Technological Tying and the Intensity of Price Competition: An Empirical Analysis of the Video Game Industry

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Abstract

Using data from the 128-bit video game industry I evaluate the impact technologically tying has on the intensity of console price competition and the incentives for hardware firms to tie their produced software to their hardware. Tying occurs when a console hardware manufacturer produces software that is incompatible with rival hardware. There are two important trade-offs an integrated firm faces when implementing a technological tie. The first is an effect that increases console market power and forces hardware prices higher. The second, an effect due to the integration of the firm, drives prices lower. A counterfactual exercise determines technological tying of hardware and software increases console price competition; console makers subsidize consumer hardware purchases in order to increase video games sales, in particular their tied games, where the greatest proportion of industry profits are made. Moreover, I determine technological tying to be a dominant strategy for hardware manufacturers when software development costs are low.

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1 Introduction

In high-technology industries the availability and quality of complementary products can impact platform adoption. For instance, in the home video game console market a consumer must choose between a PlayStation 3, Microsoft Xbox 360 or Nintendo Wii before he is able to play any video games. Yet, many video games are compatible with multiple consoles and thus create little additional differentiation across consoles. There are also complements that are exclusive to one platform–to play The Conduit consumers must purchase the Nintendo Wii, and to play Gran Turismo 5 consumer must purchase a Sony PlayStation 3.[1] Unlike complements that are compatible with multiple platforms, exclusive complements bring added demand to the platform. This raises a platform manufacturer's market power and the incentive to increase its hardware price through greater variety of complementary products [Church and Gandal, 2000]. A console manufacturer can also replicate this effect by integrating with the software market and creating a technological tie between its console and games. A technological tie occurs when a hardware manufacturer produces software that is incompatible with rival hardware, a combination of exclusivity and integration. A consumer wanting that hardware manufacturer's software must also purchase the console made by that firm, and only that firm. A few examples of technological tying in practice are Nintendo's production of the Super Mario Brothers video game series or Microsoft's production of Halo. These strategic moves by Nintendo and Microsoft–and as well as Sony–raise the questions of i) what role does technological tying have on console price competition and ii) how do software development costs impact this strategic decision?

The focus of this paper is to determine the effects of and the incentives for hardware firms to integrate into the software market and elect to tie their software to their own hardware. I answer the above research questions using data from the 128-bit video game industry, which comprises Nintendo GameCube, Sony PlayStation 2 and Microsoft Xbox, and by employing a model that incorporates the durable nature of video game consoles and games. I allow consumers to be forward-looking and form expectations about the evolution of each market. The model timing for consumers who do not own hardware is they decide in each period (month) whether or not to purchase a console. Once consumers have purchased hardware they exit the console market and enter the software market. In each period post-hardware purchase, consumers decide which game to purchase, if any. Thus, unlike the hardware market consumers never exit the software market. The framework I use to estimate consumer demand for consoles and video games builds upon the dynamic demand frameworks of Hendel and Nevo [2006], Gowrisankaran and Rysman [2012] and Melnikov [2013]. These papers employ an approach that reduces the state space to a manageable number by forming an inclusive value term. This term embeds the possible variations in product availability, pricing and other unobservable factors that might evolve over time.

To address the competitive response invoked by technological tying I employ several counterfactual simulations where I assume hardware and software firms are profit-maximizing entities with hardware firms competing in price. A manufacturer is willing to lower its console price in order to increase demand for its console and, in particular, its technologically tied video games, which is where the largest proportion of industry profits are made. I, therefore determine the adoption of technological tying in the home console market increases console price competition. However, it is important to highlight a key caveat in these simulations. Unlike my consumer demand model, which accounts for forward-looking consumer behavior, I abstract away the supply-sided dynamics due to the computational complexity. I assume hardware firms are myopic while software firms hold prices to those observed in the data. Consequently, my pricing results, which alter the availability of technological tying to hardware firms, are conservative estimates. This is because I underestimate the change in indirect network effects and the revenue hardware firms receive from game developers by not accounting for future software profits in counterfactual

[1] Exclusive complements are a result of a formal contract between producers of complementary goods.

simulations.

The literature regarding technological tying is relatively sparse. Yet, there are similarities to the literature covering tying and raising rivals' costs. In addition, this study adds to several other areas of research: exclusionary strategies, network externalities, multiproduct pricing and two-sided markets. Indirect network effects play a vital role in the adoption and diffusion of video game consoles and many other platforms. Much of the literature (empirically and theoretically), however, has defined network effects as a function of the number of users who are in the same "network" [Katz and Shapiro, 1985] and has abstracted away from the fact that game heterogeneity may also play an important role in the formation of the network effect. Many empirical studies, however, elect to adopt Katz and Shapiro's definition due to the limited availability of the necessary data to incorporate heterogeneity into the formation of the indirect network effect (See i.e. Nair et al. [2004], Clements and Ohashi [2005], Prieger and Hu [2012], Liu [2010], Dube et al. [2010]). I build upon the innovative research of Nair et al. [2004], Dube et al. [2010], and Liu [2010], by creating a structural demand model for video game consoles that accounts for game heterogeneity in the formation of the network effect by specifically connecting the consumer utilities in the console and software markets rather than using only the number of games.

The primary contribution of this paper is to explain how technological tying impacts hardware competition in the 128 bit video game market. There are three main economic forces that impact the intensity of console price competition when a manufacturer technologically ties its software to its hardware. The first is a result of the tie foreclosing rival console manufacturers access to games produced by a console. The second is the consequence of console manufacturers electing to design and produce video games themselves. The third is the competitive response of its rival. Each of these three forces impacts hardware competition in its own way. The first force generates an incentive for the hardware maker to raise its console price since there is a relative increase in utility from the simple fact that rivals have one less available game. For instance, in order for a consumer to play a game produced by the hardware manufacturer he must purchase the respective console, an act that increases the console manufacturer's market power. The second force, however, leads to a different effect. If we think of software as the input or upstream supplier to the production of the downstream hardware [Salop, 2005] then the "vertical" integration of these two products can produce efficiency effects similar to the elimination of the double marginalization; thus, an incentive to decrease console price is created [Cournot, 1838]. And lastly, the third economic force, the competitive response of the rival indirectly affects a tying console manufacturer's incentive to lower or raise its console price.

I also contribute to the make-versus-buy literature of Williamson [1971] and Coase [1937]. When hardware firms strategically decide to integrate and tie software to hardware their actions consist of a dominant strategy Nash equilibrium when software development costs are low. Furthermore, such an action is a dominant strategy because integration allows each hardware firm to recover larger software profits. By integrating and tying software and hardware, the hardware firm receives the difference between the integrated software price and the marginal cost rather than a royalty rate it would have received if the game was not integrated.

Lastly, this paper is closely related to the work on video games (Clements and Ohashi [2005], Nair [2007], Liu [2010], Dube et al. [2010], Prieger and Hu [2012], Derdenger and Kumar [2013], Lee [2013]) and in particular those that study exclusionary strategies. Prieger and Hu [2012] and Lee [2013] attempt to study the impact of exclusive titles on the console platform market and determine whether exclusive titles are anti-competitive. In Prieger and Hu [2012] they employ a static structural model to estimate the demand for video game consoles. They use a reduced form approach to model the indirect network effect from video games using a simple count of games available to each console at a given time. They determine exclusive games do not alter the demand for video game consoles nor create a significant barrier to entry. Lee addresses a similar question as Prieger and Hu but focuses on the welfare cost of software incompatibility. Lee implements a methodology that accounts for heterogeneity among software titles and consumer dynamics but also makes a strong simplifying assumption regarding the software market and prices. The model assumes software titles are neither substitutes nor complements to one another and that hardware and software prices are not allowed to change when addressing the impact of software exclusivity. Lee does model and recover porting costs, which permits him to allow independent software to re-optimize their platform decisions when running counterfactual simulations.

This paper is quite different from Lee [2013] in the questions that are addressed and the model that is estimated. I specifically analyze the pricing implications of integration and technological tying as well as the incentives for such actions. In doing so, I allow console prices to be re-optimized; yet, I do not allow independent software to reconsider their platform decisions when running counterfactuals.

2 Data

The data used in this study originates from marketing group NPD Funworld, which tracks sales and pricing for the video game industry. It is collected using point-of-sale scanners linked to a majority of the consumer electronics retail stores in the United States, and NPD extrapolates that data to project sales for the entire country. Included in the data are quantity sold and total revenue for three consoles and all compatible video games for each month of the data set, which covers 48 months from November 2001 through October 2005.

During the 128-bit video game console life cycle (2000-2006) the industry saw three of the most revolutionizing consoles come to market, the Sony PlayStation 2, Microsoft Xbox and Nintendo GameCube. These consoles brought larger computing power, more memory, enhanced graphics, better sound and the ability to play DVD movies. In addition, the producing firms each launched an expansive line of accessories to accompany their platforms. Sony enjoyed a yearlong first mover advantage with its launch of PlayStation 2 in October 2000. Its success was attributed to debuting first, but more significant was its large catalog of games exclusively produced for its console. Many of its biggest software hits were exclusive to PlayStation 2 but only one was produced by Sony. Microsoft Xbox was launched in very November 2001 and was by far the most technologically advanced console, with faster processing speeds and more memory than the Sony Playstation 2. Microsoft, however, struggled to gain market share as a result of its inability to attract developers to produce software titles exclusively for its console [Pachter and Woo, 2006]. The inability to secure third party exclusive games forced Microsoft to design and produce video games internally. Within weeks of the Microsoft Xbox launch Nintendo introduced its GameCube (November 2001), which was the least technologically advanced of the three consoles. Instead of competing in technology with Sony and Microsoft, Nintendo targeted younger children for its console. "The GameCube's appeal as a kiddie device was made apparent given the fact that the device did not include a DVD player and its games tilt[ed] towards an E rating" [Pachter and Woo, 2006]. The GameCube's limited success was a result of Nintendo leveraging its "internal development strength and target[ing] its loyal fan base, composed of twenty somethings who grew up playing Nintendo games and younger players who favored more family friendly games" [Pachter and Woo, 2006].

General statistics of the home video game industry are provided in the tables below. In Table 1 I present statistics regarding the release date, prices and sales (average, min and max in each month) for each console. In Table 2 I present the total number of games, total number of integrated and tied games, average sales, and average prices by console.

Table 1: Console Summary Statistics

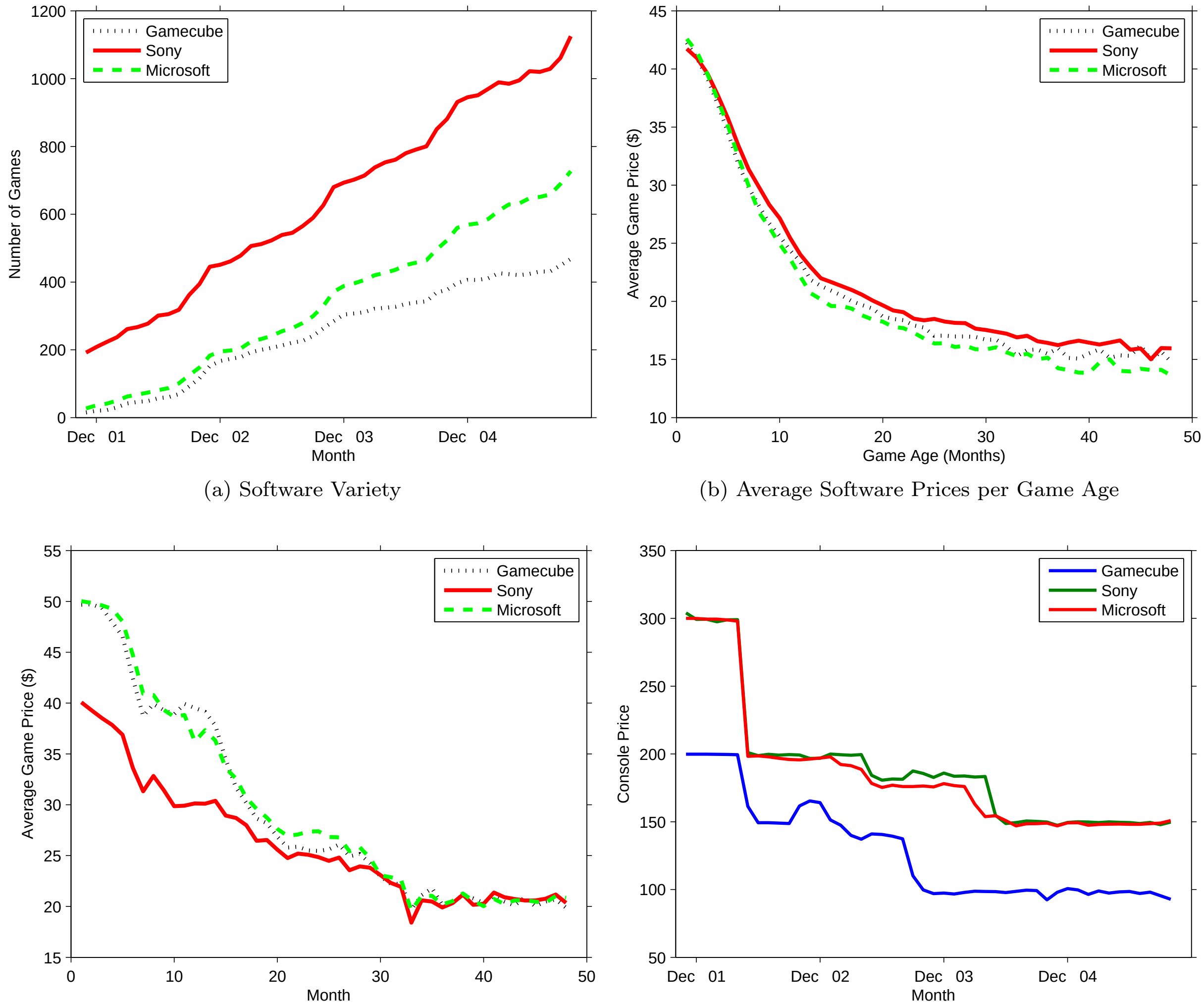
	Nintendo	Microsoft	Sony
Release Date	Nov. 18, 2001	Nov. 15, 2001	Oct. 26, 2000
Installed Base (Oct. 2005)	9,728,789	13,212,844	29,832,232
Price			
Average	$127.80	$185.49	$189.23
Max	199.85	299.46	299.54
Min	92.37	146.92	147.36
Sales			
Average	204,833	277,559	534,632
Max	1,158,229	1,079,382	2,686,288
Min	42,416	77,456	188,670
DVD Playability	No	Yes	Yes
Max Number of Controllers	4	4	2
Total Number of Observations	48	48	48

Table 2: Video Game Summary Statistics

	Nintendo	Microsoft	Sony
Release Date	Nov. 18, 2001	Nov. 15, 2001	Oct. 26, 2000
Number of Games	484	737	1156
Number of Integrated Games	43	56	105
Overall			
Average Price	24.1332	24.1768	23.7821
Average Sales	6,523	7,460	9,434
Integrated Games			
Average Price	33.8752	23.6240	22.7546
Average Sales	25,650	14,562	11,946
Total Number of Observations	12,085	16,568	30,752

In Figure 1 I present the number of games available on each console over time, the average price of a game given its age, the average software price for each console and the price of hardware over time. Figure 1a illustrates the number of software titles available each period. It is quite evident the number of games increases with time, generating greater demand for the console, all else constant. Figure 1b shows software prices declining with age. Particularly, software prices fall faster in the early stage of its life cycle than later. Figure 1c and Figure 1d present declining software and hardware prices over time, respectively. Each of these figures provides support for a model that accounts for forward-looking behavior by consumers. Below I also present statistics regarding the introduction of technologically tied games. These statistics also lend further support for a dynamic model of console and software demand.

Figure 1: Hardware and Software Statistics



(a) Software Variety

(b) Average Software Prices per Game Age

(c) Average Software Prices

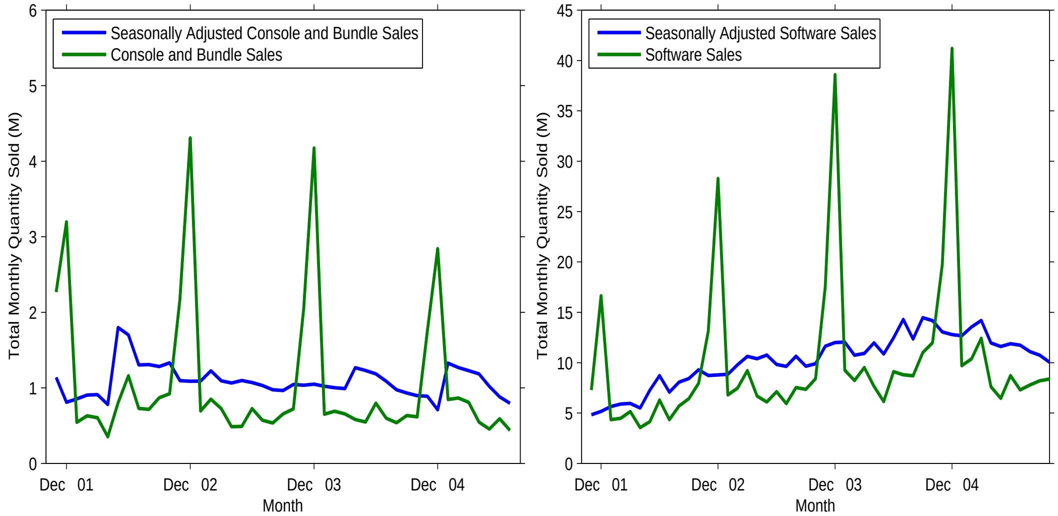
(d) Hardware Prices

I now briefly discuss three important facts regarding the industry. The first: it exhibits a large degree of seasonality in both console and video game sales. Figure 2 illustrates the total number of consoles and video games sold in each month, both of which increase considerably in the months of November and December. Since it is important to account for the large degree of seasonality in estimation, I deseason the data with the use of the X11 program from the US Census.[2] I am able to do so without much bias to the estimated model parameters from the fact hardware and software price do not differ between holiday (November and December) and non holiday time periods.[3]

[2]Similar to Gowrisankaran and Rysman [2012].

[3]I run two price regressions to determine if prices differ over holiday periods than from the rest of the calendar year. For software, I regress software prices on a vector of product characteristics, firm fixed effects, console fixed effects and a seasonal indicator variable. The regression finds no statistically significant seasonal effect on game prices (the seasoanl parameter estimate is 0.1325 with a standard error of 0.1124). As for hardware, a similar procedure is used regressing console prices on hardware charactersitics, firm fixed effects and a seasonal indicator variable for the months of November and December. Like software, there is no statistically significant seasonal effect on hardware price (the seasonal parmeter estimate is 5.5089 with a standard error of 4.1841).

Figure 2: Seasonally Adjusted Sales for Hardware and Software



The second fact is there is a large variety of video games; have a look at any consumer electronics store's video game shelves. There are seven genres of games, ranging from action to simulation. Action games have the largest share of the market with 24%, and simulation games are the smallest genre with 1%. Sales for individual games also range in the number of units sold. There are "hits" such as "Grand Theft Auto: Vice City," which has cumulative sales of more than six million on PlayStation 2, and "busts" such as "F1 2002," which sold only 48,000 units on the same console. It is this characteristic that is the driving factor for the construction of a console demand model that accounts for video game heterogeneity.

Tables 2 and 3 present statistics regarding technological tying in the video game market to further support a model that accounts for video game heterogeneity. Table 2 highlights the make-up between overall and integrated video games for each console. From this table, it is evident that Nintendo has the fewest number of video games and on average sells the fewest units, with Sony selling the most–this could be a result of the differences in the number of consumers who own a console over time. However, even though Sony produces the largest number of integrated and tied games, the firm sells the fewest on average, while Nintendo sells the most (at a substantially higher price).

Further evidence of the role of integrated and tied games is found in Table 3. This table indicates the total units of technologically tied games for each console sold in January of the reported years as well as the number of technologically tied games and a "pseudo" HHI, calculated by summing the squared market shares of each integrated and tied game.[4] The HHI index measures the concentration of tied games for each console. A small index indicates technologically tied games have little impact on total video game sales while a large index signifies the opposite. The HHI is a more encompassing measure for technologically tied game importance than the measures of number of games or total units sold, which do not account for the quality of available games; nor does the latter indicate the quantity of available games. Table 3 also brings light to the relative importance of integrated and tied games for Nintendo and Microsoft. In January 2002 both Nintendo's and Microsoft's HHIs were roughly 50 and 30 times the size of Sony's and by January 2005 the magnitude decreased to only eight and six times, respectively. An explanation for that sizable variation over time can be found in observing that Nintendo and Microsoft each sold a large number of technologically tied games over time and more instrumentally at the start of each console's life cycle. As the console aged, however, the introduction of more independent games led to a decrease in the HHI

[4]Market shares are determined using the raw sales data and are calculated from within market sales; no outside option is included

Table 3: Integrated and Technologically Tied Game Statistics

	Units Sold of Technologically Tied Games			
	2002	2003	2004	2005
Nintendo	179,011	193,347	427,153	427,449
Sony	267,545	925,290	546,351	553,758
Microsoft	382,599	234,258	414,433	454,117
	Number of Technologically Tied Games			
Nintendo	5	12	21	33
Sony	24	45	66	87
Microsoft	10	20	38	48
	Pseudo HHI of Technologically Tied Games			
Nintendo	535.94	59.49	54.44	38.10
Sony	10.28	55.29	8.02	5.37
Microsoft	305.02	17.39	29.09	29.97

Note: Statistics calculated for January of the corresponding year.

even though total units sold of tied games increased. The relative role of integrated and tied games consequently decreased with time for Nintendo and Microsoft.[5]

3 Demand Model

In this section I discuss the structural model that captures the complementary relationship between consoles and video games and the forward-looking behavior of consumers in both the hardware and software markets. The interconnectedness of hardware and software can play an important role in product adoption in platform markets [Nair et al., 2004]. Before entering the hardware market consumers may consider the number and quality of software titles that exist for the platform as well as how the number and quality of titles is expected to evolve in the future. Consumers not only form expectations about these software characteristics over time but also about hardware and software prices. Dynamics thus play a crucial role in consumer adoption. Given that I study a market consisting of durable goods it is important to specifically model a consumer's forward-looking behavior.

The timing of the model is as follows: for consumers who do not own hardware they decide whether or not to purchase a console in each period (month). They continue to make such a decision in each period until they elect to purchase a console. Once consumers have purchased hardware they exit the console market and enter the software market, where, unlike in the console market, they remain. In each period after the purchase of hardware, consumers decide what piece of software to purchase, if any. In order to estimate a model of demand that incorporates the discussed model timing and a consumer's forward-looking behavior, I use the frameworks of Gowrisankaran and Rysman [2012] and Melnikov [2013]. These papers employ an approach that reduces the state space to a manageable number, by using the inclusive value term as the state variable. This term embeds the possible variations in product availability, pricing, and other unobservable factors that might evolve with time.

The linkage of the software demand back to hardware is also a very important feature of the model. I connect consumer utility in the console and software markets through the use of an indirect network effect. Consumers are assumed to have expectations over the evolution of the software market and the value provided by software in determining whether to purchase a console. The expected value function accounts for the future evolution of the software market, which incorporates changes in software availability through the entry of new and the exit of old

[5] Sony's HHI is relatively small because in January 2002 the console was over a year old and already had a large number of independent games associated with its console causing the market share of these games to be small.

games as well as software price fluctuations.

Next, I outline the utility specifications for hardware and software, first discussing the associated utilities for consoles and then software.

Console Utility

In this section I develop a model of console choice, where each consumer $i \in \mathbf{I}$ considers whether or not to purchase a console from the available set $\mathbf{C_t}$, in each period (month) $t \in \mathbf{T}$. Once a consumer purchases a video game console he exits the market for consoles. I assume consumers exit that market entirely; The North American Consumer Technology Adoption Study determines the fraction of the U.S. gaming population that owns two or more video game consoles of the same generation is less than 4.5%. Multihoming in consoles is therefore not an important factor.

Consumer i determines in period t whether or not to purchase console c. Consoles are assumed to be durable and receive a stream of utility in each period post-purchase. Since I do not allow consumers to replace a previously purchased console with a second, the idea of a flow utility is moot and instead can be thought of as a one-time lump sum of utility in the period of adoption. If consumer i decides to purchase console c in period t , he obtains utility given by

$$u^h_{i,c,t} = \alpha_c + \alpha^{x,h} x_{c,t} + \alpha^{p,h} p_{c,t} + \varphi \Upsilon_{i,c,t} + \xi_{c,t} + \epsilon_{i,c,t} \tag{1}$$

where $x_{c,t}$ are observable console c characteristics, $p_{c,t}$ is the price of console c in period t, and $\xi_{c,t}$ is an unobservable characteristic (to the econometrician) that varies both over time and across consoles.[6] Examples of physical console characteristics are processing speed, graphics quality, volume of the console, CPU bits, and the number of controllers. Unobserved characteristics include other technical characteristics and market-specific effects of merchandising. I control for both the unobserved and observed product characteristics, which do not vary over time, with the inclusion of console specific fixed effects, α_c. Furthermore, the utility of a gaming console is also related to the expected value of optimally purchasing software associated with console c for consumer i in period t and is captured with the term $\Upsilon_{i,c,t}$. The functional form of $\Upsilon_{i,c,t}$ will be discussed in the next subsection, which is derived from the software demand model.

The coefficient $\alpha^{x,h}$ indicates the effect of console characteristics on the consumer's utility. $\alpha^{p,h}$ is the consumer's price coefficient. Lastly, I assume $\epsilon_{i,c,t}$ for $c \in \{0\} \cup \mathbf{C_t}$ to be distributed as a Type I Extreme Value random variable, which is independently and identically distributed across consumers, products, and time periods.

Video Game Utility

Now consider a consumer who owns console c and is in the market for compatible video games. The potential market for games is thus driven by the number of consumers who currently own console c. I do not allow consumers who do not own a console to purchase video games. I denote the choice set of video games available for purchase in period t for console c as $\mathbf{S_{ct}}$, which includes the no-purchase option 0. I assume each video game competes with all others compatible with console c. This implies consumers substitute across games but are restricted to purchasing only one video game in any given period t. For consumer i, the utility from game g on console c in period t is

$$u^s_{i,g,c,t} = \alpha^s_i + \alpha^{w,s} w^s_{g,c,t} + \alpha^{p,s} p_{g,c,t} + \chi_{g,c,t} + \epsilon_{i,g,c,t} \tag{2}$$

where $w^s_{g,c,t}$ represents the observable characteristics of the game g on console c in period t–including age, game rating, genre, the creating firm, exclusivity of the game and the log number of games in period t. I include the last

[6] Let superscript h denotes utility for hardware.

covariate because of the potential bias associated with the estimation of demand with a large choice set and a logit assumption. Ackerberg and Rysman [2005] shows that this feature implies logit-based models "will perform poorly in contexts where consumers face different numbers of products over time" and recommends researchers include a suitable transformation of the number of products as a regressor to alleviate this issue. I follow Ackerberg and Rysman [2005] and employ the log number of video games available in period t in a consumers utility function to correct for the large and growing choice set. Like above, the unobservable software characteristic is represented by $\chi_{g,c,t}$. The price of the software title g compatible with console c in period t is captured by the variable $p_{g,c,t}$. The error term $\epsilon_{i,g,c,t}$ is comprise of idiosyncratic shocks that are distributed as Type I Extreme Value random variables, independent across consumers, games, consoles and time periods. The coefficient α_i^s represents the value that individual i attaches to playing video games (a gaming preference), whereas $\alpha^{p,s}$ denotes the price coefficient.

In order to combine measures of hardware and software utility, as I do in the above hardware utility function with the variable Υ, I scale the standard deviation of the error term for software by ψ. An alternative way to interpret ψ is on the extent of consumer utility based on unobservable factors. This scaling allows for the comparison of hardware and software utilities, which is required because I assume that the error terms for both hardware and software have the same variance ($\frac{\pi^2}{6}$ for a Type-I extreme value random variable)

$$\tilde{u}^s_{i,g,c,t} = \frac{1}{\psi}\left(\tilde{\alpha}^s_i + \tilde{\alpha}^{w,s} w^s_{g,c,t} + \tilde{\alpha}^{p,s} p_{g,c,t} + \tilde{\chi}_{g,c,t}\right) + \widetilde{\epsilon}_{i,g,c,t}.$$

It is typical to assume consumer i who purchases game g in period t exits the market for game g; when consumer i decides to not purchase game g in period t he remains in the market for game g and receives a utility of $u_{i,0,0,t} = \epsilon_{i,0,0,t}$. In order to introduce software competition I assume consumers are able to repurchase an already owned title. I make this assumption for the mere fact a multinomial logit model of game demand becomes computationally infeasible to estimate when a more precise tracking mechanism of each game's potential market size is accompanied by the assumption of competition among games. The downside of this assumption is that consumers may purchase the same game multiple times during the data period. Like Derdenger and Kumar [2013] I believe this to be unlikely to happen frequently for two reasons: "(a) consumers in general have a low purchase probability for any game title, given that there are hundreds of titles. (b) software titles reach their peak pretty early in their life-cycle and decline in sales beyond that, so if a consumer hasn't found a high-enough utility in an early period, she's not likely to obtain a high utility in later periods." Software $g_c\acute{}s$ potential market size is therefore the cumulative sum of console c sales up to and including period t. As a result, I do not adjust the potential market size downward to account for software previously sold.

An alternative to the above assumption is to model the market for each video game separately, leading to monopoly markets for each game [Lee, 2013]. This assumption would enable the tracking of the number of consumers who have purchased the specific software. In doing so I could update the potential market in each period to include the number of households that own the product. However, the biggest drawback for this alternative approach is that competitive interactions between software titles would not be accounted for, leading to overestimation of quality if one believes competition is an important feature.[7] Consequently, I elect to introduce competition into the software model but allow consumers to possibly repurchase software titles, an approach that conservatively estimates the quality of software driven by the larger-than-actual potential market size.

Lastly, in estimation I impose a restriction on the model to fix a consumer's price sensitivity to be equal for hardware and software. This restriction takes the form $\alpha^{p,s} = \frac{\alpha^{p,h}}{\psi}$. From a structural viewpoint, the price coefficient for consumers would be different for hardware and software only because the purchase of a hardware console would cause a change in wealth effects leading to a change in price sensitivity. I assume this is unlikely given video games are no more than six times more expensive than games, which are roughly $50.

[7]See appendix for test of importance of competition.

3.1 Consumer's Problem

I now formally outline the consumer's decision process for hardware and software, which incorporates the interdependence of hardware and software as wells as a consumer's forward-looking behavior. I focus on a consumer's decision problem for hardware first and software second.

To rehash the timing of the model, in period t, each consumer makes a discrete choice from the set of $\mathbf{C_t}$ available consoles. After purchasing console c he exits the market for hardware and enters the market for software, where he may purchase one video game compatible to console c in period t and repeats the software purchase decision in each future month, again purchasing only one game each month.

Console Market

Consumer i's decision problem for a console in a specific period t equates to an optimal stopping problem; he determines whether to buy a product now or wait until the next period. This is a consequence of the fact that the model does not allow for a consumer to purchase a second console.[8] Each consumer anticipates the evolution of all state variables $\Omega^h_{i,t}$ that will affect the value of his hardware adoption decision. Such variables include the future evolution of console characteristics (both observable and unobservable) and future price levels, as well the video games that might be released in the future.

For a consumer in the hardware market, the Bellman equation that describes the consumer's value for being in a current state $\Omega^h_{i,t}$ prior to his realization of ϵ is:

$$EV(\Omega^h_{i,t}) = \int \max\{\epsilon^h_{i,0,t} + \beta \mathbf{E}\left[EV^h\left(\Omega^h_{i,t+1}|\Omega^h_{i,t}, \epsilon^{\mathbf{h}}_{\mathbf{it}}\right)\right], \max_{c\in\mathbf{C_t}} u^h_{i,c,t}\} g(\epsilon^h) d\epsilon^h \tag{3}$$

where the first term is the utility associated with the decision to not purchase any console and the second is that of purchasing a console in period t.

Given that $\Omega^h_{i,t}$ encompasses a large number of state variables it would be computationally demanding to estimate the demand model with the above equation 3. I follow Gowrisankaran and Rysman [2012] and assume consumers do not concern themselves with all possible state variables included in $\Omega^h_{i,t}$. Rather they concern themselves only with a consumer-specific logit inclusive-value state variable $\delta^h_{i,t}$ that captures the effects of all the variables in $\Omega^h_{i,t}$. The logit inclusive value term is the ex-ante present discounted lifetime value of buying the preferred console, as opposed to holding the outside option. Note, given consumers exit the market after the purchase of hardware and are unable to replace/upgrade their console, the logit inclusive value is also the ex-ante current lifetime value. With the employment of the extreme value distribution for ϵ and the inclusive value, I can transform the above function into a much simpler form:

$$EV\left(\delta^h_{i,t}\right) = ln\left(\exp\left(\beta \mathbf{E}_\delta\left[EV(\delta^h_{i,t+1})|\delta^h_{i,t}\right]\right) + \exp\left(\delta^h_{i,t}\right)\right) \tag{4}$$

where the first term again is the value of holding the outside option and the second is the logit inclusive value or the expected maximum utility associated with the set of $\mathbf{C_t}$ available consoles defined as

$$\delta^h_{i,t} = ln\left(\sum_{c\in\mathbf{C_t}} \exp\left(\alpha_c + \alpha^{x,h} x_{c,t} + \alpha^{p,h} p_{c,t} + \varphi \Upsilon_{i,c,t} + \xi_{c,t}\right)\right).$$

Implicit in the formulation of equation (4) I assume that consumers predict future values of δ^h based only on the current δ^h, rather than on the full information set Ω^h. The one downside to this approach is that it requires the inclusive value sufficiency (IVS) assumption, implying that all states with the same δ^h have the same future. For

[8]Again, based on data from The North American Consumer Technology Adoption Study only 4.5% of consumers surveyed own multiple consoles.

example, δ^h could be high in a given period either because there are three consoles in the market all with low prices or because there are three consoles in the market each with a large Υ. I like, Gowrisankaran and Rysman [2012], interpret the IVS assumption as based on how potentially boundedly rational consumers perceive the market. In the industry, I believe there are two sources of dynamics that are most important since all other console characteristics remain constant over time; the two stem from consumers' expectations in early periods of declining prices and the increase in game quality via manufacturers' accumulation of compatible games, integrated and non-integrated. I, therefore, assume the consumer is on average correct about the future. Consumers are assumed to perceive the inclusive value $\delta^h_{i,t}$ to evolve according to an $AR(1)$ process, and I estimate the parameters of the following process

$$\delta^h_{i,t+1} = \gamma_{i,1} + \gamma_{i,2}\delta^h_{i,t} + \zeta_{i,t} \tag{5}$$

where $\zeta_{i,t}$ is normally distributed with mean zero and standard deviation σ_ζ, and is iid across consumers and time periods. The individual-specific parameters $\gamma_{i,1}$ and $\gamma_{i,2}$ define the evolution of the inclusive value state, and yield a probability distribution for the future state, conditional on the current.

Once the expected value functions $EV\left(\delta^h_{i,t}\right)$ are obtained by solving the Bellman equation, I use them to determine the individual purchase probabilities for consumers. Consumer i's probability of purchasing product c is given as a function of the inclusive value, $\delta^h_{i,t}$ and is

$$\hat{s}_{i,c,t}(\delta^h_{i,t}) = \frac{\exp\left(\delta^h_{i,t}\right)}{\exp\left(EV\left(\delta^h_{i,t}\right)\right)} \frac{\exp\left(\delta^h_{i,c,t}\right)}{\exp\left(\delta^h_{i,t}\right)} = exp(\delta^h_{i,c,t} - EV\left(\delta^h_{i,t}\right)). \tag{6}$$

where $\delta^h_{i,c,t} = u^h_{i,c,t} - \epsilon_{i,c,t}$.

Software Market

The consumer's decision problem for software is different from the hardware decision described above. There is no optimal stopping problem, a result of the consumer remaining in the software market even after the purchase of his first video game title. Also, his purchase is not one that acts to replace his previously owned games but, rather, adds to his software portfolio, providing continuous flow utility. The consumer in each period faces the choice of purchasing a video game title or making no purchase at all. In period t, the consumer's current software portfolio provides utility $F^s_{i,t}$ and is accounted for in his decision-making process. Gowrisankaran et al. [2010], however, illustrate how a model with a similar setup can be transformed so that the accumulated software flow utilities, $F^s_{i,t}$, do not impact the consumer's current or future software purchase decisions. For such a transformation to occur I assume there exists no diminishing marginal returns to purchasing larger number of video games. Consequently, I specify a consumer model that "ignores" a consumer's software portfolio.[9] With this assumption consumers no longer concern themselves with the number of games they hold and how that might impact their purchase decisions in the future. There are two sources of dynamics associated with the consumer's software purchase decision. They originate from declining software prices and an increase in the variety of games available. As is evident from Figure 1, software prices decline with the age of the title and over time generating an intertemporal tradeoff for consumers. Consumers either can consume now at a higher price or delay purchase expecting a lower future price. Yet, delaying the purchase of software increases a game's age but decreases its software quality. Moreover, the number of available games is increasing with time (evident from Figure 1) generating a disincentive to postpone the consumption of video games from greater software congestion.[10] Although portfolio effects are "ignored", there still exists important sources of dynamics to account for in the consumer's software decision process. Below I describe

[9]This assumption and transformation does not impact the linkage between hardware and software (see below) given that consumers do not own any video games prior to purchasing hardware.

[10]See Ackerberg and Rysman [2005] for congestion interpretation. Although the way I model such is in a reduce form approach.

this decision making process.

Like in the hardware market, a consumer's decision problem is dependent on the software state variables Ω^s. The corresponding Bellman equation for software compatible with hardware c is

$$EV(\Omega^s_{i,c,t}) = \int \max\{\epsilon^s_{i,0,t} + \beta \mathbf{E}\left[EV^s\left(\Omega^s_{i,c,t+1}|\Omega^s_{i,c,t}, \epsilon^{\mathbf{s}}_{\mathbf{it}}\right)\right], \max_{g\in\mathbf{S_{c,t}}}\left(u^s_{i,g,c,t} + \beta\mathbf{E}\left[EV^s\left(\Omega^s_{i,c,t+1}|\Omega^s_{i,c,t}, \epsilon^{\mathbf{s}}_{\mathbf{it}}\right)\right]\right)\}g(\epsilon^s)d\epsilon^s \tag{7}$$

The first term is the utility associated with the decision to not purchase any video game and the second is that of purchasing a video game in period t. Note here that both the no purchase and purchase options have the same continuation value associated with remaining in the software market. These terms do not differ as I do not account for any marginal disutility associated with owning a greater number of video games like that of Gowrisankaran et al. [2010].

Also similar to the hardware market, I reduce the large dimension of the state variable Ω^s by employing the logit inclusive value state variable. With the employment of the extreme value distribution for ϵ^s and the inclusive value I can transform the above function into a much simpler form:

$$EV(\delta^s_{i,c,t}) = ln\left(\exp\left(\beta\mathbf{E}_\delta\left[EV(\delta^s_{i,c,t+1})|\delta^s_{i,c,t}\right]\right) + \exp\left(\delta^s_{i,c,t}\right)\right)$$

where

$$\delta^s_{i,c,t} = ln\left(\sum_{g\in\mathbf{S_{c,t}}}\exp\left(\alpha^s_i + \alpha^{w,s}w^s_{g,c,t} + \alpha^{p,s}p_{g,c,t} + \chi_{g,c,t} + \beta\ \mathbf{E}_\delta\left[EV(\delta^s_{i,c,t+1})|\delta^s_{i,c,t}\right]\right)\right).$$

and includes the continuation value of remaining in the software market even when purchasing a video game. The downside to this approach, like that of the above hardware model, is that it requires the inclusive value sufficiency (IVS) assumption, implying that all states with the same δ^s have the same future. For example, δ^s could be due to a large number of low quality games or because there is one game with high quality. A consumer's decision could be quite different under these two scenarios. Therefore, in the robustness section I report the results of a model that accounts for the number of software titles available in a given period as a second state variable.[11]

I also assume $\delta^s_{i,c,t}$ is perceived by consumers as evolving in accordance with an $AR(1)$ process, and I estimate the parameters of the following process:

$$\delta^s_{i,c,t+1} = \gamma^s_{i,1} + \gamma^s_{i,2}\delta^s_{i,c,t} + \zeta^s_{i,j,t}. \tag{8}$$

Once the value functions $EV\left(\delta^s_{i,c,t}\right)$ are obtained by solving the Bellman equation, I use them to determine the individual purchase probabilities for consumers. Consumer i's probability of purchasing game g available on console c is given as a function of the inclusive value, $\delta^s_{i,c,t}$ and is as follows:

$$\hat{s}_{i,g,c,t}(\delta^s_{it}) = \frac{\exp\left(\delta^s_{i,c,t}\right)}{\exp\left(EV\left(\delta^s_{i,c,t}\right)\right)}\frac{\exp\left(\delta^s_{i,g,c,t}\right)}{\exp\left(\delta^s_{i,c,t}\right)} \tag{9}$$

where $\delta^s_{i,g,c,t} = u^s_{i,g,c,t} - \epsilon_{i,g,c,t} + \beta\ \mathbf{E}_\delta\left[EV(\delta^s_{i,c,t+1})|\delta^s_{i,c,t}\right]$.

I now close the model and the consumer's decision problem by linking software demand back to the hardware demand model. The effect of software on hardware is a crucial feature of the model as complementary products can

[11] In this model consumers assume the number of video games evolves exogenously and according to an AR(1) process.

play a pivotal role in the consumer adoption of a platform [Nair et al., 2004]. I connect the utility for a consumer in the console and software markets through the use of an indirect network effect–consumers form expectations of the evolution of the software market and the value provided by software in determining whether to purchase a console. The expected value of being present in the software market is thus a vital part of console utility and is classified as the indirect network effect. With the formulation of the expected value function for software on console c for consumer i in period t, the expected value of optimally purchasing software over time associated with console c is

$$\Upsilon_{i,c,t} = EV\left(\delta^s_{i,c,t}\right).$$

4 Estimation and Identification

The estimation procedure I use to recover the structural model parameters follows that of Gowrisankaran and Rysman [2012]. I jointly estimate console and video game demand to further aid in the identification of the model parameters. I model heterogeneous consumers with the heterogeneity represented by $\alpha_i^s = \bar{\alpha^s} + \nu_i \sigma_{\mathbf{s}}$. Consistent with the dynamic demand literature of the video game industry I set the discount factor to be $\beta = 0.975$ [Nair, 2007].

The demand estimation is based on GMM, and the minimization of the objective function equals to

$$F_{GMM} = [\xi(\theta,\psi,\sigma_{\mathbf{s}});\chi(\theta,\psi,\sigma_{\mathbf{s}})]\mathbf{ZWZ'}\begin{bmatrix}\xi(\theta,\psi,\sigma_s)\\ \chi(\theta,\psi,\sigma_s)\end{bmatrix}, \tag{10}$$

which is based on the orthogonality of the unobservable characteristics and the instruments.

In order to recover $\xi(\theta,\psi,\sigma_s)$ and $\chi(\theta,\psi,\sigma_s)$ I have to determine the aggregate market shares for each piece of hardware and software. Using equations 6 and 9 I can solve for the predicted aggregate market shares for hardware and software by integrating over consumers i in each time period. The integration is performed using a Gaussian-Hermite quadrature approach with 15 nodes. I approximate an integral as a weighted sum of the integrand evaluated at a finite set of well-specified points called N nodes with weights λ (or fraction of people) [Skrainka and Judd, 2011].[12] Yet, before the integration occurs I first account for the evolution of consumer types in the hardware and software markets.[13]

Once aggregated market shares are determined, I employ the contraction mapping of Berry et al. [1995] to recover the time dependent mean consumer value associated with each piece of hardware$\left(\bar{\delta}^h_{c,t}\right)$ and software $\left(\bar{\delta}^s_{g,c,t}\right)$ as a function of (ψ,σ_s). This requires solving the equations of

$$\begin{aligned} s_{c,t} &\equiv \tfrac{Q^h_{c,t}}{M^h_t} = \textstyle\sum_i \lambda^h_{i,t}\hat{s}_{i,c,t}(\bar{\delta}^h_{c,t},\Upsilon_{i,c,t},\psi,\sigma_s)\\ s_{g,c,t} &\equiv \tfrac{Q^s_{g,c,t}}{M^s_t} = \textstyle\sum_i \lambda^s_{i,c,t}\hat{s}_{i,g,c,t}(\bar{\delta}^s_{g,c,t},\psi,\sigma_s)\end{aligned}$$

where $s_{c,t}$ and $s_{g,c,t}$ are the observed market shares, $\hat{s}_{c,t}$ and $\hat{s}_{g,c,t}$ are the predicted market shares from the above model, and $\lambda^h_{i,t}$ and $\lambda^s_{i,c,t}$ are the fraction of consumers of type i in period t that remains in the market for hardware and the fraction of consumers of type i in period t who have purchased hardware c prior to and in period t. Lastly, M_t is the potential market of consumers in period t in either the hardware or software markets.

Calculating the potential market size for consoles is a crucial step in estimating demand and I use the number

[12] The reader can think of the N nodes as also being N discrete types of consumers each with a different weight. These two objects then approximate a normal distribution for consumer preference toward software.
[13] Further discussion on how these weights evolve is found in the appendix.

of households with a TV in 2000 as the initial potential market size.[14] Specifically, I adjust the initial market for hardware in November 2001 to be 105 million consumers minus the total number of Sony consoles sold previously. The initial market for video games is zero with the exception of Sony as I have the installed base measure in the beginning of November 2001. Note, however, the initial distribution of potential consumers for Sony hardware is identical to its competitors, which does not eliminate the initial condition bias; I still under-report the distribution of high type consumers on Sony's platform.

Recall that consumers first purchase a console and then purchase software games. The construction of the potential market size for consoles reflects the idea that a consumer is a first-time buyer and does not re-enter the market to purchase additional consoles. The potential market size for hardware evolves according to

$$M_t^h = M_{t-1}^h(1 - \sum_c \sum_i \lambda_{i,t-1}^h \hat{s}_{i,c,t-1}).$$

After purchasing hardware, the consumer consequently enters the market for video games. Thus, the potential market size of game purchasers in period t includes consumers who have purchased console c across all periods up to and including period t. The evolution of the potential market for software is

$$M_{c,t}^s = M_{c,t-1}^s + Q_{c,t}^h$$

where $Q_{c,t}^h$ is the aggregate demand for console c in period t. I reiterate that I do not allow the potential market size to adjust for previous purchases of software; this is because of the intractability of tracking the number of specific consumers for each game given the multinomial logit model assumption.

In summary, the estimation procedure is[15]

1. Make an initial guess of$\left(\bar{\delta}_{c,t}^h, \bar{\delta}_{g,c,t}^s, \psi, \sigma_s, \lambda_{i,t}^h, \lambda_{i,c,t}^s\right)$ as inputs;
2. Using guess of $\left(\bar{\delta}_{g,c,t}^s, \psi, \sigma_s, \lambda_{i,c,t}^s\right)$ predict individual software purchase probabilities using equation 9;
3. Recover $\bar{\delta}_{g,c,t}^s$via Berry et al. [1995] contraction mapping and recover corresponding $\Upsilon_{i,c,t}$;
4. Using the initial guess of $\left(\bar{\delta}_{c,t}^h, \psi, \sigma_s, \lambda_{i,t}^h\right)$and the recovered $\Upsilon_{i,c,t}$ from the software model, predict individual hardware purchase probabilities using equation 6;
5. Recover $\bar{\delta}_{c,t}^h$via Berry et al. [1995] contraction mapping;
6. Update guess of $\lambda_{i,t}^h$ and the resulting $\lambda_{i,c,t}^s$;
7. Iterate steps (2) - (6) until tolerance on $\Upsilon_{i,c,t}$ is reached;
8. Compute the GMM objective function defined in equation (10)
9. Search over (ψ, σ_s) repeating steps 2-8 until the GMM objective function, Equation 10, is minimized.

[14]Dube et al. [2010] and others use a similar approach.
[15]This procedure is similar to the one used in Derdenger and Kumar [2013] and Lee [2013].

Identification

I use instrumental variables to correct for price endogeneity to accurately estimate and identify a consumer's price sensitivity for hardware and software. For instance, producers could set higher prices for higher quality games, but because not all measures of quality are observable to the econometrician it could lead to an upward bias in the price coefficients since price and quality are correlated. Both Berry [1994] and Berry et al. [1995] show that proper instruments for price are variables that shift markups. I use standard BLP instruments for software price. Instruments include functions of game age, rating and number of games from a software firm and of the remaining competing firms. I deviate from standard BLP type instruments with instruments that proxy for marginal cost for hardware. I use a one-month lag in the Japanese to U.S. exchange rate, and the producer price index for computers. The foreign exchange rate is a suitable instrument given the manufacturing of most consoles and games occurs in Japan and would consequently affect the retail price of consoles in the U.S. I employ a one-month lag to allow for time between shipping, displaying, and purchasing. Instruments are interacted with console indicator variables to allow each variable to enter the production function of each console differently. This method is similar to that of Villas-Boas [2007].

Next, consider the software characteristics. Age is identified by increasing or decreasing sales over time. The variables corresponding to software exclusivity and the interaction of exclusivity and integration are identified from variation in sales relative to non-exclusive titles. Lastly, the console-specific effect for software is identified from variation in sales of a game on multiple consoles.

The variance of the software heterogeneity parameter α_i^s is identified with the use of both hardware and software data. The first source originates from variation of the expected software value function over time and across platforms, since the function incorporates α_i^s. As this function changes for a given console, if consumers substitute to a console with a similar expected software value it then would indicate the presence of consumer heterogeneity in the software preference parameter. Yet, if consumers substitute to consoles proportional to observed console market shares then no heterogeneity is identified. This is the typical strategy employed in BLP type models to identify heterogeneity. The second source originates from the dynamic nature of the problem. Given the hardware installed base is the potential market size for software, the mixture of consumers types over time also aids in identification of σ_s. The proposed model, conditional on consumer heterogeneity existing, implies that consumers with the highest value for software purchase hardware earlier than those consumers who have a lower valuation. This dynamic effect, along with the change in product characteristics of hardware over time is an additional source of variation that aids identification. Yet, given the nature of the data that omits Sony software sales for the first 13 months, I am unable to estimate console and video game demand for these months. This creates an initial conditions problem and I am very aware of this shortfall. Besides finding data for this time period, there is little I can do except acknowledge and discuss its impact on estimation. This problem has a direct impact on the model primitives that capture consumer heterogeneity. Also affected is the software demand model because data on high preference consumers who own a Sony console is under-reported over time. I attempt to mitigate the bias associated with this problem by allowing the potential market for hardware in November 2001 to be adjusted downward by the number of Sony consoles previously sold. This is by no means a complete solution as doing so will only lessen the bias, not eliminate it. Note, the assumption regarding the ability to repeat purchase a video game also makes identification more challenging than would be the case if I was computationally able to track consumer purchases through time. The consequence of such an assumption is that it slows the decline of the relative mixture of high software consumers to low over time making it appear as though a lesser degree of consumer heterogeneity is present.

In the hardware market, the product characteristics coefficients are identified by variations in console characteristics over time. The coefficients of product characteristics are identified both from the variation of console sales and prices and from whether increased sales for a specific product come from other products that are "more or less"

Table 4: Estimation Results

	Dynamic Model	
Variable	Coefficient	Std. Error
Video Game Utility Parameters		
Constant	1.600**	0.137
Game Age	-0.125**	0.001
Rating	0.455**	0.005
Exclusive	0.568**	0.144
Exclusive*Independent	-0.729**	0.145
Log(Number of Games)	-1.040**	0.015
Nintendo	-0.495**	0.018
Sony	0.421**	0.016
Sigma Software(σ_s)	0.001	0.107
Console Utility Parameters		
Console Price	-0.022**	0.005
Nintendo	-20.813**	0.184
Sony	-18.269**	0.172
Microsoft	-19.079**	0.124
Console Age	0.002	0.005
Scale Parameter(ψ)	0.498**	0.104

Notes:****indicates significant at 95%;**

Game Genre and Firm FE in all models not reported

similar in terms of product characteristics. While these sources of variation are standard elements needed for identification. The identification of the normalization parameter ψ that permits direct comparison of the hardware and software utilities follows from a restriction of $\alpha^{p,s} = \frac{\alpha^{p,h}}{\psi}$. The identification of ψ originates from the consumer's relative responsiveness to hardware and software price sensitivity.

5 Results

I present the parameter estimates for the consumer's utility model in Table 4. I first discuss the video game utility results and then the console results. The implicit coefficient of software price is negative, which means consumers have a marginal disutility toward price ($\alpha^{p,s} = \frac{\alpha^{p,h}}{\varphi} = -0.044$). Consumers dislike older games, evident from the negative parameter estimates associated with game age. When a game is available on multiple consoles consumers value the game the most on Sony's console, followed by Microsoft's and then Nintendo's. The model also determines that there is not significant consumer heterogeneity in valuation for software, with a standard deviation of $\sigma_s = 0.001$, which is statistically not different from zero. This is most likely a result of the initial conditions problem associated with not being able to track consumer types that purchased Sony consoles and compatible games in 2000 and 2001. Note that these consumers are most likely the ones who have strong software valuations and, thus, would buy hardware first. Lastly, I determine that consumers value exclusivity (0.568) but have disutility towards an independent exclusive game (-0.729). This disutility is perhaps a result of selection by software firms; these video games could have been of lesser quality and not worthy of being released for multiple consoles, thus driving the developing firm to volunteer for exclusivity.

I now discuss the demand parameters associated with console utility. Consumers have disutility for price at an estimate of $\alpha^{p,h} - 0.022$. I also estimate the relative variance of the software idiosyncratic error term to that of hardware to be $\psi = 0.498$. This value also can be interpreted as the marginal effect of software on hardware. Consumers value software when purchasing hardware. The positive sign associated with this parameter is consistent

Table 5: Robustness

	(1)		(2)		(3)		(4)	
Variable	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Video Game Utility Parameters								
Constant	1.607**	0.137	1.729**	0.139	1.600**	0.137	1.402**	0.137
Game Age	-0.125**	0.001	-0.124**	0.006	-0.125**	0.001	-0.131**	0.007
Rating	0.455**	0.005	0.452**	0.005	0.455**	0.005	0.471**	0.005
Exclusive	0.568**	0.144	0.568**	0.144	0.568**	0.144	0.603**	0.144
Exclusive*Independent	-0.728**	0.145	-0.732**	0.145	-0.729**	0.145	-0.754**	0.144
Log(Number of Games)	-1.041**	0.015	-1.060**	0.015	-1.040**	0.015	-1.018**	0.014
Nintendo	-0.495**	0.018	-0.499**	0.018	-0.494**	0.018	-0.456**	0.018
Sony	0.421**	0.016	0.425**	0.017	0.420**	0.017	0.292**	0.017
Sigma Software(σ_s)					0.001	1.172		
Console Utility Parameters								
Console Price	-0.022**	0.005	-0.022**	0.003	-0.022**	0.005	-0.023**	0.003
Nintendo	-20.806**	0.184	-25.744**	0.177	-20.829**	0.184	-21.749**	0.246
Sony	-18.269**	0.172	-23.152**	0.169	-18.299**	0.172	-19.058**	0.232
Microsoft	-19.078**	0.124	-23.995**	0.122	-19.104**	0.124	-20.024**	0.225
Console Age	0.002	0.005	-0.001	0.004	0.003	0.005	-0.013**	0.004
Scale Parameter(ψ)	0.494**	0.103	0.520**	0.006	0.496**	0.109	0.428**	0.001
Sigma Software(σ_h)					0.001	0.113		

Notes: ****indicates significant at 95%; Game Genre and Firm FE in all models not reported**

with the theoretical literature on indirect network effects, underscoring the value of video game software and its influence in hardware purchasing decisions. Consumers also place higher utility toward Sony's hardware even after controlling for important characteristics such as console age.

In Table 5 I report the results for several additional models as robustness checks. The first (i) reports the result employing deseasoned data and no consumer heterogeneity. The second includes the log number of video games as an additional state variable in the consumer's software value function.[16] I include the log number of software titles as an additional state variable to explore the importance of the IVS assumption. The results of this model are similar to the above primary results and those of models (1) and (3), where model (3) includes heterogeneous preferences for both hardware and software, signifying the IVS assumption is reasonable. The last model run is one that does not employ the deseasoned data. In particular model (4) is identical to model (1) but is estimated with the raw data. In estimating this model, a month of year variable is included as an additional state variable, which adds computational time to the estimation procedure. Month of year fixed effects are also incorporated into both the hardware and software utility functions to help capture seasonality effects in purchasing.[17] Notice the results from model (4) do not dramatically differ from that of model (1) .

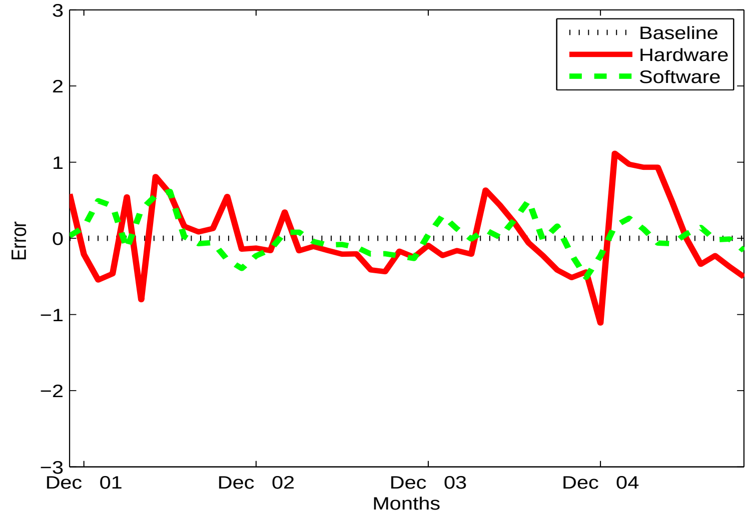
Model Fit

I assess model fit by reporting the average console estimation error term over the 48-month time period. Figure 3 presents this information. From this figure I see no strong evidence of systematic auto-correlation or heteroscedasticity of the average console or software error term over the time period.

[16]In estimating this model the log number of games available in period t was included as second covariate in equation 8.

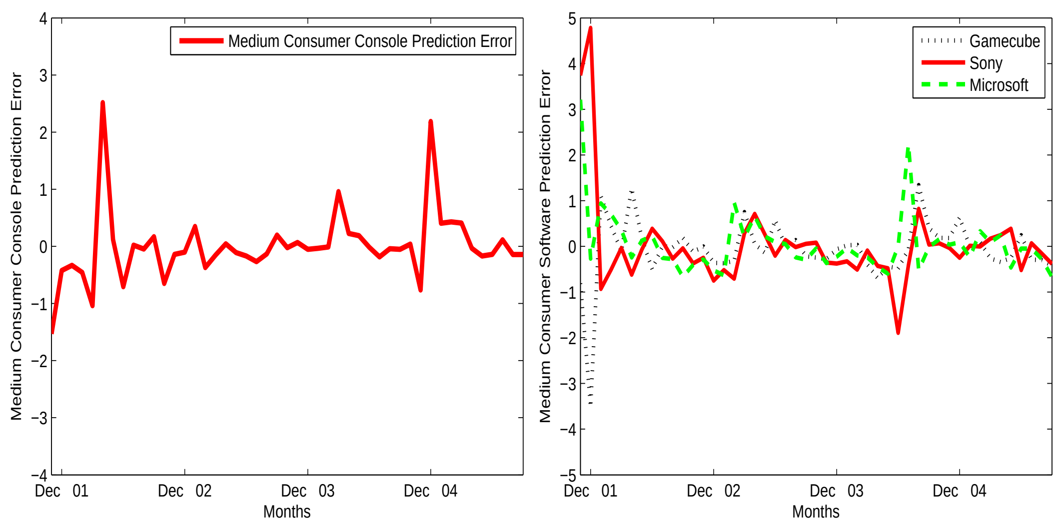
[17]Model 4 also varies slightly from the models run on deseasoned data. Given that the number of software purchases is larger than the installed based during several holiday periods for all three consoles, I allow consumers to purchase video games four times a month (a weekly level) and then aggregate up market shares to the month level to match with the observed data. With two assumptions – that consumers may repurchase an already owned game and that the model does not track consumers who have already purchased a piece of software – one may also simply assume that the potential market size for software is four times the number of consumers who own console c in period t and thus match observed and predicted shares accordingly.

Figure 3: Average Hardware and Software Estimation Error by Month



Next, to further determine the appropriateness of the AR(1) assumption pertaining to how consumers perceive the inclusive value statistic evolves–I plot the error term from the console and software decision problems $(\delta^h_{i,t+1} - (\gamma^h_{i,1} + \gamma^h_{i,2}\delta^h_{i,t}))$ and $(\gamma^s_{i,t+1} - (\gamma^s_{i,1} + \gamma^s_{i,2}\delta^s_{i,t}))$. I find the error terms to be essentially random and therefore conclude that such an assumption on consumer expectations is reasonable.

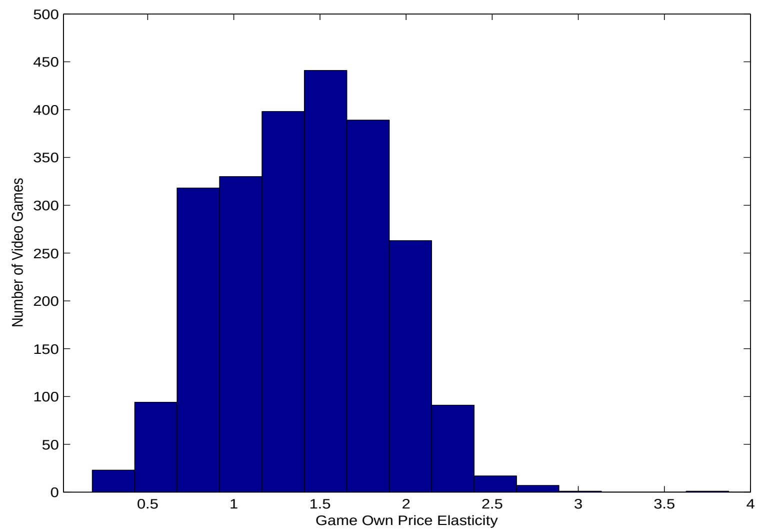
Figure 4: Hardware and Software Prediction Error



Substitutions and Margins

The estimation of a structural model supplies the necessary information to find consumer substitution patterns, which helps in determining console and software markups. Table 6 provides own- and cross-price console elasticities estimates. The model predicts that a permanent one percent reduction in the price of a console would lead to an approximately 2.25-3% increase in the *total* number of that console sold during the time period; the cross-price elasticities range from approximately -0.4 to -2%. As the table indicates, all the diagonal elements are positive and greater than one, which is consistent with oligopolistic behavior in which firms price on the elastic portion of the

Figure 5: Histogram of Game Own Price Elasticities



demand curve.

Table 6: Console Elasticities

	Nintendo	Sony	Microsoft
Nintendo	2.35	-1.81	-0.90
Sony	-0.42	2.23	-0.89
Microsoft	-0.42	-1.78	3.02

Note: Cell entry i, j, where i indexes row and j column, gives the percent change in **total quantity** of brand i with a 1 percent **decrease** in the price of j.

Figure 5 presents a histogram of the video game price elasticities. From this figure all games have positive price elasticities from a permanent 1% price decline, with the mean price elasticity of roughly 1.5.

I also gain insight into firms' pricing behavior with the recovery of hardware marginal costs and margins. It is important to realize that I do not jointly estimate console marginal cost with console and software demand. Instead, I impose a myopic pricing model and employ the recovered demand primitives to back out console margins and marginal costs. I elect to do so because of the discrepancy in consumer and firm behavior–one is forward-looking and the other myopic–and the imposition the supply model would have on the recovery of a consumer's console price sensitivity. Recovering marginal cost in this setting is not as straightforward as it would be if the consumer demand model was static. This is from the fact the partial derivative of firm profit with respect to price is no longer analytical. Consequently, I find the numerical derivative of firm market share with respect to price to calculate console marginal cost.

The profit function of a console manufacturer differs from that of a standard single product firm. Console firms face three streams of profits: selling consoles, selling video games and licensing the right to game developers to produce a game. They take each into consideration when setting console prices. I assume console producers set prices simultaneously to maximize profits, and that each producer acts myopically. Thus, while doing so, console firms account only for the dynamic nature of a consumer's decision and do not take into account the effect today's price has on future profits. Furthermore, I assume console producers face a marginal cost of $2 associated with the production and packaging of its video games. The console manufacturer also stamps all video games for quality control purposes. To recoup this cost as well as licensing the rights to create video games compatible with its console, hardware manufacturers exogenously set a royalty rate at 20 percent of the retail price per game, which equates to \$10 per new release game sold at \$50. I make the previous two assumptions from an industry expert's inside knowledge.

Console maker $c\acute{}s$ profit function in time t is

$$\Pi_{c,t} = (P_{c,t} - MC_{c,t})M_t^h S_{c,t}(P, X, \lambda; \vartheta) + \sum_{d_c \in F_c}(IB_{c,t-1} + M_t^h S_{c,t}(P, X, \lambda; \vartheta))s_{d_c,t}(\vartheta)(p_{d_c,t} - mc) + \sum_{k_c \notin F_c}(IB_{c,t-1} + M_t^h S_{c,t}(P, X, \lambda; \vartheta))s_{k_c,t}(\vartheta)(p_{k_c,t} * r - mc)$$

where $P_{c,t}$ is the console price; $MC_{c,t}$ the console marginal cost; M_t^h the potential market for consoles; $S_{c,t}$ the average probability consumers purchase console c; $s_{d_c,t}$ the probability game d, which is produced by the console manufacturer, is purchased by consumers who own console c; mc the marginal cost of software and assumed to be constant across games at a value of \$2 for packaging; $s_{k_c,t}$ the probability consumers who own console c purchase game k, an independently produced game; r the royalty charge by the console firm to independent developers, which incorporates any packaging or production costs. Lastly, $IB_{c,t}$ is the installed base of console c and the potential market size for a video game. The above profit function differs from a standard single product profit function in that there are two additional profit streams. The first term is the usual single product profit. The second and third terms are profits the console maker receives from interacting with game developers and selling its own games. Specifically, the second term is the profit from creating and selling its integrated games and the third term is the profit it receives from independent developers. The resulting first order condition for firm j in period t assuming firms compete in a Bertrand-Nash fashion, is

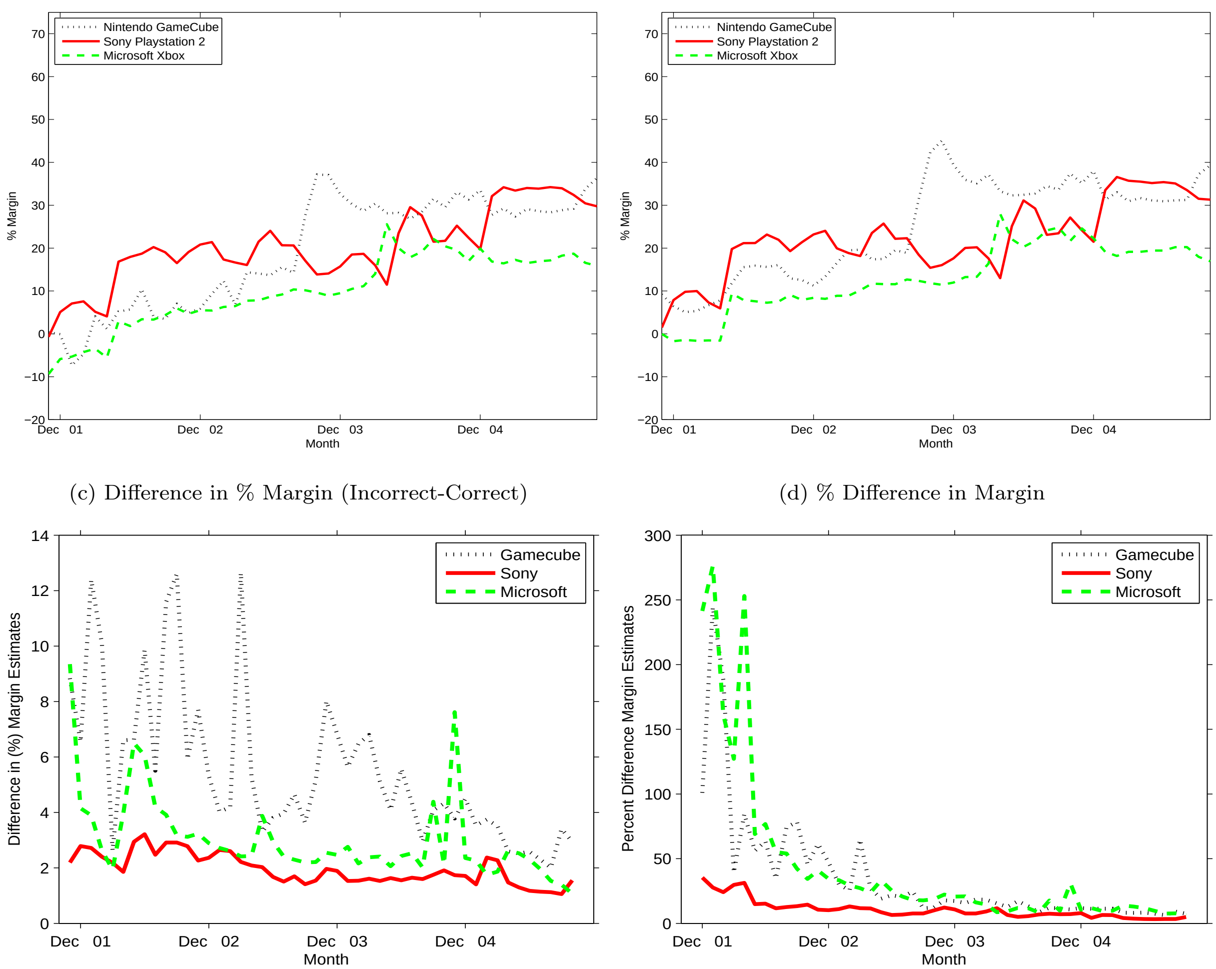
$$S_{c,t}(P, X, \lambda; \vartheta) + (P_{c,t} - MC_{c,t} + \Omega_{c,t})((\partial S_{c,t}(\centerdot))/(\partial P_{c,t})) = 0$$

$$\Lambda_{c,t} = \sum_{d_c \in F_c} s_{d_c t}(\delta)(p_{d_c,t} - mc) + \sum_{k_c \notin F_c} s_{k_c,t}(\delta)(p_{k_c,t} * r - mc)$$

where $\Lambda_{c,t}$ is the marginal profit a console producer receives from independent developers and selling integrated games when one additional console is sold. Or otherwise put, the internalization of console price on software profits.

Figure 6a depicts the estimated console margins assuming a 20% royalty rate. It is evident from this figure, margins are roughly 0 to -10% at the start of the data period and slowly increase over time. The resulting magnitudes and trend of console margins are in line with public information. A WSJ article titled "Cost Cutting Pays Off at Sony" (2/5/2010) reports Sony's PlayStation3's margin to be roughly negative 6%. Although this number corresponds to the current console generation, one might expect a similar magnitude for the generation in which this study analyzes. I alternatively calculate console margins from a supply model that does not allow console producers to internalize the effect of console price on software profits (one can view these estimates originating from a standard single product firm). I present these measures in Figure 6b. Additionally, Figure 6c highlights the differences in margin and Figure 6d presents the percent difference$\left(\frac{correct - incorrect}{incorrect}\right) * 100$. The last graph illustrates the percent difference in margins is roughly 1 to 2.5 times in magnitude for Microsoft and Nintendo at the beginning of the data period and quickly declines over time to roughly 5-10% at the end. In summary, the average percentage differences for Nintendo, Sony and Microsoft are 68%, 12% and 44%. These estimates highlight the importance of accounting for the internalization of console price on software profits. The figure also underscores the imprecision a model, which does not allow for the internalization of the pricing externalities, has on recovering console margins.

Figure 6: Console Margin-20% Royalty



(a) Correct Supply Model

(b) Incorrect Supply Model

(c) Difference in % Margin (Incorrect-Correct)

(d) % Difference in Margin

6 Counterfactuals

To address the impact of technological tying on console price competition I employ the above estimated model primitives in two counterfactual simulations that use all available data. I also implement additional simulations to more clearly describe and discuss why hardware makers may elect to integrate and technologically tie. It is important to remind the reader that in the empirical model above and the counterfactual experiments below, a consumer's choice of video games and console is dynamic but firms are myopic with setting console prices while software prices are fixed at the observed levels. Moreover, I do not fully account for changes in software availability or investment in console or software quality. The counterfactual results below consequently capture only partial effects and are conservative estimates of the impact, given i) the myopic pricing assumption and ii) the holding of software prices fixed at the observed levels.

Competitive Price Effects of Technological Tying

The results of the first counterfactual simulation are presented in Table 5. Counterfactual one employs all available data and assumes games that were once technologically tied are now compatible with all consoles and are assumed to be produced by an independent manufacturer.[18] The prices of these games are assumed to be identical across all three consoles and follow the observed data price. Likewise, the utility of each game is adjusted for the increase in the quantity of games available on a given console, the elimination of the exclusivity effect and the relative quality improvement associated with producing video games for specific consoles. To conclude, I assume prices of independent video games remain fixed at the observed levels–software prices of these games do not change. The second counterfactual is identical to the first with the exception that what were technologically tied games are now available on all consoles but remain integrated with a console manufacturer. The resulting profit functions for console c in period t are

$$\Pi_{c,t}^{CF1} = (P_{c,t} - MC_{c,t})M_t^h S_{c,t}(P,X,\lambda;\vartheta) + \sum_{k_c \notin F_c} (IB_{c,t-1} + M_t^h S_{c,t}(P,X,\lambda;\vartheta)) s_{k_c,t}(\vartheta)(p_{k_c,t} * r - mc)$$

and

$$\begin{aligned}\Pi_{c,t}^{CF2} = (P_{c,t} - MC_{c,t})M_t^h S_{c,t}(P,X,\lambda;\vartheta) + \textstyle\sum_{d_c \in F_c} (IB_{c,t-1} + M_t^h S_{c,t}(P,X,\lambda;\vartheta)) s_{d_c,t}(\vartheta)(p_{d_c,t} - mc) \\ + \textstyle\sum_{k_c \notin F_c} (IB_{c,t-1} + M_t^h S_{c,t}(P,X,\lambda;\vartheta)) s_{k_c,t}(\vartheta)(p_{k_c,t} * r - mc) \\ + \textstyle\sum_{j \neq c} \sum_{d_j \in F_c} (IB_{j,t-1} + M_t^h S_{j,t}(P,X,\lambda;\vartheta)) s_{d_j,t}(\vartheta)(p_{d_j,t} * (1-r)),\end{aligned}$$

respectively. It is important to highlight how these two profit functions differ from the function corresponding to the observed data. The profit function for simulation one differs in its inability of hardware manufacturers to generate any additional revenue outside of collecting royalties and payment for hardware. The second profit function retains such ability but firms have to consequently pay royalties to each console for the compatible games it sells.

With these counterfactuals, and in particular the first, I determine the technological tying increases console price competition from the incentive such games generate–selling consoles is a means to selling video games, in particular console manufactured video games. The results of the first counterfactual are in Table 7 and Figure 7.[19] I determine technologically tied games benefit Microsoft and Nintendo more than Sony. The simulation predicts average console prices for all three consoles are lower when technological tying does occur than when it does not. Average decline in price for Nintendo, Sony, and Microsoft are -3.38%, -1.78% and -1.56, respectively. Although the predicted changes appear small, if prices were found to increase by similar magnitudes rather than decline, such a practice would receive heavy government scrutiny–in antitrust merger cases a 5% price increase would likely lead to a federal challenge of the proposed merger. Thus, such changes should not be viewed as inconsequential.

The resulting decline in prices is found to increase the total number of consoles sold for the observed time period. Nintendo's and Microsoft's respected quantities increase by roughly 14% and 1% while Sony's PlayStation 2 sales decreased by 1.77%. As discussed above the price effect is greatest for Microsoft and Nintendo, a result of these two producing "hit" games. To illustrate this fact, Table 8 shows the 10 leading titles on each platform for the given time period, nine are produced by Nintendo and five by Microsoft. Table 3 in the data section above also illustrates this result via the reported pseudo HHI measures, where Microsoft's and Nintendo's measures are larger than Sony's.

[18] Think of each of the console manufacturers spinning off their video game design studios.

[19] I also run each of the simulations assuming a 10% royalty rate and the results do not qualitatively change

The attractiveness of each console is greater with tying because the indirect network effect (Υ) is larger due to less congestion in the software market, which drives console prices up. I plot the medium consumer's software indici in Figure 8 where the observed values from the estimated model are larger than corresponding values from the simulation. I denote this the demand effect. The implementation of technology tying by a console manufacturer also creates an incentive to decrease console price through the increase of additional profit it receives from selling its own games and leasing the rights to independent developers when one more console is sold. I determine this effect is a significantly more important driver of price than the demand effect. Thus, prices fall and, in particular, are lowest for Nintendo and Microsoft with tying.

In summary there are three main economic forces that impact the intensity of console price competition when manufacturers technologically tie their software to their hardware. The first is a result of the tie foreclosing rival console manufacturers access to games produced by a console. The second is the consequence of console manufacturers electing to design and produce video games themselves. The third is the competitive response of its rivals. More specifically, the first force generates an incentive for the hardware maker to raise its console price since there is a relative increase in utility from the simple fact that rivals have one less available game; for instance, in order for a consumer to play a game produced by the hardware manufacturer he must purchase the respective console, an act that increases the console manufacturer's market power. The second force, however, leads to a different effect. If we think of software as the input or upstream supplier to the production of the downstream hardware [Salop, 2005] then the "vertical" integration of these two products can produce efficiency effects similar to the elimination of the double marginalization; thus, an incentive to decrease console price is created [Cournot, 1838]. And lastly, the third economic force, the competitive responses of the rivals indirectly affects a tying console's incentive to lower or raise its console price. From this simulation exercise, I determine the implementation of technological tying in the home console market increases console price competition. A console manufacturer is willing to forgo the incentive of raising its hardware price in order to increase demand for its console and, in particular, its integrated and tied video games, where the largest proportion of industry profits are made.

Table 7: Counterfactual 1 Results

		CF (No T. Tying)	T. Tying (Data)	% Change
Mean Console Price	Nintendo	132.27	127.7973	-3.38%
	Sony	192.65	189.2305	-1.78%
	Microsoft	188.44	185.4917	-1.56%
Consoles Sold	Nintendo	8,089,849	9,199,204	13.71%
	Sony	32,256,076	31,684,571	-1.77%
	Microsoft	13,803,690	13,993,397	1.14%

Figure 7: Counterfactual 1 - % Price Change

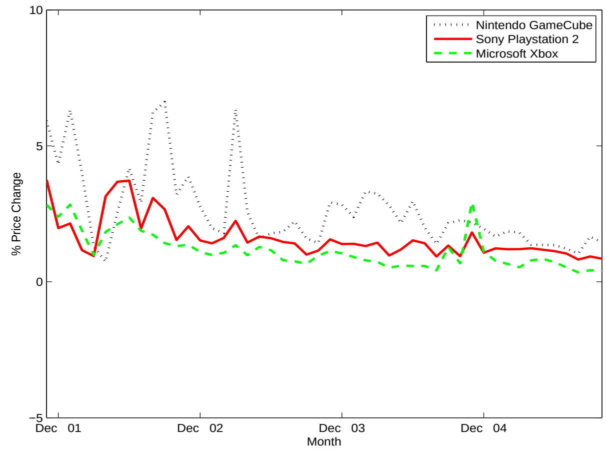
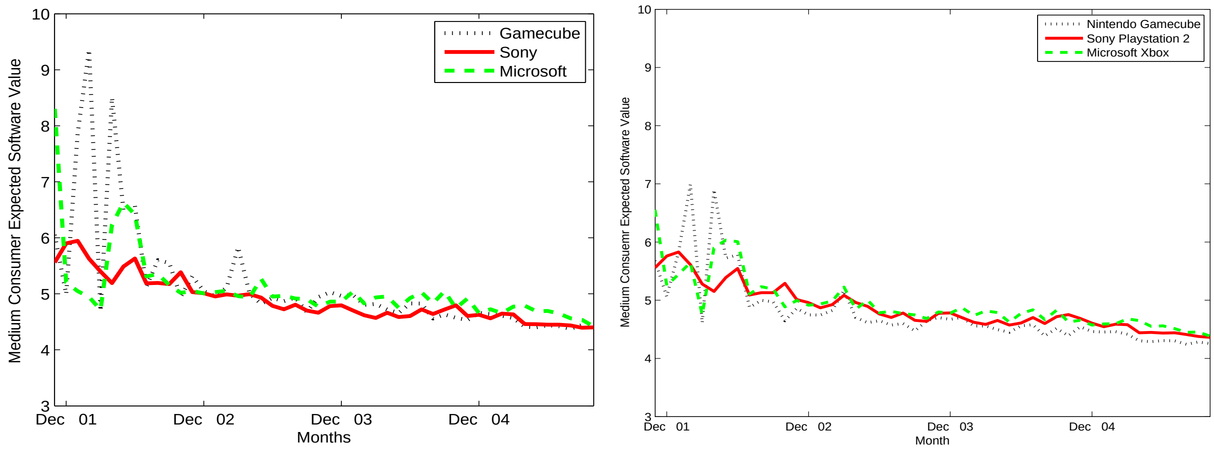


Table 8: Top 10 Video Game Titles (Nov 2001-Oct 2005)

Console	Title	Publisher	Quantity
Nintendo	SUPER SMASH BROS. MELEE	NINTENDO	2,958,802
	SUPER MARIO SUNSHINE	NINTENDO	2,157,029
	ZELDA: THE WIND WAKER	NINTENDO	2,000,442
	MARIO KART: DOUBLE DASH	NINTENDO	1,922,268
	LUIGI'S MANSION	NINTENDO	1,745,338
	METROID PRIME	NINTENDO	1,313,057
	SONIC ADVENTURE 2	SEGA	1,186,182
	ANIMAL CROSSING	NINTENDO	1,099,748
	POKEMON COLOSSEUM	NINTENDO	983,633
	MARIO PARTY 4	NINTENDO	978,253
Sony	GRAND THEFT AUTO:VICE CITY	TAKE 2 INTERACTIVE	6,686,526
	GRAND THEFT AUTO: SAN ANDREAS	TAKE 2 INTERACTIVE	5,796,575
	GRAND THEFT: AUTO 3	TAKE 2 INTERACTIVE	5,312,567
	MADDEN NFL 2004	ELECTRONIC ARTS	3,446,339
	MADDEN NFL 2005	ELECTRONIC ARTS	3,198,615
	GRAN TURISMO 3:A-SPEC	SONY	2,962,486
	MADDEN NFL 2003	ELECTRONIC ARTS	2,731,541
	NEED FOR SPEED: UNDERGROUND	ELECTRONIC ARTS	2,533,018
	KINGDOM HEARTS	SQUARE ENIX USA	2,460,418
	MEDAL HONOR: FRONTLINE	ELECTRONIC ARTS	2,327,109
Microsoft	HALO	MICROSOFT	4,160,006
	HALO 2	MICROSOFT	3,146,824
	HALO 2 LIMITED ED	MICROSOFT	1,675,039
	T.CLANCY'S SPLINTER	UBISOFT	1,525,315
	GRAND THEFT AUTO PACK	TAKE 2 INTERACTIVE	1,378,500
	MADDEN NFL 2005	ELECTRONIC ARTS	1,223,426
	PROJECT GOTHAM RACING	MICROSOFT	1,215,905
	STAR WARS: KNIGHTS	LUCASARTS	1,210,290
	ESPN NFL 2K5	TAKE 2 INTERACTIVE	1,200,342
	FABLE	MICROSOFT	1,125,427

Figure 8: Counterfactual Υ

(a) Model Medium (Υ) (b) Counterfactual 1- Medium (Υ)



I present the results from the second counterfactual exercise in Table 9. This exercise determines the impact of exclusivity on price competition. Although this is not the main contribution or purpose of this paper I present the results for completeness. Notice there is a lesser price impact than in simulation 1. This is a direct result of the hardware firms retaining control of software but facing additional software competition.

Table 9: Counterfactual 2 Results

		CF (Exclusivity)	T. Tying (Data)	% Change
Mean Console Price	Nintendo	131.44	127.7973	-2.77%
	Sony	192.44	189.2305	-1.66%
	Microsoft	187.83	185.4917	-1.24%
Consoles Sold	Nintendo	8,167,481	9,199,204	12.63%
	Sony	32,477,267	31,684,571	-2.44%
	Microsoft	13,880,614	13,993,397	0.081%

Finally, it is important to discuss the ramifications of the assumptions regarding holding software prices fixed at observed levels and the hardware producers' myopic behavior. By assuming video game prices are held constant I underestimate the console price effects. The logic is as follows. Take counterfactual one for instance: If game prices adjusted, the counterfactual game prices would be lower because of increased competition, loss of exclusivity and greater number of games to choose from. It is important to highlight there is one effect moving against these. With games having different qualities across platforms, a game that is priced for a console where it had lower utility will increase in quality without tying, and should therefore increase its price. Yet, this increase in quality is only a partial effect. It is more than offset by the fact these games lose the benefit of being exclusive, and so quality falls resulting in lower demand and lower prices. Furthermore, the increase in available games also leads to a decrease in utility for any game on any console from the inclusion of the log(number of games) as a covariate in the software utility function. The lowering of game price in turn would generate a larger $\Upsilon_{i,c,t}$ in each period than what was simulated above. This increase provides a larger incentive to raise console price via greater demand for hardware. The assumption also impacts the revenue that hardware firms receive from game developers. Given lower software prices, the marginal revenue from an additional console sold would be smaller than what was simulated above. This is because the royalty fee is a percentage of the software price. Consequently, the smaller measure of additional revenue from royalties leads to a lesser incentive to lower console price than what was simulated above. The assumption therefore underestimates the true effect.

The assumption regarding hardware producers setting price in a myopic manner is clearly a limitation of the model. Yet, this assumption also leads to an underestimation of the true hardware price effect. Given that I determine the internalization of software profits is an important driver of hardware price, the internalization of future software profits should arguably have an even greater impact. Expected discounted profits from future software sales should be larger than current profits.[20] Consequently, the assumption regarding myopic behavior underestimates the true results, because the internalization of all software profits (current and future) should be larger for the case of technological tying than when all integrated and tied games are compatible with all other consoles and are produced by an independent game developer. In summary, the combination of these two important assumptions produce conservative estimates of the true impact of technological tying.

Incentive to Integrate and Technologically Tie

Understanding the implications of a technological tying strategy is an important research question and I have shown that tying can increase console price competition. Understanding when and under what conditions such a strategy is optimal is also important. Having highlighted the effect of technological tying on console price competition, I move my attention to one possible explanation for why hardware manufacturers elect to engage in this action. Particularly, how software fixed development costs moderate a firms decision to technologically tie software to hardware. Or more broadly, address the role of economic governance, especially the boundaries of the firm, in technology markets. Such an explanation is related to the classic "make versus buy" decision of a firm (Williamson [1971]; Coase [1937]). I address this relationship by using the estimated model parameters and data from Nintendo's console and Nintendo produced games for all 48 months. For ease of understanding what role fixed development costs play in deciding to integrate and tie software, I elect to make several simplifying assumptions. I assume there are two hardware manufacturers that produce identical consoles in the form of Nintendo's GameCube and that there are only two independent software providers that produce games with characteristics (price, age, genre, etc) and quality identical to Nintendo-designed and -produced software.

The timing of the game is as follows. In the first stage, the firms simultaneously make decisions to integrate and tie software to its hardware via the acquisition of a software development firm or allow independent software firms to develop games for its console. At this time each firm has perfect foresight as to what games are available when, for how long and to the demand for hardware and software. Firms are consequently taking such an action once, as opposed to in each period, and must live with their choice in all future periods (48 of them). After choosing an action, hardware firms simultaneously set hardware prices in each of the 48 periods (software prices are assumed to not change from the data) and realize profits at the end of each month. Consequently, at the strategy selection stage (stage 1) firms are able to perfectly predict aggregate profits (from hardware sales, software sales and royalty payments).

There are four possible industry structures associated with two players and two actions (tying or not tying): (i) a non-tying market structure where neither console has chosen to integrate and tie software, (ii, iii) a partially tied structure where one, and only one, hardware firm integrates with one software development company and ties software to hardware while the rival hardware firm allows the remaining independent software firm to develop software for both consoles and (iv) an tied structure where each hardware firm integrates with a software development firm and elects to tie software to hardware.

[20] I thank a referee for pointing to this fact.

I solve this game with backward induction. First, I find the optimal hardware prices and profits of each console firm for the four given industry structures, conditional on its own and its competitor's integration and tying decisions, and then I determine the optimal action with regard to technological tying.

The results in Table 10 highlight the effect of integration and tying in a competitive environment. It is important to direct attention to the fact that when both firms technologically tie console price competition increases, as illustrated in counterfactual one above. Total demand for consoles increases with greater console price competition relative to the no integration and tying scenario. I determine lower console prices drive consoles sales, which results in greater software sold even in the face of lower expected software utility. This intriguing result is a consequence of each firm losing half of its games, causing a decrease in the console indirect network effect. Moreover, the console that engages in a unilateral tying setup also exhibits a decline in price relative to the scenario of no tying because the demand effect remains unchanged, but the price effect associated with complementary product pricing increases. The console manufacturer that does not tie also experiences a decline in price and market share from a reduced number of compatible software titles. The decline in price is a direct competitive response to lessen the profitability of the firm that elected to technologically tie.

Table 10: Simulation Results

		(i)	(ii)	(iii)	(iv)
Mean Console Price	Console 1	–	-7.83 %	-4.87 %	-9.31 %
	Console 2	–	-4.87 %	-7.83 %	-9.31 %
Consoles Sold	Console 1	27,908,679	34,076,517	22,309,056	27,793,153
	Console 2	27,908,679	22,309,056	34,076,517	27,793,153
Profit	Console 1	2,328,559,428	10,687,596,635 -F_1	1,696,437,292	11,592,997,420 -F_1
	Console 2	2,328,559,428	1,696,437,292	10,687,596,635 -F_2	11,592,997,420 -F_2

From the simulation results above, which correspond to the four possible market structures, it is trivial to construct the normal form representation of the tying game being played between the two firms. Table 11 presents this representation as a function total software development costs. Consequently, the equilibrium strategies played by each firm will depend upon the total fixed development costs with the associated fixed cost cutoff values being determined by locating the point where a firm is indifferent between two dominant strategies (Tie and No Tie).[21] For a dominant strategy to exists for either firm, it is straight forward to determine the two total fixed development cost constraints associated with each firm, $F_i \leq 10,687,596,635 - 2,328,559,428$ and $F_i \leq 11,592,997,420 - 1,696,437,292$, must hold. Given the first constraint binds, as it generates the lowest level of fixed cost for the dominant tying strategy to exist for each firm, the latter constraint is ignored. The opposite holds true for the existence of a no tying dominant strategy. The binding constraint in this case is $F_i \geq 11,592,997,420 - 1,696,437,292$.

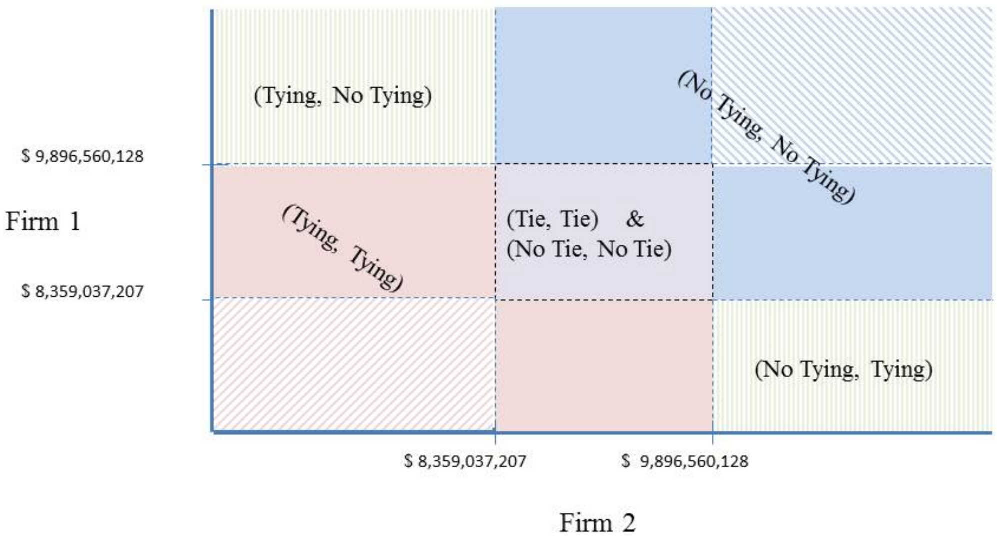
Table 11: Normal Form Tying Game

		Firm 2	
		No Tie	Tie
Firm 1	No Tie	2,328,559,428; 2,328,559,428	1,696,437,292; 10,687,596,635 -F_2
	Tie	10,687,596,635 -F_1 ; 1,696,437,292	11,592,997,420 -F_1; 11,592,997,420 -F_2

Figure 9 graphically present the equilibria associated with this game in terms of total software development costs. The four corner regions of the figure correspond to dominant strategy equilibria (which are also Nash equlibria) and

[21]The cutoff values are also consistent with the associated Nash equilibria

Figure 9: Mapping of Equilibrium



the remaining portion Nash equilibria. From this analysis I determine that if the total fixed software development costs are low then both hardware providers would prefer to tie. The driving incentive making tying a dominant strategy coincides with the above intuition regarding console prices falling with tying. Console manufacturers are willing to decrease console price in order generate greater demand for their console and in particular their own video games. This increase in demand then allows the firm to recover a video game margin that is larger than the royalty fee levied from what was once an independent game. Thus, each firm finds it profitable to trade off small, or if not negative, console margins for larger software profits.

Were the total fixed development cost of software substantially large, then technological tying would not be profitable and would no longer be the dominant strategy. With high development costs, the variable profits from tied games are not enough to cover the fixed cost to develop. Lastly, if fixed development costs fall within a medium range, there exist multiple Nash equilibria. These costs are not at a level to strictly deter firms from choosing either action. An alternative explanation is related to the classic "make versus buy" decision of a firm (Williamson [1971]; Coase [1937]). When development costs are high the firm prefers to delegate to independent developers as a way to escape the high fixed costs; when cost are low the firm prefers to produce internally and bear the fixed cost but receive a substantial margin in return.

7 Discussion, Limitations and Conclusion

In order to understand the impact integration and tying has on hardware price competition the above analysis extends the literature by constructing a model that allows consumer demand for video game consoles to depend upon the set of available games rather than simply the number of games. The estimation technique differs from prior research by incorporating video game variety and software competition into the demand models.

This study certainly has limitations and could always be improved with work that removes these limitations. I develop a model based on individual consumers with forward-looking behavior but have only access to aggregate market-level outcome data and data for console and software sales a year after Sony's launch of the PS2. While aggregate data is shared by most empirical studies of durable goods, having access to dis-aggregate individual-level data would enable me to better examine the heterogeneity in consumer behavior. Moreover, with data of the first year of the 128-bit console generation I could better capture consumer heterogeneity and eliminate the initial conditions problem. Doing so would enable more precise marketing suggestions. Also, my model could be extended to allow independent game developers to re-optimize their console decisions. However, incorporating such an aspect into the model should not qualitatively change the results: total number of games should decrease given console prices rise (when holding the game data to what was observed in the data) leading to smaller demand for consoles and software. Lastly, the assumptions regarding fixed software prices and myopic pricing behavior by console producers are clear limitations of this paper. To ascertain a more precise impact of technological tying, future research should relax these assumptions to allow for the full internalization of software profits on hardware prices.

In this paper I empirically quantify the change in the intensity of console price competition when a console producer integrates and ties its hardware and software. From several counterfactual experiments I conclude the tying of complementary products by integrated firms intensifies console price competition from the fact that manufacturers are willing to forgo the incentive to raise console prices to increase demand for their console and, in particular, their own integrated video games, where the largest proportion of industry profits are made. Moreover, when software development costs are low hardware manufacturers have a dominant strategy to tie hardware and software. Although I cannot generalize these results to other similar-type industries because the question is empirical, my paper does provide the necessary framework to study the competitive price effects of an integrated firm tying its complementary products. It also provides the methodology to analyze the impact complementary products have on consumer adoption of an associated platform.

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Appendix A: Computational Details

Here I briefly describe how I update $\lambda^h_{i,t}$. It involves determining market shares in the first period given $\lambda^h_{i,t=0}$ and then computing the distribution of consumers who remain in the market according to rule

$$\lambda^h_{i,t+1} = \frac{M^h_{t=0}\lambda^h_{i,t=0}\prod_{t=0}^{t}(1-s_{i,t})}{\sum_{i=1}^{I}(M^h_{t=0}\lambda^h_{i,t=0}\prod_{t=1}^{t}(1-s_{i,t}))}$$

where $s_{i,t}$ is the probability a consumer buys a piece of hardware in period t. For completeness, to recover the expected value function I implement a standard value function iteration procedure with a linear interpolation between the 40 discrete grid points to calculate the expected value function in period t. This procedure is run in steps 2 and 4 of the estimation procedure above.

Appendix B: Video Game Competition

In the model above, one of the main assumptions I implement is in regard to software competition. I make the assumption that video games do compete with one another rather than assume games are monopolists as the previous works of Nair [2007] and Lee [2013] do. In order to validate this assumption I present the results of two tests below. The first determines whether cross-price effects are present while the second tests whether falling prices are a consequence of competitive conditions. In determining whether there are cross-price effects among software titles I implement a nested logit model for software demand. Under such model, however, there are several concerns. One is that cross-price substitution might be underestimated if game developers strategically release video games as to minimize the cannibalization of similar games currently in the market. I follow a similar specification to that of Nair [2007] that tries to account for this endogeneity with a nested logit model with nests corresponding to the video game genre. I also include a covariate that captures game age. The video game demand specification is

$$ln(s_{k_jt}/s_{0_jt}) = \alpha_j + \lambda(t - r_{k_j}) + \beta p_{k_jt} + \sigma ln(s_{k_jt|g}) + \eta ln(Num^{SW}_t) + \psi_{k_jt}$$

where t indexes month, r_{k_j} is the release date of game k_j, p_{k_jt} is the price, s_{k_jt} is the market share, s_{0_jt} is the outside good's share, $s_{k_jt|g}$ is the within-genre share of game k_j in period t, and $ln(Num^{SW})$ is the log of the total number of available games on platform j. Moreover, the parameter σ captures the degree of correlation of utilities among games in a given genre. A small σ near zero infers little correlation among genre games while a larger value indicates larger cross-price effects. Thus, a test of competition among software titles would be to determine if σ is statistically different from zero. Nonetheless, to properly test that we need to account for the endogeneity of price, release timing, and within-genre share. To correct for software price I employ the same price instruments as the main model. The endogeneity of release time is addressed with the inclusion of software fixed effects. "With the inclusion of such all variation in demand arising from aspects of game-quality is controlled for," writes Nair [2007]. Lastly, the number of video games in a given genre in a given period instruments for within genre share. The results of several models are presented below including OLS and 2SLS with and without including instruments for price. I additionally include specifications with quadratic and cubic software age covariates. From the results it is evident that video games compete against one another and are not monopolists.

If the results from the first test are not conclusive enough I present a second test to illustrate that software video game prices largely decline because of increased video game competition. For this test I pool all game data across each console and regress software price on age, game fixed effects, and the interaction of age and console-specific month fixed effects. I hence measure the rate at which prices fall after controlling for game quality via game fixed effects. Negative and statistically significant estimates of the interaction terms therefore indicate that prices fall because of the competitive interaction of software titles.

Table 12: Competitive Software Tests

	OLS						2SLS w/ Instruments for price & within share					
	Coeff	Std Err	Coeff	Std Err	Coeff	Std Err	Coeff	Std Err	Coeff	Std Err	Coeff	Std Err
Price	-0.0033	0.0003	-0.0059	0.0003	-0.0073	0.0004	-0.0118	0.0024	-0.0406	0.0052	-0.0446	0.0046
Sigma	0.8461	0.0024	0.8384	0.0025	0.8345	0.0025	0.4295	0.0180	0.5476	0.0168	0.5392	0.0165
Age	-0.0363	0.0007	-0.0506	0.0012	-0.0669	0.0019	-0.0777	0.0022	-0.1408	0.0075	-0.2045	0.0108
Age^2			0.0003	2.155e-05	0.0012	8.841e-05			0.0014	0.0001	0.0053	0.0003
Age^3					-1.503e-05	1.364e-06					-6.168e-05	4.714e-06

Table 13: Competitive Software Tests

	Nintendo		Sony		Microsoft	
	Coeff	Std Err	Coeff	Std Err	Coeff	Std Err
Age*Jan 02	-5.4529	1.0222	-1.6653	0.0547	-3.0832	0.7258
Age*Feb 02	-3.6220	0.5786	-1.4666	0.0501	-1.6532	0.4230
Age*Mar 02	-3.1827	0.4097	-1.4273	0.0464	-1.4513	0.3029
Age*Apr 02	-3.5630	0.3034	-1.5153	0.0428	-1.8278	0.2268
Age*May 02	-3.5875	0.2373	-1.4950	0.0398	-2.2919	0.1797
Age*Jun 02	-2.6575	0.1911	-1.1600	0.0371	-1.7465	0.1465
Age*Jul 02	-2.1446	0.1594	-1.0911	0.0347	-1.6151	0.1234
Age*Aug 02	-1.9688	0.1351	-1.1288	0.0326	-1.5409	0.1057
Age*Sep 02	-1.6433	0.1166	-1.0795	0.0308	-1.4478	0.0920
Age*Oct 02	-1.5569	0.1025	-0.9048	0.0292	-1.6418	0.0814
Age*Nov 02	-1.5079	0.0904	-0.8429	0.0277	-1.4118	0.0724
Age*Dec 02	-1.2210	0.0805	-0.6623	0.0264	-1.1323	0.0650