The Dynamic Effects of Bundling as a Product Strategy

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Abstract

Several key questions in bundling have not been empirically examined: Do consumers value bundles over and beyond their component products, indicating synergy? Is mixed bundling more effective than pure bundling or pure components? Does correlation in consumer valuations make bundling more or less effective? Does bundling serve as a complement or substitute to network effects? To address these questions, we develop a consumer-choice model from micro-foundations to capture the essentials of our setting, i.e. the handheld video game console market. In doing so, we provide a framework to understand the dynamic, long-term impacts of bundling on demand. We find that hardware sales diminish in the absence of bundling, and consumers who had previously purchased bundles may not always purchase pure consoles, even though consoles may be cheaper than bundles. The type of bundling chosen is critical to extracting value from consumers, with pure bundling performing significantly worse than both mixed bundling and pure components. We find that consumers perceive a negative synergy between the components of a bundle. Modeling the dynamic nature of durable good purchases also helps us uncover a finding that contradicts prior static models: positive correlation between products enables bundling to be more effective than negative correlation.

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1 Introduction

We investigate the practice of bundling as a product strategy, with the aim of determining the demand drivers that determine its effectiveness. Although bundling has been a well-known strategy that is commonly used by firms, the empirical literature on bundling primarily documents effects at the market or aggregate level. Several demand-side explanations have been advanced for the prevalence of bundling, and our key objective is to investigate the relative degrees of each of these effects. The primary effect is that bundling increases the surplus captured by the firm from consumers due to diminished consumer heterogeneity.\footnote{Supply side reasons often include economies of scale or scope and other production efficiencies and we do not focus on these in the present paper.} We focus on disentangling demand side explanations that are based on: (a) leveraging the heterogeneity of consumer demand for different products in the bundle, and being able to exercise better price discrimination between consumers, and (b) informational or synergy effects that are based on differential consumer valuation for the bundle, when compared to the individual products that comprise the bundle. Given the multiple explanations that have been offered for the prevalence of bundling, it is striking to observe a lack of empirical evidence that identifies the practical importance of these effects, and the present paper seeks to make progress by characterizing the demand-side effects of bundling.

The specific setting we explore is the handheld video game market, which is an example of a platform market, but our methodology and insights should extend to similar settings. As platform markets become more common in consumer technologies, extending from personal computers to video games to smartphones, we witness in each case, the development of an ecosystem of software applications that are used in conjunction with and based on the platform. Thus, in platform markets, consumers first purchase the hardware that serves as infrastructure and then software that is specifically compatible with that platform to derive effective utility for the platform. Platform markets have received much attention in marketing and economics, and specific settings that have been examined include video game consoles and games, personal computers and software, and smartphones and apps. In the video game industry, the manufacture of consoles involves a hardware production process whereas video games are produced or replicated at essentially zero marginal cost,
since they are information goods. Thus, supply side factors are unlikely to be significant, and we focus on exploring demand-side explanations in this paper.

There are two types of bundling commonly explored: pure bundling refers to the practice of selling two or more discrete products only as part of a bundle, mixed bundling refers to the practice of selling a bundle of the products as well as the individual products themselves. Both types of bundling are commonly used in the technology and media industries as well as many others, both in bundling hardware with software and in bundling different software products. An example of pure bundling is Microsoft Word being included as part of Microsoft Office, whereas an example of mixed bundling is Apple incorporating the iLife software suite as part of its Operating System with every new Mac computer, ranging from the iMac to Macbook Pro as well as making it available for sale through its retail channels. In music, media and content industries, bundling is a key decision: a music album can be thought of as a bundle of singles, and record companies make both singles and entire albums (often at a discount) available for downloading. Note that this form of bundling involves bundling similar products, i.e. two music singles, or several articles into a magazine etc. In contrast, we are interested in understanding bundling in a platform setting, where the platform (console) is purchased once, and then consumers purchase potentially several software (complementary) products (games) over a long period of time.

Our objective in this paper is to characterize the dynamic effects of bundling, and we are specifically interested in evaluating the following product strategy issues involving multiple dimensions along which bundling may influence consumer choices in a durable goods setting:

1. **Synergy**: Do consumers value a bundle over and above the individual components indicating a positive synergy between hardware and specific software titles, or is there a negative synergy indicating a lower preference for bundles?

2. **Cannibalization and Market Expansion**: To what degree does bundling result in incremental sales of consoles and games? What’s the extent of cannibalization of pure consoles and games due to the presence of bundles? Do the incremental sales make up for the cannibalization?

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2Note that pure components refers to the strategy of selling individual products without bundling.
3. **Network Effects**: Does the presence and strength of the indirect network effect make bundling relatively more or less profitable as a product strategy?

4. **Bundling Types**: Is mixed bundling a more effective product strategy choice than pure components?

To examine the issues above, we must capture the durable nature of products, both hardware consoles and software games, which implies that consumers may postpone purchase, indirect network externalities so that consumers value consoles more when there are more games available for purchase, and the presence of bundles in the marketplace. Our focus on dynamics and complementary goods in a two-sided market as opposed to examining related goods of the same type makes both our methodology and result very different from other empirical work on bundling related to music albums and cable TV channels [Crawford, 2008, Elberse, 2010].

We develop a model of bundling in platform markets that builds upon the dynamic demand framework of Gowrisankaran and Rysman [2009] (G&R hereafter), which we extend to account for indirect network externalities and incorporates the presence of consoles, video games and bundles of consoles and games that are available to consumers. The model includes a number of heterogeneous consumers who can make choices in two separate but related markets: the market for hardware (consoles) and the market for software (games). Consumers who do not own hardware must decide whether or not to purchase a console in each period prior to purchase. Consumers who own a console only make choices of games to purchase in each period after they acquire a console. In addition to the above, consumers who don’t own consoles may purchase a bundle of a console with a specific video game instead of a plain vanilla console. Consumers value consoles more when there is a larger number of games compatible with the console, both in the current period and in the future.

Accounting for the dynamic effects explicitly permits us to incorporate the option value of waiting for both console and game purchases, the value of indirect network externalities (having more game titles available) as well as direct evaluation of bundling as a product strategy. The modeling approach builds upon G&R and approximates the expected future value of both consoles and games separately by an inclusive value, and thus ensures that tractability in a market where the number of consoles and video game titles vary dynamically over significant time periods. An
important tradeoff common in the literature (including G&R) that we also make in our dynamic demand model in furtherance of better understanding consumer response to mixed bundling in platform markets is to abstract from supply-side decisions like product development, design or pricing and instead evaluate different supply-side configurations as counterfactuals.

The phenomenon of bundling, both of the pure and mixed varieties has received much attention in the theoretical literature in marketing and industrial organization, which we detail later in this section. However, there has been little empirical understanding of the effects of bundling from a product strategy viewpoint, which is clearly required to characterize both the short-term product substitution effects as well as dynamic long-term effects we seek to study.

A survey of the major practical tradeoffs in constructing bundles at a conceptual and theoretical level is presented in Venkatesh et al. [2009]. Bundling has traditionally been considered a price discrimination strategy to extract more surplus from consumers who have heterogeneous valuations for different products, as explicated in an early work by Adams and Yellen [1976], and modeled in detail by Schmalensee [1984]. These papers recognize that consumer heterogeneity is the primary reason why a monopolist would not be able to extract full surplus from consumers, and contribute the key idea that heterogeneity across consumers is diminished by bundling. Recall that consumer heterogeneity is a primary reason that a monopolist cannot fully extract most of the surplus from consumers. The reduction in heterogeneity due to bundling happens because the variance in the sum of product valuations is lower than the sum of variances in product valuations, which then allows a monopolist to more effectively extract surplus.

Recent research on mixed bundling indicates that this strategy is likely to be more profitable when the products to be bundled are sufficiently asymmetric in production costs as well as network effects [Prasad et al., 2010], whereas more similarity between products makes pure bundling or pure components profitable. It is noteworthy that the authors point to the lack of empirical research at the confluence of network effects and bundling, echoing more general calls for an empirical measurement of the market effects of bundling [Kobayashi, 2005]. A contrary view advancing the optimality of pure bundling in the context of a monopolist with products of different qualities indicates that pure bundling prevails over pure components (i.e. individual products), when consumer valuations for the products are super-additive, indicating the presence of a synergy. Given the sheer number and variety of results that apply under different conditions, the lack of empirical study of mixed or even
pure bundling is especially striking.

A different theoretical lens, i.e. *informational leverage*, is employed by Choi [2008], who investigates how bundling can serve as a signal of quality to consumers, when there is ex ante uncertainty on the quality of a new product that has been introduced by a monopolist who produces a related well-known product with no quality uncertainty. He finds that the monopolist firm can bundle the new product with the old to successfully signal to consumers the high quality of the new product. We borrow the key idea of information leverage from Choi [2008], and aim to uncover the extent of this effect, but we do not include his strong assumption that there is an irrevocable bundling and the new product is not available as a pure component. Thus, while the idea is similar, the settings do not have a one-to-one mapping. In an experimental study, Sharpe and Staelin [2010] demonstrate that consumers perceive the value of products within a bundle to be higher than the sum of the value for each products, and attribute the effect to transaction costs. We term this the *synergy* effect: while we aim to empirically disentangle it from the other effects due to reduced heterogeneity, we do not attempt to establish which of the multiple rationales for synergy is a more significant effect.

A related literature on tying, where a product is only offered for purchase in conjunction with another product has received significant attention for its anti-competitive effects. Tying can be best thought of as an extreme form of bundling, involving a primary good and an aftermarket good, where the consumer is essentially forced to purchase the aftermarket product, unless she bears switching costs in switching to a different primary good. Tying can be used as a coordination tool in platform settings, and can actually help raise social surplus [Amelio and Jullien, 2007], and can also have channel implications resulting from consumer choice of retailers [Hartmann and Nair, 2010].

We take our model of dynamic demand in two-sided markets with bundling, and apply it to the handheld videogame console and game markets. In this market, consumers purchase a videogame console or a bundle of a console with a game, and owners of consoles purchase videogame titles over time. Note that in such a setting, consumers only value the experience of playing a game on a console, which requires the purchase of both products. We find significant heterogeneity among consumers in the valuation for both hardware consoles and software game titles. Consumers with a higher utility for hardware purchase consoles or bundles earlier in the lifecycle, whereas consumers with lower utilities wait for more game titles, for lower prices etc before purchasing hardware. There is a high degree of positive correlation between consumer preferences for hardware and for
software, which is consistent with our \textit{a priori} expectation regarding the videogame market. We find that consumers have a higher value for newer titles, and this value declines with the age of the game, although the rate of decline becomes lower over time. We also find that consumers value the number of game titles available for a console, i.e. the indirect network effect on consoles is positive and significant. To explore whether there are any demand synergies present in bundling, we examine consumers’ purchase of bundles along with their purchases of consoles and videogame titles, and find that there is a negative synergy in bundling, i.e. consumers actually have a lower value for a bundle of a console and specific game title than they have for purchasing the same console and game separately. Bundles thus serve as damaged goods, in the sense of Deneckere and McAfee [1996], and help segment consumers more efficiently, and leads to some consumers advancing their purchases, which allows the firm to extract higher revenues. Thus, dynamics play a very important role in our setting, especially because consumers can choose to postpone their purchase decision in an environment where both prices and product availability change significantly over time must be incorporated in a model to recover accurate estimates of consumer preferences.

We perform several counterfactuals to better understand how a firm may alter its strategy in light of our dynamic demand model of consumer response in the videogame market. First, we eliminate bundles, and find that in their absence, the monopolist takes in lower revenue because some consumers who would have purchased bundles delay hardware purchases. Second, we examine whether pure bundling can serve as an alternative and perhaps more effective strategy than the mixed bundling that we observe in this market. We find that pure bundling performs significantly worse than mixed bundling but also worse than pure components, i.e. when consumers can purchase only consoles and games, and no bundles are available. The bundling literature has focused on the role of correlation between consumer valuation for products in the bundle, and several papers have pointed to the fact that negative correlation leads to higher profits for the monopolist. In contrast, in our counterfactual where we eliminate the positive correlation in consumer preferences, we find that bundling is actually less effective as a product strategy, and leads to lower incremental revenues. Finally, we find that bundling and network effects serve substitute roles in product strategy, and bundling is less effective in the presence of strong network effects.
2 Industry Structure and Data Description

We focus on the handheld videogame market, studying its structure during the years 2001-2005. During these years, the industry resembled a monopoly market, with Nintendo as the dominant company. In the abstract, our industry can be described as a prototypical platform market where a platform interacts with two different end users — consumers and content developers — and there exists payments between end users.\(^3\) A platform permits two end users to interact via its platform creating externalities for each side of the market, where the demand-side indirect network effects pertain to the effect that content has on a platform’s value to the consumer as well as the benefit a content developer receives when an additional consumer joins the platform. The size of these cross group externalities depends on how well the platform performs in attracting the other side. Within this generalized industry structure there are three classes of players: the platform, consumers, and content developers. A consumer purchases access to the platform in order to access content. Moreover, a consumer pays a fixed fee for access to the platform and a fixed price for a piece of content. However, in order for a consumer to access content, the developer is required to pay the platform a variable fee for the rights to the code which allows the developer to make his content compatible with the platform. Let us call this price the platform royalty rate. This royalty rate is not a one-time fixed fee. Rather, a developer pays a royalty rate for each copy of its content that is bought by a consumer. Figure 1 presents an illustration of the discussed market structure.

Figure 1: Video Game Market Structure

The structure makes a distinction between two different types of content developers (or software producers). The first pertains to integrated developers such as Sony in the high definition DVD market or Nintendo in the video game industry. This content is produced by the platform’s own

integrated content design studio. The second type is produced by independent firms not associated with the producing platform. We denoted these developers as independent content developers. In addition to selling access to consumers and producing content, the platform can also offer a bundle which provides access to its platform and includes a piece of content developed by its integrated development studio.

Data

The data used in this study originates from NPD Funworld. Data from the marketing group NPD Funworld tracks sales and pricing for the video game industry and is collected using point-of-sale scanners linked to a majority of the consumer electronics retail stores in the United States. NPD extrapolates the data to project sales for the entire country. Included in the data are quantity sold and total revenue for two consoles and three bundles and all of their compatible video games, roughly 700. The data set covers 45 months starting in June 2001 and continues through February 2005, during which Nintendo was a monopolist in the portable video game market and before Sony’s PlayStation Portable entered the market.

During the early 2000s through February 2005, Nintendo was a monopolist in the production of portable video game consoles. Specifically, it was a multi-product monopolist producing two versions of its very popular Game Boy Advance (GBA) console as well as a portfolio of games to be played on its console. Each version was internally identical, but the second version dubbed the GBA SP was reoriented with the display lying horizontally rather than vertically. The GBA SP looked like a mini laptop computer and was close to half the size of the original GBA. Moreover, it is usually the case with the introduction of a new device that new games are released which are not backwards compatible. However, with the introduction of the GBA SP, this was not the case since the internal hardware of both devices were identical, and both devices could share the same set of games. The target market of these two devices was toward younger kids rather than teenagers or young adults, which was the targeted demographic for the home console. The portable console market most drastically differs from the traditional home video game console market in that it is extremely portable with the size of the device being no larger than an adult hand. It can easily travel with a consumer and be played in a car or airplane, while a home console is restricted to a
location which has a television display and electricity.

General statistics of the portable video game industry are provided in the tables below. We also present a plot of aggregate sales data for hardware and software in Figure 2.\footnote{Sales data is presented in its raw and deseasoned form, where the data is deseasoned with the use of the X11 program from the US Census.} In Tables 1 and 2 we present statistics regarding the release date, total units sold and the number of months on the console market, average (min and max) prices and total standalone units sold of the bundle games for the two standalone consoles and three bundles. From these tables it is evident that Nintendo elected to release its bundles at the height of the holiday time period—the first being a GBA device bundled with the hit game Mario Kart in November 2001. Additionally, all bundled games were high quality hit video games each selling over one and half million standalone units.

### Table 1: Portable Console Market Statistics

<table>
<thead>
<tr>
<th>Nintendo</th>
<th>Release Date</th>
<th>Units</th>
<th>Months on Console Market</th>
</tr>
</thead>
<tbody>
<tr>
<td>GBA</td>
<td>June 2001</td>
<td>12,821,233</td>
<td>45</td>
</tr>
<tr>
<td>GBA SP</td>
<td>March 2003</td>
<td>13,070,720</td>
<td>24</td>
</tr>
<tr>
<td>GBA w/ Mario Kart</td>
<td>November 2001</td>
<td>215,394</td>
<td>29</td>
</tr>
<tr>
<td>GBA w/ Mario Advance 2</td>
<td>November 2002</td>
<td>199,225</td>
<td>17</td>
</tr>
<tr>
<td>GBA SP w/ Mario Advance 4</td>
<td>November 2003</td>
<td>149,065</td>
<td>4</td>
</tr>
</tbody>
</table>

### Table 2: Portable Console and Bundle Prices

<table>
<thead>
<tr>
<th>Nintendo</th>
<th>Average Price</th>
<th>Max Price</th>
<th>Min Price</th>
<th>Independent Games Sold</th>
</tr>
</thead>
<tbody>
<tr>
<td>GBA</td>
<td>$72.00</td>
<td>$94.46</td>
<td>$52.37</td>
<td></td>
</tr>
<tr>
<td>GBA SP</td>
<td>$93.73</td>
<td>$100.30</td>
<td>$70.60</td>
<td></td>
</tr>
<tr>
<td>GBA w/ Mario Kart</td>
<td>$86.17</td>
<td>$150.54</td>
<td>$61.50</td>
<td>2,027,636</td>
</tr>
<tr>
<td>GBA w/ Mario Advance 2</td>
<td>$67.33</td>
<td>$71.73</td>
<td>$56.60</td>
<td>2,438,732</td>
</tr>
<tr>
<td>GBA SP w/ Mario Advance 4</td>
<td>$97.62</td>
<td>$99.85</td>
<td>$94.92</td>
<td>1,673,304</td>
</tr>
</tbody>
</table>
We note several interesting observations from Figure 3, which illustrates the sales of consoles and bundles over time. First, we see that there are significant dynamics in this marketplace. Both sales and prices of products are generally declining over the period of 45 months in the data, but there are also periods of stability and even increases. Second, we observe that bundles can be both short-lived, like the "Gameboy Advance SP with Mario Adv 4" which is only available for 4 periods, or can persist over a long period of time, like in the case of "Gameboy Advance with MarioKart". Third, we observe sales for both GBA and GBA SP even after the GBA SP is introduced approximately in the middle of the time spanned by our data. The video game industry exhibits a large degree of
seasonality in raw console sales with significant increases in the months of November and December. It, therefore, is important to account for the large degree of seasonality in our empirical model by employing the deseasoned data.

To get an approximate idea of the dynamics of video game software sales (in units), we regress the current period sales as a function of lagged sales, current price, age and age^2 as well as whether there is currently a bundle present or was present in the previous period:

\[ s_{g,t} = \theta_1 s_{g,t-1} + \theta_2 I(bundle_t) + \theta_3 I(bundle_{t-1}) + \theta_4 p_{g,t} + \theta_5 age + \theta_6 age^2 + \omega_{g,t} \]  

(1)

where \( \omega_{g,t} \) is distributed iid as a standard normal random variable. We estimate the above specification using the Arellano-Bond GMM estimation procedure given the endogeneity of the one period lagged measure of the dependent variable and price. Standard instruments of lagged regressors are used.

Examining the results of the regression in Table 3, we find that having a bundle sold in period \( t \) or \( t - 1 \) increases software sales, and age has a negative effect, although the positive coefficient on age^2 indicates that the magnitude of the marginal effect is diminished as the game ages. This finding implies that there is likely to be pent up demand for games, and significant sales are achieved quickly after release, beyond which games decline in sales. Note that the above analysis is not intended to comprehensively prove a causal effect, given multiple concerns including endogeneity; rather we use it in conjunction with the model-free evidence in Figure 3 to motivate the need for investigating the dynamics of the market by modeling the micro-foundations of consumer decisions, which can help in explaining and understanding these dynamic patterns.
3 Model

There are several models of demand that allow for individual consumer choices in a differentiated marketplace to be aggregated up to the market-level demand. Most structural approaches are based on [Berry et al., 1995] (BLP, hereafter), who demonstrated how to incorporate unobservable heterogeneity among individual consumers into the model in a static framework where consumers had to choose between a set of discrete alternatives. Heterogeneity is especially important to include in a model of dynamic demand, since the selection of consumers results in different distributions of consumers over time, and can lead to very different market patterns. For example, if consumers who are more price-sensitive delay purchases relative to consumers who are less so, then the population of consumers on the market exhibits an increasing response to price changes over time. Several others have built upon the BLP framework to extend it to incorporate dynamic effects [Melnikov, 2001, Schiraldi, 2010, Carranza, 2010]. Dynamic effects matter especially in markets for durable goods, where consumers face the option of delaying purchases, and their purchases continue to provide flow utility in periods following purchase. We base our model on the approach first suggested by Melnikov [2001] and further refined by Gowrisankaran and Rysman [2009] (G&R, hereafter), which formulate a model of dynamic demand where the evolution of the market is captured by a single inclusive value variable that is both specific to an individual consumer and varying over time; this specification captures much of the dynamic effects in a parsimonious manner, enabling the development of a tractable dynamic model that aggregates the behavior of forward-looking consumers and allows for estimation with market-level data. The idea of collapsing the entire state space into an inclusive variable allows us to capture multiple sources of dynamics in a tractable manner. Such dynamic changes might include a rich array of possible uncertain dimensions, e.g. the introduction of new hardware and software products and their features, price changes, promotions that are unobservable to the researcher. An alternative way to approach this problem is to choose a small number of primary dimension of interest, and model a consumer expectation process for those specific variables, e.g. Gordon [2009] in his study of the personal computer market considers the CPU Speed as the primary quality dimension, and the price as an additional dimension which helps keep the state space more tractable. We consider first the trade-offs faced by consumers who already own a console, and are in the market for video games, and then proceed to examine how
consumers make decisions in the console market.

3.1 Demand – Software (Video Games)

We consider here consumers who own a console and are in the market for video games which are compatible with the console. The potential market for video games is thus driven by the number of consumers who have purchased consoles in the past, i.e. consumers who do not own consoles will not purchase video games. Consumers face a choice of which video game to purchase, and we denote the choice set of video games (or software) available for purchase in period $t$ as $S_t$, which includes the no purchase option 0. Each video game is assumed to be a different market, and consumers do not substitute across games, but consider separately whether or not to purchase each available video game in a specific period. Consumers may thus purchase several video games in each period, or none at all. For consumer $i$, her utility from game $g$ in period $t$ is:

$$u_{igt}^s = \frac{1}{\psi} \left( \tilde{\alpha}_i^s + \alpha^{w,s} w_{g,t} + \tilde{\alpha}_g^s g_{t} + \alpha^{p,s} p_{g,t} \right) + \epsilon_{igt} = \left( \alpha_i^s + \alpha^{w,s} w_{g,t} + \chi_{g,t} + \alpha^{p,s} p_{g,t} \right) + \epsilon_{igt} \tag{2}$$

In the above consumer utility expression, $w_{g,t}^s$ represents the observable characteristics of the game $g$ in period $t$ including variables like age, genre etc. of the game. The unobservable software-time effect is represented by $\chi_{g,t}$, and rationalizes sales over time in BLP-type models. The price of the software title $g$ in period $t$ is captured by the variable $p_{g,t}$. In our setting with a monopolist console manufacturer, all games are compatible with each console available on the market, so there are no additional compatibility variables to be tracked for each game. The error term $\epsilon_{i,g,t}$ is comprised of idiosyncratic shocks.

The coefficient $\alpha_i^s$ represents the value that individual $i$ attaches to owning any software game, whereas $\alpha^{w,s}$ represents consumer valuation for product characteristics and $\alpha^{p,s}$ denotes the price coefficient. The parameter $\psi$ is a scaling parameter, and allows us to compare the utilities of hardware and software, and is required since we assume that the error terms for both hardware and software have the same variance ($\frac{\pi^2}{6}$ for a Type-I extreme value random variable). An alternative way to interpret $\psi$ is based on the extent of consumer utility based on unobservable factors.
Given the durability of video games, the terms denoted by $v^{g}_{igt}$ in the utility are persistent “flow utility” in the event of a purchase. Thus, consumer $i$ who purchases game $g$ in period $t$ exits the market for game $g$, but continues to receive a flow utility $v^{g}_{igt} + \epsilon_{igt}$ in all periods $\tau > t$. When consumer $i$ decides not to purchase game $g$ in period $t$, she receives a utility of $u_{igt} = \epsilon_{igt}^{0}$ and remains in the market for game $g$ in future periods. The error terms $\epsilon_{igt}$ and $\epsilon_{igt}^{0}$ to be distributed as Type I Extreme Value random variables, independent across consumers, games and time periods.

### 3.2 Demand – Hardware (Consoles and Bundles)

We develop a model of hardware choice, where each consumer considers whether or not to purchase a console from the available consoles $J_t$ or bundles $B_t$. For simplicity of exposition, we first outline the utility specification for consoles, and then characterize the utility for bundles. Note that the hardware choices are allowed to vary over time.

**Consoles**

Consider the decision process when only consoles are available in the market: consumers can choose to purchase a console during each period, provided they have not already purchased a console in the past; we do not allow for repeat purchases. For households with multiple users that purchase multiple consoles, our model would treat them as separate consumers, in line with the current literature on aggregate demand models. Thus, consumer $i \in I$ determines in period $t \in T$ whether or not to purchase console $j \in J_t$, and we denote this decision as $d_{ijt} \in \{0, 1\}$. Consoles are assumed to be infinitely durable, and consumers receive a stream of flow utilities in all periods following a purchase. If consumer $i$ decides to purchase console $j$ in period $t$ ($d_{ijt} = 1$), she will obtain a period utility given by:

$$u_{ijt} = \alpha_{i}^{h} + \alpha_{xijt}^{h} x_{j,t} + \xi_{jt} + W(N_{g}^{t}) + \alpha_{p}^{h} p_{j,t} + \epsilon_{i,j,t}$$

Each console is characterized by both observable characteristics $x_{j,t}$ and an unobservable characteristic $\xi_{jt}$, which may vary both over time as well as across consoles. Note that the unobserved characteristic $\xi_{jt}$ is observed and accounted for by consumers and by the console manufacturer, but is not observed by the researcher. Corresponding with BLP, this factor could include product characteristics like style and design and usability as well as all other factors that are not present in
the data. The price of console \( j \) in period \( t \) is denoted \( p_{j,t} \).

The period utility of a gaming console is also directly related to how many games are available for the consumer to purchase in period \( t \) and his expectation of the number of games available in the future after adopting hardware. Without games, a console itself is of little value – we capture this with the term \( W(N^g_t) \), where \( W(N^g_t) \) represents the present discounted software value available for the platform in period \( t \), \( N^g_t \) is the number of games available in period \( t \) and \( \beta \) is the discount factor:

\[
W(N^g_t) = \mathbb{E} \left[ \sum_{s=0}^{\infty} (\beta)^s \alpha^g N^g_{t+s} \mid N^g_t \right]
\]

The utility from games can vary over time, depending on the variety of games available for purchase in each period. The coefficient \( \alpha^h_i \) is a vector that denotes how intensely consumer \( i \) values a video game console, whereas \( \alpha^{x:h} \) indicates the effect of consoles characteristics on the consumer’s utility. The coefficient corresponding to the indirect network effect, \( \alpha^q \), denotes how consumer value for the variety of games influences utility for hardware and finally \( \alpha^{p:h} \) is the consumer’s price coefficient.

While it is challenging to capture the exact nature of how consumers value a large number of games available for the platform, it is reasonable to assume a linear functional form as a first-order approximation. We assume that consumers form expectations on the evolution of the number of games available in a given period to follow a simple AR(1) process. Note that the terms denoted by \( v_{ij,t} \) in the utility are persistent “flow utility” in the event of a purchase in period \( t \). If consumer \( i \) purchases the product in period \( t \), then she exits the hardware market, but continues to receives a flow-utility in each period \( \tau > t \) equal to: \( v_{ij,t}^c + \varepsilon_{ij,\tau} \).\(^5\)

**Bundles**

The above utility specification for hardware only considered consoles; however, in addition to the console, consumers also have the choice to purchase a bundle of a console and a video game in periods when a bundle is available. We denote this selection by \( B_t \), where a bundle \( b \in B_t \) is represented as \( b = (j, g) \), i.e. the bundle comprises of hardware console \( j \) and software game \( g \). The overall

\(^5\) Observe that only the term \( v_{ij,t}^c \) is fixed at the time of purchase, whereas the other terms depend on period \( \tau \).
choice set for a consumer who has not purchased a console or bundle is then \( H_t = \{0\} \cup J_t \cup B_t \).

In periods where there is no bundle available in the market, we set \( B_t = \emptyset \) and consumers in those periods can only purchase consoles and games, i.e. pure components. Note that if the consumer purchases a bundle \( b = (j, g) \), he exits the market for hardware (bundles and consoles) as well as the market for the specific video game \( g \). We model only consumers who have not purchased a console or a bundle to make up the market of potential buyers of bundle \( b \). Thus, the potential markets for bundles and consoles are explicitly identical, and we term this the hardware market.

When consumer \( i \) considers the bundle option, the utility she derives from the purchase of bundle \( b = (j, g) \) in period \( t \), denoted by \( d_{ibt} = 1 \), is given by \( u_{ibt}^b \):

\[
\begin{align*}
u_{ibt}^b &= \alpha_h^h + \alpha_x^h x_{jt} + \delta^h + \alpha^w s w_{gt} + \chi_{gt} + \mu_{b,t} + \epsilon_{i,b,t} \\
&= \alpha_h^h + \alpha_x^h x_{jt} + \delta^h + \alpha^w s w_{gt} + \chi_{gt} + \mu_{b,t} + \epsilon_{i,b,t}
\end{align*}
\]

Thus, for consumer \( i \), the utility of a bundle includes the deterministic components of the utility of console \( j \), i.e. \( v_{ijt}^c \) and the utility of the game that is included, \( v_{igt}^s \) along with a bundle-specific unobservable utility \( \mu_{b,t} \) and the error term specific to the bundle \( \epsilon_{i,b,t}^b \) that is assumed to be an unobservable error term distributed iid as an extreme value and uncorrelated with the other unobservables. Note that the time-varying unobservable \( \mu_{b,t} \) characteristics of the bundle could include promotions, packaging, design and other factors that may impact its utility above and beyond the utility of its constituent console and video game. We thus capture the synergy effect using \( \mu_{b,t} \) as the additional value that consumers have for the bundle over and beyond the value of the constituent hardware console and software game. We assume that \( \mu_{b,t} \) does persist beyond the period in which it is purchased, i.e. it appears in the flow utility of the bundle, and the terms denoted by \( v_{ibt}^b \) in the utility are persistent “flow utility” in the event of a purchase. Thus, consumer \( i \) who has purchased a bundle \( b \) in period \( t \) continues to receive a flow-utility of \( v_{ibt}^b + \epsilon_{i,b,t} \) in period \( \tau > t \). Consumers who are in the hardware market and choose not to purchase the bundle receive utility identical to those who decide not to purchase the console, specified as \( u_{ibt}^b = u_{ibt}^c = \epsilon_{i,0,t} \).

We also note that consumer heterogeneity enters through the preference for consoles and gaming in general (a console constant and software constant), but all other coefficients are homogeneous in our model specification.
On the other hand, if the consumer decides not to purchase any hardware in period \( t \), she receives a utility \( \epsilon_{i,0,t} \), and remains in the market for hardware, retaining the option to purchase in future periods. Lastly, to specify the error term, we follow Rust [1987] and model \( \epsilon_{i,j,t} \) for \( j \in \{0\} \cup J_t \) to be distributed as a Type I Extreme Value random variable, which is independently distributed across consumers, products and time periods. With aggregate data, we integrate as usual over the error term and the extreme value error is convenient as it allows analytical integration. Note that only consumers who have never purchased a console remain in the market, and upon making a purchase, consumers exit the market for consoles.

Lastly, in estimation we impose a restriction on the model to fix consumers price sensitivity to be equal for hardware and software. This restriction takes the form \( \alpha^{p,h} = \psi \alpha^{p,s} \). From a structural viewpoint, the price coefficient for consumers would be different for hardware and software only because the purchase of a hardware console would cause a change in wealth effects leading to a change in price-sensitivity.\(^6\)

**Heterogeneity**

We specify consumers to be heterogeneous in their value for hardware (\( \alpha_i^c \)) and their value for software (\( \alpha_i^s \)), but identical in terms of the strength of the indirect network effect (\( \alpha^g \)), response to the characteristics of hardware (\( \alpha^{x,c} \)) and software (\( \alpha^{x,s} \)), as well as in the price coefficient (\( \alpha^{p,s} \)). We discuss the nature of identification issues and detail the reasons for this modeling choice in §4. The heterogeneity of consumer preferences is captured by characterizing consumer \( i \)'s value for a hardware purchase \( \alpha_i^c \) and for a software purchase \( \alpha_i^s \) to be jointly distributed random variables, as follows:

\[
\begin{pmatrix}
\alpha_i^c \\
\alpha_i^s
\end{pmatrix}
\sim N
\left(
\begin{pmatrix}
\tilde{\alpha}_i^c \\
\tilde{\alpha}_i^s
\end{pmatrix},
\Sigma
\right),
\text{ where }
\Sigma = 
\begin{pmatrix}
\sigma_s^2 & \rho \sigma_s \sigma_c \\
\rho \sigma_s \sigma_c & \sigma_c^2
\end{pmatrix}
\]

Notice that the above specification generalizes the standard practice of assuming preferences for products across multiple categories are independent, used in all the dynamic demand literature. We allow the data to determine the correlation between console and gaming preferences, and do not impose a specific form of dependence. We include this dependence to allow better flexibility in

\(^6\)We ought to expect this effect to be very small, given the low price of consoles, relative to average income levels; indeed, our results when using different price coefficients for hardware and software are quantitatively very similar and qualitatively the same as with the primary specification.
representing purchase patterns across the software and videogame markets and more importantly, to characterize the degree to which bundling reduces heterogeneity of consumer valuations and helps a monopolist extract surplus.

**Consumer’s Decision Problem**

Consider consumer $i$’s decision problem for the console or bundle in a specific period, $t$: he has to decide whether to buy a product now or wait until the next period. In order to account for the value of waiting followed by adoption at some point in the future, the consumer has to anticipate the evolution of all variables $\Omega_t$ that will affect the value of his future adoption decision. The variables that ought to be present in $\Omega_t$ include the future evolution of console characteristics (both observable and unobservable), future price levels, as well the video games that might be marketed in the future, since they all affect the utility of a future adoption.

We allow consumers in any period to purchase a hardware product, including a console or bundle, $h \in H_t = \{0\} \cup J_t \cup B_t$, implying that consumers compare their utilities from all console and bundle options available in that period. We therefore denote that a consumer who is considering purchasing a console or bundle to be in the hardware market. Once a consumer purchases a bundle or console, she exits the hardware market and does not return, thus ruling out multihoming. After a consumer purchases hardware, she enters the software market in each future period and may purchase any video game $g \in S_t$ that she has not purchased in period $t$. Like the hardware market, once a consumer purchases a piece of software she exits the market and is unable to repurchase the video game. Given this setup, the fact that consumers can postpone purchases and cannot purchase the same product twice, the decision problem is inherently dynamic, and the consumer faces a choice of when and whether to purchase both hardware and software products. We denote the vector of error terms $\varepsilon^H_{it}$ for consumer $i$ to be: $\varepsilon^H_{it} = (\varepsilon_{i0t}, \varepsilon_{i1,t}, \ldots, \varepsilon_{i|J_t|t}, \varepsilon_{i1,t}, \ldots, \varepsilon_{i|B_t|t})$.

For a consumer in the hardware market, the Bellman equation that describes the consumer’s value for being in a current state $\Omega_t$ is:

$$V^H(\Omega_t, \varepsilon^H_{it}) = \max\{\varepsilon^H_{i0t} + \beta \mathbb{E}[V^H(\Omega_{t+1}, \varepsilon^H_{i,t+1} | \Omega_t)], \max_{h \in H_t} u_{iht} + \beta \mathbb{E}[W_i(v_{iht})]\} \quad (5)$$

The value function $V^H$ depends on the state variable when the consumer is still in the hardware
market, and has not made a console or bundle purchase.

Note that the Expected Value function is obtained by integrating out the error terms in the value function:

\[
EV(\Omega_t) = \int_{\mathcal{H}} VH(\Omega_t, \delta_{it})
\]

The inclusion of all relevant variables is problematic from the viewpoint of tractability, in the sense that the state space of the dynamic problem grows exponentially, and is also rather demanding computationally on consumers. We follow the basic simplification introduced by Melnikov [2001] and explained further by Gowrisankaran and Rysman [2009], by collapsing all the state variables that affect future utility into a consumer-specific inclusive-value state variable \(\delta_{it}\) that captures the effects of variables in \(\Omega_t\). Note that while this simplification ensures that the state space is tractable, we capture but cannot explicitly evaluate the effects of specific product introduction or innovation choices made by firms.\(^7\) Similar to G&R, we assume that the inclusive value is sufficient to represent choice probabilities, and thus drastically reduce the state space to one dimension where \(v_{iht}^f\) is the flow utility for hardware (console or bundle):

\[
\delta_{it} = \log \left( \sum_{h \in \mathcal{H}_t} \exp \left( v_{iht}^f + \alpha^{p,c} p_{h,t} \right) \right)
\]

where \(\delta_{iht}\) is the mean expected discounted utility for purchasing hardware \(h\) (console or bundle) in period \(t\). This utility is defined as:

\[
\delta_{iht} = v_{iht}^H + \alpha^{p,c} p_{h,t} + \beta \mathbb{E} [EV_i(\delta_{ih,t+1}) | \delta_{it}]
\]

The Bellman equation is consequently transformed to:

\[
EV_i(\delta_{it}) = \log (\exp (\delta_{it}) + \exp (\beta \mathbb{E} [EV_i(\delta_{i,t+1}) | \delta_{i,t}]))) + \kappa
\]

The inclusive value \(\delta_{i,t}\) is perceived by the consumer as evolving according to an AR(1) process,

\(^7\)Note that the approach by Hendel and Nevo [2006] also collapses the function of the current flow utilities of available products into a state variable, but does not incorporate the option value of waiting and holding the current product.
and we estimate the parameters of the following process:

\[ \delta_{i,t+1} = \gamma_{i,1} + \gamma_{i,2}\delta_{i,t} + \zeta_{i,t} \]  

(6)

where \( \zeta_{i,t} \) is distributed as a standard normal, and is iid across consumers and time periods. The individual-specific parameters \( \gamma_{i,1} \) and \( \gamma_{i,2} \) define the evolution of the inclusive value state, and yield a probability distribution for the future state, conditional on the current state.

Once the value functions \( \text{EV}_i \) are obtained by solving the Bellman equation, we use it to determine the conditional purchase probabilities for consumers. We find that consumer \( i \)'s probability of purchasing product \( k \) is given as a function of the inclusive value in the corresponding period, \( \tilde{\delta} \) as follows:

\[
\hat{s}_{ij}(\tilde{\delta}) = \frac{\exp(\tilde{\delta})}{\exp\left(\text{EV}_i(\tilde{\delta}) - \kappa\right)} \frac{\exp(\tilde{\delta}_j)}{\exp(\tilde{\delta})} 
\]

(7)

where \( \kappa \) is Euler’s constant. The first fraction represents the probability of purchase for consumer \( i \) and the second represents the probability of choosing alternative \( j \), conditional on deciding to make a purchase.

The above formulation of hardware demand, including the expected value function, implicitly assumes that consumers first purchase hardware, and face a choice between consoles and bundles. Note that bundles include the console characteristics, as well as additional bundle-specific characteristics that determine the synergy effect, which impact how consumers formulate expectations, as well as the evolution of the individual-specific state variable \( \delta_{it} \).

The model of a consumers decision problem for software is similar to the above hardware problem, in the sense that consumers face choice options of purchasing a durable good or delaying (no purchase option). The primary distinction is that there is only one hardware market, whereas we have each software title representing a separate market. A consumer thus faces a decision for each available video game in each period \( t \) following a hardware purchase. Consequently, the above state variable \( \delta_{it} \) for software is formulated as \( \delta_{it} = \left( \delta^f_{igt} + \alpha^{pg}p_{g,t} \right) \).
4 Identification and Estimation

We have previously developed a model of consumer demand in a dynamic durable goods platform market for a monopolist firm with multiple hardware consoles, and a software market characterized by a variety of videogames produced over time. Consumers in this market face several decisions, ranging from which hardware to purchase, and when, as well as determining which software titles to purchase in each period. We next discuss how the parameters of the consumer utility model are identified using the variation in the data from the handheld videogame market, and detail as the estimation process for our dynamic demand model using aggregate sales data on consoles and videogame titles.

Identification

We discuss the identification of the parameters in the above model to help understand what variation in the data permits the estimation of each of the parameters. First, consider the consumer utility for video game software, $\alpha^s_t$: a higher value of this coefficient implies that more game sales, with other factors being the same. The heterogeneity of consumer preferences for software ($\sigma^s$) is identified by the rate of increase (or decrease) in sales of a specific title over time. Consider the extreme case with no heterogeneity, in which case the only difference between consumers is due to the error term. In such a case, the sales spike would be sharp both upward and downward compared to the case with significant heterogeneity, where we would find the sales rate increase (or decrease) to be more gradual. Note that we consider heterogeneity in consumer valuation for consoles and software (the intercept term), rather than heterogeneity in price sensitivity. We focus on the above heterogeneity because a key objective is to understand the effect of correlation in consumer valuation across products that comprise a bundle, and to evaluate the setting where there is no such correlation. We would be unable to capture these bundling effects if we had chosen to focus on the coefficient of price heterogeneity.

Next, consider the game characteristics, which are all dynamically varying: age, and higher powers of age are identified by increasing or decreasing sales over time for specific games. Average effects of these time trends identify these parameters while the game-specific unobservable $\chi_{gt}$ for game $g$ in period $t$ rationalizes market sales. The price coefficient is identified as usual by dynamic variation in price levels and sales levels. The coefficients of product characteristics $\alpha^{w,s}$ are identified
by primarily by the changes in product characteristics and sales over time, because games do not compete with one another.

In the hardware market, the product characteristics coefficients are identified by similar variations in console characteristics over time. The coefficients of product characteristics are identified both from the variation of console sales and prices across markets (time periods in our setting), and from whether increased sales for a specific product come from other products that are “more similar” or “less similar” in terms of product characteristics. While these previous sources of variation are the basic elements in BLP and much of the literature, an additional source of variation that helps in identification results from the explicit dynamic model that incorporates intertemporal trade-offs. Recall that in our model, consumers with the highest value for hardware ($\alpha_i^c$) purchase earlier and exit the hardware market, implying that consumers who remain have a lower valuation. This dynamic effect along with the change in product characteristics of hardware over time is an additional source of variation that helps in identification of product characteristics coefficients. Consumer valuation for software (indirect network effect coefficient $\alpha^g$) is identified by the dynamic variation in the number of games available for a specific console, and the more sales of hardware change when the number of games changes, the stronger the indirect network effect.

The identification for consumer heterogeneity in the hardware ($\sigma_e$) is similar to that of software, but the variation in the availability of bundles over time provides an additional source for its identification, because it allows the rate of increase (and decrease) of bundle sales to be used for this purpose. Note that the unobservable product-period specific shocks to consoles and games also carry over to the bundles that include them. The identification of the normalization parameter $\psi$ that permits direct comparison of the hardware and software utilities follows from the restriction we impose on the marginal disutility toward hardware and software price, $\alpha^{p,h} = \psi \alpha^{p,s}$. Consequently, the identification of $\psi$ orginates from the differences in consumer responsiveness to hardware and software prices.$^8$

An alternative approach would be to use an approach from Bass (1969) that illustrates how to infer the initial potential market size of a product from its sales data. "An approximation to the discrete-time version of the model implies an estimation equation in which current sales are related linearly to cumulative sales and (cumulative sales)$^2$" [Nair, 2007]. Let $k_t$ and $K_t$ denote the aggregate sales of all consoles in month $t$ and cumulative sales up to and including month $t$, respectively. Also, let $k_t = a + bK_t + cK_t^2 + v_t$ be the equation we estimate. Given the estimates, the Bass model implies the initial potential market size for all handheld consoles is $M = (a/f)$, where $f$ is the positive root of the equation $f^2 + fb + ac = 0$ and $a$ is from the regression above. This model gives a potential market size of 35.8 million.

$^8$
We treat the network effect similar to an exogenous variable that varies over time, which then allows for the identification of \( \alpha^g \), which follows from . Next, we illustrate how the correlation between the value for hardware and software is identified. For the purposes of the discussion, we focus first on the case when the correlation between \( \alpha^s_i \) and \( \alpha^c_i \) is positive, and each parameter is positive as well. Consumers with a high value of \( \alpha^c_i \) are more likely to purchase consoles earlier, whereas consumers with low values are likely to delay the purchase \textit{ceteris paribus}. Note that consumers with high value of \( \alpha^s_i \) value video games more, and are likely to buy a larger number of games in each period after they have purchased a console. Note that a highly positive correlation between \( \alpha^s_i \) and \( \alpha^c_i \) imply that it is more likely that both values are relatively high or low, rather than one being high and the other low. When consumers with high values of \( \alpha^c_i \) also have a high value of \( \alpha^s_i \), the ratio of per-period video game purchases to the installed base will tend to decline over time, because the consumers who enter the video game market later (i.e. the consumers with low \( \alpha^s_i \)) buy fewer video games per period because \( \alpha^s_i \) is low. Conversely, when \( \alpha^s_i \) and \( \alpha^c_i \) are negatively correlated, we ought to expect the above ratio to increase with the installed base of consoles, since the consumers who enter later have a higher value for video games, and will tend to purchase more video games in each period. We also note following the above discussion that micro-moments would be a good alternative approach to help with identification of the correlation parameter, and in settings where micro-data are available, it would be a useful approach. Given the availability of micro survey data we employ we employ them to aid in identification. However, it is important to point out that in our setting with market-level data, per-period video game purchases and the console installed base are both matched to the data, since they are a function of market shares.

We cannot separately identify the total potential market size, and so we set the initial market for hardware to be 35.7 million, and the initial market for video games to be zero. The determination of a potential market size for consoles is an important step in properly estimating console demand. One useful measure which is often used is the number of households with a TV in 2001, since the introduction of the GBA occurred in 2001. But the GBA is geared toward families with children so the measure of households with a TV seems to over estimate the potential market size.\(^9\) Instead, we employ the number of households who have children under 18 living at home, which is roughly

\(^9\)Dube et al. [2010] and others use a similar approach.
35.7 million in 2008. The predicted initial market size is thus 35.7 million households with the potential market in period \( t \) as \( M_t = \text{M-cumulative console sales till month } t \). The construction of the potential market size reflects the idea that a consumer is a first time buyer and does not re-enter the market to purchase additional goods. Consequently, we do not account for multihoming consumers.

Again, it is important to note that while the discussion here provides some intuition for the specific patterns in the data that move down parameter values to vary in magnitude and sign, in practice all the variation in the data is used to estimate each of the parameters, given the intertemporal substitution possibilities available to consumers as well as the linkage between the console and video game markets.

**Estimation**

We model heterogeneous consumers, with the consumer’s type drawn from a discrete distribution of \( N_s \) types. The coefficients are represented by \( \alpha_i = \bar{\alpha} + \nu_i \Sigma^1 \). We examine both Monte Carlo simulations in drawing individual-specific coefficients and then summing over the individuals to obtain a simulation-based approximation, as well as the quadrature approach [Skrainka and Judd, 2011] that takes a direct polynomial approximation approach to compute the integral.\(^\text{10}\) Consistent with the dynamic demand literature, we set the discount factor to be \( \beta = 0.975 \) as the discount factor across periods in the model.

Our dataset on the videogame industry spans the years 2001-2005. The Nintendo Gameboy Advance (GBA) introduced in Spring 2001 was a very significant leap in the handheld console market, and began a new generation of consoles. This feature of the data and our setting helps us in our estimation process because it mitigates concerns about whether the initial conditions present in the market at the beginning of our data may present persistent effects that may make accurate estimation of existing consumer inventory more challenging. Having data from the beginning of a significant market shift also permits us to consider a more tractable state space in the model, which

\(^{10}\) Specifically, we implement a Gaussian-Hermite quadrature approach with ten nodes (\( N_s = 10 \)).
enables our estimation process to converge in a reasonable time, and permits us to incorporate richer substitution effects and correlation between consumers preferences for hardware and software.

To account for the relationship between consumer preferences for hardware consoles and for software video games, we allow for a flexible covariance structure that allows consumers to have either a positive or a negative correlation. In estimation we limit consumer heterogeneity to hardware and software constant terms with some magnitude of correlation to be estimated. All other utility parameters are assumed to be homogeneous across consumers. We thus build upon from a large literature of static or dynamic aggregate data models that assume a strict independence structure.

Given \( N \) discrete types of consumers, we denote the sets of consumers of each type to be \( S_1, S_2, \ldots, S_N \). The potential market size for console or bundle purchases at period \( \tau \) can be captured by the variable \( M_{\tau}^c \), defined as a \((N \times 1)\)-vector that captures the fraction of each of the \( N \) types that have not purchased at the beginning of period \( \tau \):

\[
M_{\tau}^c = (m_1(\tau), m_2(\tau), \ldots, m_N(\tau))
\]  

(8)

Each consumer who purchases a console or bundle exits the market for hardware and enters the market for video games. Thus, the potential market size of video game purchasers in period \( t \) includes the consumers who have purchased consoles across the previous periods minus those who already have purchased video game \( g \) (includes consumers who purchased a bundle with game \( g \)):

\[
M_{\tau}^g = (m_1(1) - m_1(\tau) - N_{1,t}, \quad m_2(1) - m_2(\tau) - N_{2,t}, \ldots, \quad m_N(1) - m_N(\tau) - N_{N,t})
\]  

(9)

where \( N_{k,t} = \sum_{i \in S_k} \sum_{\tau=1}^t d_{igt} \).

We model the process of market evolution for the hardware and software markets jointly in a consistent manner that corresponds to observed behavior, where consumers first purchase a console and then purchase software games.

Our estimation is based on GMM, and the criterion function gives us the estimator:

\[
(\hat{\alpha}, \hat{\Sigma}) = \arg \min_{\alpha, \Sigma} \xi'(\alpha, \Sigma)ZWZ'\xi(\alpha, \Sigma),
\]

which is based on the orthogonality of the unobservable characteristics and the instruments, i.e.
\[ E[Z'\xi] = 0. \]

We also supplement our estimation with the use of micro level survey data which originates from Forrester Research’s 2005 Technographics survey. This data allows us to form a micromoment based upon the difference between the predicted distribution of consumers who own less than twenty video games to the observed the data. We expand the traditional weighting matrix used in simulated GMM \((Z'Z)\) in one element in each dimension to include the inverse of the variance of the micromoment. For the variance we use \(\text{var}_{mm} = \frac{p(1-p)}{n_c}\) where \(p\) is the value of the moment in the data and \(n_c = 626\) is the number of consumers sampled in the survey. Given this variance is very small this puts a substantial weight on the micromoment and thus attempts to match it very closely.

We follow the assumption that each video game comprises of a separate and distinct market, which has been supported empirically by Nair [2007] in the home video game market.

In order to accurately estimate and identify a consumer’s price sensitivity for hardware, software and bundles, we use instrumental variables to correct for endogeneity in prices. Price endogeneity is known to be present for a variety of reasons. For instance, producers may set higher prices for games with higher quality, where the latter is not observable by the researcher, which will result in the price coefficients being biased upward. We partially resolve this through the use of game indicator variables. Even with the use of fixed effects the proportion of the unobservable which is not accounted for may still be correlated with price as a result of consumers and producers correctly observing and accounting for the deviation. Under this assumption, market specific markups will be influenced by the deviation and will bias the estimate of hardware or software price sensitivity. Both Berry [1994] and BLP both show that proper instruments for price are variables that shift markups. We use instruments which proxy for marginal cost since Nintendo is a monopolist in the hardware market, and the standard BLP argument of the dependence between markups and the distance between products in feature space becomes less useful. The instruments for video games include one-month lags of the Japanese to US exchange rate and the software producer price index. The producer price index is interacted with additional variables to capture cost differences between game age, rating and integrated games. Specifically, the software producer price index is interacted with game rating, with game rating and game age, with game rating and a indicator variable for an integrated game, and with game rating, game age, and the integrated indicator
variable. The implementation of such instruments captures and proxies for variable software costs among young and old games, game type and quality levels. For hardware we use a one month lag of the Japanese to US exchange rate again, the retail price of Nintendo’s home video game console the GameCube and there squared values as console price instruments. We also include an indicator variable of whether an additional console type is available (i.e: whether the Gameboy Advance SP has reached the market) to account for the multi-product pricing effect. The foreign exchange rate is a suitable instrument given the manufacturing of the console and games occur in Japan and would consequently affect the retail price of consoles in the US. We employ a one month lag of the exchange rate to allow for the duration between shipping, displaying and purchasing. Lastly, each instrument is interacted with console indicator variable for either the GBA or the GBA SP to allow each variable to enter the production function of each console differently. This method is similar to that of Villas-Boas [2007]. Handling the endogeneity of the bundle price is slightly more complicated than either software or hardware alone. One might think to only use the instruments from hardware to instrument for bundle price but given our model specification above this would still leave our bundle price correlated with the unobserved error term given the error term is a summation of the structural error term for software, hardware and a bundle specific component. We correct for the endogeneity problem with the use of both software and hardware instruments.

Results

We detail our parameter estimates for the consumer’s utility for both hardware and software utility in Table 4 below. We first focus on the software results and then proceed to the console and bundle results. The software results are quite sensible in magnitude and in sign and conform to our expectations. For instance, the coefficient of software price is negative and significant, and consumers on average have a marginal disutility toward price ($\alpha^{p.s} = -0.0590$). We also find significant consumer heterogeneity in valuation for software, with a standard deviation at $\sigma_s = 1.3220$. We also determine that software utility declines as a game becomes older, as is evident from the corresponding signs on game age variables.

We now discuss the demand parameters for the hardware market, consisting of consoles and bundles. As we discussed above, we assume a consumer has the same marginal disutility towards
**Table 4: Estimation Results**

<table>
<thead>
<tr>
<th>Variable</th>
<th>No Consumer Heterogeneity</th>
<th>With Heterogeneity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Myopic Model</td>
<td>Dynamic Model</td>
</tr>
<tr>
<td></td>
<td>Coefficient</td>
<td>Std. Error</td>
</tr>
<tr>
<td>Software Utility Parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Game Price</td>
<td>-0.0599**</td>
<td>0.0137</td>
</tr>
<tr>
<td>Game Age</td>
<td>-0.2299**</td>
<td>0.0029</td>
</tr>
<tr>
<td>Game Age^2</td>
<td>0.0012**</td>
<td>0.0001</td>
</tr>
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<td>Scale Parameter (ψ)</td>
<td>0.3339</td>
<td>0.2607</td>
</tr>
<tr>
<td>Sigma Software (σ_s)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Console Utility Parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-4.6259**</td>
<td>0.7429</td>
</tr>
<tr>
<td>Age of Console</td>
<td>-0.0493</td>
<td>0.0361</td>
</tr>
<tr>
<td>Age of Console^2</td>
<td>-0.0024**</td>
<td>0.0008</td>
</tr>
<tr>
<td>Synergy</td>
<td>-3.9035**</td>
<td>0.2353</td>
</tr>
<tr>
<td>Indirect Network Effect (α_h)</td>
<td>0.00012**</td>
<td>0.00003</td>
</tr>
<tr>
<td>Sigma Console (σ_c)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correlation (ρ)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GMM Objective</td>
<td>164.1169</td>
<td>176.248</td>
</tr>
</tbody>
</table>

Notes:* indicates significant at 95%; ** indicates significant at 90%; Game FE in all models not reported

The price of a standalone console or a bundle, i.e. the price coefficients for bundle price and console price are identical: we impose the restriction $\alpha^{p,h} = \psi \alpha^{p,s}$, where the marginal disutility to hardware price is equal to a scaled value of the disutility of software price. We determine the scale coefficient to be statistically significant ($\psi = 0.9508$). Consumers’ disutility for price is captured by a scaled hardware price coefficient of $\alpha^{p,h} = -0.0561$. We introduce heterogeneity in a consumer’s preference for hardware in general; observe that $\alpha^c_i$ is individual-specific, and the above price-coefficients reflect population averages. In fact, we find that there is a significant degree of consumer heterogeneity toward hardware with a standard deviation of ($\sigma_h = 6.7100$) and that consumer preferences for games and hardware are highly correlated at an estimate of ($\rho = 0.9713$), both of which are significant. Heterogeneity plays a vital role in the model as consumer valuation for hardware alters the distribution of consumers who own a console and are thus present in the software market.
In estimation we discretize consumers into $N_s = 100$ different segments, and the number of consumers belonging to each specific segment changes dynamically in each market, depending on consumers’ purchase decisions. Note that at this point, preference for hardware is the only determinant of consumer heterogeneity for hardware. Figure 4 reflects the distribution of three consumer types over time for the hardware market. Group 1, for instance, is a group which possesses a relatively low preference for hardware. With this low preference consumers within this group postpone consumption which causes its percentage of consumers who remain in the market for consoles to increase over time (similarly for Group 2 for the first part of the data period). On the other hand, Group 3 has relatively large preference for hardware and as a result do not postpone consumption into the future as much as groups 1 and 2. This subsequently leads to a decline over time.

Consumers positively value the number of video games available to play and purchase in a given month ($\alpha^g = 0.00074$), and account for this factors when making a hardware purchase decision. The positive sign associated with the indirect network effect is consistent with the theoretical literature on indirect network effects, underscoring the value of video game software and its influence in hardware purchase decisions. Furthermore, a consumer’s valuation for a console (whether standalone or in a bundle) decreases as product ages.

Lastly, we have examined whether bundling results in any demand-level synergies so that consumers value the bundles over and above the individual elements (console & game). A positive synergy or complementarity would provide a demand-side rationale for bundling creating additional
Table 5: Console and Bundle Semi-elasticities

<table>
<thead>
<tr>
<th></th>
<th>GBA</th>
<th>GBAMA2</th>
<th>GBAMK</th>
<th>SP</th>
<th>SPMA4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gameboy Advance (GBA)</td>
<td>1.0361</td>
<td>-0.0197</td>
<td>-0.0535</td>
<td>-0.4716</td>
<td>-0.0041</td>
</tr>
<tr>
<td>GBA with MarioAdvance2 (GBAMA2)</td>
<td>-3.2990</td>
<td>3.2438</td>
<td>-0.0260</td>
<td>-0.0151</td>
<td>-0.0001</td>
</tr>
<tr>
<td>GBA with MarioKart (GBAMK)</td>
<td>-4.1212</td>
<td>-0.0031</td>
<td>7.2179</td>
<td>-0.0232</td>
<td>-0.0001</td>
</tr>
<tr>
<td>GBA_SP (SP)</td>
<td>-0.8639</td>
<td>-0.0046</td>
<td>-0.0013</td>
<td>0.8870</td>
<td>-0.0236</td>
</tr>
<tr>
<td>GBA_SP_MARIO ADV 4 (SPMA4)</td>
<td>-1.0756</td>
<td>-0.0070</td>
<td>-0.0034</td>
<td>-3.5087</td>
<td>5.1427</td>
</tr>
</tbody>
</table>

value for consumers, which in turn could allow the firm to extract such surplus. However, we find, from the bundle indicator variable result, it is evident that the utility of the bundle on average is lower than the sum of utility of the console and game. This is somewhat surprising as ex ante we expected bundles to have an additional benefit due to the complementary nature of the products. However, given the limited sales of these bundles relative to standalone consoles, matching the model to the data implies a generally negative synergy effect; we also find a negative parameter value for the console age variable, indicating that sales of consoles drop significantly after introduction.

The estimation of a structural model supplies sufficient information to better investigate consumer substitution patterns. Table 5 provides own and cross price console and bundle semi-elasticities estimates. We evaluate the semi-elasticity by considering a 1% price cut that is made permanently, and is known by consumers as well as the firm to be a permanent cut, i.e. there is no uncertainty regarding the future price cut unlike the case of a promotion. The model predicts that a permanent 1% percent reduction in the price of a console would lead to an approximately 1-7% increase in the total number of a given console sold during the time period. Also note that the own price elasticity for bundles is substantially larger than for consoles. This result is consistent with previous literature where consumers are more price sensitive to bundles than components [Sharpe and Staelin, 2010]. The cross-price elasticities correspond to the effect of a price cut on consoles on sales of bundles, and vice versa and range from 0 to -4%. Moreover, the off-diagonal elements are negative and the estimated cross-price semi-elasticity measures are consistent with the beliefs a standalone console’s closest “competitor” is the bundle with the particular console included. For instance, the closest “competitor” to the standalone Gameboy Advance console is the GBA bundle with Mario Advance 2 and not the GBA SP, which would not be apparent without developing a
structural model.

Figure 5 displays the intertemporal handheld console market elasticities. We present three variants of an elasticity measure to highlight the role of consumer expectations, as proposed in G&R. We compare the effects of a temporary 1% price decline at time period $t$ when consumers believe the price change is temporary to one in which consumers believe it is permanent. Our last measure we include is a 1% price decline that is permanent and is believed to be permanent. Implementing each measure follows the methodology of G&R, where any such price change is not expected by consumer before period $t$.

The below elasticity measures correspond to the medium time period $t$ being month 22 of the data. Like G&R, the below figure shows that expectation play a vital role in how consumers respond to price changes. For a temporary and unexpected 1% price change, we see that sales remain unchanged prior to period $t$ and increase by roughly 5% in that period. Equally interesting, we find that such an unexpected and temporary price change only results in a gain in sales in the period the price decline is present and a subsequent decline in sales after period $t$. However, when the temporary price change is believed to be permanent, we see a smaller reaction in consumer sales, roughly 2%, than when the price decline is temporary and believed to be temporary. This is due to consumers’ beliefs that such a price decline will be available next period and so they are willing to postpone their purchase until a future period. But when period $(t+1)$ prices return to their higher price levels consumers consumers who otherwise would have purchased in period $(t+1)$ with lower price do not. What is evident from this figure is that temporary price cuts only have temporary effects on sales, the positive increase in sales is only for one period.

We also study the effects of a permanent 1% price decline from period $t$ onward. The effects on console sales in period $t$ is identical to the temporary price change which is believed permanent by construction. However, the long run effects are quite different. Unlike the temporary price change all future period prices are discounted, which consumers form correct expectations of, leading to an increase in console sales in all future periods.

Lastly, we analyze semi-price elasticities for video games. From Figure 6, we see that all games have a positive semi-price elasticity which ranges from 0.5-2.25. The model fit results are detailed in Appendix B.
Figure 5: Industry Dynamic Price Elasticities

Figure 6: Histogram of Game Own Price Semi-Elasticities
Counterfactuals

A key objective we had in developing a structural model of consumer behavior was to enable us to evaluate the effect of realistic counterfactuals, some of which may involve factors that are outside the range of factors of the data. More specifically, these counterfactuals help us answer the questions (1)-(4) listed in §1. Since we want to understand the effectiveness of bundling as a product strategy, we want to compare market outcomes with those that result when bundling is eliminated as an option for the firm. This baseline scenario will allow us to evaluate the degree to which bundles may potentially cannibalize sales of standalone consoles and how they may induce consumers to advance purchases. It is important to note that we do not allow the firms to reoptimize with respect to price in the counterfactuals below, i.e. prices remain fixed at the levels observed in the data.

We begin with the alternative scenario of eliminating bundling as a product strategy; the results are detailed in Table 6, and the dynamics of the change in installed base is illustrated in Figure 7. We find that total hardware sales increase by 143,331 units or approximately 0.55% under a mixed bundling regime. We also determine that the use of mixed bundling leads to a cannibalization of roughly 127,114 consoles, which is more than offset by the sale of bundles leading to an overall increase in hardware. Perhaps even more important is the effect that such an increase in hardware sales has on software sales. As the table illustrates, this small increase in hardware sales generates roughly 1.2 million more videos games sold with, approximately 191,935 being high margin integrated games. Thus, revenues from mixed bundling are approximately $27 million larger than with a component only product strategy. Note that revenues are calculated by summing over three monthly revenues streams with 45 months of data: (i) hardware sales (bundles and consoles) (ii) royalty fee from independent software sales, which is set at $8 per software title sold, and (iii) revenue from integrated games, i.e. those produced by the monopolist firm. Once monthly revenues are calculated, we discount revenues back to the first period of the data. Although the results illustrate an increase in hardware and software sales from a mixed bundling strategy, the timing of these additional adoptions is important. A console wants to sell as much hardware as early in its life cycle as possible, which results in an increase in software demand due to indirect network effects. Figure 7 depicts the important dynamics of how the hardware installed base under a console only
strategy differs from a mixed bundling strategy. We see that bundling is particularly successful in time-shifting purchases of consoles earlier in the lifecycle, due to the fact that the difference between the two regimes is positive for the entire 45 months but more importantly growing at an increasing rate for the early months of the life cycle.

Furthermore, this result is consistent with the theory of damaged goods, proposed by Deneckere and McAfee [1996], where the monopolist introduces a damaged version of a product to serve as a price discrimination tool to separate out consumers with different quality valuations. We thus find a new role for bundling in the creation of damaged goods, whereby bundling hardware and software increases consumer value for the bundle above the base hardware, but to a degree that is lower than the sum of the valuations for both. We expect this novel role for bundling to be especially useful in settings where one of the products (at least) has low marginal costs of production, and be appropriate for bundling. We also note that our result on negative synergy and its consequent implications have not been examined in the literature, to the best of our knowledge.

![Figure 7: Counterfactual 1: Dynamics of Installed Base](image)
Table 7: Counterfactual 2: Only Pure Bundling

<table>
<thead>
<tr>
<th></th>
<th>Model (Base)</th>
<th>CF (Pure Bundling)</th>
<th>Model-CF</th>
<th>% Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Console Sales</td>
<td>25,850,560</td>
<td>17,967,960</td>
<td>7,882,600</td>
<td>30.50%</td>
</tr>
<tr>
<td>Bundle Sales</td>
<td>270,445</td>
<td>5,427,608</td>
<td>-5,157,163</td>
<td>-1906.91%</td>
</tr>
<tr>
<td>Independent Software Sales</td>
<td>77,646,591</td>
<td>64,323,653</td>
<td>13,322,938</td>
<td>17.15%</td>
</tr>
<tr>
<td>Integrated Software Sales</td>
<td>39,206,491</td>
<td>29,545,896</td>
<td>9,660595</td>
<td>24.64%</td>
</tr>
<tr>
<td>Discounted Revenue</td>
<td>2,256,663,786</td>
<td>1,788,045,253</td>
<td>468,618,533</td>
<td>20.76%</td>
</tr>
</tbody>
</table>

Next, we evaluate the scenario where we consider pure bundling as an alternative, and where consumers must buy a bundle in order to own a console. Counterfactual 3 examines the scenario of removing pure consoles from the choice sets of consumers. However, it is worth noting that bundles are not present in every period and we allow the standalone console to be sold in those periods. We expect that such a strategy would not be as profitable as the mixed bundling strategy since mixed bundling has an additional tool (standalone console price) to more efficiently extract consumer surplus. We find this to be the case. Table 7 provides the simulation results while Figure 12 illustrates the change in the installed base over time. We again see the same pattern as the first counterfactual scenarios—consumers postponing consumption in the counterfactual exercise. However, unlike the previous results consumers wait to purchase only the console (seen from the sharp increase in Figure 12). The end result of only selling the bundle is detrimental—revenues decrease by roughly 21% over the mixed bundling scenario, total number of bundles or consoles sold declines by 2.725 million, and total software units fall by 23 million with a decline of roughly 10 million integrated software sales.

Our results from the structural model point to the finding that consumer value for hardware and software are highly positively correlated. While this result is not surprising, given that consumers value the overall experience from gaming, which requires them to purchase both hardware consoles and software games, it raises the question of whether bundling would be more effective or less effective in cases where the firm bundles products that may not be positively correlated. Note that a primary explanation in the literature for the prevalence of bundling has been that a higher degree of negative correlation is more helpful for firms to extract surplus [McAfee et al., 1989, Schmalensee, 1984], since consumers become more homogeneous in their valuation of the bundle in the presence of negative correlation. However, these models take a static view, and our incorporation
Figure 8: Counterfactual 2: Dynamics of Installed Base

of dynamics in the model results leads us to find support for the opposite view. We examine the
effect of correlation empirically in Counterfactual 4 by setting the correlation parameter $\rho = 0$, which implies that consumer preferences for hardware and software are uncorrelated. Note that we
do not alter any other aspect of consumer behavior, including the marginal distributions from which
we draw the hardware and software valuation for heterogeneous consumers. The results from Table 8
indicate that surprisingly, bundle sales and overall sales are actually higher with positive correlation
compared with the case of zero correlation, and that bundling is relatively more profitable with positive correlation. Moreover, the impact of bundling is substantially less effective when consumer preferences are independent than when they are positively correlated, and hardware revenues also
decline due to the reduced effectiveness of bundling. Our simulation also predicts total software
sales decline, which is a result of consumers who have higher value for hardware and are early
buyers purchase fewer software titles compared to the case with $\rho > 0$. Thus, the effectiveness of
bundling as a product strategy is enhanced in the presence of positive correlation between consumer
preferences for hardware and software. Our finding that correlation of preferences plays a significant
role in the effectiveness of a bundling strategy has not, to the best of our knowledge, been empirically
recognized and quantified. It is perhaps instructive to highlight the impact when we take the extreme
case of perfect negative correlation, $\rho = -1$. Under this scenario, a consumer who values hardware
highly and purchases early in the console life cycle would not purchase software until later in the life
cycle when prices of software fall. Moreover those who would purchase software early do to having
Table 8: Counterfactual 3: No correlation in Software and Hardware Preferences

<table>
<thead>
<tr>
<th>Model (Base)</th>
<th>Model (⇢ = 0)</th>
<th>CF (⇢ = 0)</th>
<th>Model (⇢ = 0) - CF (⇢ = 0)</th>
<th>% Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Console Sales</td>
<td>25,850,560</td>
<td>25,881,852</td>
<td>26,115,217</td>
<td>-233,365</td>
</tr>
<tr>
<td>Bundle Sales</td>
<td>270,445</td>
<td>244,257</td>
<td>0</td>
<td>244,257</td>
</tr>
<tr>
<td>Independent Software Sales</td>
<td>77,646,591</td>
<td>42,290,552</td>
<td>42,032,986</td>
<td>257,566</td>
</tr>
<tr>
<td>Integrated Software Sales</td>
<td>39,206,491</td>
<td>23,759,929</td>
<td>23,700,803</td>
<td>59,126</td>
</tr>
<tr>
<td>Discounted Revenue</td>
<td>2,256,663,786</td>
<td>1,822,231,074</td>
<td>1,817,638,228</td>
<td>4,592,846</td>
</tr>
</tbody>
</table>

Table 9: Counterfactual 4: Effect of increased Indirect Network Effect

<table>
<thead>
<tr>
<th>Model (Base)</th>
<th>Model (NE)</th>
<th>CF (NE)</th>
<th>Model (NE)-CF(NE)</th>
<th>% Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Console Sales</td>
<td>25,850,560</td>
<td>28,803,356</td>
<td>29,080,577</td>
<td>-277,221</td>
</tr>
<tr>
<td>Bundle Sales</td>
<td>270,445</td>
<td>278,937</td>
<td>0</td>
<td>278,937</td>
</tr>
<tr>
<td>Independent Software Sales</td>
<td>77,646,591</td>
<td>84,484,517</td>
<td>84,444,965</td>
<td>39,552</td>
</tr>
<tr>
<td>Integrated Software Sales</td>
<td>39,206,491</td>
<td>43,724,713</td>
<td>43,801,551</td>
<td>-76,838</td>
</tr>
<tr>
<td>Discounted Revenue</td>
<td>2,256,663,786</td>
<td>2,587,638,469</td>
<td>2,583,446,020</td>
<td>4,192,449</td>
</tr>
</tbody>
</table>

a high preference for games do not do so because they do not buy the hardware until late in the life cycle, again when prices are lower. Thus, there is a mismatch in dynamic preferences between hardware and software that would not have been obvious without modeling consumer preferences as correlated.

Finally, we examine Counterfactual 4, where we investigate whether an increase in the indirect network effect makes bundling as a product strategy more or less attractive. We set the marginal benefit of an additional game to increase by altering the parameter ρ so to be 10% higher, which allows us to determine dynamic comparative statics of the network effect. Consumers thus attach a greater utility to the present discounted utility of game titles in this counterfactual. In Table 9, we find that a higher network effect increases both hardware and software sales, as expected, and leads to a 14.9% increase in overall discounted revenues. Moreover, we find that bundling has a smaller effect when the indirect network effect is stronger, suggesting that its use as a product strategy is likely to be less effective in markets with strong interdependencies between hardware and software. Thus, we find that bundling could serve as a substitute to network effects rather than as a complement, and expect bundling to be more effectively used in cases where the firm is not able
to create a product with strong indirect network effects.

**Discussion, Limitations and Conclusion**

We have examined the impact of bundling decisions of firms on consumer choices and market outcomes in a platform setting, using data from the handheld video game market. Such a setting involves consumer purchases of durable goods that are characterized by indirect network effects, and where dynamics are especially important. We develop a dynamic structural model based on individual maximizing behavior, where consumers face a choice of consoles, bundles and video games. Consumers first enter the market for hardware (consoles), and enter the software (video games) market after they make a hardware purchase. The model allows for forward-looking consumers who have expectations over the future evolution of hardware and video games, and captures this effect in a tractable manner, and builds upon recent work by Gowrisankaran and Rysman [2009].

We set out to examine how bundling as a product strategy affects sales of consoles (cannibalization) as well as video games, how the presence of indirect network effects interacts with bundling, and whether alternative strategies like pure bundling may perform more effectively in place of mixed bundling. We find that console sales (pure console & consoles in bundles) diminish in the absence of bundling, implying that consumers who had purchased bundles may not always purchase pure consoles, even though consoles may be cheaper than bundles. Video game sales drop by 0.9 million units and the overall discounted revenue reduces by more than $26.9 million. Thus, we identify, characterize and measure the value of bundling on the demand side.

Our dynamic demand model helps us evaluate whether bundling complementary products actually creates more value for consumers, over and above the components of the bundle, that we termed the *synergy effect (informational leverage)*. We find that consumers do not value the synergy between the components of a bundle, i.e. a console and video game, but rather perceive a bundle to be a *damaged good*, in the sense of Deneckere and McAfee [1996]. This finding implies that low-priced bundles may serve as a price-discrimination mechanism to appeal to consumers with a lower valuation for hardware and a low taste parameter for software, i.e. they do not value a specific software title, so it serves as a damaged good to other users. Note that this is a different mechanism than the traditionally conceptualized manner of reducing consumer heterogeneity in valuation. Bundling is a flexible product strategy option that allows firms to create entire product lines where only one
product existed. In fact, mixed bundling proves better in segmenting consumers than pure bundling, since there is significant heterogeneity in valuation of specific video games. While our findings on bundling are especially true for information goods with low or zero marginal costs, its effectiveness as a product strategy would be interesting to examine in other markets.

This study could be enhanced by further work that could remove the limitations below. First, we develop a model based on individual consumers with forward-looking behavior but only have access to aggregate market-level outcome data. While this limitation is shared by most empirical studies of durable goods, having access to dis-aggregate individual-level data would enable us to better examine the heterogeneity in consumer behavior, and could lead to more precise marketing suggestions. Second, our model could be extended to include supply-side considerations, and evaluate optimal choices of pricing as well as bundling, from the viewpoints of product positioning and product introduction time frames. Third, we do not model competition between various video games that are available to consumers and assume that each game is its own market. While it becomes quickly intractable to model competition between all games, it might be useful to explore approaches incorporating competition from 'similar' games.

While our results lay the ground for a more empirically grounded understanding of bundling, there remain several interesting avenues for further research. It would be useful to examine the dynamic introduction and phase-outs of bundles, including the choice of games to be included in bundles and the choice of whether exclusive software should be marketed only as part of bundles. Another prospect is to evaluate the competitive dynamics between firms in introducing bundles, and in characterizing the incentives of third-party game producers to sell their products bundled with consoles. More broadly, our examination of the role for bundling brings up the issue of how firms ought to think about product line decisions for individual products when bundling permits the creation of differentiated products that can be designed to be temporary or persist for long periods.

References


Appendix A: Computational Details

Recall that we implement heterogeneity in preferences for software and hardware by implementing a Gaussian-Hermite quadrature approach. Specifically, we approximate a multi-dimensional integral as a weighted sum of the integrand evaluated at a finite set of well-specified points called $N$ nodes (or discrete groups of people) with weights $\lambda$ (or fraction of people). Since we introduce two degrees of heterogeneity we elect to employ the Gaussian Product Rule to determine the corresponding nodes and weights. Formally, we do so by computing these nodes by forming all possible tensor products of the nodes which are associated with the one dimensional rule. The corresponding weights are the product of the weights which again correspond to ten one-dimensional nodes [Skrainka and Judd, 2011]. Consequently, we evaluate the integrand at 100 points. However, given the dynamic nature of the problem, the associated weights given from the product rule only correspond the first period. In periods $2, \ldots, T$, weights evolve according to who remains in the market for either hardware or software. Further discussion on how these weights evolve follow below.

Our estimation procedure follows these steps for a given parameter $\Theta$:

i) Hardware Adoption: for a given $\Theta$ determine the mean handheld console utilities which match predicted shares of the model to observed data shares. Then, update the distribution (weights) of consumer types who own handhelds $\lambda$.

As G&R illustrate, mean hardware utilities are sufficient to recover the expected probability of purchasing a specific piece of hardware in period $t$ for consumer $i$.

$$\hat{s}_{iht}(\delta) = \frac{\exp(\delta_t)}{\exp\left(\sum_i EV_i(\delta_t) - \kappa\right)} \frac{\exp(\delta_{ht})}{\exp(\delta_t)}$$

Yet, given our data is aggregate market shares and not individual probabilities we aggregate over individual purchase probabilities to determine the predicted aggregate market share $\hat{s}_{ht}(\delta)$. More specifically,

$$\hat{s}_{ht}(\delta) = \sum \lambda_{i,t} \hat{s}_{iht}(\delta)$$

where $\lambda_{i,t}$ are the weights from above, which evolve over time and are determined by the population who have purchased in prior periods. Updating $\lambda_{i,t}$ involves determining market shares in the first period given $\lambda_{i,t=0}$ and then computing the distribution of consumers who remain in the
market according to the following rule:

\[ \lambda_{i,t+1} = \frac{M_{t=0} \lambda_{i,t=0} \prod_{t=0}^{T} (1 - s_{i,t})}{\sum_{i=1}^{I} (M_{t=0} \lambda_{i,t=0} \prod_{t=1}^{T} (1 - s_{i,t}))} \]

where \( s_{i,t} \) is the probability a consumer buys a piece of hardware in period \( t \). We also implement the standard value function iteration procedure with cubic interpolation between the 40 discrete grid points to calculate the expected value function in period \( t \). This procedure is run in each stage of the contraction mapping introduced in [Berry et al., 1995] to recover mean consumer hardware utilities. Once we recover mean hardware utilities, we recover the structural error term via the method in BLP.

ii) Software Adoption: Given the distribution of consumers who own a handheld, compute the mean software utilities that matches predicted shares to observed shares in the data. Like the hardware side, mean software utilities are sufficient to recover the expected probability of purchasing a specific piece of software in period \( t \). Our model predicts the share of people who purchase title \( k \) in period \( t \) is

\[ \hat{s}_{ikt} = I \sum_{i=1}^{I} \lambda_{ik,t} \hat{s}_{ikt} \]

where \( \lambda_{ik,t} \) is the share of consumers of type \( i \) who own a piece of hardware and have yet to purchase software \( k \), either individually or in a bundle. Note that the share of consumers is a function of console adoption decisions of consumers in all periods prior to and including period \( t \). The procedure for recovering mean software utilities follow quite closely to the methodology employed in the hardware adoption section above. We employ the identical contraction mapping procedure and use the same standard value function iteration procedure with cubic interpolation between 40 discrete grid points to calculate the expected value function in period \( t \).

iii) Compute the GMM objective function defined above.

**Calculation of the Present Discounted Software Value:**

Given that we do not introduce any heterogeneity among how consumers value the present discounted value of software available to them in a given period we are able to determine this value outside of the model. We do so by first assuming that consumer expectations for the number of
available games in period \( t \) follows an AR(1) process

\[
N_{t+1}^G = \gamma_1 + \gamma_2 N_t^G + \epsilon_t
\]

where \( \epsilon_t \sim N(0, \sigma^2) \) and where \( \gamma_1 \) and \( \gamma_2 \) are incidental parameters. After estimating the above equation we recover the expected value function in each period

\[
W(N_t^g) = E\left[\sum_{k=0}^{\infty} \beta^k \alpha^g N_{t+k}^g | N_t \right]
\]

with forward simulation of the evolution of software out to period \( T = 150 \) for a set of \( n_{sim} = 5,000 \) individuals. We then average over the individuals to determine the present discounted software value in period \( t \). It is important to note, however, that we are again able to do such a calculation prior to estimation because the marginal utility of an additional game \( \alpha^g \) can be factored out of the above equation and estimated in the identical manner as consumer price sensitivities.

**Appendix B: Model Fit**

Table 10 presents the seasonally adjusted raw sales data and the model predictions. As the table illustrates, our above model does quite nicely in predicting console and bundle sales. We determine the model has a prediction error of 0.44\% for hardware and 6.59\% for software, which indicates the model over predicts sales. We note that our prediction errors correspond quite favorably with other results Carranza [2010], Gowrisankaran et al. [2010].

<table>
<thead>
<tr>
<th>Data</th>
<th>Model</th>
<th>Prediction Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hardware Sales</td>
<td>26,244,205</td>
<td>26,121,005</td>
</tr>
<tr>
<td>Software Sales</td>
<td>108,933,410</td>
<td>116,853,082</td>
</tr>
<tr>
<td>Discounted Revenue</td>
<td>2,112,881,756</td>
<td>2,256,663,786</td>
</tr>
</tbody>
</table>

We also assess model fit by reporting the average console estimation error term over the 45 month time period. Figure 9 presents this information. From this figure we see no evidence of systematic auto-correlation or heteroscedasticity of the average console error term over the time period.
Next, to further determine the appropriateness of the IVS assumption, that consumers form expectations about next periods inclusive value with only information on today’s inclusive value and a simple autoregressive specification, we plot the error term from the console and software decision problems \((\delta_{i,t+1,c} - (\gamma_{i,1,c} + \gamma_{i,2,c} \delta_{i,t,c}))\) and \((\gamma_{i,t+1,s} - (\gamma_{i,1,s} + \gamma_{i,2,s} \delta_{i,t,s}))\). Recall that the IVS assumption tractably captures all of the information about future product introductions and prices as well as any key variables over which consumers have expectations; it is useful to note that despite such simplification, we find the error terms to be essentially unpredictable.

Figure 10 show errors terms that fluctuate quite drastically between negative and positive values
as well as show no sign of any trend to becoming more negative or positive over time for both
the console and software. These results inform us that a consumer’s miscalculation of expected
future values are driven by unanticipated changes in product attributes over time, leading to the
conclusion that the IVS assumption we impose on consumer expectations about how the future
evolves is reasonable.