Vertical Integration and Exclusivity in Platform and Two-Sided Markets

By Robin S. Lee*

This paper measures the impact of vertically integrated and exclusive software on industry structure and welfare in the sixth-generation of the U.S. videogame industry (2000-2005). I specify and estimate a dynamic model of both consumer demand for hardware and software products, and software demand for hardware platforms. I use estimates to simulate market outcomes had platforms been unable to own or contract exclusively with software. Driven by increased software compatibility, hardware and software sales would have increased by 7% and 58% and consumer welfare by $1.5B. Gains would be realized only by the incumbent, suggesting exclusivity favored the entrant platforms.
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In many networked industries, consumers visit, join, or adopt a platform or intermediary—such as a hardware device, content distribution service, payment system, or health insurance network—in order to access that platform's set of complementary goods and services. Platform providers compete with one another to get the firms that produce these goods onboard their network, and often rely on exclusive contracts or vertical integration in order to do so. This paper studies the impact of these exclusive vertical arrangements on industry structure, competition, and welfare.

Whether or not such arrangements are primarily pro- or anti-competitive or harmful to consumers is a source of active debate and an open empirical question. On the one hand, exclusive contracts raise anti-competitive issues since they may deter entry or foreclose rivals (Mathewson and Winter (1987), Rasmusen, Ramseyer and Wiley (1991), Bernheim and Whinston (1998)); these concerns may

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be exacerbated in the presence of network externalities (Shapiro (1999)).[1] Vertical arrangements can also limit consumer choice by preventing consumers on competing platforms from accessing exclusive content, products, or services; such arguments have been used to inform regulatory policy encouraging compatibility in these *platform* and *two-sided markets*.[2]

On the other hand, theory has argued that exclusive arrangements may have pro-competitive benefits, such as encouraging investment and effort provision (Marvel (1982), Klein (1988), Besanko and Perry (1993), Segal and Whinston (2000)). Integration by a platform provider may also be effective in solving the "chicken-and-egg" coordination problem in two-sided markets. Furthermore, exclusivity may be a tool used by entrant platforms to break into established markets: by preventing contracting partners from supporting the incumbent, an entrant can spur adoption of its own platform and spark greater platform competition.

Given the growing prevalence of networked and platform industries, addressing this tradeoff is crucial for policy and regulation. It is at the heart of recent antitrust cases—e.g., *U.S. v. Microsoft* [253 F.3d 34 (2001)], *European Union v. Microsoft* [COMP/C-3/37.792 (2004)], and *U.S. v. Visa* [344 F.3d 229 (2003)]—and central to evaluating the effects of closed hardware-software systems or exclusive carriage deals in media. Furthermore, there is little empirical evidence on the welfare impact of product incompatibility (one of the consequences of exclusivity), particularly in settings where dynamics and consumers expectations are important.[3] Indeed, if consumers are not significantly affected by a restricted choice set—which may occur if consumers can join multiple platforms easily, or the set of incompatible products are redundant or low-quality—and entry and investment by new products is not deterred, then incompatibility *per se* may not warrant concern.

This paper contributes to the literature by studying a canonical hardware-software market—the sixth-generation of the U.S. videogame industry (2000-2005)—and measuring the impact of exclusivity (via integration and exclusive contracts) between hardware and software providers. During this generation, over 60% of all software titles were exclusive to one of three hardware platforms. By comprising multiple differentiated hardware platforms each with its own distinct base of software, the videogame industry exhibits features easily generalizable to a variety of networked environments; given the poor substitutability of videogame software, focusing on this industry also abstracts away from potential anti-competitive effects in software development and instead focuses on foreclosure and entry-deterrence in hardware provision alone.

[1] Whinston (2006), Rey and Tirole (2007), and Riordan (2008) provide overviews of the literature.

[2] E.g., in U.S. vs. Microsoft, the DOJ argued (and the courts ultimately agreed) that Microsoft stifled compatibility with rivals (Gilbert and Katz (2001)).

[3] Papers which have estimated the welfare losses due to incompatibility have primarily done so in static settings, and include Ohashi (2003) on VCRs; Rysman (2004) on yellow pages; Ho (2006) on insurer-hospital networks; and Ishii (2008) and Knittel and Stango (2011) on ATM networks.

To simulate counterfactual environments where exclusive vertical arrangements were prohibited, I develop and estimate a structural discrete choice model of dynamic consumer demand for both hardware platforms and their affiliated products, and then combine these estimates with a model of hardware adoption by software developers. Modeling both sides of the market captures the *dynamic indirect network effects* exhibited in this industry, and allows agents to respond to past and anticipated future actions of others. I also specify and recompute an equilibrium in which all agents' beliefs adjust so that they are consistent with the counterfactual evolution of the industry. The counterfactuals are partial in that they assume that platform providers offer the same non-discriminatory contracts to all firms, and the quality and set of available products do not change.

The main finding of this paper is that prohibiting exclusive arrangements would have benefited the incumbent and harmed the smaller entrant platforms. Without exclusive arrangements, high quality software would have primarily been released on the incumbent due to its larger installed base, and only later, if at all, on either entrant; consequently, neither entrant would have been able to significantly differentiate themselves from the incumbent. Exclusive software thus appears to have been leveraged by the entrants to gain traction in this networked industry.

The finding that banning exclusivity would hurt the entrant platforms is not obvious nor predetermined by the model. Rather, results from the demand system are integral in conducting this analysis: although certain exclusive titles on the incumbent platform sold more copies than any title on the entrant platforms, estimates indicate that these titles did not influence hardware demand as much as those onboard the entrants. If it were the case that the most valuable software products were exclusive to the incumbent in the data, then the predictions of the counterfactual would have been reversed. Although this paper does not explicitly address why the entrants were able to secure access to more valuable games, I provide potential explanations when discussing the counterfactual findings.

In the counterfactual environments without exclusive vertical arrangements (holding fixed product characteristics and prices), consumers may have benefited from the resulting greater compatibility of hit software titles: total hardware and software adoption would have increased by 7% and 58%, yielding consumer welfare gains of approximately \$1.5B (approximately 4% of total industry revenues during the five-year period). However, due to increased market concentration or reduced investment incentives, prices may have increased or software quality fallen. Though a full equilibrium model of dynamic contracting, investment, pricing, and entry/exit is beyond the scope of this paper, robustness checks are conducted which attempt to relax some of these restrictions. Indeed, I find consumers welfare gains from increased compatibility—though still positive—can be substantially mitigated if hardware prices are allowed to adjust or if previously integrated titles are of lower quality. Although these alternative specfications highlight the importance of accounting for a greater range of dynamic effects when evaluating welfare consequences, they all still find that exclusionary vertical agreements favored the entrant platforms.[4]

The demand system is estimated using a new panel dataset containing monthly aggregate sales, prices, and characteristics for all hardware and software products released during the sixth-generation of the videogame industry. One of the main innovations is the specification of an internally consistent measure of software utility for each platform that comprises the option value of purchasing each software product that is or will be available. Variation in this measure of software utility—induced by the arrival of new software products with varying quality over time—identifies both the impact of total software availability and the marginal impact of an *individual* software title on hardware demand. Controlling for heterogeneity in software products is crucial as consumers in many networked industries often choose which platform to purchase based on the presence of particular "hit" titles or "killer applications." Estimates confirm the skewness of the impact of software on hardware demand: though most titles do not significantly affect hardware sales, there are a handful of titles that can shift it by as much as 5%. I also find evidence that vertically integrated software was higher quality than non-integrated and non-exclusive titles.

In addition, this paper stresses the need to appropriately control for dynamics. Failure to control for forward looking consumers, product durability, and the selection of heterogeneous consumers onto platforms over time yields different counterfactual magnitudes for welfare gains and market tipping; nonetheless, I also show the main result—that the entrants benefitted from exclusivity—is robust to relaxing assumptions on dynamic behavior.

There are two main assumptions used in the analysis. First, consumers do not view software products as substitutes for one another. Although this assumption is primarily imposed for feasibility, it is less problematic for this particular industry than others (e.g., unlike computer applications, where users typically only need one word processor, browser, or media player, videogames are more similar to "disposable" media goods which are continually replaced), and robustness tests indicate that software substitution effects are not substantial for most titles. Second, I assume that consumers and firms perceive that expected lifetime utilities from purchasing any product follow first-order Markov processes that depend only on a limited set of state variables, and beliefs are consistent with realized empirical distributions.

A. Contributions and Related Literature

Previous empirical work on measuring the effects of exclusive contracting and vertical integration has primarily focused on supply-side consequences and the threat of "upstream" foreclosure (e.g., Chipty (2001), Asker (2004), Sass (2005);

[4]This analysis does not apply to "forced exclusive" contracts, where a software developer can only join a platform exclusively; these contracts have not been utilized in the videogame industry since the early 1990's, and courts have ruled them to be anti-competitive in other industries (e.g., *U.S. v. Visa*).

see Lafontaine and Slade (2008) for a survey).[5] In contrast, this paper focuses on "downstream" competition, and how exclusivity interacts with network effects to either deter or enable platform entry.

This paper also contributes to the empirical literature estimating *indirect network effects* (Katz and Shapiro, 1985; Farrell and Saloner, 1986) and demand systems in platform markets. Previous papers have largely ignored or adopted a reduced form approach to one side of the market, often using a function of the total number of products or adopters as a proxy for total complementary good utility (Gandal, Kende and Rob (2000), Nair, Chintagunta and Dubé (2004), Clements and Ohashi (2005), Corts and Lederman (2009), Dubé, Hitsch and Chintagunta (2010), Karaca-Mandic (2011); see Lee (2012) for a survey); however, this proves to be a poor approximation when software quality is heterogeneous and sales are skewed. This paper is the first to use both hardware and software sales data to control for heterogeneous complementary products and their differential impact on hardware demand within a dynamic setting.[6]

There are several challenges which this paper addresses. First, when there is significant consumer heterogeneity in preferences over complementary products, a selection problem must be addressed: just as consumers choose a local community to best satisfy their preferences as in Tiebout (1956)'s model of local expenditures, so do they behave with respect to selecting a particular platform (see also Dubin and McFadden (1984)). As consumers who have purchased a hardware platform are pre-disposed to purchasing software, failing to account for this selection will lead to significant upward biases in estimates of the quality of complementary products. To control for unobservable heterogeneity and the endogenous selection of consumers onto and across platforms over time, I introduce new computational fixed point routine which iteratively estimates hardware and software demand until the implied distribution of consumer heterogeneity is internally consistent; this technique has also been employed in other work (e.g., Crawford and Yurukoglu (2012)).

Secondly, platform markets are often inherently dynamic environments: goods are durable and are not repurchased, and consumers may delay purchase due to favorable expectations over future product availability, pricing, and quality. A large literature has shown the limitations of applying static methods to dynamic settings, and I adapt a number of previously introduced techniques—including those pioneered in Rust (1987), Berry (1994), and Berry, Levinsohn and Pakes (1995), and later synthesized in a dynamic demand environment by Melnikov (2001) and Hendel and Nevo (2006)—to estimate dynamic demand. In particular, I adapt and extend techniques introduced in Gowrisankaran and Rysman (forthcoming) to markets with complementary goods. Finally, I use the impact of variation in future software availability on current hardware sales to identify consumers' dis-

[5]The literature on vertical restraints typically refers to an "upstream" firm as the supplier of a (possibly intermediate) good, and a "downstream" firm as a firm that uses the good to produce another product, or a wholesale or retail firm that resells the good to final consumers (Tirole, 1988).

[6]See also Gowrisankaran, Park and Rysman (2011).

count factors, which typically are assumed and not separately identified in many dynamic discrete choice settings.

In the software supply section, I specify and compute a new equilibrium for a dynamic network formation game in which every title is allowed to freely choose which platforms to develop for. The equilibrium is one in which each title employs a strategy that depends only on the value and evolution of certain "payoff-relevant" state variables, and beliefs of all agents over the evolution of product lifetime utilities are restricted to lie within the class of first-order Markov processes. This approach is similar to certain dynamic macroeconomic models where agents use summary statistics such as first moments to track the evolution of high-dimensional state variables (e.g., as in Krusell and Smith (1998)). Given the restriction on beliefs, the solution concept used is equivalent to Markov Perfect Nash Equilibrium (Maskin and Tirole (1988, 2001)) and the model is similar in spirit to the industry dynamics literature (see Ericson and Pakes (1995)). Using this framework, this paper is one of the first to account explicitly for the rematching process between contracting partners within a counterfactual regime, and to my knowledge the only one that does so in a dynamic environment.

B. Road Map

In the next section I describe the U.S. videogame industry, the role of exclusive vertical arrangements, and important stylized facts. Section II presents a model of dynamic consumer demand for hardware and software products, as well as a model of how software products choose which platforms to support. Section III discusses the estimation, identification, and computation of demand parameters and underlying porting costs borne by software firms, with results presented in Section IV. Finally, I analyze counterfactual regimes in which exclusive agreements are prohibited in Section V, and conclude in Section VI.

I. Application: The U.S. Videogame Industry

A primitive electronic version of table tennis called *Pong* launched the U.S. videogame industry in the 1970s. Since then, videogames have matured into a \$25B industry (\$60B worldwide), and are no longer soley the domain of children and hobbyists: nearly 70% of heads of household engage in gaming and half of all television households own at least one dedicated videogame device.[7]

A videogame system comprises a hardware platform (the *console*) and software (its games). Consoles are tightly integrated and standardized devices that are required to use any software created for the system; historically, consoles have been produced by a single firm (the platform provider). Videogame software is brought to market by two vertically related entities: *developers*, who undertake the programming and creative execution of each title; and *publishers*, who market

[7] "Essential Facts (Sales, Demographic and Usage Data)," *Entertainment Software Association*, 2006-12.

and distribute each game. As the costs of developing games have increased over time, software developers have increasingly relied on integration or exclusive arrangements with publishers, granting exclusive distribution and publishing rights in exchange for financing (Coughlan, 2001).

Console manufacturers are also integrated into software publishing and development. Any title produced or published by the console provider is exclusive and known as a *first-party* title. All other games are *third-party* titles and are published by other firms. Within a generation, games developed for one console are not compatible with others; in order to be played on another console, the game must explicitly be "ported" by a developer and another version of the game created. These porting costs are non-negligible, and range from a few hundred thousand to a few million dollars (Eisenmann and Wong, 2005). The choice of which platforms to develop for is thus strategic: a third-party software developer can release a title exclusively for one console and forgo selling its game to consumers on other platforms, or *multihome* and release versions on multiple platforms at a higher cost. Furthermore, a developer can choose to make a game exclusive in multiple ways: it can voluntarily be exclusive, enter into an exclusive publishing agreement with the console provider, or opt to sell the game or entire firm outright.

Since consoles usually have little if any stand-alone value, consumers purchase them only if there are desirable software titles available. At the same time, software publishers release titles for consoles that either have or are expected to have a large installed base of users. These cross-side network effects are manifest in most hardware-software industries, and partly give rise to observed pricing behavior: most platforms subsidize hardware sales, selling consoles close to or below cost, while charging publishers and developers a royalty for every game sold. Platform profits are thus derived primarily not from hardware, but rather from software sales.

As the dominant videogame platform provider during most of the 1980's and 1990's, Nintendo used to write forced exclusivity contracts with developers, committing them to two-year exclusive deals in exchange for the right to develop for its system. Nintendo dropped these practices following a 1992 antitrust investigation related to *Atari Games Corp v. Nintendo of America, Inc.* [975 F.2d 832 (1992)] (Shapiro (1999), Kent (2001)). Since then, forced exclusivity contracts have not been observed within the industry. In their place, console manufacturers have primarily relied on internal development, integration, or favorable contracting terms to third party developers or publishers (e.g., lump sum payments or marketing partnerships) in order to secure exclusive titles.

A. The Sixth Generation: 2000 - 2005

Hardware specifications remain fixed within a generation, and new consoles are released approximately every five years. In October 2000, Sony released its Playstation 2 (PS2) console, the first of the "sixth-generation" of videogame con-

Table 1—Industry Summary Statistics

		PS2	XB	GC	ALL
Hardware	Release Date	Oct. 2000	Nov 2001	Nov 2001	
	Avg. Quantity (M) / Month	0.49	0.28	0.20	0.87
	Installed Base (M)	30.07	13.32	9.83	53.22
	Household Penetration (M)				44.1
Software	Total # Titles Released	1161	749	487	1581
	% Exclusive	52.4	33.4	27.5	62.7
	% On all 3 Consoles	21.6	33.5	51.5	15.9
	Avg. # Titles Released / Month	19	13	8	37
	(Min, Max)	(2,54)	(0,45)	(0,38)	(5,127)

Note: Summary statistics for the PS2 are for the 61-month period between October 2000 and October 2005; statistics for the other two consoles are for a 48-month period beginning on November 2001. Installed base and household penetration are for October 2005, the last period in the sample.

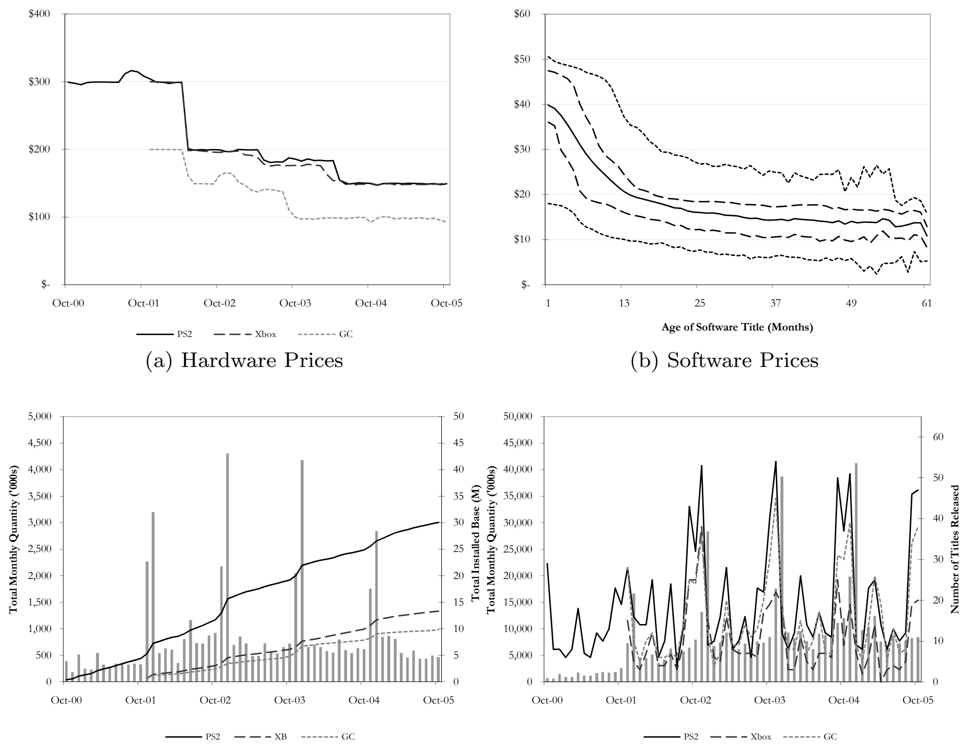
soles. The PS2 was a followup to Sony's wildly successful Playstation (PS1), released in 1994. In November 2001, industry veteran Nintendo released its Gamecube (GC) console, and new entrant Microsoft introduced its Xbox (XB) console. By that point, the PS2 had sold 5M consoles and—since the PS2 could use software developed for the PS1—had a software library of over a thousand titles. For these reasons, I refer to Sony as the incumbent of this generation, and Microsoft and Nintendo as the entrants. By the time the first seventh-generation console entered in October 2005, the PS2 had sold almost double the number of hardware devices of both its competitors combined.

This paper focuses on the sixth-generation for several reasons. First, it marked the arrival of Microsoft, a firm new to videogames but a veteran and competitor in other platform industries. Prior to entering the market, Microsoft acquired several software developers; whether or not Microsoft would have been able to gain a foothold into vidoegames absent integration or exclusive contracting is an open question. Secondly, the three platform providers active during the sixth-generation are also active in the seventh-generation, providing timeliness to this line of inquiry. Finally, the sixth-generation placed the videogame industry squarely within the convergence battle between personal computers and other general consumer electronics; as a result, the success or failure of these partiular platforms had and continue to have a dramatic impact on industries far removed from videogames.

B. *Data and Descriptive Statistics*

The analysis relies on a panel data set obtained from the NPD Group, a market research firm, containing monthly observations from September 2000 to October 2005. The data includes the average selling price and quantity sold for the three sixth-generation videogame consoles, and the average selling price, quantity sold, genre and release date for 1581 unique software titles.[8] Prices are normalized

[8] The data is collected from approximately two dozen of the largest retailers in the U.S., which account for approximately 85% of videogame sales, and is extrapolated by NPD for the entire U.S. market.



(a) Hardware Prices

(b) Software Prices

(c) Hardware Installed Base and Quantity

(d) Software Releases and Quantity

FIGURE 1. HARDWARE AND SOFTWARE STATISTICS

Note: (a) Average monthly (nominal) prices faced by consumers in retail stores for each platform. The PS2 and XB started retailing for \$300, and both simultaneously cut their prices by \$100 in May 2002; Nintendo followed with a \$50 price cut of its own. In May 2004, Microsoft and Sony again dropped their prices. (b) Price paths of software titles over time. Solid line indicates average selling price for software at a given age; dashed lines represent 75 percent/25 percent and dotted lines 95 percent/5 percent levels. (c) Bars represent the total number hardware consoles sold across all three platforms in each month in thousands (scale on left); lines indicate the total installed base for each console in millions (scale on right). (d) Bars represent the total number of software titles sold across all three platforms in each month in thousands (scale on left); lines indicate the number of software titles released for each console in each month.

using the Consumer Price Index. For the population of potential consumers, I use the number of television households provided on a yearly basis from Nielsen and interpolated to the monthly level. The number of total households that own a videogame console is obtained from monthly survey data from ICR Centris, a market research firm. General descriptive statistics are provided in Table 1 and Figure 1. Additional stylized facts include:

Software Incompatibility and Exclusivity: Incompatibility of software is the norm during this generation, with 63% of all unique software titles exclusive to one console and only 16% of games available on all three systems. There is

Table 2—Top 10 Selling Videogame Titles by Platform Sold

PS2			XB			GC		
Title	Date	Q	Title	Date	Q	Title	Date	Q
GTA: VC[a]	10/02	6.7	Halo 2*	11/04	4.8	Smash Bros.*	12/01	3.0
GTA: SA[a]	10/04	5.8	Halo*	11/01	4.2	Mario Sun.*	8/02	2.2
GTA 3[a]	10/01	5.6	Splinter Cell	11/02	1.5	Zelda WW*	3/03	2.0
GT3: A-Spec*	7/01	3.8	GTA Pack	10/03	1.4	Mario Kart*	11/03	1.9
Madden 2004	1/00	3.4	Madden 2005	8/04	1.2	Luigi's Mans.*	11/01	1.7
Madden 2005	8/04	3.2	PG Racing*	11/01	1.2	Metroid*	11/02	1.3
Madden 2003	8/02	2.7	Star Wars †	7/03	1.2	Sonic Adv. 2†	2/02	1.2
Need for Speed	11/03	2.5	ESPN NFL	7/04	1.2	Animal Cros*	9/02	1.1
King. Hearts†	9/02	2.5	Fable*	9/04	1.1	Pokemon Coll.*	3/04	1.0
MOH Frontline	5/02	2.3	Ghost Recon	11/02	1.0	Mario Party 4*	10/02	1.0

Note: Quantity sold in millions for the 61-month period between October 2000 and October 2005. Date indicates the release date for each title. * indicates first-party exclusive titles, † indicates third-party exclusive titles, and [a] indicates titles that were exclusive on the PS2 for a limited time (GTA: VC and GTA 3 were not released on the XB until 2003; GTA: SA, though developed for both XB and PS2, was not released for the XB until 6 months after the PS2 version's release).

significant variation in software exclusivity across platforms: over half the titles on the PS2 are exclusive, whereas the majority of GC titles are available on all systems. This pattern reverses for the top 10 titles on each console: e.g., although the top GC titles are all exclusive, the top PS2 titles are primarily non-exclusive.

Concentrated Software Sales: As with motion pictures, the videogame industry is primarily hit-driven with sales concentrated among a few top-selling games. The top 10 titles on the PS2, XB, and GC (listed in Table 2) accounted for 13%, 16%, and 20% of platform software sales. On average, over 50% of total sales occurring within the first 3 months of release.

Prices: Hardware prices are shown in Figure 1a. Most platform providers initially sold hardware platforms close to or below cost, with margins increasing over time as production costs fell. Figure 1b shows significant variation in starting software prices and price declines; software prices fall the most in the first few months of a title's release. Such patterns are consistent with firms "skimming" and targeting high valuation customers early, reducing prices later to capture lower valuation users (Nair (2007)); it also is consistent with older games becoming less desirable to play.

Seasonality: There is considerable seasonality both in consumer demand and software supply. Figure 1c shows the number of total hardware consoles sold each month; during holiday months (November and December) the number of consoles sold is easily double or triple the average number sold in other months. Figure 1d shows the number of software titles sold and released in a given month. In some months, over 100 new titles are released across all systems; in others, less than 5.

Significant Consumer Heterogeneity: The heaviest 20% of videogame players account for nearly 75% of total videogame console usage by hours played, averaging 345 minutes per day. Though 6-9 games on average were sold per console in this generation, "heavy gamers" reported owning collections of over 50+ games and purchasing more than 1 game per month.[9]

II. Industry Model

The validity of the counterfactual exercises conducted in this paper relies on an ability to predict industry and consumer responses to a restriction on exclusive vertical arrangements. In this section, I first specify a structural model of dynamic consumer demand for both hardware and software. This model specifies how a consumer chooses products based on their underlying characteristics; it informs the estimation and recovery of policy invariant parameters which subsequently can be used to predict how hardware demand is influenced by software availability in counterfactual scenarios not observed in the data. Next, I present a model of software "demand" for platforms in which titles develop for the set of platforms that maximize their expected profits; this will also be used to inform the estimation and recovery of unobserved porting costs. Finally, I specify an equilibrium of this industry in which consumers and software titles behave optimally in each period given their information sets and beliefs, and these beliefs are in turn consistent with the actions of all agents.

A. *Consumer Demand*

Institutional realities motivate several dynamic considerations. First, hardware consoles and software titles are durable goods, and heterogeneous consumers leave the market for a product after purchase; this implies that the composition of each product's potential market and installed base changes over time. Failure to control for this selection will bias estimates of product qualities upwards for titles released early relative to those released later. Second, when purchasing hardware, consumers anticipate the utility they derive from software that is not only currently available, but also will be released in the future; ignoring this and misspecifying a platform's "software utility" will affect the degree to which consumers substitute across platforms in response to counterfactual changes in software availability. Finally, consumers may be forward looking and "time" their purchases (i.e., delay purchase in anticipation of future quality or price adjustment); static estimation under such dynamic behavior can yield biased price elasticities (Aguirregabiria and Nevo, 2012), and hence affect welfare predictions. I discuss the identification of these dynamic effects in section III.A, and the impact of ignoring them in section IV.B.

I assume every month, each consumer visits the market and may purchase any videogame console $j \in \mathcal{J}_t$ she does not already own, where $\mathcal{J}_t$ is the set of consoles

[9] Sources: "The State of the Console," *Nielsen*, 2007; "Video Game Culture: Leisure and Play Preferences of B.C. Teens," *Media Awareness Network*, 2005; "'Digital Gaming in America Survey' Results," *Gaming Age*, 2002.

available at time t; consumers can only purchase one console per month.[10] If a consumer has purchased console j in the current or any previous month, she may then purchase any software title $k \in \mathcal{K}_{j,t}$ that she has not previously purchased, where $\mathcal{K}_{j,t}$ is the set of available titles on console j at time t.

Hardware Adoption

Consider first the hardware purchase decision for consumer i. Since a consumer purchases any console at most once, she considers the *lifetime expected utility* of the product in deciding when, if ever, to purchase it. Let $\iota \in \mathcal{I} \equiv \{0,1\}^3$ denote the consumer's inventory of consoles owned at time t. The lifetime expected utility i receives from purchasing a console j she does not already own ($j \notin \iota$) at time t is:

$$u_{i,j,t,\iota} = \underbrace{\boldsymbol{\alpha}^x \boldsymbol{x}_{j,t} + \alpha_i^{p,hw} p_{j,t} + \alpha^\Gamma \Gamma_{j,t}(\alpha_i^{p,sw}, \alpha_i^\gamma; \iota) + D(\iota) + \xi_{j,t}}_{\delta_{i,j,t,\iota}} + \epsilon_{i,j,t,\iota} \ , \tag{1}$$

where $\{\boldsymbol{\alpha}^x, \{\alpha_i^{p,hw}, \alpha_i^{p,sw}\}, \{\alpha^\Gamma, \alpha_i^\gamma\}\}$ are coefficients that reflect how intensely consumer i prefers console characteristics, prices for hardware and software, and software in general;[11] $\boldsymbol{x}_{j,t}$ are observable characteristics of console j at time t, which include a console-specific and month-of-year fixed effects, as well as age and age squared terms; $p_{j,t}$ is the console's price; $\Gamma_{j,t}(\cdot;\iota)$ is the expected present-discounted value of being able to purchase software for the console in the current and future periods (which depends on an individual's preferences and inventory); $D(\iota)$ is a term that denotes any complementarity or substitutability effects that may exist with ownership of multiple consoles, where $D(\cdot) = D$, a constant, if a consumer owns at least one other console, and $D(\cdot) = 0$ otherwise; $\xi_{j,t}$ is a console-time-specific characteristic observable to the consumer but not to the econometrician; and $\epsilon_{i,j,t,\iota}$ is an individual-console-time-inventory specific component that represents idiosyncratic consumer heterogeneity unobservable to the econometrician but realized by the consumer only at time t.[12] Let $\delta_{i,j,t,\iota}$ denote individual i's expected lifetime utility or price-adjusted quality from console j at time t given inventory ι, net of her idiosyncratic unobservable.

One innovation of this paper is the specification of $\Gamma_{j,t}(\cdot;\iota)$, which will be defined in the software adoption portion of the model; it represents the option value of being able to purchase software that is available on a given console, and will not take into account software titles that can be accessed on consoles a consumer already owns. For now, I assume that $\Gamma_{j,t}(\cdot;\iota)$ differs across agents only as a

[10] As relaxing this assumption did not significantly change results, a simpler model is presented for clarity.

[11] The model allows consumers to have different hardware and software price coefficients for flexibility; otherwise, the restriction $\alpha^{p,hw} = \alpha^\Gamma \alpha^{p,sw}$ would be imposed. I return to this point again later when discussing estimates.

[12] A previous version of the paper controlled for installed base; this did not substantially change results.

function of their price sensitivity and software preference $\{\alpha_i^{p,sw}, \alpha_i^{\gamma}\}$, and that it enters linearly into a consumer's lifetime expected utility from hardware.

In every period, a consumer can buy a console she does not yet own, or not purchase any console. If she does not purchase a console, she consumes an outside good yielding utility $u_{i,0,t,\iota} = \epsilon_{i,0,t,\iota}$, which represents the best alternative to purchasing any console in that period. This outside option depends on i, t and ι, and may include utility from previous generation videogame consoles.[13] I assume that $\epsilon_{i,j,t,\iota}$ is independently and identically distributed according to the type I extreme value distribution, demeaned by Euler's constant.

A consumer seeks to maximize her discounted stream of expected lifetime utilities from participating in the market, which involves deciding when, if at all, to purchase each console. Conditional on following her optimal policy—which will depend on her inventory ι, preferences, current product qualities, prices, software availability, and expectations over future values of these characteristics—a consumer's *value function* from being able to purchase consoles is given by:

$$V_i(\iota, \boldsymbol{\epsilon}_{i,t}, \boldsymbol{\Omega}_{i,t}) = \max \Bigg\{ \underbrace{\max_{j \in \mathcal{J}_t, j \notin \iota} u_{i,j,t,\iota}(\boldsymbol{\Omega}_{i,t}) + \beta E[V_i(\iota \cup \{j\}, \boldsymbol{\epsilon}_{i,t+1}, \boldsymbol{\Omega}_{i,t+1}) | \boldsymbol{\Omega}_{i,t}]}_{\text{Buy best platform today, return next period with new inventory;}},$$
$$\underbrace{u_{i,0,t,\iota} + \beta E[V_i(\iota, \boldsymbol{\epsilon}_{i,t+1}, \boldsymbol{\Omega}_{i,t+1}) | \boldsymbol{\Omega}_{i,t}]}_{\text{consume outside good, return next period with same inventory.}} \Bigg\}, \tag{2}$$

where $\boldsymbol{\epsilon}_{i,t} \equiv \{\epsilon_{i,j,t,\iota}\}_{j \in \{\mathcal{J}_t \cup \{0\}, \iota \in \mathcal{I}\}}$, and $\boldsymbol{\Omega}_{i,t}$ includes any variables in consumer i's information set at time t that affect her utility, value from waiting, and current and future product attributes. It is assumed to evolve according to some Markov process $P(\boldsymbol{\Omega}_{i,t+1} | \boldsymbol{\Omega}_{i,t})$.

Software Adoption

I now turn to analyze the software purchase decisions for a consumer, which is used to construct the *total software utility* a consumer derives from any given platform j ($\{\Gamma_{j,t}(\cdot)\}$ in (1)). Importantly, I assume that each consumer makes the decision to purchase a title k independently of her decision to purchase any other title $k' \neq k$. I discuss the implications of this assumption and robustness tests at length in Section IV.B.

Each software titles is purchased at most once; as a result, a consumer evaluates the *lifetime expected utility* for each title k that she has not already purchased (and available on any console j she already owns) to determine whether or not to

[13] As I do not explicitly control for previous-generation hardware in the analysis, I assume that consumers who purchase sixth-generation consoles in the first few years of the sample period have similar holdings of previous-generation consoles. I also assume that near the end of the sample period, older generation consoles did not affect purchase decisions of sixth-generation consoles for late adopters.

purchase that title or wait until the next period. This lifetime expected utility is:

$$\tilde{u}^{sw}_{i,j,k,t} = \tilde{\alpha}^{\gamma}_i + \tilde{\boldsymbol{\alpha}}^w \boldsymbol{w}_{j,k,t} + \tilde{\eta}_{j,k,t} + \tilde{\alpha}^{p,sw}_i p_{j,k,t} + \tilde{\epsilon}_{i,j,k_1,t} \ , \tag{3}$$

where $\boldsymbol{w}_{j,k,t}$ are observable software characteristics (which include a title-console-specific fixed effect, monthly fixed effects, and age and age squared terms), $\tilde{\eta}_{j,k,t}$ is a title-console-time-specific characteristic unobservable to the econometrician but observable to the consumer, $p_{j,k,t}$ is the price, and $\tilde{\epsilon}_{i,j,k_1,t}$ is an individual-title-console-time specific utility shock. Finally, $\tilde{\alpha}^{\gamma}_i$ and $\tilde{\alpha}^{p,sw}_i$ are individual specific gaming preferences and software price sensitivities. I assume that consumers anticipate being able to purchase any software title, once released, for the lifetime of each console.

A consumer can decide not to buy a title at time t and return to the market in the next period; this yields the outside option utility $\tilde{u}^{sw}_{i,j,k_0,t} = \tilde{\epsilon}_{i,j,k_0,t}$. Mirroring the hardware side, I assume that these individual-specific utility shocks are independently and identically distributed from the (demeaned) type I extreme value distribution, but scaled by a factor of α^{Γ}. To compare measures of software and hardware utility with different variances in the idiosyncratic error terms (Train (2003)), define *scaled software utility* as:

$$u^{sw}_{i,j,k,t} \equiv \tilde{u}^{sw}_{i,j,k,t}/\alpha^{\Gamma} = \underbrace{\alpha^{\gamma}_i + \boldsymbol{\alpha}^w \boldsymbol{w}_{j,k,t} + \eta_{j,k,t} - \alpha^{p,sw}_i p_{j,k,t}}_{\zeta_{i,j,k,t}} + \epsilon_{i,j,k_1,t} \ , \tag{4}$$

where $\{\alpha^{\gamma}_i, \boldsymbol{\alpha}^w, \alpha^{p,sw}_i, \eta_{j,k,t}, \epsilon_{i,j,k_1,t}\} = \{\tilde{\alpha}^{\gamma}_i, \tilde{\boldsymbol{\alpha}}^w, \tilde{\alpha}^{p,sw}_i, \tilde{\eta}_{j,k,t}, \tilde{\epsilon}_{i,j,k_1,t}\}/\alpha^{\Gamma}$, and $\zeta_{i,j,k,t}$ represents the (scaled) lifetime expected utility of purchasing a title (or price-adjusted quality) net of individual-specific-unobservable $\epsilon_{i,j,k_1,t}$. Since software titles are assumed independent, a consumer solves a separate optimal stopping problem for each available software title k on console j to determine when, if at all, to purchase the title; the (scaled) value function that arises is given by:

$$W_{i,j,k}(\boldsymbol{\Omega}_{i,t}, \boldsymbol{\epsilon}_{i,j,k,t}) = \max\{ \underbrace{u^{sw}_{i,j,k,t}}_{\substack{\text{Purchase} \\ k \text{ today}}}, \underbrace{u^{sw}_{i,j,k_0,t} + \beta E[W_i(\boldsymbol{\Omega}_{i,t+1}, \boldsymbol{\epsilon}_{i,j,k,t+1})|\boldsymbol{\Omega}_{i,t}]}_{\substack{\text{Consume outside good,} \\ \text{return next period}}} \} \ , \tag{5}$$

where $\boldsymbol{\epsilon}_{i,j,k,t} = \{\epsilon_{i,j,k_0,t}, \epsilon_{i,j,k_1,t}\}$.

Let $EW_{i,j,k}(\boldsymbol{\Omega}_{i,t}) \equiv \int_{\boldsymbol{\epsilon}} W_{i,j,k}(\boldsymbol{\Omega}_{i,t}, \boldsymbol{\epsilon}_{i,j,k,t}) dP(\boldsymbol{\epsilon}_{i,j,k,t})$ denote the expectation of the value function over ϵ, or the *option value* of being able to purchase title k at time t. Given software titles are assumed to be independent, the value of being able to purchase software on a given platform, $\{\Gamma_{j,t}(\cdot)\}$, will be a sum of these option values for (i) software currently available and (ii) software that will be released in future periods:

$$\Gamma_{j,t}(\alpha_i^p, \alpha_i^\gamma; \iota) = \underbrace{\left[\sum_{k \in \tilde{\mathcal{K}}_{j,t}(\iota)} EW_{i,j,k}(\mathbf{\Omega}_{i,t}) \right]}_{\text{(i) Current Software Utility} \equiv \Lambda^c_{i,j,t,\iota}} + \underbrace{E\left[\sum_{\tau=1}^{T-t} (\beta)^\tau \left(\sum_{k \in \tilde{\mathcal{K}}^R_{j,t+\tau}(\iota)} EW_{i,j,k}(\mathbf{\Omega}_{i,t+\tau}) \right) | \mathbf{\Omega}_{i,t} \right]}_{\text{(ii) (Expected) Future Software Utility} \equiv E[\Lambda^f_{i,j,t,\iota} | \mathbf{\Omega}_{i,t}]} , \tag{6}$$

where $\{\tilde{\mathcal{K}}_{j,t}(\iota), \tilde{\mathcal{K}}^R_{j,t}(\iota)\}$ denotes the set of titles on console j that {have been released by time t, are released at time t}, but not available on any console $j' \in \iota$ (i.e., a user does not value titles onboard a new console that she can access on a console that she already owns). The first term, $\Lambda^c_{i,j,t,\iota}$, represents the utility from currently available software. The second term, $E[\Lambda^f_{i,j,t,\iota} | \mathbf{\Omega}_{i,t}]$, represents the expected utility from titles that will be released in the future (up until some terminal date T), conditioning on each agent's information set.[14]

Simplifications and Additional Assumptions

State Space

To reduce the state space and allow each consumer's dynamic hardware and software adoption problems to be computationally solvable, I assume that consumers perceive sufficient statistics for the evolution of product lifetime utilities to be previous values of these variables:

ASSUMPTION II.1: *For all consumer types i and inventory states $\iota \in \mathcal{I}$, consumers perceive that hardware lifetime expected utilities $\{\delta_{i,j,t,\iota}\}_{j \in \mathcal{J}_t, \forall t}$ can be summarized by a first-order Markov process:*

$$F(\{\delta_{i,j,t+1,\iota}\}_{j \in \mathcal{J}_{t+1}} | \mathbf{\Omega}_{i,t}) = F_{i,\iota}(\{\delta_{i,j,t+1,\iota}\}_{j \in \mathcal{J}_{t+1}} | \{\delta_{i,j,t,\iota}\}_{j \in \mathcal{J}_t}, m(t)) , \tag{7}$$

where $m(t)$ represents the month at time t, and $F_{i,\iota}$ is individual and inventory-state specific. The processes take the following functional form:

$$\delta_{i,j,t+1,\iota} = \varphi_{i,j,\iota,0} + \sum_{j'=1}^{3} \varphi_{i,j,\iota,j'} \delta_{i,j',t,\iota} + \sum_{m=1}^{11} \varphi_{i,j,\iota,m} \chi_m(t) + \upsilon_{i,j,\iota,t} , \tag{8}$$

[14] Since consumers have already controlled for the option value of purchasing software when buying a given console, and since titles onboard an owned console do not enter into the utility of buying another console, whether or not a consumer purchases a given title does not affect future purchasing decisions over consoles she does not yet own.

where $\chi_m(t)$ is an indicator variable equal to 1 if t is in month m.

ASSUMPTION II.2: *Consumers perceive that software lifetime expected utilities $\{\zeta_{i,j,k,t}\}_{\forall k,t}$ can be summarized by a first-order Markov process:*

$$G(\zeta_{i,j,k,t+1}|\mathbf{\Omega}_{i,t}) = G_{i,j}(\zeta_{i,j,k,t+1}|\zeta_{i,j,k,t}, m(t)) \,, \tag{9}$$

where $G_{i,j}$ is specific to individual i and console j. The processes take the following functional form:

$$\zeta_{i,j,k,t+1} = \varphi^j_{i,0} + \varphi^j_{i,1}\zeta_{i,j,k,t} + \varphi^j_{i,2}(\zeta_{i,j,k,t})^2 + \sum_{m=1}^{11} \varphi^j_{i,m}\chi_m(t) + \upsilon^j_{i,j,k,t} \tag{10}$$

As noted in Hendel and Nevo (2006), such first order processes may be reasonable approximations to consumer expectations.[15] However, these assumptions rule out correlations in beliefs across different inventories, and may not be consistent with an underlying supply model.[16]

Given these assumptions, both (2) and (5) can be analytically integrated over ϵ to provide an *expected value function* for consumer i (McFadden (1973); Rust (1987)); i.e.:

(11)
$$\begin{aligned}
EV_i(\{\delta_{i,j,t,\iota}\}_{j\in\mathcal{J}_t,\iota\in\mathcal{I}}, \iota_{i,t}, m(t)) &\equiv \int_{\boldsymbol{\epsilon}} V_i(\iota_{i,t}, \boldsymbol{\epsilon}_{i,t}, \mathbf{\Omega}_{i,t}) dP(\boldsymbol{\epsilon}_{i,t}) \\
&= \int_{\boldsymbol{\epsilon}} V_i(\iota_{i,t}, \boldsymbol{\epsilon}_{i,t}, \{\delta_{i,j,t,\iota}\}_{j\in\mathcal{J}_t,\iota\in\mathcal{I}}, m(t)) dP(\boldsymbol{\epsilon}_{i,t}) \\
&= \ln\Bigg(\sum_{j'\notin\iota_{i,t}} \big(\exp(\delta_{i,j',t,\iota} + \beta E[EV_i(\{\delta_{i,j,t+1,\iota}\}_{j\in\mathcal{J}_{t+1},\iota\in\mathcal{I}}, \\
&\qquad \iota_{i,t}\cup\{j'\}, m(t+1)|\{\delta_{i,j,t,\iota}\}_{j\in\mathcal{J}_t,\iota\in\mathcal{I}})]) \big) \\
&\quad + \exp(\beta E[EV_i(\{\delta_{i,j,t+1,\iota}\}_{j\in\mathcal{J}_{t+1},\iota\in\mathcal{I}}, \iota_{i,t}, m(t+1))|\{\delta_{i,j,t,\iota}\}_{j\in\mathcal{J}_t,\iota\in\mathcal{I}}]) \Bigg) \,,
\end{aligned}$$

represents consumer i's expected option value of being able to purchase consoles (and associated software) not already contained in her inventory $\iota_{i,t}$ prior to the

[15]These assumptions differ from those used in prior work on dynamic demand which restrict the evolution of industry *inclusive values* (e.g., Melnikov (2001), Hendel and Nevo (2006)); e.g., equation (7) allows each product's price-adjusted quality to evolve separately as a function of, among other things, the proximity of other products' qualities to its own.

[16]E.g., even if individual product attributes (e.g., prices, characteristics, etc.) evolved as first-order Markov processes, it would be unlikely that their sums ($\{\delta_{i,j,t,\iota}\}$) would as well.

realization of $\epsilon_{i,t}$, and

$$
\begin{aligned}
(12)\quad EW_{i,j}(\zeta_{i,j,k,t}, m(t)) &\equiv \int_{\boldsymbol{\epsilon}} W_{i,j,k}(\boldsymbol{\Omega}_{i,t}, \boldsymbol{\epsilon}_{i,j,k,t}) dP(\boldsymbol{\epsilon}_{i,j,k,t}) \\
&= \int_{\boldsymbol{\epsilon}} W_{i,j,k}(\zeta_{i,j,k,t}, m(t), \boldsymbol{\epsilon}_{i,j,k,t}) dP(\boldsymbol{\epsilon}_{i,j,k,t}) \\
&= \ln(\exp(\zeta_{i,j,k,t}) + \exp(\beta E[EW_{i,j}(\zeta_{i,j,k,t+1}, m(t+1)) | \zeta_{i,j,k,t}, m(t)])) \ ,
\end{aligned}
$$

represents i's expected option value of being able to purchase software title k onboard platform j (which she owns) prior to the realization of $\epsilon_{i,j,k,t}$. As shown in the appendix, the predicted share of consumers that purchase each platform and software title in each period can be constructed from price-adjusted qualities and these expected value functions; predicted shares are matched to those observed in the data to estimate model parameters.

The simplified model thus implies each consumer i at time t solves multiple dynamic decision problems of which products to purchase, conditioning only on: (i) $m(t)$, the month at time t; (ii) $\{\delta_{i,j,t,\iota}\}_{\forall j \in \mathcal{J}_t, \iota \in \mathcal{I}}$, the set of all hardware expected lifetime utilities at every inventory state; (iii) $\{\zeta_{i,j,k,t}\}_{\forall j \in \mathcal{J}_t, k \in \mathcal{K}_{j,t}}$, the set of software expected lifetime utilities for all titles on all platforms; (iv) $\iota_{i,t}$, consumer i's inventory of hardware currently owned ($2^3 \equiv 8$ potential values); and (v) consumer i's set of all software products currently owned (so that she cannot purchase them again).[17]

For the construction of expected future software utility onboard a platform, I assume that consumers have rational expectations over future software utility that is consistent with the data: $E[\Lambda^f_{i,j,t,\iota} | \boldsymbol{\Omega}_{i,t}]$ for each consumer i is obtained via a regression of $\Lambda^f_{i,j,t,\iota}$ (specified in (6)) on a platform-specific intercept, month dummies, current software utility $\Lambda^c_{i,j,t,\iota}$, and a console's age, number of available titles, and installed base (in levels and logs).[18]

Consumer Heterogeneity

I assume that consumer preferences for software α^γ are independent and normally distributed with standard deviation σ^γ. Since α^γ enters linearly in utility, its mean is not separately identified from shifts in each software title's fixed effect and is normalized to 0. I assume that price sensitivities are parameterized as follows: $\alpha^{p,l}_i = \alpha^{p,l}_0 - \sigma^{p,l} y_i$ for $l \in \{hw, sw\}$, where y_i is consumer i's annual household income, and impose the restriction $\sigma^{p,hw} = \alpha^\Gamma \sigma^{p,sw}$. Following Berry,

[17] The model does not explicitly prevent a consumer from purchasing the same title on multiple consoles. I discuss this issue further in section IV.B.

[18] Adjusting the explanatory variables or allowing for a separate coefficient on $E[\Lambda^f_{i,j,t,\iota} | \boldsymbol{\Omega}_{i,t}]$ in (6) did not substantively affect results. I am also implicitly assuming that consumers condition on a larger set of state variables when forming expectations over $\{\Lambda^f_{i,j,t,\iota}\}$ than over future lifetime product utilities $\{\delta_{i,j,t,\iota}\}$ and $\{\zeta_{i,j,k,t}\}$.

Levinsohn and Pakes (1995), I assume that disposable household income y_i for the population is (independently) distributed log normally with mean and standard deviation estimated separately from the March 2001 Current Population Survey (CPS), and I draw from this distribution.

B. Software "Demand" for Platforms

I now specify a model of software "demand" for hardware. I assume any software title commits τ months in advance of release to develop for a (non-empty) set of consoles $\boldsymbol{s}_k \in \mathcal{S} \equiv \{\{0,1\}^3 \setminus \{0,0,0\}\}$; this action is private and unobserved until the title is released. Developing for a console provides access to its installed base of users, but requires the outlay of additional porting costs. I assume that title k's expected discounted profit captures this tradeoff, and is given by:

$$(13)\quad E[\pi_k(\boldsymbol{s}_k;\boldsymbol{\theta}_C)|\boldsymbol{\Omega}_{k,r_k-\tau}] = E[\Bigg(\sum_{t=r_k}^{T} \beta^{\tau+t-r_k} \sum_{j\in \boldsymbol{s}_k} Q_{j,k,t}((1-mk)p_{j,k,t} - mc_j)\Bigg)|\boldsymbol{\Omega}_{k,r_k-\tau}] - C_k(\boldsymbol{s}_k;\boldsymbol{\theta}_C)\ ,$$

where r_k is title k's release date, $Q_{j,k,t}$ is the quantity of title k sold on platform j at time t, mk denotes the markup captured by retailers, mc_j is the marginal cost of production on console j (which includes royalties paid to the platform provider), and $C_k(\boldsymbol{s}_k;\boldsymbol{\theta}_C)$ are the costs of producing title k for all platforms within $\boldsymbol{s}_k$ which depend on some vector of parameters $\boldsymbol{\theta}_C$, and includes all fixed costs related to the production of the game (e.g., programming, distribution and marketing costs). Expectations are conditional on $\boldsymbol{\Omega}_{k,r_k-\tau}$, software title k's information set at time $r_k - \tau$. As with consumers, I assume software information sets evolve according to some Markov process.

For every title k that is not contractually exclusive, I assume that its choice of platforms $\hat{s}_k$ maximizes its expected profits at time $r_k - \tau$:

$$(14)\qquad E[\pi_k(\hat{\boldsymbol{s}}_k;\boldsymbol{\theta}_C)|\boldsymbol{\Omega}_{k,r_k-\tau}] \geq E[\pi_k(\boldsymbol{s}'_k;\boldsymbol{\theta}_C)|\boldsymbol{\Omega}_{k,r_k-\tau}]\ \forall\ \boldsymbol{s}'_k \in \mathcal{S}\ .$$

Simplifications and Additional Assumptions

I assume the set of titles that are released in a given period $\mathcal{K}_t^R$ is exogenous, and platforms are non-strategic.[19] I thus focus only on changes in contracting partners, assuming that the set of available hardware and software products is given, and porting costs, royalty rates, retailer markups, and release dates do not change. Later, I discuss potential ways of relaxing some of these restrictions.

[19] Without exclusive vertical arrangements, I rule out any preferential treatment by platform providers towards software titles since these deals are primarily made in exchange for exclusivity. Additionally, as platforms typically pre-announce and commit to royalty rates that are charged to third-party software developers in advance of a system's release (Kent (2001), Hagiu (2006)), I assume that these royalty rates do not change in the counterfactuals.

Since software titles compete in independent markets, a software title is affected by the actions of other titles only if the installed base of each console is impacted. Since this can only occur through hardware lifetime expected utilities $\{\delta_{i,j,t,\iota}\}$, beliefs over their evolution are sufficient for each title to account for the future responses of all other agents. I assume software titles share the same beliefs as consumers over the evolution of product lifetime expected utilities:

ASSUMPTION II.3: *Software titles perceive $\{\delta_{i,j,t,\iota}\}$ can be summarized by first-order Markov processes $\boldsymbol{F} \equiv \{F_{i,\iota}(\cdot)\}_{\forall i,\iota}$ given by* (7). *Furthermore, each software title perceives the evolution of its own $\{\zeta_{i,j,k,t}\}$ to be summarized by first-order Markov processes $\boldsymbol{G} \equiv \{G_{i,j}(\cdot)\}_{\forall i,j}$ given by* (9).

I assume that: firms share the same discount factor β as consumers; every software title knows its release prices $\{p_{j,k,r_k}\}$ and qualities $\{\zeta_{j,k,r_k}\}$ on all consoles it can join, and observes the size and composition of the installed base on each console at time $r_k - \tau$; each title believes that it impacts the level of $\{\delta_{i,j,t,\iota}\}$ if it joins console j, but not the transition processes $\boldsymbol{F}$ and $\boldsymbol{G}$. I also assume that the retailer markup is fixed at 35% and marginal costs are constant across platforms at \$10 (reflecting royalty rates of approximately \$7 and production costs of \$3). These figures are consistent with information provided by industry and public sources (e.g. Takahashi (2002)). Given this information, any title k at time $r_k - \tau$ can compute the number of copies $\{Q_{j,k,t}\}_{j\in\mathcal{J}_t, t\geq r_k}$ it expects to sell on any subset of consoles, and determine its optimal strategy.

C. Market Equilibrium

In each period t, I assume that the timing of actions is:

(i) all titles $k \in \mathcal{K}_t^R$ are released and added to the stock of existing software products for each platform according to $\{\boldsymbol{s}_k\}_{\forall k\in\mathcal{K}_t^R}$;

(ii) $\{\delta_{i,j,t,\iota}\}$ and $\{\zeta_{i,j,k,t}\}$ for all platforms and released software titles are determined;

(iii) consumers make hardware and software purchase decisions; and

(iv) every title $k \in \mathcal{K}_{t+\tau}^R$ that will be released in τ periods chooses $\boldsymbol{s}_k$.

Given the timing of the game and assumptions II.1, II.2, and II.3 on consumer and firm beliefs, a *first-order Markov equilibrium* will comprise a set of strategies $\{\hat{\boldsymbol{s}}_k\}_{\forall k}$ and first-order Markov transition processes $\hat{\boldsymbol{F}}$ and $\hat{\boldsymbol{G}}$ such that:

(i) every title k not contractually exclusive chooses $\hat{\boldsymbol{s}}_k$ to maximize (14), given beliefs $\hat{\boldsymbol{F}}$ and $\hat{\boldsymbol{G}}$;

(ii) consumers purchase hardware and software according to the dynamic model specified in the previous subsection, with software availability given by $\{\hat{\boldsymbol{s}}_k\}_{\forall k}$ and beliefs $\hat{\boldsymbol{F}}$ and $\hat{\boldsymbol{G}}$; and

(iii) transition processes $\hat{\boldsymbol{F}}$ and $\hat{\boldsymbol{G}}$ are consistent with realized values of $\{\delta_{i,j,t,\iota}\}$ and $\{\zeta_{i,j,k,t}\}$, which in turn are consistent with actions $\{\hat{\boldsymbol{s}}_k\}_{\forall k}$ and consumer behavior.

In this equilibrium, each software title conditions only on its own mean qualities, prices, and other "payoff-relevant" state variables when determining its optimal strategy; additionally, a consumer's decision to purchase a particular platform or software title is only a function of her own characteristics and the product's expected lifetime utility. A *first-order Markov equilibrium* is thus a *Markov-Perfect Nash Equilibrium* in the sense of Maskin and Tirole (1988, 2001) with the additional restriction that agents' beliefs over the transition probabilities $\hat{\boldsymbol{F}}$ and $\hat{\boldsymbol{G}}$ are contained within the class of first-order Markov processes (see also Krusell and Smith (1998)). This equilibrium is also subgame perfect: as long as every agent chooses its optimal action as a function only of its own payoff-relevant state variables, any agent's decision remains optimal and is a best-response even when considering more general deviations (e.g., non-Markovian strategies).

III. Estimation, Identification, and Computation

A. Consumer Demand

Let r_j denote the release date for console j and r_k the release date for title k. From the model, the implied values of unobserved product characteristics $\{\xi_{j,t}\}_{j\in\mathcal{J}_t, r_j\le t}$ and $\{\eta_{j,k,t}\}_{j\in\mathcal{J}_t,k\in\mathcal{K}_{j,t},r_k\le t}$ can be computed as a function of parameters $\boldsymbol{\theta}$ to be estimated. I assume:

ASSUMPTION III.1: *Unobserved product characteristics for each console and software title evolve according to a first-order autoregressive (AR(1)) process, where the errors*

$$
\begin{aligned}
\nu^{hw}_{j,t}(\boldsymbol{\theta}) &= \xi_{j,t}(\boldsymbol{\theta}) - \rho^{hw}\xi_{j,t-1}(\boldsymbol{\theta}) && \forall j\in\mathcal{J}_{t-1}, t>r_j \\
\nu^{sw}_{j,k,t}(\boldsymbol{\theta}) &= \eta_{j,k,t}(\boldsymbol{\theta}) - \rho^{sw}\eta_{j,k,t-1}(\boldsymbol{\theta}) && \forall j\in\mathcal{J}_{t-1},\ \forall\, k\in\mathcal{K}_{j,t-1}, t>r_k\ ,
\end{aligned}
\tag{15}
$$

are mean zero, independent, and

$$
E[\boldsymbol{Z}^{hw}_{j,t}\nu^{hw}_{j,t}(\boldsymbol{\theta})]=0 \qquad E[\boldsymbol{Z}^{sw}_{j,k,t}\nu^{sw}_{j,k,t}(\boldsymbol{\theta})]=0 \tag{16}
$$

$$
E[\boldsymbol{Z}^{hw,\Delta}_{j,t}\Delta\nu^{hw}_{j,t}(\boldsymbol{\theta})]=0 \qquad E[\boldsymbol{Z}^{sw,\Delta}_{j,k,t}\Delta\nu^{sw}_{j,k,t}(\boldsymbol{\theta})]=0\ , \tag{17}
$$

where $\Delta\nu^{(\cdot)}_{(\cdot),t}\equiv\nu^{(\cdot)}_{(\cdot),t}-\nu^{(\cdot)}_{(\cdot),t-1}$ *and* $\{\boldsymbol{Z}^{hw}_{j,t},\boldsymbol{Z}^{hw,\Delta}_{j,t},\boldsymbol{Z}^{sw}_{j,k,t},\boldsymbol{Z}^{sw,\Delta}_{j,k,t}\}$ *are vectors of instruments.*

The instruments are detailed later in subsection III.A. Relying on moments from the innovations in product unobservables ($\{\boldsymbol{\nu}^{hw},\boldsymbol{\nu}^{sw}\}$) and not the product unobservables themselves ($\{\boldsymbol{\xi},\boldsymbol{\eta}\}$) allows for the possibility that initial values of ξ_{j,r_j}

and η_{j,k,r_k} at release may be correlated with observable characteristics, and is robust to the possibility that product release dates are timed.

Let $\boldsymbol{\theta}_1 \equiv \{\beta, \rho^{hw}, \rho^{sw}, \{\alpha_0^{p,l}, \sigma^{p,l}\}_{l\in\{hw,sw\}}, \alpha^\Gamma, \sigma^\gamma, D\}$ and $\boldsymbol{\theta}_2 \equiv \{\boldsymbol{\alpha}^x, \boldsymbol{\alpha}^w\}$. The parameters to be estimated are $\boldsymbol{\theta} \equiv \{\boldsymbol{\theta}_1, \boldsymbol{\theta}_2\}$.[20]

The GMM estimator is $\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \boldsymbol{\Psi}(\boldsymbol{\theta})'(\boldsymbol{Z}'\boldsymbol{Z})^{-1}\boldsymbol{\Psi}(\boldsymbol{\theta})$, where $\boldsymbol{\Psi}(\boldsymbol{\theta})$ is a vector of stacked moments from (16) and (17), and $\boldsymbol{Z}$ are the set of instruments.

Identification

Distinguishing forward-looking behavior from static optimization is difficult with only aggregate market level data (Aguirregabiria and Nevo, 2012). Furthermore, the discount factor in dynamic discrete choice models is typically unidentified without additional restrictions (Rust, 1994).[21] However, time-series variation in hardware sales as software titles of varying quality are released over time (see Figure 1(d)) identifies forward looking behavior: i.e., a myopic model ($\beta = 0$) would be rejected if current hardware sales are influenced by variation in observed availability and estimated quality of future software; similarly, no discounting ($\beta = 1$) is rejected if a popular software title has a greater influence on hardware sales as its release date approaches. I rely on the structural model and assume the discount factor used when a consumer times her purchases (as in the value functions in (2) and (5)) is the same as the discount factor identified from the impact of future software on hardware sales (as in the specification of $\Gamma_{j,t}$ in (6)). Finally, although product durability is assumed in this model, the intuition used to identify consumer heterogeneity (discussed later) can be used to reject a model in which consumers do not leave the market after purchase.[22] In IV.B I discuss how results are affected as assumptions on dynamic behavior are relaxed.[23]

Components of $\boldsymbol{\alpha}^x$ and $\boldsymbol{\alpha}^w$—which include month-of-year fixed effects as well as age and age squared terms—are identified from time variation in sales as such characteristics change. I assume that hardware and software age effects are shared across all hardware and software products, and month-of-year effects are the same across years and the same for all hardware platforms (but may differ across platforms for software). Conditional on β, identification of mean household price sensitivities $\{\alpha_0^{p,l}\}_{l\in\{hw,sw\}}$ relies on variation in prices and sales across time and platforms. Instead of imposing the restriction $\alpha_0^{p,hw} = \alpha^\Gamma \alpha_0^{p,sw}$, I estimate hardware and software coefficients separately so that α^Γ is not identified

[20] Note the stationarity coefficients $(\rho^{hw}, \rho^{sw}) \in \boldsymbol{\theta}$ are estimated; any drifts in the processes in (15) are not separately identified from product fixed effects contained within $\boldsymbol{\alpha}^x$ and $\boldsymbol{\alpha}^w$ and are assumed to be 0.

[21] Recent exceptions include Fang and Wang (2010) and Yao et al. (2012).

[22] I.e., in a model without product durability, the potential market for a platform does not change over time, and two titles of the same estimated quality released in different periods should have the same impact on platform sales.

[23] Fixing the discount factor to .99 (as is commonly done in the literature) did not significantly affect results.

from differences in price responsiveness between hardware and software; rather, α^{Γ} is primarily identified as hardware sales responds to variation in software utility (both within and across platforms), which in turn is caused by variation in software availability and sales over time.

Typically, the variance in consumer preferences is identified from variation in product characteristics.[24] The panel data also provide another source of identification through the endogenous shift in the distribution of consumer valuations over time. If household heterogeneity in either α^{p} and α^{γ} is substantial, then consumer responses over time to changes in price or software availability *on* a given platform versus *for* a given platform will be different. To illustrate, consider two different titles released at different points in time but purchased by the same share of consumers onboard a platform. In the absence of heterogeneity in α^{γ}, estimated price adjusted qualities for each title would be the same, and the model would predict each title would have the same impact on demand for that platform upon release (controlling for beliefs and other product utilities). However, in the presence of heterogeneity, the installed base of a console will have a higher share of consumers with a high value of α^{γ} earlier than later. As a result, a title released later in a console's lifetime that attracts the same share of consumers as a title released earlier would be predicted to have a higher quality (since being released later means it must have appealed to a less predisposed base of users), and consequently will have a different impact on demand for the platform upon release than the other title. Thus, observing consumer demand for both a software title and for the platform as a result of that title's introduction allows for the identification of consumer heterogeneity in gaming preferences (σ^{γ}). Similarly, heterogeneity in price sensitivity ($\sigma^{p,hw}$) can be identified if earlier platform purchasers respond less to software price changes than later purchasers.

Variation in the degree to which games multihome over time and observing how their impact varies as the population of existing console owners increase helps identify D. To illustrate, consider two games released in separate periods which sell to the same share of consumers onboard the XB. Let the first be exclusive to the XB, and the other be released also on the PS2. Since the PS2 was released a year earlier, very high values of D would imply previous PS2 owners comprise the majority of early XB and GC owners. But this can be rejected if the release of these two games had similar impacts on resultant XB sales (controlling for other variables) since the second game should not influence the purchase decisions of existing PS2 owners. In addition, very low values of D (e.g., $D = -\infty$) imply console owners would singlehome and leave the market after purchasing. Though the data shows 53.2M sixth-generation videogame consoles were sold by October 2005, ICR Centris predicts that 44.1M households owned a videogame console (of any generation) at that time. I use the excess number of households the model

[24]E.g., as characteristics change for one product, substitution to products with similar characteristics indicates the presence of heterogeneity; on the other hand, if consumers substitute equally to all goods, then consumers are more homogeneous in their preferences.

predicts to own a console as an additional moment to rule out very low values of D and too few multihoming households.[25]

Instruments

Define *hardware total-mean-utilities* $\{\delta_{j,t}\}$ as the values of $\delta_{i,j,t,\iota}$ in (1) for an individual with mean preferences $\{\alpha_i^\gamma, \alpha_i^{p,hw}, \alpha_i^{p,sw}\}$ at inventory state $\iota = 0$, and let $\{\zeta_{j,k,t}\}_{j\in\mathcal{J}_t, k\in\mathcal{K}_{j,t},\forall t}$ represent *software total-mean-utilities*, defined similarly. Given Assumption III.1, hardware and software total-mean-utilities can be re-expressed as:

$$\begin{aligned}
\delta_{j,t}(\boldsymbol{\theta}) &= \rho^{hw}\delta_{j,t-1} + \boldsymbol{\alpha}^x(x_{j,t} - \rho^{hw}x_{j,t-1}) - \alpha_0^{p,hw}(p_{j,t} - \rho^{hw}p_{j,t-1}) \\
&\quad + \alpha^\Gamma(\Gamma_{j,t}(\cdot;\iota=0) - \rho^{hw}\Gamma_{j,t-1}(\cdot;\iota=0)) + D(1-\rho^{hw}) + \nu_{j,t}^{hw}(\boldsymbol{\theta}) \\
\zeta_{j,k,t}(\boldsymbol{\theta}) &= \rho^{sw}\zeta_{j,k,t} + \boldsymbol{\alpha}^w(w_{j,k,t} - \rho^{sw}w_{j,k,t-1}) - \alpha_0^{p,sw}(p_{j,k,t} - \rho^{sw}p_{j,k,t-1}) + \nu_{j,k,t}^{sw}(\boldsymbol{\theta})\ .
\end{aligned}$$

Following the literature on dynamic panel data models, I use moments of $\{\nu^{hw}, \nu^{sw}\}$ in both levels and first differences, given by (16) and (17); using both sets of moments has been shown to yield dramatic improvements when instruments for moments in first differences alone are weak (Arellano and Bover (1995), Blundell and Bond (1998)). Validity of the instruments $\{\boldsymbol{Z}^l, \boldsymbol{Z}^{l,\Delta}\}_{l\in\{hw,sw\}}$ relies on assumption III.1 which rules out any time-persistent component of these error terms, thereby insuring consumer hardware and software purchase and firm software release decisions are made without knowledge of future values of ν^{hw} and ν^{sw}. I will discuss the elements of $\{\boldsymbol{Z}_{j,t}^{hw}, \boldsymbol{Z}_{j,k,t}^{sw}\}$ which contain either current, current and one-period lagged, or one- and two-period lagged values of certain instruments; unless explicitly mentioned, the same instruments lagged by one additional period are used in $\{\boldsymbol{Z}_{j,t}^{hw,\Delta}, \boldsymbol{Z}_{j,k,t}^{sw,\Delta}\}$.

Instruments used to identify ρ^{hw} and ρ^{sw} are one- and two-period lagged values of $\delta_{j,t}$ and $\zeta_{j,k,t}$. Current values of exogenous explanatory variables in $\boldsymbol{x}_{j,t}$ and $\boldsymbol{w}_{j,k,t}$ (which contain product and month-of-year fixed effects and age effects) are valid instruments for $\boldsymbol{\alpha}^x$ and $\boldsymbol{\alpha}^w$.

Current prices for both hardware and software may be correlated with innovations in product unobservables (e.g., firms may be able to quickly adjust prices), thereby complicating identification of $\alpha^{p,hw}$ and $\alpha^{p,sw}$. However, as long as firms cannot forecast future values of ν^{hw} and ν^{sw} when setting prices, one- and two-period lagged prices are valid instruments. As consoles are primarily manufactured in Japan, I use the current and lagged monthly average Japanese-U.S. exchange rate as potential cost shifters. In the spirit of Berry, Levinsohn and Pakes (1995), I also use instruments that affect hardware pricing margins comprising the sum of the following competitor characteristics: percent household penetration, installed base, and current software utility $\Lambda_{j,t}^c$ (contained within $\Gamma_{j,t}$).

[25] The appendix provides further intuition for these identification arguments.

For software, I employ two additional sets of pricing instruments for the price $p_{j,k,t}$ of a τ-month old game released at time r. The first set of instruments uses the average price of all τ-month old games released before time r: e.g., for the January 2003 price of a game released in October 2002, the instrument used is the average 4-month price of all games released before October 2002. This instrument by construction will not be correlated with the innovation in the title's unobservable characteristic, and will capture any trends in costs not fully captured in the age effects. The second set of instruments uses the average price of all games on other consoles in different genres at month t, which—similar to Hausman, Leonard and Zona (1994) instruments—captures any software-wide cost shocks while eliminating the inclusion of prices for similar games (as well as the same game ported to different consoles); note these instruments would be only invalid if software demand shocks across different *platforms and genres* were correlated.[26]

To identify α^{Γ} and β, I use current and lagged values of current software utility $\Lambda^{c}_{j,t}$ and one- and two-period lagged values of expected future software utility (in addition to the sum of current software utility of competitors, as before). Identification of these parameters relies on a timing assumption: software firms cannot immediately respond to realizations of monthly hardware shocks $\nu^{hw}_{j,t}$ or predict them in advance when timing releases.[27] This is consistent with software firms committing to release dates months in advance, and does not preclude the possibility that software firms choose platforms based on expectations of trends or growth patterns (as software releases may still be correlated with previous values of $\{\delta_{j,t}\}$).

Computation

The approach for recovering the unobservable utility components $\{\xi_{j,t}(\cdot)\}$ for hardware and $\{\eta_{j,k,t}(\cdot)\}$ for software as a function of the parameter vector $\boldsymbol{\theta}$ builds on Gowrisankaran and Rysman (forthcoming), which extends the methodologies of Rust (1987), Berry (1994), and Berry, Levinsohn and Pakes (1995) to a dynamic environment. This paper simultaneously estimates hardware and software demand and employs a new nested fixed point routine in order to control for the selection of heterogeneous consumers across platforms and time. Once the unobserved product characteristics $\xi_{j,t}$ and $\eta_{j,k,t}$ are recovered, the GMM objective function is computed. An overview follows, with additional details contained in the appendix.

First, the observed share of consumers purchasing console j at time t is constructed from the data as follows: $s^{o}_{j,t} = q_{j,\tau}/(M_t - \sum_{\tau<t}(q_{j,t}))$, where $q_{j,t}$ is the

[26] First-stage estimates of these pricing instruments are reported in the appendix; estimating the model without instrumenting for price did not change the main counterfactual implications of this paper.

[27] Sweeting (2012) uses a similar timing assumption; as noted therein, this is similar to the literature on the structural estimation of production functions to address the endogeneity of input choices (e.g., Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg, Caves and Frazer (2006)).

quantity of console j sold and M_t is the number of television households at time t. I assume that the potential market for consoles at the beginning of the sample is equal to the total number of television households in 2000; new television households that enter during the time period ($<$ 6M during the sample) are distributed according to the initial distribution of consumer heterogeneity with no existing inventory. The observed share of consumers purchasing any title k on console j at time t is constructed as follows: $s^o_{j,k,t} = q_{j,k,t}/(IB_{j,t} - \sum_{\tau<t}(q_{j,k,\tau}))$, where $q_{j,k,t}$ is the quantity of title k sold and $IB_{j,t}$ is the installed base of console j at time t.

To evaluate a given parameter vector $\boldsymbol{\theta}$, I obtain starting values for $\{\Gamma_{j,t}\}$ for all platforms and inventories by assuming that the distribution of consumer heterogeneity across new console purchasers is stationary and then estimating software demand (described later). Utilizing these initial values $\{\Gamma^0_{j,t}\}$, I estimate the hardware adoption side of the market. Mean platform utilities $\{\delta_{j,t}\}$ (corresponding to a consumer with mean preferences and 0 inventory) which match predicted market shares with observed market shares are found via the contraction mapping introduced in Berry, Levinsohn and Pakes (1995). For each iteration of the mapping, each consumer i's beliefs over the evolution of $\{\delta_{i,j,t,\iota}\}$ are updated according to a regression based on (8). The hardware dynamic programming problem is solved by assuming there exists a terminal period at which hardware utility decays to 0; this is motivated by the introduction of the next generation of consoles, which occurred in October 2005.[28] This predicts the set of consumers at each inventory state in each period, and can be used to form predicted market shares for each month.

Once the hardware adoption side is computed for given values of $\{\Gamma^n_{j,t}\}$ (where n denotes the iteration of the procedure), I use the computed probabilities of consumer hardware adoption to form $\{dP^n_{j,t}(\alpha^{p,sw}, \alpha^\gamma)\}$, the distribution of consumer types across each platform. This updated distribution is used to estimate the software adoption decision for each console, which proceeds via a similar nested routine: mean utilities $\{\zeta_{j,k,t}\}$ for each title are recovered via a similar contraction mapping which matches predicted to observed shares, where in each iteration consumer expectations are updated according to (10) and the consumer's optimal stopping problem is solved via value function iteration on a discretized grid. After $\{\zeta_{j,k,t}\}$ converges for a given set of probability distributions $\{dP^n_{j,t}(\alpha^p, \alpha^\gamma)\}$, updated values of $\{\Gamma^{n+1}_{j,t}\}$ are computed for every inventory state (which also requires updating expected utilities from future software via the regression described in section II.A).

The procedure iterates between estimating hardware and software adoption using updated values of $\{\Gamma_{j,t}\}$ and $\{dP_{j,t}(\alpha^p, \alpha^\gamma)\}$ until values converge. Finally, $\{\xi_{j,t}\}$ and $\{\eta_{j,k,t}\}$ are recovered from obtained values of $\{\delta_{j,t}\}$ and $\{\zeta_{j,k,t}\}$ via linear regression. Using multiple starting values, a non-derivative based Nelder and Mead (1965) simplex algorithm is used to search for $\hat{\boldsymbol{\theta}}_1$ ($\boldsymbol{\theta}_2$ can be solved for

[28]Using different horizons of January 2006, July 2006, and January 2007 did not significantly change results.

as a function of $\boldsymbol{\theta}_1$). No problems with convergence were encountered.

B. Software Development and Porting Costs

To estimate unobserved differences in porting and development costs $C_k(\cdot;\boldsymbol{\theta}_C)$, I use a methods of moments estimator based on inequality constraints developed in Pakes et al. (2011). I assume each third-party title k decided τ months in advance of release to develop for the set of platforms that maximized its expected profits, *holding fixed the actions of all titles released up to that point in time.*[29] I rewrite (14) based on observables:

$$E\left[\pi_k(\boldsymbol{s}_k^o;\boldsymbol{\theta}_C) - \pi_k(\boldsymbol{s}';\boldsymbol{\theta}_C)|\boldsymbol{\Omega}^o_{k,r_k-\tau}\right] \geq 0 \;\forall\; \boldsymbol{s}' \in \mathcal{S}\;.$$

where s_k^o is title k's observed choice of platforms, and $\boldsymbol{\Omega}^o_{k,r_k-\tau}$ denotes the *observed* state of each title's information set at time $r_k-\tau$. Since I do not observe software products that are not released on any platform, I restrict attention to strategies that involve joining at least one platform.

I assume that $C_k(s_k;\boldsymbol{\theta}_C) = c^g(\boldsymbol{s}_k) + \nu_k^c$, and $\boldsymbol{\theta}_C \equiv \{c^g(\boldsymbol{s})\}_{\forall \boldsymbol{s}\in\mathcal{S}}$, where g represents the genre of title k; ν_k^c represents title-specific costs that affect all strategy choices equally.[30] The difference in costs between two different titles are thus assumed to be contained within differences in genres and some unobservable title-specific component (i.e., there is no title-platform specific unobservable). I assume that the econometrician's estimate and a title's estimate of expected profits are the same.[31]

Let $\mathcal{K}_{\boldsymbol{s}}$ denote the set of titles that choose strategy $\boldsymbol{s}$. For each $\boldsymbol{s}$ and $\boldsymbol{s}' \neq \boldsymbol{s}$, converting expectations into sample means yields the following inequality moments:

$$\frac{\sqrt{\#\mathcal{K}_{\boldsymbol{s}}}}{\#\mathcal{K}_{\boldsymbol{s}}} \sum_{k\in\mathcal{K}_{\boldsymbol{s}}} (E[\pi_k(\boldsymbol{s};\boldsymbol{\theta}_C) - \pi_k(\boldsymbol{s}';\boldsymbol{\theta}_C)]) \otimes g(\boldsymbol{\Omega}_{k,t-\tau}) \geq 0\;, \tag{18}$$

for any $\boldsymbol{\Omega}_{k,r_k-\tau} \in \boldsymbol{\Omega}_{k,r_k-\tau}$, where $\otimes$ represents the Kronecker product and $g(\cdot)$ is any positive valued function. I weight by the square root of the number titles that choose each strategy $\boldsymbol{s}$ since there should be less expectational noise in computing profits for strategies chosen by many titles.

Equation (18) defines 42 inequalities (7 non-zero strategies, each with 6 alternative strategy comparisons) to be used in estimation, using only a constant as

[29] For the purposes of this analysis, I will assume that the decision of which platforms to join is made independently for each title, even if the title is released by a third-party publisher with multiple titles.

[30] The alternate specification $C_k(\boldsymbol{s}_k;\boldsymbol{\theta}_C) = c_0^g(\boldsymbol{s}_k) + \sum_{j\in\boldsymbol{s}_k} c_j^g \alpha^w_{0,j,k} + \nu_k^c$, where $\alpha^w_{0,j,k}$ represents the software fixed effect for title k on platform j perceived by the mean consumer (estimated from the demand side), was also employed; estimates from this specification did not significantly change results of the counterfactual exercises.

[31] As long as this error is mean zero across titles and strategy choices and independent of instruments chosen, the following analysis does not change (Pakes et al. (2011)).

an instrument. If there are multiple values of $\boldsymbol{\theta}_C$ that satisfy the inequalities, all values are admissible and a set estimate is provided; otherwise, the value $\hat{\boldsymbol{\theta}}_C$ that minimizes the absolute value of deviations in the inequalities is obtained.[32,33] Since only strategies that involve joining at least one platform are compared, only relative differences between $c^g(\boldsymbol{s})$ and $c^g(\boldsymbol{s}')$ are identified. Nonetheless, for the subsequent analysis, only relative differences are required to determine the optimal choices for software titles. In estimation, $c^g(\{1,0,0\})$, the constant cost for developing only for the PS2, is fixed to be 0 for all g.

IV. Estimation Results

A. Consumer Demand

Parameter estimates from the demand system are presented in Table 3. Heterogeneity in price sensitivity was not found to be statistically significant, and $\sigma^{p,hw} = \sigma^{p,sw} = 0$ for the reported results. All remaining parameters are significant at the 10% level with the exception of D, the coefficient on age^2 for hardware, and certain month effects. Significant and non-zero coefficients on α^Γ and the discount factor β indicate consumers respond to both current and future software availability when making hardware purchasing decisions.[34]

Estimated heterogeneity in α^γ, a consumer's taste for software and gaming, given by σ^γ is substantial: the 90% percentile of the distribution perceives each software title worth approximately \$50 more than the average consumer. This implies most consumers at the lower end of the distribution of α^γ do not purchase a console; indeed, the majority of console owners in the first three years are predicted to be in the top quintile of the distribution of α^γ.

An estimate of $D = 0$ indicates that there is little complementarity or substitutability effects across additional consoles once duplicate titles are removed from consideration (recall a consumer's utility from purchasing an additional console does not include utility from software that she can already use). The total number of households predicted by the model to own a console matches the ICR data used as a moment in estimation (44.1M). Furthermore, the model predicts 6.7M (15%) of households own two consoles, with another 1.0M (2%) owning all three.

[32]Point estimates despite the absence of error between estimated profits by the econometrician and agents may indicate that ν_k^c should be choice-specific. However, Pakes (2008) shows in another empirical application that this type of specification error does not yield significant bias.

[33]When constructing inequalities for estimation, I also omit "high-quality" third-party exclusive titles, which I assume that to be those with estimated fixed effects and unobserved characteristic at release (η_{j,k,r_k}) in the top 25% for all titles. The reason is that these exclusive titles, although not first-party, may have been subject to unobserved exclusive deals involving lump sum payments, development assistance, or joint marketing promotions. The underlying assumption is that all other titles—those that multihomed were of low enough quality—did not receive any exclusive contracts or preferential treatment from console providers. Though estimated porting costs are influenced by the cutoff rule, the main counterfactual results are not affected by using different cutoffs.

[34]The estimated 95% confidence interval for β implies an annual discount factor in the range [.26, .74]. Allowing for a separate coefficient on future software utility $\Lambda^f_{i,j,t,\iota}$ yielded an estimated $\beta = .99$, but did not change the main results of the paper; as a result, the simpler model is presented here.

TABLE 3—ESTIMATED PARAMETERS OF DEMAND SYSTEM

Nonlinear	β	0.934*** *(.021)*	Hardware	$\alpha_0^{p,hw}$	-0.013*** *(.003)*
Parameters	ρ^{hw}	0.619*** *(.024)*	Parameters	d_{PS2}	-1.902** *(.869)*
(θ_1)	ρ^{sw}	0.695*** *(.002)*		d_{XBOX}	-3.349*** *(.769)*
	σ^γ	1.939*** *(.139)*		d_{GC}	-4.399*** *(.635)*
	α^Γ	0.663*** *(.204)*		age	-0.036** *(.017)*
	D	0.000 *(.466)*		age^2	0.000 *(.000)*
GMM Obj.		259.567	Software	$\alpha_0^{p,sw}$	-0.040*** *(.003)*
# HW Obs.		151	Parameters	age	-0.183*** *(.005)*
# SW Obs.		44207		age^2	0.001*** *(.000)*

		Hardware	Software		
		All	PS2	XB	GC
Month	d_{Feb}	0.167** *(.071)*	0.108*** *(.007)*	0.094*** *(.009)*	0.055*** *(.010)*
Effects	d_{Mar}	0.176* *(.093)*	0.084*** *(.011)*	0.079*** *(.013)*	0.032** *(.015)*
	d_{Apr}	-0.189* *(.105)*	-0.207*** *(.013)*	-0.251*** *(.015)*	-0.303*** *(.019)*
	d_{May}	-0.390*** *(.116)*	-0.279*** *(.014)*	-0.372*** *(.017)*	-0.387*** *(.020)*
	d_{Jun}	0.050 *(.131)*	0.127*** *(.015)*	0.062*** *(.018)*	0.030 *(.021)*
	d_{July}	-0.247** *(.116)*	0.086*** *(.016)*	0.012 *(.019)*	0.002 *(.022)*
	d_{Aug}	-0.278** *(.114)*	-0.006 *(.016)*	-0.056*** *(.019)*	-0.013 *(.022)*
	d_{Sep}	-0.038 *(.118)*	0.082*** *(.016)*	-0.011 *(.018)*	0.003 *(.022)*
	d_{Oct}	-0.146 *(.109)*	-0.114*** *(.016)*	-0.190*** *(.018)*	-0.091*** *(.022)*
	d_{Nov}	0.676*** *(.133)*	0.129*** *(.014)*	-0.070*** *(.015)*	0.234*** *(.018)*
	d_{Dec}	1.562*** *(.081)*	1.122*** *(.009)*	0.990*** *(.010)*	1.195*** *(.011)*

Note: β is the discount factor; ρ^{hw} and ρ^{sw} are the estimated coefficients on the autoregressive processes for $\xi_{j,t}$ and $\eta_{j,k,t}$ in (15); σ^γ is the standard deviation of consumer heterogeneity for gaming intensity α^γ; α^Γ is the coefficient on software utility; $\alpha_0^{p,hw}$ and $\alpha_0^{p,sw}$ are price sensitivity coefficients; D is the hardware complementarity term. For the remaining hardware and software coefficients, d_j are fixed effects for platform or month j, and *age* and *age*^{2} are monthly decay effects. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent levels.

The estimated fixed effect for the PS2 is significantly larger than the fixed effects of its rival platforms, which may be a result of its ability to play DVD movies and the PS1's existing library of over 1,000 games. The age of a console and software title are estimated to affect expected lifetime utility from purchase negatively. With hardware, the negative effect may reflect fewer periods remaining to enjoy the console before the next generation of videogame systems (i.e., obsolescence); with software, the title may no longer be popular or desirable to play. Finally, the model also predicts that seasonality effects dramatically influence when people purchase goods with holiday months exhibiting highly positive and significant coefficients.

PRICE ELASTICITIES

Price sensitivities $\{\alpha_0^{p,hw}, \alpha_0^{p,sw}\}$ are estimated separately; I cannot reject the restriction that consumers exhibit the same price sensitivity for hardware as they do software (i.e., $\alpha_0^{p,hw} = \alpha^\Gamma \alpha_0^{p,sw}$). Table 4 reports own and cross-price elasticities for hardware platforms and own-price elasticities for three hit software titles. Since platforms are active for multiple periods, the price change is assumed to

Table 4—Price Elasticities

		PS2	XB	GC	Outside
HW Price	PS2	-1.973	0.148	0.061	0.695
		(-2.714, -1.347)	*(-0.162, 0.456)*	*(-0.222, 0.360)*	*(0.480, 0.974)*
	XBOX	0.032	-2.004	0.048	0.238
		(-0.040, 0.108)	*(-2.738, -1.373)*	*(-0.022, 0.131)*	*(0.153, 0.347)*
	GC	0.011	0.019	-1.432	0.116
		(-0.024, 0.050)	(-0.018, 0.068)	(-1.967, -0.982)	(0.074, 0.172)
SW Price		-1.275	-1.144	-0.958	
		(-1.435, -1.101)	(-1.290, -0.975)	(-1.083, -0.814)	

Note: Hardware price elasticities provide the percent change in quantity sold of the column-console with a permanent 1% increase in the price of the row-console (where *Outside* represents non-purchasers). Software price elasticities present percentage change in total quantity sold of a top selling title on each column-console conditional on a permanent 1% increase in the price of that title. The software titles are *Grand Theft Auto III* for the PS2, *Halo* for the XB, and *Super Smash Bros.* for the GC. 95% confidence intervals are provided in parenthesis below estimates.

apply across the entire time period, and market shares are computed from final installed bases. Platform installed bases fall approximately 1.4 to 2.0% from a 1% price increase; cross price elasticities are smaller in magnitude, with a 1% increase in price of the PS2 increasing sales of the XB and GC by approximately .1%. Most consumers opt to consume the outside good rather than purchase another console following a price increase. Own-software price elasticities are found to be close to unit elastic. Average software price elasticities for all titles on the PS2 is -1.3, which is comparable to other estimates in the literature (e.g., Nair (2007)).

Hardware Responsiveness to Software

Table 5 presents the top five titles on each console that are predicted to have had the greatest impact on own-platform sales. These "software-elasticities" are computed by removing each software title from each hardware's set of available software products, and do not account for the possibility that other future software releases are affected; this also holds fixed consumer beliefs over the evolution of product qualities. Given losing a hit title might cause fewer titles to be released for a platform in the future, the elasticities reported here in a sense can be seen as a lower bound of a title's impact. These elasticities can be large: if Microsoft lost *Halo*, the full model predicts over .7M (5.5%) fewer XB consoles would have sold. A similar story holds for the other hit titles onboard the other consoles: the PS2 would have sold .3M (1.0%) fewer and the GC .4M (3.8%) fewer consoles upon losing their top hit title.

Although the top titles on all consoles are predicted to have had a large and significant impact on console sales, the effect drops sharply for other titles: only 1 title on the PS2, 3 on the XB, and 5 on the GC are able to impact hardware sales on their own by more than 1%, with the vast majority of titles not having any significant individual impact on hardware sales. Titles that do have large impacts are primarily early releases: 7 of the top 15 titles listed in Table 5 are released in the first month of the console's existence, and 10 of the top 15 are all released

Table 5—Titles With Largest Impact on Hardware Sales

		Release Date	PS2	XB	GC	Outside
PS2	GTA: VC[a]	Oct 2002	-1.032	0.188	0.053	0.259
	GTA 3[a]	Oct 2001	-0.742	0.357	0.143	0.156
	GT3: A-Spec*	Jul 2001	-0.234	0.242	0.138	0.037
	Metal Gear Solid 2[a]	Oct 2000	-0.296	0.142	0.051	0.062
	Madden 2001	Nov 2001	-0.174	0.205	0.097	0.032
XBOX	Halo*	Nov 2001	0.291	-5.453	0.731	0.198
	Halo 2*	Nov 2004	0.027	-2.497	0.026	0.189
	PG Racing*	Nov 2001	0.100	-1.163	0.319	0.020
	Dead or Alive 3†	Nov 2001	0.088	-0.971	0.287	0.015
	NFL Fever 2002*	Nov 2001	0.073	-0.785	0.239	0.010
GC	Smash Bros*	Nov 2001	0.094	0.345	-3.889	0.059
	Luigi's Mansion*	Dec 2001	0.046	0.092	-3.749	0.089
	Star Wars: RS†	Nov 2001	0.062	0.244	-2.387	0.026
	Mario Sunshine*	Aug 2002	0.008	0.018	-1.225	0.034
	Mario Kart*	Nov 2003	0.010	0.018	-1.208	0.029

Note: Cell entries i, j, where i indexes row and j indexes column, provides the percentage change in sales of console j upon console i losing a top software title (where *Outside* represents non-purchasers). * indicates first-party exclusive titles, † indicates third-party exclusive titles, and [a] indicates titles that were exclusive on the PS2 for a limited time.

in the first year. That early hit titles have a greater impact on lifetime sales of hardware than later hit titles follows from the durability of consoles, presence of network effects, and consumers basing their adoption decisions on expectations of future software releases. The impact of a software title on hardware sales is not proportional to that title's sales, which can be seen by comparing Table 2 to Table 5.

Effect of Integration on Product Quality

Table 6 presents a regression of recovered software title fixed effects on dummy variables indicating whether or not the title was exclusive, and, if so, if it was a first-party title published by the platform provider; the results also control for the platform on and month in which it was released.[35] Results indicate first-party exclusive titles had higher recovered fixed effects for the two industry veterans—Sony and Nintendo—but not for the entrant, Microsoft. This is consistent with integration enhancing quality for those firms with experience, but does not rule out first-party titles being selected upon before being acquired, or integrated studios being naturally higher quality. There is also a significantly negative coefficient for third-party exclusive titles onboard all titles save the GC. This is consistent with a selection story where most third-party exclusive titles on the PS2 and XB were not compensated via an exclusive contract, but rather voluntarily chose to be exclusive since they were low quality and potential gains from multihoming were outweighed by porting costs.

[35]The estimator is equivalent the minimum-distance procedure proposed by Chamberlain (1982), as used in Nevo (2001). See also Saxonhouse (1974).

TABLE 6—SOFTWARE FIXED EFFECTS REGRESSION

	All Titles		PS2 Only		XB Only		GC Only	
Exclusive, 1st Party	2.100***	*(.252)*	2.018***	*(.392)*	-0.531	*(.416)*	6.190***	*(.524)*
Exclusive, 3rd Party	-1.312***	*(.157)*	-1.777***	*(.224)*	-0.779***	*(.280)*	-0.569	*(.364)*
d_{PS2}	-26.434***	*(.328)*	-26.345***	*(.459)*				
d_{XBOX}	-25.074***	*(.333)*			-25.468***	*(.550)*		
d_{GC}	-24.221***	*(.343)*					-23.934***	*(.714)*
d_{Feb}	-0.226	*(.402)*	-0.070	*(.627)*	0.305	*(.670)*	-1.020	*(.848)*
d_{Mar}	-0.344	*(.410)*	-0.847	*(.551)*	1.790**	*(.798)*	0.115	*(1.052)*
d_{Apr}	0.492	*(.475)*	0.940	*(.715)*	1.399*	*(.776)*	-2.270**	*(1.062)*
d_{May}	0.198	*(.434)*	1.401**	*(.685)*	-0.575	*(.702)*	-0.556	*(.934)*
d_{Jun}	-1.761***	*(.425)*	-2.188***	*(.584)*	0.250	*(.783)*	-2.634***	*(1.009)*
d_{July}	-0.399	*(.452)*	-1.162	*(.768)*	0.467	*(.706)*	-1.456	*(.952)*
d_{Aug}	0.033	*(.379)*	0.614	*(.623)*	0.662	*(.629)*	-1.288	*(.792)*
d_{Sep}	0.663*	*(.361)*	0.943*	*(.522)*	0.916	*(.622)*	0.262	*(.809)*
d_{Oct}	0.311	*(.352)*	0.569	*(.524)*	0.591	*(.595)*	-0.224	*(.778)*
d_{Nov}	-0.270	*(.360)*	-0.168	*(.500)*	0.533	*(.672)*	-1.658**	*(.831)*
d_{Dec}	0.487	*(.438)*	0.558	*(.611)*	0.449	*(.766)*	0.949	*(1.070)*
R^2	0.079		0.080		0.006		0.126	
# Observations	1713		771		551		391	

Note: Feasible-GLS regression of recovered software fixed effects for each software title active for at least 10 months on dummy variables indicating whether or not it was exclusive, the platform it was released on, and the month of release. "Exclusive, 1st Party" indicates title was published by a platform provider; "Exclusive, 3rd Party" indicates the title was published by a third-party publisher. Results are robust to different cutoffs, including 5 and 20 months. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent levels.

B. *Model Fit, Alternative Specifications, and Robustness Tests*

Further details and results of alternative specifications and tests discussed in this section are contained in the appendix unless otherwise noted.

MODEL FIT

I find the restriction on consumer beliefs given by $F_{i,\iota}(\cdot)$ to fit the evolution of $\{\delta_{i,j,t,\iota}\}$ well, with errors comprising $< 4\%$ of the absolute value of $\{\delta_{i,j,t,\iota}\}$ in each period for a consumer with the 90th percentile value of α_i^{γ} and no inventory, and errors not serially correlated or exhibiting other time trends. Changes in unobserved product characteristics $(\nu_{j,t}^{hw}, \nu_{j,t}^{sw})$ are also not found to be serially correlated, and no common shocks across platforms are found.

ALTERNATIVE SPECIFICATIONS

I estimate several versions of the model, removing dynamic considerations (e.g., consumers do not leave the market, time their purchases, or account for future software releases, and unobservable product characteristics are not assumed to be persistent), consumer heterogeneity, and the ability for consumers to own multiple consoles. A static model biases hardware price sensitivities to zero, and models without consumer heterogeneity overstate substitution to and from the outside good when software products are removed or added to consoles, leading to unrealistic predictions. A model without consumer multihoming understates the degree to which the two entrant platforms lose sales when their exclusive titles are onboard other platforms.

I also estimate the model assuming full consumer myopia (no utility from future software or timing of purchases) or partial myopia (allowing for future software utility, but no timing of purchases), while still controlling for all other dynamic features (e.g., durability of goods, serial correlation of demand shocks). These models yield different estimates of software utility and hardware price sensitivities closer to 0 (due to non-forward looking models understating the degree of selection onto hardware platforms over time, they attribute non-purchase in the face of declining prices to price-insensitivity rather than to there being less predisposed gamers). However, though these specifications understate the magnitude of industry tipping that occurs in the counterfactuals (discussed later), they yield similar welfare estimates; furthermore, the main result—i.e., exclusivity benefited the entrants—is unchanged.

Software Independence

One crucial assumption in the analysis is that software products compete in independent markets.[36] This rules out budget and time constraints, and assumes that software titles do not compete with other titles on the same console or on other consoles. Despite this, the model delivers predictions on consumer holdings which are similar to those found in available survey data: the model predicts that the top 5% (10%) of console owners purchase on average between 50-75 (26-36) games. A survey of teenagers in this generation found "extensive collections of 50+ games were owned by a large number of heavy players," and "heavy players" owned 23 games on average (*Media Awareness Network*, 2005).

To test substitutability of titles onboard the same console, I also estimate the model controlling for both the number of software titles released in a given month as well as the total number available in a given month, segmenting titles by genre and whether or not they were a "hit" (i.e., sold over 1M copies). Insofar software titles are not independent, other titles on a given platform should be have an impact on sales. I find that for most titles this is not the case: for hit titles, the release of another hit title in a given month would be equivalent to a price increase of less than \$0.50 for a title on the PS2, and even less on other consoles. As only hit titles have been shown to meaningfully influence sales of hardware, assuming such software titles compete in independent markets may not

[36]With substitutable software, a consumer's dynamic programming problem would require tracking each consumer's inventory and subsequent changes in her choice set, and is computationally infeasible given the large number of software titles. If goods were non-durable or the setting was static, extending the model to account for software substitutability could be achieved by nesting an appropriate discrete choice model over all software bundles. However, there would be the need to make further assumptions regarding the degree of complementarities across titles, as well as the number of titles a consumer could purchase each month. For this particular application, a limit of one software title purchased per month per consumer is rejected by the data.

be completely unreasonable in this application; this is also consistent with there being a large number of titles (even within a particular genre), each with its own distinct idiosyncracies.[37]

The model also does not constrain consumers from purchasing the same title on different consoles if they multihomed. This may bias downwards estimates of the impact of a multihoming title by understating purchase shares (i.e., some consumers may not have purchased a title because they purchased it on another console). More complicated variants of the model were estimated to relax this assumption; estimates and the main predictions of the model did not change.[38]

C. *Porting Cost Estimates*

Table 7 presents genre-specific porting cost estimates for different sets of consoles, and assumes titles commit to platforms 3 months prior to release. Costs for developing solely for the PS2 are fixed to be 0, and thus estimates reflect the relative costs of porting to a particular set of consoles: e.g., estimates suggest that for action games, developing for all three consoles would cost an additional \$400K if the PS2 version was already developed. Developing for two consoles is found to be generally more expensive than developing for one, but still cheaper than developing for all three. On average across genres, porting a title costs \$150K to port to a second console and \$200K for the third. Consistent with industry sources, estimates suggest the XB and GC are to be significantly cheaper to develop for than the PS2.[39] Repeating the exercise for different values of τ (including 6 and 9 months) and using different sets of instruments changed porting cost estimates, but did not affect the main counterfactual results.

V. Policy Experiment: Banning Exclusive Vertical Arrangements

In this section I examine environments in which console providers are prevented from integrating into software development, and are unable to offer exclusive contracts to third-party titles. As stressed in the introduction, the counterfactuals that are examined are "partial" in the sense that they do not account for other potential equilibrium responses such as adjustments in product characteristics,

[37]Nair (2007) also finds empirically that videogames are not strong substitutes for one another, and shows for software released between 1998-2000 on Sony's original PS1 console, cross-price effects across games to be low (even when accounting for strategic timing on the part of game developers), consumers do not exhibit intertemporal substitution within genres, entry by hit games do not have a significant effect on sales or prices of games within a genre, and rates at which game prices fall are independent of competitive conditions within the market.

[38]As consumers purchase are assumed to purchase at most only one console per month and do not value titles they already have access to when deciding to purchase a second or third console, welfare and counterfactual hardware purchases were not significantly affected. Furthermore, biases in the number of predicted software sales are driven only by multihoming consumers, which are substantially fewer in the counterfactual environments.

[39]E.g., the PS2 with a new CPU architecture had a reputation of being difficult to develop for, whereas the XB was essentially an Windows-Intel PC using APIs with which many developers were already familiar.

Table 7—Porting Cost Estimates, By Genre

	(i) Action	(ii) Family	(iii) Fighting	(iv) Platformer	(v) Racing
XB	-0.04	-0.05	-0.04	-0.09	-0.09
	(-0.07, -0.03)	*(-0.05, -0.04)*	*(-0.07, -0.04)*	*(-0.11, -0.04)*	*(-0.11, -0.08)*
PS2 & XB	0.16	0.04	0.05	0.02	0.11
	(0.13, 0.17)	*(0.04, 0.05)*	*(0.05, 0.07)*	*(0.02, 0.04)*	*(0.11, 0.12)*
GC	-0.03	-0.01	-0.04	-0.04	-0.03
	(-0.03, -0.03)	*(-0.01, 0.00)*	*(-0.07, -0.02)*	*(-0.04, -0.02)*	*(-0.03, -0.02)*
PS2 & GC	0.16	0.05	0.08	0.06	0.10
	(0.14, 0.18)	*(0.05, 0.07)*	*(0.08, 0.10)*	*(0.06, 0.08)*	*(0.09, 0.10)*
XB & GC	0.01	0.04	-0.01	0.01	0.00
	(0.01, 0.01)	*(0.03, 0.06)*	*(-0.01, 0.02)*	*(0.01, 0.08)*	*(-0.02, 0.01)*
All 3	0.39	0.14	0.51	0.11	0.24
	(0.36, 0.41)	*(0.12, 0.19)*	*(0.40, 0.59)*	*(0.11, 0.12)*	*(0.21, 0.26)*
# Titles	197	76	56	70	138
	(vi) RPG	(vii) Shooter	(viii) Sports	(ix) Other	
XB	-0.04	*-0.02*	*-0.06*	-0.05	
	(-0.05, -0.02)	*(-0.03, -0.02)*	*(-0.06, -0.03)*	*(-0.06, -0.05)*	
PS2 & XB	0.08	*0.15*	*0.16*	0.10	
	(0.06, 0.11)	*(0.14, 0.31)*	*(0.13, 0.17)*	*(0.08, 0.11)*	
GC	-0.04	*-0.01*	*-0.05*	-0.06	
	(-0.06, -0.03)	*(-0.02, 0.00)*	*(-0.05, -0.04)*	*(-0.06, -0.05)*	
PS2 & GC	0.07	*0.14*	*0.13*	0.13	
	(0.07, 0.07)	*(0.13, 0.15)*	*(0.10, 0.14)*	*(0.10, 0.15)*	
XB & GC	0.01	*1.50*	*0.03*	0.05	
	(0.01, 0.07)	*(0.15, 3.49)*	*(0.03, 0.03)*	*(0.04, 0.11)*	
All 3	0.27	*0.63*	*0.35*	0.20	
	(0.25, 0.29)	*(0.32, 0.74)*	*(0.28, 0.36)*	*(0.15, 0.21)*	
# Titles	113	*108*	*203*	137	

Note: Estimates of $\boldsymbol{\theta}_C$ used to parameterize porting costs (units in \$M), separately estimated by genre. Estimates provide relative differences in costs for supporting different platforms compared to only the PS2 (normalized to 0). 95 percent confidence intervals are constructed taking 40 sample draws from the empirical distribution of the moment inequalities and re-estimating costs (see Pakes et al. (2011) for details).

quality, and availability. Given the complexity and infeasibility of solving for a dynamic oligopolistic equilibrium for both hardware and software provision along all dimensions, I assume that the stock, characteristics, and price paths of products are the same as those observed in the data.[40] Furthermore, I assume that all platforms offer the same non-exclusive contracts to each software title and do not change their royalty rates. Relaxing this last assumption requires a model of bilateral contracting, which is outside the scope of the paper (see Lee and Fong (2012)).

In each counterfactual, I solve for a new market equilibrium described in Section II.C for consumers and all software titles that are no longer contractually exclusive or integrated. Since I do not observe platform-specific fixed effects, unobservable characteristics $\eta_{j,k,t}$, prices, and the release date of a software title on any platform it was not released for in the data, I assume that they are the same

[40] Allowing software prices to follow a first-order Markov process estimated from the data did not affect results.

as the version of the title that was released.[41] The counterfactual admits dynamic and forward looking agents, and I update consumer beliefs over the evolution of hardware and software product qualities (i.e., $F_{i,\iota}$ and $G_{i,j}$) so that they are consistent with the realized counterfactual industry evolution. Though there may be multiple equilibria, certain assumptions and features of the model help mitigate this concern;[42] counterfactuals were computed using multiple starting beliefs, and different equilibria were not encountered.[43]

A. *Model Fit*

To evaluate the fit of the model, I first compute a new equilibrium holding fixed the actions of all first-party and "contractually-exclusive" third-party titles, but allow all other third-party titles to freely choose a set of platforms to support.[44] The first two columns of Table 8 presents a comparison between the observed data and the computed equilibrium. The model predicts installed bases and market shares for platforms to be close to the data. Although the PS2 is predicted to have fewer titles and the XB more, restricting attention to only "hit" titles—titles selling over 1M copies on a given console—indicates a better fit. Since the actions of these hit titles are the only ones that significantly affect platform market shares, as long as their actions are accurately predicted, estimated aggregate industry figures such as market shares, installed bases, and software sales will be similar to those observed in the data.

Counterfactual results will be compared to the predicted fit of the model.

B. *Counterfactual Results*

I examine three main counterfactual environments. In the first, only the incumbent (Sony) loses its contractually exclusive titles while the two entrants (Microsoft and Nintendo) keep theirs; I do not allow the entrants to renegotiate or sign additional exclusive arrangements. In the second counterfactual, there are no integrated or contractually exclusive titles, and all software products choose which consoles to join (titles may still voluntarily be exclusive). The final counterfactual forces all titles to be compatible with all consoles.

[41] If the title was released on two different consoles, I use values for the title onboard the console that is highest in the following priority list: PS2, XB, and then GC. Predicted fixed effects and unobservables across consoles for titles that multihomed in the data were found to be broadly similar.

[42] E.g., the space of beliefs are restricted to the parameterizations given by (8) and (10); additionally, there are bounds on the set of sustainable beliefs in equilibrium since there are minimum and maximum attainable values of $\{\delta_{j,t}\}_{j\in\mathcal{J}_t,\forall t}$, which correspond to hardware mean-utilities without any or with all software titles onboard.

[43] For most hit titles, the decision of which consoles to support was robust to small changes in beliefs, F: as long as there are sufficient numbers of consumers onboard each platform at a given moment, hit titles join all platforms. In turn, since only hit titles meaningfully shift values of $\{\delta_{j,t}\}_{j\in\mathcal{J}_t,\forall t}$, the actions of other low and mid-tier titles have marginal impacts on the optimal decisions of others, drastically limiting the scope for multiplicity.

[44] As in the estimation of porting costs, since I do not observe which third party titles were contractually exclusive (as opposed to those that were voluntarily exclusive), I assume that they comprise titles with estimated fixed effects and unobserved characteristic in the top quartile of the estimated distribution.

Table 8—Counterfactual Results

		Obs. Data	Predicted Outcome	(i) No PS2 Exclusives	(ii) No Exc. For Any Console	(iii) Forced Compatibility
Consoles Sold (M)	PS2	30.07	29.6	28.8	36.4	36.6
			(29.2,29.8)	*(28.0,29.2)*	*(35.4,38.4)*	*(35.5,39.2)*
	XB	13.32	14.1	14.7	12.0	11.2
			(13.7,15.0)	*(14.1,16.0)*	*(11.6,13.1)*	*(10.6,11.8)*
	GC	9.83	10.0	10.5	8.8	9.0
			(9.8,10.2)	*(10.3,10.8)*	*(8.4,9.2)*	*(8.7,9.3)*
Titles Sold (M)	PS2	305.09	271.5	235.1	671.6	772.8
			(252.6,274.8)	*(214.6,244.9)*	*(621.7,720.8)*	*(713.8,843.5)*
	XB	118.05	143.4	196.0	78.2	58.4
			(133.4,169.1)	*(179.5,231.3)*	*(67.4,111.4)*	*(50.3,75.5)*
	GC	79.17	81.3	118.3	36.1	53.2
			(70.6,97.4)	*(102.3,135.9)*	*(31.3,46.0)*	*(45.3,64.5)*
# of Titles	PS2	1161	700	637	770	1569
			(624,711)	*(553,657)*	*(628,847)*	*(1569,1569)*
	XB	749	924	1033	1066	*1420*
			(873,1105)	*(974,1235)*	*(989,1316)*	*(1420,1420)*
	GC	487	415	496	495	*1424*
			(301,503)	*(362,588)*	*(382,640)*	*(1424,1424)*
# of "Hit" Titles	PS2	67	66	53	183	188
			(63,68)	*(51,54)*	*(169,195)*	*(175,203)*
	XB	9	10	23	7	5
			(10,14)	*(15,29)*	*(6,8)*	*(3,7)*
	GC	8	12	18	5	5
			(10,13)	*(16,19)*	*(3,8)*	*(3,8)*
Δ Cons. Welfare				94.1	1512.2	1766.6
				(60.6,312.3)	*(1512.2,3911.8)*	*(1733.3,4358.6)*

Note: Predicted industry outcome is computed by holding fixed the actions of "contractually exclusive" titles, and allowing other third-party titles to optimize which consoles to support. Specification (i) fixes only the actions of XB and GC contractually exclusive titles; (ii) allows all titles to re-optimize; and (iii) assumes all titles are available on all consoles. "Hit" Titles are those with > 1M in sales. Change in consumer welfare is with respect to predicted results. Estimates are computed using porting cost estimates from Table 7. 95 percent confidence intervals are constructed via parametric bootstrap of demand system estimates, where software expected profits, porting costs, and a new equilibrium are recomputed for each draw.

The results from the counterfactual simulations are presented in Table 8. In the first specification when only the PS2 loses its exclusive titles, both entrant platforms gain total and hit titles, and sell an additional 1.1M (5%) hardware consoles and 90M (40%) software titles combined; the PS2 sells .8M (3%) fewer consoles and 36M (13%) fewer software titles. Results differ in the second counterfactual where all titles—including those that were released on XB and GC—are no longer contractually exclusive or integrated. Here, the PS2 would sell nearly 7M (23%) more consoles and more than double the number of software titles it would sell (which, at \$7 in royalties per game, would yield approximately \$2.8B in additional profit); both XB and GC perform worse, selling 3M (14%) fewer consoles and a combined 110M (49%) fewer titles, representing profit reductions of approximately \$.8B on software royalties alone.

There are two main reasons that the PS2 benefitted more than the XB and GC from banning exclusivity. First, the two entrant consoles had a higher quality stock of exclusive titles than the incumbent; this meant gaining access to the XB and GC exclusive titles were more valuable to the PS2 than maintaining exclusivity over its own hit titles. Second, in both counterfactuals, consumers with high values of α^{γ}—many who had originally multihomed in order to access exclusive hit titles on the entrants—only purchase the PS2: whereas approximate 70% of the top quintile of consumers in the original demand model would have multihomed, less than 5% are estimated to do so in the counterfactuals, and as such entrant software sales are much lower.

The final counterfactual forces all software titles to be compatible with all consoles. The incremental effect of forcing compatibility is smaller than the initial effect of removing exclusive arrangements, increasing software sales by an additional 100M units for the PS2 and reducing sales by 30M units for the entrants. The diminishing impact is due to the fact that titles that did not voluntarily multihome under the second counterfactual (but did so when they were forced) were those for whom porting costs were binding, and as such were lower quality titles. The incumbent is predicted to sell even more consoles at the expense of the two entrants.

Consumer Welfare

I calculate the (expected) consumer surplus for consumers who are predicted to purchase a console in each counterfactual environment:

$$CS = \sum_{i,j,t,\iota} \hat{n}_{i,j,t,\iota} \times (\delta_{i,j,t,\iota} + \tilde{\epsilon}_{i,j,t,\iota})/\alpha_i^{p,hw},$$

where $\hat{n}_{i,j,t,\iota}$ are the number of consumers of type i with inventory ι predicted to purchase platform j at time t, and $\tilde{\epsilon}_{i,j,t,\iota}$ represents the expectation of the idiosyncratic error conditional on such a consumer purchasing platform j at time t.[45] Since $\delta_{i,j,t,\iota}$ contains each agent's anticipated lifetime utility from both hardware and software consumption, consumer welfare is computed from the hardware side alone. Also, since total platform software utility, $\Gamma_{j,t}$, does not include titles a consumer already has access to, increasing software compatibility only affects computed welfare insofar it provides consumers access to titles they previously could not play.[46]

Changes in consumer welfare from the predicted fit of the model are presented in the bottom row of Table 8. Removing exclusive arrangements increases access to hit titles onboard each system: allowing PS2 exclusives to multihome increases

[45] I.e., $\tilde{\epsilon}_{i,j,t,\iota} \equiv E\big[\epsilon_{i,j,t,\iota} | u_{i,j,t,\iota} + \beta E[EV_i(\iota \cup \{j\}, \{\delta_{i,j,t+1,\iota}\}, m(t)) | \{\delta_{i,j,t,\iota}\}] \geq u_{i,j',t,\iota} + \beta E[EV_i(\iota \cup \{j'\}, \{\delta_{i,j,t+1,\iota}\}, m(t)) | \{\delta_{i,j,t,\iota}\}] \; \forall \, j' \in \mathcal{J}_t \cup \{0\}\big]$.

[46] Increasing the set of software titles affects welfare only through changes in total software utility $\Gamma_{j,t}$ (and not additional draws on ϵ). Though adding a title to a console cannot negatively affect $\Gamma_{j,t}$ (the option value of a title, $EW_{i,j}(\cdot)$ given by (12), is strictly positive), for the vast majority of titles, this option value is close to 0. Thus welfare changes are driven predominantly by higher quality, hit titles.

consumer welfare by \$200M, while allowing all titles to multihome increases welfare by \$1.5B (representing 4% of total hardware and software revenues during the 5 year period). Forcing compatibility of all titles would only increase welfare by an additional \$.2B: since the vast majority of consumer welfare gains derive from a handful of "hit" software products, allowing titles to voluntarily choose which platforms to support would realize nearly 90% of the gains from forced compatibility, and require a lower outlay of porting costs.

C. *Robustness Tests*

Platform Pricing

The counterfactuals ignore the possibility that platforms may have adjusted console prices; e.g., Microsoft or Nintendo may have reduced prices or Sony may have increased its prices in response to changes in software availability across consoles. Solving for a dynamic pricing game is beyond the scope of this paper. However, as a robustness check, I allow for the possibility that firms could have increased or decreased their prices paths uniformly from observed prices.

Since I do not observe hardware margins, I infer them as follows: holding fixed the supply of software and the prices of other platforms (but allowing beliefs to adjust), I compute hardware and software sales for a given platform had it adjusted up or down its prices for the entire generation in increments of \$25; I find the range of average hardware margins for each console such that no platform could have increased its profits by adjusting prices.[47]

Using the minimum, average, and maximum of the estimated ranges for hardware margins, I recompute platform profits under counterfactual (ii)—where all titles can freely multihome—allowing any platform to raise or lower its complete price paths in increments of \$25; I then solve for an Nash equilibrium in prices, where each platform best responds to the price adjustments of other platforms. I find that no platform would wish to increase or decrease its prices uniformly by more than \$25 in the counterfactual. Consumer welfare gains are lower but remain in the range [\$.9B,\$1.2B]; in all cases, only profits for the incumbent platform increase from the baseline.

Integration & Investment

To examine how results might change if the quality of first-party titles were lower if integration were prohibited (potentially due to lower investment incentives), I also compute counterfactual (ii) and adjust first-party software titles by

[47] I.e., for each platform i, let $q_i^l, l \in \{hw, sw\}$ be the observed sales of hardware or software, and $\tilde{q}_i^l(x)$ be the predicted sales if i adjusted its prices upwards by \$x during the entire period and the supply of software and prices on other platforms was held fixed. I assume hardware margins m_i satisfy: $(m_i+25)\times\tilde{q}_i^{hw}(25)+7\tilde{q}_i^{sw}(25) \leq m_i\times q_i^{hw}+7q_i^{sw}$ and $(m_i-25)\times\tilde{q}_i^{hw}(-25)+7\tilde{q}_i^{sw}(-25) \leq m_i\times q_i^{hw}+7q_i^{sw}$, where \$7 is the assumed royalty for each software title sold. The range of estimated margins are [\$55,\$91] for the PS2, [\$24, \$50] for the XB, and [\$22, \$53] for the GC.

the estimated console-specific first-party effects reported in Table 6. I find the incumbent would still sell more consoles and titles (4M and 140M) and the entrants less (3M and 115M); however, consumer welfare gains are reduced by 80%. Thus, if the inability of consoles to vertically integrate into software production adversely affected investment in former first-party titles, both entrant platforms are still predicted to be worse off, but consumer welfare gains are moderated.

Porting Costs

The counterfactual exercises are also repeated using fixed porting costs (both $500K or $1M to develop for an additional console). The main counterfactual findings are found to be unchanged, with magnitudes broadly similar. This is consistent with the fact that hit titles would have multihomed across all consoles in the counterfactuals for these ranges of porting costs, and the actions of these titles drive the main results.

D. Discussion and Policy Implications

Counterfactual experiments suggest that exclusive vertical arrangements harmed the incumbent and aided platform entry. Since the PS2 had 5M users before its two competitors entered, without exclusivity, software developers may only have supported the XB and GC after supporting the PS2. Hence, without a software advantage over the incumbent, the entrants would have sold far fewer software products, and—due to the importance of software royalties—may not have entered or exited. Although welfare gains are sensitive to the dynamic consequences of unmodeled behavior, the implications governing market concentration and platform competition appear to be robust.

This result—that the larger platform gains and smaller platforms lose from product compatibility—runs counter to standard theory which finds the converse (e.g., Katz and Shapiro (1985), Chen, Doraszelski and Harrington (2009)), and is driven by software heterogeneity: whereas only two of the top five games impacting hardware demand onboard the PS2 were exclusive, all of the top five onboard the XB and GC were exclusive; furthermore, those titles on the XB and GC had a much greater impact on own hardware sales than those on the PS2. Thus, as banning exclusivity would have given the PS2 access to more high quality games than the XB and GC would have gained from the PS2, consumers who previously multihomed would have been more likely to only purchase the PS2.

There is a question of why the entrants were able to secure access to higher quality exclusive titles. First, the observed allocation of software titles across platforms may have been efficient from the perspective of the contracting parties: e.g., due to platform differentiation (XB's market expansion gains outweighed business stealing losses incurred by the PS2) or spillovers to related business, Microsoft may have been able to outbid Sony for higher quality exclusives. Another explanation, put forth by some industry sources, was that Sony did not actively pursue third-party exclusive titles at the start of the generation, believing it did not need to given the PS1's success.

It is worth stressing that although exclusive arrangements may have encouraged *platform* competition, this does not necessarily imply that they encouraged *software* competition. In the videogame industry, without explicitly modeling the entry and exit of new titles, the effect on software entry is ambiguous: e.g., having only a single monopoly platform to support might have reduced expected porting costs, but have reduced investment in first-party software, increased royalty rates, or reduced development and marketing assistance. In other industries, the trade-off might have been more clear. Microsoft's integration of its platform (Windows OS) into the browser and media application space was ruled by courts in both *U.S. v. Microsoft* and *European Union v. Microsoft* to have foreclosed competing software vendors (e.g., Netscape and Real Networks). Although both the videogame industry and the PC industry are hardware-software environments, the fact that PC applications are very close substitutes for one another (e.g., consumers typically only use one word processor, browser, media player, or spreadsheet program) may indicate that "upstream" foreclosure may be more of a concern with software substitutability. However, it still may be the case that exclusive software aided other *platform providers*, such as MacOS and Linux.

One suitable comparison to the videogame industry is in television distribution. In the U.S., DirecTV's exclusive contracts with certain content providers substantially contributed to its success and ability to induce consumers to substitute away from cable. The impact of this competition was substantial: Goolsbee and Petrin (2004) estimate that entry by satellite providers reduced cable prices by about 15% and encouraged improvements in cable quality, yielding aggregate welfare gains of approximately $5B. In this regard, intervention preventing exclusive deals, motivated by a static efficiency desire to expand consumer access, may have negative effects on industry competition.[48]

Platform competition may not always be desirable, particularly when a platform cannot exercise market power upon establishing a dominant position. E.g., following the recent standards battle between Blu-ray and HD-DVD, neither standard sponsor could increase prices as both had committed to licensing rates with hardware manufacturers and content providers. Furthermore, having a single standard from the beginning would have reduced uncertainty and likely spurred consumer adoption, thereby increasing total welfare. In this case, exclusive arrangements between the standard sponsors and content providers—although potentially having encouraged the existence of multiple formats—may also have contributed to

[48]The comparison here is between videogames and television programs, as both are perishable and are continually replaced. To some extent the results of this paper relies on the incumbent platform repeatedly competing with entrants for new content. Television channels or networks are less perishable which raises the possibility that an incumbent multichannel television distributor could potentially foreclose entry by acquiring exclusive access to certain channels. As a result, program access rules which prohibit vertically integrated cable operators from denying access to its own content to rival distributors may actually encourage entry when content production is limited.

an undesirable and lengthy standards battle.

VI. Concluding Remarks

This paper has provided evidence suggesting that integration and exclusive contracting between hardware manufacturers and software developers in the videogame industry aided platform entry. In platform markets where upstream foreclosure is not a concern and where forced exclusivity contracts are not permitted, intervention or regulation may not be necessary. Although counterfactuals indicate that the industry is more concentrated when exclusive arrangements are prohibited, consumers may still have benefited from access to a wider selection of software onboard each platform. When evaluating the possibility of foreclosure or entry deterrence in dynamic networked environments, traditional static analysis may fail to accurately and comprehensively detail the consequences of exclusive vertical arrangements.

This paper also developed a framework to measure the impact of these exclusive arrangements. I presented a consumer demand system that accounts for the dynamic selection of forward-looking, heterogeneous consumers across and onto platforms; the demand system also recovers the contribution of an individual title to a platform. Additionally, I detailed and estimated a computationally tractable dynamic network formation game that allows agents to anticipate the future actions of other players by conditioning on a small dimensional set of state variables. By explicitly modeling the platform adoption decisions of individual consumers and firms, the structural framework here can be applied to analyze other related industries that exhibit similar indirect network effects; it also can be used as a launching point for even more sophisticated models with richer dynamic and strategic elements, which may be necessary to analyze other empirical applications.

REFERENCES

Ackerberg, Dan, Kevin Caves, and Garth Frazer. 2006. “Structural Identification of Production Functions.” Unpublished.

Aguirregabiria, Victor, and Aviv Nevo. 2012. “Recent Developments in Empirical Dynamic Models of Demand and Competition in Oligopoly Markets.” In *Advances in Economics and Econometrics: Theory and Applications. Tenth World Congress of the Econometric Society.*

Arellano, Manuel, and Olympia Bover. 1995. “Another Look at the Instrumental Variable Estimation of Error-Components Models.” *Journal of Econometrics*, 68: 29–51.

Asker, John. 2004. “Measuring Advantages from Exclusive Dealing.” Unpublished.

Bernheim, B. Douglas, and Michael D. Whinston. 1998. "Exclusive Dealing." *Journal of Political Economy*, 106(1): 64–103.

Berry, Steve. 1994. "Estimating Discrete-Choice Models of Product Differentiation." *RAND Journal of Economics*, 25(2): 242–262.

Berry, Steve, James Levinsohn, and Ariel Pakes. 1995. "Automobile Prices in Market Equilibrium." *Econometrica*, 63(4): 841–890.

Besanko, David, and Martin K. Perry. 1993. "Equilibrium Incentives for Exclusive Dealing in a Differentiated Products Oligopoly." *RAND Journal of Economics*, 24: 646–667.

Blundell, Richard, and Stephen Bond. 1998. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." *Journal of Econometrics*, 87: 115–143.

Chamberlain, Gary. 1982. "Multi Variate Regression Models for Panel Data." *Journal of Econometrics*, 18: 5–46.

Chen, Jaiwei, Ulrich Doraszelski, and Joseph E. Harrington, Jr. 2009. "Avoiding Market Dominance: Product Compatibility in Markets with Network Effects." *RAND Journal of Economics*, 40(3): 445–485.

Chipty, Tasneem. 2001. "Vertical Integration, Market Foreclosure, and Consumer Welfare in the Cable Television Industry." *American Economic Review*, 91(3): 428–453.

Clements, Matthew T., and Hiroshi Ohashi. 2005. "Indirect Network Effects and the Product Cycle: U.S. Video Games, 1994 - 2002." *Journal of Industrial Economics*, 53(4): 515–542.

Corts, Kenneth S., and Mara Lederman. 2009. "Software Exclusivity and the Scope of Indirect Network Effects in the US Home Video Game Market." *International Journal of Industrial Organization*, 27(2): 121–136.

Coughlan, Peter J. 2001. "Note on Home Video Game Technology and Industry Structure." Harvard Business School Case 9-700-107.

Crawford, Gregory S., and Ali Yurukoglu. 2012. "The Welfare Effects of Bundling in Multichannel Television." *American Economic Review*, 102(2): 643–685.

Dubé, Jean-Pierre, Gunter J. Hitsch, and Pradeep Chintagunta. 2010. "Tipping and Concentration in Markets with Indirect Network Effects." *Marketing Science*, 29(2): 216–249.

Dubin, Jeffrey A., and Daniel L. McFadden. 1984. "An Econometric Analysis of Residential Electric Appliance Holdings and Consumption." *Econometrica*, 52(2): 345–362.

Eisenmann, Thomas, and Justin Wong. 2005. "Electronic Arts in Online Gaming." Harvard Business School Case 9-804-140.

Ericson, Richard, and Ariel Pakes. 1995. "Markov-Perfect Industry Dynamics: A Framework for Empirical Work." *Review of Economic Studies*, 62: 53–82.

Fang, Hanming, and Yang Wang. 2010. "Estimating Dynamic Discrete Choice Models with Hyperbolic Discounting, with an Application to Mammography Decisions." NBER Working Paper 16438.

Farrell, Joseph, and Garth Saloner. 1986. "Installed Base and Compatibility: Innovation, Product Preannouncements, and Predation." *American Economic Review*, 76: 940–955.

Gandal, Neil, Michael Kende, and Rafael Rob. 2000. "The Dynamics of Technological Adoption in Hardware/Software Systems: the Case of Compact Disc Players." *RAND Journal of Economics*, 31: 43–61.

Gilbert, Richard J., and Michael L. Katz. 2001. "An Economist's Guide to U.S. v. Microsoft." *Journal of Economic Perspectives*, 15(2): 25–44.

Goolsbee, Austan, and Amil Petrin. 2004. "The Consumer Gains from Direct Broadcast Satellites and the Competition with Cable TV." *Econometrica*, 72: 351–381.

Gowrisankaran, Gautam, and Marc Rysman. forthcoming. "Dynamics of Consumer Demand for New Durable Goods." *Journal of Political Economy.*

Gowrisankaran, Gautam, Minsoo Park, and Marc Rysman. 2011. "Estimating Network Effects in a Dynamic Environment." Unpublished.

Hagiu, Andrei. 2006. "Pricing and Commitment by Two-Sided Platforms." *RAND Journal of Economics*, 37(3): 720–737.

Hausman, Jerry, Gregory Leonard, and J. Douglas Zona. 1994. "Competitive Analaysis with Differentiated Products." *Annales D'Economie et de Statistique*, 1(34): 159–180.

Hendel, Igal, and Aviv Nevo. 2006. "Measuring the Implications of Sales and Consumer Inventory Behavior." *Econometrica*, 74(6): 1637–1673.

Ho, Katherine. 2006. "The Welfare Effects of Restricted Hospital Choice in the US Medical Care Market." *Journal of Applied Econometrics*, 21(7): 1039–1079.

Ishii, Joy. 2008. "Compatibility, Competition, and Investment in Network Industries: ATM Networks in the Banking Industry." Unpublished.

Karaca-Mandic, Pinar. 2011. "Role of complementarities in technology adoption: The case of DVD players." *Quantitative Marketing and Economics*, 9(2): 179–210.

Katz, Michael, and Carl Shapiro. 1985. "Network Externalities, Competition, and Compatibility." *American Economic Review*, 75: 424–440.

Kent, Steven L. 2001. *The Ultimate History of Video Games.* New York, NY:Three Rivers.

Klein, B. 1988. "Vertical Integration as Organizational Ownership: The Fisher Body–General Motors Relationship Revisited." *Journal of Law, Economics and Organization*, 4: 199–213.

Knittel, Chris, and Victor Stango. 2011. "Strategic Incompatibility in ATM Markets." *Journal of Banking and Finance*, 35.

Krusell, Per, and Anthony A. Smith. 1998. "Income and Wealth Heterogeneity in the Macroeconomy." *Journal of Political Economy*, 106: 867–896.

Lafontaine, Francine, and Magaret Slade. 2008. "Exclusive Contracts and Vertical Restraints: Empirical Evidence and Public Policy." In *Handbook of Antitrust Economics.* , ed. Paolo Buccirossi. Cambridge, MA:MIT Press.

Lee, Robin S. 2012. "Home Videogame Platforms." In *The Oxford Handbook of the Digital Economy.* , ed. Martin Peitz and Joel Waldfogel, 83–107. Oxford University Press.

Lee, Robin S., and Kyna Fong. 2012. "Markov Perfect Network Formation: An Applied Framework for Bilateral Oligopoly and Bargaining in Buyer-Seller Networks." Unpublished.

Levinsohn, James, and Amil Petrin. 2003. "Estimating Production Functions Using Inputs to Control for Unobservables." *Review of Economic Studies*, 70(2): 317–341.

Marvel, H. P. 1982. "Exclusive Dealing." *Journal of Law and Economics*, 25: 1–25.

Maskin, Eric, and Jean Tirole. 1988. "A Theory of Dynamic Oligopoly: I & II." *Econometrica*, 56(3): 549–600.

Maskin, Eric, and Jean Tirole. 2001. "Markov Perfect Equilibrium." *Journal of Economic Theory*, 100: 191–219.

Mathewson, G. F., and R. A. Winter. 1987. "The Competitive Effects of Vertical Agreements." *American Economic Review*, 77: 1057–1062.

McFadden, Daniel. 1973. "Conditional Logit Analysis of Qualitative Choice Behavior." In *Frontiers in Econometrics.* Vol. 3, , ed. P. Zarembka. New York, NY:Academic Press.

Melnikov, Oleg. 2001. "Demand for Differentiated Products: The case of the U.S. Computer Printer Market." Unpublished.

Nair, Harikesh. 2007. "Intertemporal Price Discrimination with Forward-looking Consumers: Application to the US Market for Console Video-Games." *Quantitative Marketing and Economics*, 5(3): 239–292.

Nair, Harikesh, Pradeep Chintagunta, and Jean-Pierre Dubé. 2004. "Empirical Analysis of Indirect Network Effects in the Market for Personal Digital Assistants." *Quantitative Marketing and Economics*, 2(1): 23–58.

Nelder, John A., and R. Mead. 1965. "A Simplex Method for Function Minimization." *Computer Journal*, 7: 308–313.

Nevo, Aviv. 2001. "Measuring Market Power in the Ready-to-Eat Cereal Industry." *Econometrica*, 69(2): 307–342.

Ohashi, Hiroshi. 2003. "The Role of Network Effects in the U.S. VCR Market: 1978–1986." *Journal of Economics and Management Strategy*, 12: 447–496.

Olley, G. Steven, and Ariel Pakes. 1996. "The Dynamics of Productivity in the Telecommunications Equipment Industry." *Econometrica*, 64: 1263–1295.

Pakes, Ariel. 2008. "Theory and Empirical Work on Imperfectly Competitive Markets." NBER Working Paper 14117.

Pakes, Ariel, Jack Porter, Kate Ho, and Joy Ishii. 2011. "Moment Inequalities and Their Application." Unpublished.

Rasmusen, Eric B., J. Mark Ramseyer, and John Shepard Wiley. 1991. "Naked Exclusion." *American Economic Review*, 81(5): 1137–1145.

Rey, Patrick, and Jean Tirole. 2007. "A Primer on Foreclosure." In *Handbook of Industrial Organization*. Vol. 3, , ed. Mark Armstrong and Rob Porter. Amsterdam:North-Holland Press.

Riordan, Michael H. 2008. "Competitive Effects of Vertical Integration." In *Handbook of Antitrust Economics*. , ed. Paolo Buccirossi. Cambridge, MA:MIT Press.

Rust, John. 1987. "Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher." *Econometrica*, 55: 999–1033.

Rust, John. 1994. "Structural Estimation of Markov Decision Processes." In *Handbook of Econometrics*. Vol. 4, , ed. Robert F. Engle and Daniel L. McFadden. Amsterdam:North Holland.

Rysman, Marc. 2004. "Competition Between Networks: A Study of the Market for Yellow Pages." *Review of Economic Studies*, 71: 483–512.

Sass, Tim. 2005. "The Competitive Effects of Exclusive Dealing: Evidence from the U.S. Beer Industry." *International Journal of Industrial Organization*, 23: 203–225.

Saxonhouse, Gary R. 1974. "Estimated Parameters as Dependent Variables." *Econometrica*, 66(1): 178–183.

Segal, Ilya, and Michael D. Whinston. 2000. "Exclusive Contracts and Protection of Investments." *RAND Journal of Economics*, 31: 603–633.

Shapiro, Carl. 1999. "Exclusivity in Network Industries." *George Mason Law Review*, 7: 673–683.

Sweeting, Andrew. 2012. "Dynamic Product Repositioning in Differentiated Product Industries: The Effect of Fees for Musical Performance Rights on the Commercial Radio Industry." Unpublished.

Takahashi, Dean. 2002. *Opening the Xbox.* Roseville, CA:Prima Publishing.

Tiebout, Charles. 1956. "A Pure Theory of Local Expenditures." *Journal of Political Economy*, 64(5): 416–424.

Tirole, Jean. 1988. *The Theory of Industrial Organization.* Cambridge, MA:MIT Press.

Train, Kenneth E. 2003. *Discrete Choice Methods with Simulation.* Cambridge, U.K.:Cambridge University Press.

Whinston, Michael D. 2006. *Lectures on Antitrust Economics.* Cambridge, MA:MIT Press.

Yao, Song, Carl F. Mela, Jeongwen Chiang, and Yuxin Chen. 2012. "Determining Consumers Discount Rates With Field Studies." *Journal of Marketing Research*, 30(3): 447–468.