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

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Abstract

An existing theoretical literature finds that resale markets cannot reduce monopolist 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. 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.

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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 allow for 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.

A simple example shows that when we relax the assumption of the canonical model and

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1 Reisinger (2008).
2 Bulow (1982), Hendel and Lizerri (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 Resale can lower firm profit if there are resale transaction costs.
6 (Anderson and Ginsburgh, 1994; Ghose, Telang, and Krishnan, 2005; Miller, 1974).
allow users to tire of products, resale markets can lower producer profits even for goods 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 period following the first sales.

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 (1st use) + $3 (2nd use) = $15. Profits are $15 * size (group-A). 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 (1st use) + $3(2nd use) − $4 (2nd 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 (1st use) + $4 (2nd resale price) − $5 (1st period price) = $11 (utility from waiting to 2nd period)), given that resale occurs in period 2 only. One can verify that the firm’s optimal strategy is to charge $5 in the 1st period, yielding profits equal to $5 * size (A), 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.} 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.\textsuperscript{12}

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.\textsuperscript{13}

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 lead to 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 ex-ante (Coase, 1972; Stokey, 1979). But a number of empirical papers on information good markets have shown that firms can commit to not lowering prices.\textsuperscript{14} 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 and the heterogeneity in valuations for products. These parameters are identified by the timing of purchases and resales, and the price path. Next, using these estimated

\textsuperscript{12}See Whitney (2010), and Galante (2010).


\textsuperscript{14}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.
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 substantially, vindicating practitioners’ views. I show that this is due to the fact that price declines substantially over time when resale is allowed. When it is not, I find that the firm’s optimal strategy is to maintain high prices. This latter result suggests a large part of the declining prices observed in markets for entertainment durable goods may be due to resale markets.

In the next section, I describe the data. Then, in sections 3 and 4, I detail the model of consumer demand and the limited supply side, and then explain the estimation strategy. In section 5, I present the estimation results. In section 6, I present the counterfactual simulation results, and determine the impact of resale markets on the video game industry. I then conclude, and discuss broader issues.

2 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.\textsuperscript{15} 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.\textsuperscript{16}

The resulting dataset contains monthly time-varying and time-invariant variables for each XBOX 360 game 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 sales. Time-invariant variables include the games’ composite critic review scores, genres, ESRB ratings, and publishers from the NPD group and the "replay value"

\textsuperscript{15}NPD observes over 80% of point of sales transactions of video games and scales them up to the market.
\textsuperscript{16}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: $\omega = \frac{(Q_{new, month}^{2-month} + Q_{used, month}^{2-month})}{25Q_{used, month}^{2-month}}$. 

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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 typically 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 different 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.

3 Model

In this section, I explain the demand side and present a supply side model which is used
only to implement an optimal price level constraint in the estimation procedure. Details
are provided below.
3.1 Demand

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. If they buy or keep the product, at the beginning of the period, they receive full flow utility from using the game. If they wait to buy or sell the product, they receive no flow utility from the game.

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 subsection, I present the specifics of the demand model for a single game. The process is then repeated for each game separately. 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.

3.1.1 Flow Utility

There are four possible actions consumers can take at some point: buying, waiting to buy, keeping, and selling. The flow utilities of each action are presented below. Note, however, that the choice set, i.e. which of these options are available, is conditional on the ownership state variable. For example, non-owners do not have the option to sell.

The mean flow utility of buying a game is:
\[ u_{\text{buy}} (\delta_{i,t}, P_t) = \delta_{i,t} - \alpha P_t + \varepsilon_{i,t} = \bar{u}_{\text{buy}} (\delta_{i,t}, P_t) + \varepsilon_{i,t} \]

where $\delta_{i,t}$ is the "intrinsic" flow utility of the product to individual $i$ in period $t$, $\alpha$ is the price sensitivity, $P_t$ is the price, and $\varepsilon_{i,t}$ is the individual, product, and time specific shock. The term $\bar{u}_{\text{buy}} (\delta_{i,t}, P_t)$ equals the flow utility of buying minus $\varepsilon_{i,t}$, 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:

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

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.\footnote{I assume $h = 100$.} For $h > 100$, I assume $h = 100$.

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

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

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:

\[ u_{\text{sell}} (P^{\text{sell}}_t, \zeta_t) = \omega + \alpha (P^{\text{sell}}_t - \zeta_t) + \varepsilon_{i,0,t} = \bar{u}_{\text{sell}} (P^{\text{sell}}_t, \zeta_t) + \varepsilon_{i,0,t} \]

where $P^{\text{sell}}_t$ is the price at which owners can resell the product, $\zeta_t$ 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 $P^{\text{sell}}_t$ is a function of $P_t$ to be estimated from the data. That is

\[ P^{\text{sell}}_t = f (P_t) \]

Deviations from this relationship are accounted for in $\zeta_t$.\footnote{In the future, I intends to estimate this function non-parametrically.}
3.1.2 Heterogeneity

Managers have noted the video game market consists of two groups of consumers, "hard-core gamers" and the "mass market." 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 $\delta_t$, and the high type has intrinsic value equal to $\delta_t + \beta$. 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.

3.1.3 State and Control Space

While there is only one control variable, ownership, there are several relevant state variables. They are the price ($P_t$), mean intrinsic value ($\delta_t$), previous periods of ownership ($h$), transaction cost shock ($\zeta_i$), ownership status, individual and time specific utility shocks ($\varepsilon_{i,t}$ 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.

Following Nair (2007), I assume that expected changes in prices and mean intrinsic utilities from the consumers perspective are random and correlated. Specifically, I assume that the price process is Markovian, and thus is well approximated as:

$$P_t = g(P_{t-1}) + \eta_t$$  \hspace{1cm} (6)

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

$$\delta_{t+1} = \delta_t + \xi_{t+1}$$  \hspace{1cm} (7)

where $\xi_t$ 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 $\eta_t$ and $\xi_t$ are distributed jointly normal, with nonzero correlation ($\rho_{\xi,\eta}$).\footnote{See Nair (2007). In the future, I will test whether the normality assumption strongly impacts results.}

\footnote{See Nair (2007). In the future, I will test whether the normality assumption strongly impacts results.}
Each of the remaining state variables \((\zeta_i, \varepsilon_{i,t}, \varepsilon_{i,0,t})\) 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 \(\zeta_i\) are distributed normally, and \(\varepsilon_{i,t}\) 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.

3.1.4 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 \(\zeta_t\), \(\varepsilon_{i,t}\), 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 \(\varepsilon_{i,t}\) and \(\varepsilon_{i,0,t}\) can be integrated over analytically, following Rust (1987), however \(\zeta_t\) must be integrated out numerically.\(^{20}\)

Following the steps above, the Bellman equation for an individual of type \(k\) can written as in equation 8 below.

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

(8)

where \(\varphi\) is the discount factor, \(E [\cdot]\) denotes the expectation taken over \(\delta_{k,t+1}\) and \(P_{t+1}\) given \(\delta_{k,t}\) 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:

\[
W_{NO} (\delta_{k,t}, P_t, t) = \ln \left\{ \exp (\bar{u}_{buy} (\delta_{k,t}, P_t) + \varphi E [W_O (\delta_{k,t+1}, P_{t+1}, 1, t + 1)]) + \exp (\bar{u}_{wait} + \varphi E [W_{NO} (\delta_{k,t+1}, P_{t+1}, t + 1)]) \right\}
\]

(9)

I assume at the terminal time period \((T = 100)\), consumers must decide between selling the

\(^{20}\)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.
product and keeping it. If they keep the product, I assume that they are allowed to dispose of the product, but not sell it in subsequent periods.

3.1.5 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 the product 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:

$$\bar{u}_{sell}(P_{sell}^t, \zeta_t) + \varphi V_{Sold} + \varepsilon_{i,0,t} > \bar{u}_{own}(\delta_{i,t}, h) + \varphi E[W_O(\delta_{i,t+1}, P_{t+1}, h+1, t+1)] + \varepsilon_{i,t}$$ (10)

Assuming the error terms $\varepsilon_{i,t}$ 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:

$$s_k^{sell}(\delta_t, P_t, h, \zeta_t) = \frac{\exp(\bar{u}_{sell}(P_{sell}^t, \zeta_t) + V_{Sold}(t))}{\exp(\bar{u}_{sell}(P_{sell}^t, \zeta_t) + V_{Sold}(t)) + \exp(\bar{u}_{own}(\delta_{k,t}, h) + \varphi E[W_O(\delta_{k,t+1}, P_{t+1}, h+1, t+1)])}$$ (11)

Following analogous steps, the probability of non-owner $i$ of type $k$ buying can be written as:

$$s_k^{buy}(\delta_t, P_t, t) = \frac{\exp(\bar{u}_{buy}(\delta_{k,t}, P_t) + \varphi E[W_O(\delta_{k,t+1}, P_{t+1}, 1, t+1)])}{\exp(\bar{u}_{buy}(\delta_{k,t}, P_t) + \varphi E[W_O(\delta_{i,t+1}, P_{t+1}, 1, t+1)]) + \exp(\bar{u}_{wait} + \varphi E[W_{NO}(\delta_{k,t+1}, P_{t+1}, t+1)])}$$ (12)

3.2 Supply

The supply side’s optimal price level is found using a completely separate equilibrium game between consumers and a firm. In this game, the firm makes output decisions for all periods up front for an average product. Consumers make decisions on when to buy and resell this product based on prices and expectations of future prices. In this game, a firm’s output path implies a set of prices that occur in equilibrium when these same prices are anticipated by consumers ex-ante, i.e. a set of rational expectations equilibrium prices. Profit maximizing output, and corresponding prices, can then be found by searching over possible firm output
paths. The first period price from the optimal price path is then used to evaluate an optimal pricing constraint in the estimation procedure.

This game between the firm and consumers is akin to a Stackelberg game. The firm, the leader, chooses in the first period the quantities in all future periods. Each period, owners of the game, i.e. the followers, each decide whether or not to resell the product they own given the firm’s output.

The game between the firm and consumers is simplified in order to yield a tractable rational expectations equilibrium. Specifically, I assume that the mean shocks ($\xi_t$, $\zeta_t$, and $\eta_t$) no longer occur, and that the intrinsic value $\delta$ equals the mean across time and games from demand estimation. With these assumptions, I can search for an optimal price path satisfying a rational expectations equilibrium. It is also assumed that the marginal cost equals $11.50 ($1.50 in production cost plus about $10 in royalty fees), and the output path is parameterized by the function $Q(t|\psi_1,\psi_1) = \psi_1 \exp(\psi_2 \ast t)$, where $\psi_1$ and $\psi_2$ are parameters.\footnote{Based on information gleaned from interviews with industry managers, Nair (2007) notes that the marginal costs faced by published are usually close to $11.50.}

Profit maximizing prices are found by searching over a grid of $\psi_1$ and $\psi_2$. For each, the rational expectation price path is found, accounting for new and used sales of the game. Discounted total profits can then be computed.

For a given output path choice, equilibrium prices are found by searching for a set of expected prices minimizing the difference between expected prices and the prices that result when consumers anticipate those prices. The trial price paths are approximated with a piecewise linear function, with flexible nodes. I find I am typically able to yield a set of expected prices that on average differ from the equilibrium prices by less than 2% at the profit-maximizing output paths.

Evaluating potential expected price paths to determine if they are an equilibrium price path requires calculating the prices that result in the market if the trial expected price path is anticipated by consumers. In the remainder of this section, I explain how the market-clearing prices resulting from a set of expectations are found, in steps. First, I present the value functions of owning and not owning in this game. This implies the policy functions, which are then used to find the market clearing prices each period.

The consumer value functions in this simulation are similar to the value functions earlier in this section, in equations 8 and 9. The main difference is that price, demand and transactions shocks, $\eta_t$, $\xi_t$ and $\zeta_t$, are assumed away. This has two two primary consequences. First, this assumption implies that the state space can be reduced from $[\delta, P, h, t]$ to $[k, h, t]$, since the intrinsic flow value $\delta$ is unchanging, and that the expected price is completely
determined by the time state. Second, the transaction cost shock no longer exists and hence
does not need to be numerically integrated out of the value function. The value functions of
owning (O) and not owning (NO), are:

\[
W_O(k, h, t) = \ln \left\{ \exp \left( \bar{u}_{own}(\delta_k, h) + \varphi W_O(k, h + 1, t + 1) \right) + \exp \left( \bar{u}_{sell}(P_{used}(t), 0) + V_{Sold}(t) \right) \right\}
\]

\[
W_NO(k, t) = \ln \left\{ \exp \left( \bar{u}_{buy}(\delta_k, P(t)) + \varphi W_O(k, 1, t + 1) \right) + \exp \left( \bar{u}_{wait} + \varphi W_NO(k, t + 1) \right) \right\}
\]

(13) (14)

The market clearing price in a period, given expectations for the future, can be 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:

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

(15)

where \(Q^Firm_t\) is the firm output in period \(t\), and \(\text{prob}(\text{buy}|P_t, k, t)\) and \(\text{prob}(\text{sell}|P_t, k, h, t)\),
the probabilities of purchasing and selling, are given by

\[
\text{prob}(\text{buy}|P_t, k, t) = \frac{\exp(\bar{u}_{buy}(\delta_k, P(t)) + \varphi W_O(k, 1, t + 1))}{\exp(\bar{u}_{buy}(\delta_k, P(t)) + \varphi W_O(k, 1, t + 1)) + \exp(\bar{u}_{wait} + \varphi W_NO(k, t + 1))}
\]

(16)

\[
\text{prob}(\text{sell}|P_t, k, h, t) = \frac{\exp(\bar{u}_{sell}(P_{used}(t), 0) + V_{Sold}(t))}{\exp(\bar{u}_{sell}(P_{used}(t), 0) + V_{Sold}(t)) + \exp(\bar{u}_{own}(\delta_k, h) + \varphi W_O(k, h + 1, t + 1))}
\]

(17)

There is a unique fixed point price that clears the market, since the left-hand side of equation
15 is strictly decreasing in price, and the right-hand side is strictly increasing in price.

4 Estimation

The model is estimated by maximum likelihood with a constraint that the price level of video
games is nearly optimal. Specifically, I require that the solution satisfies the constraint that
the predicted optimal price at game release for the average game, \(\hat{P}_1\), is within an amount
\(X\) of the average observed price at release for games used in estimation, \(\bar{P}_1\).

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 pa-
rameters via maximum likelihood with the price sensitivity fixed. I then update the price
sensitivity using a Newton step. This process is repeated 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 likelihood function equals:

\[
L(data; \text{parameters}) = \prod_{j,t} L \left( P_t, Q^\text{new}_t, Q^\text{used}_t; \lambda, \alpha, \beta, \gamma, \sigma_\xi, \sigma_\eta, \sigma_\zeta, \rho_{\xi,\eta}, \varphi \right) \tag{18}
\]

where \( j \) denotes game, \( \lambda \) determines the rate of boredom, \( \alpha \) is the price sensitivity, \( \beta \) and \( \gamma \) determine the distribution of types, \( \sigma_\xi, \sigma_\eta, \text{and} \sigma_\zeta \) are the standard deviations of \( \xi_t, \eta_t \) and \( \zeta_t \), \( \rho_{\xi,\eta} \) is the correlation between \( \xi_t \) and \( \eta_t \), 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:

\[
L(\eta_t, \xi_t, \zeta_t; \theta) = \prod_{j,t} f(\eta_t, \xi_t) f(\zeta_t) \|J\| \tag{19}
\]

where \( \|J\| \) is the Jacobian determinant. The derivation of the Jacobian is shown in Appendix A. The price shocks \( \eta_t \) are estimated a priori from the data, according to equation 6. The demand and transaction cost shocks, i.e. \( \xi_t \) and \( \zeta_t \), are recovered within each iteration, by the method described next.

### 4.1 Recovering Error Terms

To compute the values of the demand and transaction cost shocks, \( \xi_t \) and \( \zeta_t \), for a single product, 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 \( \xi_t \) 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 \( \zeta_t \) are computed using a similar procedure. Details are provided below.

The values of \( \xi_t \) are found sequentially using Berry, Levinsohn, and Pakes’ (1995) contraction mapping to find the values \( \delta_t \) which equalize observed and predicted aggregate share buying.\(^{22}\) The values of \( \xi_t \) can then be calculated from equation 7. The formula for the

\(^{22}\)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.
model’s predicted market share buying is:

\[ s_{\text{buy}} = \frac{\sum_k M_{k,t} \cdot s_{\text{buy}}^k (\delta_t, P_t, t)}{\sum_l M_{l,t}} \]  (20)

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

The mass of each group in each period, \( M_{k,t} \), is determined by the initial mass of each group at product launch and previous buying behavior. The initial mass of each group, \( M_{k,1} \), equals the market size multiplied by the probability of being that type. I estimate the initial market size (\( \sum_k M_{k,1} \)) 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:

\[ M_{k,t+1} = M_{k,t} \cdot (1 - \Pr (\text{buy}|\delta_{k,t}, P_t, t)) \]  (21)

Given the base intrinsic values \( \delta_t \), we can find the transaction cost shocks (\( \zeta_t \)) through a similar method. In each period beyond the first, \( \zeta_t \) 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).\textsuperscript{23} The formula for the predicted share selling is:

\[ s_{\text{sell}} = \frac{\sum_{k,h} R_{k,h,t} \cdot s_{\text{sell}}^k (\delta_t, P_t, h, \zeta_t, t)}{\sum_{k,h} R_{k,h,t}} \]  (22)

where \( R_{k,h,t} \) is the mass of owners of type \( k \) with \( h \) previous ownership periods at the beginning of period \( t \).

The mass of owners of each type, time period, and previous ownership length, \( R_{k,h,t} \), 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:

\[ R_{k,h,t+1} = \begin{cases} M_{k,t} \Pr (\text{buy}|\delta_{k,t}, P_t, t) & \text{for } h = 1 \\ R_{k,h-1,t} \left(1 - \Pr (\text{sell}|\delta_{k,t}, P_t, h - 1, t)\right) & \text{for } h > 1 \end{cases} \]  (23)

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 of type \( k \) in period \( t \). The mass of owners of

\textsuperscript{23}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.
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.

4.2 Controlling for Endogeneity

The now standard method of controlling for endogeneity in discrete choice models of demand, which involves interacting the mean error terms, $\xi_t$ and $\zeta_t$, 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 thus must use an alternative method to control for endogeneity. Villas-Boas and Winer (1999), Rossi et al. (2005), Nair (2007) and Jiang et al. (2009) 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. Note that the residuals encompass the endogenous component of price. Then, with these residuals known, the dependence of price changes on demand changes can be explicitly accounted for by allowing the demand shocks and the price residuals from this IV regression to be correlated, where the exact extent of the correlation is estimated within the model.

4.3 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 on average over time. However, the quality $\delta_t$ 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 profit maximizing price level equals the observed price level. This constraint does not by itself identify $\alpha$, since an infinite number of combinations of $\alpha$ and the mean value of use $\delta_t$ yield the same profit maximizing prices, but the constraint does impose a one-to-one relationship between $\alpha$ and $\delta_t$, providing further information on the value of $\alpha$.

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 individual’s 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 for a person who buys, but less than that amount for one who does not. A series of inequalities like these allow the coefficient of lost interest to be separately identified from the heterogeneity parameters.

Cross-sectional variation in used sales and prices allows separate identification of the 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 $\alpha \ast \eta_t$ and $\xi_t$, where $\eta_t$ is known. In either equation alone, $\alpha$ and the correlation between $\eta_t$ and $\xi_t$ are not separately identified. But, because $\xi_t$ 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.

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24In the static case with homogeneous buyers, one can show that the derivative of profits with respect to price can equal zero at an observed price for an infinite number of combinations of the price sensitivity and mean utility of use, implying the profit-maximizing condition alone is insufficient for identification.
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:

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

where \( j \) denotes the game. The results are shown in 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 autoregression, and only include games in the highest quintile of critic review scores. Specifically, prices are assumed to be a submartingale, according to the following equation:

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

where \( \eta_{t+1} \) is the portion of next period price which is not anticipated by consumers. The parameter \( \kappa \) equals 0.96, and and \( \eta \) is normally distributed with \( \sigma(\eta) \approx 4.93 \).

To estimate equation 5, which defines the expected relationship between buying and reselling prices, accounting for transaction costs in the secondhand market, I use a simple regression of \( P_{t}^{\text{sell}} \) on \( P_t \). The regression, which yields an R-square of 0.78, implies the following relationship between \( P_{t}^{\text{sell}} \) and \( P_t \):

\[ P_{t}^{\text{sell}} = -4.217 + 0.677P_t \]  

The regression result shows that the difference between buying and reselling prices increases

\[ ^{25}\text{Interviews with store employees provided the information that the amount brick and mortar stores pay to buy used games from consumers is similar to used prices at online auction websites.} \]
with the price of new games.

I then estimate the model, including in the likelihood function only months January through October. The Christmas season (Nov-Dec) was omitted due to concerns that the assumption that used and new goods are perfect substitutes breaks down then. The values of parameters, and their standard errors, are reported in Table 4. Note that the standard errors imply that each parameter value is statistically highly significant.

The rate at which consumers tire of products and the heterogeneity in initial valuations, the two factors expected to have the biggest impact on the effect of resale markets, are depicted graphically in Figure 3. Before owning the product, the "hardcore gamers" value one-period use of the game about $14 more than do the "mass market" types. Both types lower value of one-period use quickly with ownership length. The high types, for example, value one period of use about $50 more than they value the outside good before having used the product, but after about 5 months of use, the outside good on average provides greater one-period value to them than the game does. The fast rate at which consumers lose interest, combined with non-negligible heterogeneity, suggests that the impact of resale markets on firm profits may be substantial.

The path of sales in the model across the different types verifies the anticipated pattern that "hardcore gamers," i.e. high-type consumers, predominately buy first, and resell the products in later periods contributing to the supply of goods available for purchase, while the "mass market," the low types, buy later. This pattern is depicted in Figure 4. The sales in this figure result from first normalizing sales by the number of consumers of each type in the market for each game at release, and then averaging across games. The figure shows that nearly 40% of high-type consumers buy in the first period. Sales from this group slow even though, conditional on not owning the game, they are more likely to buy over time as prices fall, due to the fact that there are fewer and fewer potential buyers of this type as time progresses. The number of goods resold by the high-types begin to pick up around the 4th month post-release. The buying behavior of low-type consumers is much different. Generally, the pattern shows that a greater share of sales to this group occur later in the game’s life cycle, when a substantial portion of sales are of used games.

Hence there are two main changes to the market that occur over time that strongly impact firm behavior. First, the valuations of remaining non-owners become less heterogeneous. Second, used sales from consumers who have bought and grown tired of the product increasingly compete with new sales.

Price elasticities can shed light on the supply side’s problem, but there is no clear "cor-

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26Work in progress shows that this assumption has minimal impact when the profit-maximizing price level restriction is included in estimation, suggesting it will not be needed in subsequent drafts of this paper.
rect" method for estimating the magnitude of price elasticities in dynamic models. With a monopolist good and a logit specification for the probability of purchase each period, all consumers will eventually buy either a new or used copy of the good. To address this problem, one could estimate the price elasticity of demand for new goods by computing how the fraction of consumers that eventually purchase a new good, as opposed to a used good, depends on the initial price level chosen by firms. However, the results from such a method depend strongly on out-of-sample assumptions and thus may be inaccurate. Alternatively, one could report static elasticities, i.e. the percent change in quantity sold in a given period for a percent change in price that period. These elasticities could seem very high for a monopolist, but are deceiving, since an increase in goods sold in the period does not equate to additional sales. Rather, sales partially reflect demand displaced from future periods, and additional revenue in a period does not equal additional revenue overall. Therefore, it is not clear what is a "reasonable" elasticity. Chen, Esteban and Shum (2008) and Nair (2007) discuss some of these and related issues in greater detail.

A more interesting question relates to the relative sizes of the elasticities of demand for new goods and for total goods bought, new plus used. The static values of these elasticities, i.e. using the percent change in quantity in a single period ignoring changes in quantity in later periods, are computed and reported by game age in Figure 5. Both of these elasticities start out at about -10 in the first period. While total demand typically becomes less elastic over time, demand for new goods becomes increasingly elastic over time. This reflects the fact that lowering prices impacts new good sales in two ways when used goods exist. First, as usual, more goods are demanded at lower prices. Second, lowering the market price reduces the supply of used good in the resale market that period, which if present in the market would displace new good sales. Hence, resale markets give firms additional incentive to lower price substantially in later periods, and the commitment problem (Coase, 1972) is particularly acute in this context.

The estimated values of the standard deviations of $\xi_t$ and $\zeta_t$ show that the change in $\delta_t$ tends to be much smaller in magnitude than the transient transaction cost shock, the latter of which seems a little higher than expected. The standard deviation of the demand shock $\xi_t$, or equivalently of $\delta_t$, equals about 3.4. This represents about 11% of the typical difference between the mean value of $\delta_t$ 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 $\delta_{k,t}$ for the high type and $\omega$. The

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27Estimated elasticities are somewhat higher than estimated elasticities in papers omitting used good sales. Omitting such sales, which occur disproportionately later in a product's lifecycle, can result in an underestimation of the heterogeneity in valuations, which in turn can impacts elasticities.
magnitude of the standard deviation of $\zeta$ is partially explained by random deviations from the relationship between the buying and selling prices in equation 21, but is also in part due to restrictive functional form assumptions on the rate of boredom, both in terms of its shape and the assumption that it is the same across games.

The impact of functional form assumptions can be tested using the values of the demand and transaction cost error terms in the model, which are assumed to be mean zero each period. Specifically, I can test the functional form assumptions by looking for systematic deviations over time. Figures 6A and 6B show box-plots of the demand shocks and transaction cost shocks, respectively, over game age. Figure 6A shows that apart from the second period shock, which may not be mean zero, the fit is quite good, suggesting that the latent class model works well in this context. Figure 6B, by contrast, does show a systematic relationship between time and bias in the transaction cost shock. Early in a product’s life cycle, the transaction cost shock is typically negative, suggesting with the assumed functional form that selling is not attractive enough relative to holding onto the product. At around the sixth month, this pattern reverses - then the functional form assumptions result in selling being too attractive relative to keeping, and the transaction cost shock must be positive in order to induce consumers to keep the product.

The estimation results 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.

6 Counterfactual Simulations

To determine impact of resale markets on prices and producer and consumer welfare, I simulate optimal prices and the corresponding new and used quantities both under the cases where resale is allowed and the counterfactual case where it is not.

The simulation method follows the method described in section 3.2. The simulations when resale is not allowed differ slightly in that I assume consumers receive no compensation when giving up the good (i.e. $P_{sell} = 0$), and that disposed goods do not re-enter the market.

6.1 Results

The summary statistics from the simulations, 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 prohibited compared to when it is allowed. Part of this is due to transaction costs of
reselling, which are not incorporated by forward-looking consumers into initial willingness to pay. But, even when removing transaction costs of reselling, shutting down resale markets raises profits substantially, by nearly 100%. These results confirm 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. By contrast, 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 7 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 allowed, 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:

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

(27)

where $\alpha$ is the price sensitivity, and $W_{NO,YR}(k,1)$ and $W_{NO,NR}(k,1)$ are the value functions at game release, conditional on not owning the good, when resale is and is not allowed, respectively. 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.

Total welfare calculations are not possible because there is a third group not considered here, second-hand retailers that broker used sales transactions between consumers. Calculation of their profit is not possible in this model.

### 7 Discussion and 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 substantially, because it allows firms to maintain high prices.

A related question, not directly investigated in my paper, is whether resale will change the size of investments in video game development. I argue that it is unclear whether these investments will change. One the one hand, if firms are able to capture a greater share of the area under the demand curve, then they have more incentive to invest in products. One the other hand, they are limited greatly by the availability of technology, which is likely exogenous to video game development, because computing power and software development tools evolve to fit the needs of many different industries, of which video games are a small part. If video game developers are already utilizing the most modern development tools, then resale markets should not impact the quality of aspects like graphics or special effects. However, if resale is prohibited, it is also possible that developers will invest more in the game’s storyline. So I cannot rule out the possibility that the existence of resale markets
alters optimal investments in game development.

A third question is whether the ability to shut down resale markets by distributing products digitally will lead to firms utilizing inefficient distribution channels. For example, book publishers may only distribute digital versions of their products, forcing individuals to buy a Kindle or similar device in order to read books, even if the large marginal production costs of Kindles makes such distribution inefficient. I leave this issue for future work.

References


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


Appendices

A Jacobian

Note, the quantity predicted to be bought, \( Q_{\text{bought}}^{\text{pred}} \), equals:

\[
Q_{\text{bought}}^{\text{pred}} (\delta_t, P_t, t, M) = \sum_k M_{k,t} \Pr (\text{buy}|\delta_{k,t}, P_t, t)
\]  

(28)

Similarly, the quantity predicted to be resold in a period, \( Q_{\text{resold}}^{\text{pred}} \), equals:

\[
Q_{\text{resold}}^{\text{pred}} (\delta_t, P_t, \zeta_t, t, R) = \sum_{k,h} R_{k,h,t} \Pr (\text{sell}|\delta_{k,t}, P_t, h, \zeta_t, t)
\]  

(29)

From these equations, and the pricing equation, the shocks (\( \xi, \eta, \) and \( \zeta \)) can be found. \( \xi_t \) is found by solving:

\[
Q_{\text{bought}}^{\text{pred}} (\delta_t, P_t, t, M) - Q_{\text{bought}}^{\text{actual}} = 0
\]  

(30)

and given that \( \delta_t = \delta_{t-1} + \xi_t \),

\[
\xi_t = Q_{\text{bought}}^{-1} (\delta_{t-1}, P_t, t, M, Q_{\text{bought}}^{\text{actual}})
\]  

(31)

\( \eta \) is found by:

\[
\eta_t = P_t - \kappa P_{t-1}
\]  

(32)

and \( \zeta_t \) is found by solving:

\[
Q_{\text{resold}}^{\text{pred}} (\delta_t, P_t, \zeta_t, t, R) - Q_{\text{resold}}^{\text{actual}} = 0
\]  

(33)

\[
\Rightarrow \zeta_t = Q_{\text{resold}}^{-1} (\delta_t, P_t, t, R, Q_{\text{resold}}^{\text{actual}})
\]  

(34)

The Jacobian determinant thus equals (since \( \delta_t \) is a function of \( \xi_t \), which, by the above functions, is a function of \( Q_{\text{bought}}^{\text{actual}} \)):

\[
\begin{vmatrix}
\frac{\partial \xi_t}{\partial Q_{\text{bought}}^{\text{actual}}} & \frac{\partial \xi_t}{\partial P_t} & \frac{\partial \xi_t}{\partial Q_{\text{resold}}^{\text{actual}}} \\
\frac{\partial \eta_t}{\partial Q_{\text{bought}}^{\text{actual}}} & \frac{\partial \eta_t}{\partial P_t} & \frac{\partial \eta_t}{\partial Q_{\text{resold}}^{\text{actual}}} \\
\frac{\partial \zeta_t}{\partial Q_{\text{bought}}^{\text{actual}}} & \frac{\partial \zeta_t}{\partial P_t} & \frac{\partial \zeta_t}{\partial Q_{\text{resold}}^{\text{actual}}}
\end{vmatrix}
= \begin{vmatrix}
\frac{\partial \xi_t}{\partial Q_{\text{bought}}^{\text{actual}}} & \frac{\partial \xi_t}{\partial P_t} & 0 \\
0 & 1 & 0 \\
0 & \frac{\partial \zeta_t}{\partial P_t} & \frac{\partial \zeta_t}{\partial Q_{\text{resold}}^{\text{actual}}}
\end{vmatrix}
= \begin{vmatrix}
\frac{\partial \xi_t}{\partial Q_{\text{bought}}^{\text{actual}}} & \frac{\partial \xi_t}{\partial Q_{\text{resold}}^{\text{actual}}}
\end{vmatrix}
\]  

(35)
A.1 Computing $\frac{\partial \zeta_t}{\partial Q_{\text{resold}}}$

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

$$\frac{\partial \zeta_t}{\partial Q_{\text{resold}}} = -\frac{-1}{\frac{\partial}{\partial x} \left( \sum_{k, h} R_{k, h, t} \Pr (\text{sell}|\delta_{k, t}, P_t, h, \zeta_t, t) \right)}$$  \hspace{1cm} (36)

Note

$$\frac{d}{dx} e^{A+x} = e^B \frac{e^{A+x}}{(e^B + e^{A+x})^2} = \frac{e^B}{(e^{A+x} + e^B)}$$  \hspace{1cm} (37)

Hence,

$$\frac{\partial}{\partial \zeta} (\Pr (\text{sell}|\delta_{k, t}, P_t, h, \zeta_t, t)) = (1 - \Pr (\text{sell}|\delta_{k, t}, P_t, h, \zeta_t, t)) \times \Pr (\text{sell}|\delta_{k, t}, P_t, h, \zeta_t, t)$$  \hspace{1cm} (38)

and we can rewrite:

$$\frac{\partial \zeta_t}{\partial Q_{\text{resold}}} = -\frac{-1}{\sum_{k, h} R_{k, h, t} (1 - \Pr (\text{sell}|\delta_{k, t}, P_t, h, \zeta_t, t)) \times \Pr (\text{sell}|\delta_{k, t}, P_t, h, \zeta_t, t)}$$  \hspace{1cm} (39)

A.2 Computing $\frac{\partial \zeta_t}{\partial Q_{\text{bought}}}$

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

$$\frac{\partial \zeta_t}{\partial Q_{\text{bought}}} = -\frac{-1}{\frac{\partial}{\partial x} \left( \sum_k M_{k, t} \Pr (\text{buy}|\delta_{k, t}, P_t, t) \right)}$$  \hspace{1cm} (40)

In this case, because $\zeta_t$ 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 a exponential function with nonzero plateau, given by the following equation:

\[ \bar{Q}_j(t) = (a_j - c_j) \exp(b_j(t - 1)) + c_j \]  

(41)

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 fixed. Specifically:
\[ \log(Dependent_t) = \alpha + \beta_1 \cdot \text{rev\_score}_j + \beta_1 \cdot \text{rev\_score}_j^2 + \lambda_{age(t)} \cdot I(\text{age}(t)) + \gamma_t \cdot I(t) + \varepsilon_t \]  

(42)

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

\[ \text{D Technical Details} \]

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 \( \max(\bar{u}_{\text{own}}(\delta_{t,t}, 100), \omega) \) 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 \((h \text{ and } t)\), I interpolate the value function over a grid of the continuous state variables \((\delta \text{ and } P)\) using third order tensor product Chebyshev polynomial regressions. Following Gowrisankaran and Rysman (2009), I assume that \( \delta \text{ and } P \) 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>
<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>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>
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<tr>
<td>5</td>
<td>5.0</td>
<td>2.8</td>
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<td>6</td>
<td>4.4</td>
<td>3.2</td>
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<td>7</td>
<td>4.0</td>
<td>4.6</td>
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<td>8</td>
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<td>9</td>
<td>2.7</td>
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<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></th>
<th>Dependent Variable is $Q(\text{used})/Q(\text{new})$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Game Age (in Months)</td>
<td>0.0126**</td>
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<tr>
<td></td>
<td>(0.0007)</td>
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<tr>
<td>Review Score</td>
<td>0.0010</td>
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<tr>
<td></td>
<td>(0.0006)</td>
</tr>
<tr>
<td>Game Informer Replay Value</td>
<td></td>
</tr>
<tr>
<td>Moderately Low</td>
<td>-0.0038</td>
</tr>
<tr>
<td></td>
<td>(0.0621)</td>
</tr>
<tr>
<td>Moderate</td>
<td>0.0100</td>
</tr>
<tr>
<td></td>
<td>(0.0511)</td>
</tr>
<tr>
<td>Moderately High</td>
<td>0.0313</td>
</tr>
<tr>
<td></td>
<td>(0.0504)</td>
</tr>
<tr>
<td>High</td>
<td>0.0050</td>
</tr>
<tr>
<td></td>
<td>(0.0503)</td>
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<tr>
<td>ESRB rating</td>
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<tr>
<td>Teen</td>
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<tr>
<td></td>
<td>(0.0171)</td>
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<tr>
<td>Mature</td>
<td>0.0289</td>
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<tr>
<td></td>
<td>(0.0197)</td>
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<tr>
<td>Constant</td>
<td>0.0619**</td>
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<tr>
<td></td>
<td>(0.1325)</td>
</tr>
<tr>
<td>Observations</td>
<td>323</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.49</td>
</tr>
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</table>

Standard errors in parentheses.
** denotes significance at 5% level
Table 3
Price Path Regressions

<table>
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<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>Dependent Variable is Price</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P(t-1)</td>
<td>0.962**</td>
<td>0.960**</td>
<td>0.955**</td>
<td>0.955**</td>
<td>0.955**</td>
<td>0.95**</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.021)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</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>(0.022)</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>
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</tr>
<tr>
<td></td>
<td>(0.319)</td>
<td>(0.316)</td>
<td>(0.340)</td>
<td>(0.321)</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>(0.333)</td>
<td>(0.330)</td>
<td>(0.341)</td>
<td>(0.347)</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>(0.324)</td>
<td>(0.321)</td>
<td>(0.336)</td>
<td>(0.332)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5th (Highest)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.058**</td>
<td>1.063**</td>
</tr>
<tr>
<td>Critic Quintile</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.946**</td>
<td>1.075**</td>
</tr>
<tr>
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<td></td>
<td>(0.364)</td>
<td>(0.361)</td>
</tr>
<tr>
<td>Month FE</td>
<td>Yes**</td>
<td>Yes**</td>
<td>Yes**</td>
<td></td>
<td></td>
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<tr>
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<tr>
<td>Release Month</td>
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<td>[0.920]</td>
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<td></td>
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<tr>
<td>Constant</td>
<td>-0.801**</td>
<td>-0.587</td>
<td>-0.625</td>
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<tr>
<td></td>
<td>(0.299)</td>
<td>(0.335)</td>
<td>(0.348)</td>
<td>(0.488)</td>
<td>(0.775)</td>
<td>(0.518)</td>
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<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>

Standard errors in parentheses.
F-statistics in brackets
** 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></th>
<th>Value</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rate of Tiring Coef.</td>
<td>$\lambda$</td>
<td>-0.271</td>
</tr>
<tr>
<td>Hard-core Gamers Additional Value</td>
<td>$\beta$</td>
<td>13.937</td>
</tr>
<tr>
<td>Fraction Hard-Core Gamers</td>
<td>$\gamma$</td>
<td>0.48</td>
</tr>
<tr>
<td>Stand. Dev. (Demand Shock)</td>
<td>$\sigma(\xi)$</td>
<td>3.434</td>
</tr>
<tr>
<td>Stand. Dev. (Trans. Cost Shock)</td>
<td>$\sigma(\zeta)$</td>
<td>24.199</td>
</tr>
<tr>
<td>Correlation Btw Demand and Supply Shocks</td>
<td>$\rho_{\xi,\eta}$</td>
<td>0.668</td>
</tr>
<tr>
<td>Price Sensitivity</td>
<td>$\alpha$</td>
<td>1.156</td>
</tr>
</tbody>
</table>

### Table 5

**Counterfactual Results**

<table>
<thead>
<tr>
<th>Welfare in First Twelve Months Post Release</th>
<th>Allowed Resale</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Emp. Trans. Cost</td>
</tr>
<tr>
<td>Profit (in millions)</td>
<td>$11.0$</td>
</tr>
<tr>
<td>Quantity of New Goods Sold (in hundreds of thousands)</td>
<td>2.0</td>
</tr>
<tr>
<td>Quantity of Used Goods Resold (in hundreds of thousands)</td>
<td>2.1</td>
</tr>
</tbody>
</table>
Figure 1

Plot of the Ratio of Quantity Used Sold to Quantity New Sold Against Game Age as of Dec 2008
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

Flow Value from Use over Time (Tiring of Goods)

Figure 4
Share Buying by Type over Time
Figure 6 A
Box-Plot of Demand Shocks Across Time

Figure 6 B
Box-Plot of Transaction Cost Shocks Across Time
Figure 7
Price Path Over Time in Counterfactuals