Hardware quality vs. network size in the home video game industry

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ARTICLE INFO

Article history:
Received 23 July 2009
Received in revised form 14 July 2010
Accepted 22 July 2010
Available online 6 August 2010

JEL classification:
L13
L63
C33
D43

Keywords:
Indirect network effects
Excess inertia
Video games
Quality vs. quantity

ABSTRACT

This paper analyzes competition between multiple proprietary and incompatible hardware systems when indirect network effects are present and software is provided competitively by third party developers. A discrete-choice demand structure is employed within a game theoretic setting to allow for a continuum of market share possibilities. Empirical evidence supports the claim that excess inertia is not a pervasive problem. Two data sets covering the life of the home video game industry (yearly from 1976 to 2003 and monthly January 1995 to October 2007) yield three main results: (1) market share is 11.4 times more sensitive to hardware quality than network size, (2) the number of available games is 3.69 times more sensitive to hardware quality than network size, and (3) hardware quality has a larger impact than network size on the probability of hardware success.

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1. Introduction

Positive network externalities exist when consumer benefit increases with the number of adopters of a network. These externalities are indirect when an increase in consumers results in an increase of complementary products provided for the network. For example, more software is made available for a video game system as more consumers adopt that system; consumers are more likely to adopt a system that has a greater amount of available software.1 Researchers note that industries characterized by network effects often tip to a dominant standard. This is demonstrated in Viscusi et al. (2001, 275): “In a market characterized by network effects, one product often becomes the standard (or the market ‘tips’ to one product). This outcome is especially likely if, as in the software industry, there are large economies of scale (or increasing returns).”

One concern is that the tipping effect can be associated with ‘excess inertia’, or the failure to adopt a new superior standard due to a large network effect associated with an existing inferior standard (Farrell and Saloner, 1986; Katz and...
Shapiro, 1986, 1992; Church and Gandal, 1993; Woeckener, 2000; Shy, 2001; Clements, 2005).\(^2\) Shapiro (1996, 6) highlights the antitrust concerns: “... antitrust enforcers must be alert in these industries, because the very nature of the ‘positive feedback’ cycle means that monopolization may be accomplished swiftly. And, once achieved, the network effects that helped create dominance may make it more difficult for new entrants to dislodge the market leader than in other industries lacking network characteristics.” That is, quantity may trump quality when a consumer is considering which network to join. Evidence presented here suggests this outcome is unlikely in the U.S. home video game industry.

Commonly cited examples of excess inertia are the QWERTY keyboard vs. Dvorak (David, 1985) and VHS video cassette recorder (VCR) format vs. Betamax. However, most studies of this phenomenon have relied on qualitative evidence rather than quantitative tests of hypotheses. For example, Liebowitz and Margolis (1990, 1994, 1999) and Liebowitz and Margolis (1996, 1999) argue vigorously by presenting convincing qualitative evidence that the QWERTY and VHS grew in popularity once they were demonstrated to be better than their alternatives; they are, in fact, examples of superior standard adoption. Other authors argue just as vigorously that both examples are instances of excess inertia (see, among others, Cusumano et al., 1992; Grindley, 1992; David, 2007).

Shankar and Bayus (2003) point out that there has been little empirical investigation of network effects in multiproduct industries with incompatible technologies. Recent literature has begun to address this deficit. Some exceptions to the qualitative studies of the VCR industry include Ohashi (2002) and Park (2004). Ohashi (2002) provides evidence for both camps: empirical estimates suggest superior VHS quality was more important than Betamax’s network advantage early in the industry lifecycle while Betamax’s quality advantage was not enough to overtake VHS’s network advantage toward the end of the standards competition. Park (2004) confirms Ohashi’s (2002) finding that VHS network size was more important than Betamax’s quality advantage in the years before Betamax exited the market.

Other papers have examined network effects in industries where hardware is proprietary. Nair et al. (2004), in an examination of the personal digital assistant industry, provide guidance for managers who seek to increase their market share through either encouraging increased software provision or improving hardware attributes. The present study adds to this literature by comparing the relative importance of hardware quality and network size in determining market share outcomes in the U.S. home video game industry. Clements and Ohashi (2005) also empirically examine the video game industry, but their focus is on pricing and network effects over the hardware lifecycle.

The current paper employs a discrete-choice demand structure incorporating indirect network effects and differing hardware quality within a game theoretic setting to allow for a continuum of market share possibilities. Relative importance of each variable is assessed by comparing market share sensitivities. A monthly data set (January 1995–October 2007) finds market share is roughly 11.4 times more elastic with respect to quality than to network size. A yearly data set (1976–2003) shows entrant hardware quality has a larger effect than incumbent hardware network size on the probability of entrant success.

Similar to Nair et al. (2004), we show that hardware quality affects hardware demand in two ways: directly through the hardware demand equation and indirectly through the number of available software titles equation. Further emphasizing the importance of hardware quality, we find the number of available software titles is 3.69 times more elastic with respect to hardware quality than to network size.

Finally, this paper also models licensing arrangements between hardware and software firms. The model suggests that, ceteris paribus, a hardware firm with a larger installed base will charge a higher licensing fee to third party software developers. This practice is seen in the video game industry as hardware firms alter licenses according to their market position such that greater relative network size yields more favorable agreements.

The rest of the paper is organized as follows. Section 2 briefly discusses the home video game industry. Section 3 constructs a game theoretic model with a discrete-choice demand structure of hardware adoption. Section 4 describes the data, estimates hardware demand and software availability equations derived in Section 3, and obtains estimates on the probability of entrant success based on quality and network size. Section 5 reviews how licensing agreements change according to market position and considers policy implications for antitrust authorities. Section 6 concludes and discusses possibilities for future research.

2. The home video game industry

The home video game industry began in 1976 with the introduction of the Fairchild Video Entertainment System which had the ability to operate interchangeable software. Before this consumers were limited to hardware programmed with non-interchangeable software. Since then hardware quality has increased dramatically; from 8-bit central processing unit processors in the first generation systems to multiple 128-bit processors in current hardware systems.

Over the lifetime of the home video game industry quality improvements were embodied by the introduction of new hardware systems. Some hardware systems went on to displace all other competitors, establishing a new product generation. Other systems were able to capture a significant share of the market, but not take a leadership role. Finally, other systems failed shortly after introduction.

\(^2\) It should be noted that recent experimental evidence suggests this outcome may be unlikely; Hossain and Morgan (2009, 435) find no evidence of excess inertia in their experimental study: “our subjects never got stuck on the inferior platform – even when it enjoyed a substantial first-mover advantage”.

There have been several product generations over the lifecycle of the home video game industry. Table 1 displays each generation, the market leaders in that generation, and notable competitors. It is important to note that in only one generation, Generation 2, did a console (Nintendo Entertainment System) ever attain a monopoly position. In all other generations either there were multiple leaders or the notable competitors obtained a significant market share and survived well into the introduction of the next generation console. These dynamics make the home video game industry ideal for study. Competition for leadership within a generation and the introduction of new product generations allows for empirical estimation of market share sensitivity to hardware quality and network size.

Another interesting characteristic of the home video game industry is the interaction between hardware and software firms. Third party software developers produce the majority of games released on competing hardware systems. Games are usually developed for use on a specific system. From 1995 until 2003 only 21.08% of games in this sample were released on multiple systems.

One reason is due to incompatibility among hardware systems. Technology that translates program code compatible with one system into code compatible with another is costly (Takahashi, 2002). In fact, most games released on multiple systems are big sellers on a single system first. Another reason for this has to do with the relationship between hardware firms and software firms. Third party software developers typically pay a licensing fee, or royalty, to the hardware firm for each game sold. Aside from the royalty, some licensing agreements involve exclusivity restrictions (Coughlan, 2001). In Section 5 it is shown that indirect network effects are important in determining the terms of licensing agreements.

### 3. The Model

This section develops a model where hardware firms and software firms interact in an industry characterized by indirect network effects. The goal is to provide a theoretical framework for the empirical estimations in Section 4.

Market share of competing hardware systems is based on two characteristics: (1) hardware quality and (2) network size. To focus on these two characteristics it is assumed that hardware and software provide no stand-alone benefit, that is, consumers purchase hardware systems in order to have access to compatible software titles. As such, greater hardware quality is experienced through increased benefit of consuming software on the system. However the main purpose of this assumption is to highlight the indirect network effect: a hardware system becomes more attractive to consumers when a greater variety of compatible software is available, and it is more attractive for software firms to provide for a hardware system with a larger network of consumers. This formulation is conducive to comparing the relative effects of hardware quality and network size on market share. The formal model is given below.

A partial equilibrium model is used to determine market share of competing hardware systems. Consumers have access to compatible software once a unit of hardware is purchased. Software is provided competitively by third party firms and is incompatible between hardware systems. For simplicity assume a software firm produces a single title for one hardware system. Further, software firms must pay a per-unit licensing fee to the hardware firm for each unit of software sold. Also, the number of software firms (and therefore, number of software titles) is determined endogenously according to the zero profit condition.

There are two types of consumers in the model, new consumers, \( N_1 \), and installed base consumers, \( N_0 \). Installed base consumers own hardware while new consumers do not; this is the only way the two types differ in the model. There may be installed base consumers for each type of hardware (new hardware has no installed base consumers). The number of hardware firms and their initial installed bases are exogenously given.

The model is analyzed as a multi-stage game with the order of play as follows. First hardware firms simultaneously set system price. Then new consumers (not installed base consumers) decide which hardware system to purchase. After new consumers make their decision, hardware firms set the licensing fee for compatible software firms. Upon observing the licensing fee, compatible software firms enter the market competitively and then set software prices. After this, new consumers complete system purchases, and finally, both new and installed base consumers purchase compatible software. Note that only new consumers buy hardware while both new and installed base consumers buy compatible software.

Consumers, software, and hardware are indexed by \( i = 1 \cdots N_1 \), \( j = 1 \cdots J \), and \( k = 1 \cdots K \), respectively. Assuming no stand-alone benefit for hardware, new consumer \( i \) will choose to buy hardware \( k \) if doing so maximizes \( i \)'s utility

\[
U_i^k = E(U_{i,j,k}^k) + \varepsilon_i^k
\]
where $E(U_{i,J}^k)$ is $i$'s expected utility of consuming $j^k$ software titles compatible with hardware $k$, net of software prices and the price of hardware $k$, and $\epsilon_i^k$ is an individual specific shock (formal assumptions on $\epsilon_i^k$ are given in Section 4). Subgame perfect Nash equilibria are computed using generalized backwards induction. As such, the software consumption decision is analyzed first.

### 3.1. Software demand

All consumers are assumed to have the same preference for software. Consumer $i$’s utility for software compatible with hardware $k$ is modeled using CES preferences as follows:

$$\max_{x_j^k} U_{i,J}^k = x_0 + (z^k)^{1/\beta}$$

with $z^k = \left( \sum_{j=1}^{J_k} (x_j^k)^{1/\beta} \right)^{\beta}$, $\alpha \geq 1$ and $\beta > 1$.

### 3.2. The number of software titles

In this subsection we use the demand for software found in Eq. (3) to set up the software firm’s maximization problem and solve for software price. Then we use the zero profit condition to find the free entry equilibrium number of software firms. This gives us guidance on the functional form of the software availability estimation equation in Section 4.

Software firm $j$’s profit function is given by

$$\Pi_j^k = (p_{s,j}^k - c_s - \bar{f}_k)x_j^kN_j^k - f_s$$

where $c_s$ and $f_s$ are the marginal and fixed costs of software, respectively, and $\bar{f}_k$ is the per-unit licensing fee paid to hardware firm $k$. Software firms take the licensing fee as given since they are determined by hardware firm $k$ in a previous stage of the game.

---

1. CES preferences are often used to model network effects (Chou and Shy, 1990; Church and Gandal, 1992; Park, 2002; Nair et al., 2004; Clements and Ohashi, 2005).

2. The model simplifies the analysis by considering quantity a continuous variable. This approach is used throughout the literature on network effects because it yields a tractable model capturing consumer preferences over software variety (see cites in the above footnote as well as Spence, 1976; Dixit and Stiglitz, 1977). Another approach is to model quantity choices discretely. Consumers who own console hardware would decide whether or not to buy each unit of compatible software on an individual basis. The discrete-choice demand specification would have $\sum_{r=1}^{R} f^r/|r|(j^r - r)|$ (Wackerly et al., 1996) software consumption choices, where $j^r$ is the number of compatible units of software, as the consumer considers all possible combinations of software. Anderson et al. (1992) approaches this formulation by assuming consumers purchase a variable amount of a single variant of software.

3. This specification is analogous to Nair et al. (2004). Clements and Ohashi (2005) also use this specification to derive econometric estimates of the elasticity of hardware adoption with respect to software variety.

4. This type of price index was introduced by Dixit and Stiglitz (1977) and has been used extensively in the network effects literature. See for example Church and Gandal (1992, 1993), Park (2002), Nair et al. (2004), and Clements and Ohashi (2005).
Software price is found by maximizing (4) with respect to \( p_{s,j}^k \) and solving. After obtaining the first order condition we assume all software products are symmetric for simplicity:\(^{7}\) in equilibrium, \( p_{s,j}^k = p_{s}^k \) and \( \theta_j^k = \theta_k \) for all \( j \), where \( \theta_k \) is the average quality of a software title available for hardware \( k \). Because consumers buy hardware to obtain the corresponding software, \( \theta_k \) is referred to as hardware quality.

It is important to note we assume the price index for software is not significantly affected by the change in the price of a single software title, or \( \partial \Omega^k_s/\partial p_{s,j}^k = 0 \). This is a standard simplifying assumption in the literature that allows for a closed form solution for the equilibrium number of software titles. The foundation for this assumption is that it is usually assumed the number of software titles is so large that a change in the price of a single software title will only have a negligible affect on the price index. When this is the case, solving for \( p_{s,j}^k \) yields

\[
p_{s,j}^k = \beta(C_s + f_h^k).
\]  

(5)

In Appendix B we relax this assumption and show licensing fees are positively related to network size. This relationship is examined in Section 5.

The free entry equilibrium number of symmetric software firms (and number of titles since we assume each firm produces one title), \( f^k \), is found by substituting equilibrium software price in (5) and \( x^k \) from (3) into (4) and using the zero profit condition:

\[
J^k = \left( \frac{(\beta - 1)\alpha^\beta - 1}{(\alpha \beta^2)^{1/(\alpha \beta) - 1} (C_s + f_h^k)} \right)^{1/(\beta(\alpha - 1))} (N^k_{s,j} / \alpha^{\beta/(\alpha \beta - 1)} \theta^k)^{1/(\beta(\alpha - 1))}.
\]  

(6)

Eq. (6) captures the network effect: an increase in the number of consumers has a positive effect on the number of games. It is also interesting to note that hardware quality and the number of games are positively related. This suggests including both the installed base number of consumers and hardware quality as regressors in the software availability estimations in Section 4.

### 3.3. Hardware demand

Hardware firms use the equilibrium number of software titles defined in (6) along with software price and software demand to solve for their optimal per-unit licensing fee, \( \hat{\ell} \). With the equilibrium licensing fee we are able to obtain the network benefit function, or the utility consumers receive from software consumption net of software price, in terms of the expected number of software titles and hardware quality. With the network benefit function we are able to determine an appropriate functional form for the hardware demand estimations in Section 4.

The profit of hardware firm \( k \) is

\[
\Pi^k_h = (p_{h}^k - c_0)N^k_{s,j} + N^k_{s,j}x^k f^k - f_h^k
\]  

(7)

where \( c_0 \) and \( f_h \) are the marginal and fixed cost of hardware, respectively. The first part of this equation is profit from hardware sales to new consumers; the second part is licensing fee profit from software title sales to both new and installed base consumers (the number of consumers, \( N^k_{s,j} \), times the demand for each software title, \( x^k \), times the per-unit licensing fee, \( f^k \), times the total number of compatible software titles, \( f^k \)).

The equilibrium licensing fee is found by maximizing (7) with respect to \( \hat{\ell} \) after substituting the number of games from Eq. (6), software demand from Eq. (3), and equilibrium software price from Eq. (5). Solving the first order condition yields

\[
\hat{\ell} = \beta(\alpha - 1)c_s.
\]

(8)

Next, it is convenient to find the equilibrium quantity demanded for software by substituting the equilibrium licensing fee found above and software price from (5) into (3):

\[
x^k = \left( \frac{1}{\alpha \beta^2 (\beta(\alpha - 1) + 1)c_s} \right)^{\alpha \beta/(\alpha \beta - 1)} (J^k)^{\beta/(\alpha \beta - 1)} (f^k)^{1/(\alpha \beta - 1)}.
\]  

(8)

Finally, to find the indirect utility of software consumption, substitute (8), along with software price from (5), the equilibrium licensing fee, the budget constraint, and \( x^k \) into (2) to obtain

\[
V^k = y - p_{s,j}^k + \left( \frac{(\alpha \beta - 1)\alpha^\beta - 1}{(\alpha \beta)^2 \beta (\beta(\alpha - 1) + 1)c_s} \right)^{1/(\alpha \beta - 1)} (J^k)^{1/(\alpha \beta - 1)} (f^k)^{1/(\alpha \beta - 1)}.
\]  

(9)

---

\(^{7}\) While beyond the scope of this paper, symmetric software is clearly not the case for the video game industry. Out of all video games released in 1998, only 10% made a profit. By the late-1990s the top 10 best-selling games accounted for 1/3rd of global revenue (Coughlan, 2001). In 2000, only about a quarter of the 1300 games produced that year were able to sell enough copies to make back their development costs (Hillis, 2001). The assumption of symmetric software allows a more tractable solution for software price.
where the last term on the right hand side is the network benefit function. We assume consumers have rational expectations regarding the expected utility of each system. Therefore new consumer \( i \)'s expected utility of purchasing hardware \( k \) is found by substituting Eq. (9) into (1).

Notice Eq. (9) captures the indirect network effect as it is increasing in the number of software titles, \( J^k \) (recall \( J^k \) is increasing in the total number of consumers, \( N^k \)). We could substitute \( J^k \) from (6) into (9) and state the network benefit function as a function of the number of installed base consumers directly. However, our strategy below is to have separate estimations for hardware market share and software availability.

4. Empirical results

The goal of this section is to empirically examine the effect of hardware quality and network size on hardware market share as well as overall hardware success. First, the different data sets are described and a measure of console quality is obtained for each, second we estimate the hardware demand and software availability equations found in Section 3, and finally we compare the relative effects of hardware quality and network size on the probability of console success at time of entry.

4.1. Data

The study employs two main data sources: a monthly data set covering January 1995 through October 2007 and a yearly data set covering 1976 through 2003. The monthly data set is provided by The NPD Group, a marketing research firm, and includes console (hardware) and game (software) point of sale data from approximately 65% of U.S. game retailers. The data set contains observations on the quantity of consoles sold, average console price, the number of game titles available for a console in a month, and introduction and exit dates (where applicable). It covers 15 consoles with 935 console/month observations in total.

The yearly data set is similar to the one used in Gretz (2010) and provided by www.allgame.com. The data set contains console entry and exit dates (where applicable), market share for each console competing from 1985 on, the number of game (software) titles available each year for each console, and console characteristics (such as processor speed, central processor unit bit size, console random access memory, the maximum amount of program code available for a game title on the console, whether or not the console is an add-on to an existing system, whether or not the console uses disk based games, and whether or not the console can play DVD movies). The data set covers 34 different consoles with 179 console/year observations.

It is necessary to obtain a measure of console quality in order to test the relative importance of quality and network size. The quality variable for the yearly data set is created using hedonic estimates provided by Gretz (2010) and the relevant console characteristics. For example, Sega Genesis uses a 16-bit 7.67 megahertz (MHz) processor and it can play games with up to 4000 kb worth of program code. Using these values the quality measure is constructed with the relevant betas from the hedonic estimates provided by Gretz (2010). In this case, our quality measure for Sega Genesis from Gretz (2010) is 3.705 (=ln(1 + 7.67) × 0.110 + ln(4000) × 0.418) where 0.110 and 0.418 are the betas for MHz of 16-bit processors and maximum amount of game code, respectively. It should be noted we employ the same transformations used in Gretz (2010) to obtain our quality measures; Gretz (2010) estimates a log–log hedonic model and adds 1 to all processor speeds (in order to ensure positive logged values for processor speeds less than 1 MHz).

For the monthly data set we use an approach similar to Stavins (1997) where a quality measure is constructed from the hedonic equation of price on characteristics and year dummies. In Stavins (1997) the betas from the hedonic estimation serve as weights when constructing a summary quality variable. Here, price is regressed on year/month dummies, console dummies, and console age for the monthly data set. Console dummies capture implicit prices of technical characteristics since they remain unchanged throughout the lifecycle. They also capture any console specific attributes such as marketing effort or technical support. Console age is measured in months from console introduction where the console is 1 month old in the first month. Descriptive statistics and results for the hedonic estimation are shown in Tables 2 and 3, respectively.

Console quality for this data set is constructed from Table 3 using the constant term, the console dummy beta (except in the case of Sony PlayStation), and the age effect. For example, the quality of Microsoft Xbox is 5.759 (=6.056 – 0.277 – 0.020 × 1) in its first month, 5.739 (=6.056 – 0.277 – 0.020 × 2) in its second month, and so on.

The next two subsections employ the monthly data set to estimate hardware demand and software availability. The final subsection uses the yearly data set to estimate the effect of quality and network size on the probability of console success.

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8 We use a summary quality variable to be consistent with the theory presented in Section 3. Another approach would be to include console dummy variables in the hardware estimations since technical characteristics of consoles do not change over the lifecycle. However, including console dummies linearly would ignore the non-linear specification suggested in Eq. (9). On the other hand, including console dummies in a non-linear fashion would drastically increase the dimensionality of the estimation problem since parameters incorporated in the interaction between \( \phi^k \) and \( f^k \) would be separately estimated for each console.

9 Using an age variable instead of age dummies did not significantly decrease explanatory power of the regression.
Table 2
Summary statistics for hedonic regression: 924 observations.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Natural log of inflation corrected average monthly console price</td>
<td>4.091</td>
<td>0.760</td>
<td>0.728</td>
<td>5.689</td>
</tr>
<tr>
<td>Independent variable</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Console age</td>
<td>51.728</td>
<td>35.775</td>
<td>1.000</td>
<td>146.000</td>
</tr>
<tr>
<td>Dummy variables</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3DO</td>
<td>0.047</td>
<td>0.211</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Sega Dreamcast</td>
<td>0.051</td>
<td>0.220</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Nintendo GameCube</td>
<td>0.078</td>
<td>0.268</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Sega Genesis</td>
<td>0.088</td>
<td>0.283</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
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<td>0.055</td>
<td>0.228</td>
<td>0.000</td>
<td>1.000</td>
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<tr>
<td>Atari Jaguar</td>
<td>0.042</td>
<td>0.201</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Super Nintendo</td>
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<td>0.273</td>
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</tr>
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<td>Sony PlayStation</td>
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<td>0.365</td>
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<td>1.000</td>
</tr>
<tr>
<td>Sony PlayStation 2</td>
<td>0.092</td>
<td>0.289</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Sony PlayStation 3</td>
<td>0.013</td>
<td>0.113</td>
<td>0.000</td>
<td>1.000</td>
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<tr>
<td>Sega Saturn</td>
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<td>0.250</td>
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</tr>
<tr>
<td>Nintendo Wii</td>
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<td>0.113</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Microsoft Xbox</td>
<td>0.078</td>
<td>0.268</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Microsoft Xbox 360</td>
<td>0.026</td>
<td>0.159</td>
<td>0.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Summary statistics for month/year interaction dummies included but not displayed for brevity.

* Indicates significance at the 1% level.

4.2. Hardware demand estimations

The goal of this section is to estimate market share for consoles as a function of console price, the number of available games, and console quality; Eq. (9) provides guidance to the function form of the relationship. Also, we impose standard assumptions on \( \epsilon_k^i \) from Eq. (1) to generate a logit estimation. Using the techniques developed by Berry (1994) and Berry et al. (1995) for differentiated product discrete-choice demand models along with the assumptions on \( \epsilon_k^i \) yields the following regression model

\[
\ln(s_k^t) - \ln(s_0^t) = \delta_0 + \delta \gamma_t + \delta_p p_{k,t}^k + \delta_{Jk} \left( \theta_{Jk} \right)^{1+\omega} + \epsilon_k^i
\]  

(10)

where \( s_k^t \) is the market share of console \( k \) at time \( t \), \( s_0^t \) is the market share of the outside option at time \( t \), \( \delta_0 \) is a constant, \( \gamma_t \) represents time specific constants where \( \delta \) are the coefficients on these constants, \( p_{k,t}^k \) is the average price of console \( k \)

Table 3
Hedonic regression: price on console dummies, console age, and month/year interaction dummies.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>6.056(^*)</td>
<td>0.130</td>
</tr>
<tr>
<td>3DO</td>
<td>-0.488(^*)</td>
<td>0.060</td>
</tr>
<tr>
<td>Sega Dreamcast</td>
<td>-0.874(^*)</td>
<td>0.076</td>
</tr>
<tr>
<td>Nintendo GameCube</td>
<td>-0.695(^*)</td>
<td>0.094</td>
</tr>
<tr>
<td>Sega Genesis</td>
<td>0.066</td>
<td>0.091</td>
</tr>
<tr>
<td>Sega Genesis CDX</td>
<td>-0.682(^*)</td>
<td>0.054</td>
</tr>
<tr>
<td>Atari Jaguar</td>
<td>-1.099(^*)</td>
<td>0.061</td>
</tr>
<tr>
<td>Super Nintendo</td>
<td>-0.077</td>
<td>0.069</td>
</tr>
<tr>
<td>Nintendo 64</td>
<td>-0.433(^*)</td>
<td>0.041</td>
</tr>
<tr>
<td>Sony PlayStation 2</td>
<td>-0.063</td>
<td>0.080</td>
</tr>
<tr>
<td>Sony PlayStation 3</td>
<td>-0.234</td>
<td>0.173</td>
</tr>
<tr>
<td>Sega Saturn</td>
<td>-0.552(^*)</td>
<td>0.049</td>
</tr>
<tr>
<td>Nintendo Wii</td>
<td>-1.043(^*)</td>
<td>0.173</td>
</tr>
<tr>
<td>Microsoft Xbox</td>
<td>-0.277(^*)</td>
<td>0.094</td>
</tr>
<tr>
<td>Microsoft Xbox 360</td>
<td>-0.365(^*)</td>
<td>0.152</td>
</tr>
<tr>
<td>Console age</td>
<td>-0.020(^*)</td>
<td>0.001</td>
</tr>
<tr>
<td>Number of observations</td>
<td>924</td>
<td></td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.879</td>
<td></td>
</tr>
<tr>
<td>Adjusted ( R^2 )</td>
<td>0.852</td>
<td></td>
</tr>
</tbody>
</table>

The dependent variable is the natural log of inflation adjusted average monthly console price. Console dummies included with Sony PlayStation as the base age category. Month/year interaction dummies included but not displayed for brevity. * Indicates significance at the 1% level.
Table 4
Descriptive statistics for hardware demand and software availability estimations.

<table>
<thead>
<tr>
<th>Hardware demand descriptives: 923 observations</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \ln (x_t) - \ln (x_t) )</td>
<td>-7.477</td>
<td>3.250</td>
<td>-16.875</td>
<td>-2.145</td>
</tr>
<tr>
<td>Endogenous regressors(^a)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inflation corrected avg. console price</td>
<td>0.778</td>
<td>0.567</td>
<td>0.021</td>
<td>2.955</td>
</tr>
<tr>
<td>Number of available games</td>
<td>4.392</td>
<td>4.130</td>
<td>0.050</td>
<td>18.130</td>
</tr>
<tr>
<td>Exogenous regressor</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Console quality</td>
<td>4.677</td>
<td>0.613</td>
<td>3.136</td>
<td>6.036</td>
</tr>
<tr>
<td>Instruments(^b)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg. game age ( (GA) \times ) console age ( (CA) )</td>
<td>19.730</td>
<td>24.644</td>
<td>0.000</td>
<td>114.275</td>
</tr>
<tr>
<td>Electronic computer manufacturing PPI ( (ECM) )(^b)</td>
<td>2.273</td>
<td>1.339</td>
<td>0.666</td>
<td>5.401</td>
</tr>
<tr>
<td>Computer storage device manufacturing PPI ( (CSDM) )(^b)</td>
<td>1.873</td>
<td>0.810</td>
<td>0.872</td>
<td>3.590</td>
</tr>
<tr>
<td>Audio and Video equipment manufacturing PPI ( (AVEM) )(^b)</td>
<td>0.755</td>
<td>0.053</td>
<td>0.641</td>
<td>0.841</td>
</tr>
<tr>
<td>Magnetic and optical recording media manufacturing PPI ( (MORMM) )(^b)</td>
<td>0.754</td>
<td>0.053</td>
<td>0.650</td>
<td>0.848</td>
</tr>
<tr>
<td>GA \times CA \times ECM</td>
<td>3688.10</td>
<td>4423.62</td>
<td>0.00</td>
<td>20279.24</td>
</tr>
<tr>
<td>GA \times CA \times CSDM</td>
<td>3260.02</td>
<td>3919.52</td>
<td>0.00</td>
<td>19006.86</td>
</tr>
<tr>
<td>GA \times CA \times AVEM</td>
<td>1463.11</td>
<td>1790.29</td>
<td>0.00</td>
<td>8502.03</td>
</tr>
<tr>
<td>GA \times CA \times MORMM</td>
<td>1462.41</td>
<td>1790.41</td>
<td>0.00</td>
<td>8479.18</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Software availability descriptives: 913 observations</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \ln (\text{number of available games}) )</td>
<td>5.295</td>
<td>1.091</td>
<td>1.609</td>
<td>7.250</td>
</tr>
<tr>
<td>Endogenous regressor</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \ln (\text{installed base}) )</td>
<td>15.551</td>
<td>1.696</td>
<td>10.418</td>
<td>18.076</td>
</tr>
<tr>
<td>Exogenous regressor</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \ln (\text{console quality}) )</td>
<td>1.532</td>
<td>0.134</td>
<td>1.143</td>
<td>1.794</td>
</tr>
<tr>
<td>Instruments:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \ln (\text{avg. game age}) )</td>
<td>-1.689</td>
<td>0.956</td>
<td>-4.980</td>
<td>-0.239</td>
</tr>
</tbody>
</table>

\(^a\) Values divided by 100 for presentation purposes.
\(^b\) Instruments also used in software estimations.

at time \( t \), \( \delta_k \) is the coefficient on price, \( f^k_t \) is the number of available game titles compatible with console \( k \) at time \( t \),\(^{10}\) \( \theta^k_t \) is the quality of console \( k \) at time \( t \), and \( \delta_{k,t} \) is the coefficient on the number of available game titles/console quality interaction term where the number of available game titles is raised to the \( \omega_j \) power and console quality is raised to the \( \omega_j \) power.

Notice \( \delta_{j,t} \), \( \omega_j \), and \( \omega_j \) correspond to \( (\alpha \beta - 1)\alpha^{\beta - 1} / (\alpha \beta \beta - \beta (\alpha - 1) + 1) \) \( C_\beta \) \((\alpha \beta - 1), (\beta - 1)\), \( (\alpha \beta - 1), \) and \( 1/((\alpha \beta - 1), \) from Eq. (9), respectively. Finally, \( v^k_t \) is the error term which represents the effect of unobserved (to the econometrician) console characteristics.

We are concerned about potential endogeneity of two explanatory variables: average console price and the number of available game titles. First, console price is set by profit maximizing firms that likely take into account unobservable (to the econometrician) console characteristics. Second, Clements and Ohashi (2005) show the number of available game titles is likely influenced by the market share of new consumers, especially if errors are autocorrelated.\(^{11}\)

We employ a variety of cost side instruments as suggested by Nevo (2000). Console age is interacted with average game age (i.e. the average age of available game titles in months) as an instrument for console price. Coughlan (2001) finds evidence that console costs decrease with console age. The interaction term is employed because console age is highly correlated with console quality; it is used with console dummy variables from the hedonic estimates in Table 3 to construct quality measures. Dubé et al. (2010) use producer price indexes for Electronic Computer Manufacturing, Computer Storage Device Manufacturing, and Audio and Video Equipment Manufacturing to instrument for endogeneity in console price. We employ these and interact them with the product of console age and average game age. The producer price indexes capture industry wide cost changes while the interaction terms produce console specific measures. Finally, we include the Magnetic and Optical Recording Media Manufacturing producer price index and its interaction with the product of console age and average game age as instruments for the number of game titles. Descriptive statistics and estimation results are displayed in Tables 4 and 5, respectively.

We include linear estimations along with the non-linear specification shown in Eq. (10) for comparison. However, we defer to the latter because of the strong support for the non-linear relationship derived in Section 3. The \('\text{interaction term}', 'games: exponent', and 'quality: exponent' rows correspond to the non-linear estimates of \( \delta_{j,t}, \omega_j \), and

\(^{10}\) We accommodate consoles with ‘backward compatible’ capabilities – they can play games designed for a previous generation system – by summing available game titles for the current generation and previous generation system. For example, we include available PlayStation game titles when calculating the number of available game titles for PlayStation 2 since the latter can play games designed for the former.

\(^{11}\) It is unlikely console quality is endogenous since it is determined before a console enters the market. The quality variable calculated from the hedonic estimates in Table 3 is essentially a constant with a monthly age adjustment.
Table 5
Hardware demand estimations: natural log of console share subtracted from natural log of outside option share on console price, number of available games, and console quality.

<table>
<thead>
<tr>
<th></th>
<th>OLS estimations</th>
<th>2SLS estimations</th>
<th>Joint GMM estimations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Non-linear</td>
<td>Linear</td>
<td>Non-linear</td>
</tr>
<tr>
<td>Inflation corrected avg.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Console price</td>
<td>–0.286 (0.253)</td>
<td>–1.223** (0.239)</td>
<td>–0.433 (0.736)</td>
</tr>
<tr>
<td>Number of available games</td>
<td>0.159** (0.016)</td>
<td>0.705** (0.063)</td>
<td></td>
</tr>
<tr>
<td>Console quality</td>
<td>3.897** (0.196)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interaction term</td>
<td>–63.818** (5.068)</td>
<td>0.077 (0.088)</td>
<td></td>
</tr>
<tr>
<td>Games: exponent</td>
<td>–0.035** (0.015)</td>
<td>0.306** (0.080)</td>
<td></td>
</tr>
<tr>
<td>Quality: exponent</td>
<td>–0.790** (0.284)</td>
<td>2.560** (0.594)</td>
<td></td>
</tr>
<tr>
<td>Number of observations</td>
<td>923</td>
<td>923</td>
<td>923</td>
</tr>
<tr>
<td>R²</td>
<td>0.536</td>
<td>0.529</td>
<td></td>
</tr>
<tr>
<td>J Statistic</td>
<td>3.114</td>
<td>5.873</td>
<td></td>
</tr>
<tr>
<td>1-stg F-Stats:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inflation corrected avg.</td>
<td>319.388**</td>
<td>26.420**</td>
<td></td>
</tr>
<tr>
<td>Console price</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of available games</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interaction term</td>
<td>207.782**</td>
<td>53.606**</td>
<td></td>
</tr>
<tr>
<td>Games: exponent</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quality: exponent</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Heteroskedastic consistent standard errors are presented in parentheses.
The dependent variable is the natural log of console share subtracted from the natural log of outside option share.
A constant as well as year and month dummies are included in estimations but not displayed for brevity.

Instruments for 2SLS and GMM estimation are listed in Table 4.

a Estimated jointly with software availability equation (estimation (9) in Table 7).
b Estimated jointly with software availability equation (estimation (10) in Table 7).
* Indicates significance at the 5% level.
** Indicates significance at the 1% level.

Table 6
Market share elasticities computed from hardware demand estimation coefficients in Table 5.

<table>
<thead>
<tr>
<th></th>
<th>OLS estimations</th>
<th>2SLS estimations</th>
<th>Joint GMM estimations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Non-linear</td>
<td>Linear</td>
<td>Non-linear</td>
</tr>
<tr>
<td>Number of available games</td>
<td>0.625</td>
<td>0.693</td>
<td>1.916</td>
</tr>
<tr>
<td>Ratio of console quality elasticity to number of available games elasticity</td>
<td>22.539</td>
<td>26.163</td>
<td>8.355</td>
</tr>
</tbody>
</table>

* Elasticities calculated at average variable values.

ωpq, respectively. ‘number of available games’ and ‘console quality’ are used when those variables enter the model linearly.

Table 5 displays non-linear and linear Ordinary Least Squares (OLS), 2-Stage Least Squares (2SLS), and joint Generalized Method of Moments (GMM) parameter estimates for hardware demand. In the next subsection we estimate software availability (results are displayed in Table 7). However, joint estimation improves efficiency if errors from both equations are correlated. As such, hardware demand and software availability are jointly estimated to obtain joint GMM results (estimations (5) and (6)). OLS and 2SLS results (estimations (1)–(4)) are for hardware demand separate from software variety.

J Statistics and 1-stg F-Stats suggest the instruments are strong. Changes in coefficients from OLS to other estimates imply OLS is biased. Further, the Hausman (1978) statistic is significant in both the linear and non-linear specifications. As such, we prefer either the GMM or 2SLS estimates; we yield to GMM because it is more efficient in the presence of heteroskedasticity.

Overall, parameter estimates conform to priors: price has a negative effect on market share while the number of available games and console quality have a positive effect. We display estimated elasticities of market share with respect to the number of available games and console quality in Table 6 to help with interpretation of coefficients and determine relative effect sizes. Elasticity of market share with respect to the number of available games and console quality are given by ωpq(∂J/∂pq)(∂pq/∂sk)(1 − sk) and ωpq(∂J/∂pq)(∂pq/∂sk)(1 − sk) in the non-linear specification. Therefore, when software availability is included with hardware demand, we expect price to have a negative impact on market share with nonlinear elasticities, as indicated by the negative interaction term coupled with the negative power terms for the number of available games and console quality implying both of those variables exert a positive effect on market share.

Note for the non-linear OLS estimation the negative interaction term coupled with the negative power terms for the number of available games and console quality implies both of those variables exert a positive effect on market share.

12 Note for the non-linear OLS estimation the negative interaction term coupled with the negative power terms for the number of available games and console quality implies both of those variables exert a positive effect on market share.
We control for this potential endogeneity by using cost side instruments similar to those PlayStation 2 purchasers because PlayStation games can be played on the PlayStation 2 console. In the installed base calculations. For example, the installed base for the number of available PlayStation games includes the current period. We accommodate backward compatibility by including all consoles that can play a particular game base and the natural log of console quality. The installed base is the cumulative number of adopters of a console prior to

\[ = 3.858 \times \]

ingcreases market share by 15.664% from Table 6. Second, the indirect effect: a 1% increase in quality will yield a 7.454% two effects when determining the total effect of quality on market share. First, a 1% increase in console quality directly

\[ 2.021\% = 1.046 \times \]

causes a 2.021% (=1.046 \times 1.046) increase in market share. Further, Eq.(6) shows console quality is also a determinant of the number of available games. The last row of Table 6 displays the ratio of console quality and number of available games elasticities to gauge relative importance in terms of market share effects. Our preferred specification (non-linear joint GMM) suggests a 1% increase in console quality implies a roughly 8% greater increase in market share than a 1% increase in the number of available games.

We now turn to estimating the number of available games using Eq.(6) as a guide. Our goal is to ascertain how a console’s installed base effects market share. Further, Eq. (6) shows console quality is also a determinant of the number of available games. This implies two effects of quality on market share: direct through the hardware estimation and indirect through the number of available games estimation.

### 4.3. Software availability estimations

Eq. (6) suggests the natural log of the number of available games depends linearly on the natural log of the installed base and the natural log of console quality. The installed base is the cumulative number of adopters of a console prior to the current period. We accommodate backward compatibility by including all consoles that can play a particular game in the installed base calculations. For example, the installed base for the number of available PlayStation games includes PlayStation 2 purchasers because PlayStation games can be played on the PlayStation 2 console.

Unobserved shocks in the software market in the previous period can produce an increase in the current periods installed base (Clements and Ohashi, 2005). We control for this potential endogeneity by using cost side instruments similar to those described in the previous section. Descriptive statistics are given in Table 4 while the software availability estimations are displayed in Table 7.

We refer to the GMM estimations for our discussion below because evidence suggests the OLS estimate is biased (the Hausman (1978) statistic is significant) while the instruments are strong. It should be noted OLS and 2SLS results are for software availability separate from hardware demand. However, software availability is jointly estimated with hardware demand to obtain joint GMM results. Specifically, estimation (9) and estimation (10) are the software portions of estimation (5) and estimation (6) in Table 5, respectively. We show estimation (10) for comparison, but yield to estimation (9) for our discussion below since it corresponds to non-linear hardware demand.

The coefficients in Table 7 are elasticity estimates given the log–log specification. Evidence from estimation (9) shows the number of available games is 3.69 (=3.858/1.046) times more sensitive to console quality than the installed base. This reinforces the dominance of the quality effect over the network effect.

Using market share elasticities based on the non-linear joint GMM estimates in Table 6, a 1% increase in the installed base will cause a 2.021% (=1.046 \times 1.932) increase in market share. However, as stated above, we must take into account two effects when determining the total effect of quality on market share. First, a 1% increase in console quality directly increases market share by 15.664% from Table 6. Second, the indirect effect: a 1% increase in quality will yield a 7.454% (=3.858 \times 1.932) increase in market share by increasing the number of available games for a console. This implies the total effect of a 1% increase in console quality is a 23.118% (=15.664% + 7.454%) increase in market share. In other words, a 1%
Table 8
Summary statistics for entrants: 31 observations.

<table>
<thead>
<tr>
<th>Dependent variables</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Success</td>
<td>0.323</td>
<td>0.475</td>
<td>0.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entrant Quality</td>
<td>1.193</td>
<td>0.407</td>
<td>0.633</td>
<td>2.397</td>
</tr>
<tr>
<td>Incumbent Network Size</td>
<td>10.094</td>
<td>11.192</td>
<td>0.500</td>
<td>47.000</td>
</tr>
</tbody>
</table>

Table 9
Probit model: entrant success vs. failure.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>−1.073 (0.763)</td>
<td>−0.378 (0.256)</td>
</tr>
<tr>
<td>Entrant quality</td>
<td>0.712 (0.605)</td>
<td>0.251 (0.212)</td>
</tr>
<tr>
<td>Incumbent network size</td>
<td>−0.027 (0.026)</td>
<td>−0.010 (0.009)</td>
</tr>
</tbody>
</table>

Number of observations: 31
Log likelihood: −18.35

Standard errors in parentheses.

Next we examine the relative effects of console quality and network size on overall console success when a console enters the market. We use the yearly data set here because it provides a larger sample since more consoles are represented compared to the monthly data set (34 to 15).

4.4. Quality vs. network size on the probability of entrant success

Consoles are separated into five generations along similar technological dimensions. Generation 1 includes the first consoles to appear in the industry and covers all consoles introduced before 1983. Generation 2 begins with the introduction of the Nintendo Entertainment System in 1985 and includes other 8-bit systems introduced shortly thereafter.

Generation 3 includes 16-bit CPU processor systems Sega Genesis, Sega Genesis CDX, and Super Nintendo. 32-Bit and 64-bit systems 3DO, Atari Jaguar, Atari Jaguar CD, Nintendo 64, Sony PlayStation, and Sega Saturn are included in Generation 4. Microsoft Xbox, Nintendo GameCube, Sega Dreamcast, and Sony PlayStation 2 are Generation 5 systems that use 128-bit processors. The yearly data set does not cover Microsoft Xbox 360, Nintendo Wii, and Sony PlayStation 3.

Consoles are classified as market leaders, laggards, and failures. Market leaders obtain at least 45% of the total market share within a generation. This definition covers situations where two hardware firms split the market. This occurs in the 16-bit generation when the Sega Genesis and the Super Nintendo are equally successful. Laggards are hardware systems that are successful but do not lead. A laggard is defined as a system that obtains at least 15% of the total market share but does not have the largest market share.\(^{13}\) This definition is extended to the 1976 through 1983 era, where market share is not directly observed. Over this time period the percent of software titles available for a console within a generation is used as proxy for the total market share.\(^{14}\)

Probit estimations are used to test whether an entrant’s quality has a larger absolute effect on console success than an incumbent’s network size. A console is considered successful if it becomes either a leader or laggard in its generation. Two independent variables are used. The first is a measure of an entrant’s initial quality advantage. It is given by the entrant’s quality relative to the quality of its largest competitor in the same generation at the time of console introduction. The second is a measure of the incumbent’s network size advantage. This is given by the number of software titles available for the market leader divided by the number of software titles available for an entrant during its first year in the market. Summary statistics and the probit estimation are reported in Tables 8 and 9, respectively.

\(^{13}\) For this industry the cut offs do not matter a great deal. Leaders, laggards, and failures are easy to distinguish. Failures leave the industry almost immediately with few, if any reported sales. Laggards obtain a small but significant market share and survive well into the next product generation. Leaders clearly dominate.

\(^{14}\) As a result the Atari VCS is considered the generation leader while the Mattel Intellivision and Colecovision are laggards. This classification is consistent with the above footnote.
While the estimation is imprecise, both independent variables have the appropriate sign: greater entrant quality increases the likelihood of success while greater incumbent network size does the opposite. It is important to note coefficient values in probit models may be misleading since they do not have a linear relationship with the dependent variable. Often it is useful to report separate marginal effects to interpret results (Greene, 2008). In this case a 10% increase in the entrant’s relative quality above its mean will increase the probability of success by 2.99 percentage points (0.1193 × 0.251 = 0.0299) while a similar relative increase in the incumbent’s network size will decrease the probability of success by 1.01 percentage points (1.0094 × −0.010 = −0.0101). This suggests an entrant’s quality advantage has a larger absolute impact on the probability of success than an incumbent’s network size advantage.

That quality has more import than network size in determining market share and console success may be due in part to the strategic relationship between hardware firms and software firms. This is examined in the next section.

5. Licensing agreements

It is shown in Appendix B that licensing fees are increasing in network size (total number of console consumers) under more general assumptions regarding the price index. In this case, by controlling licensing fees, the hardware firm can indirectly choose the number of software titles available for a system. New hardware firms have an incentive to lower licensing fees in order to induce software firms to develop titles for their system. That is, higher quality entrants can buy their way into the market by offering licensees favorable deals. On the other hand, hardware firms with many consumers, or incumbent systems, have an incentive to raise licensing fees since their large consumer base is attractive to software firms.

While quantitative data is not available, qualitative data from the home video game industry suggests this occurs. For example, before the Microsoft Xbox entered the market in 2001, executives “knew it would be useful to be extremely friendly to developers in ways that the other console makers weren’t.” (Takahashi, 2002, 176). Software firms received cost incentives when developing for the Microsoft Xbox. In fact, Microsoft paid up to 60% of development costs and half of marketing costs of a new software title developed by a third party software firm.15 However, holding other things constant, Sony PlayStation 2 was more attractive to develop software for because of their larger installed base of consumers. As such, Sony was less likely to offer similar incentives when software firms developed for the PlayStation 2.

In contrast, Nintendo used very aggressive licensing tactics when the Nintendo Entertainment System dominated the market from 1986 to 1989. Their strategy was so aggressive that antitrust action was brought against Nintendo in 1991 by the District of Columbia and the attorney generals of all 50 states. Among the many charges was “overregulating licensees” (Kent, 2001, 389) where game developers entered into exclusive agreements with Nintendo barring them from developing the same game for competing systems for a period of 2 years.

This case, and the potential anticompetitive effects of exclusive dealings, was addressed by Shapiro (1996, 19) in his speech to the American Law Institute and American Bar Association: “Nintendo’s exclusivity requirement reduced the attractiveness of the Atari and Sega systems, and made it all the more likely that the market would tip entirely towards Nintendo.” However, we would urge antitrust authorities to use caution when evaluating these instances.

The exclusivity requirements increased costs for game developers (e.g. the opportunity cost of not developing games for a competing system) consistent with our competitive framework. This necessarily limited the number of available games for Nintendo thereby reducing the attractiveness of its network. This allows for a more competitive environment in the hardware market: potential console entrants will not face as large a network disadvantage and become attractive alternatives for game developers.

However, antitrust action against this type of behavior may have perverse effects. Also in his speech, Professor Shapiro (1996, 8) stated “the single most important goal of antitrust in network industries is to insure that competition from new products and new technologies is not stifled.” Artificially decreasing software licensing costs for leading consoles through antitrust action will increase their game offerings and, by extension, their network advantage. As a result, higher quality entrants will find it more expensive to buy their way into the market with favorable licensing deals. In short, entrants are less likely to succeed. This may stifle competition in exactly the way Professor Shapiro warned against.

6. Conclusion

This paper develops a game theoretic model using a discrete-choice demand structure to characterize competition between incompatible hardware systems. Overall, evidence implies quality is more important than network size in the home video game industry. Quality affects market share in two ways: first, there is a direct effect of quality on hardware demand, and second, greater hardware quality positively affects the number of available games. In fact, hardware quality has a greater effect on the number of available games than network size. In total, market share is 11.4 times more sensitive to hardware quality than network size. Finally, hardware quality has a larger impact than network size on the probability of hardware success. These results help clarify the role of indirect network effects and quality improvements in standards competition.

15 Interview of Steve Allison, Vice President of Marketing, Infogrames, conducted by this author (2003).
While quality is important, strategic interaction between hardware and software firms may also influence results. Theoretical and qualitative evidence demonstrates hardware firms with larger relative networks are able to dictate more favorable licensing terms with their third party software providers. Or conversely, entrants are likely to provide incentives to induce third party software providers to develop for their hardware. However, antitrust policy could have a perverse affect on hardware turnover by indirectly making it more difficult for high quality entrants to attract software.

Further research comparing industries with different strategic settings would be useful. Results may differ when higher quality entrants do not have the ability to buy their way into the market. This could be a reason why Ohashi (2002) and Park (2004) find evidence of excess inertia in their studies of the VCR industry.

Another interesting extension would be to compare the relative effects of console quality and network size while taking into account differences in software quality. That is, our analysis has assumed games are symmetric; clearly this is not the case for the video game industry. For example, Coughlan (2001) finds the top 10 best-selling games in the late-1990s account for 1/3rd of global revenue. Given this, it is likely that some games have a much larger influence on console adoption than others. A key issue is comparing the network effect for the most important games (in terms of console adoption) vs. all other games. Our estimate of the network effect based on the number of available games (not taking into account software asymmetry) will be overstated if the network effect for the most important games is less than the network effect for all other games. We suspect this is likely given “industry wisdom seems to be that software provision is crucial for the establishment of a console” (Clements and Ohashi, 2005, 539). That is, consoles have an incentive to introduce those games with a much larger influence on adoption early in the console’s life (i.e. when the network is small) in order to obtain greater market penetration.

Role of the funding source

The Bradley University Foster College of Business Administration Faculty Development Grant was used to purchase data from the NPD Group.

Appendix A.

The decision process in the two-stage budgeting procedure is as follows: first consumers maximize by allocating income between the numeraire good, \(x_0\), and the quantity index for software compatible with hardware \(k\), \(z^k\), then consumers choose the optimal quantity for each software title, \(x^k_j\). Analysis begins in the second stage where the goal is to find \(x^k_j\) as a function of \(z^k\).

A.1. Second stage of the budgeting process

In the second stage of the two-stage budgeting process new consumer \(i\) chooses \(x^k_j\) to maximize

\[
U^k_{i,k} = y - p^h_k - \sum_{j=1}^{k} p^k_{j,j}x^k_j + \left(\sum_{j=1}^{k} (x^k_j/\delta^k_j)^{1/\beta}\right)^{1/\alpha} \tag{A1}
\]

Plugging the budget constraint into (2) gives (A1). By manipulating the first order condition and substituting in for \(z^k = \left(\sum_{j=1}^{k} (x^k_j/\delta^k_j)^{1/\beta}\right)^{\beta}\) we obtain

\[
(x^k_j/\delta^k_j)^{1/\beta} = (\alpha\beta)^{-1/\beta - 1}(z^k)^{-(\alpha - 1)/(\alpha\beta - 1)}(p^k_{j,j}/\delta^k_j)^{-1/\beta - 1} \tag{A2}
\]

Plugging the right hand side of (A2) into \(z^k\) and manipulating yields the useful equality

\[
z^k(\Omega^k)^{\beta/(\beta - 1)} = (\alpha\beta)^{-\beta/(\beta - 1)}(z^k)^{-(\alpha - 1)/(\alpha\beta - 1)} \tag{A3}
\]

where \(\Omega^k = \left(\sum_{j=1}^{k} (p^k_{j,j}/\delta^k_j)^{-1/\beta - 1}\right)^{-1/\beta - 1}\) is a modification of the price index for software introduced by Dixit and Stiglitz (1977).\(^\dagger\)

\(^\dagger\) This price index differs from Dixit and Stiglitz (1977) in that price is relative to quality, \(\delta^k_j\).
Solve \( (A2) \) for \( x_j^k \) and substitute in for the right hand side of \( (A3) \) to obtain the goal of the second stage
\[
x_j^k = z^k(\Omega^k)^{\beta/(\beta - 1)} \left( \frac{p_j^k}{\partial J_j^k} \right)^{-\beta/(\beta - 1)} \frac{1}{\partial x_j^k}
\]  
(A4)

Now we move to the first stage of the budgeting process where the goal is to find the optimal \( z^k \).

A.2. First stage of the budgeting process

Substitute \( (A4) \) into \( (A1) \) and plug in for the price index of software, \( \Omega^k \), to write the consumers optimization problem in the first stage as
\[
U_{i,h}^k = y - p_h^k - z^k \Omega^k + (z^k)^{1/\alpha \beta}
\]

(A5)

Maximizing \( (A5) \) subject to \( z^k \) and solving gives
\[
z^k = (\alpha \beta)^{-\alpha \beta/((\alpha \beta - 1) \Omega^k)^{-\alpha \beta/((\alpha \beta - 1)}}
\]

(A6)

Finally, substitute \( (A6) \) into \( (A4) \) to obtain the demand for software title \( j \) shown in Eq. (3).

Appendix B.

In this appendix we allow for the possibility that the number of software titles is sufficiently small to invalidate the standard assumption of \( \partial \Omega^k / \partial p_{s,j}^k = 0 \). This is often the case in the video game industry when a new hardware entrant with a relatively small selection of games competes with an established hardware system. The deviation from the literature is necessary to highlight the affect of network size on licensing fees. We proceed as follows: first we find the equilibrium number of software titles implicitly defined in \( (B3) \) to solve for their optimal licensing fee. Note \( x^k \) is a function of both \( k \) and \( \theta^k \) in \( (B2) \) and \( j^k \) is a function of \( \theta^k \) in \( (B3) \). The first order condition for licensing fees from the hardware firm’s profit given by \( (7) \) is thus
\[
N^k \left( p_s^k \frac{\partial J^k}{\partial p_s} + j^k \left( x^k + j^k \left( \frac{\partial x^k}{\partial k} + \frac{\partial j^k}{\partial k} \right) \right) \right) = 0
\]

(B4)

Taking the partials of \( x^k \) given in \( (B2) \) yields
\[
\frac{\partial x^k}{\partial j^k} = -\frac{\beta k x^k (j^k (\alpha \beta - 1) (\alpha - 1) + j^k (\alpha \beta - 1) \beta (\alpha - 1) + \beta (\alpha - 1)^2)}{j^k (\alpha \beta - 1) (j^k (\alpha \beta - 1) - \beta (\alpha - 1)) (j^k (\alpha \beta - 1) - \alpha + 1)}
\]

(B5)
and

$$\frac{\partial x^k}{\partial x^k} = \frac{-\alpha \beta x^k}{(\alpha \beta - 1)(c_3 + I)}$$  \hfill (B6)

However $\partial j^k / \partial x^k$ is not as straightforward since $j^k$ does not have a closed form solution. It is helpful to define the left hand side of the zero profit condition in (B3) as $\Phi$ so that $\partial j^k / \partial x^k = - (\partial \Phi / \partial \Phi^k)(\partial \Phi / \partial j^k)$. The partial in the denominator is given by

$$\frac{\partial \Phi}{\partial j^k} = \beta(\alpha - 1)(j^k)^{\beta - 1}(j^k(\alpha \beta - 1) - \alpha + 1)^{\beta - 1} \times \frac{j^k(\alpha \beta - 1)(j^k(\alpha \beta - 1) - \beta(\alpha - 1)) - (\alpha - 1)(\beta - 1)}{(j^k(\alpha \beta - 1) - \beta(\alpha - 1))^2}$$  \hfill (B7)

It is convenient to substitute from the zero profit condition for the partial in the numerator as follows:

$$\frac{\partial \Phi}{\partial x^k} = \left(\frac{(\beta - 1)(2\beta - 1)N_k^k}{f_s}\right)^{2\beta - 1} \frac{\partial}{\partial x^k} \frac{j^k(\alpha \beta - 1) - \beta(\alpha - 1)}{(2\beta^2)^{2\beta}(c_3 + I^k)^2} = \frac{(j^k)^{1-\beta}(j^k(\alpha \beta - 1) - \alpha - 1)^{\alpha \beta}}{(j^k(\alpha \beta - 1) - \beta(\alpha - 1))(c_3 + I^k)}$$  \hfill (B8)

Dividing (B8) by (B7) and multiplying by $-1$ gives

$$\frac{\partial j^k}{\partial x^k} = -\frac{j^k(j^k(\alpha \beta - 1) - \beta(\alpha - 1)) - (\alpha - 1)(\beta - 1)}{j^k(j^k(\alpha \beta - 1) - \beta(\alpha - 1)) - (\alpha - 1)(\beta - 1)}$$  \hfill (B9)

Substitute (B5), (B6), and (B9) into (B4) and solve for $j^k$ to obtain

$$j^k = \frac{\beta(\alpha - 1)c_3(j^k(j^k(\alpha \beta - 1) - \beta(\alpha - 1)) - (\alpha - 1)(\beta - 1))}{j^k(j^k(\alpha \beta - 1) - \beta(\alpha - 1)) - (\alpha - 1)(\beta - 1)}$$  \hfill (B10)

B.3. Licensing fees and network size

Since $N^k$ is not explicitly in the right hand side of (B10) we use the chain rule, $\partial j^k / \partial N^k = (\partial j^k / \partial f^k)(\partial f^k / \partial N^k)$, to obtain the effect of network size on licensing fees. The first part of the equation,

$$\frac{\partial j^k}{\partial N^k} = \frac{\beta(\alpha - 1)^2(\beta - 1)c_3(j^k(j^k(\alpha \beta - 1) - \beta(\alpha - 1)) + 2\alpha - 1)}{(j^k)^2(\alpha \beta - 1) - \alpha + 1)^2}$$  \hfill (B11)

is found directly from (B10) however the partial $\partial j^k / \partial N^k$ is not as straightforward. We use a method similar to the one employed in the above subsection when finding $\partial j^k / \partial f^k$ to obtain $\partial j^k / \partial N^k$. First substitute the profit maximizing licensing fee given in (B10) into the zero profit condition for software firms given in (B3) to obtain the equality

$$\frac{c_3(j^k(\alpha \beta - 1) - \alpha + 1)^{\alpha \beta - 1}}{(j^k)^{\beta}(\alpha \beta - 1)} = \frac{\beta(\alpha - 1)(\alpha \beta - 1))}{1}$$  \hfill (B12)

Moving all of (B12) to one side and labeling the quantity $A$, it is the case that $\partial j^k / \partial N^k = - (\partial A / \partial N^k)(\partial A / \partial j^k)$.

The numerator and denominator are given below:

$$\frac{\partial A}{\partial N^k} = - \frac{(\alpha \beta - 1)(\beta(\alpha - 1) - 1)}{N^k(\alpha \beta - 1) + 1)^{\alpha \beta - 1}} \frac{\partial j^k}{(\alpha \beta)^{\alpha \beta}}$$

and

$$\frac{\partial A}{\partial j^k} = \frac{\beta(\alpha - 1)c_3(j^k(j^k(\alpha \beta - 1) - \beta(\alpha - 1) + 2\alpha - 1)(\beta - 1)) + (\alpha - 1)(\beta - 1)}{(j^k)^{\beta+1}(\alpha \beta - 1) + 1)^{\alpha \beta - 1}}.$$

Using (B12) to substitute for part of the numerator we can express $\partial j^k / \partial N^k$ as

$$\frac{\partial j^k}{\partial N^k} = \frac{(\alpha \beta - 1)(\beta(\alpha - 1) + 1) + (\alpha - 1)(\beta - 1)}{(j^k)^{\beta}(\alpha \beta - 1) + 1)^{\alpha \beta - 1}} \times \frac{\beta(\alpha - 1)(\alpha \beta - 1) - \alpha + 1}{\beta(\alpha - 1)N^k}$$  \hfill (B13)

Multiplying (B11) and (B13) gives

$$\frac{\partial j^k}{\partial N^k} = \frac{j^k(\alpha \beta - 1)(\beta(\alpha - 1) + 1) + (\alpha - 1)(\beta - 1)}{(j^k)^{\beta}(\alpha \beta - 1) + 1)^{\alpha \beta - 1}} \times \frac{j^k(\alpha \beta - 1) - \beta(\alpha - 1)) + (\alpha - 1)(\beta - 1)}{(j^k)^{\beta}(\alpha \beta - 1) + 1)^{\alpha \beta - 1}}$$

Finally, we sign the derivative in the proposition below:
Proposition. In a symmetric software equilibrium, when the derivative of the price index for software with respect to a single price is different from zero, or \( \frac{\partial Q_k}{\partial p_k} \neq 0 \), software licensing fees are (weakly) positively related to the number of consumers. Formally, \( \frac{\partial F}{\partial N_k} \geq 0 \).

Proof. With \( \alpha > 1 \) and \( \beta > 1 \) by assumption (see Eq. (2)) Eq. (B14) is unambiguously non-negative if the second part is positive (Eq. (B14) is zero when \( \alpha = 1 \)). The requirement is for \( f_k(\alpha \beta - 1) - \alpha + 1 \) and \( f_k(\alpha \beta - 1)\frac{\partial f_k}{\partial p_k}(\alpha \beta - 1 + 2) - \alpha + 1 \) to have the same sign. Recall that the equilibrium \( f_k \) solves Eq. (B12). For (B12) to hold the left hand side has to be positive since the right hand side is positive for valid parameter ranges (positive numbers for consumers, costs, quality, etc.). This implies \( f_k(\alpha \beta - 1) > \alpha - 1 \) for any valid \( f_k \). Therefore \( f_k(\alpha \beta - 1) - \alpha + 1 \) and \( f_k(\alpha \beta - 1)\frac{\partial f_k}{\partial p_k}(\alpha \beta - 1 + 2) - \alpha + 1 \) are each positive.

We discuss implications of the positive relationship between network size and licensing fees in Section 5.

References