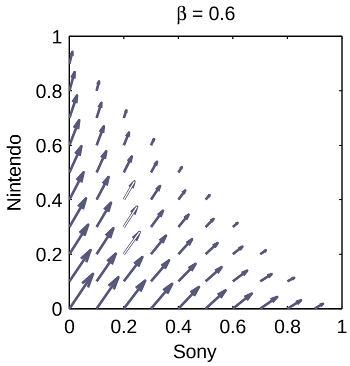

Figure 8: Predictions from estimated parameter values: Equilibrium pricing policies and price paths for di erent consumer discount factors ( ).