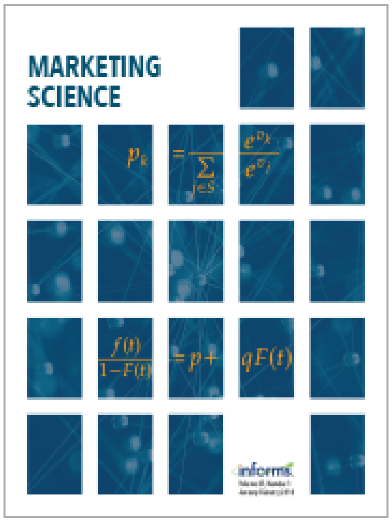

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Dynamic Demand for New and Used Durable Goods Without Physical Depreciation: The Case of Japanese Video Games

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Abstract. For information/digital products, the used goods market has been viewed as a threat by producers. However, it is not clear whether this view is justified because the used goods market also provides owners with an opportunity to sell their products. To investigate the impact of the used goods market on new goods sales, we collect a unique data set from the Japanese video game market. On the basis of the data, we develop and estimate a new dynamic structural model of consumers' buying and selling decisions. The estimation results show that potential buyers' consumption value from a game deteriorates by 50% from the release week to the second week, and game owners' consumption value deteriorates by 23%–58% after the first week of ownership, and the rate depends on game characteristics. Examination of the cross-price elasticities suggests that the elasticities tend to be high especially when the used-game inventory at retailers is low, but they quickly decrease as the inventory is accumulated. Using the estimates, we quantify the impact of eliminating the used game market on publishers' profits and consumer welfare. We find that holding the new-copy price at the observed level, this policy would increase publishers' profits by 7.3% but reduce the consumer surplus by 0.9%, resulting in an overall decrease in social surplus by 0.3%. However, if firms adjust prices optimally, it would increase the profits by 26.8% and also increase the consumer surplus by 1.4% owing to lower new game's prices. Overall, the social surplus increases by 2.7%.

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1. Introduction

The existence of used goods markets has been viewed as a serious problem by producers in information/digital product categories such as books, CDs/DVDs, and video games. They argue that the competition from used goods significantly lowers their profits and reduces the incentive to develop new products. For instance, book publishers and authors expressed their annoyance to Amazon over used books sold on its websites (Tedeschi 2004). Video game publishers in Japan attempted to kill off used video game retailing by suing used video game retailers (Hirayama 2006). Their main argument is that although products like books and video games physically depreciate negligibly, owners' consumption values can decline very quickly because of satiation. As a result, unlike products that physically depreciate more considerably over time (such as cars), producers of information/digital products may face competition from used goods that seem to be almost identical to new goods soon after the release of a new product.

However, their argument focuses only on one aspect of used goods markets (substitution effect) and ignores the possibility that costs of buying and selling used goods could reduce the substitutability between new and used goods. Moreover, the existence of used goods markets provides consumers with a selling opportunity. If consumers are forward-looking and account for the future resale value when making a buying decision, the effective price consumers pay for a product will be lower than the actual price (resale effect). This feature implies that the existence of used goods markets could increase the sales of new goods. Thus, whether the existence of used goods markets hurts or benefits new-good producers is an empirical question, and the answer depends on which effect, substitution or resale effect, dominates. The objective of this paper is to use a structural modeling approach to address this research question.

The question of whether used goods markets help or hurt new-good producers has been investigated in the automobile market (e.g., Esteban and Shum 2007, Schiraldi 2011, Chen et al. 2013) and the housing market (e.g., Tanaka 2013). A general finding among these papers is that the elimination of used goods markets helps new-good producers. For example, Chen et al. (2013) find that opening the used good market lowers firms' profits by 35%. However, it is not clear whether these findings can be extended to other markets where the sales of new goods is highly concentrated around the release period and declines quickly afterward (e.g., books, pop songs, video games). If the incentive for consumers to buy new goods in the release period is largely driven by the future resale opportunity, then the elimination of the used goods market could significantly reduce the initial sales of new copies, and new-good producers might not be able to recover its initial loss in subsequent periods even if cannibalization from used goods is eliminated.

This paper addresses these issues and contributes to the existing literature in two important dimensions. First, we assemble a new data set from the Japanese video game market, which includes weekly aggregate level data for 20 video game titles released in Japan between 2004 and 2008. The novel aspect of this data set is that, in addition to the sales and prices of new and used goods, which are the main variables studied in previous works, it includes three new important variables: (i) resale values of used goods,[1] (ii) quantities of used goods retailers purchased from consumers, and (iii) aggregate inventory level of used goods at retailers. This novel data set allows us to empirically capture important distinctions between video games and other typical durable goods, such as cars and houses, studied in previous works. One common feature assumed in most of the previous research (both theoretical and empirical) is that durability is measured by the quality deterioration rate, and it is common across buyers and sellers. This assumption will likely be violated in information/digital product categories such as CDs/DVDs and video games because for product owners, consumption values deteriorate mainly due to satiation (satiation-based deterioration); but for potential buyers, consumption values may deteriorate due to freshness of a product (freshness-based deterioration). Our new data on used game trading activities (weekly used-copy quantities demanded and supplied by consumers and associated weekly prices and resale values) help separately identify these two forms of consumption value deterioration.

Second, on the basis of the data set and institutional details about the video game market, we develop and estimate a new structural model of consumers' buying and selling decisions of durable goods that do not exhibit physical depreciation. To our knowledge, this is the first dynamic model of forward-looking consumers that incorporates all of the following features: (i) new and used goods buying decisions, (ii) used goods selling decision, (iiia) consumer expectations about future prices of new and used goods, (iiib) consumer expectations about future resale values and inventory levels of used goods, (iv) costs of buying and selling used goods, (v) the impact of used goods availability on buying decisions, and (vi) deterioration of both owners' and potential buyers' consumption values. In particular, features (iiib)–(vi) are new to the literature. In our model, the expected discounted value of future payoffs from buying a product is determined by a dynamic consumer selling decision problem, which depends on the deterioration rate of owners' consumption values and future resale values. This modeling approach allows us to study the role of consumer expectation about future price, resale value, and inventory of used copies on current buying decisions.

We estimate our discrete choice dynamic programming model using the generalized method of moments (GMM). The preference parameter estimates suggest that consumer heterogeneity in price sensitivity and costs of buying and selling used copies plays an important role in explaining the observed sales paths and substitution patterns. The demand patterns are well-explained by three types of consumers: (1) consumers who purchase new copies and become the supplier of used copies in the used goods market (approximately 2% of the population), (2) consumers who purchase new and used copies but hardly sell (approximately 49% of the population), and (3) consumers who purchase new copies and sell, but their buying and selling probabilities are much lower than those for the first type of consumers; this type of consumers account for the majority of nonpurchasers (approximately 49% of the population).

Using the estimated model, we conduct counterfactual experiments and quantify the impact of eliminating the used video game market on new-copy sales, profits, consumer surplus, and social surplus. We first conduct an experiment by holding the prices of new copies at the observed level. We find that the profits improve by 7.3%, but the consumer welfare decreases by 0.9%, resulting in an overall decrease in social surplus by 0.3%. We then compute the optimal prices of new copies when there is no used game market and quantify the change in profits, consumer surplus, and social welfare. We find that the optimal flat prices are on average 37% lower than the observed prices, and the elimination of the used video game market would increase the profits of new-game publishers by 26.8% and the consumer surplus by 1.4%. Interestingly, the consumer surplus improves even though the used-game market is eliminated, and this is primarily due to the lower new game's prices.

The rest of the paper is organized as follows. Section 2 reviews the previous literature. Section 3 describes the Japanese video game data used in this paper and presents some empirical regularities that have not been documented in the previous literature. Section 4 describes the dynamic discrete choice model of consumer buying and selling decisions. Section 5 explains the estimation strategy and identification. In Section 6, we discuss the parameter estimates and the counterfactual experiment results. Section 7 concludes.

2. Literature Review

There is a large body of theoretical literature in economics and marketing that analyzes the interaction between new and used durable goods. Theoretical studies in economics are mainly concerned with durability choice, pricing, the role of market frictions, etc., for durable goods monopolists (e.g., Swan 1970, Bulow 1986, Rust 1986, Anderson and Ginsburgh 1994, Waldman 1996, Hendel and Lizzeri 1999, Johnson 2011). In marketing, several papers examine a variety of marketing practices in new and used durable goods markets, including leasing contracts (e.g., Desai and Purohit 1998, 1999), channel coordination (Desai et al. 2004, Shulman and Coughlan 2007), trade-ins (Rao et al. 2009), and retail versus peer-to-peer used goods markets (Yin et al. 2010). These studies provide important theoretical foundation for our research question. For example, in the seminal work, Swan (1970) shows that the existence of used goods markets does not affect profits of a monopoly producer (Swan's Independence Result). Rust (1986) develops an equilibrium model that relaxes the assumption of exogenous scrappage value of used goods and finds that under certain conditions it is optimal for a monopoly producer to kill off used goods markets by setting zero durability.

Our empirical setting is related to Johnson (2011), who develops a model whereby used goods trading is driven by changing consumer valuation (rather than quality deterioration and consumers with heterogeneous sensitivity to quality). He considers a situation in which consumer valuation of a product declines owing to consumption and finds that when the marginal cost of production is sufficiently small, it is optimal for a monopoly producer to shut down used goods markets. One important distinction between our model and Johnson's is that he assumes a constant arrival rate of new consumers every period (e.g., new students for textbook purchase every semester), whereas our model is best described as an optimal stopping problem in which the initial set of consumers make buying and selling decisions over time.

Empirical studies on the impact of used goods markets on new-good producers' profits and social welfare mostly focused on cars and houses (e.g., Purohit 1992, Esteban and Shum 2007, Engers et al. 2009, Schiraldi 2011, Chen et al. 2013, Tanaka 2013). A notable exception is Shiller (2013), who recently investigated this question in the context of the U.S. video game market. However, owing to the limited data availability, he focuses only on data from used game exchange through online auctions, which is a relatively small portion of the entire used game trading.

These papers find that the elimination of used goods markets helps new-good producers. However, it is not clear about the robustness of this result because their demand models all rely on some strong assumptions: (i) resale value equals used good price; (ii) the used good market clears every period. Our data show that these assumptions are far from a good approximation for the Japanese video game market—we consistently observe used good price to be significantly higher than resale values, and there is excess supply of used goods. Thus, our dynamic structural demand model will control for both resale values and used good prices, and it will not impose the market-clearing condition in the used goods market. In particular, we will take advantage of the observed aggregate inventory of used copies and allow the cost of buying a used copy to depend on it (to capture the idea that a high inventory level may reduce the search cost of finding a used copy at retailers). Additionally, by separately observing buying and selling behaviors, we can identify the two forms of consumption value deterioration.

Finally, our research contributes to structural works on video game markets (e.g., Nair 2007, Dubé et al. 2010, Liu 2010, Lee 2013) and demand models for durable goods in general (e.g., Song and Chintagunta 2003, Gordon 2009, Carranza 2010, Goettler and Gordon 2011, Gowrisankaran and Rysman 2012, Melnikov 2013). We extend the literature by incorporating rich features into a model of consumers' buying and selling decisions for new and used goods, and we examine the potential impact of the used good market on the demand for new games, firms' profits, consumer welfare, and social welfare.

3. Background and Data

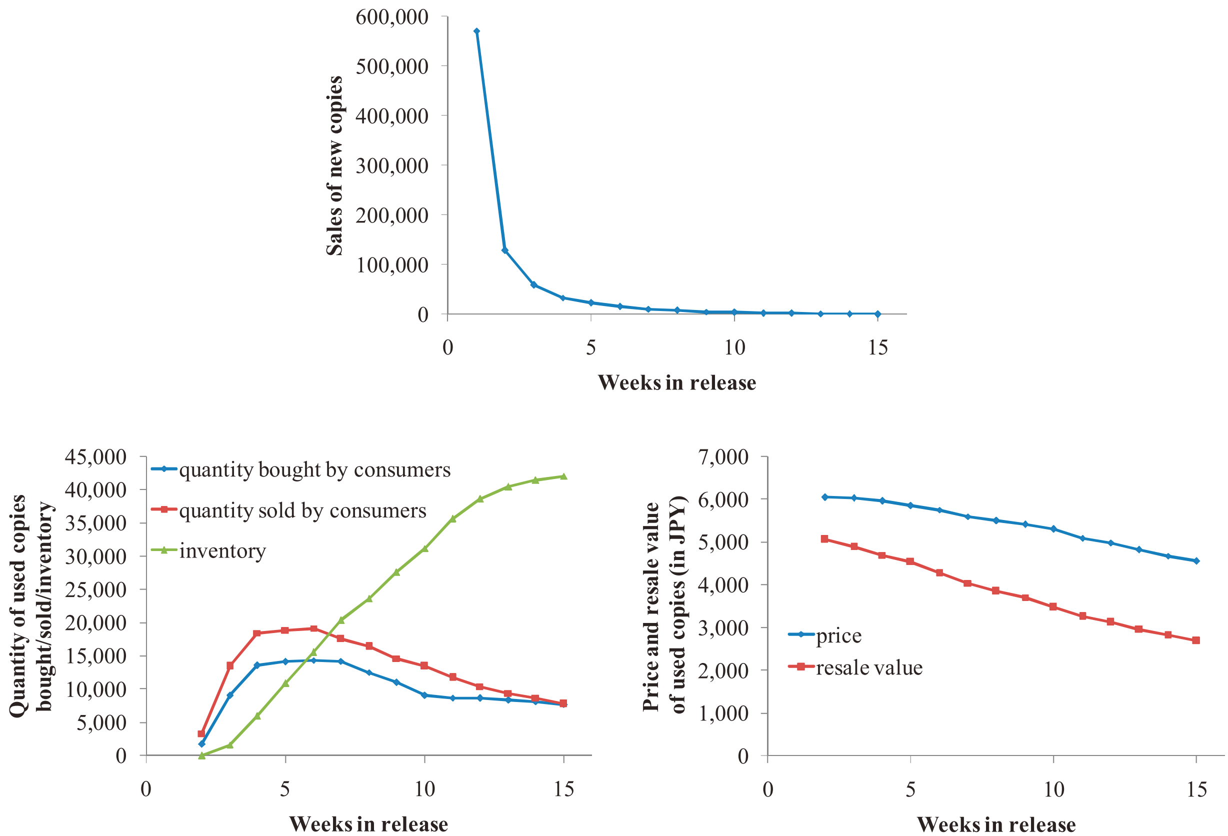
3.1. Japanese Video Game Industry

Since the mid-1980s, the Japanese video game market has grown rapidly. The size of the industry in 2009 reached $5.5 billion on a revenue basis (including sales of hardware, software, and other equipment). This is approximately three times larger than the theatrical movie revenue in Japan, and it has become one of the most important sectors in the Japanese entertainment industry. The video game publishers have considered the existence of the used good market a serious threat since the 1990s. In 2009 the sales of used video games (software) alone amounted to $1.0 billion on a revenue basis. One reason for the large used video game market in Japan could be that video game renting by third-party companies is prohibited by law in Japan.[2] Another reason argued by Hirayama (2006) is the flat-pricing strategy commonly adopted by video game publishers—the price of new games is maintained at the initial level at least one year after the release.[3] This may provide an opportunity for used goods market to grow and capture the segment of consumers who do not mind buying used goods. However, it can also be argued that the existence of the used market has induced publishers to adopt the flat-pricing strategy. Liang (1999) uses a theoretical model to show that when used goods markets are present, durable goods monopolists may be able to credibly commit to a high price (avoiding the Coase Conjecture).[4] Although investigating the optimality of the flat-pricing strategy is interesting, we will leave this topic for future research. Instead, we will take the flat pricing strategy as given and focus on understanding consumers' dynamic buying and selling decision problem.

3.2. Japanese Video Game Data

We have collected a data set of 20 video games that were released in Japan between 2004 and 2008.[5] The data come from several sources. For each video game, weekly aggregate sales of new copies and its manufacturer suggested retail price are obtained from the weekly top 30 ranking published in *Weekly Famitsu Magazine*, a major weekly video game magazine in Japan published by Enterbrain, Inc. The average number of weeks observed across games is nine weeks. In Japan, the sales of new copies sharply decline after the release week (see the top panel of Figure 1). In our data set, the median percentage of new game copies sold in the release week (relative to the total annual sales for the first year[6]) is 54%, and the median percentage of new game copies sold within the first month (four weeks) after release is 82%. Thus, the sales of new copies are highly concentrated within the first month in Japan. In addition to the data from the primary market, we have collected the following data for the used market by game title: we collected (i) weekly aggregate trading volumes (both buying and selling), (ii) weekly average retail prices, and (iii) weekly average resale values. The used market data are collected from the Annual Video Game Industry Report published by Media Create Co., Ltd.[7] The average number of weeks observed across games is 33 weeks. According to an annual industry report by Enterbrain, Inc., approximately 80% of used video game trading occurs at retailers during our sample period (Enterbrain, Inc. 2006). Thus, we do not consider other channels of selling used copies in our model (e.g., online auctions).

Figure 1. (Color online) Quantity of New Copies Demanded (Top), Quantity of Used Copies Demanded and Supplied, and Inventory Level (Bottom Left), and Price and Resale Value of Used Copies (Bottom Right)



We also collected video game characteristics from *Weekly Famitsu Magazine*, including average critic and user rating, story-based game dummy, and (offline) multi-player game dummy. During our sample period (2004–2008), online game features were limited, and most of our games are not social games that are played by a large number of users online. Finally, the potential size of market for a video game is measured by the installed base of the platform in which the video game was released. The platforms of the 20 games include three consoles (PlayStation 2, PlayStation 3, Nintendo GameCube). We collected the weekly sales of all three consoles above from their release week to calculate the cumulative sales.

Table 1 shows the summary statistics. The average price of used copies across games and weeks is approximately two-thirds of the price of a new copy. The average retailer markup for used copies is large: 1,687.2 in JPY (73.0%). This number is in contrast to the average retailer markup for new copies, which is 760 in JPY (approximately 10%) (Tachibana 2006), and provides strong incentives for retailers to trade used copies. The average relative size of the used game market to the new game market, defined as the ratio of cumulative sales of used copies to that of new copies at the end of the used-copy sales sample period, is 0.46, with a maximum of 0.63 and a minimum of 0.35.[8] Our data show that we have variation in the ratio across games, and it helps identify the difference in the utility function between new- and used-copy purchase after controlling for observed factors such as prices. Finally, the average market size (number of console owners) for a game is approximately 14 million, and this number is much larger than the average sales of new and used copies: for any given game in our sample, the percentage of console owners who buy it is at most 10%.

3.3. Some Empirical Regularities

In this section we will discuss some new empirical regularities along three dimensions: (i) the quantities of used goods demanded and supplied over time, (ii) the inventory level of used goods over time, and (iii) the price and the resale value of used goods.

The bottom left panel of Figure 1 plots the average quantities of used copies demanded and supplied, as well as the average inventory level of used copies over 15 weeks. The inventory level of used copies in week t for a game is defined as the difference between the cumulative quantity of used copies supplied by consumers up to week $t-1$ and the cumulative quantity of used copies demanded by consumers up to week $t-1$.

First, both quantities of used copies demanded and supplied sharply increase in the first few weeks after the opening of the used game market (second week after release), reach their peaks, and gradually decrease afterward. The initial increase is probably because it takes a few weeks for owners of a game to become satiated with their games. As the quantity of used copies supplied by owners increases, the sales of used copies also follows.

Second, on average, the inventory level of used copies carried by retailers grows in the first 15 weeks. Approximately half of the games in our data set exhibit a decline after some point during the sample period. It is clear that in the Japanese video game market, the used market does not clear in every period. As mentioned earlier, unlike previous studies that assume the used goods market clears in each period, we will make

Table 1. Summary Statistics

	Average	Standard deviation	Min	Max
Price of new copies (JPY)	7,613.1	629.1	7,140	9,240
Price of used copies (JPY)	4,515.3	1,087.8	2,219	7,433
Resale value of used copies (JPY)	2,828.1	1,182.7	1,036	6,547
Markup for used copies (JPY)	1,687.2	382.2	435	2,786
Markup for used copies (%)	73.0	36.5	7.3	210.7
Weekly sales of new copies	100,650.4	259,022.3	2,772	2,236,881
Weekly sales of used copies	7,184.6	6,478.8	458	62,734
Ratio of cumulative sales of used to new copies[a]	0.462	0.091	0.350	0.627
Weekly quantity sold by consumers	8,121.4	8,436.8	1,012	55,830
Weekly inventory of used copies	31,022.5	28,347.7	0	129,462
Market size (installed base)	14,866,067.6	6,097,167.2	746,971	20,822,775
Cumulative no. of games on the same platform	57.6	43.5	1	171
Cumulative no. of games on other platforms	72.6	58.0	0	273
Dummy for story-based games	0.700	0.470	0	1
Dummy for multi-player games	0.450	0.510	0	1
Critic rating (in 10-point scale)	8.99	0.656	7.75	10
User rating[b]	56.4	9.20	41.6	67.4

Note. USD 1 ≈ JPY 100.
[a]Computed by setting sales of new copies to zero for those weeks in which it is below top 30 ranking.
[b]User rating is a standardized score against a set of video games released in the same year (by Enterbrain, Inc.).

use of this excess supply information when estimating our dynamic model. Also note that although retailers accumulate used-copy inventory, their buy-early-sell-late strategy still allows them to make positive profits owing to a high markup.

Third, as shown in the bottom right panel of Figure 1, both the average price and resale value of used goods gradually decrease over time, and the resale value decreases slightly faster. This suggests that both potential buyers' and owners' consumption values deteriorate over time, and their deterioration rates could be different. We will incorporate these features into our model.

4. Model

In this section we present our dynamic discrete choice model of consumer buying and selling decisions for durable goods that do not depreciate physically. To make our presentation more concrete, we will describe our model in terms of video games, because this is the market that we will study. We assume that consumers make buying and selling decisions separately for each game.[9] Let i index consumers, g index games, and t index time. To capture consumer heterogeneity, we allow discrete consumer types. At the beginning of the initial period $t = 1$ (i.e., the period in which the new game is released), no consumers own game g, and used games are not available yet. Thus, consumers' decision problem in period $t = 1$ is to decide whether to buy a new good. In period $t > 1$, consumers who have not bought the game up to $t - 1$ observe the prices of new and used copies and the resale value and inventory level of used copies at retailers, and they decide whether to buy a new or used good or not to buy anything. Let $j = 0, 1, 2$ denote no purchase option, new good purchase, and used good purchase, respectively. If consumers have already bought game g before time t and have not sold it yet, then they observe the resale value and inventory level and decide whether to sell the game in period t. Let $k = 0, 1$ denote keeping and selling options, respectively. If consumers sell their game, they exit the market. Because video games will eventually become outdated, we assume a terminal period $t = T$ after which consumers can neither buy nor sell. For consumers who own the game and did not sell at the terminal period, we allow them to continue to enjoy the game for additional T' periods (with appropriate satiation-based deterioration).

Motivated by the institutional details, our model assumes that (i) the price of new copies is constant over time ($p_{1t} = p_1\ \forall t$); (ii) physical depreciation for games does not affect their functional values but only affects their appearance, and thus consumption value from a new copy is identical to that from a used copy[10]; (iii) the decision to buy a used copy may be influenced by factors other than consumption values and prices (such as the availability of used copies at retailers, psychological cost for using preowned goods, etc.); and (iv) products do not generate network externality.[11]

We will first describe the single-period utility functions for buying and selling decisions and then move to the description of the value functions.

4.1. Single-Period Utility Functions

In each period, consumers derive a consumption value from owning game g. Let $v^g(t,\tau)$ be a consumer's single-period consumption value of game g at time t if he has owned game g for τ periods before time t. Note that if a consumer buys game g at time t, he will receive $v^g(t,0)$ in that period; if he then keeps it at time $t+1$, he will receive $v^g(t+1,1)$. Later in this section we will describe how we allow the two forms of deterioration, freshness-based and satiation-based, to affect the consumption value over time.

Suppose that a consumer has not bought game g up to time $t > 1$. Consumer i's single-period utility for buying decisions at time t is given by:

$$u^g_{ijt} = \begin{cases} v^g(t,0) - \alpha_i p^g_{1t} + \gamma D^g_t + \xi^g_{1t} + \epsilon^g_{i1t} & \text{if buying a new copy } (j=1),\\ v^g(t,0) - \alpha_i p^g_{2t} - l_Y(Y^g_t;\lambda_i) + \gamma D^g_t + \xi^g_{2t} + \epsilon^g_{i2t} & \text{if buying a used copy } (j=2),\\ l_C(C^g_t;\pi) + \epsilon^g_{i0t} & \text{if no purchase } (j=0), \end{cases} \tag{1}$$

where p^g_{1t} (p^g_{2t}) is the price of new (used) copies of game g at time t; ξ^g_{1t} (ξ^g_{2t}) is the unobserved demand shock to the demand for new (used) copies; α_i is the price sensitivity; and D^g_t is a vector of holiday dummies and γ captures the holiday effects on sales. As justified by the stylized facts discussed earlier, we assume that the price of new copies is constant over time (i.e., $p^g_{1t} = p^g_1$ for all t) in our application to the Japanese video game market. We assume that Y^g_t is the retailers' aggregate inventory level of used copies for game g at the beginning of period t. $l_Y(Y^g_t;\lambda_i)$ is the one-time cost that consumers incur when buying a used good (search costs, psychological costs for preowned games, etc.), and λ_i is a vector of parameters. In our empirical specification, we specify

$$l_Y(Y^g_t;\lambda_i) = \lambda_{0i} + \lambda_1 \exp(-\lambda_2 Y^g_t) \tag{2}$$

to capture the ideas that (i) consumers might be heterogeneous in psychological costs for preowned games (λ_{0i}) and (ii) search costs may depend on the availability of used copies Y^g_t, and the effect is measured by (λ_1, λ_2). The heterogeneity in λ_{0i} is motivated by a consumer survey conducted by Enterbrain, Inc., which shows that approximately 15% of consumers never intend to purchase a used copy.[12]

This suggests that there is a segment of consumers who have high psychological costs of buying a used copy. This reduced-form specification implies that when no used copies are available at the beginning of a period (i.e., $Y_t^g = 0$),[13] the cost is $\lambda_{0i} + \lambda_1$. If λ_1 and λ_2 are positive, the cost of buying a used copy decreases as Y_t^g increases; in particular, as the availability of used copies increases to infinity, the cost approaches λ_{0i}.

C_t^g is the cumulative number of games introduced on the console for game g at time t since the introduction of game g (including the games released in the same week as game g), and $l_C(C_t^g; \pi)$ captures the competitive effect from other newly introduced games. In our application, it is specified as

$$l_C(C_t^g; \pi) = \pi_1 \ln(1 + C_t^g). \tag{3}$$

We assume that idiosyncratic errors, ϵ_{ijt}^g, are independently and identically distributed (*i.i.d.*) across consumers and time but allow them to be correlated across options j. We model the correlation in a nested logit framework. Let $\epsilon_{ijt}^g = \zeta_{iht}^g + (1 - \rho_b) v_{ijt}^g$, where ζ_{iht}^g and v_{ijt}^g are extreme value distributed, and h indexes nest and takes two possible values: $h = 1$ groups the buying options (i.e., buying a new or used copy), and $h = 0$ is the no-purchase option. Thus, the consumer buying decision problem here is equivalent to a two-stage decision making whereby consumers first decide whether to buy, and if buying, then choose a new or used copy. In this setup, the parameter $\rho_b \in [0, 1)$ measures the within-nest correlation. If $\rho_b = 0$, then our model reduces to a multinomial logit model.

Next, consider consumers' selling decisions. Suppose that a consumer has bought game g and kept it for τ periods. Consumer i's single-period utility for selling decisions at time t is given by

$$w_{ikt}^g(\tau) = \begin{cases} \alpha_i r_t^g - \mu_i + \xi_{st}^g + e_{i1t}^g & \text{if selling to a retailer } (k = 1), \\ v^g(t, \tau) + e_{i0t}^g & \text{if keeping the game } (k = 0), \end{cases} \tag{4}$$

where r_t^g is the resale value of game g at time t; μ_i captures any additional cost of selling (cost to go to a retailer to sell in person, endowment effects, etc.) and is allowed to depend on consumer type. This is again motivated by the same consumer survey by Enterbrain, which indicates that not all consumers sell their games; ξ_{st}^g is the unobserved shock to owners for selling decisions at time t; e_{ikt}^g is an idiosyncratic error, and we assume it is *i.i.d.* extreme value distributed across consumers and time, with zero mean and the scale parameter ρ_s.

For the single-period consumption value, $v^g(t, \tau)$, we will assume the following evolution over time. In the release period, we set $v^g(1, 0) = c^g$, where c^g is a game-specific constant. To capture the freshness-based deterioration, we model $v^g(t, 0)$ as a function of t. Let $\varphi(t)$ be the freshness-based deterioration rate from t to $t+1$, and we assume $v^g(t+1, 0) = (1 - \varphi(t)) v^g(t, 0)$, where

$$\varphi(t) = \frac{\exp(\phi_1 \mathbb{I}(t = 1) + \phi_2 \mathbb{I}(t > 1))}{1 + \exp(\phi_1 \mathbb{I}(t = 1) + \phi_2 \mathbb{I}(t > 1))}, \tag{5}$$

$\mathbb{I}(\cdot)$ is an indicator function.

Note that we treat the freshness-based deterioration in the first period ($\varphi(t = 1)$) to be different from the rest of the periods ($\varphi(t > 1)$). This is motivated by the observations that the sales of new copies from the release week to the second week usually suffer from the largest decline in the video game market.[14]

Next, we model the satiation-based deterioration rate as a function of observed product characteristics and the duration of ownership. Consider a consumer who has owned game g for $\tau \geq 0$ periods before time t. If she does not sell the game at time t, she enjoys the consumption value $v^g(t, \tau)$. We assume that the consumption value deteriorates as $v^g(t+1, \tau+1) = (1 - \kappa(X^g, \tau)) v^g(t, \tau)$, where $\kappa(X^g, \tau)$ is the rate of satiation-based deterioration, and X^g is a vector of observed product characteristics of game g (in our application, we include an intercept, dummies for story-based games and multi-player games, and average critic and user ratings). We model $\kappa(X^g, \tau)$, the deterioration rate from τ to $\tau + 1$, as

$$\kappa(X^g, \tau) = \frac{\exp(\sum_{k=1}^{5} \delta_k X_k^g + \delta_6 \tau)}{1 + \exp(\sum_{k=1}^{5} \delta_k X_k^g + \delta_6 \tau)}. \tag{6}$$

We allow the satiation-based deterioration rate to change as the duration of ownership (τ) increases. For example, if δ_6 is positive, the rate becomes higher as τ increases (i.e., more satiation-based deterioration for additional period of ownership).

In summary, v^g evolves as follows: before purchase, v^g starts with $v^g(1, 0) = c^g$ at $t = 1$ and deteriorates at the rate of $\varphi(t)$. Suppose that a consumer purchased the game at time t'. Then, from that period on, v^g deteriorates at the rate of $\kappa(X^g, \tau)$. That is, at the time of buying at time t', $v^g(t', 0) = c^g \prod_{t=1}^{t'-1} (1 - \varphi(t))$. After purchase and owning the game for τ periods, the consumption value at time $t' + \tau$ becomes $v^g(t' + \tau, \tau) = v^g(t', 0) \prod_{t=t'}^{t'+\tau-1} \cdot (1 - \kappa(X^g, t - t'))$. We note that although we do not explicitly model heterogeneity in v^g, the above formulation implies that game owners' consumption value is heterogeneous and depends on the timing of purchase.

Finally, we emphasize that our proposed model allows for consumer heterogeneity in price sensitivity (α_i), and the costs of buying (λ_{0i}) and selling (μ_i) a used copy. In addition, game owners are heterogeneous with respect to (t, τ): owners' consumption value depends on when they bought the game and how long they have kept it.[15] In general, other preference parameters, such as initial consumption value, freshness- and satiation-based deterioration rates, etc., could be heterogeneous. We have experimented with several other specifications and found that after controlling for consumer heterogeneity in $(\alpha_i, \lambda_{0i}, \mu_i)$, heterogeneity in other preference parameters does not play a significant role in explaining the observed sales pattern. We provide more details on this in Appendix A.1.

4.2. Value Functions and Choice Probabilities

Because the dynamic consumer selling decision problem is nested within the dynamic consumer buying decision problem through the expected future payoff, we start off by describing the dynamic consumer selling decision problem, and we then describe the dynamic buying decision problem. To simplify the notation, we will drop g superscript.

Let $s_{i,t,\tau} = (\eta_{ist}, Y_t, t, \tau)$ be the vector of state variables relevant to the selling decision problem for consumer i who has owned the game for τ periods by time t, where η_{ist} is defined as

$$\eta_{ist} = \alpha_i r_t + \xi_{st}. \tag{7}$$

We interpret η_{ist} as a type-specific price-adjusted unobserved shock to selling decision. Because the resale value is part of η_{ist}, we include Y_t in $s_{i,t,\tau}$ and allow consumers to use Y_t to predict η_{ist+1} (implicitly via r_{t+1}). Let $W_i(s_{i,t,\tau})$ be the integrated value function (or Emax function) of the selling decision problem for consumer i, and $W_{ik}(s_{i,t,\tau})$ be the corresponding alternative-specific value function for action k. Let β be the discount factor common across consumers. The Bellman equation can be written recursively as

$$\begin{aligned} W_i(s_{i,t,\tau}) &= E_e \max_{k\in\{0,1\}} \{W_{ik}(s_{i,t,\tau}) + e_{ikt}\} \\ &= \rho_s \ln\left\{\sum_{k\in\{0,1\}} \exp\left(\frac{W_{ik}(s_{i,t,\tau})}{\rho_s}\right)\right\}, \end{aligned} \tag{8}$$

where the second equality follows from the assumption that e_{ikt}'s are extreme value distributed with the scaling parameter ρ_s, and

$$W_{ik}(s_{i,t,\tau}) = \begin{cases} \eta_{ist} - \mu_i & \text{if selling } (k = 1), \\ v(t,\tau) + \beta E[W_i(s_{i,t+1,\tau+1}) | s_{i,t,\tau}] & \text{if keeping } (k = 0). \end{cases} \tag{9}$$

The expectation in $E[W_i(s_{i,t+1,\tau+1})|s_{i,t,\tau}]$ is taken with respect to η_{ist+1} and Y_{t+1}. We will discuss the specification of consumer expectation processes in the next section.

Assuming that e_{ikt}'s follow the *i.i.d.* extreme value distribution, the probability of selling the game by consumer i at $s_{i,t,\tau}$ is given by

$$\Pr(k = 1|s_{i,t,\tau}; i) = \frac{\exp\left(\frac{W_{i1}(s_{i,t,\tau})}{\rho_s}\right)}{\sum_{k'=0}^{1} \exp\left(\frac{W_{ik'}(s_{i,t,\tau})}{\rho_s}\right)}. \tag{10}$$

Next, consider the dynamic consumer buying decision problem. Let $b_{i,t} = (\eta_{i1t}, \eta_{i2t}, \eta_{ist}, Y_t, C_t, t)$ be the vector of state variables relevant to the buying decision problem, where η_{ijt} is defined as

$$\eta_{ijt} = -\alpha_i p_{jt} + \xi_{jt} \quad \text{for } j = 1, 2. \tag{11}$$

Again, we interpret η_{ijt} as a type-specific price-adjusted shock to buying decision. Let $V_i(b_{i,t})$ be the integrated value function for consumer i who has not bought the game before time t, and $V_{ij}(b_{i,t})$ be the corresponding alternative-specific value function of action j. The Bellman equation is given by

$$\begin{aligned} V_i(b_{i,t}) &= E_\epsilon \max_{j\in\{0,1,2\}} \{V_{ij}(b_{i,t}) + \epsilon_{ijt}\} \\ &= \ln\left\{\exp(V_{i0}(b_{i,t})) + \left[\sum_{j\in\{1,2\}} \exp\left(\frac{V_{ij}(b_{i,t})}{1-\rho_b}\right)\right]^{1-\rho_b}\right\}, \end{aligned} \tag{12}$$

where

$$V_{ij}(b_{i,t}) = \begin{cases} v(t,0) + \eta_{i1t} + \beta E[W_i(s_{i,t+1,\tau=1})|s_{i,t,\tau=0}] \\ \qquad \text{if buying new copy } (j = 1), \\ v(t,0) + \eta_{i2t} - l_Y(Y_t; \lambda_i) + \beta E[W_i(s_{i,t+1,\tau=1})|s_{i,t,\tau=0}] \\ \qquad \text{if buying used copy } (j = 2), \\ l_C(C_t; \pi) + \beta E[V_i(b_{i,t+1})|b_{i,t}] \\ \qquad \text{if no purchase } (j = 0). \end{cases} \tag{13}$$

The expectation in $E[V_i(b_{i,t+1})|b_{i,t}]$ is taken with respect to η_{i1t+1}, η_{i2t+1}, η_{ist+1}, Y_{t+1}, and C_{t+1}.

The choice probability for option j by consumer i at $b_{i,t}$ is given by

$$\Pr(j|b_{i,t}; i) = \Pr(h = 1|b_{i,t}; i) \cdot \Pr(j|h = 1, b_{i,t}; i), \tag{14}$$

where

$$\Pr(h = 1|b_{i,t}; i) = \frac{\left[\sum_{j'=1}^{2} \exp\left(\frac{V_{ij'}}{1-\rho_b}\right)\right]^{1-\rho_b}}{\exp(V_{i0}) + \left[\sum_{j'=1}^{2} \exp\left(\frac{V_{ij'}}{1-\rho_b}\right)\right]^{1-\rho_b}}, \tag{15}$$

$$\Pr(j|h = 1, b_{i,t}; i) = \frac{\exp\left(\frac{V_{ij}}{1-\rho_b}\right)}{\sum_{j'=1}^{2} \exp\left(\frac{V_{ij'}}{1-\rho_b}\right)}. \tag{16}$$

Given the finite-horizon assumption, the value functions for both buying and selling decisions can be computed by backward induction from the terminal period, T.

In our application, we set $T = 100$. We assume that after the terminal period, consumers can neither buy nor sell but can continue enjoying the game if they have bought it by the terminal period. We thus assume that consumers who own the game at the end of $t = T$ derive a terminal value equal to the present discounted value of future consumption utilities, taking the satiation-based deterioration into account. In the empirical application, we approximate it by the present discounted value of consumption values for another 100 periods (i.e., $T' = 100$) beyond the terminal period.

4.3. Consumer Expectation Processes

In both dynamic buying and selling decision problems, the time since release (t) and duration of ownership (τ) evolve deterministically and increase by one every period. The remaining state variables are ($\eta^g_{i1t}, \eta^g_{i2t}, \eta^g_{ist}, Y^g_t, C^g_t$). We assume that consumers perceive that these state variables follow a conditional first-order Markov process. Our approach is similar to Hendel and Nevo (2006), Gowrisankaran and Rysman (2012), and Lee (2013), who argue that a first-order Markov process is a reasonable approximation to consumer expectations.[16] Février and Wilner (2016) provide empirical evidence to support such an approximation approach.

Assumption 1. *We assume that consumers perceive that $\eta^g_{i1t}, \eta^g_{i2t}, \eta^g_{ist}, Y^g_t$, and C^g_t follow a conditional first-order Markov process. Let $D^g_{t,k}$ be a holiday dummy for Golden Week ($k = 1$) and Christmas ($k = 2$),[17] and X^g be a vector of observed game characteristics (an intercept, dummies for story-based games, and multi-player games, and average critic and user ratings).*

1. *For ($\eta^g_{i1t}, \eta^g_{i2t}, \eta^g_{ist}$), we assume the following functional form for consumer i:*[18]

$$\begin{aligned}\eta^g_{ijt+1} &= \varpi_{ij,0} + \varpi_{ij,1}\eta^g_{ijt} + \varpi_{ij,2}Y^g_t \\ &\quad + \sum_{k=1}^{2}(\varpi_{ij,2+k}D^g_{t,k} + \varpi_{ij,4+k}D^g_{t+1,k}) \\ &\quad + \sum_{k=1}^{5}\varpi_{ij,6+k}X^g_k + \varepsilon^g_{ijt+1}, \quad j = 1,2, \\ \eta^g_{ist+1} &= \varpi_{is,0} + \varpi_{is,1}\eta^g_{ist} + \varpi_{is,2}Y^g_t \\ &\quad + \sum_{k=1}^{2}(\varpi_{is,2+k}D^g_{t,k} + \varpi_{is,4+k}D^g_{t+1,k}) \\ &\quad + \sum_{k=1}^{5}\varpi_{is,6+k}X^g_k + \varepsilon^g_{ist+1},\end{aligned}$$

where $\varepsilon^g_{ijt} \sim N(0, \sigma^2_{\varepsilon_{ij}})$ for $j = 1,2$ and $\varepsilon^g_{ist} \sim N(0, \sigma^2_{\varepsilon_{is}})$.

2. *For Y^g_t, we assume the following functional form is common across all consumers:*

$$\begin{aligned}Y^g_{t+1} &= \varpi^Y_0 + \varpi^Y_1 Y^g_t + \sum_{k=1}^{2}(\varpi^Y_{1+k}D^g_{t,k} + \varpi^Y_{3+k}D^g_{t+1,k}) \\ &\quad + \sum_{k=1}^{5}\varpi^Y_{5+k}X^g_k + \varepsilon^g_{Yt+1},\end{aligned}$$

where $\varepsilon^g_{Yt} \sim N(0, \sigma^2_{\varepsilon_Y})$.

3. *For C^g_t, we assume the following functional form for each console m (PlayStation 2, Nintendo GameCube, and PlayStation 3) is common across all consumers:*

$$C^g_{t+1} = \varpi^C_{m0} + \varpi^C_{m1}C^g_t + \varepsilon^g_{Ct+1} \quad \textit{if game g's console is m},$$

where $\varepsilon^g_{Ct} \sim N(0, \sigma^2_{\varepsilon_{mC}})$ if game g's console is m.

4.4. Consumer Types, Aggregate Sales, and Evolution of Potential Buyers and Sellers

We model consumer heterogeneity by L discrete types. Let ψ_l be the population proportion of type-l consumers and $\sum_{l=1}^{L}\psi_l = 1$. To derive the aggregate demand for new and used copies and aggregate volume of used copies sold to retailers by owners, we need to derive the evolution of the size of each consumer type. Let M^d_{lt} be the size of type-l consumers who have not bought the video game. It evolves according to

$$M^d_{lt+1} = M^d_{lt}\left(1 - \sum_{j=1}^{2}\Pr(j|b_{l,t}; l)\right) + N_{lt+1}, \tag{17}$$

where N_{lt+1} is the size of new type-l consumers who enter the market at time $t+1$. We assume that the proportion of new type-l consumers follows the population proportion, ψ_l.[19]

Next, let $M^s_{lt}(\tau)$ be the size of type-l consumers who have bought and owned the game for τ periods at time t. It evolves according to

$$M^s_{lt+1}(\tau) = \begin{cases} M^d_{lt}\sum_{j=1}^{2}\Pr(j|b_{l,t}; l) & \text{for } \tau = 1, \\ M^s_{lt}(\tau-1)\cdot\Pr(k=0|s_{l,t,\tau-1}; l)) & \text{for } 1 < \tau \le t. \end{cases} \tag{18}$$

The aggregate demand for option j at state $b_t = \{b_{l,t}\}_l$ is then

$$Q^d_j(b_t) = \sum_{l=1}^{L} M^d_{lt}\Pr(j|b_{l,t}; l), \tag{19}$$

where $j = 1$ is new copies and $j = 2$ is used copies. The aggregate quantity supplied to retailers by consumers at state $s_t = \{s_{l,t,\tau}\}_{l,\tau}$ is given by

$$Q^s(s_t) = \sum_{l=1}^{L}\sum_{\tau=1}^{t-1} M^s_{lt}(\tau)\Pr(k=1|s_{l,t,\tau}; l). \tag{20}$$

5. Estimation Strategy

We estimate the consumer preference parameters using a GMM approach similar to Lee (2013). We start with the description of the moment conditions and discuss the market-share inversion procedure, the set of instruments used in this paper, and the identification strategy.

5.1. Moment Conditions

Assumption 2. *We assume that unobserved shocks to buying and selling decisions* $(\{\xi_{jt}^g\}_{j=1}^2, \xi_{st}^g)$ *follow a first-order autoregressive process, where the errors*

$$\nu_{jt}^g = \xi_{jt}^g - \omega_d \xi_{jt-1}^g, \quad \nu_{st}^g = \xi_{st}^g - \omega_s \xi_{st-1}^g \tag{21}$$

are mean zero and independent across time (t) *and games* (g). *Let* $\{Z_{jt}^g, Z_{jt,\Delta}^g\}_{j=1}^2, Z_{st}^g$, *and* $Z_{st,\Delta}^g$ *be vectors of instruments. Then we assume that*

$$E[Z_{jt}^g \nu_{jt}^g] = 0, \quad E[Z_{jt,\Delta}^g \Delta\nu_{jt}^g] = 0 \quad \text{for } j = 1, 2,$$
$$E[Z_{st}^g \nu_{st}^g] = 0, \quad E[Z_{st,\Delta}^g \Delta\nu_{st}^g] = 0,$$

where $\Delta\nu_{jt}^g = \nu_{jt}^g - \nu_{jt-1}^g$ *and* $\Delta\nu_{st}^g = \nu_{st}^g - \nu_{st-1}^g$.

This specification allows for a possibility that the unobserved shocks to buying and selling decisions could be correlated over time. We then generate moment conditions based on $(\{\nu_{jt}^g\}_{j=1}^2, \nu_{st}^g)$ instead of directly working on $(\{\xi_{jt}^g\}_{j=1}^2, \xi_{st}^g)$. Moreover, following Lee (2013), we use both levels and first differences of $(\{\nu_{jt}^g\}_{j=1}^2, \nu_{st}^g)$, which have been shown to be helpful (Arellano and Bover 1995, Blundell and Bond 1998).

5.2. Obtaining $(\{\nu_{jt}^g\}_{j=1}^2, \nu_{st}^g)$: Inversion of the Demand System

We define the mean-utility levels for buying and selling decisions as the mean of the type-specific price-adjusted unobserved shocks across consumers:

$$\eta_{jt}^g = -\bar{\alpha} p_{jt}^g + \xi_{jt}^g \quad \text{for } j = 1, 2, \text{and } \eta_{st}^g = \bar{\alpha} r_t^g + \xi_{st}^g,$$

where $\bar{\alpha}$ is the average price sensitivity. Let $\theta^d = (\{c^g\}, \alpha, \gamma, \lambda, \mu, \pi, \phi, \delta, \rho)$. For each trial parameter vector, we start with an initial guess $(\{\eta_{jt}^{g,0}\}_{j=1}^2, \eta_{st}^{g,0})$. Let n be the current iteration for the inversion of the demand system. Given $(\{\eta_{jt}^{g,n}\}_{j=1}^2, \eta_{st}^{g,n})$, we first estimate the expectation processes for $(\{\eta_{ljt}^g\}_{j=1}^2, \eta_{lst}^g)$ for each consumer type l. We then compute the value functions $(V_l(b_{l,t}), W_l(s_{l,t,\tau}))$ by backward induction and compute the predicted volume of used copies bought and sold by consumers $(\{Q_{jt}^d\}_{j=1}^2, Q_t^s)$. We then update the vector of $(\{\eta_{jt}^g\}_{j=1}^2, \eta_{st}^g)$ by

$$\eta_{jt}^{g,n+1} = \eta_{jt}^{g,n} + \ln(\mathbf{q}_{jt}^{d,g}) - \ln(Q_{jt}^{d,g}(\eta_1^{g,n}, \eta_2^{g,n}, \eta_s^{g,n}, \theta^d)) \quad \text{for } j = 1, 2,$$
$$\eta_{st}^{g,n+1} = \eta_{st}^{g,n} + \ln(\mathbf{q}_t^{s,g}) - \ln(Q_t^{s,g}(\eta_1^{g,n}, \eta_2^{g,n}, \eta_s^{g,n}, \theta^d)),$$

where $\mathbf{q}_{jt}^d$ and $\mathbf{q}_t^s$ are observed quantities of new copies $(j = 1)$ and used copies $(j = 2)$ demanded and sold by consumers for game g at time t, respectively. Given the updated vector $(\{\eta_{jt}^{g,n+1}\}_{j=1}^2, \eta_{st}^{g,n+1})$, we repeat the above procedure until convergence. With $(\{\eta_{jt}^g\}_{j=1}^2, \eta_{st}^g)$ and Equation (21), we can $(\{\nu_{jt}^g\}_{j=1}^2, \nu_{st}^g)$ as

$$\nu_{jt}^g = \eta_{jt}^g - \omega_d \eta_{jt-1}^g + \bar{\alpha}(p_{jt}^g - \omega_d p_{jt-1}^g) \quad \text{for } j = 1, 2, \tag{22}$$
$$\nu_{st}^g = \eta_{st}^g - \omega_s \eta_{st-1}^g - \bar{\alpha}(r_t^g - \omega_s r_{t-1}^g). \tag{23}$$

We provide the details of the estimation procedure for our model in Appendix A.2.

5.3. Instruments

In this subsection, we will describe our instruments in $\{Z_{jt}^g, Z_{jt,\Delta}^g\}_{j=1}^2, Z_{st}^g$ and $Z_{st,\Delta}^g$ and discuss what model assumptions are necessary for making them valid.

For Z_{1t}^g, because the new-copy price of a game is constant over time and the utility for buying a new copy includes game-specific consumption value, we only include in Z_{1t} a vector of included exogenous variables such as game-fixed effects and their interaction with game age, which are also included in Z_{2t}^g and Z_{st}^g.

The elements in Z_{2t}^g and Z_{st}^g are used for innovations in shocks for used-copy buying and selling. We assume that used-copy retailers observe ξ_{2t}^g and ξ_{st}^g (i.e., they observe ν_{2t}^g and ν_{st}^g) before used-copy price and resale value are determined. The assumption that ξ_{2t}^g and ξ_{st}^g follow an AR(1) process implies that lagged values of used-copy price and resale value are correlated with their current values. However, because we assume the innovations in unobserved shocks, ν_{2t}^g and ν_{st}^g, are *i.i.d.* across time, lagged values of used-copy price and resale value are uncorrelated with them.[20] Hence, as the second set of instruments, we will include $(p_{2,t-1}^g, p_{2,t-2}^g)$ in Z_{2t}^g, and (r_{t-1}^g, r_{t-2}^g) in Z_{st}^g.

Note further that the current period used-copy inventory (Y_t^g) is the starting inventory in the current period (Section 4.1, below Equation 1). That is, Y_t^g is determined before the realization of ν_{2t}^g and ν_{st}^g at time t. Hence, it is uncorrelated with ν_{2t}^g and ν_{st}^g. This argument also implies that lagged used-copy inventory is also a valid instrument. Therefore, as the third set of instruments, we include (Y_t^g, Y_{t-1}^g) in both Z_{2t}^g and Z_{st}^g.

The next set of instruments for used-copy price and resale value are based on Lee (2013).[21] It captures potential cost shifters for used-game retailers. First, for the price (resale value) of an m-week old game in calendar week n, we compute the average price (resale value) of m-week old games released before the focal game (i.e., these games became m-week old before calendar week n, and these games may have been released at different points in calendar time). This average price (resale value) captures any common shocks associated with a certain game age to used-game retailers, beyond the age effect on demand.

By construction, these past games were m-week old before calendar week n. Thus, the average price (resale value) is independent of the innovations in unobserved shocks for the focal game in calendar week n. We include this average price (resale value) in Z^g_{2t} (Z^g_{st}).

Second, for a game in calendar time n, we compute the average price (resale value) in calendar time n of all games available on platforms other than the focal game's platform. This variation captures calendar-time-specific shocks to costs common across all games in the same calendar week. Because ν^g_{2t} and ν^g_{st} are assumed to be *i.i.d.* across games, this average price (resale value) is a valid instrument. We include this average price (resale value) in Z^g_{2t} (Z^g_{st}).

Finally, we include one- and two-period lagged values of $\{\eta^g_{jt}\}^2_{j=1}$ and η^g_{st} as instruments in $\{Z^g_{jt}\}^2_{j=1}$ and Z^g_{st}, respectively, for identifying ω_d and ω_s. For $\{Z^g_{jt,\Delta}\}^2_{j=1}$ and $Z^g_{st,\Delta}$, we include the same set of instruments lagged by one additional period.

As a validity check, we conduct the first-stage regressions of used-copy price and resale value, both in levels and first-differences, on excluded instruments, and find that they are reasonable instruments. See Appendix A.3 for the detail of the first-stage analysis.

5.4. Identification

In this section we provide an informal discussion for the identification of our proposed model. To facilitate our discussion, we first describe the identification when there is no heterogeneity in the costs of buying and selling a used copy and price sensitivity (i.e., $\lambda_{0l} = \lambda_0$, $\mu_l = \mu$, and $\alpha_l = \alpha$ for all l). We then discuss what data variation helps us identify the heterogeneity. We note that the identification of our model parameters relies on the parametric assumptions made on the utility functions.

We first consider the price sensitivity (α), the impact of used-copy inventory on the costs of buying a used copy ($\lambda_0, \lambda_1, \lambda_2$), and the competitive effect (π_1) in $l_C(C^g_t; \pi)$. These are identified by variation in the sales of new and used copies, and the variation in used-copy prices and resale values, used-copy inventory, and the number of competing games, respectively. The within-group correlation (ρ_b) is identified by the extent to which the conditional market share of new (or used) copies is correlated with the unconditional market share of new (or used) copies (Berry 1994). The scaling parameter for selling decision (ρ_s) is identified because the price sensitivity parameter is common in both buying and selling decisions, and the scaling parameter of the idiosyncratic errors for buying decision (the error associated with the first-stage decision of the nested logit model) is normalized to one.

The game-specific constant (c^g) is identified by the level of sales over time for each game. The freshness-based deterioration rate (φ's), which is common across games, is identified by the average declining rate of sales of new games across games over time. Given c^g, φ's and α, the parameters that determine the satiation-based deterioration rate (δ's), which is a function of observed game characteristics, and the cost of selling (μ) are identified by the variation in the volume of used copies sold by consumers to retailers over time across games. Holiday effects (dummies for Golden Week and Christmas holidays) are identified by the variation in sales due to holidays across games and across years.

We should note that the functional form assumption is part of the structure of the model. It allows game characteristics to explain the demand for new games, and demand and supply for used games in a parsimonious way. However, we find that this basic structural model is not flexible enough to explain the actual data patterns. We therefore allow for unobserved consumer types to introduce more flexibility to the model. As we discussed in the Model section, the unobserved heterogeneity is well-motivated by the survey done by Enterbrain, Inc.

To explain the intuition about how the heterogeneity parameters ($\alpha_l, \lambda_{0l}, \mu_l$) and the proportion of each consumer type (ψ_l) are identified, let us consider a two-period model and assume away *i.i.d.* idiosyncratic errors in the utility function.

We start with the identification of the proportion of each type (ψ_l). In a two-period model, we need four types of consumers to explain the data: (type-i) consumers who buy a new copy in period 1 and sell in period 2; (type-ii) consumers who buy a used copy in period 2; (type-iii) consumers who buy a new copy in period 1 and do not sell in period 2; and (type-iv) consumers who do not buy at all.[22] The proportion of type-i consumers can be identified by the observed amount of used copies supplied in period 2 (because only type-i consumers will supply used copies). The proportion of type-iv consumers can also be identified because they are simply the consumers who did not buy at all. Given the proportion of type-i, we can identify the proportion of type-iii consumers according to the observed market share of new copies in period 1 (it represents the sum of type-i and type-iii consumers). The proportion of type-ii can be identified by the observed market share of used copies sales in period 2. If we extend the model to a three-period model, it can be shown that in the absence of *i.i.d.* idiosyncratic errors, we need to add at least one more type of consumers to the model (we need at least one more type of consumers who only buys used copies in period 3). In general, an N-period model would require at least $N + 2$ types of consumers to explain the data.

The *i.i.d.* extreme value idiosyncratic error term makes the demand (and supply) a smooth function of the parameters. This helps us to reduce the need of having more types in a multiperiod model. In the above example, when we extend the model to have three periods, even if we keep the number of consumer types unchanged, the logit demand model can still explain why some consumers choose to buy used copies in period 3. With market share data, we can essentially treat each observed market share as a moment. Intuitively, what the estimation procedure does is pick the parameter values to match these moments as closely as possible. In our estimation results, we find that three types of consumers are sufficient to fit the data very well. On the basis of their choice probabilities, they can be characterized as follows: (1) consumers who buy new games and sell them to the used game market but almost never buy used games (similar to type-i in the two-period model example above); (2) consumers who buy new and used games but hardly sell them (similar to a combination of type-ii and type-iii above); and (3) consumers who seldom buy any games but when they buy are likely to sell them to the used game market (similar to a combination of type-i, type-ii, and type-iv above).

6. Results

6.1. Parameter Estimates

We allow for three types of consumers who differ in their price sensitivity and costs of buying and selling at used goods retailers (i.e., α_l, λ_{0l}, and μ_l). We fix the discount factor at 0.86 on the basis of the value of the GMM objective function: we estimate the model at $\beta = 0.83, 0.84, \ldots, 0.95$, and the GMM objective function displays a U-shape with the lowest value attained at $\beta = 0.86$.[23] The parameter estimates for the demand model and consumer expectation processes are reported in Tables 2 and 3, respectively.

We start with the demand estimates in Table 2. All of the parameters show the expected signs. Price-sensitivity parameters (α_l) are positive because it enters the utility function as a negative term. The magnitudes of the price coefficients (α_l's) are relatively small (note that prices are in JPY, and 1 JPY $\simeq$ 0.01 U.S. dollar). We find that type-1 consumers (approximately 2% of the console owners) have the smallest price coefficient, type-2 consumers (approximately 49 of the console owners) have the intermediate price coefficient, and type-3 consumers (approximately 49% of the console owners) have the largest price coefficient. Mainly because of the high price coefficient, type-3 consumers have the lowest probability of purchasing a game among the three segments, and they account for the overall low probability of purchase (relative to the number of console owners) for each game.

As for the cost of buying a used copy ($\lambda_{0l}, \lambda_1, \lambda_2$), recall that we use the following functional form: $l_Y(Y_t^g; \lambda_l) = \lambda_{0l} + \lambda_1 \exp(-\lambda_2 Y_t^g)$. The estimates for λ_1 and λ_2 are positive, indicating that the (search) cost of buying a used copy decreases as the inventory level rises. To quantify the range of the cost of buying a used copy in monetary terms, we divide l_Y by the price coefficient. As we will show later, we find that λ_{0l} for type-1 consumers is so large that they hardly purchase a used copy, even if the used-copy inventory level is high. The cost of buying a used copy falls in [303, 3,093] in JPY for type-2 consumers, and [744, 1,926] for type-3 consumers.[24] The average price difference between new and used copies in the first few weeks is approximately JPY 1,500. Thus, when the used-copy inventory is very low in the first few weeks, they will also purchase new copies. As the used-copy inventory increases, some of their demand will shift to used copies. We also find a significant difference in the selling costs between these three types. Type-1 has the lowest cost, type-3 has the intermediate cost, and type-2 has the highest cost. In Section 6.2 we will illustrate how the heterogeneity in the costs of buying and selling a used copy leads to different new- and used-copy buying and selling patterns across types.

We find that both the Golden Week and Christmas season have a positive impact on sales. The parameter for the competitive effect from other games on the same console (π_1) is positive, suggesting that the increasing number of new game introductions may make it less attractive for consumers to buy the focal game.

Parameters for the freshness-based deterioration rate include two parameters (ϕ_1 for the first week, and ϕ_2 from the second week on). The estimated deterioration rate from the first to the second week (captured via ϕ_1) is approximately 50%, and that from the second week onward (captured via ϕ_2) is 2.7%. These numbers are consistent with the observed pattern of the sales of new copies, which declines quickly during the first two weeks after release.

For the deterioration rate of owners' consumption values due to satiation, we include the following product characteristics in X^g: an intercept, story-based game dummy, multi-player game dummy, and average critic and user rating. A positive coefficient of a variable implies that the variable will increase the deterioration rate. Our estimates suggest that story-based games and multi-player games exhibit a lower deterioration rate. Depending on product characteristics, the weekly deterioration rate for owners from $\tau = 0$ to $\tau = 1$ ranges from 23% to 58%. Finally, the duration of ownership has a positive, but not significant, effect on the deterioration rate.

Table 2. Demand Estimates

Variable	Estimate	Standard error
Preference parameters		
Discount factor (β)	0.860	Fixed
Price sensitivity		
Type 1 (α_1)	7.39e-5**	2.39e-5
Type 2 (α_2)	3.20e-4**	3.81e-5
Type 3 (α_3)	7.57e-4**	6.94e-5
Cost for buying a used copy		
Intercept: type 1 (λ_{01})	7.58**	1.99
Intercept: type 2 (λ_{02})	0.097*	0.045
Intercept: type 3 (λ_{03})	0.563	0.407
Inventory-related parameters		
Constant (λ_1)	0.894**	0.160
Coefficient for inventory level (λ_2)	9.46e-4**	2.08e-4
Cost for selling a used copy		
Type 1 (μ_1)	0.222	0.261
Type 2 (μ_2)	7.62**	1.60
Type 3 (μ_3)	3.19**	0.493
Holiday dummies		
Golden week (early May) (γ_1)	0.777**	0.138
Christmas (late December) (γ_2)	0.656**	0.105
Outside option		
Same-console competitive effect (π_1)	0.225**	0.019
Segment proportion		
Type 1 (ψ_1)	–3.27**	0.250
Type 2 (ψ_2)	–8.78e-4**	1.10e-4
Proportion of type 1	0.019**	0.005
Proportion of type 2	0.490**	0.002
Proportion of type 3	0.491**	0.002
Deterioration rates		
Potential buyers		
1st week ($\boldsymbol{\varphi}_1$)	0.002*	0.001
From 2nd week on ($\boldsymbol{\varphi}_2$)	–3.58**	0.696
Game owners		
Intercept (δ_1)	0.525**	0.179
Dummy for story-based games (δ_2)	–1.30**	0.456
Dummy for multi-player games (δ_3)	–0.003+	0.002
Critic rating (δ_4)	0.017	0.018
User rating (δ_5)	–0.008	0.007
Ownership duration (logged) (δ_6)	0.449	0.525
Parameters for error terms		
Within-group correlation for buying decision (ρ_b)	0.503**	0.038
Scaling parameter for selling decision (ρ_s)	0.520**	0.049
Serial correlation for buying decision (ω_b)	0.974**	0.009
Serial correlation for selling decision (ω_s)	0.941**	0.015
GMM objective function	754,545.1	

Notes. Twenty game-specific initial consumption values (c^g) are estimated but not reported here. Segment proportions are modeled by a logit formula and estimated ψ_1 and ψ_2.
+10% significance level; *5% significance level; **1% significance level.

The estimates for consumer expectation processes are reported in Table 3. Panel A shows the process for $\eta_{l1t}(=\xi_{1t})$, η_{l2t}, and η_{lst}. For each process, we include a lagged value as well as time- and game-specific controls. The values of R^2, which ranges from 0.808 to 0.963, indicate that these processes capture the evolution of the state variables well. We find that both time- and game-specific controls are important in predicting all processes. For example, Christmas dummy is negative for η_{l2t}-process (i.e., price-adjusted shock to buying a used copy), suggesting that consumers expect η_{l2t} to be lower in the Christmas week. However, lagged Christmas dummy is positive, suggesting that consumers expect η_{l2t} to be higher in the week after Christmas. Panel B shows the consumer expectation process for Y_t. Similar to panel A, we include a lagged value and time- and game-specific controls for Y_t-process. We find that used-copy inventory in the Christmas week tends to be higher than in other weeks and that game characteristics play an important role in predicting Y_t. For example, story-based games tend to have more inventory than

Table 3. Estimates for Consumer Expectation Processes

Panel A: Price-adjusted unobserved shocks

	ξ_{1t} (new copy demand)		η_{l2t} (used copy demand)						η_{lst} (used copy supply)					
			Type 1		Type 2		Type 3		Type 1		Type 2		Type 3	
Variable	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Lagged value	0.913**	0.028	0.888**	0.013	0.900**	0.013	0.901**	0.011	0.798**	0.021	0.749**	0.021	0.696**	0.018
Lagged inventory			3.01e-6**	5.26e-7	3.03e-6**	5.29e-7	3.39e-6**	5.58e-7	1.80e-7	8.63e-7	−9.24e-7	9.04e-7	−3.70e-6**	1.02e-6
Lagged golden week	0.677**	0.182	0.422**	0.053	0.389**	0.049	0.318**	0.047	−0.060	0.097	−0.045	0.097	−0.027	0.102
Lagged Christmas	0.109	0.157	0.502**	0.067	0.466**	0.061	0.396**	0.060	0.065	0.123	0.140	0.123	0.293*	0.130
Golden week	−1.07**	0.180	−0.482**	0.052	−0.441**	0.047	−0.372**	0.046	−0.005	0.096	−0.008	0.096	−0.013	0.101
Christmas	−0.271^{+}	0.160	−0.506**	0.064	−0.475**	0.058	−0.420**	0.057	−0.135	0.118	−0.181	0.119	−0.244^{+}	0.125
Story-based games	−0.021	0.115	−0.041	0.035	−0.028	0.032	−0.010	0.031	0.381**	0.075	0.452**	0.076	0.516**	0.076
Multi-player games	0.033	0.109	0.070^{+}	0.038	0.064^{+}	0.034	0.063^{+}	0.033	0.014	0.068	0.011	0.068	−0.009	0.072
Critic rating	0.063	0.070	−0.019	0.023	−0.022	0.021	−0.023	0.020	−0.133**	0.042	−0.138**	0.042	−0.121**	0.044
User rating	−0.003	0.005	0.004**	0.002	0.004**	0.001	0.004**	0.001	−0.002	0.003	−0.003	0.003	−0.005^{+}	0.003
Constant	−0.275	0.607	−0.155	0.210	−0.202	0.196	0.361^{+}	0.194	1.16**	0.380	1.42**	0.382	1.82**	0.401
SD of the error	0.419		0.263		0.240		0.233		0.485		0.486		0.512	
R^2	0.897		0.917		0.939		0.963		0.819		0.808		0.827	
No. of observations	152		667		667		667		667		667		667	

Panel B: Used-copy inventory level, Y_t

Variable	Estimate	SE
Lagged value	0.959**	0.006
Lagged golden week	−2,194.0**	929.9
Lagged Christmas	−2,120.6*	932.4
Golden week	1,797.6*	708.1
Christmas	1,215.4	915.7
Story-based games	1,582.6**	474.7
Multi-player games	−428.2	501.9
Critic rating	1,281.9**	310.8
User rating	−91.6**	21.0
Constant	−5,010.8^{+}	2,763.3
SD of the error	3,551.4	
R^2	0.984	
No. of observations	647	

Table 3. (Continued)

Panel C: Cumulative number of newly introduced games, C_t						
	PlayStation 2		Nintendo GameCube		PlayStation 3	
Variable	Estimate	SE	Estimate	SE	Estimate	SE
Constant	3.58**	0.225	0.375	0.334	0.475**	0.158
Lagged value	1.00**	0.003	1.02**	0.054	1.01**	0.011
SD of the error	2.80**	0.084	0.766**	0.124	0.806**	0.061

Note. SD, standard deviation; SE, standard error.
[+]10% significance level; *5% significance level; **1% significance level.

non–story-based games. Panel C shows the consumer expectation process for the cumulative number of newly introduced games. Because the frequency of new game introduction differs across game consoles, we estimate the process separately for the three consoles.

6.2. Roles of Heterogeneity in Transaction Costs

Having recovered three latent classes of consumers, we investigate how the heterogeneity in transaction costs generates different buying and selling decisions across consumer types. We use our simulation results to compute the average proportion of (i) new-copy sales, (ii) used-copy sales, (iii) volume of used copies supplied by owners, by consumer type. The results are reported in Table 4. The following patterns characterize the three consumer segments. Type-1 consumers have the smallest price coefficient and purchase new copies in the earlier weeks. However, because of their high cost of buying a used copy, they do not purchase used copies. Although type-1 consumers are a small proportion of the console owners (approximately 2%), 17.3% of new copy demand at $t = 1$ is generated by type-1 consumers. This is because of their high purchase probability as compared with the other two segments. As for the proportion of used-copy supply by type-1 consumers, it is initially smaller than that by type-3 consumers (44.6% versus 55.4%). This is because the resale value of used copies in the early weeks is high and type-3 consumers have a larger price coefficient than type-1 consumers. As the resale value decreases over time, type-3 consumers' incentive to sell decreases much more than type-1 consumers', resulting in an increase in the proportion of used-copy supply by type-1 consumers.

Type-2 consumers (approximately 49% of the console owners) explain a significant proportion of new-copy sales (approximately 75%). Although their choice probability of buying a new copy is much lower than type-1 consumers' (mainly owing to a larger price coefficient and a higher cost of selling), their large segment size makes them the main purchasers of new copies in terms of the breakdown. They also explain most of used-copy sales because their cost of buying a used copy is low. As for selling behavior, type-2 consumers hardly supply used copies because of their high cost of selling a used copy.

Type-3 consumers (approximately 49% of the console owners) have a small probability of buying a game because of their high price coefficient. However, because their segment size is large, they generate a nonnegligible amount of new- and used-copy sales. As we noted above, type-3 consumers also supply used copies, but the proportion explained by them decreases as the resale value decreases.

Table 4. Proportion of Predicted Quantities by Consumer Segment

	New-copy demand			Used-copy demand			Used-copy supply to retailers		
Weeks in release	Type 1	Type 2	Type 3	Type 1	Type 2	Type 3	Type 1	Type 2	Type 3
1	0.173	0.728	0.099	—	—	—	—	—	—
2	0.177	0.765	0.058	0.000	0.898	0.102	0.446	0.000	0.554
3	0.187	0.762	0.051	0.000	0.906	0.094	0.488	0.000	0.511
4	0.200	0.754	0.045	0.000	0.911	0.089	0.534	0.000	0.466
5	0.205	0.752	0.043	0.000	0.912	0.088	0.578	0.000	0.422
6	0.215	0.744	0.041	0.000	0.909	0.091	0.644	0.000	0.356
7	0.214	0.746	0.040	0.000	0.904	0.096	0.682	0.001	0.316
8	0.223	0.738	0.039	0.000	0.901	0.099	0.693	0.023	0.284
9	0.215	0.746	0.039	0.000	0.897	0.103	0.700	0.027	0.273
10	0.194	0.766	0.040	0.000	0.890	0.110	0.711	0.035	0.254
11	0.178	0.781	0.041	0.000	0.878	0.122	0.722	0.040	0.238
12	0.185	0.775	0.040	0.000	0.873	0.127	0.727	0.033	0.240
13	0.184	0.778	0.038	0.000	0.862	0.138	0.723	0.041	0.236
14	0.176	0.786	0.038	0.000	0.854	0.146	0.734	0.043	0.223
15	0.172	0.788	0.039	0.000	0.846	0.154	0.734	0.035	0.231

6.3. Elasticities and Switching Behavior

This section discusses elasticities of demand and supply and consumer switching behavior. The cross-price elasticity of demand between used and new copies will inform us of whether they are close substitutes from consumers' viewpoint. Moreover, our dynamic model is able to quantify (i) the inventory elasticities of demand, and (ii) the price elasticities of used-copy supply (i.e., volume sold to retailers by consumers). These two types of elasticities have not been examined in the literature because data on used-copy inventory and volume of used copies supplied were not available. Our results for these two elasticities may shed some light on why retailers accumulate used-copy inventory for future sales instead of procuring just enough for their current period sales.

Table 5 shows seven types of elasticities (labeled by E.1–E.4) and switching behavior (S.1 and S.2). E.1.1 and E.1.2 investigate the percentage change in the sales of new and used copies in week t in response to a 1% change in new-copy price, whereas E.2.1 and E.2.2 show the percentage change in the sales of new and used copies in response to a 1% change in used-copy price. In our application, new-copy price is constant over time. Thus, we consider a permanent 1% change in new-copy price (i.e., the price increases by 1% for all weeks and consumers are aware of it) and examine the change in the sales in each week. For used-copy price, we compute the change in the sales due to a temporal price change in a given week. Our primary focus here is on E.1.2 and E.2.1, which show the cross-price elasticity of demand for new and used copies, respectively.

Under E.1.2, a permanent 1% increase in new-copy price increases the demand for used copies in week 2 by 3.1%. This high percentage is driven mainly by very small base sales of used copies in week 2. As time goes on, the cross-price elasticity quickly drops in weeks 3–5 and gradually declines afterward. The smaller elasticities in later weeks are mainly because the demand for new copies drops very rapidly over time. In other words, the base sales of new copies become much smaller.

Under S.1, we compute the proportion of consumers who switch from new to used copies as a result of a permanent 1% increase in new-copy price. Because we consider a permanent change in price, the increase in used-copy demand in week t under E.1.2 consists of two sources: (i) those who immediately switch from new to used copies in week t, and (ii) those who intertemporally switch from new to used copies (i.e., those who switch from new copies to the outside option in a week before t and then purchase a used copy in week t). To gain insights about both sources, the column "Immediate switchers" reports the proportion of switchers who immediately switch in the same week, and the column "Intertemporal switchers" reports the proportion who intertemporally switch from new to used copies. We explain the definition of these two proportions in Appendix A.4. First, we discuss the column "Immediate switchers" in S.1. We find that in week 2, out of those who switch away from new copies, only 2.4% of them immediately switch to used copies, and the rest of them switch to the outside option. However, in week 3 we see that the percentage of consumers who switch to used copies surges to 18%. Recall that type-1 and type-3 consumers have a high cost of buying a used copy. As a result, those who switch to used copies are mostly type-2 consumers, and the surge in switching rate mainly comes from an increase in the used-copy inventory, which results in a lower cost of buying a

Table 5. Elasticities

	E.1.1	E.1.2	S.1		E.2.1	E.2.2	S.2	E.3.1	E.3.2	E.4
	Elasticities of demand w.r.t. new-copy-price		Proportion of switchers: from new to used copies		Elasticities of demand w.r.t. used-copy price		Proportion of switchers	Elasticities of demand w.r.t. used-copy inventory		Elasticities of supply w.r.t. resale value
Weeks in release	New-copy demand	Used-copy demand	Immediate switchers	Inter-temporal switchers	New-copy demand	Used-copy demand	From used to new copies	New-copy demand	Used-copy demand	Used-copy supply to retailers
1	–2.147	—	—	—	—	—	—	—	—	—
2	–2.005	3.101	0.024	0.0002	0.037	–4.290	0.507	—	—	4.481
3	–2.304	2.585	0.176	0.0010	0.318	–3.872	0.454	–0.038	0.489	3.549
4	–2.533	2.121	0.277	0.0014	0.546	–3.483	0.382	–0.018	0.129	3.011
5	–2.572	1.765	0.302	0.0015	0.594	–3.161	0.435	–0.004	0.040	2.645
6	–2.638	1.582	0.332	0.0014	0.667	–2.981	0.399	–0.012	0.069	2.204
7	–2.613	1.465	0.324	0.0015	0.639	–2.831	0.332	–0.011	0.062	1.891
8	–2.652	1.336	0.344	0.0013	0.676	–2.698	0.304	–0.005	0.046	1.751
9	–2.564	1.327	0.318	0.0011	0.598	–2.656	0.472	–0.004	0.042	1.662
10	–2.491	1.400	0.272	0.0010	0.499	–2.669	0.446	–0.004	0.037	1.473
11	–2.419	1.447	0.238	0.0011	0.417	–2.616	0.363	–0.004	0.031	1.329
12	–2.433	1.368	0.254	0.0009	0.432	–2.522	0.355	–0.005	0.026	1.269
13	–2.401	1.365	0.242	0.0009	0.400	–2.459	0.323	–0.006	0.023	1.199
14	–2.370	1.336	0.225	0.0009	0.358	–2.387	0.363	–0.007	0.021	1.104
15	–2.346	1.324	0.215	0.0008	0.317	–2.340	0.322	–0.002	0.022	1.060
Average	–2.433	1.680	0.253	0.0011	0.464	–2.926	0.390	–0.009	0.080	2.045

Note. w.r.t., with respect to.

used copy for type-2 consumers. The proportion of consumers who switch from new to used copies continues to increase up until week 8. After week 8, the proportion decreases over time. This is mainly because the outside option becomes more attractive than used copies over time owing to the increase in the number of competing game titles on the same console.

The column "Intertemporal switchers" in Table 5 shows a similar inverted-U-shape pattern of the switchers' proportion over time, but the absolute value of the proportion is much smaller than the "immediate switchers" proportion. For example, out of those who switched from new copies to the outside option in week 1, only 0.02% will buy a used copy in week 2. In week 3, the proportion is 0.1%. This is mainly because consumers who switch from new copies to the outside option include type-1 and type-3 consumers, and these two types of consumers will keep choosing the outside option after the switch.

Under E.2.1 we investigate the cross-price elasticities when the used-copy price increases by 1% temporarily. In week 2, the elasticity is very small (0.037). This is again due to very small base sales of used copies, relative to very large base sales of new copies. However, out of those who switch away from used copies, 51% of them switch to new copies (S.2).[25] In week 3, the elasticity increases to 0.318, and it further increases slowly to 0.676 in week 8. This is because (i) the base sales of used copies become larger, and (ii) the cost of buying a used copy is still relatively high because of a low used-copy inventory. As a result, type-2 consumers will increasingly more likely switch to new copies. However, we see a decline in the cross-price elasticity after week 8. This is because (i) the base sales of used copies after week 8 become smaller, and (ii) the outside option becomes more attractive over time. This pattern can also be seen under S.2, where the proportion of consumers who switch to new copies decreases slowly over time to 32%.

In summary, the substitution between new and used copies is mainly determined by type-2 consumers. Initially, new copies are more attractive for them because the high cost of buying a used copy outweighs the price differential between new and used copies. As the used-copy inventory increases in the first few weeks, the cost decreases and new and used copies become equally attractive for them, resulting in the high cross-price elasticities. As time passes by further, the outside option becomes more attractive than new or used copies, reducing the cross-price elasticities. These results add important insights to the finding by Ghose et al. (2006). They use data from Amazon.com and find that the cross-price elasticity of new-book demand with respect to used book prices is very small (0.088). Our results suggest that when used copies inventory level is zero, the cross-price elasticity could be as low as what they find. However, as the used-copy inventory accumulates, the cross-price elasticity can become high, just like our estimates for weeks 3-9. Because the sales of new goods in the entertainment industry typically decline quickly after release, the high cross-price elasticity in the earlier product lifecycle is crucial for new-good producers. Our results highlight the importance of examining the cross-price elasticity over the product's lifecycle.

Next, E.3.1 and E.3.2 of Table 5 show the inventory elasticities of demand (i.e., the percentage change in the sales of new and used copies due to a 1% change in the inventory of used copies). We find that the effects on both new and used copies are largest in week 3 and that the effects decline over time. This is because the impact of used-copy inventory in reducing the cost of buying a used copy is diminishing as used-copy inventory increases.

Finally, E.4 examines the elasticity of used-copy volume supplied to retailers by consumers. Note that most of type-1 and type-3 consumers' new-copy purchases occur in the earlier weeks. Thus, as more of these consumers sell and exit, the percentage of game owners who are type-2 increases. Because type-2 owners have a high cost of selling and they are very inelastic in selling used copies, the increase in the percentage of game owners who are type-2 over time causes the elasticity of supply of used-copy to decrease over time. This pattern also suggests one possible reason why retailers accumulate used-copy inventory in the earlier stage of product lifecycle: it becomes harder for them to procure used copies in the later part of product lifecycle as game owners become more inelastic with respect to the resale value.

6.4. Elimination of the Used Game Market

Video game publishers often claim that the existence of the used game market lowers the sales of new games. The claim is often based on the conjecture that if there were no used game market, most of the used-copy buyers would switch to a new copy. Our cross-price elasticity analysis in the previous section indicates that this concern might be valid because type-2 consumers will likely purchase new copies if used copies are not available. However, if the used game market is shut down, it is possible that the demand for new copies may drop because the total expected discounted value from buying a new copy could be lowered owing to the lack of selling opportunities. As a result, we expect type-1 and type-3 consumers to demand less new copies. To find out whether it is worthwhile for video game publishers to pursue the strategy to shut down the used game market, we will use our estimated model to conduct a counterfactual experiment.

We conduct the experiment under two scenarios. In the first scenario we assume that video game publishers keep the currently observed prices of new copies even after the elimination of the used good market. Thus, the change in profits is purely due to the change in demand for new copies. In the second scenario we compute the optimal flat-prices of new copies in the absence of the used good market. We maintain the flat-pricing scheme because it has been an industry practice in Japan for a long time. In both scenarios the supply-side is modeled as a monopoly publisher who sets the price of new copies before the release of the focal game, and the marginal cost (including the licensing fee to the platform provider, manufacturing cost, etc.) is JPY 1,000 (Tachibana 2006).[26]

We compute the statistics on the percentage and absolute changes in video game publishers' profits, consumer surplus, and social surplus, aggregated across games. For consumer surplus, we follow McFadden (1981) and Small and Rosen (1981) and compute the ex ante consumer surplus for each consumer type l using the following closed form formula.

$$E[CS_l] = \frac{1}{\alpha_l} E\left[\max_{\epsilon} V_{lj}(b_1) + \epsilon_{ij1}\right] = \frac{1}{\alpha_l} \ln\left[\sum_{j=0}^{1} \exp(V_{lj}(b_1))\right],$$

where $V_{lj}(b_1)$ is the alternative-specific value function at time $t = 1$, and $b_1 = (p_1, C_1, t = 1)$. We use the observed market size M_t^d at $t = 1$ and the proportion of each type ψ_l to construct the market-level consumer surplus for each game and then sum them up across games to get the aggregate consumer surplus. For publishers' profits (producer surplus), we also compute the ex ante present discounted value of future profits for a game as

$$E[PS] = E\left[\sum_{t=1}^{T} \beta_f^{t-1} \pi\right] = E\left[\sum_{t=1}^{T} \beta_f^{t-1}(p_1 - c) \sum_{l=1}^{L} M_{lt}^d \Pr(j = 1|b_t; l)\right],$$

where c is the marginal cost, and β_f is the publishers' discount factor. We assume that β_f is calibrated according to the weekly interest rate ($\beta_f = 0.999$). To compute the expected present discounted value over future demand shocks, we simulate a sequence of demand shocks and integrate them out using the Monte Carlo integration.

Table 6 summarizes the results. We first discuss the scenario in which we maintain the price of new copies at the currently observed level. The aggregate profit change across all games in our sample is 7.27%, or JPY 15.3b (approximately 153m U.S. dollars). Three games experience a decrease in profits, with the minimum

Table 6. Welfare Changes Due to Elimination of Used Game Market: Aggregate Across All Games

	Percentage change	Change in JPY
Under observed flat-pricing		
Producer surplus	7.27	15.3 billion
Consumer surplus (average per person)	–0.90	–1,992
Type 1	–5.87	–83,621
Type 2	–0.165	–464
Type 3	–0.347	–401
Consumer surplus (aggregate)	–0.90	–24.4 billion
Social surplus	–0.257	9.08 billion
Under optimal flat-pricing		
New-copy price[a]	–37.0	–2,806
Producer surplus	26.8	56.4 billion
Consumer surplus (average per person)	1.41	3,096
Type 1	–4.37	–62,232
Type 2	2.89	8,102
Type 3	0.369	427
Consumer surplus (aggregate)	1.41	38.9 billion
Social surplus	2.71	95.3 billion

Note. JPY 1 ≈ USD 0.01.
[a]Per-game change from observed price.

of –27%, and the rest experience an increase in profits, with the maximum of 42%. This finding suggests that although the resale effect exists, the substitution effect may dominate the resale effect for many of the games. The elimination of used goods markets does reduce the consumer surplus for all games. Without the used game market, type-1 consumers either keep purchasing new copies or switch to no purchase. Because type-1 consumers no longer benefit from the selling opportunity, this lowers their average welfare significantly by 5.87%, or JPY 83,621.

However, type-2 and type-3 consumers are much less affected. Their consumer surplus also decreases, but the absolute change is relatively small (JPY 464 and JPY 401 for type-2 and type-3 consumers, respectively). Some type-2 consumers who used to purchase used copies switch to new copies in the early periods. Because they are not the supplier of used copies, the reduction in their consumer surplus is not very large. Type-3 consumers have a low probability of purchasing a game and hence are less affected by this counterfactual experiment. However, some of them are the suppliers of used copies, and thus the lost opportunity for future resale slightly lowers their consumer surplus. Overall, the social surplus is also negative for many of the games, and the aggregate social surplus decreases by 0.257%, or JPY 9.08b, because of the large decrease in the consumer surplus.

Next, we consider a situation in which video game publishers adjust the price of new copies optimally after the used game market is shut down. For each game, we compute the optimal flat-price that maximizes the ex ante present discounted value of future profits and then examine changes in price, profits, consumer surplus, and social surplus. We find that the optimal flat-prices are on average 37.0% lower than the observed prices. This large decline is mainly to induce price-sensitive type-2 and type-3 consumers (approximately 98% of the population) to purchase new copies. The aggregate producer surplus increases by 26.8% owing to the elimination of the used game market. Interestingly the aggregate consumer surplus increases owing to the lower new games' prices. Type-1 consumers are still hurt by the elimination of the used game market, but the consumer surplus improves for type-2 and type-3 consumers. Overall, the aggregate social surplus across all games improves by 1.41%.

As a caveat, we note that our counterfactual quantities (price and welfare measures) under the optimal new-copy price are compared against the quantities computed in the presence of the used game market under the observed new-copy price. A more accurate comparison is to compute the latter quantities under the "optimal" new-copy price and used-copy prices and resale values. However, this requires us to explicitly model the supply-side competition and solve for the equilibrium prices and resale values using the demand estimates. As we pointed out in the data section, the observed firm behaviors (flat pricing by the publisher and accumulation of used-copy inventory by use game retailers) have not been investigated in the previous literature. We believe that developing a new supply-side model that rationalizes these firm behaviors is challenging and deserves rigorous analysis in a separate paper. Therefore, our comparison results here should be interpreted with caution: if the observed prices were not the optimal prices, the profits increase and welfare changes in our experiment might be partly due to the suboptimal pricing observed in the data. For example, the profits increase should be considered an upper bound (i.e., if the observed prices are not optimal, we are overestimating the profits increase). Consumer and social welfare may be either over- or under-estimated.

7. Conclusion

On the basis of our newly collected data set from the Japanese new and used video game markets, we develop a new empirical framework for studying consumers' dynamic buying and selling decisions. Our framework, together with this unique data set, allows us to estimate deterioration rates of potential buyers' and owners' consumption values separately and costs for buying and selling used goods separately. We find that our estimated model is able to explain dynamic patterns of buying and selling decisions very well. Our estimates suggest different rates of potential buyers' and game owners' consumption value deterioration.

Using the estimated model, we examine the cross-price elasticity of new-copy demand with respect to used-copy prices. We find that the cross-price elasticity tends to be high especially when the inventory of used copies at used game retailers is low; but then it quickly decreases as the inventory builds up later during the product life-cycle. We also compute two new elasticities, inventory elasticity of used-copy demand and elasticity of used-copy supply, which have not been examined in the literature before. In particular, the elasticity of used-copy supply declines over time. This pattern suggests one possible reason why retailers accumulate used-copy inventory in the earlier stage of product lifecycle. Future research on developing a supply-side model could make use of this insight.

Our counterfactual experiment suggests that the resale effect plays an important role in generating new-copy sales: without adjusting the price of a new copy optimally, video game publishers could lose profits by shutting down the used game market. If publishers can adjust the price optimally, the elimination of the used game market is beneficial to both publishers and consumers, leading to an improvement in social welfare.

This paper does not explicitly model the supply-side competition between video game publishers and used game retailers. As we discussed before, the Japanese video game market shows interesting supply-side observations, such as the flat pricing by new-game publishers and accumulated inventory of used copies at used game retailers. Future research should consider developing a supply-side model that rationalizes the aforementioned supply-side observations. Such an equilibrium model allows us to conduct many interesting counterfactual experiments. For example, it may be interesting to consider vertical integration between publishers and used game retailers. Vertical integration allows publishers to control the used game trading activity, and yet consumers can have the opportunity to sell. As a result, publishers could potentially capture more profits by maintaining consumers who value the resale opportunity at the time of their purchase decisions. Additionally, our estimated elasticities suggest that if the opening of the used game market were delayed by several weeks, it could avoid the competition from used copies and yet maintain the future selling opportunity for consumers. This remedy was actually proposed during the used video game lawsuit in Japan, but it was not adopted. To examine the impact of this policy, we need to model the supply-side competition between new game publishers and used game retailers. We leave these analyses for future research.

Finally, we note that our model may not be suitable for applications whereby digital products can physically depreciate over time or network externality exists. Readers who are applying our approach should carefully adjust the model according to their specific empirical applications.

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Appendix

A.1. Discussion on Unobserved Heterogeneity

The proposed model in Section 4 allows unobserved heterogeneity in price sensitivity (α_l) and costs of buying and selling a used copy (λ_{0l} and μ_l, respectively). In this section, we explain why we choose these parameters to be heterogeneous. In general, the following parameters of the model might also be potentially heterogeneous: (i) consumption values (c^g), (ii) freshness-based deterioration (ϕ), (iii) satiation-based deterioration (δ), (iv) competitive effect (π), (v) holiday effect (γ), and (vi) discount factor (β).

First, we assume that the competitive effect and holiday effect are homogeneous, because these elements are included rather as controls and not central to our main analysis. Heterogeneity in consumption values helps explain why the sales decline over time (e.g., consumers with a higher consumption value buy first). However, the freshness-based deterioration generates a similar declining sales pattern, and we find that at least for the Japanese video game data that show a very steep decline in sales of new copies, the freshness-based deterioration seemed to work better. We tried to estimate a model in which we eliminate the freshness-based deterioration and allow for heterogeneity in consumption values. However, we could not calibrate the model to fit the pattern of the sharp sales decline for new copies. Thus, we decide not to allow for heterogeneity in consumption values.

We also assume that the freshness-based deterioration is homogeneous across consumers. Allowing for heterogeneity in the freshness-based deterioration could help explain why some consumers buy a used copy instead of a new copy (those who do not care too much about freshness), similar to what the heterogeneity in the cost of buying a used copy can generate. We tried a specification that allows for heterogeneity in freshness-based deterioration, but it cannot fit the data well. We believe this is because the freshness-based deterioration is restricted between 0 and 1, and its impact depends on the consumption value. As a result, the way this dimension of heterogeneity can explain the sales pattern is rather restrictive. Thus, we decide to only incorporate heterogeneity in the cost of buying a used copy. On the basis of a similar reason, we choose to incorporate heterogeneity in the cost of selling a used copy instead of heterogeneity in the satiation-based deterioration. Finally, we assume a homogeneous discount factor because we do not estimate it.

A.2. The Estimation Procedure

In this section we discuss the details for the estimation algorithm described in Section 5. The model parameters to be estimated include consumer preference parameters (θ^d), consumer expectation process parameters (say θ^e), and the correlation parameters for aggregate shocks $\omega = (\omega_d, \omega_s)$. Our estimation starts with an initial guess of θ^d, ω, and $\boldsymbol{\eta} = \{\eta_t^g = (\{\eta_{jt}^g\}_{j=1}^2, \eta_{st}^g\})\}_{g,t}$. We use the observed sales and market size (the number of hardware owners) to compute initial $\boldsymbol{\eta}$. For θ^e, we estimate the parameters of the process for Y_t^g and C_t^g outside the structural estimation. The initial guess for θ^e in the processes $(\{\boldsymbol{\eta}_{ljt}\}_{j=1}^2, \eta_{lst}^g)$ is obtained given initial $\boldsymbol{\eta}$ and θ^d.

Let $\boldsymbol{\nu}$ be the stacked vector of the levels and first differences of innovations in aggregate shocks and $\mathbf{Z}$ be the stacked matrix of the corresponding instruments. Our GMM estimator minimizes

$$F(\theta^d, \omega) = \boldsymbol{\nu}'\mathbf{ZWZ}'\boldsymbol{\nu},$$

where $\mathbf{W}$ is an weighting matrix. We use a two-step GMM: we start with $\mathbf{W} = (\mathbf{Z}'\mathbf{Z})^{-1}$ and obtain the first step estimates of (θ^d, ω). We then set $\hat{\mathbf{W}} = (N^{-1}\sum_{i=1}^N \hat{\boldsymbol{\nu}}_i^2 \mathbf{Z}_i\mathbf{Z}_i')^{-1}$ and minimize $F(\theta^d, \omega)$ by replacing $\mathbf{W}$ with $\hat{\mathbf{W}}$.

The step-by-step estimation procedure is as follows:

1. We start with an initial guess of θ^d, ω, and $\boldsymbol{\eta}$, and $\mathbf{W}$.
2. In iteration m of parameter search, given (θ^d, ω), we perform the following steps to obtain $\boldsymbol{\nu}(\theta^d, \omega)$.

   a. Given $\boldsymbol{\eta}$ and θ^d, obtain θ^e. Note that θ^e includes parameters of the processes $(\{\eta_{ljt}^g\}_{j=1}^2, \eta_{lst}^g)$. As we discussed, we model $\eta_{l1t}^g = \eta_{1t}^g$, which is independent of consumer type. Thus, we have $(2L+1)$ processes to estimate.

   b. Given θ^e and θ^d, we compute the value functions for buying and selling decision problems in Equations (8) and (12) by backward induction. We use Monte Carlo integration with 100 draws for approximating the expected value functions.

   c. For each g, we sequentially solve for the fixed point of η_t^g. Starting with $t=1$, we obtain the fixed point of $\eta_{1,t=1}^g$ by the method of successive approximation using the predicted quantity demanded for new copies at $t=1$. Once $\eta_{1,t=1}^g$ converges, we move to $t=2$ and solve for the fixed point of $(\eta_{1,t=2}^g, \eta_{2,t=2}^g, \eta_{s,t=2}^g)$. We repeat this process sequentially for all observed periods.[27] For each fixed point computation, we set the tolerance level to 10^{-12}. To facilitate the speed of the market share inversion, we use the squared polynomial extrapolation method (SQUAREM) in Reynaerts et al. (2012). Let $\boldsymbol{\eta}^{new}$ be the updated vector.

   d. Repeat a–c until we get $\sup|\boldsymbol{\eta}^{new} - \boldsymbol{\eta}| < 10^{-12}$.

   e. Given the fixed point $\boldsymbol{\eta}$, $\bar{\alpha}$, and ω, we compute $\boldsymbol{\nu}$ using Equations (22) and (23).
3. Once we obtain the first step estimates of (θ^d, ω), we repeat step 2 by replacing $\mathbf{W}$ with $\hat{\mathbf{W}}$.
4. Let $(\hat{\theta}^d, \hat{\omega})$ be the estimates. We compute the standard errors using the estimated variance covariance matrix:

$$\hat{\mathbf{V}}(\hat{\theta}^d, \hat{\omega}) = N\left[\hat{\mathbf{D}}'\mathbf{Z}\hat{\mathbf{W}}\mathbf{Z}'\hat{\mathbf{D}}\right]^{-1}\left[\hat{\mathbf{D}}'\mathbf{Z}\hat{\mathbf{W}}\hat{\mathbf{S}}\hat{\mathbf{W}}\mathbf{Z}'\hat{\mathbf{D}}\right] \cdot \left[\hat{\mathbf{D}}'\mathbf{Z}\hat{\mathbf{W}}\mathbf{Z}'\hat{\mathbf{D}}\right]^{-1},$$

where

$$\hat{\mathbf{D}} = \left.\frac{\partial \boldsymbol{\nu}}{\partial(\theta^d, \omega)'}\right|_{(\hat{\theta}^d, \hat{\omega})} \quad \text{and} \quad \hat{\mathbf{S}} = \frac{1}{N}\sum_{i=1}^N \hat{\boldsymbol{\nu}}_i^2(\hat{\theta}^d, \hat{\omega})\mathbf{Z}_i\mathbf{Z}_i'.$$

A.3. First-Stage Results of Excluded Instruments

Our identification for the price sensitivity (α) relies on the instruments we proposed in Section 5.3. A common approach to checking the strength of instruments is to run the first-stage estimation and provide the F-statistic of excluded instruments (e.g., Staiger and Stock 1997, Stock and Yogo 2005, Derdenger and Kumar 2013, Chintagunta et al. 2018). Because our moment conditions are similar to those in Lee (2013), we conduct similar first-stage regressions considered in Lee (2013). Recall Equations (22) and (23). We can rewrite them as

$$\begin{aligned}
\eta_{2t}^g &= \omega_d \eta_{2t-1}^g + \bar{\alpha} p_{2t}^g - \bar{\alpha}\omega_d p_{2t-1} + \nu_{2t}^g, \\
\eta_{st}^g &= \omega_s \eta_{st-1}^g - \bar{\alpha} r_t^g + \bar{\alpha}\omega_s r_{t-1} + \nu_{st}^g, \\
\Delta\eta_{2t}^g &= \omega_d \Delta\eta_{2t-1}^g + \bar{\alpha}\Delta p_{2t}^g - \bar{\alpha}\omega_d \Delta p_{2t-1} + \Delta\nu_{2t}^g, \\
\Delta\eta_{st}^g &= \omega_s \Delta\eta_{st-1}^g - \bar{\alpha}\Delta r_t^g + \bar{\alpha}\omega_s \Delta r_{t-1} + \Delta\nu_{st}^g,
\end{aligned}$$

where the difference operator is defined as $\Delta x_t \equiv x_t - x_{t-1}$. The first two equations show that we need instruments for p_{2t}^g (r_t^g) because it is correlated with ν_{2t}^g (ν_{st}^g). Similarly, the

Table A.1. First-Stage Results of Excluded Instruments

	Used-copy price		Resale value	
Variable	p_{2t} estimate	$p_{2t} - p_{2t-1}$ estimate	r_t estimate	$r_t - r_{t-1}$ estimate
Excluded instruments				
Used-copy price, lagged (t–1)	0.878**	—	—	—
	(0.054)	—	—	—
Used-copy price, lagged (t–2)	0.035	–0.021	—	—
	(0.051)	(0.069)	—	—
Used-copy price, lagged (t–3)	—	0.009	—	—
	—	(0.069)	—	—
Resale value, lagged (t–1)	—	—	0.977**	—
	—	—	(0.051)	—
Resale value, lagged (t–2)	—	—	–0.069	0.138*
	—	—	(0.048)	(0.062)
Resale value, lagged (t–3)	—	—	—	–0.157*
	—	—	—	(0.060)
Used-copy inventory (t)	–0.010**	—	–0.015**	—
	(0.002)	—	(0.003)	—
Used-copy inventory, lagged (t–1)	0.006**	–0.010**	0.012**	–0.014**
	(0.002)	(0.001)	(0.002)	(0.001)
Used-copy inventory, lagged (t–2)	—	0.009**	—	0.014**
	—	(0.002)	—	(0.001)
Average used-copy price of past games with same age (t)	–0.012	—	—	—
	(0.011)	—	—	—
Average used-copy price of past games with same age, lagged (t–1)	—	–0.004	—	—
	—	(0.005)	—	—
Average resale value of past games with same age (t)	—	—	–0.014	—
	—	—	(0.016)	—
Average resale value of past games with same age, lagged (t–1)	—	—	—	–0.018*
	—	—	—	(0.008)
Average used-copy price of games on other platforms in same week (t)	0.016	—	—	—
	(0.009)	—	—	—
Average used-copy price of games on other platforms in same week, lagged (t–1)	—	–0.007	—	—
	—	(0.005)	—	—
Average resale value of games on other platforms in same week (t)	—	—	0.022*	—
	—	—	(0.010)	—
Average resale value of games on other platforms in same week, lagged (t–1)	—	—	—	0.002
	—	—	—	(0.006)
Included instruments				
Game-fixed effect	O		O	O
Age effect	O	O	O	O
Holiday dummies	O	O	O	O
Adjusted R^2	0.989	0.229	0.991	0.429
No. of observations	627	607	627	607
F-statistic of excluded instruments	1,303.5	22.78	1,840.9	72.43

Note. Game-level cluster-robust standard errors are reported in parentheses.
$^{+}$10% significance level; *5% significance level; **1% significance level.

bottom two equations show that we need instruments for Δp^g_{2t} (Δr^g_t).

Table A.1 reports the first-stage regressions of used-copy price and resale value, both in levels (p^g_{2t}, r^g_t) and first-differences ($\Delta p^g_{2t}, \Delta r^g_t$), on excluded instruments we proposed in Section 5.3. We control for included instruments (game fixed effects, game age, and holiday dummies) and calculate the F-statistic of excluded instruments. The F-statistics of excluded instruments for used-copy price are 1,303.5 (level) and 22.78 (first-difference), and those for resale value are 1,840.9 (level) and 72.43 (first-difference). These indicate that the instruments have reasonable explanatory power for the endogenous variables.

A.4. Definitions of Immediate Switchers Proportion and Intertemporal Switchers Proportion

We compute the "Immediate switchers" proportion in week t by holding the number of potential buyers in week t at the baseline level and compute the change in used-copy demand (due to the change in choice probability) divided by the absolute value of the change in new-copy demand in week t. If the number of consumer types is one, we can compute the proportion as

$$\text{prop}_t^{immed} = \frac{M_t(\Pr_t(j=2;cf) - \Pr_t(j=2;base))}{M_t(\Pr_t(j=1;base) - \Pr_t(j=1;cf))},$$

where M_t is the number of potential buyers at time t in the baseline scenario, and $\Pr_t(j;base)$ and $\Pr_t(j;cf)$ are the probability of choosing j in the baseline scenario and the counterfactual scenario in which we permanently increase new-copy price by 1%, respectively.

We compute the "Intertemporal switchers" proportion in week t as the percentage of consumers who buy a used copy in week t among those who switched from new copies to the outside option before week t and have not bought a new or used copy yet. Let S_t be the cumulative number of such switchers in week t. For example, $S_2 = M_1(\Pr_1(j=1;base) - \Pr_1(j=1;cf))$ and $S_3 = S_2 \Pr_2(j=0;cf) + M_2(\Pr_2(j=1;base) - \Pr_2(j=1;cf))(1-\text{prop}_2^{immed})$. Then, the "Intertemporal switchers" proportion in week t is given by

$$\text{prop}_t^{inter} = \frac{S_t \Pr_t(j=2;cf)}{S_t}.$$

Extending the above derivations to multiple types is straightforward.

Endnotes

[1] We define resale value as the amount consumers receive when they sell their used video games to retailers. In Japan, retailers usually set a take-it-or-leave-it resale value for each game, and consumers sell their games at that resale value. Negotiation is uncommon.

[2] In principle, video game publishers can run the rental business for their own video games. However, only one publisher attempted to operate it in the history and did not succeed and exited.

[3] Note that in Japan, resale price maintenance is illegal for video games, although it is legal for books, magazines, newspapers, and music.

[4] The idea is similar to Ching (2010) and Frank and Salkever (1992), who argue that endogenous market segmentation can allow brand-name firms to sustain a high price when facing entry of generic products in the prescription drug market.

[5] These 20 games in the data capture a small portion of the total number of video games released in Japan during our sample period (approximately 1,000 video games). The Annual Industry Report by Media Create publishes used video game trading data for only 10 games per year. Therefore, the used video game trading data are not available for the majority of video games released during our sample period. We also checked that these 10 games are not necessarily the most popular games of the year. Moreover, increasing the number of games in the sample significantly increases the computational burden of estimating the dynamic programming model we propose in this paper.

[6] We separately collected the total annual sales from the Annual Famitsu Game Hakusho (white paper).

[7] Both Enterbrain and Media Create have partnerships with retailers across the nation and obtain point-of-sales data (those retailers are listed in every industry report by the two companies). Note that used games are traded in many large used goods franchises that also deal with used books, CDs/DVDs, and electronics (such as Book Off, GEO, and TSUTAYA) and that Media Create obtains point-of-sales data from these franchises as well.

[8] For new-copy sales, we assume zero sales after a game drops out of the top 30 ranking. This assumption should not affect the number significantly because the sale of new copies is highly concentrated in the first few weeks, so its cumulative number will not increase much in subsequent weeks.

[9] We do not explicitly model the choice among different games because our focus is to study the choice between new and used copies of the same game title. We control for the impact of the availability of other games on the purchase decision of the focal game by including the cumulative number of other newly introduced games since game g's release. Note that Nair (2007) finds evidence that the substitutability between two different video games is very low in the U.S. market, and consequently, he also does not model the choice among different games.

[10] Consequently, we assume that retailers do not adjust the price of used copies on the basis of their physical conditions.

[11] Most of the games in our sample are offline games, because of our sample period (2004–2008). Thus, we do not model the network externality.

[12] See Famitsu game Hakusho 2006, page 217 (Enterbrain, Inc. 2006).

[13] Note that $Y_t^g = 0$ does not mean that there are no used copies available for purchase in period t, because some owners would sell their copies to the market during the period.

[14] We also tried a specification that allows the deterioration rate in the second period to be different from that in the third or later periods (i.e., three parameters). However, doing so did not help improve the model fit.

[15] To reduce the computational burden, we assume that owners' consumption value stops deteriorating after they own for $\tau_{\max}$ periods and we set $\tau_{\max} = 10$.

[16] Our approach is most closely related to Lee (2013), who assumes that consumers treat the type-specific total software utility as a single state and form expectation about its future value. As we will show, our approach differs in that instead of treating the entire type-specific utility as one state variable, consumers form expectation about each of the observed states (i.e., used-copy inventory and cumulative number of competing games) and type-specific price-adjusted unobserved shocks.

[17] We assume that at time t, consumers form expectation about the value at $t+1$ (e.g., η_{ijt+1}^g) on the basis of $D_{t+1,k}$ (e.g., the fact that time $t+1$ is Christmas might affect consumers' expectation about η_{ijt+1}^g) and $D_{t,k}$ (e.g., the fact that the current period is Christmas might affect consumers' expectation about η_{ijt+1}^g).

[18] Because there are no used-copy buying and selling at $t=1$, we assume that consumers form expectations about $\eta_{i2,t=2}^g$ and $\eta_{is,t=2}^g$ on the basis of new-copy price. Specifically, we assume $\eta_{i2,t=1}^g = -\alpha_i p_1^g + \xi_{1t}^g$ and $\eta_{is,t=1}^g = \alpha_i p_1^g + \xi_{1t}^g$. Moreover, in our application, $p_{1t}^g = p_1^g \; \forall t$. Thus, we assume $\eta_{i1t}^g = \xi_{1t}^g \; \forall i$.

[19] We use the total installed base of the corresponding game console in the release week to calibrate $N_{l,t=1}$. For $t>1$, N_{lt} can be calibrated according to the weekly sales of the corresponding game console.

[20] This is because at time $t-n$, knowing $\nu_{2,t-n}^g$ and $\nu_{s,t-n}^g$ cannot help forecast their future values at time t.

[21] To compute these two types of instruments, we collected data on weekly price and resale value of used copies for an additional 21 games that were released before and during our sample period.

[22] Because the price of new copies is fixed over time and the price of used copies declines over time, consumers who do not buy a new copy in period 1 will not buy it in period 2. Hence, we do not need to consider a type who buys a new copy in period 2.

[23] It should be noted that the used-copy inventory (Y_t^g) in the selling decision problem generates exclusion restrictions that help identify the discount factor (Ching et al. 2014, Fang and Wang 2015, Abbring and Daljord 2018, Ching and Ishihara 2018, Ching and Osborne 2018). More specifically, here consumers' current utility of selling a used game does not depend on Y_t^g, but their expected future payoffs do because they use it to predict game g's future resale values. Ishihara and Ching (2018) and Ching and Osborne (2018) treat the discount factor as a parameter and estimate it using a Bayesian estimation algorithm.

[24] The minimum number represents the cost when $Y_t^g \to \infty$, and the maximum represents the cost when $Y_t^g = 0$.

[25] The proportion here is "immediate switchers," because we only consider a temporal change in used-copy price and demand for new and used copies.

[26] We do not consider an interaction between the publisher and retailers who sell new copies because we do not observe the wholesale price.

[27] One issue in our data is that for every game, we observe a longer time-series for used-copy sales than new-copy sales. Thus, there will be weeks in which we observe used-copy sales but not new-copy sales. For those weeks, we integrate out η_{1t}^g using 100 draws when computing the market share of used copies conditional on η_{2t}^g.

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