Digital Downloads and the Prohibition of Resale Markets for Information Goods*

Benjamin Shiller†

JOB MARKET PAPER

Abstract

An existing theoretical literature finds that resale markets cannot reduce producer profits for perfectly durable goods. If the model is relaxed to allow consumers to tire of goods, resale markets may prevent firms from maintaining high market prices resulting in lower profits, contradicting prevailing wisdom. I investigate empirically the welfare effects of curtailing resale in the video game market, one of the industries that can soon legally prevent resale by distributing products solely as digital downloads from places like iTunes, Kindle Store, and PlayStation Network. I first estimate a dynamic model of demand for video games in a market with allowed resale using data on new and used video game sales. I then use the estimated parameters to simulate purchase behavior, optimal prices, and welfare under prohibited resale. I find that when resale is allowed, firms are unable to maintain high market prices for their goods because used goods satisfy residual demand. The ability to do so when resale is prohibited yields significant profit increases.

*I owe much gratitude to my two principal advisors, Joel Waldfogel and Katja Seim, and special thanks to Alon Eizenberg. I would also like to thank Lorin Hitt for useful comments, Jie Bai, Tim Derdenger, Ulrich Doraszelski, Adam Isen, David Muir, Andrew Paciorek, David Rothschild, Kent Smetters, Walter Theseira, and Jeremy Tobacman for their suggestions and Hamilton Chu and David Edery for imparting to me some of their wisdom on the video game industry. Data used in an earlier version of this paper were kindly provided by VideoGamePriceCharts.com.

†Business and Public Policy Department, Wharton School, University of Pennsylvania. Contact: bshiller@wharton.upenn.edu, http://benjaminshiller.com.
1 Introduction

A common implication of theoretical models of perfectly durable products is that resale markets do not reduce producer profits. But in some information good industries practitioners vehemently disagree. For example, Phil Harrison, president of Atari, stated that "...there's no doubt that second-hand game sales have a macro-economic impact on the [video game] industry and a lot of people get miserable about it." While practitioners may be mistaken about the effects of resale, it is also possible that this discrepancy in viewpoint arises because existing theory does not take into account an important characteristic of these products. Many information products like video games, movies, books and language learning software have the feature that consumers lower their valuation with use, either because they tire of the products or absorb their information. This feature has large implications for the effect of resale markets on profits and may help explain the practitioners' view. In this paper, I investigate empirically the impact of allowed resale in the market for one category of information goods, video games. I find that resale markets substantially reduce firm profits, suggesting that firms have the incentive to utilize technological advances that allow them to legally prevent resale of their products.

In the canonical model of resale markets, where consumers do not tire of products with use, the typical finding is that resale markets can increase, but not lower, firm profits (Hendel and Lizzeri, 1999; Rust, 1986). The reasoning behind this finding is that forward-looking consumers incorporate future resale opportunities into initial willingness to pay, and as a result firm revenue should not be negatively impacted by resale markets. Since the firm typically produces fewer products and hence has lower total production costs when resale markets exist, this implies that resale markets may increase firm profits. While a minority of the papers that allow for imperfect durability, i.e. quality depreciation that for example occurs in cars, find that resale can harm firm profits, these papers still find that resale markets do not lower producer profits for perfectly durable goods. For goods that are perfectly durable, such as information goods, the existing literature unanimously concludes that resale markets do not lower producer profits.

A simple example shows that when we relax the assumption of the canonical model and allow users to tire of products, resale markets can lower producer profits even for goods

---

1 Reisinger (2008).
2 Bulow (1982), Hendel and Lizzeri (1999), and Rust (1986) show that imperfect durability on its own may lower profits, because owners have the option of keeping a good they purchased earlier rather than returning to the market to buy a new product.
3 Ghose, Telang and Krishnan (2005), do allow for consumers to tire of goods in a supply chain model.
5 (Anderson and Ginsburgh, 1994; Ghose, Telang, and Krishnan, 2005; Miller, 1974).
that are perfectly durable. Suppose the market is comprised of two equally-sized groups of individuals, denoted \( A \) and \( B \), and that group-\( A \) individuals value initial use of the product at $12, and group-\( B \) individuals value it at $4. I assume further that the good’s quality does not depreciate over time, i.e. that it is perfectly durable. Despite the fact that the product’s quality does not decline over time, both types lower their valuation for a second period of use by 75\%, and have zero value for a third period of use. I also assume that the monopolist producer of the good commits to prices ex-ante, and faces a negligible marginal cost. These assumptions mimic traits common among information products. For simplicity, I also assume that resale can only occur in the second period.

In this example, the firm’s optimal price strategy depends heavily on whether or not resale is prohibited. If it is prohibited, the firm’s optimal strategy is to charge $15 in all periods. Under this strategy, the good is only sold to group-\( A \) individuals, who value two periods of use at $12 (1^{st} \text{ use}) + $3 (2^{nd} \text{ use}) = $15. Profits are $15 \times \text{size (group-} A \text{)}$. Lowering the price over time to attract type \( B \) consumers is suboptimal, because if type \( A \) consumers know they can buy the product for less later, they will not be willing to pay as much. Alternatively, if resale is allowed, first period buyers can choose whether or not to sell in the second period. Suppose only group-\( A \) individuals buy in the first period. In the second period, if an \( A \)-type keeps the product, she receives $3 worth of utility from second use. Alternatively, she could sell to a group-\( B \) individual who values two periods of use at $4 + $1 = $5. Assuming an egalitarian bargaining solution, the secondhand market price would be $4. Since the second period yields $4 under resale rather than $3 worth of use when resale is prohibited, group-\( A \) individuals have a higher value for owning in the first period when resale is allowed. But resale also introduces an incentive compatibility constraint, since group-\( A \) individuals have the option of not buying the product in the first period and buying it for $4 in the second, for net utility equal to $11 ($12 (1^{st} \text{ use}) + $3 (2^{nd} \text{ use}) - $4 (2^{nd} \text{ period price}))$. As a result, the highest price the firm can charge in the first period while still selling to group-\( A \) individuals is $5 ($12 (1^{st} \text{ use}) + $4 (2^{nd} \text{ resale price}) - $5 (1^{st} \text{ period price}) = $11 (utility from waiting to 2^{nd} \text{ period}))$, given that resale occurs in period 2 only. One can verify that the firm’s optimal strategy is to charge $5 in the 1^{st} \text{ period}, yielding profits equal to $5 \times \text{size (} A \text{)}$, i.e. two thirds less than when resale was not allowed.

The intuition behind why resale of perfectly durable goods only reduces profits when consumers tire of products is as follows. When goods decline in value to owners with use, residual demand is eventually satisfied with used goods at a price under the price charged in the first period. Consumers will anticipate the lower price in later periods and will not be willing to pay as much in earlier periods, limiting the firm’s power. By contrast, if consumers do not tire of the product, then, in the example above, group-\( A \) individuals would value the
product higher than group-B individuals regardless of length of ownership, and there would be no gains to trade. In this case, allowed resale would not harm firm profits.

User-specific depreciation is an important feature of many information good markets. Take for example the video game market. Many consumers routinely buy and then resell games months later, after they have completed the game, accomplished the goals, grown tired of the multi-player functionality, etc. Many stores, such as Gamestop (which owns EB Games), Bestbuy, Amazon, and eBay, earn hefty profits from used games sales. For example, due to the high markup on used games, Gamestop earns more in profits from selling used games than from selling new ones.\footnote{See Kane and Bustillo (2009).}

A few statistics verify that, in the market for video games, used sales are substantial. Fifteen percent of video game expenditures are for used games, and the percent of used game transactions is likely much higher, since used game transactions tend to occur later in a game’s life cycle when market prices are lower.\footnote{N. Williams and M. Kumar. "Analysis: 49 Million U.S. Gamers Buy Used Games." Gamasutra, April 9, 2008.} The data in this paper show that a game is resold nearly 0.2 times on average by the end of the first year following release, and 0.6 times by the three year mark.

Resale markets are currently protected by U.S. law, but technological advances will soon allow firms to extinguish resale markets legally. While the first-sale doctrine (17 U.S.C. section 109) gives owners the right to resell goods, even if they are copyrighted, the first-sale doctrine only applies to the original copy and therefore does not cover downloaded goods.\footnote{The first-sale doctrine dates back to an 1854 Supreme Court case, Stevens v. Royal Gladding, which ruled that a cartographer’s right to sole distribution ended at first sale. It was subsequently codified in 1909, and updated in 1976. In the Balance Act of 2003, Congress considered instituting a digital first-sale doctrine, allowing resale of digital goods via the "forward and delete" resale method. However, the bill did not pass. It has been unclear whether the first-sale doctrine applies to licensed goods. A District Court judge decided in Vernor v. Autodesk in 2008 that permanent licenses constituted sales, and as a result were covered by the first-sale doctrine. In September 2010, the Ninth Circuit Court of Appeals reversed this ruling, determining that firms can legally prohibit resale in their licensing agreement even if they never intended for the good to be returned to them. See Graham (2002), Hinkes (2007), Long (2008), and Seringhaus (2009).} To resell a downloaded good, one would need to sell the hard drive that contains it.\footnote{See Graham (2002), Hinkes (2007), Long (2008), and Seringhaus (2009).} In many cases, this would mean selling the entire device, along with all other information goods downloaded to it. Hence, firms can effectively eliminate information goods’ resale markets by distributing such products solely through the download channel.\footnote{Firms can enforce this with access control software, and following the Digital Millennium Copyright Act (1998) can prosecute creators of software designed to circumvent such software.}

Technological changes that enable firms to prohibit resale are arriving quickly. Today, one can buy books on a Kindle or iPad, download mainstream video games through Direct2Drive
or the PlayStation Network, download games to an iPhone, download movies and TV shows through Apple TV, or buy music through iTunes. Moreover, the share of sales that are digital has been increasing. For example, digital sales now exceed physical sales for PC based video games, and Amazon announced that they now sell more copies of books in digital form for the Kindle than they sell in hardcover.\(^{11}\)

It is important to understand the effects of shutting down resale markets for information goods that consumers tire of. The impact could be large, since the four major entertainment industries (books, video games, movies, and music) together yield annual sales of around $90 billion in the US.\(^{12}\)

The most obvious question is what effect resale markets have on consumer and producer welfare. The existing theory shows that resale markets either have no effect or raise profits for producers of perfectly durable goods. However, my example shows that when individuals tire of products, it is possible that resale markets reduce profits. Therefore, whether resale markets raise or lower profits of information product producers is an empirical question. Similarly, I found via simulations that, after accounting for the firm’s response, resale markets may raise or lower consumer welfare. Hence, the effects of resale markets on welfare is an empirical question.

A second question is whether resale markets can explain the rapidly declining prices in these industries. The typical explanation for declining prices is the Coase Conjecture, which says that firms will have the ex-post incentive to lower price over time and sell to residual demand, even though this lowers profits (Coase, 1972; Stokey, 1979). But a number of empirical papers on information good markets have shown that firms can commit to not lowering prices, leaving us without a suitable explanation for declining prices.\(^{13}\) My example above suggests that if resale markets exist, price may fall over time even if firms can commit to not lowering price.

To answer these questions, I employ a two-step approach. I first estimate demand parameters in a market where resale exists, using a dynamic structural model of the consumer’s purchase and resale decisions and a dataset containing new and used sales of video games. Key parameters recovered in estimation determine the extent to which consumers tire of products, the heterogeneity in valuations for products, and the price sensitivity. These parameters are identified by the timing of purchases and resales, and their variation across

\(^{11}\)See Whitney (2010), and Galante (2010).
\(^{13}\)Clerides (2002) notes that publishers go to great lengths to maintain book prices of a given cover type and Chevalier and Goolsbee (2009) find that prices for new copies of textbooks remains constant over their lifecycles.
products. Next, using these estimated parameters, I simulate profit maximizing firm output paths under the counterfactual where resale is prohibited, assuming that firms can commit to future production ex-ante. I find the optimal output path by searching over possible trial output paths. For each trial output path, I find a rational expectations price path equilibrium, i.e. a price path that results when consumers expect the same price path ex-ante. I can then answer the questions posed above.

I find that prohibiting resale raises firm profits over 350%, vindicating practitioners’ views. I show that this is due to the fact that price declines substantially over time only when resale is allowed. When it is not, I find that the firm’s optimal strategy is to maintain high prices. This latter result on its own suggests that the declining prices observed in markets for entertainment durable goods may be due to resale markets, and not the explanation of Coase (1972). I also find that consumers are worse off when resale is prohibited, but that overall welfare is improved by prohibiting resale, since the gain to firms from prohibiting resale outweighs the loss to consumers.

In the next section, I present the model of consumer demand. Then, in section 3, I detail the estimation strategy. In section 4, I describe the data. I then present the estimation results in section 5. In section 6, I explain computation of the counterfactuals, and present the results. I then conclude and discuss future work.

2 Demand Model

The model of consumer demand is cast as a discrete choice problem, where at the beginning of each period each consumer decides whether to be an owner of each game, independent of which other games they own. If, at the beginning of a time period, they do not own the product in question, this framework requires that they decide between buying and not buying the product that period. If they do own the product, they alternatively decide between keeping the product and selling.

This setup implicitly makes several assumptions. First, it assumes consumers do not have use for more than one copy of a particular game. This seems reasonable given that the second copy does not provide any additional functionality. Second, this framework implies that games are not substitutable for one another, and consumers do not explicitly choose between them. This assumption was shown to be reasonable in the context of video games in Nair (2007). Specifically, he demonstrated that (1) current and lagged prices of other games in the same genre do not significantly impact sales, (2) neither sales nor prices are significantly impacted by hit game releases in the same genre, and (3) that concentration
in a genre does not significantly impact the rate at which prices decline. Recent papers in this industry (Lee 2010a, 2010b) have also used this assumption. Third, this setup implies that used and new games are perfect substitutes for one another. The fact that used games are sold for about 10% less than new games in brick and mortar stores, and about 5% less online, suggests that this assumption roughly holds.

In the remainder of this section, I present the specifics of the model. I start by presenting the flow utilities. Then, I describe the transition processes of the state variables from the perspective of consumers. Next, I introduce the value functions. Finally, I describe the policy functions, which are an input in the estimation procedure.

2.1 Flow Utility

There are four possible actions consumers can take: buying, waiting to buy, keeping, and selling. The flow utility of each are presented below.

The mean flow utility of buying is:

\[ u_{\text{buy}}(\delta_{i,j,t}, P_t) = \delta_{i,j,t} - \alpha P_{j,t} + \varepsilon_{i,j,t} = \bar{u}_{\text{buy}}(\delta_{i,j,t}, P_t) + \varepsilon_{i,j,t} \]  

(1)

where \( \delta_{i,j,t} \) is the "intrinsic" utility of product \( j \) to individual \( i \) in period \( t \), \( \alpha \) is the price sensitivity, \( P_{j,t} \) is the price, and \( \varepsilon_{i,j,t} \) is the individual, product, and time specific shock. The term \( \bar{u}_{\text{buy}}(\delta_{i,j,t}, P_t) \) equals the flow utility of buying minus \( \varepsilon_{i,j,t} \), and will be used subsequently for notational purposes. The "intrinsic" utility of a product is defined here as the flow utility provided by the product before the consumer has owned it.

The mean flow utility of owning is given by:

\[ u_{\text{own}}(\delta_{i,j,t}, h) = \delta_{i,j,t} B(h) + \varepsilon_{i,j,t} = \bar{u}_{\text{own}}(\delta_{i,j,t}, h) + \varepsilon_{i,j,t} \]  

(2)

where \( B(h) \) is a function that reflects the decrease in value due to length of previous ownership \( h \). I parameterize \( B(h) \) with the function \( \exp(-\lambda h) \), up to \( h = 100 \), where \( \lambda \) is a parameter.\(^\text{14}\) For \( h > 100 \), I assume \( h = 100 \).

The mean flow utility of the outside good is assigned to a positive constant \( \omega \) such that \( \delta_{i,j,t} > 0, \forall i, j, t \). As long as this condition is met, the actual value is inconsequential. If \( \delta_{i,j,t} \) were less than zero, growing tired of the good would raise the value of the good. Formally, the flow utility of waiting equals:

\[ u_{\text{wait}} = \omega + \varepsilon_{i,0,t} = \bar{u}_{\text{wait}} + \varepsilon_{i,0,t} \]  

(3)

---

\(^{14}\)In the future, I intend to estimate this function non-parametrically.
where \( \varepsilon_{i,0,t} \) is the individual and time specific shock to the utility of not owning.

The mean flow utility of selling is given by:

\[
\mu_{sell} \left( P_{j,t}^{sell}, \zeta_t \right) = \omega + \alpha \left( P_{j,t}^{sell} - \zeta_{j,t} \right) + \varepsilon_{i,0,t} = \mu_{sell} \left( P_{j,t}^{sell}, \zeta_t \right) + \varepsilon_{i,0,t} 
\]  

(4)

where \( P_{j,t}^{sell} \) is the price at which owners can resell product \( j \), \( \zeta_{j,t} \) is a product and time specific transaction cost shock common across individuals, and \( \alpha \) is the same as in the buying equation. The transaction cost shocks result, for instance, from differences between the quality perceived by non-owners and realized quality of the product.

I assume that the \( P_{j,t}^{sell} \) is a function of \( P_{j,t} \) to be estimated from the data. That is

\[
P_{j,t}^{sell} = f \left( P_{j,t} \right) 
\]  

(5)

Deviations from this relationship are accounted for in \( \zeta_{j,t} \).

### 2.2 Heterogeneity

Managers have noted the video game market consists of two groups of consumers, "hard-core gamers" and the "mass market."\(^{15}\) I use latent class approximation to the bimodal distribution of valuations (Kamakura and Russell, 1989). I assume there are two types, where type is denoted by \( k \). For each product and period, the low type has intrinsic value of ownership equal to \( \delta_{j,t} \), and the high type has intrinsic value equal to \( \delta_{j,t} + \beta \). The fraction of high types amongst the population is given by the parameter \( \gamma \).

The fraction among non-owners and owners, however, changes endogenously over time. In early periods, high type consumers are more likely to purchase, so naturally the fraction of remaining non-owners that are of the low type increases over time.

### 2.3 State and Control Space

While there is only one control variable, ownership, there are several relevant state variables. They are the price \( (P_{j,t}) \), mean intrinsic value \( (\delta_{j,t}) \), previous period of ownership \( (h) \), transaction cost shock \( (\zeta_{j,t}) \), ownership status, individual and time specific utility shocks \( (\varepsilon_{i,j,t} \text{ and } \varepsilon_{i,0,t}) \), and time \( (t) \). For some of these, the evolution is trivial. Time evolves in a predetermined manner, and the ownership status and previous ownership periods are deterministic. The rest of the state variables are stochastic from the perspective of consumers.

I assume that expected changes in prices and mean intrinsic utilities from the consumers perspective are random and correlated. As Nair (2007) does, I assume that the price process

\(^{15}\)See Nair (2007).
is Markovian, and thus is well approximated as:

\[ P_{j,t} = g(P_{j,t-1}) + \eta_{j,t} \] (6)

where the \( g(P_{j,t-1}) \) is a function to be estimated from the data, and \( \eta \) is the component of the change in price unpredictable to consumers. As Lee (2010a, 2001b) does, I assume that the mean intrinsic value (\( \delta_{j,t} \)) evolves randomly. Specifically, I assume the process is a random walk, i.e.:

\[ \delta_{j,t+1} = \delta_{j,t} + \xi_{j,t+1} \] (7)

where \( \xi_{j,t} \) is the unanticipated component of mean utility common across individuals. It arises due to changes in "coolness," for example due to the product being featured on a popular TV show. I assume \( \eta_{j,t} \) and \( \xi_{j,t} \) are distributed jointly normal, with nonzero correlation (\( \rho_{\xi,\eta} \)).

Each of the remaining state variables (\( \zeta_{j,t} \), \( \varepsilon_{i,j,t} \), \( \varepsilon_{i,0,t} \)) are assumed to be independently distributed across time, and hence are uncorrelated with all state variables. This implies that they follow Rust’s (1987) conditional independence assumption, though the assumption here is actually stronger. For functional forms, I assume \( \zeta_{j,t} \) are distributed normally, and \( \varepsilon_{i,j,t} \) and \( \varepsilon_{i,0,t} \) follow the type 1 extreme value distribution with location parameter equal to the negative of Euler’s constant and scale parameter equal to one.

### 2.4 Value Functions

The non-substitutability of video games implies that the ownership control variable is binary. Hence the value function can be broken into two "alternative specific" value functions, one for owning and one for not owning.

For both value functions, we can yield a simplified Bellman equation on a reduced state space without \( \zeta_{j,t} \), \( \varepsilon_{i,j,t} \), and \( \varepsilon_{i,0,t} \), by integrating over these three states, since they are distributed independently of all state variables and thus do not inform on the probabilities of future states. This results in the expected value of the value function before any of these three variables are known (Rust, 1987). The states \( \varepsilon_{i,j,t} \) and \( \varepsilon_{i,0,t} \) can be integrated over analytically, following Rust (1987), however \( \zeta_{j,t} \) must be integrated out numerically.\(^{17}\)

Following the steps above, the Bellman equation can written as in equation 8 below.

---

\(^{16}\)In the future, I will test whether the normality assumption strongly impacts results.

\(^{17}\)When \( \varepsilon_1 \) and \( \varepsilon_2 \) follow the type 1 extreme value distribution with location parameter equal to the negative of Euler’s constant, and scale parameter equal to one: \( E[\max(A + \varepsilon_1, B + \varepsilon_2)] = \ln(e^A + e^B) \). See Rust (1987), equation 4.12.
Note, the $j$ subscript has been omitted to save space.

\[
W_O (\delta_{i,t}, P_t, h, t) = \int \ln \left\{ \exp \left( \bar{u}_{own} (\delta_{i,t}, h) + \varphi E [W_O (\delta_{i,t+1}, P_{t+1}, h + 1, t + 1)] \right) + \exp \left( \bar{u}_{sell} (P_{t}^{sell}, \zeta_t) + \varphi V_{Sold} \right) \right\} df(\zeta_t) 
\]

where, $\varphi$ is the discount factor, $E[]$ denotes the expectation taken over $\delta_{i,t+1}$ and $P_{t+1}$ given $\delta_{i,t}$ and $P_t$, and $V_{Sold}$, the expected expected discounted value of the outside good, equals $\omega/ (1 - \varphi)$.

Likewise, the value function of non-ownership, $W_NO$, can be written as:

\[
W_NO (\delta_{i,t}, P_t, t) = \ln \left\{ \exp \left( \bar{u}_{buy} (\delta_{i,t}, P_t) + \varphi E [W_O (\delta_{i,t+1}, P_{t+1}, 1, t + 1)] \right) + \exp \left( \bar{u}_{wait} + \varphi E [W_NO (\delta_{i,t+1}, P_{t+1}, t + 1)] \right) \right\}
\]

### 2.5 Policy Functions

Since the only control variable is ownership status, each individual has only two choices each period. Non-owners choose between buying the product and waiting until the next period. Owners can hold onto the product or sell it.

An owner will sell product $j$ if the expected discounted utility of selling exceeds the expected discounted of utility of keeping. Specifically, the optimal policy is selling if and only if:

\[
\bar{u}_{sell} (P_{t}^{sell}, \zeta_t) + \varphi V_{Sold} + \varepsilon_{i,0,t} > \bar{u}_{own} (\delta_{i,t}, h) + \varphi E [W_O (\delta_{i,t+1}, P_{t+1}, h + 1, t + 1)] + \varepsilon_{i,t}
\]

Assuming the error terms $\varepsilon_{i,j,t}$ and $\varepsilon_{i,0,t}$ follow the type 1 extreme value distribution, the probability that non-owner $i$ of type $k$ with $h$ previous ownership sells can be written analytically as:

\[
s_{sell}^k (\delta_t, P_t, h, \zeta_t, t) = \frac{\exp \left( \bar{u}_{sell} (P_{t}^{sell}, \zeta_t) + V_{Sold}(t) \right)}{\exp \left( \bar{u}_{sell} (P_{t}^{sell}, \zeta_t) + V_{Sold}(t) \right) + \exp \left( \bar{u}_{own} (\delta_{k,t}, h) + \varphi E [W_O (\delta_{k,t+1}, P_{t+1}, h+1, t+1)] \right)}
\]

Following analogous steps, the probability of non-owner $i$ of type $k$ buying can be written as:
\[ s_{\text{buy}}^k(\delta_t, P_t, t) = \frac{\exp\left(u_{\text{buy}}(\delta_{k,t}, P_t) + \varphi E[W_{\text{O}}(\delta_{k,t+1}, P_{t+1}, t+1)]\right)}{\exp\left(u_{\text{buy}}(\delta_{k,t}, P_t) + \varphi E[W_{\text{O}}(\delta_{k,t+1}, P_{t+1}, t+1)] + \exp\left(u_{\text{wait}} + \varphi E[W_{\text{NO}}(\delta_{k,t+1}, P_{t+1}, t+1)]\right)\right)} \] (12)

### 3 Estimation

I estimate the model by maximum likelihood with an optimal pricing constraint. Specifically, I require that the solution satisfies the constraint that the predicted optimal price at game release for the average game, \( \bar{P}_1 \), equals the average price at release for games used in estimation, \( P_1 \), where the method for finding \( \bar{P}_1 \) is explained in section 6.

This method helps estimate the model by providing an additional source of identification for the price sensitivity. The optimal price level logically declines with the magnitude of the price sensitivity, and therefore provides substantial information on the value of \( \alpha \).

I implement this constraint in practice by searching over the price sensitivity until this constraint is satisfied. For a given price sensitivity, I calculate the value of all other parameters via maximum likelihood with the price sensitivity fixed. I then update the price sensitivity, and repeat this process until the constraint is satisfied. The method is similar to the process used in Chu, Leslie, and Sorensen’s (2009) paper to estimate the market size. The method is a useful way to include the constraint when it is infeasible to calculate deviation from constraint in each step of the maximum likelihood procedure, in this case due to computing power limitations.

The likelihood function equals:

\[ L(\text{data}; \text{parameters}) = \prod_{j,t} L\left(P_{j,t}, Q_{j,t}^{\text{new}}, Q_{j,t}^{\text{used}}, \lambda, \alpha, \beta, \gamma, \sigma_{\xi}, \sigma_{\eta}, \sigma_{\zeta}, \rho_{\xi,\eta}, \varphi\right) \] (13)

where \( \lambda \) determines the rate of boredom, \( \alpha \) is the price sensitivity, \( \beta \) and \( \gamma \) determine the distribution of types, \( \sigma_{\xi}, \sigma_{\eta}, \) and \( \sigma_{\zeta} \) are the standard deviations of \( \xi, \eta \) and \( \zeta, \rho_{\xi,\eta} \) is the correlation between \( \xi \) and \( \eta \), and \( \varphi \) is the discount factor. Prior literature has noted problems in estimating the discount factor in dynamic models. Following Nair (2007), I assume the value of the month-to-month discount factor equals 0.975.

After a change of variables transformation, the likelihood can be written in terms of the price, demand, and transaction cost shocks, as:

\[ L\left(\eta_{j,t}, \xi_{j,t}, \zeta_{j,t}; \theta\right) = \prod_{j,t} f\left(\eta_{j,t}, \xi_{j,t}\right) \times f\left(\zeta_{j,t}\right) \times J \] (14)
where \(||J||\) is the Jacobian determinant. The derivation of the Jacobian is shown in Appendix A. The price shocks \(\eta\) are estimated a priori from the data, according to equation 6. The demand and transaction cost shocks, i.e. \(\xi\) and \(\zeta\), are recovered within each iteration, by the method described next.

### 3.1 Recovering Error Terms

To compute the values of the demand and transaction cost shocks, \(\xi\) and \(\zeta\), I follow the method in Gowrisankaran and Rysman (2010), Nair (2007), and Schiraldi (2010). In each iteration in the maximization procedure, the value functions are computed first. Next, the demand shocks \(\xi\) are computed sequentially for each period and product, by finding the value that equalizes the observed share buying with predicted share buying. Finally, following Schiraldi (2010), the transaction cost shocks \(\zeta\) are computed using a similar procedure. Details are provided below.

The values of \(\xi_{j,t}\) are found sequentially using Berry, Levinsohn, and Pakes’ (1995) contraction mapping to find the values \(\delta_{j,t}\) which equalize observed and predicted aggregate share buying.\(^{18}\) The values of \(\xi_{j,t}\) can then be calculated from equation 7. The formula for the model’s predicted market share buying is:

\[
\bar{s}_{\text{buy}} = \frac{\sum_k M_{k,j,t} \star s_{\text{buy}}^{k} (\delta_t, P_t, t)}{\sum_l M_{l,j,t}} \tag{15}
\]

where \(M_{k,j,t}\) equals the mass of non-owners of type \(k\) in market \(j\) at the beginning of period \(t\).

The mass of each group in each period, \(M_{k,j,t}\), is determined by the initial mass of each group at product launch and previous buying behavior. The initial mass of each group for product \(j\), \(M_{k,j,1}\), equals the market size multiplied by the probability of being that type. I estimate the initial market size \((\sum_k M_{k,j,1})\) under the assumption that all consumers will buy the game within the first four years, during which time the price typically falls to under $6. See Appendix B for details. At the beginning of subsequent periods the masses of non-owners are updated by the formula below:

\[
M_{k,j,t+1} = M_{k,j,t} \star (1 - \Pr (\text{buy}|\delta_{k,j,t}, P_{j,t}, t)) \tag{16}
\]

\(^{18}\)Gowrisankaran and Rysman (2009) note that the BLP contraction mapping is not guaranteed to be a unique fixed point in the dynamic analogue to BLP. Despite the lack of theoretical justification, I find, as they and others have, that the BLP contraction consistently converges, and that the point contracted to does not depend on starting values.
Given the base intrinsic values $\delta_{j,t}$, we can find the transaction cost shocks $(\zeta_{j,t})$ through a similar method. In each period beyond the first, $\zeta_{j,t}$ is found by equalizing the model’s predicted and actual share of owners selling, again using the contraction mapping in Berry, Levinsohn, and Pakes (1995).\footnote{Because $\zeta$ follows Rust’s conditional independence assumption, and hence does not impact expected future payoffs, the BLP contraction mapping is guaranteed to yield a unique fixed point.} The formula for the predicted share selling is:

$$\bar{s}_{\text{sell}} = \frac{\sum_{k,h} R_{k,j,h,t} \cdot s_{\text{sell}}^k (\delta_t, P_t, h, \zeta_t, t)}{\sum_{k,h} R_{k,j,h,t}} \quad (17)$$

where $R_{k,j,h,t}$ is the mass of owners of type $k$ with $h$ previous ownership periods in market $j$ at the beginning of period $t$.

The mass of owners of each type, time period, and previous ownership length, $R_{k,j,h,t}$, evolves similarly to masses of non-owners. Before the product is introduced, there are no owners. After the good is released, the masses of owners are updated each period by:

$$R_{k,j,h,t+1} = \begin{cases} M_{k,j,t} \text{Pr (buy$|\delta_{k,j,t}, P_{j,t}, t$)} & \text{for } h = 1 \\ R_{k,j,h-1,t} \left(1 - \text{Pr (sell$|\delta_{k,j,t}, P_{j,t}, h-1, t$)}\right) & \text{for } h > 1 \end{cases} \quad (18)$$

That is, in period $t + 1$, the number of owners of discrete type $k$ with one period of previous ownership simply equals the mass of buyers in period $t$. The mass of owners of type $k$ with $h > 1$ previous periods of ownership equals the mass of individuals of type $k$, who in the previous period $t$ had $h - 1$ previous ownership periods and decided not to sell.

### 3.2 Controlling for Endogeneity

The now standard method of controlling for endogeneity in discrete choice models of demand, which involves interacting the mean error terms, $\xi_{j,t}$ and $\zeta_{j,t}$, with a set of instruments (Berry, Levinsohn, and Pakes, 1995), does not work in this context because it requires having at least as many instruments as parameters. The only variables varying across time in this dataset are prices, quantities (new and used), and number and age of other goods. Typical instruments constructed from these variables are not strong in this context. Bresnahan style instruments (Bresnahan 1981, 1987), which assume competitive conditions influence the price-cost markup, cannot be used since games have been shown empirically not to be substitutable for each other. Hausman style instruments (Hausman, 1996, Hausman and McFadden, 1984), which rely on the assumption that marginal cost shocks are correlated across markets, are ruled out, since the marginal production costs of video games, and more generally information goods, are close to zero.
I am forced to use an alternative method to control for endogeneity. Villas Boas and Winer (1999) and Nair (2007) use such an alternative. The method involves first estimating a reduced form regression of price on an instrument for price, typically lagged price, and recording the residuals. Then, with these residuals known, we can explicitly account for the dependence of price changes on demand changes by allowing the demand shocks and the price residuals to be correlated. The exact extent of the correlation is estimated within the model.

### 3.3 Identification

The heterogeneity in intrinsic valuations \((\beta, \gamma)\) is identified by the average trends in prices and in the share of non-owners buying. Both the price and implicit rental cost, i.e. the price at time of purchase minus the amount received when selling the product, decline over time on average. However, the quality \(\delta_{j,t}\) is assumed to follow a random walk, and thus on average, stays the same. Hence, the expected gain from buying typically increases over time. If valuations were homogenous, the share of non-owners buying should increase over time as well. If valuations are heterogeneous, higher valuation individuals buy with higher probability, leaving in later periods a greater share of low valuation types, who are less likely to buy than high types. As a result, the share buying can decline over time. The exact trends in share buying reflects the extent of heterogeneity.

There are two sources of identification for the price sensitivity \((\alpha)\). The first source is cross-sectional variation in prices and share of non-owners buying, along with the assumption that heterogeneity is the same across products. The latter assumption allows the model to pin down responses in the share buying due to price shocks separately from that due to heterogeneity. The second source of identification is the constraint that predicted first period price equals the observed first period price. Assuming that the optimal price level declines in the magnitude of \(\alpha\), and the prices in the data are fixed, there is a unique fixed point. While I am unable to prove formally that the price level declines monotonically in \(\alpha\) because the other parameters change when \(\alpha\) changes, I found in estimation that increasing the magnitude of \(\alpha\) always lowered the optimal price level.

Cross-sectional variation in used sales and prices allow separate identification of correlation parameter \(\rho_{\xi,\eta}\) and the price sensitivity \(\alpha\). Both the equations for the probability of buying and for the probability of selling depend on \(\alpha \ast \eta_{j,t}\) and \(\xi_{j,t}\), where \(\eta_{j,t}\) is known. In either equation alone, \(\alpha\) and the correlation between \(\eta_{j,t}\) and \(\xi_{j,t}\) are not separately identified. But, because \(\xi_{j,t}\) is interacted with \(B(h)\) only in the equation for the probability of selling, the two equations provide distinct information about \(\alpha\) and \(\rho_{\xi,\eta}\), allowing separate
identification of $\rho_{\xi,\eta}$. This argument is analogous to solving for two unknowns, using two equations. If the two equations are linearly independent, then the second equation provides additional information, and both parameters can be separately determined.

The coefficient of lost interest ($\lambda$) generates the time pattern of used sales over time, and is pinned down by within-game variation in used sales and the distribution of length of ownership, which reflects previous buying behavior. Higher boredom implies consumers are more likely to sell the product soon after purchase, which translates into a more active resale market.

The coefficient of lost interest and heterogeneity parameters are separately identified. While an infinite number of sets of $\lambda$ and initial valuations can result in an individual wanting to sell the game after $h$ periods but not after $h - 1$ periods, given price, not all the sets can explain the individuals willingness to buy initially, because the individual must yield enough usage utility (in expectation) to justify paying the price to purchase the product initially. This implies that her first $h$ uses must be valued at least as high as the difference in the buying and selling prices. A series of inequalities like these allow the coefficient of lost interest to be separately identified from the heterogeneity parameters.

4 Data

The data used in this paper are assembled by combining data from two sources. The first dataset, from the NPD group, provides information on total new sales of XBOX 360 video games in the U.S.\footnote{NPD observes over 80\% of point of sales transactions of video games and scales them up to the market.} The data on used sales come from a popular online auction marketplace, and thus comprise only a share of the market. Before combining the data, the used sales data are scaled up by a factor of approximately forty, in order to approximate the entire secondhand market.\footnote{To scale them up, I employ the fact that 4\% of sales in the first two months at GameStop, a national video game retailer, are used games (Kim, 2009). I assume that this holds for the market generally, and that the used data’s share of the used market is steady. With these assumptions, the appropriate scale-up factor $\omega$ is given by: $\omega = \frac{(Q_{\text{new, NPD}}^{2\text{-month}} + Q_{\text{used, raw}}^{2\text{-month}})}{25Q_{\text{used, raw}}^{2\text{-month}}}$.}

The resulting dataset contains monthly time-varying and time-invariant variables for each XBOX 360 game released from the time the XBOX 360 platform was first released in November 2005 through December 2008. Time-varying variables are quantities sold and average prices of new and used games. Total purchases of a game in a period are constructed by summing new and used game sales. Time-invariant variables include the games’ composite critic review scores, genres, ESRB ratings, and publishers from the NPD
group and the "replay value" scores from Game Informer Magazine’s reviews for a subset of games. This last variable has five values, ranging from "Low - you’ll quit playing before you complete the game" to "High - you’ll still be popping this game in five years from now."

The trends in the price data, shown in Table 1, suggest that the decisions of when to buy and when to sell are non-trivial. If consumers buy a game right after it is released, they typically pay about $55 for the game. But, if they wait to buy the game, they can acquire the game for much less, since the price typically declines rapidly. They can on average save 20% by waiting 6 months, and about 50% by waiting a full year to buy the game. The implied rental prices (the buying price minus the amount received when reselling later) also decline over time. Thus, since both prices and implied rental prices decline over time, consumers must trade off between buying and using the product immediately and buying later at a lower price.

The sales data, also summarized in Table 1, show that sales are more front-loaded than in the classic diffusion model, in which sales start slow and increase over time. This front-loading may be due to the firm’s response to competition from used sales. In the market for video games, about 40% of total sales of a game in the first year occur in the first two months, on average. Not surprisingly, almost all of these games are new, and the firm profits from these sales. As time progresses, while total sales typically decline, the number of used sales initially increases, reaching a peak in the fifth month, and thereafter declines slightly before appearing to plateau. Since new sales continue to decline, the relative proportion of game sales that are of used games increases over time. By the end of the first year, monthly used sales account for over 40% of per month sales of a game. Hence, later on, the firm faces steep competition from used goods.

The cumulative sales of used games, relative to cumulative new games sales, also suggest used sales are an important component of this market. This is evident in Figure 1 which plots the ratio of cumulative quantity used to cumulative quantity new in last period in the data against game age at that time. In the first few months of a game’s release, used sales are a very small fraction of total sales. But, by the end of the first year, cumulative used sales equal nearly 20% of cumulative new sales, and by the three year mark they equal 60% of cumulative new sales. This implies that three years after a game is released, each new game is resold 0.6 times on average. The mere frequency at which games are resold suggests used sales are an important feature of this market.

The importance of the used market seems to vary across games. Figure 1 shows that the fraction of cumulative sales that are used varies substantially after controlling for game age. At first glance, one might think that sampling error in the used game data explains this variation. Specifically, it is possible that the fraction of used game transactions that
occur through the online auction marketplace is random, and that this randomness explains the variation apparent in Figure 1. To test this, I first regress the ratio of cumulative used to cumulative new sales on game age indicator variables and record the residuals. If sampling error explains this variation, then the magnitude of the residual should decline in expectation with the total number of sales. In Figure 2, I show a box plot of the absolute value of these residuals over deciles of cumulative new sales of the game. This figure shows that there is no apparent pattern between the size of the sample and the absolute value of the residual. Hence, sampling error cannot explain variation in used game sales relative to new game sales.

While the data suggest that there is variation across games in the frequency in which they are resold, no game characteristic is a significant predictor, including, surprisingly, the "replay value" score. To demonstrate this, I regress the ratio of cumulative used to new sales on game age and several measures hypothesized to impact used game sales. The results are shown in Table 2. Unsurprisingly, the coefficient on game age is large and significant. However, none of the other variables are significant at the 5% level.

It is difficult to determine the exact reason why observables do not predict used sales with reduced form analyses. It could be that consumers tire of games at different rates, and the rates are uncorrelated with any observable. Alternatively, the lack of explanatory power of the "replay value" score may be due to the fact that the data reflect equilibrium outcomes, and are difficult to measure using regressions. I will return to the question of whether games systematically differ in their rate of boredom, using results from the model. The structural estimation model may be more informative, because it estimates the rate owners tire of the good directly.

As with many other entertainment goods, video game sales exhibit obvious seasonality. In Appendix C, I explain the process used to deseason the data, before taking them to the model.

5 Results

The first steps are to estimate some reduced form functions that will be fed into the model. Specifically, we need exact functions for equations 5 and 6.

I attempt to estimate the price evolution process, in equation 6, from the perspective of consumers. Consumers can base their expectations of future prices on readily observable information such as current and past prices, and game characteristics like critic review scores and game genre. To test which observables impact future prices, I estimate an autoregression
of price on lagged prices and game observables. Specifically, I run regressions of the form:

\[ P_{j,t} = \gamma_1 + \gamma_2 P_{j,1} + \gamma_3 P_{j,2} + \ldots + \gamma_m P_{j,t-m} + \text{game\_characteristics}_j + \varepsilon_{j,t} \]  

(19)

The results are shown in the Table 3. The regressions show that the previous period price is a strong predictor of current period price, but the twice lagged price does not significantly add to the regression. The R-squared value shows lagged price accounts for over 90 percent of the variation in prices. Additionally, there is no evidence of autoregressive disturbances. The correlation between residuals and lagged residuals from the preferred regression (number 4) is negative, not economically meaningful, and insignificant. It is also apparent that the highest quality games have a different price trend than other games.

In the estimation model, I assume that consumers expect prices to follow an autoregressive process defined by regression 4 in Table 3, and only include games in the highest quintile of critic review scores. Specifically, prices are assumed to be a submartingale, with the following equation:

\[ P_{j,t+1} = \kappa P_{j,t} + \eta_{j,t+1} \]  

(20)

where \( \eta_{j,t+1} \) is the portion of next period price which is not anticipated by consumers. The parameter \( \kappa \) equals 0.95, and and \( \eta \) is normally distributed with \( \sigma(\eta) \approx 4.93 \).

To estimate equation 5, which defines the expected relationship between new and used prices, I use the a simple regression of \( P_{\text{sell},j,t} \) on \( P_{j,t} \).\(^{22}\) The regression, which yields an R-square of 0.78, implies the following relationship between \( P_{\text{sell},j,t} \) and \( P_{j,t} \):

\[ P_{\text{sell},j,t} = -4.217 + 0.677 P_{j,t} \]  

(21)

The regression result shows that the difference price between new and used games increases in the price of new games.

I then estimate the model, including in the likelihood function only months January through October. I drop the Christmas season due to concerns that the assumption that new and used games are perfect substitutes does not hold when games are being given as gifts. I do not drop these months entirely, however, because I still need to account for changes in the masses of owners and non-owners.

My next step is to run the model to recover the parameters. The values of parameters, and their standard errors, are reported in Table 4. Note that the standard errors imply that each parameter values is highly significant statistically.

\(^{22}\)Interviews with store employees provided the information that the amount brick and mortar stores pay to buy used games from consumers is similar to used prices at online auction websites.
The most conspicuous parameter in Table 4 is $\lambda$, the parameter defining the rate at which consumers tire of products. Its value of $-0.2707$ seemingly implies that consumers tire of video games very quickly, since the mean flow utility provided by the game after $h$ periods of use equals only $\exp(-0.2707 \times h)$ times its value had boredom not set in. However, to appropriately interpret this parameter, we need the values of $\delta_{k,j,t}$, i.e. the mean flow utility of use for each type $k$ before boredom has set in, and the value of the mean flow utility of the outside good, $\omega$. The average value of $\delta_{k,j,t}$ across games and periods is about 65 utils for the low-type group. The parameter $\beta$ implies that the average value of $\delta_{k,j,t}$ for the high group is about 14 utils higher, implying a value of about 79. The value of the outside good, $\omega$, is assumed to equal 35 utils. With these values, the parameter $\lambda$ implies that in the fourth month of use the flow utility of use of the good to the high group has declined to the point where it is only slightly higher than the mean flow utility of the outside product. In the fifth month of use, the flow utility of use is typically lower than the mean flow utility of the outside good. This result, combined with the fact that early purchases are primarily attributed to high types, can explain the high level of used sales in the data in the fourth and fifth months. After four or so months of ownership, the flow utility of using the product above that of the mean flow utility is low, and hence may not justify holding onto the product for an additional period.

The estimation results also show that the endogeneity is meaningful in the model. Out of a theoretical maximum of one and minimum of zero, the estimated correlation between the price and demand shocks, $\xi$ and $\eta$, is 0.67, implying a substantial portion of price shocks are attributable to demand shocks.

The estimated values of the standard deviations of $\xi$ and $\zeta$, show that the change in $\delta$ tends to be much smaller in magnitude than the transient transaction cost shock. The standard deviation of $\xi$ (or equivalently of $\delta_{j,t}$), i.e. the of value before boredom has set in, equals about 3.4. This represents about 11% of the typical difference between the mean value of $\delta_{j,t}$ and $\omega$, where $\omega$ is the mean flow value of the outside good. The standard deviation of the transaction cost shock, $\zeta$, seems somewhat high at about $\$24$. This is equivalently 54% of the typical difference between $\delta_{k,j,t}$ for the high type and $\omega$.

The magnitude of standard deviation of $\zeta$ is partially explained by deviations from the relationship in equation 21, but may also in part be due to two shortcomings of the model in its present form. First, the parameterized function for the rate of boredom may be too restrictive. Second, differences across games in the rate at which consumers consumers bore of them are not accounted for in the model. As as a result, such differences across games are explained in the model by $\zeta$. In the conclusion, I explain future work that will address these shortcomings.
6 Counterfactuals

In the counterfactuals, I determine the direct impact of shutting down resale by simulating prices under different legal environments. Specifically, I simulate the status quo case, where resale is allowed, and the counterfactual case, where resale markets are shut down, assuming the current cost structure in the industry for both cases. The current marginal cost faced by publishers, $11.50, equals the marginal production cost of about $1.50 plus about $10 in royalty fees. The counterfactual analyses may not determine the full welfare impact of digitalization, because they do not account for changes in the marginal costs of production and royalty fees that may occur.

Following industry behavior, I assume firms maximize revenue by choosing ex-ante how many copies of a game to sell each period. From interviews with managers in the video game industry, I learned that there is a large set-up cost for each printing. Because of this, they are pressured to determine exactly how many games they will want to sell up front, and often they only have one printing. This suggests both that firms make quantity decisions, rather than pricing decisions, and that they do commit up front to how many units they will sell in subsequent periods, providing support for the assumption that firms set quantities ex-ante.

Since firms set quantity up front, the game between firms and consumers that are considering selling is akin to a Stackelberg game, where the firm is the leader and the owners are the follower firm. Each period, the number of goods the firm sells is fixed to the amount committed to up front. Owners then decide each period whether or not to sell (if selling is allowed).

However, the situation is more complicated because the Stackelberg setup must be extended to the dynamic setting. The key difference in the dynamic setting is that the expectations of the future matter. Therefore, the market clearing prices in different periods cannot be solved in isolation, but rather depend on each other.

The fact that expectations matter can be shown with a simple intuitive example. Suppose an individual is deciding between buying today and waiting to buy. Surely, it matters whether the next period price is $100 or $10. If the next period price is $100, then the value of waiting is much lower and hence the individual is much more likely to buy in the current period.

It seems reasonable to assume that consumer expectations in equilibrium should reflect the outcomes. To ensure this, I assume prices follow a rational expectations price path equilibrium.

\[^{23}\text{See Nair (2007).}\]
I simplify the model in this section in order to yield a straightforward rational expectations equilibrium. Specifically, I assume that the mean shocks (ξ, ζ, and η) no longer occur. With this assumption, I can simply search for an optimal price path satisfying a rational expectations equilibrium, rather than having to specify how firms would react to shocks, which is complicated when assuming firms can commit to a strategy ex-ante.24

Each counterfactual is solved for using the following double looped method. In the outer loop, I search over a grid of firm output choices to find an output path which maximizes firm profits, where firm output choices are parameterized by the function $\psi_1 \exp (\psi_2 * t)$. In the inner loop, I search for a set of prices that are close to a rational expectations equilibrium. Specifically, I approximate a rational expectations equilibrium price path by searching over trial prices until the average absolute difference between the trial path, and the resulting market clearing price path when consumers anticipate the trial price path, is minimized. To aid computation, I parameterize the trial price path with a piecewise linear function, with flexible nodes.

I now explain the process used to find market clearing prices given a set of expected prices. For each period, this method involves two steps. First, the value functions must be computed given consumers’ expectations for the future. The second step involves iterating over price until the current market clearing price is found.

The value functions in the first step are similar to the value functions in section 2. The main difference is that because the demand and transactions shocks, ξ and ζ, are assumed away, the state space is reduced from $[\delta, P, h, t]$ to $[k, h, t]$. After this change, the value functions for ownership and non-ownership, in the no resale (NR) case, can be rewritten as:

$$W_{O,NR}(k, h, t) = \ln \left\{ \exp (\bar{u}_{own}(\delta, h) + \varphi W_{O,NR}(k, h + 1, t + 1)) + \exp (\omega + V_{Sold}(t)) \right\}$$ (22)

$$W_{NO,NR}(k, t) = \ln \left\{ \exp (\bar{u}_{buy}(\delta, P(t)) + \varphi W_{O,NR}(k, 1, t + 1)) + \exp (\bar{u}_{wait} + \varphi W_{NO,NR}(k, t + 1)) \right\}$$ (23)

In case where resale is allowed (YR), they can be written:

$$W_{O,YR}(k, h, t) = \ln \left\{ \exp (\bar{u}_{own}(\delta, h) + \varphi W_{O,YR}(k, h + 1, t + 1)) + \exp (\bar{u}_{sell}(P_{used}(t), 0) + V_{Sold}(t)) \right\}$$ (24)

24 Under the alternative assumption that firms cannot commit to price, Nair (2007) shows a method for calculating a rational expectations price path equilibrium with such error terms.
\[ W_{NO, YR}(k, t) = \ln \left\{ \exp (\bar{u}_{\text{buy}}(\delta_k, P(t)) + \varphi W_{O, YR}(k, 1, t + 1)) + \exp (\bar{u}_{\text{wait}} + \varphi W_{NO, YR}(k, t + 1)) \right\} \] (25)

It is worth noting a couple of points. First, the value functions are not a function of price. The reason is that the period, \( t \), implies the anticipated price that period, since the price is assumed to evolve deterministically. Second, I allow for free disposal.

In the case where resale is allowed, the market clearing price is found by searching over price until quantity bought equals the firm’s quantity sold that period. The quantity bought is given by:

\[ \sum_k M_{k, j, t} \ast \text{prob}_{NR}(\text{buy}|P_t, k, t) \] (26)

where, \( \text{prob}_{NR}(\text{buy}|P_t, k, t) \), the probability of buying equals:

\[ \text{prob}_{NR}(\text{buy}|P_t, k, t) = \frac{\exp (\bar{u}_{\text{buy}}(\delta_k, P(t)) + \varphi W_{O, NR}(k, 1, t + 1))}{\exp (\bar{u}_{\text{buy}}(\delta_k, P(t)) + \varphi W_{O, NR}(k, 1, t + 1)) + \exp (\bar{u}_{\text{wait}} + \varphi W_{NO, NR}(k, t + 1))} \] (27)

In this step, I allow the current price to enter into the equation directly, and not to be fixed to the expected value. I iterate on price until supply equals demand. The predicted quantity bought monotonically declines in price, implying that there is a unique fixed point for price that equalizes the predicted amount bought and the firm’s output.

In the case with resale, i.e. the status quo, the market clearing price is found by equalizing the number of goods bought with the sum of the number of goods sold by the firm and the number of goods resold by owners. The market clearing condition is given by the following equation:

\[ \sum_k M_{k, j, t} \ast \text{prob}_{YR}(\text{buy}|P_t, k, t) = Q^F_{t} + \sum_{k, h} R_{k, j, h, t} \ast \text{prob}_{YR}(\text{sell}|P_t, k, h, t) \] (28)

where \( \text{prob}_{YR}(\text{buy}|P_t, k, t) \) and \( \text{prob}_{YR}(\text{sell}|P_t, k, h, t) \), the probabilities of purchasing and selling, are given by

\[ \text{prob}_{YR}(\text{buy}|P_t, k, t) = \frac{\exp (\bar{u}_{\text{buy}}(\delta_k, P(t)) + \varphi W_{O, YR}(k, 1, t + 1))}{\exp (\bar{u}_{\text{buy}}(\delta_k, P(t)) + \varphi W_{O, YR}(k, 1, t + 1)) + \exp (\bar{u}_{\text{wait}} + \varphi W_{NO, YR}(k, t + 1))} \] (29)
\[ p_{yR}(\text{sell}|P_t, k, h, t) = \frac{\exp\left(\tilde{u}_{\text{sell}}(P_{\text{used}}(t), 0) + V_{\text{Sold}}(t)\right)}{\exp(\tilde{u}_{\text{sell}}(P_{\text{used}}(t), 0) + V_{\text{Sold}}(t)) + \exp(\tilde{u}_{\text{own}}(\delta_k, h) + \varphi W_{O,YR}(k, h, t))} \] (30)

\( Q_t^{Firm} \) is the firm output in period \( t \). Again, there is a unique fixed point, since the left-hand side of equation 28 is strictly decreasing in price, and the right-hand side is strictly increasing in price.

### 6.1 Results

The summary statistics form the counterfactuals, shown in Table 5, show a rather striking result. Firm profits in the first year following a games release are over 350% higher when resale is allowed than when it is not. This result confirms practitioners’ view that resale substantially lowers profits.

Table 5 also shows that the firm sells more goods when resale markets are prohibited. When resale markets do not exist, each buyer purchases their own copy from this firm. In constrast, with allowed resale markets, individuals share goods across time through used-market transactions.

Under traditional theory, resale markets should not hurt firm profits despite the fact that the firm sells fewer goods when resale is allowed. In these models, resale opportunities are fully priced into the initial selling price of the goods, and as a result, revenue is similar in the cases where resale is allowed and where it is not.

In the model for goods consumers tire of, however, I find that used sales have an additional impact which causes them to reduce firm profits. Resale markets in this model cause price declines over time, because residual demand is fulfilled by secondhand goods. This in turn introduces an incentive compatibility constraint; consumers will not pay as much to buy the product immediately if they know the price will fall quickly. Figure 3 shows the impact of resale markets on optimal prices. When resale is prohibited, the firm maintains a high price across time. As a result, consumers do not have much incentive to wait. However, when resale is allowed, price falls sharply over time, even though in this case the firm sells almost all of its goods in the first period. Consumers in the model anticipate the falling price, and fewer are willing to pay the high price initially, despite the fact that the good is worth more to them when resale is allowed, since they then have the additional option to resell the good.

An additional result supports the contention that falling prices cause the decline in profits with allowed resale. Specifically, I investigate the effect declining prices would have on profits in the case where resale is prohibited, and see if declining prices would similarly lower profits.
To investigate this, I set firm prices to the prices that are optimal when resale is prohibited, and calculate how many individuals would buy in each period. I find that almost no new goods are bought in the first year, compared with about 800,000 when resale is allowed, and 1,700,000 when resale is prohibited and prices are set optimally. Even though the price is lower in the 11th and 12th months when prices decline than in any month when prices are maintained, barely anyone buys the game when resale is prohibited and prices decline because they are waiting for the price to drop further. Thus, profits would be substantially lower without resale if prices declined as they do in equilibrium when resale is prohibited. This shows the importance of expectations of future prices of a durable good in this model.

A related question is what impact resale markets have on consumers, after accounting for the firm’s response to them. I calculate the exact net welfare gain from resale markets using Small and Rosen’s (1981) formula for Hick’s (1939) equivalent variation. The net welfare gain to an individual of type \( k \), in dollars, equals:

\[
EV_k = \frac{W_{\text{NO,YR}}(k, 1) - W_{\text{NO,NR}}(k, 1)}{\alpha}
\]  

(31)

where \( W_{\text{NO,YR}}(k, 1) \) and \( W_{\text{NO,NR}}(k, 1) \) are the value functions at game release, conditional on not owning the good, as defined above in equations 23 and 25, and \( \alpha \) is the price sensitivity. I find that resale markets raise consumer welfare by $16.20 for each low-type individual, and by $9.88 per high-type individual, for an aggregate total of approximately $29.2 million, based on the average market size of 2.3 million.

The above results show that the total welfare is raised by the prohibition of resale markets. Consumer welfare is $29.2 million higher when resale is allowed, but firm’s profits are about $42.5 million higher when resale is prohibited. Hence, foreclosing resale raises total welfare by about $13 million for the average high quality game (in top quintile of quality).

7 Conclusion

Contrary to traditional theory, which holds that resale markets should not reduce profits of producers of perfectly durable goods, I found evidence that in markets that have the feature that consumers tire of goods, allowing resale does significantly reduce firm profits. Using data from the video game market, I found that consumers in fact tire of video games very quickly, and as a result market prices decline quickly as used goods are resold to consumers with lower valuations for the product. I found that prohibiting resale raises firm profits by over 350%, because it allows firms to maintain high prices.

As the world moves towards digital distribution, it is important understand the welfare
effects. I found that consumers are worse off when resale is prohibited, but total welfare increases. However, the welfare calculations did not consider several factors. First, I did not consider whether digital distribution was efficient. The fixed costs of buying the platform may outweigh the benefits of digital distribution. For example, it may not be efficient to require everyone to buy a Kindle before they can read a book. Yet, firms may force digital distribution on consumers, because it allows them to curtail resale. Second, my welfare calculation assumed that game quality and variety did not depend on whether resale is allowed. Future work can investigate the effect that curtailing resale has on product variety and quality.

In future work, I intend to generalize the model in three ways in order to yield a better fit of the model. First, I plan to estimate the rate at which consumers tire of products non-parametrically. I feel that the parameterized boredom rate was too restrictive, and may result in too many used sales in later periods. Second, I plan to allow the boredom rate to vary across games, by allowing the boredom rate for a game to equal the "mean" boredom rate in a period multiplied by a game-specific constant. Third, I plan to use a continuous distribution for the heterogeneity of valuations, rather than using latent classes. These three modifications should improve the fit of the model, and tighten the conclusions from the counterfactuals.

References


Hicks, J. (1939): “Value and Capital,”.


Appendices

A Jacobian

Note, the quantity predicted to be bought, $Q^{\text{pred}}_{\text{bought}}$, equals:

$$Q^{\text{pred}}_{\text{bought}} (\delta_{j,t}, P_{j,t}, t, M) = \sum_k M_{k,j,t} \Pr (\text{buy} | \delta_{k,j,t}, P_{j,t}, t)$$  \hspace{1cm} (32)

Similarly, the quantity predicted to be resold in a period, $Q^{\text{pred}}_{\text{resold}}$ equals:

$$Q^{\text{pred}}_{\text{resold}} (\delta_{j,t}, P_{j,t}, \xi_{j,t}, t, R) = \sum_{k,h} R_{k,j,h,t} \Pr (\text{sell} | \delta_{k,j,t}, P_{j,t}, h, \xi_{j,t}, t)$$ (33)

From these equations, and the pricing equation, the shocks ($\xi$, $\eta$, and $\zeta$) can be found. $\xi_{j,t}$ is found by solving:

$$Q^{\text{pred}}_{\text{bought}} (\delta_{j,t}, P_{j,t}, t, M) - Q^{\text{actual}}_{\text{bought}} = 0$$  \hspace{1cm} (34)

and given that $\delta_{j,t} = \delta_{j,t-1} + \xi_{j,t}$,

$$\xi_{j,t} = Q^{-1}_{\text{bought}} (\delta_{j,t-1}, P_{j,t}, t, M, Q^{\text{actual}}_{\text{bought}})$$ (35)

$\eta$ is found by:

$$\eta_{j,t} = P_{j,t} - \kappa P_{j,t-1}$$ (36)

and $\zeta_{j,t}$ is found by solving:

$$Q^{\text{pred}}_{\text{resold}} (\delta_{j,t}, P_{j,t}, \xi_{j,t}, t, R) - Q^{\text{actual}}_{\text{resold}} = 0$$ (37)

$$\Rightarrow \xi_{j,t} = Q^{-1}_{\text{resold}} (\delta_{j,t}, P_{j,t}, t, R, Q^{\text{actual}}_{\text{resold}})$$ (38)

The Jacobian determinant thus equals (since $\delta_{j,t}$ is a function of $\xi_{j,t}$, which, by the above functions, is a function of $Q^{\text{actual}}_{\text{bought}}$):
\[
\begin{vmatrix}
\frac{\partial \xi_{j,t}}{\partial Q_{\text{actual bought}}} & \frac{\partial \xi_{j,t}}{\partial P_{j,t}} & \frac{\partial \xi_{j,t}}{\partial Q_{\text{actual resold}}} \\
\frac{\partial \xi_{j,t}}{\partial Q_{\text{actual bought}}} & \frac{\partial \xi_{j,t}}{\partial P_{j,t}} & \frac{\partial \xi_{j,t}}{\partial Q_{\text{actual resold}}} \\
\frac{\partial \xi_{j,t}}{\partial Q_{\text{actual bought}}} & \frac{\partial \xi_{j,t}}{\partial P_{j,t}} & \frac{\partial \xi_{j,t}}{\partial Q_{\text{actual resold}}} \\
\end{vmatrix} = \begin{vmatrix}
\frac{\partial \xi_{j,t}}{\partial Q_{\text{actual bought}}} & \frac{\partial \xi_{j,t}}{\partial P_{j,t}} & 0 \\
0 & 1 & 0 \\
0 & \frac{\partial \xi_{j,t}}{\partial P_{j,t}} & \frac{\partial \xi_{j,t}}{\partial Q_{\text{actual resold}}} \\
\end{vmatrix} = \frac{\partial \xi_{j,t}}{\partial Q_{\text{actual bought}}} * \frac{\partial \xi_{j,t}}{\partial Q_{\text{actual resold}}} \right) (39)
\]

A.1 Computing \( \frac{\partial \xi_{j,t}}{\partial Q_{\text{resold}}} \)

We know that \( \sum_{k,h} R_{k,j,h,t} \Pr (\text{sell}| \delta_{k,j,t}, P_{j,t}, h, \zeta_{j,t}, t) - Q_{\text{actual resold}} = 0 \). By the implicit function theorem, we have:

\[
\frac{\partial \xi_{j,t}}{\partial Q_{\text{actual}}} = -\frac{1}{\frac{\partial}{\partial \xi} \left( \sum_{k,h} R_{k,j,h,t} \Pr (\text{sell}| \delta_{k,j,t}, P_{j,t}, h, \zeta_{j,t}, t) \right)} \right) (40)
\]

Note

\[
\frac{d}{dx} \frac{e^{A+x}}{e^{A+x} + e^B} = \frac{e^B}{(e^B + e^{A+x})^2} = \frac{e^B}{(e^{A+x} + e^B)} \right) (41)
\]

Hence,

\[
\frac{\partial}{\partial \xi} \left( \Pr (\text{sell}| \delta_{k,j,t}, P_{j,t}, h, \zeta_{j,t}, t) \right) = (1 - \Pr (\text{sell}| \delta_{k,j,t}, P_{j,t}, h, \zeta_{j,t}, t)) * \Pr (\text{sell}| \delta_{k,j,t}, P_{j,t}, h, \zeta_{j,t}, t) \right) (42)
\]

and we can rewrite:

\[
\frac{\partial \xi_{j,t}}{\partial Q_{\text{actual resold}}} = -\sum_{k,h} R_{k,j,h,t} \left(1 - \Pr (\text{sell}| \delta_{k,j,t}, P_{j,t}, h, \zeta_{j,t}, t)\right) * \Pr (\text{sell}| \delta_{k,j,t}, P_{j,t}, h, \zeta_{j,t}, t) \right) \right) (43)
\]

A.2 Computing \( \frac{\partial \xi_{j,t}}{\partial Q_{\text{bought}}} \)

We know that: \( \sum_{k} M_{k,j,t} \Pr (\text{buy}| \delta_{k,j,t}, P_{j,t}, t) - Q_{\text{actual bought}} = 0 \). By the implicit function theorem, we have:

\[
\frac{\partial \xi_{j,t}}{\partial Q_{\text{actual bought}}} = -\frac{1}{\frac{\partial}{\partial \xi} \left( \sum_{k} M_{k,j,t} \Pr (\text{buy}| \delta_{k,j,t}, P_{j,t}, t) \right)} \right) (44)
\]
In this case, because \( \xi_{j,t} \) carries forward into the next period through the value function, there isn’t a formula for the above equation, and the derivative must be calculated numerically.

**B Market Sizes**

To estimate market size, I assume that the mass of potential customers equals the number of buyers in the first four years. Since used price typically declines to about $6 on average after 2.5 years, according to the data, any consumer valuing the game at or above $6 (plus shipping) would eventually buy the game. Since I do not observe the first four years of data for any game, and for some games in the sample only observe games with one year’s worth of sales, I must estimate the first four year’s worth of sales. Specifically, I assume that the sales path are well-approximated by an exponential function with nonzero plateau, given by the following equation:

\[
Q_j(t) = (a_j - c_j) \exp(b_j \times (t - 1)) + c_j
\]  

I fixed the value of \( a_j \) to equal the sales in the first month for game \( j \), and estimate \( b_j \) and \( c_j \) separately for each game. This allows the quantity path to differ across games, say due to different price paths, or marketing.

**C Deseasoning the Data**

There are several times of the year in which games tend to sell more. The most obvious one is the Christmas season. Another time is early summer, when students start summer break. And there are other seasons when sales decline. One method of accounting for seasonality is to add monthly demand shifters to the model. However, Gowrisankaran and Rysman (2010) point out the lack of intuition for why products would be enjoyed much more during the Christmas, and that adding season dummies to a dynamic model typically requires adding an additional state variable, substantially slowing estimation. Another method of accounting for seasonality is deseasoning the data prior to estimation. Gowrisankaran and Rysman (2010) show that these two methods yield roughly the same parameter estimates for the other parameters in the model. Given that the model already takes a very long time to
estimate without season dummies and that the two methods have been shown to be roughly equivalent, the deseasoning approach is used.

The data are deseasoned by running a regression of the log of the dependent variable in a period on the composite critic review score and its square, age of game dummies, and date fixed. Specifically:

\[
\text{Log}(\text{Dependent}_{j,t}) = \alpha + \beta_1 * \text{rev}_{-}\text{score}_{j} + \beta_2 * \text{rev}_{-}\text{score}_{j}^2 + \lambda_{\text{age}(t)} * I(\text{age}(t)) + \gamma_t * I(t) + \varepsilon_{j,t} \tag{46}
\]

The dependent variable is deseasoned by subtracting $\gamma_t * I(t)$ from the log of the dependent variable, and then exponentiating. This process is repeated for prices, new quantities, and used quantities.

D Technical Details

As there is no closed form solution to the value function, it must be estimated numerically. I find that assuming a finite period model speeds computation, because the value functions can be computed faster by backwards induction than value function iteration. However, I have verified that one could use value function iteration - Blackwell’s Theorem can be used to show that the Bellman equation in this model is a contraction. I assume a termination value in period 100 equals to the maximum of an infinitely lived stream of services of an amount equal to $\max(\bar{u}_{\text{own}}(\delta_{i,j,t}, 100), \omega)$ and the selling utility in the last period plus an infinite stream of services of the outside good.

For each set of the discrete state variable values ($h$ and $t$), I interpolate the value function over a grid of the continuous state variables ($\delta$ and $P$) using third order tensor product Chebyshev polynomial regressions. Following Gowrisankaran and Rysman (2009), I assume that $\delta$ and $P$ are bounded, and any shock that would place a value outside a bound instead places it at the bound. Gowrisankaran and Rysman (2009) and Schiraldi (2010) found that easing the restriction on the bounds did not have a large impact on parameter estimates.
Table 1

Price and Quantity Patterns over Time

<table>
<thead>
<tr>
<th>Age (in Months)</th>
<th>Quantity (Normalized*)</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>New</td>
<td>Used</td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>1</td>
<td>22.1</td>
<td>12.8</td>
</tr>
<tr>
<td>2</td>
<td>17.4</td>
<td>9.7</td>
</tr>
<tr>
<td>3</td>
<td>9.2</td>
<td>6.7</td>
</tr>
<tr>
<td>4</td>
<td>7.7</td>
<td>5.9</td>
</tr>
<tr>
<td>5</td>
<td>5.0</td>
<td>2.8</td>
</tr>
<tr>
<td>6</td>
<td>4.4</td>
<td>3.2</td>
</tr>
<tr>
<td>7</td>
<td>4.0</td>
<td>4.6</td>
</tr>
<tr>
<td>8</td>
<td>3.2</td>
<td>3.1</td>
</tr>
<tr>
<td>9</td>
<td>2.7</td>
<td>2.0</td>
</tr>
<tr>
<td>10</td>
<td>2.8</td>
<td>2.9</td>
</tr>
<tr>
<td>11</td>
<td>2.2</td>
<td>1.8</td>
</tr>
<tr>
<td>12</td>
<td>1.9</td>
<td>1.7</td>
</tr>
</tbody>
</table>

*Normalized by total sales (new and used) in the first 12 months, by game.
Table 2
Regression of Ratio of Cumulative Secondhand Sales to New Sales on Game Characteristics

<table>
<thead>
<tr>
<th>Dependent Variable is (\frac{Q(\text{used})}{Q(\text{new})})</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Game Age (in Months)</td>
<td>0.013</td>
<td>0.013</td>
<td>0.012</td>
<td>0.013</td>
</tr>
<tr>
<td></td>
<td>(17.60)**</td>
<td>(16.94)**</td>
<td>(11.49)**</td>
<td>(17.62)**</td>
</tr>
<tr>
<td>Review Score</td>
<td>0.001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.78)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Game Informer Replay Value</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moderately Low</td>
<td>-0.004</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moderate</td>
<td>0.010</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.20)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moderately High</td>
<td>0.031</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.62)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>0.005</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ESRB rating</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Teen</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mature</td>
<td>0.029</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.49)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.062</td>
<td>-0.006</td>
<td>0.082</td>
<td>0.055</td>
</tr>
<tr>
<td></td>
<td>(4.67)**</td>
<td>(0.13)</td>
<td>(1.72)</td>
<td>(3.47)**</td>
</tr>
<tr>
<td>Observations</td>
<td>323</td>
<td>313</td>
<td>173</td>
<td>323</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.49</td>
<td>0.49</td>
<td>0.45</td>
<td>0.50</td>
</tr>
</tbody>
</table>

T-statistics in parentheses.
** denotes significance at 5% level
## Table 3

### Price Path Regressions

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>P(t-1)</td>
<td>0.962</td>
<td>0.96</td>
<td>0.955</td>
<td>0.955</td>
<td>0.955</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td>(0.000)**</td>
<td>(0.000)**</td>
<td>(0.000)**</td>
<td>(0.000)**</td>
<td>(0.000)**</td>
<td>(0.000)**</td>
</tr>
<tr>
<td>P(t-2)</td>
<td>-0.006</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.769)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2nd Critic Quintile</td>
<td>-0.157</td>
<td>-0.135</td>
<td>-0.162</td>
<td>-0.162</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.623)</td>
<td>(0.670)</td>
<td>(0.634)</td>
<td>(0.615)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3rd Critic Quintile</td>
<td>-0.107</td>
<td>-0.106</td>
<td>-0.178</td>
<td>-0.106</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.747)</td>
<td>(0.749)</td>
<td>(0.601)</td>
<td>(0.760)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4th Critic Quintile</td>
<td>0.084</td>
<td>0.093</td>
<td>0.055</td>
<td>0.159</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.796)</td>
<td>(0.773)</td>
<td>(0.869)</td>
<td>(0.633)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5th (Highest) Critic Quintile</td>
<td>1.058</td>
<td>1.063</td>
<td>0.946</td>
<td>1.075</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.004)**</td>
<td>(0.003)**</td>
<td>(0.013)*</td>
<td>(0.005)**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Month FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)**</td>
<td>(0.000)**</td>
<td>(0.000)**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Release Month</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.920)</td>
</tr>
<tr>
<td>Genre</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.584)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.801</td>
<td>-0.587</td>
<td>-0.625</td>
<td>-0.557</td>
<td>-0.933</td>
<td>-0.489</td>
</tr>
<tr>
<td></td>
<td>(0.008)**</td>
<td>(0.080)*</td>
<td>(0.073)*</td>
<td>(0.255)</td>
<td>(0.228)</td>
<td>(0.346)</td>
</tr>
<tr>
<td>Observations</td>
<td>2423</td>
<td>2202</td>
<td>2346</td>
<td>2346</td>
<td>2313</td>
<td>2346</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.906</td>
<td>0.901</td>
<td>0.906</td>
<td>0.908</td>
<td>0.908</td>
<td>0.908</td>
</tr>
</tbody>
</table>

P-values in parentheses.

* denotes significance at 10% level

** denotes significance at 5% level

Regression includes prices in first 12 months for XBOX 360 games released prior to December, 2007 (i.e. games with at least 12 months in dataset).
### Table 4

**Estimation Results**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda$</td>
<td>-0.271</td>
<td>0.002</td>
</tr>
<tr>
<td>$\beta$</td>
<td>13.937</td>
<td>0.103</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.48</td>
<td>0.003</td>
</tr>
<tr>
<td>$\sigma(\xi)$</td>
<td>3.434</td>
<td>0.057</td>
</tr>
<tr>
<td>$\sigma(\zeta)$</td>
<td>24.199</td>
<td>0.397</td>
</tr>
<tr>
<td>$\rho_{\xi,\eta}$</td>
<td>0.668</td>
<td>0.028</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>1.156</td>
<td>NA</td>
</tr>
</tbody>
</table>

### Table 5

**Counterfactual Results**

<table>
<thead>
<tr>
<th>Measure</th>
<th>Allowed Resale</th>
<th>Prohibited Resale</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profit (in millions)</td>
<td>$11.0$</td>
<td>$53.5$</td>
<td>386.4%</td>
</tr>
<tr>
<td>Quantity of New Goods Sold (in hundreds of thousands)</td>
<td>2.0</td>
<td>14.7</td>
<td>635.0%</td>
</tr>
<tr>
<td>Quantity of Used Goods Resold (in hundreds of thousands)</td>
<td>2.1</td>
<td>NA</td>
<td>NA</td>
</tr>
</tbody>
</table>
Plot of the Ratio of Quantity Used Sold to Quantity New Sold Against Game Age
Figure 2

Box-Plot the Absolute Value of the Residuals of a Regression of Q(new)/Q(used) on Game Age, Over New Sales Deciles
Figure 3
Price Path Over Time in Counterfactuals