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An Empirical Analysis of Indirect Network Effects in the Home Video Game Market*

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Abstract: We explore the indirect network effect in the market for home video games. We examine the video game console makers' strategic choice between increasing demand by lowering console price and by encouraging the growth of software variety. We also explore the existence of an applications barrier to entry in the console market, and find that there is little evidence for such a barrier. Finally, we assess the applicability of the model to out-of-sample situations, to look at whether our model and previous similar models can generalize to other markets for purposes of marketing or antitrust inquiry. We find that the model generalizes reasonably well to the Japanese market for the same generation of gaming systems, but poorly to previous generations in the US market.

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1. Introduction

Modern high tech firms compete by leveraging economies of scale. To stimulate demand and achieve economies of scale, such firms take advantage of indirect network effects, whereby the consumer valuation of the primary product increases with the size of a complementary good market. In our application, the primary product is the video game console—GameCube, PlayStation2, or XBOX—and the complementary good is gaming software. We empirically explore the indirect network effect in the market for sixth generation home video games.

The economic issues we investigate are threefold: examination of the video game console makers' strategic choice between increasing demand by lowering console price and by encouraging the growth of software variety, exploration into the importance of applications barriers to entry, and assessment of the applicability of previous econometric studies to new situations. We begin by empirically estimate the size of the network effect and how firms may use it to achieve economies of scale. We examine the firm's choice between increasing demand by lowering console price and by encouraging the growth of software variety. This part of the study gives us a better understanding of firms' business strategies in markets for high tech consumer goods. We follow in the tradition of recent papers in this area (Nair, *et al*., 2004; Clements and Ohashi, 2005), and thus complements the growing literature on the empirical measurement of indirect network effects.

The second economic issue involves questions of public policy in network markets. After estimating our structural econometric models, our detailed price and game variety data allow us to explore the impact of a console maker's ability to negotiate the creation of games that cannot be played on its competitors' platforms. Can the console maker's negotiating power, in conjunction with the indirect network effects from the video games, create an applications barrier to entry in the console market? Because empirical assessment of applications barriers to entry are rare, our results here—essentially negative—are of particular interest for antitrust economics.

Finally, we investigate the applicability of such econometric studies to new situations. There is a growing set of empirical studies of markets with indirect network effects. Are these case studies valuable for providing general insight into network markets, or do their conclusions have little predictive power for new markets? The extant literature gives no indication at all on the extent to which results from case studies apply to new situations, which is important in the arenas of marketing and antitrust. We undertake a meta-inquiry into the generalizability of results gleaned from such studies. To approach this issue we take advantage of the fact that our data come from the next generation of video games produced after the consoles studied in Clements and Ohashi (2005). We are thus able to see how useful their results, estimated from previous hardware generations, are toward explaining consumer demand and the size of the network effect in the out-of-sample (but closely related) sixth generation video game market. We also explore how well our model, estimated with US data, would do in out-of-market extrapolation to the Japanese market.

We find significant effects of both price and software variety on console demand. Indirect network effects are present, but the ability to which software can substitute for lower prices is modest: a one percent increase in software variety is equivalent to a 0.39 percent price reduction. We also find evidence that software is perishable, in the sense that the existence of older titles does not affect hardware demand as do newer titles.

Furthermore, we find that there is little evidence for the existence of an applications barrier to entry in the console market. Firms appear to have little power to build or maintain market share through developing large stocks of games for their systems. Finally, when we compare our results to out-of-sample situations, to look at whether our (and similar) models can generalize to other markets, we find that the model generalizes reasonably well to the Japanese market for the same generation of gaming systems, but poorly to previous generations in the US market. Similarly, models estimated by others for previous generation markets do not extrapolate well to our market data. These latter results provide a cautionary note on the applicability of structural models of indirect network effects to new markets and data.

In the rest of this section we mention the literature we build upon and how our study differs. Empirical studies of markets in which indirect network effects are introduced through a complementary good include Gandal, Kende, and Rob (2000), Dranove and Gandal (2003), Nair, *et al*. (2004), and Clements and Ohashi (2005). These studies build upon an earlier empirical literature on direct network effects in such markets as fax machines (Economides and Himmelberg, 1995) and spreadsheets (Gandal, 1994). We follow the New Empirical IO program and adopt a structural empirical model developed by Nair, *et al*. (2004), who derive it from a theoretical model of consumer preferences for hardware and software and competitive provision of software. The indirect network effect is then identified from the interaction of the hardware and software markets. Two equations are estimated, one for console market share and another for software variety.

Our choice of industry and econometric model are similar to that of Clements and Ohashi (2005). However, we investigate different issues, focusing less on the evolution of the product life cycle than the potential for applications barriers to entry and the generalizability of the results. We also explore in the hardware demand estimation whether games become entirely “played out” after a few months, and find that they do.

We describe the home video game market in the next section. In section 3 we present the theoretical and empirical models of indirect network effects. We present and discuss our data in section 4, and the estimations in section 5. In section 6, we explore the potential for an applications barrier to entry. In the following section, we compare our results to previous studies and explore the out-of-sample predictive power of the model.

2. The Market for Sixth Generation Home Video Games

Video games play a large role in the American entertainment market. In the US, 75% of household heads play computer or video games, and the average gamer spends more than triple the amount of time playing video games each week than time spent in exercise, reading, and community, religious, and creative activities combined.[1] In 2004, US households purchased software for two video games on average, and the total sales of consoles, portable devices, and software in the video game industry is nearly $10 billion, greater than that of Hollywood’s box office.

In Figure 1, we depict a simplified market structure showing the interaction between agents involved in the video game industry. A video game system is a

[1] Entertainment Software Association, “Essential facts about the computer and video game industry,” May, 18, 2005.

combination of hardware and software, each with separate producers. We focus on the sixth generation 128-bit[2] video game system, which includes PlayStation2 (Sony), XBOX (Microsoft), GameCube (Nintendo) and Dreamcast (Sega). Since Sega dropped out of the market in 2000 and was never a major player, we do not include Dreamcast in the analysis.

As shown in Table 1, PlayStation2 entered the US market first, in October 2000, while XBOX and GameCube appeared simultaneously in the US market one year later. Entering later allowed Microsoft to introduce a console with the best hardware quality, evaluated in terms of the speed of the graphics processing unit (GPU), central processing unit (CPU), and memory (RAM). Except for memory size, GameCube also has better hardware quality than PlayStation2. Even with higher hardware quality, XBOX and GameCube did not set higher prices than PlayStation2. Table 1 shows that Microsoft priced its XBOX similarly to PlayStation2, while Nintendo set GameCube's price well below the other two.

The great advantage enjoyed by PlayStation2 is its large amount of available software. During our data period (March 2002-Dec 2004), PlayStation2 started with the most software and maintained its lead by providing almost half of the new software available in the market. PlayStation2's leading position in software provision strengthens hardware sales, due to the complementary nature of hardware and software, and helps to explain why PlayStation2 is the best-selling console in the market given its higher price and poorer hardware quality. Figure 2 (monthly sales) shows that within our data period

[2] Console generations are distinguished by the instruction word length of the CPU, which indicates the maximum complexity of any single command sent to the processor. In 1977, Atari introduced the 2600, a 4-bit video game system that was the first generation of home gaming systems.

PlayStation2 has the highest console sales each month, except for the occasional banner month by XBOX.

Different brands of hardware are not compatible with each other[3]—software designed for one brand cannot be played on another. As a result, when a consumer buys a console, he can enjoy the machine only by purchasing the software designed for that specific console. Because of the mutual incompatibility among consoles, buying a console and consequently purchasing games is akin to choosing a platform to trade with software providers. Due to this two sided market feature, there are two sources of revenue for console producers: revenue from consumers by selling hardware and revenue from game publishers by charging license fees and royalties to game developers.

To attract consumers, console producers advertise in the media and exhibit at trade shows at great expense. Microsoft spent an industry-record $500 million in 18 months for the marketing of XBOX, attempting to catch up to PlayStation2 (Schilling, 2003). The tremendous effort expended chasing console sales is not for the purpose of profiting from the hardware. There is evidence that at least Microsoft and Sony set console prices below marginal cost.[4] Instead, console makers hope to earn their profit from the sales of gaming software. Low console prices play a dual role for hardware manufacturers. Through low prices, console manufacturers increase their installed base, which due to the indirect network effects increases sales of profitable software. Low prices may also be a response to a potential holdup problem: if after buying the console a

[3] The exception is the backward compatibility of different generation of hardware produced by the same manufacturer. For example, the software for PlayStation (5th generation) can be played in PlayStation 2, and XBOX games can be played on XBOX 360 (7th generation) with a peripheral.
[4] A Merrill Lynch report, reported in *D. Becket and J. Wilcox, "Will Xbox Drain Microsoft?" CNET News.com, 2001*, estimates that XBOX would cost Microsoft $375 per unit. This appears to be the marginal cost of the hardware only, and does not include sales, marketing, or development costs. The price at launch for XBOX was $299. The article also cites an IDC analyst who claims Microsoft's per-unit loss on XBOX is comparable to Sony's loss on PlayStation2.

consumer could be exploited to pay high prices for software, forward-looking consumers would be willing to pay lower prices for hardware.

The business model of the gaming industry—consoles as loss leaders for software—makes it crucial for hardware manufacturers to maintain good relationship with game publishers to ensure they create appealing games. In Table 2 we present the information of software provision. Independent software publishers produce the most software (92% of the total), with a far smaller amount created by the console manufacturers. A software publisher may produce its games in-house or contract out to independent developers.[5] Even when games are produced by independent developers, due to royalty agreements the console maker profits directly from game sales. The average cost of developing a 128-bit game is about $6 million,[6] which includes licensing fees paid to content providers.[7]

A game publisher will consider a console's current and expected installed base when deciding for which platform to write a game. Negotiations over license fees and royalties hinge on the game's potential popularity (about which much may be known [e.g., yearly editions of the popular *Madden NFL* sports game]) and whether it is provided exclusively for the console. In Table 2 we also show the proportion of software that is provided exclusively, which is one measure of product differentiation among systems. PlayStation2 has the greatest proportion of exclusive software, showing its bargaining strength with software publishers and developers. Software publishers undertake their own marketing as well through advertising and trade show participation.

[5] The main independent publishers are: EA, Ubisoft, VUGames, THQ, Sega, Namco, Midway, Konami, Acclaim, Atari, and Activision.
[6] Southwest Securities, *Interactive Entertainment Software: Industry Report*, Fall, 2000.
[7] For example, publishers of NBA basketball games have to pay license fees to the NBA.

Costs are certain but rewards are not: only a small portion of games are profitable.[8] The distribution of returns is highly skewed: a mega-hit such as *Grand Theft Auto – San Andreas* has a return more than 40 times of the average development cost.

3. Modeling Indirect Network Effects

3.1 Hardware Adoption

Our focus is on the hardware adoption and software provision of a hardware-software system. The techniques we intend to use are now well established in the empirical literature on indirect network effects, and we therefore present them here in abbreviated form. Our empirical models are derived from a theoretical model of consumer utility for hardware and software and competitive, free entry supply of software. The hardware supply side is left unspecified. The theoretical model is derived by Chou and Shy (1990) and Church and Gandal (1992, 1993), and extended by Nair, *et al*. (2004).

Consumers maximize utility in a static framework through the choice of a video game console and software. Utility comes from hardware attributes and from complementary software. Consumers choose among $J + 1$ alternative systems in the market, including the outside option of purchasing no system. Utility is additively separable in hardware and software. Utility from software is in CES form (à la Dixit and Stiglitz, 1977), which leads to a closed form expression for demand for software titles (of which there are N_{jt} for system j in month t) as a function of software prices. Specifying CES utility implies that each consumer values all (compatible) software equally.[9]

[8] In the late 1990 only 10% of software released can turn into profit (Coughlan, 2004).
[9] Refer to Clements and Ohashi (2005) for discussion of this simplifying assumption.

To derive an estimating equation for console demand, we begin with utility for consumer i for gaming system j in month t:

$$U_{jt}^{i} = \beta_0 + \beta_p p_{jt} + \beta_x x_j + \delta N_{jt} + \xi_{jt} + \varepsilon_{jt} \qquad (1)$$

where p_{jt} is the hardware price of system j and x_j represents hardware attributes. Hardware attributes are characteristics such as the instruction word length of the CPU (e.g. 128 bit), the speed of the CPU and the Graphics Processing Unit (GPU), and the amount of RAM. Thus $\beta_x x_j$ reflects the average benefit derived from hardware quality. The term δN_{jt} is the indirect network effect derived from the theoretical model for software demand. The static formulation of the model restricts consumers to making decisions in month t based only on software currently available, not anticipated future stocks of software.

In moving from the theoretical model to the empirical model, in this version of the paper we simplify estimation by restricting N_{jt} to enter (1) in linear (or quadratic, in some specifications) form.[10] The term ξ_{jt} captures the deviation of average hardware quality of console j known to the consumers but not the econometrician, and we assume that (conditional on exogenous observables) $E(\xi_{jt}) = 0$. The variable ξ_{jt} incorporates all variables pertaining to consumer perceptions about the hardware brand not elsewhere included in the data, such as advertising, the "word on the street", etc. To control for various time varying effects on demand, we also include holiday dummies and year dummies, and their interactions with brand dummies. When brand (console) dummies are included, β_x is not estimable, because x_j does not change over time within our sixth-

[10] The theory implies that N_{jt} enters as a power function with coefficient between 0 and 1. Clements and Ohashi (2005) find that when they allow more flexible functional forms for N_{jt} they cannot reject a linear relationship.

generation data. Furthermore, when we include console effects, ξ_{jt} is then interpreted as deviations over time (net of the average tastes for console j) in consumer tastes for the console brand. Allowing ξ_{jt} to vary over time reflects the non-constant nature of advertising and evolving consumer perceptions of the brand.

Assuming ε_{jt} follows a nested logit distribution leads to the familiar nested logit model. The decision tree for the consumers has two levels. In the first stage, consumers decide whether to buy any console at all. If households decide to buy, they next choose which brand of console to buy. This model leads to an intuitive substitution pattern: when a household switches away from a console it is more likely switch to another console than to not buying. This decision tree leads to the following nested logit estimating equation:

$$\ln(s_{jt}) - \ln(s_{0t}) = c_j + d_t + \beta_p p_{jt} + \beta_x x_j + \delta N_{jt} + \sigma \ln(s_{jt}|_g) + \xi_{jt} \qquad (2)$$

where s_{jt} represents the market share of hardware j in month t, and s_{0t} is the market share of outside alternatives. In (2), we explicitly include the brand dummies c_j and the holiday and year dummies d_t. To avoid possible confusion, note that the time dummies d_t do not amount to a full set of period (monthly) dummies; with our brand-month data this is not possible. Rather than assuming that each household purchases anew each period, we remove the household from the market base in future periods if it has already purchased a system, tantamount to assuming that each household buys one console only. We relax this assumption when we check the robustness of our empirical results. The term $s_{jt}|_g$ represents the within-group market share of console j (defined as $s_{jt}/(1 - s_{0t})$); its coefficient σ represents the correlation between consumer choices within the nest, and thus is bounded between zero and one. Higher values of σ reflect a greater likelihood that a consumer switching away from one gaming console will choose another system rather than none at all (the outside good, which is the single element of the other nest). In our empirical work, we found that the nested logit model did not provide a good fit for the hardware demand data, and so the estimates we discuss most come from a simpler logit model, which is identical to (2) with $\sigma = 0$. We estimate the model via an efficient version of linear instrumental variables (IV), a procedure suggested by Berry (1994) that is commonly used in discrete choice demand estimation using aggregate data. Rather than using traditional two-stage least squares, we use a GMM procedure that is efficient in the presence of heteroskedasticity and autocorrelation.[11] Autocorrelation can arise in the model from the interpretation of the error term as incorporating consumers attitudes about brands. While these may change month to month, it is likely that there will be persistence due to the effects of advertising campaigns and the like. Autocorrelation in the errors is not ignorable in this model (i.e., it does not affect merely the efficiency of the estimates) because it gives rise to an endogeneity problem, described in section 4.

3.2 Software Supply

On the software supply side, there are many potential firms, each of which can produce one software title for one platform. Marginal cost is constant and fixed costs are present, ensuring a well-defined free-entry equilibrium with symmetric prices (the latter ensured by the CES demand for software). The equilibrium number of software titles, N_{jt}, is derived from the theoretical model. Given the assumptions, log N_j is affine in the log

[11] In particular, we use the `ivreg2` add-on command for Stata with the "`gmm robust bw(2)`" option. This estimates the two-step efficient GMM estimator, where the covariance matrix used for estimation and standard errors is robust to both heteroskedasticity and autocorrelation. The Bartlett kernel (with bandwidth set to one lag) is used to estimate the autocorrelation. For the joint estimations, we cannot use ivreg2 and instead use the `gmm` command in TSP, with similar options chosen.

of console installed base, Y_{jt}, which leads to a simple form for econometric estimation. The estimating equation for software supply is:

$$\ln(N_{jt}) = \alpha_j + d_t + \gamma \ln (Y_{jt}) + \eta_{jt} \qquad (3)$$

where α_j is a brand fixed effect, Y_{jt} is the installed base of system j up to time t–1, and η_{jt} is a mean zero error term. Because the brand effect could change over time, we control for year dummies, holiday dummies, and their interactions (d_t).[12]

Equation (3) for software supply is the second estimating equation. Equations (2) and (3) may be estimated consistently by themselves, or jointly for more efficient estimation. We do both below.

It is important to note that we do not estimate a fully dynamic structural model here. In particular, the software supply decision is made anew each period, based on the current installed base of systems, without taking into account the role of expected future console sales (except through the console-level and console-year fixed effects). Similarly, hardware demand is based only on the current stock of software available, without explicitly accounting for expected future software variety. Again, some of these expectations no doubt contribute to the console-level and console-year fixed effects in the demand estimation.

4. Data and Endogeneity Issues

4.1 Data

The data we analyze is for the sixth-generation home video game market, including consoles PlayStation2 (Sony), XBOX (Microsoft) and GameCube (Nintendo). The potential market size for hardware is calculated as the total number of households

[12] Again, note that d_t do not take different values every month.

with at least one television, which is found in the Census Bureau's 2004-2005 *Statistical Abstract of the United States* (2002 vintage data). The monthly console sales data are from NPD Fun Group, acquired from gaming news site PCvsConsole.com. The console sales data, along with the calculated market size, allows us to create all market share variables from March 2002 to December 2004 (34 months). The start of the sample period is chosen to accord with XBOX's entrance into the Japanese market, since we use Japanese market data as instruments below. The end of the period is chosen to minimize the possible impact on demand due to the anticipated introduction of next generation systems (specifically, XBOX360). XBOX360 entered the market November 2005, and the press heralded its advent as early as Microsoft's official announcement in May 2005. Since we do not model forward-looking behavior in our static model, we end our sample period well before XBOX360 was announced. Summary statistics on the data are in Table 3.

We collected monthly hardware price data (average of weekly prices) from the websites of seven major retail chains, including CompUSA, Electronics Boutique, Target, Game Stop, Fry's Electronic, Toys 'R' Us and KB Toy Works. Prices are adjusted by the consumer price index.[13] Console characteristics are from manufacturer's websites.

The game title data for software is from Gamespot.com, which maintains a complete list of games published for PS2, XBOX and GameCube.[14] These data show the publisher's identity, date of issue, and for which consoles the game is available. When constructing the software variety variable N_{jt} from these data, we assume the software is to some degree "perishable" to consumers. Instead of adopting the commonly used

[13] CPI: All urban consumers, all items.
[14] Unlike Clements and Ohashi (2005), we do not have sales data for software.

measure of *total* software variety, accumulated since the introduction of the console, we assume that potential consumers care more about recent titles. Thus, we split software into two categories: new titles issued in the current and previous three months, and the rest of the accumulated (older) titles. This treatment for accumulated software is suggest by evidence that often the life cycle of a video game title is brief, often with more than 50% (and sometimes as much as 80%) of sales typically occurring during the first three months after its release (Coughlan, 2001, 2004). A longer-run reason for software perishability is that the most popular titles are regularly updated (e.g., Halo vs. Halo2; NFL 2003 vs. NFL2004), which reduces demand for older versions.

For the holiday dummies, we allow console demand and software supply to differ during peak game purchasing times: June for the start of summer vacation, and November/December for the year-end holiday season.

4.2 Endogeneity and Instruments

In the rest of this section we address the potential for endogeneity of several of the variables appearing on the right side of the hardware adoption and software provision estimating equations, and discuss our solutions.

Endogeneity in the Hardware Adoption Equation

In the hardware adoption model, the variables we suspect may be correlated with the error term in (2) are observed hardware characteristics, within group share, console price, and software variety. The unobserved hardware attributes, ξ_{jt}, could be generated from the impact of promotional activity, brand image, or other unobserved systematic shocks to demand. Such effects and shocks are likely to be correlated with observed hardware characteristics x_j because brand image (for example) could be affected by hardware quality, and evolve over time as exposure to advertising increases. The endogeneity of within group market share, $s_{jt|g}$, arises by definition: it contains the dependent variable, s_{jt}. Within group market share appears in the nested logit specification but not the simple logit. Console price p_{jt} is most likely positively correlated with the unobserved attributes because an improvement in brand image will increase consumer's willingness to pay for consoles, which affects prices in the market. Finally, the endogeneity of game variety arises due to the interaction between hardware adoption and software provision: a positive shock in hardware demand increases the installed base the next period, which in turn leads to increased software provision at time t. Therefore if ξ_j is an autocorrelated series, N_{jt} and ξ_{jt} are positively correlated. Note that unlike previous papers we explicitly account for the presence of autocorrelation in our GMM estimation procedure.[15]

The solutions we propose for these endogeneity issues are as follows. First, the observed hardware characteristics do not change within our single generation of consoles, and so we include console dummies to subsume the hardware characteristics. To control for endogeneity of the within group market share, we cannot adopt Berry's (1994) suggestion to use competitors' hardware attributes as instruments. These do not change over time in the sample, and these instruments add nothing to the estimation when the console dummies are included in the specification. Since we do not have an obvious time-varying instrument available for within group share,[16] we are not surprised that we

[15] Clements and Ohashi (2005) test for and find autocorrelation, but do not use it to increase the efficiency of their estimation and apparently do not adjust their standard errors for its presence.
[16] The within group share from the Japanese market does not prove to be a good instrument.

find below that the nested logit maodel leads to poor results, and we simplify the model to simple logit.

To control for endogeneity of console price, we use the retail console price in Japan collected from Nikkei News. Prices in Japan are correlated with US prices because both depend on production costs (all consoles are manufactured at the same location). However, Japanese prices will not be correlated with unobserved console characteristics ξ_{jt} in the US hardware equation if Japanese gamers have different tastes for games and systems. An alternative data set we collected from Mediacreate[17] on console sales in the Japanese market shows some evidence for differing tastes. For example, unlike its strong performance in the US market, the sales of XBOX lag in the Japanese market, even with a similar price and game variety comparison to GameCube as in the US market. The gaming trade press also mentions difference between the preferences of US and Japanese game players.[18] In the end, however, no airtight case can be made *a priori* proving the Japanese price data are valid instruments, and we therefore will pay close attention to the results of overidentification tests to assess the performance of the instruments below.

We also use the Japanese-US current exchange rate as an instrument for price. Since some of the consoles were manufactured in Japan, fluctuations in the exchange rate should affect retail prices in the US.[19]

[17] Mediacreate collects Japanese video game market sales data. It posts weekly sales reports of consoles.
[18] For example, conventional wisdom in the trade press holds that Japanese players tend to prefer more relational games, titles based around "cute" characters, good story lines, and fantasy-based games, whereas US players tend to prefer more realistic, action-oriented, violent games with exciting graphics and do not demand continuity in the story line between game editions. See, for example, the article "Xbox Courts Japan" at JapanInc.com (http://www.japaninc.com/article.php?articleID=10).
[19] Clements and Ohashi (2005) used one year lagged exchange rates as instruments, arguing that consoles were introduced in Japan a year earlier than in the US. We use the current exchange rate for two reasons. The sixth generation consoles did not see such a long lag between Japanese and US introductions.

The endogeneity of software variety is controlled by using the accumulated game variety in Japan (from Famitsu[20]). Japanese game variety should be correlated with US game variety, because (differences in tastes notwithstanding) many game titles are provided in both countries due to scale economies, given that the lion's share of cost to produce a title is up front for development. However, Japanese game variety should not be correlated with ξ_{jt} if demand shocks in Japan are uncorrelated with demand shocks in the US.[21] In addition to the instruments above, we also use console age (the number of months since sales began) and square of age.

Endogeneity in the Software Provision Equation

The concern with endogeneity in the installed base, like that of game variety in the hardware adoption model, comes from the interaction of hardware adoption with the potential autocorrelation of η_{jt}. If software provision is affected by η_{jt-1}, hardware adoption and therefore s_{jt-1} will be affected, and hence the installed base in the next period, IB_{jt}. Therefore, if η_{jt} is autocorrelated with η_{jt-1}, endogeneity in IB_t arises. To control for the endogeneity issue in installed base, we use age and age squared, and also allow them to interact with console effect as instruments.

Furthermore, the relevant Yen cost at the time of sale from a Japanese wholesaler or factory to a US retailer is the opportunity (replacement) cost of the console, not the embedded production cost (which is a sunk cost at that point). Thus the current exchange rate appears to be the logical choice for an instrument.

[20] Famitsu is a weekly video game magazine covering details of the Japanese video game market.

[21] The reasoning is similar to that for using Japanese prices as instruments for US prices. The endogeneity of accumulated software is due to the correlation between game variety at period *t* and unobservable characteristics at period *t*-1. Similarly, unless the demand shocks of Japan and the US are correlated, Japanese software issuance will be affected by previous demand shocks in Japan but not current US demand shocks.

5. Estimation results

In this section we present the GMM estimation of the hardware adoption and software provision model. Results are presented in Tables 4 and 5. We begin by examining the explanatory power of the instruments. For each specification of Table 4, we calculate an *F*-statistic for each endogenous variable and an *F*-statistic for the joint (Anderson-Rubin) test from the first stage of regression. To conserve table space we show only the *p*-values for the joint test. The statistics, regardless of test type, lead us to reject the hypothesis of weak instruments at the 1% level for all variables unless otherwise noted below. We also calculate the statistics for the Anderson canonical correlations likelihood-ratio test for underidentification.[22] The Anderson tests do not indicate any problem with the instruments, either. Finally, since we have more instruments than instrumented variables, we can also make use of overidentification tests to assess the validity of the instruments. We present the Hansen *J* statistics in the table.[23] More details are provided in the discussion below.

5.1 Hardware Adoption:

Table 4 presents several specifications of the estimation for the hardware adoption model. As described earlier in the empirical model, instead of using total accumulated game variety in our estimation, we decompose the total game variety into two parts: the accumulation of software variety from the current and three months previous, and total software variety accumulated older than three months back. Under this setup, we are able

[22] The Anderson LR test determines if the excluded instruments are relevant. Rejection of the null indicates that the model is identified.

[23] The Hansen *J* statistic for the GMM estimator is used for the Hansen-Sargan test of the overidentifying restrictions imposed. The joint null hypothesis is that the instruments are valid instruments (i.e., uncorrelated with the error term) and that the instruments are correctly excluded from the estimated equation. A rejection of the null hypothesis of the test casts doubt on the validity of the instruments.

to examine the impact of recent changes in accumulated variety and confirm that older titles play little role in console demand.

Estimations H1-H3 are logit models. In estimation H1, we control for console, year, and holiday effects but do not allow them to interact. We found that in virtually any specification, console price enters non-linearly and we have added squared terms in price in all estimations (and squared Japanese price to the instrument set). Although the tests for weak instruments and underidentification do not indicate any problems with the instruments, the Hansen-Sargan test rejects the hypothesis that the instruments are orthogonal to errors. The coefficients of price, software variety, and within group market share are all significantly different from zero. The estimated impact of price shows the model is misspecified: demand slopes down in price only up to $158, about the average price in the sample. However, demand slopes up in recent software variety, as expected. The variable "game titles (older)" is the difference between total game variety and the stock of recently issued titles (current month plus three previous months). In H1, the coefficient for older titles is negative and significant. While we do not expect that older titles affect demand much, it is hard to imagine that their presence would negatively impact demand, and we read this result (along with the evidence that the instruments are invalid) as evidence that a better specification is desired.

In estimation H2, we allow the console and year effects to interact. Adding these interactions is intended to remove any remaining endogeneity of the instrument set. As described above, including the interaction term captures that consumers' perception of the brand image may change over time due to marketing and product "buzz". Compared to H1, the Hansen J statistic is much improved (p = 0.30); there is no longer reason to suspect the instruments are invalid. The impact of price on demand is more sensibly estimated as well, being significant and negative for all but the four highest prices in the data. Recent software variety is still significant and of the right sign. The coefficient on older software variety is still negative and significant, however. Therefore in specification H3 we include a squared term in older game titles to check for nonlinearity that may be resulting in a spuriously negative coefficient. Once the squared term is included (and squared Japanese older titles added to the instrument set), the linear relationship between older titles and console demand disappears entirely, and the higher-order effect is not significant at the 5% level. This supports our hypothesis that the effect on demand of software is perishable. The price coefficients are midway between those from the previous two estimations, and as in H2 the marginal effect of price on demand is negative for all but the four largest observations. We interpret the magnitude of the price and software coefficients in a separate section below.

In specification H4, we estimate the model as in H3, but treat the regressors as exogenous. This allows us to see by how much the endogeneity affects the estimates. The same signs are present for all coefficients, although the magnitudes of the estimates are smaller in the OLS estimation and software variety is not significant. Thus the instruments are able to identify a role for software variety in H3 that is obscured by endogeneity in H4. A Hausman test rejects the equality of the coefficients in the two estimations ($p = 0.028$), supporting the notion that the suspected variables are indeed endogenous.

As set forth in the empirical model above, we intended to use the nested logit model, to allow more flexible substitution patterns between consoles and the outside option. However, when within group share is added to the set of regressors, we do not get sensible results. The coefficient on within group share is greater than its maximum sensible value of one, in all specifications analogous to H1-H3. This may be a result of model misspecification, or it may be because we do not have good instruments for within group share. We settle upon H3 as the best model to use to assess the relative importance of price and software variety and to conduct the counterfactual exercises.

We tried other division points between older and newer titles (splitting at two and six months) as a robustness check. However, only three month splits yielded reasonable signs for the coefficients. For further robustness checking, we estimated a set of models in which we relax the assumption that households buy only one console each. We allow the installed base to depreciate at an annual rate of 10%, 20%, and (as an extreme) 100%. The estimation results (not shown) reveal that the price and software variety coefficients are virtually unchanged compared to H3, indicating that the results are robust to the size of outside alternative market share.

5.2 Software Supply

Table 5 shows the estimation result of the software provision model. In estimation S1, we control for year effect, console effect, the year-console interaction, and the holiday effect. To control for the endogeneity of the installed base of consoles, we use age, square of age, and the interaction of the age variables with the console dummy variables as instruments. The results for S1 show that there is no suspicion that the instruments are weak or that the model is underidentified, and the *J* statistic does not lead us to reject the hypothesis that the instruments are valid. Also, in this estimation we see that the coefficient on installed base is highly significant. The log specification implies that the coefficient of 2.5 is also the elasticity of software supply with respect to the installed base. Thus a one percent increase in the installed base increases software provision for the console by 2.5%.

However, console age is not included in S1. We expect that even with a constant installed base, as time passes more software may be provided for a console, if for no other reason than that software development takes time. Ideally we would like to identify the impact of the installed base due only to the network effects, independent of any effects due solely to the time the console has been on the market. However, when we add age to the main equation (estimation S2), the installed base loses significance. It is hard to conclude that age and not the installed base is the true determinant of supply, because the two are very highly correlated ($\rho = 0.93$). We also estimated a specification without installed base but including age (results not shown). Although we cannot directly compare such an OLS estimation to the GMM estimation S1, by a mean-square error criterion one would decide slightly in favor of S1 and the installed base variable.

5.3 Joint Estimation

The console demand and software supply equations can be jointly estimated to increase the precision of the estimates. Two joint estimations are reported in Table 5. Specification J1 is the joint estimation of H3 and S1, and estimation J2 is the joint estimation of H3 and S2. The coefficients are close to the single equation estimates.

5.4 Interpretation of the Results and Strategic Implications

With the estimation result for console demand, we can now examine the firm's choice between increasing demand by lowering console price and by encouraging the growth of software variety. We summarize the effects of this choice with elasticities:

elasticities of console demand share with respect to price,[24] ε_P, and software variety,[25] ε_S. The calculations, based on H3, are presented in Table 6, where we have averaged the monthly elasticities over the year.

Except for 2002 for PlayStation2 and XBOX, all price elasticities are in the elastic region of demand, as the theory of pricing with market power suggests should be the case, and the hypothesis cannot be rejected for those two cases. The results also reveal that price elasticity increases over the years 2002 – 2004, except for the last year for GameCube. This finding is in contrast to Clements and Ohashi (2005), who found that elasticities generally decreased over time. The difference is probably due to our more flexible specification for how price enters the share equation. With only a linear term in price, elasticity will generally decrease as the price falls over time. With higher order terms in price this need not happen, as we have found. When elasticities rise over time, the effectiveness of reducing price to promote console sales appears to work better later in the console's life cycle. Comparing consoles, XBOX and PlayStation2 have similar elasticities, which are generally lower than those for GameCube in the early years.

The elasticity of shares with respect to software variety does not show the same patterns as the price elasticities. The software variety elasticity is level over the years for PlayStation2 (around 1.0) and GameCube (around 0.5-0.6). The software variety elasticity for XBOX rises slightly over the years, from 0.66 in 2002 to 0.84 in 2004. Since it became clear over time that XBOX's better hardware was allowing developers

[24] The own-price elasticity of demand share s_{jt} with respect to price p at time t is $p(\beta_{p1} + 2\beta_{p2}p)(1 - s_{jt})$, where β_{p1} is the linear coefficient on price and β_{p2} is the coefficient on squared price.

[25] The elasticity of demand share s_{jt} with respect to software variety v at time t is $v\beta_v (1 - s_{jt})$, where β_v is the coefficient on recent software variety.

more leeway in designing desirable games, perhaps the rising ε_S reflects that games became increasingly valuable to Microsoft in spurring sales of consoles.

The literature on two-sided markets, as well as analysts' reports on the industry, indicates that the appropriate business model for the home video game market uses console sales as loss leader and software sales as the profit center. As a result, it is important for console manufacturers to know the trade-offs they face between lowering the hardware price and stimulating software production to increase the installed base of consoles. The elasticities calculated from our demand model allow us to measure the relative effectiveness price reductions and software provision as two of console manufacturer's strategies to attract console adoptions.

To summarize the relative effectiveness of the two available business strategies (lowering console price and increasing software variety), and the possibilities for substitution between them, we calculate the ratio of the two elasticities. This follows Gandal, Kende, and Rob (2000) and Clements and Ohashi (2005). The relative effectiveness of the strategies is obtained from $-\varepsilon_S / \varepsilon_P$, which measures the percentage reduction in console price that has equivalent effect on demand as a one-percent increase in software variety.[26] These results are also in Table 6.

The results display that the average value across consoles of the ratio is 0.39: a one percent increase in software variety is equivalent to a 0.39 percent price reduction. For each console the ratio falls over time, suggesting that it becomes relatively less effective to use software provision to attract console adoption over time. PlayStation2 has the highest relative effectiveness and GameCube the lowest. Clements and Ohashi

[26] The interpretation of the elasticity ratio follows from the definitions: since $\varepsilon_p = \%\Delta s / \%\Delta p$ and $\varepsilon_S = \%\Delta s / \%\Delta S$, the ratio is $-\varepsilon_S / \varepsilon_p = \%\Delta p / \%\Delta S$.

(2005) perform an analogous calculation for previous generations of the home video game market, and find that the elasticity ratio rose at first and then declined later in the product cycle. Thus the product cycle may have sped up in the sixth generation, jumping quickly to the phase in which the ability the stimulate sales through software provision (relative to price reductions) declines over time.

6. Is There An Applications Barrier to Entry?

Can a console maker's negotiating power with video game creators create an applications barrier to entry in the console market? Barriers to entry based on software applications for a system received much discussion in the Microsoft antitrust case (Gilbert and Katz, 2001). The government contended in the case that due to the high development costs of making software applications, programmers would not create applications for an operating system unless there were already large installed base of users. In our context, the hardware console plays the role of the operating system. If a console has few games created for it, the theory of indirect network effects predicts it will die quickly in the market place (as happened in the sixth generation with Dreamcast and in previous generations with the NEC TurboGrafx-16, the SNK NEO GEO, and the Atari Jaguar). The question of antitrust concern is then whether a console maker's ability to create games exclusively for its own system, either through self-provision or through negotiation with game developers (through exclusionary contracts), is strong enough to hinder entry by competitive systems or hasten exit of existing systems. For this strategy to be successful, indirect network effects must be present: the availability of software must increase hardware demand.

6.1 Do the Network Effects Differ for Exclusive Games?

Predatory conduct as described above will be more successful if the indirect network effects are strong for exclusive software games. Some video games can only be played on Xbox, for example, because the console producer (Microsoft, in this case) either created the game itself or negotiated an exclusive deal with a video game maker. PlayStation2, in particular, has over half of its games to itself (recall the shares of games that are unique to a console are in Table 2).

To see how the impacts on console share from games uniquely available for a single system and games available for multiple systems, we re-estimate the hardware demand equation splitting software titles into unique and non-unique games (estimation H5 in Table 7). It proved to be difficult to get sensible results from this estimation. For example, when console by year effects are included, none of the software variables are significant. Since none of the console by year coefficients are significant, we drop them. Also, there appear to be significant higher order effects for recent non-unique software variety but not for unique software, so we include a squared term for the former. Finally, we note that the strength of our instruments[27] is questionable according to the Anderson LR statistic and the first stage *F* statistic, and so the estimates may be biased. Regardless, it is interesting to note in the estimation that recent variety of unique games has no significant effect on demand at all. It is the non-unique games that are significantly and positively associated with console share.[28] This appears to limit a console maker's options to "starve" its competitors by putting many unique games on the market, if such games do not materially increase the installed base of the maker's own console.

[27] We split the Japanese software variety variables used as instruments the same way we did the US variables.
[28] The marginal effect of non-unique recent software variety is positive for all but the top quintile of variety in the data.

Another way to assess the feasibility of using the availability of games as a strategic weapon is to consider counterfactual scenarios in which no firm, or just the dominant firm, is able to offer unique games.[29]

6.2 Counterfactual #1: Full Quasi-Compatibility

In our first counterfactual, no console firm or software designer is allowed to create games exclusively for a single platform. Instead, any game is compatible with any system. We call this quasi-compatibility because the physical game DVD made for PlayStation2, for example, does not work in the other consoles. In the counterfactual, the software for the dominant console, PlayStation2, is also available in versions for XBOX and GameCube. Thus we assign the software variety of PlayStation2 to the other consoles each month as well, in place of the actual values. If the actual software variety in our data represents the equilibrium of the software supply model from section 3, then the XBOX and GameCube software markets will be "over-supplied": the software counts for these two consoles in the counterfactual will exceed the actual value. However, since putting out a version of a game for a second and third system is much less expensive than developing the original version, the counterfactual is not necessarily inconsistent with the structural supply model. The additional supply from the PlayStation2 games is assumed to squeeze out supply of any other games. In particular, we do not add XBOX and GameCube's unique games to the PlayStation2 total). Thus, all firms have symmetric software variety.

[29] Understanding the demand side is only a first step toward fully assessing the competitive importance of applications barriers to entry. Eventually we would like to add a model of strategic supply of consoles to the story, but that is probably beyond the scope of the current project.

As a cautionary note, recall that our estimation includes console, year, and interacted effects to capture the effect of brand image, advertising, and so forth. We have no way of knowing how these effects would change in the counterfactual, and so we use the estimated values from H3. We also have no structural model for the supply of consoles, and so we use the actual value of console prices. The results, based on the coefficients estimated in H3, are in Figure 3. The predicted market shares do not converge, as may have been expected a priori. Thus the benefits from the indirect network effects by themselves for XBOX and GameCube are not strong enough to overcome PlayStation2's market share dominance.

6.3 Counterfactual #2: Asymmetric Quasi-Compatibility

In our second counterfactual scenario, we consider a market in which (perhaps due to conduct restrictions imposed by an antitrust authority on the dominant firm), as before, PlayStation2 games are quasi-compatible with the other systems, but that XBOX and GameCube are allowed to have unique games. The software variety of PlayStation2 is replaced by its software variety without exclusive software. For both XBOX and GameCube, their software variety is replaced by PlayStation2's non-unique software plus their own exclusive software. Again using the coefficients from H3, we measure the predicted market share using the counterfactual values for the software variety variables.

The results are in Figure 4. As in the other counterfactual, the predicted market shares do not converge. Except for a bit more convergence of XBOX and GameCube's market shares, the general results are not too difference from the previous counterfactual. Again, the benefits from the indirect network effects by themselves for XBOX and GameCube are not strong enough to overcome PlayStation2's market share dominance.

The results of this section show that there may not be much reason for concern regarding applications barriers to entry in this market. Unique games do not appear to play as much a role in changing console markets shares as much as non-unique games do. Furthermore, the counterfactuals show that even if the amount of software available for each console were very different from the actual values, due to conduct restrictions or outlawing exclusionary game development contracts, PlayStation2 would still maintain its dominance. Thus the role of exclusive games does not seem to be central to Sony's dominance of the sixth generation video game market.

7. Out-of-Sample Prediction

In this final section, we investigate the applicability of structural econometric models of indirect network effects to new situations. There is a growing set of empirical studies of markets with indirect network effects. Are these case studies valuable for providing general insight into network markets, or do their conclusions apply only to the market and time period studied? The hope offered by structural modeling is that fundamental parameters of the economic decision-making processes are estimated, so that one could apply the results to new situations and come up with accurate predictions of outcomes. However, case studies are designed by their nature to answer a very specific question. For example: what is the magnitude of the influence of indirect network effects on the demand for personal digital assistant (PDA) hardware from PDA software during the years 1999-2002 in the US, as measured from a particular data set and using a particular set of instruments (Nair, Chintagunta, and Dubé, 2004). If the results of any one study extend no further than the bounds of the narrowly defined topic at hand, then these case studies may be mainly of academic interest.[30] However, if the case studies are to have something to say to antitrust officials and the marketing departments of technology companies, to name just two of many potentially interested parties, then we need to know how models fit to data from one market or time period do at out-of-sample prediction.

One natural comparison for our study is to Clements and Ohashi (2005), who studied previous generations of video game systems. Here we can take advantage of the fact that our data for PlayStation2 overlaps with their sample period for the first quarter of 2002. The striking fact is that our estimated elasticities differ greatly from theirs. They report a share elasticity of -1.9 for price and 5.3 for software variety, whereas our figures from Table 6 are -1.0 and 1.0, respectively. Thus their elasticity ratio of 2.8 for PlayStation2 is far from our ratio of 1.0, and would lead to quite different conclusions about the strategic options available to Sony to lower price vs. creating more software to stimulate console demand. It is difficult to know what causes the differences. We do not use the exact same instrument set, and (as noted above) found that adding non-linear terms in price improved the performance of our models. However, we suspect the difference may stem more from the fact that PlayStation2 in 2002 appears at the end of their observation period and at the beginning of ours. Thus their estimates may be influenced by average tendencies in the previous generations that changed substantially over time. Similarly, we expect that if our results were extrapolated to the earlier years and systems in their data, our model would perform poorly.

[30] …which is not to denigrate these studies in any way. We are academics, of course, and find them very interesting in any event.

A second out-of-sample market to which we compare our results is the Japanese market for sixth generation gaming systems. This estimation, H6 in Table 7, is analogous to H3 for the US market.[31] The marginal effect of prices are not too dissimilar in the Japanese and US markets. The price effects are equivalent in the two markets at a price of $140, a bit lower than the average price, with the Japanese price effect greater in magnitude for smaller prices and smaller in magnitude for higher prices. Price elasticity of demand projected for the Japanese market from the US estimation would therefore be close to the actual for market prices around $140, and somewhat too large (in absolute value) for the higher prices actually observed. The coefficient for recent software variety is very close to that estimated for the US market: 0.013 for Japan and 0.014 for the US. Thus software variety elasticity of demand projected for the Japanese market from the US estimation would be close to the actual. Instruments of the same form appear to work as well for the Japanese market as for the US market: the instruments pass the tests for strength and validity. Thus, the out-of-sample prediction for the Japanese market using our estimations based on US data would apparently be close to the results using the actual Japanese market data. Overall, then, it appears that out-of-sample prediction may work best moving laterally geographically within a single set of products, versus the poorer results obtained when comparing to previous or successive generations.

8. Conclusion

Our work in this paper raises two issues deserving further study. We found little evidence for the possibility for a firm to erect an applications barrier to entry through

[31] The one change we made was to replace the US-Japan exchange rate, used as a console cost instrument, with the Taiwan-Japan exchange rate. Some of the consoles were manufactured in Taiwan during the sample period. Otherwise the US prices and software varieties move from the main equation to the instrument set, and the Japanese prices and software varieties move to the main equation.

creating games exclusively for its own console (or through exclusionary contracts with software developers that result in the same outcome). The hopeful note for purposes of public policy is that there appears to be no warrant for antitrust scrutiny in this market. The flip side of this result is that if intervention in the market were to take place for some reason, the policy instrument of outlawing exclusive software creation appears to be ineffective toward the goal of reducing market dominance by a firm. The other less than sanguinary finding is that we find little generalizability of our results to previous markets, and vice versa. Therefore, at this point we have no reason to expect that some day there will be a set of tried and true results for indirect network effect markets that can be applied to new markets absent detailed market data and estimation on a case-by-case basis.

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TABLE 1: Platform Characteristics

Platform	Introduction Month/Year	Manufacturer	Hardware Characteristics				2002	2003	2004
			GPU (MHz)	CPU (MHz)	RAM (GB)	**% Console Sold**	0.61	0.50	0.42
						Mean Console Price	233	187	160
PlayStation2	OCT 2000	Sony	150	300	32	**% Software variety**	0.44	0.43	0.47
						% Console Sold	0.23	0.25	0.37
						Mean Console Price	237	187	157
XBOX	OCT 2001	Microsoft	233	733	64	**% Software variety**	0.30	0.33	0.34
						% Console Sold	0.17	0.26	0.21
						Mean Console Price	171	133	100
GameCube	OCT 2001	Nintendo	162	485	24	**% Software variety**	0.26	0.24	0.19
						Total Console Sales (Million Units)	14.1	12.9	10.9
						Total Software Variety	502	539	511

Notes: GPU is the speed of the graphics processing unit in megahertz. MHz is the CPU clock speed in megahertz, and RAM is the memory size in gigabytes.

Table 2: Software Provision

		2002	2003	2004	Platform Average
PlayStation2	% variety provided exclusive to the platform	65	49	48	56
	% variety provided by manufacturer	8.6	8.4	6.9	8.0
XBOX	% variety provided exclusive to the platform	34	32	37	34
	% variety provided by manufacturer	7.9	9.8	4.6	7.4
GameCube	% variety provided exclusive to the platform	30	33	35	32
	% variety provided by manufacturer	5.4	7.5	11.8	7.9

Table 3: Summary of Console Related Variables

Platform		Market Share	Within Group Share	Price	Game Titles (recent)	Game Titles (old)	Price in Japan	Japan Game Titles (recent)	Japan Game Titles (old)	Age (mo.)	US/Japan Exchange rate
PlayStation2	Mean	0.0074	0.52	175	77	474	199	178	843	34.5	
	Max	0.0337	0.64	289	137	772	231	240	1616	51.0	
	Min	0.0022	0.32	135	40	186	170	95	203	18.0	
	s.d.	0.0069	0.09	35	28	185	26	56	468	12.2	
XBOX	Mean	0.0042	0.28	176	55	216	186	22	84	21.5	
	Max	0.0183	0.51	289	101	437	265	34	170	38.0	
	Min	0.0008	0.19	135	25	20	145	13	0	5.0	
	s.d.	0.0042	0.08	37	23	136	34	5	53	10.0	
GameCube	Mean	0.0032	0.20	123	40	168	146	25	104	21.5	
	Max	0.0171	0.36	193	80	321	191	46	217	38.0	
	Min	0.0009	0.12	90	21	12	113	11	6	5.0	
	s.d.	0.0038	0.05	33	17	104	22	11	71	10.0	
Overall	Mean	0.0049	0.33	158	57	286	177	75	344	25.8	115.06
	Max	0.0337	0.64	289	137	772	265	240	1616	51.0	133.20
	Min	0.0008	0.12	90	21	12	113	11	0	5.0	103.18
	s.d.	0.0054	0.16	43	28	198	34	77	436	11.6	7.33

Table 4: Hardware Demand Estimations for Sixth Generation Game Consoles

	H1		H2		H3		H4 (OLS)	
	Coefficient	**s.e**	**Coefficient**	**s.e**	**Coefficient**	**s.e**	**Coefficient**	**s.e**
Constant	-1.845*	1.059	0.492	2.013	-1.917	1.692	-2.708	0.833
Price	-0.027***	9.96E-03	-0.053**	0.017	-0.038***	0.012	-0.020***	6.06E-03
Price, squared	4.29E-05*	2.40E-05	1.08E-04***	3.73E-05	7.99E-05***	2.72E-05	3.00E-05**	1.40E-05
Game Titles (recent)	0.018***	4.98E-03	0.0181***	5.04E-03	0.014***	3.93E-03	2.48E-03	1.78E-03
Game Titles (old)	-3.17E-03***	1.04E-03	-3.33E-03**	1.61E-03	1.66E-03	2.78E-03	7.40E-04	1.71E-03
Game Titles (old), squared	-		-		-4.48E-06*	2.49E-06		
Console Effects	YES		YES		YES		YES	
Year Effects	YES		YES		YES		YES	
Interaction between Year and console	NO		YES		YES		YES	
Hansen *J* statistic	*p*-value = 0.0418		*p*-value = 0.3602		*p*-value = 0.1480		-	
Anderson LR statistic	*p*-value = 0.0007		*p*-value = 0.0003		*p*-value = 0.0000		-	
Anderson-Rubin *F* stat.	*p*-value = 0.0000		*p*-value = 0.0000		*p*-value = 0.0000		-	

* = significant at 10% level. ** = significant at 5% level. *** = significant at 1% level.

Notes: $N = 102$. The dependent variable is the log share of households purchasing a particular console brand in a given month. *Game Titles (recent)* is the software variety accumulated during the current month and the three previous months. *Anderson LR statistic* is the Anderson canonical correlation likelihood ratio statistic for underidentification. Rejection of the null implies that the model is not underidentified (does not suffer from weak instruments).

Table 5: Software Supply and Joint Estimations for Sixth Generation Video Game Systems

	S1		S2		J1		J2	
	Coefficient	**s.e**	**Coefficient**	**s.e**	**Coefficient**	**s.e**	**Coefficient**	**s.e**
Constant (Hardware)					-2.65970	2.04725	-2.683	1.828
Price	-		-		-0.036***	0.0134	-.034***	0.012
Price, squared	-		-		0.768E-04**	0.309E-04	7.172E-05**	2.788E-05
Game Titles (recent)	-		-		0.019***	0.573E-02	.016***	5.350E-03
Game Titles (old)	-		-		0.172E-02	0.384E-02	2.305E-03	3.186E-03
Game Titles (old), squared	-		-		-.397E-05	.342E-05	-4.820E-06*	2.839E-06
Constant (Software)	38.352***	9.111	-11.118	13.114	-34.127***	8.493	-3.703	9.461
Installed Base (log)	2.535***	0.564	0.742	0.842	2.272***	.526	0.256	0.607
Hardware Age	-		0.082***	0.029	-		0.101***	0.022
Console Effects	YES		YES		YES		YES	
Year Effects	YES		YES		YES		YES	
Interaction between Year and Console	YES		YES		YES		YES	
Hansen *J* statistic	*p*-value = 0.3650		*p*-value = 0.9914		*p*-value = 0.1105		*p*-value = 0.5274	
Anderson LR statistic	*p*-value = 0.0000		*p*-value = 0.0000		-		-	
Anderson-Rubin *F* stat.	*p*-value = 0.0001		*p*-value = 0.9694		-		-	

* = significant at 10% level. ** = significant at 5% level. *** = significant at 1% level.

Notes: N = 102. The dependent variable in S1 and S2 is the log number of software titles provided for a particular console brand in a given month. See also notes to previous table.

Table 6: Demand Share Elasticities

Platform	Share elasticity	2002	2003	2004	Average
PS2	Price (ε_p)	-0.987 (0.695)	-1.804*** (0.665)	-2.175*** (0.697)	-1.799*** (0.665)
	Game variety (ε_s)	1.010*** (0.281)	1.015*** (0.283)	1.143*** (0.319)	1.059*** (0.295)
	$-\varepsilon_S / \varepsilon_P$	1.023	0.563	0.525	0.589
XBOX	Price (ε_p)	-0.851 (0.718)	-1.796*** (0.667)	-2.195*** (0.699)	-1.789*** (0.666)
	Game variety (ε_s)	0.662*** (0.185)	0.776*** (0.216)	0.839*** (0.234)	0.765*** (0.213)
	$-\varepsilon_S / \varepsilon_P$	0.778	0.432	0.382	0.427
GameCube	Price (ε_p)	-2.065*** (0.687)	-2.285*** (0.707)	-2.159*** (0.659)	-2.289*** (0.707)
	Game variety (ε_s)	0.564*** (0.157)	0.593*** (0.165)	0.500*** (0.139)	0.552*** (0.154)
	$-\varepsilon_S / \varepsilon_P$	0.273	0.260	0.232	0.241
Overall Average	Price (ε_p)	-2.057*** (0.685)			
	Game variety (ε_s)	0.792*** (0.221)			
	$-\varepsilon_S / \varepsilon_P$	0.385			

Note: Elasticities and standard errors calculated based on estimation H3. Asymptotic standard errors (in parentheses) calculated via the delta method.

Table 7: Further Hardware Demand Estimations for Sixth Generation Game Consoles

	H5		H6 (Japanese Market)	
	Coefficient	**s.e**	**Coefficient**	**s.e**
Constant	-3.777	2.524	1.807	2.994
Price	-0.025*	0.013	-0.059*	0.031
Price, squared	4.15E-05	3.16E-05	1.53E-04	8.69E-05
Game Titles (recent)	-		0.013	6.45E-03
Unique Game Titles (recent)	2.604E-03	.050	-	
Unique Game Titles (recent), squared	-1.72E-03**	8.55E-04	-	
Non-Unique Game Titles (recent)	0.160**	0.065	-	
Game Titles (old)	-4.18E-03	2.62E-03	-8.97E-03	3.23E-03
Game Titles (old), squared	-		3.40E-06	1.33E-06
Console Effects	YES		YES	
Year Effects	YES		YES	
Interaction between Year and Firm	NO		YES	
Hansen J statistic	*p*-value = 0.1566		*p*-value = 0.1257	
Anderson LR statistic	*p*-value = 0.3807		*p*-value = 0.0000	
Anderson-Rubin *F* stat.	*p*-value = 0.0000		*p*-value = 0.0019	

Figure 1: Interactions in the Video Game Industry

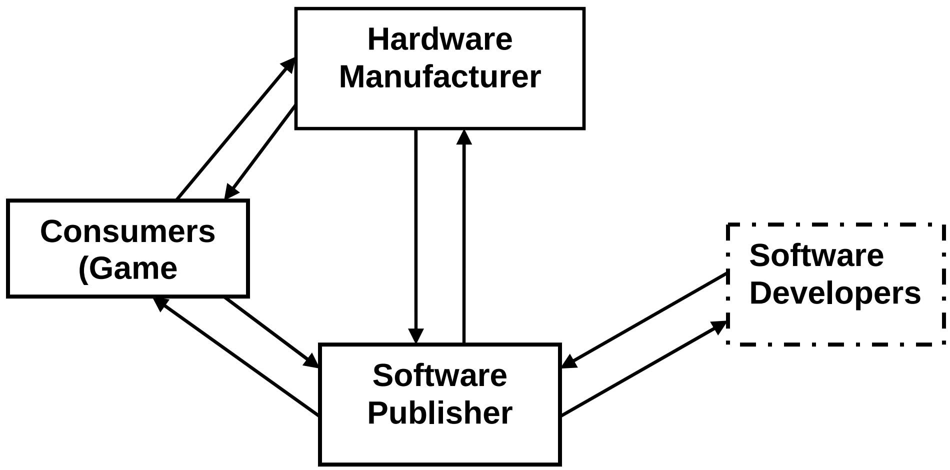

Figure 2: Market Sales of Video Game Consoles

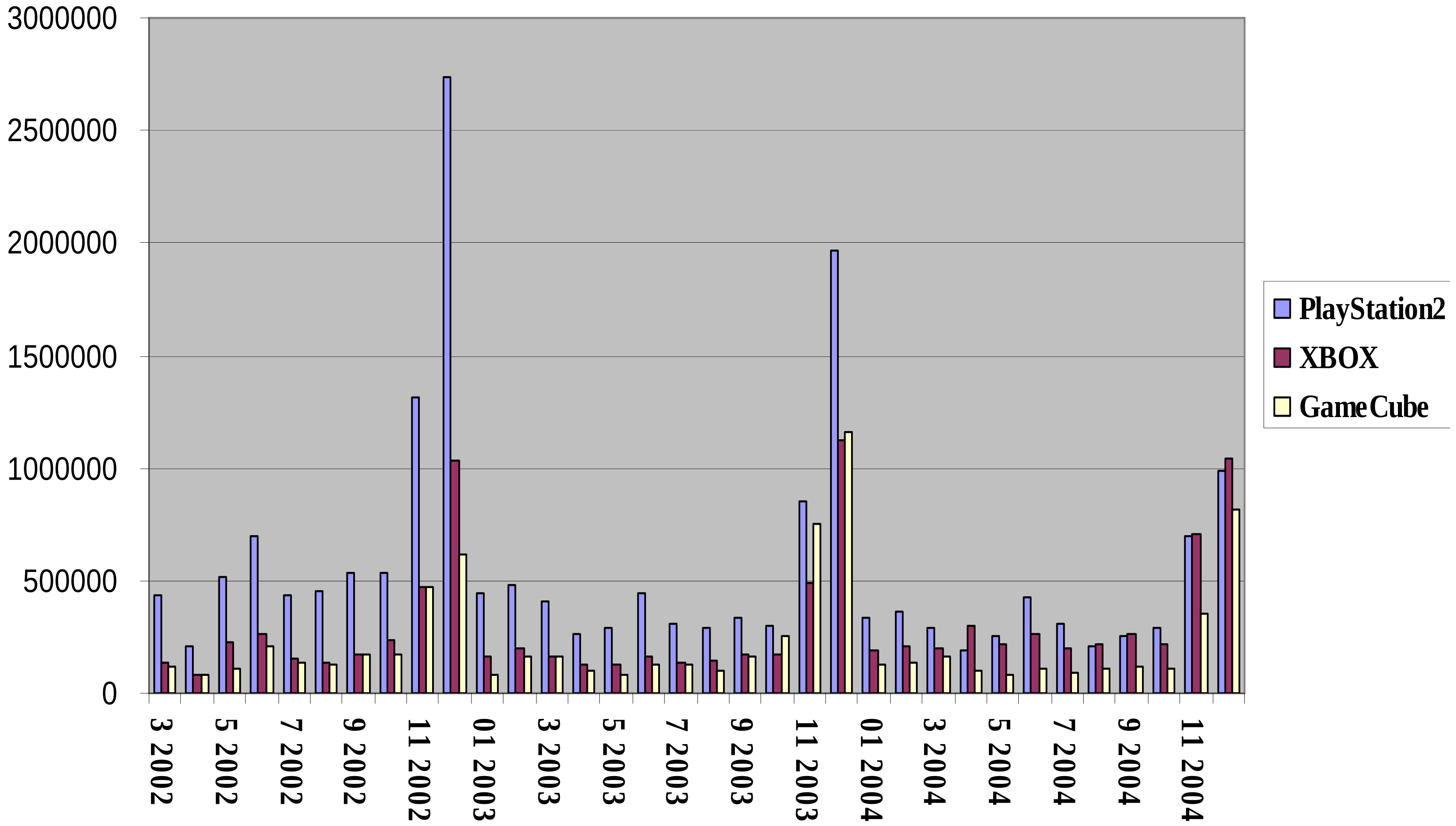

Figure 3: Results of Counterfactual #1 – Full Quasi-compatibility

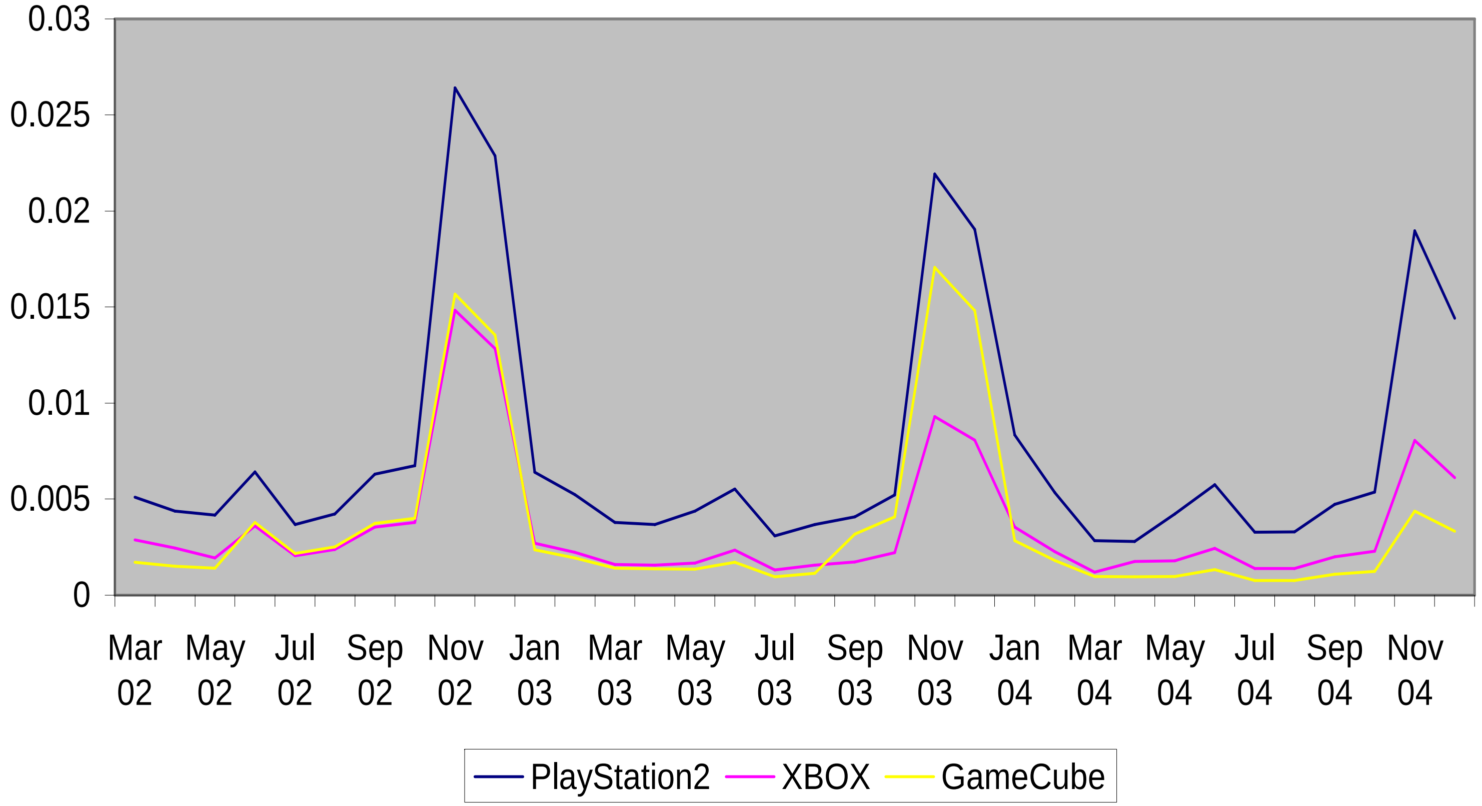

Figure 4: Results of Counterfactual #2 – Asymmetric Quasi-compatibility