ABSTRACT

Title of dissertation: ESSAYS ON PRODUCT INTRODUCTION

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This dissertation contributes to the study of product introduction from two aspects. Chapter 1 and 2 study firms' strategic decisions in product release frequencies as well as their dynamic pricing and innovation decisions in the flagship smartphone market. Chapter 3 studies consumers' multi-version consumption in response to periodic new product releases in the video game industry.

In Chapter 1, I extend the dynamic innovation framework developed by Ericson and Pakes [1995] by incorporating firms' choices of their product release timing. In this new framework, firms first commit to their product release frequencies, then based on their committed schedules, I solve for their pricing and innovation decisions upon each product release. The welfare analysis in the counterfactual analysis shows that when the market shift from the duopoly to a monopoly, social welfare improves as higher innovation dominates higher prices and slower releases in welfare impact.

In Chapter 2, I adopt the framework developed in Chapter 1, and further extend the discussion to provide managerial implications on firms' optimal product release strategies in two dimensions: staggering in product release timing, and

maintaining regular release schedules. Based on the simulated market outcome, firms should stagger their product releases with others and maintain the regular form of their release schedules.

In Chapter 3, I study consumers' responses to firms' new product releases in the video game industries. Video game players are observed to continue playing their old games even after their new purchases, which contrasts with the single-product consumption assumption in the existing durable good literature. This paper develops a new framework where video game players allocate their playing time within their game portfolios based on a latent variable, "game preference." The game preference is constructed to be flexible as it captures both contemporaneous heterogeneities across game versions and game modes, and also intertemporal heterogeneities across individuals like past gaming activities. We estimate the model parameters based on the data provided by Wharton Consumer Analytic Initiatives and report how our model fits the data pattern in three dimensions: game purchase decisions, game play decisions and game duration.

ESSAYS ON PRODUCT INTRODUCTION

by

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Dedication

To my wife, Weijia, and my parents.

Acknowledgments

Here, in the stage of graduating, I consider myself extremely lucky. I once hesitated and got frustrated for so many times, but still manage to present to the public what I have accomplished in these years. These contributions might be trivial and may need further development before it would have impacts on the real economy, but at least this is a gigantic milestone for me that I would cherish forever. I owe my gratitude to all the people who have offered help in the process of this thesis; thank you so much for making this thesis possible.

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I owe my deepest thanks to my family - my parents who unconditionally support my studies, and have always stood by me. For Weijia, thank you so much for

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Table of Contents

List of Tables

List of Figures

Chapter 1: Overview

New product introductions are prevalent across various industries, and frequently observed in our daily life: Apple's new iPhone models with better graphics and more features released in every autumn, Intel's faster and more energy-efficient CPU models released based on its "tick-tock" schedule, sports video games' new versions released periodically in every game season, new car models with new designs released at the end of each year, etc. It is natural to attribute these product introduction scenarios to firms' investment on product introduction, which generates the potential new product features and better product components to be incorporated into the new products. In this thesis, I highlight an equally important factor during this process, firms' product release strategy, and illustrate how firms utilize both strategies to schedule their new product introductions.

I first became interested in the product introduction pattern when I started to follow Apple's new phone releases. In every autumn when it was close to the release confeerence, Apple fans talked about what the new iPhone models look like, and what upgrades would be incorporated in the new model. After the release, people then shift their topic, get either excited or disappointed at the new phones, and start another cycle of forecasting phones in the next year. While consumers may only focus on each specific iPhone model and comment on its specifications like "Why does it come with only 1GB RAM while Android flagships are already equipped with 3GB RAM," what really attracts me and motivates the first two chapters in this thesis is Apple's long term plan of new product releases, where it has to guarantee enough quality improvement between consecutive releases to motivate the upgrade purchases while not making consumers concerned about being obsolete when they make the purchase. After all, when a firm designs new products while taking into account what it would release later, everything becomes complicated and challenging.

Just take an easy example and think about how a new iPhone is "designed in California": engineers in Apple come up with ideas about how the new smartphone looks like, then adopt its hardware components, e.g. CPU, RAM, GPU, battery, from the suppliers. While Apple could become determined to introduce the best phone ever and adopt the best of every component, it might risk losing current sales because of the higher price tags due to the higher cost, and also the future sales as the current buyers will have little incentive to buy if future products are not significantly better than this model. A better solution would be to spread out the potential improvement over several product generations and keep a steady pace of product improvement. and, if necessary, even alter the pace of product releases. Note that these adjustments are in addition to firms' long term innovation decisions: firms can choose their optimal investment decisions in improving product qualities in the long run, but conditional on their investment level, they still have the flexibility of materializing these improvement in one product or across several generations.

The first two chapters propose a new framework which allows firms to explicitly choose the format of their release schedules. In this framework, firms first simultaneously select their release frequencies, then they play a dynamic innovation and pricing game conditional on the pre-committed release dates. This framework facilitates the discussion of how different release schedules could impact the market outcome, including both social welfare and firms' profits. For marketing practices, this framework can also be utilized to shed light on how firms should arrange their product release schedules to maximize their long-term profits in the durable good market.

One assumption imposed in this framework is that each consumer only uses at most one unit of smartphone at any given time. This assumption is plausible for smartphones where consumers gain little value from their second units, it is hard to argue that consumers always shift their total product usage towards the new products after purchase. In the third chapter, Andrew Sweeting and I use a dataset which documents video game players' activities in a major sports video game franchise, and find two interesting patterns.

First, players utilize multiple game versions in their portfolios. Around 13% to 20%, ranging across game versions, of players continue to play their old games after buying the new game versions, which we term as "port-back."

Second, players exhibit persistent gaming experiences towards certain game modes over time. For example, a player may spent consistently more time in the career mode than average, which cannot be explained by the game mode specific preference.

To accommodate these two patterns, we construct a framework where players allocate their playing time across different games modes and game versions in their portfolios, and make purchase decisions in regards to new versions periodically released in the market. With this framework, we find that players' playing time across different game versions are weakly substituted: when players are restricted to only play the newest game version in their portfolio, their playing time in the new game only increase by 0.3%. In contrast, we also find strong correlation in players game preferences across periods: when players preferences are only determined by common utility factors like version fixed effect, mode fixed effect, time fixed effect and player random effect, their playing time in the new game will fall by 13.9%, and in the old game by 6.9%.

Chapter 2: Market Competition and Product Introduction: A Study of the Flagship Smartphone Industry

2.1 Introduction

Successful firms in durable consumer technology industries (e.g., smartphones, tablets, personal computers) are typically oligopolists who periodically release new products that contain a number of incremental improvements. These firms have to trade-off how frequently to release new products with how many innovations they can incorporate in each release. However, this trade-off is absent from the recent literature on innovation that has followed the tradition of Ericson and Pakes [1995] (EP hereafter), because in these models firms simply choose how much to invest in a stochastic innovation process and new innovations are assumed to be incorporated into products as soon as they are realized. The objective of this paper is to incorporate the distinction between release frequencies and quality changes into a dynamic innovation model that can be used to examine both optimal firm strategies and classic welfare questions from the literature on innovation.

There are at least three *a priori* reasons for including product releases explicitly into the model. First, in many consumer technology industries product releases are observed to be very regular. For example, in the smartphone industry, Apple releases new products around September each year, while Samsung has made two releases per year, around March and around September. We also observe regular product updates in the automobile industry [Blonigen et al., 2017], and in both of these consumer-focused industries the pattern likely reflects the fact that new releases can be made using incremental improvements in many components, and do not require a single drastic innovation as in the hard drive [Igami, 2017] and upstream CPU industries [Goettler and Gordon, 2011, GG hereafter]. In EP-style models, however, realized innovations tend to be irregular, because innovation success is stochastic even if a firm exerts steady effort over time

Second, the willingness to pay of forward-looking consumers for leading edge durable products is likely to depend on when they expect new versions to be released. Therefore if forward-looking consumers are to be included in the model as allowed by GG, it is natural to also include an explicit model of the release decisions of firms.

Third, it is plausible that some counterfactual environment changes will cause release frequencies and the average magnitude of incremental improvements to change in different directions whereas an EP-style framework would force them to change in only one direction. I specifically find this to be the case when I change the market structure from duopoly to monopoly, as a monopolist is predicted to release products less frequently but to increase the overall innovation rate, so that total welfare increases.

The structure of my empirical model is that firms first choose, and fully commit to, the frequency with which they release new products, and then, conditional on these frequencies, they play a dynamic game, with a Markov Perfect Equilibrium, where they choose the prices of new releases and how much to invest to increase the quality of each release. Consumers are forward-looking and make optimal choices about when to replace their current holdings based on the products that are currently available and their expectations of future prices and releases.

The model is estimated using data on flagship models sold by the leading smartphone manufacturers, Apple and Samsung. The smartphone industry is a consumer-oriented technology industry with regular release cycles and some uncertainties about how innovative each release will be. It therefore fits the assumptions of my model quite well. I allow for phones sold by other manufacturers to be present in the market, but do not model these manufacturers in a strategic way, in order to limit the computational burden. I develop a two-stage estimator that exploits the fact that under my assumptions, consumer choice sets will be known to be fixed for several periods. The supply side is estimated using a nested fixed point procedure where, following GG, I use backwards induction in order to avoid problems that may arise from a multiplicity of equilibria. Simulated and actual moments are very close, indicating that this quite restricted parameterization is able to fit the data.

Given the parameter estimates, I use the model to examine the welfare implications of market concentration, and to provide suggestions on firms' optimal product release schedules. When I change the market structure from a hypothetical symmetric and single-product duopoly to a monopoly, price goes up by 30%, the innovation rate goes up by 7.4%, and product releases become less frequent from once every 6 months to once every 12 months. Consumer surplus and social welfare both increase as the monopolist's higher innovation is only partially offset by the higher prices and slower releases.

My model is simplified in several aspects, which facilitates the computation but introduces several limitations as well. First, I adopt a single-product firm setup where I interpret product quality as reflecting the average quality of the flagship smartphones sold by each firm. In doing so I ignore important portfolio aspects of firm's problem. Second, I only include Apple and Samsung as strategic players, and represent all other manufacturers as a composite and non-strategic firm "Other". While firms like HTC and LG also introduce popular flagship smartphones, their quality frontiers fall behind the two major players and I assume they have very limited market impact in the flagship market. Third, when I estimate the model I assume that firms fully commit to their regular release schedules and cannot change them afterwards. While I do not see changes in schedules, consumers may believe that changes are possible and adjust their behaviors as a result. I examine this assumption in the counterfactual by comparing outcome to a model with partial commitment and show that commitment is valuable.

It has been discussed for decades whether, in general, market competition increases innovation. Schumpeter [1942] proposed a negative relationship between market competition and firms' innovation, where Arrow [1962] argued that competition might increase innovation, as a monopolist would not want to replace its own profits. The empirical literature has found evidence of an inverted U-shaped relationship between competition and innovation across industries [Aghion et al., 2005].

For the durable good markets, Carlton and Gertner [1989] show that competition with consumers' existing holdings incentivizes the monopolist to innovate more and results in higher social surplus; Waldman [1993, 1996] further extends this notion of competition with consumers' holdings into planned obsolescence and concludes that the monopolist over-invests to reduce the value of consumers' current holdings and increases consumers' future upgrade purchases. Gowrisankaran and Rysman [2012] provide a framework to track consumer demand in the durable good market with a rapid price decline and fast quality improvement. These papers highlight the importance of accounting for consumers' current holdings when studying durable good firms' product innovation decisions, and this paper extends their setup by allowing firms to control the pace of new product releases, which indirectly affects the evolution of consumer holdings.

This paper also contributes to the literature of dynamic oligopoly competition. Pakes and McGuire [1994] and EP established the basis for the oligopoly dynamic investment literature. This framework has been widely adapted and applied to various industries and problems, including mergers [Gowrisankaran, 1999, Gowrisankaran and Holmes, 2004], research joint ventures [Song, 2011], and investment with product differentiation [Narajabad and Watson, 2011].[1] Eizenberg [2014], Nosko [2010], and Fan and Yang [2016] study firms' product positioning decisions in a static setting, and Sweeting [2013] in a dynamic setup. Papers studying smart-

[1] Pakes and McGuire [2001], Ferris et al. [2012], Doraszelski and Pakes [2007], Borkovsky et al. [2010, 2012], and Farias et al. [2012] propose various algorithms and methods to solve this type of dynamic problems.

phone manufacturers focus on bargaining between smartphone manufacturers and wireless carriers [Sinkinson, 2014, Luo, 2016], vertical integration of upstream hardware makers and smartphone manufacturers [Yang, 2016], and smartphone manufacturers' product portfolio choice [Fan and Yang, 2016, Wang, 2017].

This paper develops a dynamic oligopoly model in the durable good context, and it is closely related to GG. GG also uses a dynamic demand and dynamic supply framework to study firms' competition in the CPU market. They show that a more concentrated market structure leads to higher innovation and higher price, and consumer surplus is lower as the loss of higher prices dominates the gain from higher innovation. This paper extends their framework by allowing firms to separately control their product releases aside from the innovation process.

The rest of the paper is organized as follows. Section 2 describes the model setup. Section 3 provides details on data. Section 4 describes estimation strategies and Section 5 provides the results. Section 6 presents counterfactual results on product release frequencies.

2.2 Model

I present a dynamic model of a differentiated-product oligopoly selling durable goods. Although this model is designed to describe the smartphone industry, it could be applied to other industries where durable goods with regular release schedules are sold, like the automobile industry where manufacturers carry out minor or major improvements in their new products every year [Blonigen et al., 2017].

In this model, in every period each consumer observes all firms' current product offerings and either buys a new smartphone and scraps her current smartphone ("purchasing"), or continues to use her current smartphone for another period ("waiting").[2] Consumers' values of purchasing and waiting, which govern their purchase decisions, are affected by their expectations of firms' product qualities, prices, and future release schedules. For example, if future products are expected to have higher qualities and lower prices, or if a better product will be available soon, consumers prefer to wait rather than immediately buy new phones.

Firms choose and commit to their product release frequencies simultaneously at the beginning of the model, which determines their product release schedules in all future periods. Given these pre-committed schedules, firms play a dynamic oligopoly game where they choose prices and invest to improve their product qualities when they are scheduled to release new products, and continue with their previous product offerings in other periods.

2.2.1 State space

Time is discrete with infinite horizon $t = 1, 2, , \ldots,$ and each period represents one month in both estimation and the counterfactual analysis. A finite number of firms are indexed by $j = 1, 2, \ldots, J$, and an infinite number of consumers are indexed by i. Both firms and consumers are infinitely present with no entry or exit. In the model, there are two active firms (Apple and Samsung) making strategic choices of

[2]According to comScore reports, smartphone penetration in the US mobile market increased from 60% in July 2013 to 79% in January 2016. This high penetration rate motivates my assumption that every consumer uses smartphone when not buying.

their release schedules, innovations, and product prices, and a third firm, "Other," included to capture competition from other firms in the flagship smartphone market, with its product characteristics evolving over time in a deterministic form.[3] I only include firm "Other" in the model when estimating the parameters and remove it in the counterfactual analysis.

Firms choose their release schedules, in terms of number of periods between their consecutive releases, simultaneously before their further product decisions.[4] To alleviate the computational burden, I restrict firms' possible choices of interval length, R_j, to factors of 12 months, e.g. $3, 6, 12$, so firms' release schedules take the form of Z releases every year where Z is some positive integer. For example, $R_j = 6$ indicates that firm j releases a new product in every 6 months, or equivalently, twice every year. In order to uniquely characterize firms' release schedules given their choices of release frequencies, I further assume that all firms release new products simultaneously in at least one period, so starting from that period, both forward and backward, all firms' future release schedules are fully determined.[5] Next I will discuss how each state variable in consumer's and firm's problem is defined, and how these variables evolve over time.

[3] In July 2013, the first month observed in my data, 92.2% of smartphone subscribers were using iPhones or Android phones, and this percentage increased over time. So firm "Other" essentially captures all other firms selling Android smartphones, such as HTC and LG. More details on firm Other will be provided when setting up firm's problem.

[4] This setup implicitly assumes that every firm's new products are released regularly and repeatedly. This assumption is made in accordance with the observed release patterns in data where both Apple and Samsung release new phones near September, while Samsung also release new phones in March.

[5] One possibility ruled out by this assumption is that, two firms choose to both release once every year, but their release periods are six months apart from each other. This is considered in the counterfactual analysis where firms are allowed to stagger their releases from those of their rivals.

State of release schedule $\mathbf{r}_t$

In period t, each firm has an indicator, $r_{jt} = 1, 2, \ldots, R_j$, which measures the number of periods left until its next scheduled product release. For example, $r_{jt} = 1$ means that at time t, firm j will release a new product in the next period. The market level release state is defined by collecting all firm level indicators as $\mathbf{r}_t = (r_{1t}, r_{2t}, \ldots, r_{Jt})$. Given firm j's commitment of release interval R_j, r_{jt} evolves in a deterministic way as follows:

$$r_{jt} = \begin{cases} r_{j,t-1} - 1, & \text{if } r_{j,t-1} > 1 \\ R_j, & \text{if } r_{j,t-1} = 1 \end{cases}.$$

That is, r_{jt} will decrease by one in each period until it reaches one, after which it is then set back to R_j and firm j's new phone is released. Firms are denoted as "active" in periods in which they are scheduled to release new products (i.e. $r_{jt} = R_j$), and "inactive" in other periods.

Quality vector $\mathbf{q}_t$

I adopt the single-product firm setup where each firm sells only one product at any time t with quality q_{jt} and price p_{jt}, which can be interpreted as average quality and average price for the multi-product firms observed in data. With this setup, I ignore the portfolio management decisions and only capture the upward quality trend resulting from firms introducing new products and discontinuing the old ones.

The market level quality and price vectors at time t collect all firms' product characteristics as $\mathbf{q}_t = (q_{1t}, q_{2t}, \ldots, q_{Jt})$, $\mathbf{p}_t = (p_{1t}, p_{2t}, \ldots, p_{Jt})$, respectively. If firm j releases a new product at time t, then q_{jt} and p_{jt} are set as its quality and price; otherwise, firm j sells the same product as in the previous period (i.e. $q_{jt} = q_{j,t-1}, p_{jt} = p_{j,t-1}$).[6]

Product quality is discrete with n_q levels of constant increment of δ, defined as $q_{jt} \in \{\underline{q}, \underline{q}+\delta, \ldots, \bar{q} \triangleq \underline{q}+(n_q-1)\delta\}$. When firms release new products, they choose an investment amount which dictates the probability of the higher quality increment. Holding all other states as fixed, higher investment increases the probability of the higher quality increment. More details are provided when I describe how I solve firms' optimal investment decisions.

In this model, firms' product qualities are non-decreasing over time and will exceed the upper bound after several product releases if not bounded. To maintain this upward quality trend brought by new product introductions as well as restrict quality values on the preset quality grids, I define the quality state space in a way such that it is bounded, as in GG. More details are provided after I have defined consumer's and firm's value functions are constructed.

Distribution of consumers' holdings Δ_t

Consumers are atomistic in the sense that each consumer believes her individual purchase decision has no effect on firms' price and quality choices. To measure competition from consumers' current holdings in each firm's problem, I follow GG

[6]Note that I assume prices cannot be adjusted when firms do not release new products so they are informative when predicting sales in the future. This setup also assumes no quality depreciation for the new products on sale.

and assume that firms keep track of the distribution of consumers' holdings Δ, which is constructed as follows. Denote the proportion of consumers using firm j's phones with quality $q_k \triangleq \underline{q} + (k-1)\delta$ at time t as Δ^j_{kt}. Summing up these proportions over all manufacturers and quality levels gives $\sum_{j,k} \Delta^j_{kt} = 1$. The market level distribution variable is defined by collecting proportion values of all three firms (Apple, Samsung and Other) and all n_q quality levels as $\Delta_t = \{\Delta^j_{kt}\}_{j,k}$.

In this model, Δ_t evolves based on consumers' purchase decisions. Intuitively speaking, if firm j's current product is not of quality q_k, then $\Delta^j_{k,t+1}$ only includes consumers in Δ^j_{kt} choosing to wait; otherwise, $\Delta^j_{k,t+1}$ also includes consumers not in Δ^j_{kt} but buying phones from firm j at time t. To formally express this evolution, denote the probability of buying quality $q_{k'}$ product from firm j' when using quality q_k product from firm j as $Pr^{j \to j'}_{k \to k'}$, where the arrow denotes the direction of change due to consumers' purchases. Then the imputed consumer distribution, $\tilde{\Delta}^j_{k,t+1}$ is calculated according to:

$$\tilde{\Delta}^j_{k,t+1} = \begin{cases} \Delta^j_{kt} \left(1 - \sum\limits_{j', q_{k'} = q_{j't}} Pr^{j \to j'}_{k \to k'} \right), & \text{if } q_{jt} \neq q_k \\ \sum\limits_{j',k'} \Delta^{j'}_{k',t} Pr^{j' \to j}_{k' \to k} - \Delta^j_{kt} \sum\limits_{j', q_{k'} = q_{j't}} Pr^{j \to j'}_{k \to k'}, & \text{if } q_{jt} = q_k \end{cases} . \tag{2.1}$$

In this expression, the two sub-cases correspond to when firm j does and does not sell a product with quality q_k, which determines if there is an inflow of consumers into $\Delta^j_{k,t+1}$. Note that the outflow of consumers only sums up over the qualities of products that the other firms sell at time t instead of all quality levels. This is because consumers are assumed never to exit the market, and the only way to leave Δ_k^j is to buy a new phone (other than firm j's phone if its quality is q_k).

The distribution variable Δ is of high dimensions so it is necessary to use a coarser approximation.[7] To alleviate the computational burden while still including Δ in the state space, I assume that Δ can take values from 20 preset candidates by first calculating imputed distribution $\tilde{\Delta}$ as in (2.1), and then reallocating it to its nearest candidate in terms of the average holding quality, to get the new distribution Δ in the new state. This reallocation proceeds as follows: for each Δ candidate, calculate its average holding quality as $q_\Delta = \sum_{k,j} q_k \Delta_k^j$; next, the closest Δ candidate to $\tilde{\Delta}$ is determined by:

$$\Delta_{t+1} = \min_{\Delta} \left\| q_\Delta - \sum_{j,k} \tilde{\Delta}_{k,t+1}^j q_k \right\|. \tag{2.2}$$

Equation (2.1), (2.2) jointly define the evolution of Δ based on consumers' purchases. This assumption of using average holding quality to approximate Δ evolution creates bias in both mean quality and other moments like variances, skewness, etc. To reduce the bias in mean quality, my 20 Δ candidates are generated such that their mean qualities are widely spread to cover extreme distributions, and also condense around observed mean qualities so even minor changes in mean qualities are reflected by moving across different Δ candidates; for other biases like moments of second or even higher orders, I assume that these biases do not affect firms' profits significantly when biases in mean quality levels are not large.

[7] Suppose each consumer proportion value Δ_{kt}^j is discrete and takes 5 values, then with only 5 quality levels and 3 firms, there will be in total $5^{5\times 3} \approx 3 \times 10^{10}$ possible values for Δ_t.

Individual holding characteristics $\mathcal{I}_{it}$

The individual holding characteristics $\mathcal{I}_{it}$ has two dimensions: its manufacturer J_{it} and quality q_{it}, which jointly determine consumers' utilities of retaining their current holdings. $\mathcal{I}_{it}$ stays the same if consumer i does not buy a new smartphone, and this implicitly assumes no quality depreciation over usage; if she buys a new phone, J_{it} and q_{it} are set as the manufacturer and the quality of her new phone.

State space for consumers and firms

In each period, firms observe the state of the release schedule $\mathbf{r}_t$, market level quality vectors $\mathbf{q}_t$, and distribution of consumers' holdings Δ; consumers observe all state variables that manufacturers observe as well as their own holdings.

2.2.2 Consumer's problem

Each consumer uses one smartphone at any time. In each period, each consumer attains utility from her smartphone based on its quality, manufacturer fixed effect, other unobserved utility shock and any disutility of monetary payment for the new phone purchase. If consumer i buys a new smartphone from firm j with quality q_{jt}, her utility of using this new smartphone for the current period is given by [8]

$$u_{ijt}(\mathcal{I}_{it}) = \alpha_q q_{jt} - \alpha_p p_{jt} + \xi_{jt} + \varepsilon_{ijt} \triangleq U_{ijt} + \varepsilon_{ijt}, \tag{2.3}$$

[8] I tried to allow for consumer types with different brand preferences but it did not help fit the demand.

where α_q, α_p measure her marginal utilities over the quality and the price, respectively. ξ_{jt} indicates the brand preference for firm j, and ε_{ijt} captures idiosyncratic variations, which is independently and identically distributed across consumers, products and time as type I extreme values. If consumer i keeps using her current phone ("waiting"), her utility is determined by the quality and the manufacturer of her current holding as

$$u_{i0t}(\mathcal{I}_{it}) = \alpha_q q_{it} + \xi_{it} + \varepsilon_{i0t} \triangleq U_{i0t} + \varepsilon_{i0t}, \tag{2.4}$$

where q_{it} represents the quality of consumer i's most recent purchase at time t. ξ_{it} is the brand preference of her current phone, which is time varying because of changes in her individual holding characteristics. Given the assumption that consumers' outside options are using smartphones as well, it is this relative quality difference between consumers' current holdings and new smartphones that motivates consumers' repeated purchases and firms' new phone introductions over time.

Each consumer makes her purchase decisions by maximizing her expected discounted utility of different purchase options and the outside option. Omitting the time and the consumer subscript, using the prime sign to indicate values in the next period, and using $j = 0$ to denote the no-purchase option, a consumer's choice specific value for product j is

$$v_j(\mathbf{q}, \Delta, \mathcal{I}, \mathbf{r}, \varepsilon) = u_{ij} + \beta \sum_{\mathbf{q}'} \int V(\mathbf{q}', \Delta', \mathcal{I}'_j, \mathbf{r}', \varepsilon') f(\varepsilon') d\varepsilon' \times h_c(\mathbf{q}'|\mathbf{q}, \Delta', \mathbf{r}, \varepsilon) g_{\Delta'}(\Delta, \mathbf{q}, \mathbf{r}, \varepsilon), \tag{2.5}$$

where h_c is the consumer's belief about future product qualities, $g_{\Delta'}$ gives Δ' after consumers' purchases in the current period, and f is the density function of ε. $\mathcal{I}'$ includes the j subscript to capture the information from consumer purchase. The value of Δ' is defined at the start of the next period, and so reflects consumers' purchases in the current period. That is why the evolution of Δ only depends on the state in the current period $(\Delta, \mathbf{q}, \mathbf{r})$, while the transition of $\mathbf{q}'$ depends on Δ'. As is discussed above, Δ' is calculated by reallocating the imputed value to its nearest Δ candidate, which always gives a unique value instead of a probability distribution over multiple values, so I use a degenerate function $g_{\Delta'}(\Delta, \mathbf{q}, \mathbf{r}, \varepsilon)$ for Δ' evolution.

The consumer's value function is defined by the value of her optimal choice, including the no-purchase option, as

$$V(\mathbf{q}, \Delta, \mathcal{I}, \mathbf{r}, \varepsilon) = \max_{j \in \{0,\ldots,J\}} v_j(\mathbf{q}, \Delta, \mathcal{I}, \mathbf{r}, \varepsilon). \tag{2.6}$$

Assuming that ε is distributed as type I extreme value, integrating over ε yields

$$\bar{V}(\mathbf{q}, \Delta, \mathcal{I}, \mathbf{r}) = \log \left\{ \sum_{j \in \{0,\ldots,J\}} \exp \left[U_j + \beta \sum_{\mathbf{q}'} \bar{V}(\mathbf{q}', \Delta', \mathcal{I}', \mathbf{r}') h_c(\mathbf{q}' | \mathbf{q}, \Delta', \mathbf{r}) g_{\Delta'}(\Delta, \mathbf{q}, \mathbf{r}) \right] \right\}, \tag{2.7}$$

from which the choice-specific value function takes the form

$$\bar{v}_j(\mathbf{q}, \Delta, \mathcal{I}, \mathbf{r}) = U_j + \beta \sum_{\mathbf{q}'} \bar{V}(\mathbf{q}', \Delta', \mathcal{I}', \mathbf{r}') h_c(\mathbf{q}' | \mathbf{q}, \Delta', \mathbf{r}) g_{\Delta'}(\Delta, \mathbf{q}, \mathbf{r}), \tag{2.8}$$

which differs from $v_j(\mathbf{q}, \Delta, \mathcal{I}, \mathbf{r}, \varepsilon)$ only in the integration of ε. Using this choice-specific value functions, consumer's individual choice probability in state $(\mathbf{q}, \Delta, \mathbf{r}, \mathcal{I})$ is

$$s_{j|\mathcal{I}}(\mathbf{q}, \Delta, \mathbf{r}) = \frac{\exp(\bar{v}_j(\mathbf{q}, \Delta, \mathcal{I}, \mathbf{r}))}{\sum_{k\in\{0,\ldots,J\}} \exp(\bar{v}_k(\mathbf{q}, \Delta, \mathcal{I}, \mathbf{r}))}. \tag{2.9}$$

Finally, aggregating individual choice probabilities of buying from each firm across all types of consumer holdings, the market share of product j is calculated as

$$s_j(\mathbf{q}, \Delta, \mathbf{r}) = \sum_k s_{j|\mathcal{I}=(j,q_k)}(\mathbf{q}, \Delta, \mathbf{r})\Delta_k^j. \tag{2.10}$$

2.2.3 Firm's problem

In each period, active firms invest to improve qualities of their new products, where higher investment increases the probability of the greater quality improvements. Once the investment outcome is realized, active firms simultaneously choose new prices which are fixed until the next release, and new products are available for consumers to buy.

I adopt the single-product firm setup in this model because of the huge computational burden to allow for multiproduct firms. Accounting for multiple products would be important for questions related to product portfolios, like product line pricing problems and quality alignment problems [Eizenberg, 2014, Nosko, 2010, Fan and Yang, 2016]. This paper studies firms' competition over the release frequency with a focus on the upward trend of product qualities and product portfolio management decisions are ignored.

I now present how I solve a firm's problem using backward induction within each period, by first solving for optimal prices given their investment outcomes, and then solve for firms' optimal investment decisions.

Optimal pricing

Given firms' choices of prices, the period profit function for firm j, excluding investment cost, is

$$\pi_j(\mathbf{p}, \mathbf{q}, \Delta, \mathbf{r}) = M s_j(\mathbf{p}, \mathbf{q}, \Delta, \mathbf{r})[p_j - mc_j] \tag{2.11}$$

where M is the fixed market size, $s_j(\cdot)$ is the market share for firm j, $\mathbf{p}$ is the vector of J prices and mc_j is the constant marginal cost for firm j's phones. Price is included in the market share function just to explicitly denote firms' price choices.

In this model, firms cannot adjust their product offerings, including both prices and qualities, until releasing new products, so firm j should take into account all of the profit in the next R_j periods when choosing new prices and investments. Suppose firm j becomes active in period t_0, then given its choice of product price and quality, p_j and q_j for the newly released product, the sum of its discounted profits until its next release takes the form

$$\Pi_{j,t_0}(p_j, q_j, \mathbf{q}_{-j,t_0}, \Delta_{t_0}, \mathbf{r}_{t_0}) = \mathbb{E}\left(\sum_{t=0}^{R_j-1} \beta^t M \pi_{j,t_0+t}(\{p_j\} \cup \mathbf{p}_{-j,t_0+t}, \{q_j\} \cup \mathbf{q}_{-j,t_0+t}, \Delta_{t_0+t}, \mathbf{r}_{t_0+t}) \middle| p_j, q_j, \mathbf{q}_{-j,t_0}, \Delta_{t_0}, \mathbf{r}_{t_0} \right), \tag{2.12}$$

where

$$\mathbb{E}\left[\pi_{j,t_0+t}(\{p_j\} \cup \mathbf{p}_{-j,t_0+t}, \{q_j\} \cup \mathbf{q}_{-j,t_0+t}, \Delta_{t_0+t}, \mathbf{r}_{t_0+t}) | p_j, q_j, \mathbf{q}_{-j,t_0}, \Delta_{t_0}, \mathbf{r}_{t_0}\right]$$
$$= \sum_{\mathbf{q}_{-j,t_0+t}} \pi_{j,t_0+t}(\{p_j\} \cup \mathbf{p}_{-j,t_0+t}, \{q_j\} \cup \mathbf{q}_{-j,t_0+t}, \Delta_{t_0+t}, \mathbf{r}_{t_0+t}) \tag{2.13}$$
$$\times h_{f_j}(\mathbf{q}_{-j,t_0+t} | \mathbf{q}_{t_0}, \Delta_{t_0}, \mathbf{r}_{t_0}) \mathbb{E} g_{\Delta_{t_0+t}}(\Delta_{t_0}, \mathbf{q}_{t_0}, \mathbf{p}_{t_0})$$

In this expression, h_{f_j} is firm j's belief about its competitors' future qualities, and $\mathbb{E}g$ gives expected Δ with randomness coming from the evolution of all other state variables between t_0 and $t_0 + R_j$. $\{p_j\} \cup \mathbf{p}_{-j,t_0+t}$ and $\{q_j\} \cup \mathbf{q}_{-j,t_0+t}$ are market level price and quality vectors, respectively, at time t, with firm j's price and quality explicitly specified as unchanged. In periods when no other firms are active, h_{f_j} is degenerate and the quality will be the same as in the previous period. In other periods when at least one other firm is active, h_{f_j} is firm j's belief of those active firms' policies. All future expectations are conditional on state variables in period t_0, which is when firm j chooses optimal investment and prices.

With a slight abuse of notation, use a prime sign to denote variables when firm j becomes active again (e.g. at $t = t_0 + R_j$). After the investment outcome is realized, firm j maximizes its expected discounted profits by choosing the optimal prices, which solves the problem

$$\tilde{W}_j(q_j, \mathbf{q}_{-j}, \Delta, \mathbf{r}) = \max_{p_j} \Pi_j(p_j, q_j, \mathbf{q}_{-j}, \Delta, \mathbf{r}) + \beta^{R_j} \mathbb{E}\left(W_j(q_j, \mathbf{q}'_{-j}, \Delta', \mathbf{r}') | p_j, q_j, \mathbf{q}_{-j}, \Delta\right). \tag{2.14}$$

Optimal investment

In the smartphone industry, downstream manufacturers' quality improvement comes from adopting better components (like CPU, RAM and display technology) and improving the manufacturing process (like optimizing hardware compatibility). Potential quality improvement for new products accumulate over time, and more frequent releases will result in less cumulative upstream innovations available for each new product. To fit this pattern, I normalize the innovation outcomes for the smartphone manufacturers based on their release frequencies. The intuition is that firms with rare releases can increase the quality by a higher amount in each release, while firms with frequent releases are constrained for minor quality improvements. The ultimate goal is to guarantee the same range of possible quality increments in each 12 months regardless of these manufacturers' chosen release frequencies.

To be specific, each firm's possible quality increment is defined as follows: if $R_j \geq 6$, its quality q_j can be increased to either $q_j + \frac{R_j}{6}\delta$ or $q_j + \frac{2R_j}{6}\delta$; if $R_j < 6$, then its quality q_j can be either unchanged, or increased to $q_j + \delta$. In this way, firms with frequencies $R_j \geq 3$ will have the same upper bound of quality increment per year 4δ, so in the long run, no firms will be at a systematic disadvantage from choosing a particular schedule. More details can be found in Table 2.1.

For example, if firm A and firm B chooses $R_A = 12, R_B = 6$, then possible qualities for their new products, given current quality level q_A and q_B, are $q'_A = q_A + 2\delta$ or $q_A + 4\delta$, $q'_B = q_B + \delta$ or $q_B + 2\delta$. In this way, in every 12 months, both firm A and B can increase their qualities by up to 4δ and down to 2δ so both firms

Table 2.1: Possible quality increment

	Per release		Per 12 months	
R	τ'	τ''	Upper bound	Lower bound
3	0	δ	0	4δ
6	δ	2δ	2δ	4δ
12	2δ	4δ	2δ	4δ

have the same range of possible quality outcomes. To facilitate future expressions, denote firm j's higher and lower possible quality increment in each release as τ''_j and τ'_j, respectively.

It is also worth noting that my choice of τ', the quality increment when the innovation fails, is not zero for $R = 6, 12$. When the innovation outcomes are realized, firms have to wait until their next releases to adjust their product qualities again, which puts firms with less frequent releases at disadvantage. This "guaranteed" quality increment reduces the potential loss as from failed innovation outcome, and maintain the quality competition in the long run.[9] A possible concern arising from this setup is that, this guaranteed quality improvement is equivalent to guaranteed product release, which may affect players' expectation and the equilibrium outcome. I tested my model framework by setting τ' to zero, and find that this has very little impact on players' strategies, as all players in the model are risk neutral and they only care about expected quality increments. More details can be found in the appendix in Chapter 2.

I also adjust investment cost in each product release. Firms invest for quality increments every time they are scheduled to release new products, and this model

[9]Even with some success guaranteed, this model predicts that firms always invest.

should guarantee that firms with similar expected quality increment per year need similar investment regardless of their release frequencies. To incorporate this property, I adjust firms' investment costs based on their R_j such that firm j's true cost of investment x_j is $\frac{R_j}{3}x_j$.[10] For example, suppose $R_A = 12, R_B = 6$, and both firms invest x_0 in each release, then both firms pay the same investment cost per 12 months: $x_A = \frac{12}{3}x_0 = 4x_0, x_B = \frac{6}{3}x_0 \cdot 2 = 4x_0$.

Denote the scale of quality improvement for firm j's product as $\tau_j = q_j' - q_j$, which takes the value of τ_j' or τ_j''. Given firm j's investment x_j, the probability of higher quality outcome is formulated as

$$\chi_j \left(\tau_j = \tau_j'' | x\right) = \frac{a_j(\mathbf{q})x}{1 + a_j(\mathbf{q})x}, \tag{2.15}$$

where

$$a_j(\mathbf{q}) = a_{0,j} \max \left\{1, a_{1,j} \left(\frac{\max \mathbf{q} - q_j}{\delta}\right)\right\}, \quad \max \mathbf{q} \triangleq \max_j\{q_j\}.^{11} \tag{2.16}$$

$a_{1,j} > 0$ introduces an "innovation spillover effect" by increasing the investment efficiency, $a_j(\mathbf{q})$ for lagging firms such that, holding investment and all other state variables fixed, higher quality outcomes are more likely for the lagging firms than the leader firms. This mechanism makes it easier for the lagging firm to catch up with the leader firm.

Next, given the value function $\tilde{W}_j(q_j, \mathbf{q}_{-j}, \Delta, \mathbf{r})$, which already incorporates

[10]The denominator 3 is included only to simplify the result. For $R_j = 3, 6, 12$, $\frac{R_j}{3} = 1, 2, 4$.
[11]This functional form is formuated in EP and adopted by GG.

the optimal price choices, firm j chooses optimal investment by solving the following problem,

$$\begin{aligned} W_j(q_j, \mathbf{q}_{-j}, \Delta, \mathbf{r}) = \max_{x_j} & \tilde{W}_j(q_j + \tau_j', \mathbf{q}_{-j}, \Delta, \mathbf{r}) \chi(\tau_j = \tau_j' | x_j) \\ & + \tilde{W}_j(q_j + \tau_j'', \mathbf{q}_{-j}, \Delta, \mathbf{r}) \chi(\tau_j = \tau_j'' | x_j) - \frac{R_j}{3} x_j \end{aligned}, \tag{2.17}$$

which takes weighted average between two investment outcome, $q_j + \tau_j'$ and $q_j + \tau_j''$, and deducted the adjusted innovation cost. Equation (2.14) and (2.17) jointly define firms' value functions.

Firms' choices of R_j at the beginning of the model is determined by their expected value for all the future periods. For each of firm's states $s = (\mathbf{q}, \mathbf{p}, \Delta, \mathbf{r})$, denote the probability of its occurrence in a sufficiently long duration as p_s, then firm j's value given choice of $(R_j, \mathbf{R}_{-j})$ is $\sum_s W_j(s) p_s$.[12] Given payoffs of each combination of R, all firms simultaneously choose their optimal R_j, which completes setup for firm's problem.

Firm "Other"

Besides Apple and Samsung, I also include a third firm "Other" in the model during estimation to capture competition from all other flagship smartphone manufacturers, like HTC, Lenovo and LG. In general these firms' quality frontier expansion paces are slower, and they sell their smartphones at cheaper prices. When solving consumers' problem, I assume that firm Other's product quality q_{Ot} and p_{Ot}

[12] I assume a random steady state starting point to calculate this value.

are completely determined by Apple and Samsung's product characteristics in the following way:

$$q_{Ot} = \min\{q_{At}, q_{St}\} - \delta, \quad p_{Ot} = .45 * (p_{At} + p_{St}).$$

With this setup, q_{Ot} is always slightly lower than Apple and Samsung's product qualities, but it will increase over time with Apple and Samsung's release of better products. In accordance to this relative quality, I set p_{Ot} to be .9 times average price of Apple and Samsung's product prices. Consumers also know this determination rule of $\{q_{Ot}, p_{Ot}\}$, so they only form expectations over future Apple and Samsung product characteristics.

2.2.4 Equilibrium

Firms choose their optimal release frequency $\{R_j\}_j$ by solving for Nash equilibrium, where their payoffs are expected values given different combinations of $\{R_j\}_j$ and all firms' optimal price and investment choices conditional on the corresponding release frequencies. I assume that such a pure strategy Nash equilibrium exists.

Conditional on the choices of $\{R_j\}_j$, I adopt the symmetric pure-strategy Markov-Perfect Nash equilibrium (MPNE) to solve for firms' product choices and consumers' purchase decisions. This MPNE specifies that (1) firms' and consumers' equilibrium strategies depend only on current state, which consists of all payoff-relevant variables; (2) consumers have rational expectations about firms' policy functions, which determine future qualities and prices, and the evolution of the ownership distribution; and (3) each firm has rational expectations about its competitors' prices and investment and about the evolution of the consumer holding distribution.

Formally speaking, an MPNE for this model, given the choice of $\{R_j\}_j$ is the set

$$\{V^*, h_c^*, g_c^*, \{W_j^*, x_j^*, p_j^*, h_{f_j}^*, g_{f_j}^*\}_{j=1}^J\},$$

which includes consumers' equilibrium value V^*, consumers' beliefs about future product quality and ownership distribution h_c^* and g_c^*, firms' equilibrium value functions W_j^*, their optimal policy functions of investment and prices x_j^*, p_j^*, firms' beliefs about future qualities and the transition of consumer holding distribution $h_{f_j}^*, g_{f_j}^*$. The expectation over future qualities is rational in that the expected distribution matches the distribution resulting from consumers and firms behaving according to their optimal policy functions.

One difficulty in estimating dynamic discrete games and conducting the counterfactual analysis is the multiplicity of equilibrium in product choice and purchase decisions, and release frequency choices. The literature has addressed this issue in numerous ways, among which one choice is to use backward induction and derive players' values starting from given future values. When solving the model, I start from a future period where I assume both consumers' and firms' values are only determined by their payoffs in that period, and then using backward induction to solve for their optimal policy functions holding fixed their actions in the next period. For choices of release intervals, it is easy to check for the existence of multiple equilibria in the normal form.

2.2.5 Bounding the state space

Firms' product qualities increase in every product release so that, over time, they can increase without bound. To numerically solve the model, I transform the state space to finite size by redefining all qualities as relative qualities to a preset quality boundary $\bar{q}$. The capability to implement this quality transformation without changing the dynamic game itself comes from the following proposition.

Proposition 1 (Goettler and Gordon (2011)) *Shifting down qualities of the two firm, q and $\tilde{q}$, by δ has no effect on firms' payoffs and lowers consumers' payoffs in each state by $\frac{\alpha_q \delta}{1-\beta}$, the discounted value of the reduced utility in each period. More formally,*

firms:

$$W_j(q_j - \delta, \mathbf{q}_{-j} - \delta, \Delta, \mathbf{r}) = W_j(q_j, \mathbf{q}_{-j}, \Delta, \mathbf{r})$$

consumers:

$$V(\mathbf{q} - \delta, \Delta, \mathcal{I} = (\tilde{q} - \delta, \tilde{J}), \mathbf{r}) + \frac{\alpha_q \delta}{1 - \beta} = V(\mathbf{q} - \delta, \Delta, \mathcal{I} = (\tilde{q}, \tilde{J}), \mathbf{r})$$

The proof for this proposition rests on the following properties of the model: (1) quality enters linearly in the utility function, so adding a constant to the utility of each alternative, including new purchase and outside option, has no effect on consumers' choices within a logit demand system; (2) firms' innovation only affects probabilities of different quality increments, and cost of innovation, as well as marginal cost per unit, is independent of quality levels; (3) Δ tracks consumer holding quality relative to the quality frontier so it is unaffected by a shift for all quality levels. In practice, when a firm's product quality is at the highest level, $\bar{q}$, and it invests to improve it by τ, I will then use this proposition and shift all quality entries by τ.

2.3 Data and industry background

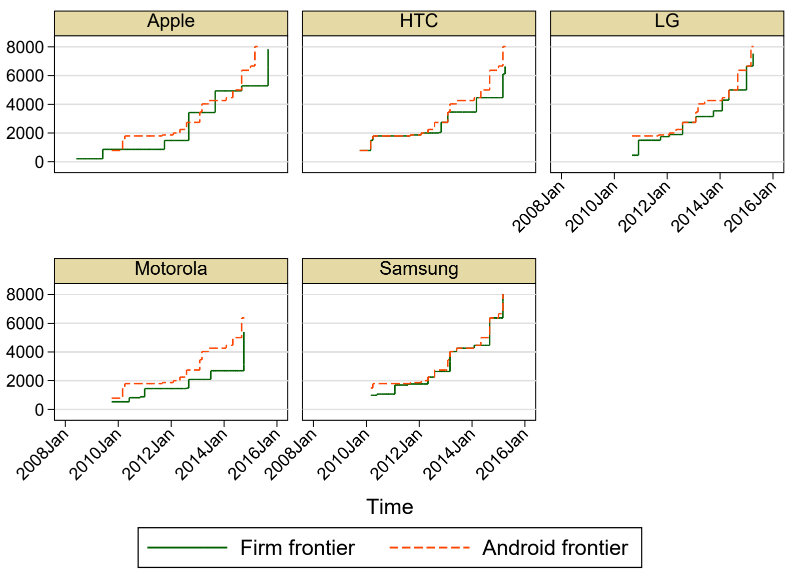
Smartphones were first introduced in 1999, and became widespread in the late 2000s.[13] One distinction between the smartphone and its predecessor, the feature phone, is that smartphone is capable of handling more complicated tasks, like playing games, GPS navigation, taking photos, etc. To meet the hardware requirement for performing these functions , smartphone manufacturers incorporate new and better hardware components into their new smartphone models, resulting in rapid improvement in smartphone qualities.

Figure 2.1 depicts this quality increasing trend from 2008 to 2016 by plotting the quality frontier for the five largest manufacturer in the US market, Apple, Samsung, LG, Motorola and HTC, where quality is measured using the benchmark score collected from http://www.iphonebenchmark.net/ and http://www.androidbenchmark.net/. These websites measure the smartphone performance on CPU, 2D and 3D graphics, memory and disk, then combine these statistics to report an aggregate benchmark score for each smartphone model, which I assume represents a smartphone's overall

[13] https://en.wikipedia.org/wiki/Smartphone

performance. According to the figure, within the Android makers, which include all firms except Apple, Samsung is leading the Android quality frontier and the other three firms are mostly followers.[14] We can also see that Apple's own quality frontier interacts with the Android frontier, which indicates active quality competition. Based on these two observations, I model the US flagship smartphone market as Apple competes with Samsung in quality improvement, with all other firms as followers and represented by a non-strategic firm "Other".

Figure 2.1: Smartphone quality frontier for top five manufacture in the US



Note: Vertical axis represents quality, represented by benchmark scores, and horizontal axis represents time. Quality frontier is defined as the highest quality among all smartphones all manufacturers sold in each period.

A second observation from Figure 2.1 is that, product release schedules are

[14] Some of the smartphones from Samsung and HTC use the Windows Phone system, but market shares of these smartphones are relatively small. By 2013 January, about 90% smartphones being used adopted iOS and Android systems, so I only consider smartphones using these two operating systems. Data source: `http://www.comscore.com/Insights/Press-Releases/2013/3/comScore-Reports-January-2013-U.S.-Smartphone-Subscriber-Market-Share?cs_edgescape_cc=US`.

very regular for both Apple and Samsung. Table 2.2 reports release dates of Apple and Samsung's flagship smartphone models. Samsung typically releases twice every year: Galaxy S series in late February/March and Galaxy Note series in every late August/September, while Apple only releases once every year in September after 2012. This regular release schedule can not be explained by the standard innovation model, where investment outcomes are random and new products are automatically released with successful outcomes. Instead it seems more plausible that firms commit to a regular release schedule, and random outcomes only affect product qualities and prices, not product release arrangements. Based on this release pattern, I approximate release schedules by assuming that Samsung releases twice every year in September and March, and Apple releases once every year in September.

To measure consumers' responses to each smartphone release, I collected weekly user percentages of major smartphone models from Fiksu.com from July 2013 to January 2016. Fiksu publishes statistics from its two user trackers, *iOS trackers* and *Android trackers*, each of which publishes weekly user percentages of smartphone models within that operating system.[15] To calculate user percentages of each smartphone model among all users, not just users from the same operating system, I collected monthly subscriber percentages of iOS and Android smartphones in the US for the same period from comScore reports, and aggregated weekly Fiksu data to monthly data by only keeping data in the first week of each month.

[15] One caveat of this data source is that, users tracked in these services are from both US and Europe, so I have to assume that user percentage of major smartphone models within their corresponding operating system are similar between US and Europe market. Note that there is no requirement for iOS and Android user percentage, which are quite different between US and Europe.

Table 2.2: Announcement dates of smartphones expanding quality frontier from Apple and Samsung

		Release date
Samsung	Galaxy Note	October 29, 2011
	Galaxy S3	May 3, 2012
	Galaxy Note 2	September 26, 2012
	Galaxy S4	March 14, 2013
	Galaxy Note 3	September 25, 2013
	Galaxy S5	February 24, 2014
	Galaxy Note 4	September 3, 2014
	Galaxy S6 Edge	March 1, 2015
	Galaxy Note 5	August 21, 2015
	Galaxy S7	February 21, 2016
	Galaxy Note 7	August 19, 2016
Apple	iPhone 4s	October 4, 2011
	iPhone 5	September 12, 2012
	iPhone 5s	September 20, 2013
	iPhone 6	September 9, 2014
	iPhone 6s Plus	September 9, 2015
	iPhone 7	September 7, 2016

Note: In case where multiple smartphones are released simultaneously, only the model with the highest benchmark score is listed. Data were collected from Wikipedia.

Smartphone sales prices are collected from archived manufacturer webpages. I use full retail prices, instead of contract prices for two reasons. First, since 2013, carriers started "unbundling" by encouraging consumers to buy new smartphones at full price and enjoy discounts on their monthly service fees.[16] Given these discounts, the actual cost of acquiring a new smartphone, with or without the subsidized price, has been close to the full retail price. Second, I am only modeling manufacturers'

[16]For example, AT&T offers a $25 discount per line for a family account if consumers buy phones at full price, and this discount will be removed if a consumer chooses to buy smartphones at the contract price. Overall expenditure between these two methods over two years are close, but the contract price locks consumers in by disallowing them to buy other smartphones during that two-year period.

pricing decisions, and in the smartphone market, this price is represented by the full retail price.[17] All prices are adjusted to the 2013 price level. My modeling assumption of constant prices within each product cycle comes from the fact that manufacturers hardly adjust their retail prices unless new phones are released, and I do not have data of discounting in the retail channels.

Smartphone benchmark scores are collected from Passmark Rating. I assume that the benchmark score of each smartphone model represents the quality of that model and it is time invariant. In case a certain smartphone model has multiple submodels, I select the submodel with the highest benchmark to represent the quality of that model.[18] Table 2.3 reports the means and standard deviations of prices and qualities for Apple and Smasung smartphones.

Table 2.3: Summary statistics

		Mean	Std. Dev.
Apple	Price ($)	558.7	40.8
	Quality (Passmark Score)	4152.1	1205.4
Samsung	Price ($)	629.6	31.7
	Quality (Passmark Score)	4973.5	1238.6

Finally, I also collected Apple and Samsung Electronics' R&D expenditure and total revenues from their quarterly SEC filings. I only collected these two firms'

[17]This choice of retail price as marginal revenue per unit is only an approximation in the firm's problem. In reality, both Apple and Samsung sell their smartphones through wireless carriers and retailers, where they sell their smartphones to these vendors at discounted prices and earn less mark-ups then selling directly on their websites. So my estimated marginal cost will be higher than the actual manufacturing cost. But this retail price is accurate in estimating consumers' preferences as it is close to consumers' actual payments regardless of their purchase methods (pay in full, special financing where consumers split the full retail price in 12 or 24 months or subsidized price where consumers pay less for the smartphone, but have to pay more for their monthly bills).

[18]For example, there are 25 sub models for Samsung Galaxy S6 smartphone, and these sub models differ slightly in hardware components like network devices. Benchmark scores among these submodels are very similar, so I choose the top performance model to represent the quality of that phone. Source: https://www.handsetdetection.com/properties/devices/Samsung/Galaxy%20S6.

overall R&D expeditures and revenues, as their smartphone-specific investments are not publicly available. But given that smartphone sales are the largest revenue sources for both firms, and flagship models require much more investment than the nonflagship model, I assume that these collected numbers are informative on firms' actual investments in their flagship models.[19] These data are used to construct moments for ratio of investment over total revenue.

2.4 Estimation

In this section, I provide details on how I estimate my model parameters using my collected data. One data constraint to studying firms' product introduction decisions is that firms are inactive for most of the time, and there are not many observations for firms' choices of new product qualities and prices. In the total 31 months of data I collected, Apple and Samsung only released for three and six times, respectively. To alleviate this constraint, I conduct my demand and supply estimation separately: first, I utilize user number variations on smartphone model level and estimate demand parameters, then given demand estimates and aggregated firm-level data, I use simulated method of moments (SMM) to estimate the supply parameters. The complete list of parameters to be estimated is as follows:

[19] In 2016, roughly 60% of Apple's revenue came from iPhone sales in 2016, and in 2016Q1, Samsung's mobile decision generates 63% of Samsung Electronics' total revenue. Source: http://www.businessinsider.com/apple-iphone-sales-as-percentage-of-total-revenue-chart-2017-1, http://www.eweek.com/mobile/samsung-smartphone-sales-help-hike-q1-2016-profit-revenue

Table 2.4: List of parameters to be estimated

Demand estimation	α_q	Quality coefficient
	α_p	Price coefficient
	ξ_A, ξ_S	Apple, Samsung fixed effects
Supply estimation	λ_A, λ_S	Marginal cost
	$a_{0,A}, a_{0,S}$	Investment efficiency
	$a_{1,A}, a_{1,S}$	Spillover effect

2.4.1 Demand estimation

Given the release schedule that Apple introduces new phones in every September, and Samsung in every March and September, their flagship offerings do not change for several months, which provides an opportunity to separate variations in consumers' expectations due to product changes and time changes.[20]

For example, suppose there are two periods, $t = 1, 2$, and each firm's product quality has not changed in these two periods. Denote consumer's choice specific value function for product j (use $j = 0$ for current holding) at time t as $v_{jt}(\mathbf{q}, \mathbf{r}, \Delta, \mathcal{I})$. Then in the second period, consumer's inclusive value before purchase is

$$V_{t=2}(\mathbf{q}, \mathbf{r}, \Delta, \mathcal{I}) = \log \left(\sum_{j \in \mathcal{J}_{t=2}} \exp(v_{j,t=2}(\mathbf{q}, \mathbf{r}, \Delta, \mathcal{I} = (q_{j,t=2}, j)) \right) \tag{2.18}$$

At $t = 1$, consumer's choice specific value for product j is

$$v_{j,t=1} = u_j + \beta V_{t=2}(\mathbf{q}, \mathbf{r}, \Delta, \mathcal{I} = (q_{j,t=1}, j)) \tag{2.19}$$

[20] In this subsection, I will denote smartphone model, instead of firms, as j. This notation only applies when describing demand estimation.

which governs consumers' purchase decisions at $t = 1$. Note that there is no uncertainty in this expression: $\mathbf{q}$ is not changed in the next period, $\mathbf{r}$ and Δ evolve deterministically, and $\mathcal{I}$ is solely determined by consumer's individual purchases. So if all choice specific values at $t = 2$ are available, consumers' demand at both $t = 1$ and $t = 2$ can be derived in a deterministic way.

My demand estimation proceeds in three steps. First, I truncate my observed periods into non-overlapping and consecutive intervals such that new product releases only occur in the last period of each interval. Next, I calculate consumers' choice-specific value functions in the last period of each interval. Finally, values for all other periods within the same interval are calculated through backward induction. Approximation only exists in the second step, where consumers' value functions in the last period of each interval are approximated by assuming continuous usage of their current phone in that period for a fixed amount of periods. Conditional on these values in the last period of each interval, values imputed for the previous periods are rational. This is because there are no uncertainties between consecutive periods (except the last period) within the same interval as both firms' product offerings have not changed. With the assumption that consumers' values in the last period of each interval is correctly calculated, all their purchase decisions are rational.

To be specific, each interval is denoted as $I = 1, 2, \ldots, n_I$, and the first and last period in interval I are $\underline{t}_I$, $\bar{t}_I$, respectively. Choice specific values of buying (using if $j = 0$) product j at time $t_{\bar{t}_I}$ is assumed to be 24 months of discounted utilities, that is,

$$V_{j,\bar{t}_I} = -\alpha_p p_{j,\bar{t}_I} \times \mathbf{1}\{j \neq 0\} + \sum_{t=0}^{23} \beta^t u_{j,\bar{t}_I}$$

where β is the value discount factor per period, and u_j denotes utility flow of using smartphone j for one period.

Given these choice-specific values, consumers' inclusive value at $\bar{t}_I$, which measures consumers' value before their idiosyncratic shocks are realized and purchases are made and after new products are released, is, (omitting other state variables for simplicity)

$$V_{\bar{t}_I}(\mathcal{I}) = \log\left(\sum_{j\in\mathcal{J}_{\bar{t}_I}} \exp(V_{j,\bar{t}_I}) + \exp(V_{0,\bar{t}_I}(\mathcal{I}))\right)$$

Then in periods $\underline{t}_I, \underline{t}_I + 1, \ldots, \bar{t}_I - 1$, consumers correctly anticipate firms' choices of prices and qualities in $\bar{t}_I$, and their value functions in period t are solved using backward induction as

$$v_{j,t}(\mathcal{I}) = u_{j,t} - \alpha_p p_{j,t} + \beta V_{t+1}(\mathcal{I} = (q_{jt}, j)), \quad V_{0,t}(\mathcal{I}) = u_{0,t} + \beta V_{t+1}(\mathcal{I})) \tag{2.20}$$

and inclusive value is

$$V_t(\mathcal{I}) = \log\left(\sum_{j\in\mathcal{J}_t} \exp(V_{j,t}(\mathcal{I})) + \exp(V_{0,t}(\mathcal{I}))\right) \tag{2.21}$$

Given these choice specific values and inclusive values, in period t, demand for product j among consumers with holding characteristic $\mathcal{I}$ is

$$s_{j|\mathcal{I}} = \frac{\exp(v_{j,t}(\mathcal{I}))}{\exp(V_t(\mathcal{I}))} \tag{2.22}$$

Then the imputed user number for product j at time $t+1$, denoted as $\tilde{n}_{j,t+1}$ is calculated as consumers who newly purchased phone j (if it is on sale) minus those who previously were using phone j but purchased another phone at t.

$$\tilde{n}_{j,t+1} = \sum_{j'} s_{j|\mathcal{I}=(q_{j'},j')} n_{j',t} - \sum_{j'} s_{j'|\mathcal{I}=(q_j,j)} n_{jt} \tag{2.23}$$

Note that I use actual instead of imputed phone users in period t, just to avoid bias to accumulate over time. Finally, demand parameters are estimated by minimizing distances between this imputed and actual user numbers in periods when no phones are released.

$$\min_{\theta^D} ||\tilde{n}(\theta^D) - n|| \tag{2.24}$$

2.4.2 Supply estimation

Given demand estimates, I use simulated method of moments estimator that minimizes the distances between a set of conditional moments and their simulated counterparts from the model. To apply the model developed in the previous section, first I convert Apple and Samsung into single-product firms. For each firm in each month, I collect its flagship smartphone models on sale and take their average quality and average price as the firm's product quality and price in that month, respectively.

For each candidate value of supply parameter estiamtes θ^S, I solve the model given $R_A = 12, R_S = 6$, and simulate S times for T periods each, starting at the industry state in the first month of my data, $(\mathbf{q}, \mathbf{r}, \Delta)$. The SMM estimator $\hat{\theta}^S$ is

$$\hat{\theta}^S = \arg\min_{\theta\in\Theta}[m_{S,T}(\theta) - m_T]' A_T [m_{S,T}(\theta) - m_T] \tag{2.25}$$

where m_T and $m_{S,T}(\theta)$ are observed and simulated moments, and A_T is a positive definite weighting matrix. My weighting matrix is attained directly from the standard deviations of moments in actual data. In the data I observe that in all of three Apple releases, Apple's product quality increased by approximately .14, and Samsung's product quality increment ranges from .02 to .1. So I set the quality step size δ such that $4\delta = .14$, and the lowest quality level $\underline{q}$ as Apple's quality in July 2013. In addition I choose quality levels $n_\delta = 13$ so Apple and Samsung's simulated qualities within the observation period will not be bounded.

My choice of moments to be matched captures firms' competitions in new product qualities and prices, given their committed product release schedules. My moment vector consists of the following 12 moments:

- Average price across all periods for each firm.
- Percentage of R&D investment over total revenue.
- Average ratio of p_j over $q_{j'}$ where $j, j' = A, S$.
- Average ratio of each firm's own quality over industry quality frontier, i.e. the higher of Apple and Samsung's product qualities.

- Average ratio of product quality over mean holding qualities.

Identification

The demand parameters are identified by variations in different phones' user numbers and their corresponding characteristics. α_q and α_p affect user shifts among phone models with different qualities and prices, and manufacturer fixed effect ξ_A, ξ_S are identified by relative changes in total user base among Apple, Samsung and other manufacturers.

The supply parameters are identified through variations in simulated moments. Firms' marginal cost parameters λ_A, λ_S are identified by average prices, where higher marginal costs will increase firms' prices. Spillover effect parameters $a_{1,A}, a_{1,S}$ are mainly identified by the ratio of each firm's own product quality over industry quality frontier, which measures to what extent each firm keeps up with its competitors in quality advancement. Larger spillover parameters will improve firms' investment efficiencies when firms lag behind, and more likely to catch up with the industry frontier, and therefore increase this ratio. Finally, investment efficiency parameters $a_{0,A}, a_{0,S}$ are identified from the ratio of investment over revenue, where higher investment efficiency will lead to less investment and smaller ratio values. Other moments, including ratio of prices over qualities, and new product qualities over consumer holding qualities are also sensitive to variation in these parameters and add to their identifications.

2.5 Estimation result

2.5.1 Estimates

I use the SMD estimator in (2.24) and (2.25) to estimate demand and supply parameters, respectively. Model setup parameters for supply estimations are fixed as follows: product prices and qualities are normalized by 1/100 and 1/1000 respectively.

Table 2.5: Parameter Estimates

			Estimates	Std. Err.
Demand Parameters	α_q	Quality coef	10.3560	0.4007
	α_p	Price coef	12.3640	3.7034
	ξ_A	Apple FE	1.6794	0.1527
	ξ_S	Samsung FE	0.2996	0.1789
Supply Parameters	λ_A	Marginal cost	0.3938	0.0005
	λ_S		0.5466	0.0180
	$a_{0,A}$	Investment efficiency	10.0942	0.4711
	$a_{0,S}$		19.3900	0.4400
	$a_{1,A}$	Spillover effect	9.8869	0.8300
	$a_{1,S}$		9.8136	0.6214

Parameter estimates are reported in Table 4.9, and model's fit in Table 2.6. Implied price elasticity by demand estimates varies from 6 to 9, and for supply estimation, the model fits the 12 moments reasonably well, despite having only 6 parameters. All demand parameters are statistically significant (except Samsung fixed effect) given the relatively small standard errors. Dividing the estimated quality coefficient by the price coefficient implies that consumers are willing to spend 120 dollars for a 1000 units increase in benchmark scores (remember that price and

Table 2.6: Empirical and Simulated Moments

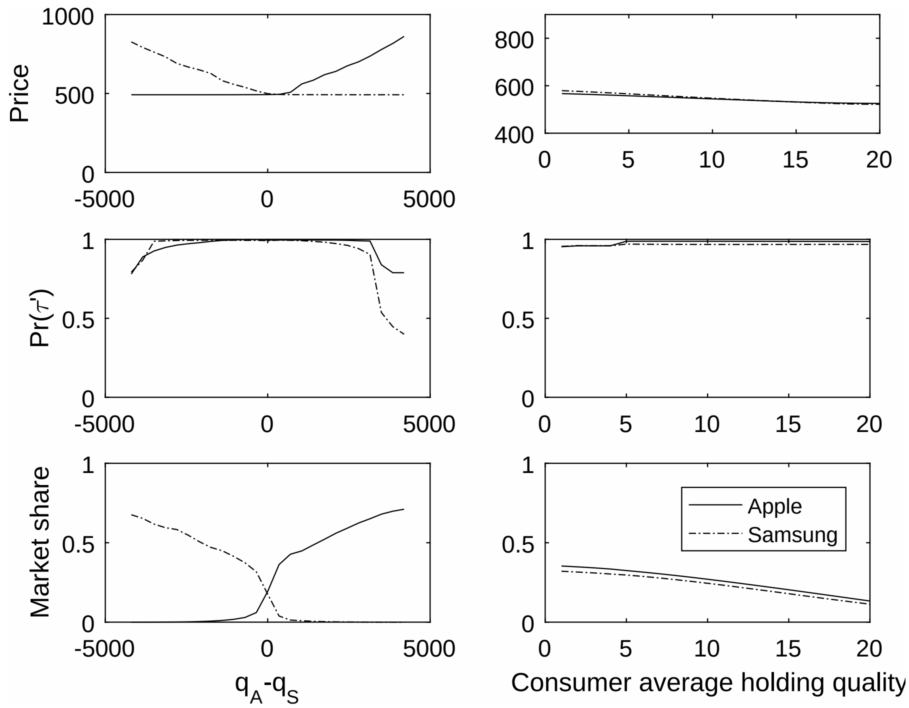
	Fitted Value	Avg moment value in actual data	Std. dev. in actual data
Average price			
Apple	0.5156	0.5587	0.0408
Samsung	0.6296	0.6165	0.0317
Ratio of investment over revenue			
Apple	0.0062	0.0361	0.0073
Samsung	0.0723	0.0722	0.0025
Ratio of price over quality			
p_A/q_A	1.3371	1.4597	0.4699
p_A/q_S	1.0502	1.1767	0.2284
p_S/q_S	1.2759	1.3177	0.3428
p_S/q_A	1.6296	1.6413	0.6226
Ratio of own quality over frontier			
$q_A/\bar{q}$	0.8035	0.8290	0.1180
$q_S/\bar{q}$	1.0000	0.9975	0.0139
Ratio of new product quality over consumer holding quality			
q_A/q_i	1.1757	1.2101	0.1600
q_S/q_i	1.4666	1.4652	0.1369

qualities are normalized by 1/100 and 1/1000, respectively). Relative brand values for Apple and Samsung with respect to other brands, calculated by dividing their brand fixed effects by price coefficients, are 13 dollars and 2.42 dollars, respectively. Investment efficiency and spillover estimates imply strong incentives in quality catch-up.

2.5.2 Empirical results

Figure 2.2 presents firms' prices, investments and profits for both Apple and Samsung across states. The three rows correspond to prices, probabilities of higher quality increment and market shares for each firm. The two columns correspond to firms' quality difference, in terms of $q_A - q_S$, and the average qualities of con-

Figure 2.2: Firms' prices, investments and profits over quality differences and consumers' average holding quality



Note: First column corresponds to firms' quality difference, in terms of $q_A - q_S$. Second column corresponds to consumers' average holding quality where larger number indicates higher quality. Three rows represent firms' prices, probabilities of higher quality increment and market share. In all the graphs, solid line denotes Apple, and dashed line denotes Samsung. Mean values are calculated with equal weights given to all states.

sumers' holdings, where larger numbers indicate higher quality of consumers' holdings. When a firm's product quality is higher than its competitors, it increases its price and earns higher market share.

Another important feature of this model is that, consumers are forward looking and their purchase decisions will be affected by the number of periods until the next product release. Figure 2.3 depicts average market share for Apple and Samsung in each 12-month window, plotted separately for the highest and lowest levels of consumer holding quality. These two subfigures correspond to Apple and Samsung's

Figure 2.3: Apple and Samsung's market share within each 12-month window

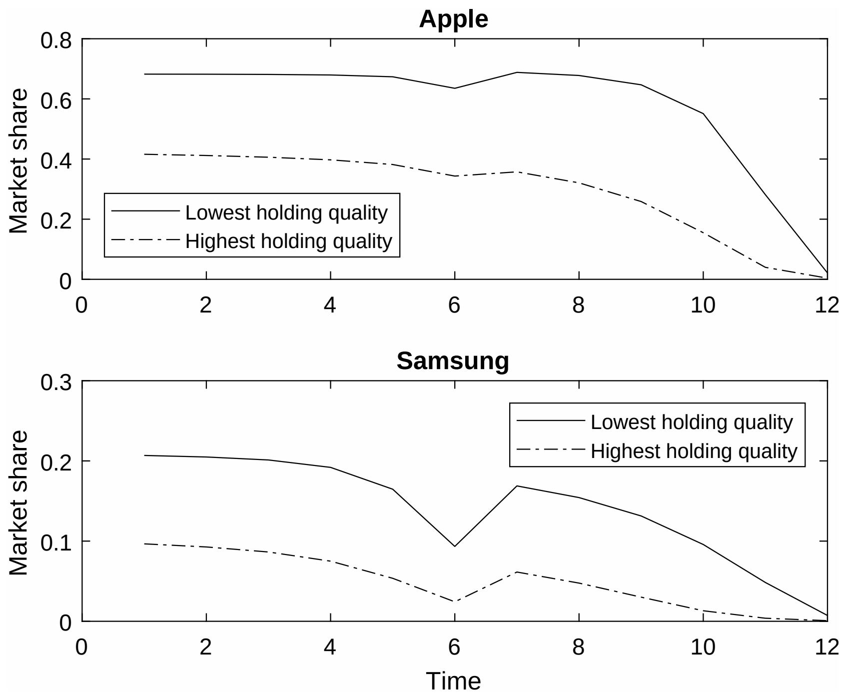
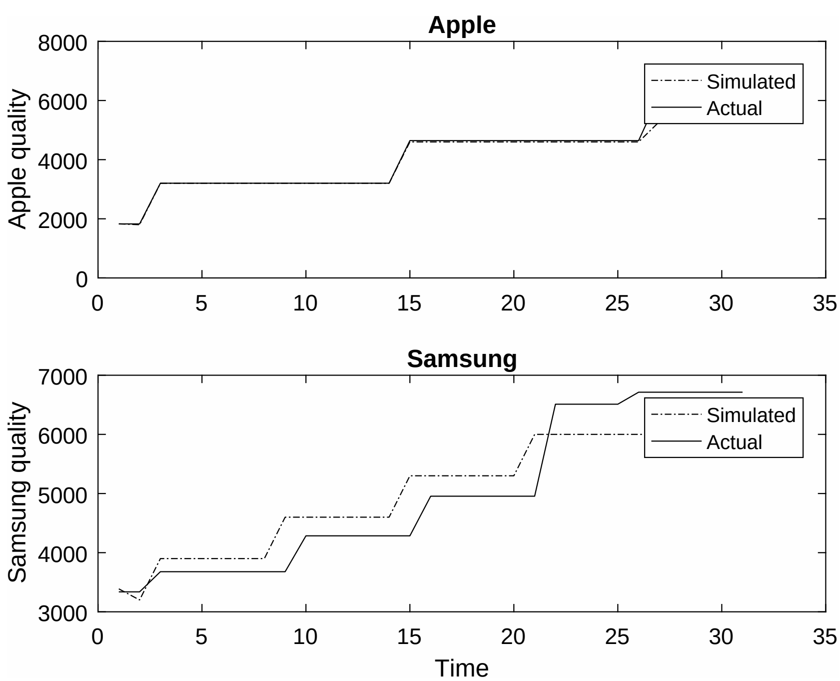


Figure 2.4: Apple and Samsung's quality path



market shares in terms of units sold within each 12-month window, where the first month is set as each September. In general, both firms' market shares decline as new product release is approaching ($T = 7$ for Samsung only, and $T = 13$ for both Apple and Samsung). At $T = 6$ both Apple and Samsung's market shares decline, but given its (slightly) higher brand preference, Apple's market share is less affected, and Samsung's market share is restored to a higher level with its newly released product. When T is close to 12, consumers will mostly stop buying and waiting for new product to release.

Finally, to see how my model fits the data, Figure 2.4 reports the actual and average simulated qualities for both Apple and Samsung starting from the industry state in the first observed month for 31 months. My model fits Apple's quality path much better than Samsung, mostly because of its almost constant quality increment in each product release. For Samsung, my model fits the average quality increment, but there is a long lasting gap just because of quality discretization.[21]

2.6 Counterfactual: effects of different release schedules

In this section, I try to understand the effects of different release schedules, in particular the trade-off between "more-but-minor" and "less-but-major". First, under a symmetric duopoly market setup, I show how firms' optimal policies (i.e. innovation and prices) change when firms choose different release frequencies, which illustrates the importance of considering product release frequencies separately. Next, with the same analysis but in a monopoly market, I discuss a monopolist's optimal product release strategy. By further comparing this monopoly market outcome with

[21] For example, when at $T = 5$, which corresponds to 2013 November, Samsung's quality is 3678 which is located between 3550 and 3900 on the quality grid, and therefore cannot be perfectly fitted.

the duopoly case, I provide analysis on overall welfare impact of market concentration and decompose the source of this impact into changes in prices, innovation and release frequencies.

2.6.1 Release schedules in the duopoly market

I adopt a symmetric duopoly market structure which is modified from the previous model as follows: there are two firms, denoted as $j = 1, 2$. The composite firm "Other" is removed; both firms' marginal costs, investment efficiency, and spillover effects are set as Apple's parameter estimates; consumers' brand preferences are set as zero for any firm.[22] With this market setup, I can ignore other firm-specific characteristics that could potentially affect the market outcome, and evaluate the pure effect of different release schedules.

One challenge to evaluate consumer surplus in this framework is that, consumers benefit from accumulated quality increment in the past, but these increments are removed when I shift all quality entries downward to bound the state space. To address this issue, I store the accumulated quality improvement along with each simulation, and use this accumulation, rather than the quality value in the state space, to calculate consumer welfare. To make the results comparable, I simulate the model for 1,000 periods in all counterfactual experiments, so higher consumer surplus only comes from higher innovation and/or lower prices.

[22]Conditional on the symmetric duopoly structure, this zero brand preference is a normalization rather than an assumption. This is because brand preference enters consumer's utility of both new purchase and current holding, and increasing these preferences by the same amount will not affect consumers' purchase decisions due to the logit demand form. So as long as these two firms have the same brand preference (because of symmetry) and consumer's brand preference comes from her past purchase, I can set both brand preferences to zero without loss of generality.

At the beginning of the model, each firm chooses its release interval R_j from $\{3, 6, 12\}$ simultaneously to maximize their sales. Given this symmetric setup, firm 1's policy functions in $\{R_1, R_2\} = \{R, R'\}$ are the same with firm 2's policy functions in $\{R_1, R_2\} = \{R', R\}$, so without loss of generality, I only report summary statistics for $R_1 \geq R_2$, i.e. firm 1 has equally or less frequent releases than firm 2. Table 2.7 reports summaries of these two firms' policies.

Table 2.7: Simulated policy function: Symmetric duopoly

	Price	Firm 1			Firm 2		
	R_2	12	6	3	12	6	3
R_1	12	\$ 548.36	\$ 569.05	\$ 608.80	\$ 547.13	\$ 590.26	\$ 583.35
	6		\$ 572.20	\$ 617.61		\$ 571.29	\$ 607.92
	3			\$ 552.67			\$ 555.64
	Prob of higher quality increment	Firm 1			Firm 2		
	R_2	12	6	3	12	6	3
R_1	12	0.940	0.977	0.981	0.938	0.869	0.863
	6		0.912	0.966		0.911	0.808
	3			0.708			0.721
	Firms' profit per period	Firm 1			Firm 2		
	R_2	12	6	3	12	6	3
R_1	12	0.078	0.100	0.132	0.077	0.104	0.091
	6		0.085	0.123		0.085	0.120
	3			0.063			0.065
		Consumer Surplus			Social Surplus		
	R_2	12	6	3	12	6	3
R_1	12	3.797	4.563	4.906	3.952	4.766	5.129
	6		3.866	4.572		4.035	4.815
	3			4.030			4.157

Note: All numbers are average value of simulated market outcomes. Differences in two firms' diagonal elements come from simulation errors.

From this table we can see that a firm charges higher prices when its competitor releases new products more frequently. For example, as firm 2's release frequency speeds up from one release per year ($R_2 = 12$) to four releases per year ($R_2 = 3$), firm

1's prices increase. One possible explanation for this pattern is that, per the model setup, any firm with less frequent product releases has higher quality advancement in each release, and this "temporary" quality boost, as compared to its competitor with frequent but smaller quality advancement, establishes quality advantage and enables it to charge higher prices. For the firm with more frequent releases, however, it does not necessarily charge higher prices. For $R_2 = 12$ or 3, firm 1's prices increase as R_1 decreases from 12 to 3, but for $R_2 = 6$, firm 1's prices peak when $R_1 = 6$.

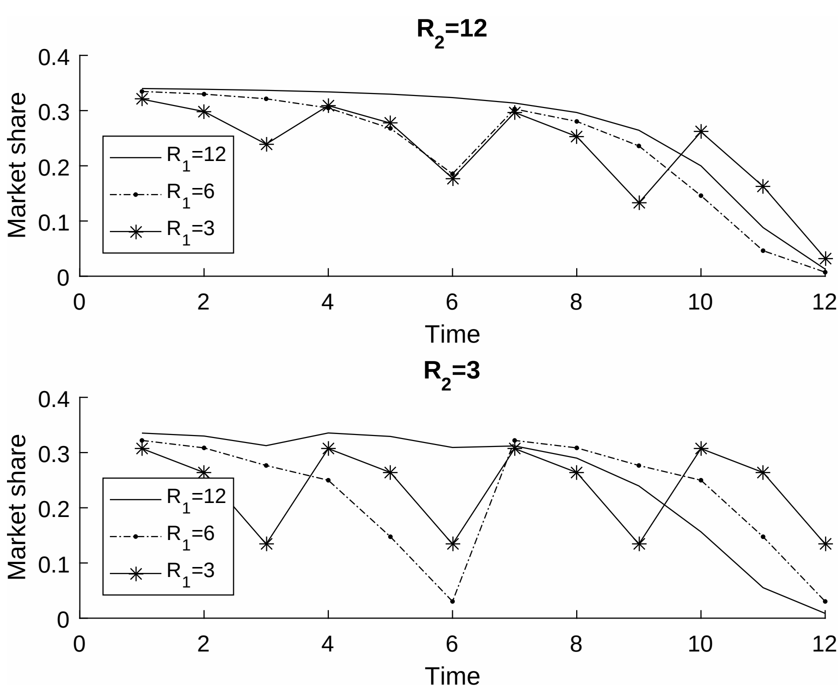
Firms' investment levels are represented by their probabilities of the higher quality increment. Note that the investment outcomes are normalized conditional on each firm's release schedules, where possible quality improvements are smaller in frequent release schedules and larger in less frequent release schedules, namely "more-but-minor" and "less-but-major". Conditional on these normalized investment outcomes, we can see that when the competitor's release becomes more frequent, a firm invests more and improves its probability of the minor quality increment. This pattern suggests that release frequencies and innovations are complimentary in firms' dynamic competition conditional on the normalized quality increments: when a firm cannot match its competitor's more frequent releases, it invests more for higher quality increment in each release; if instead this firm chooses to speed up its release frequency as well, it will spend less on its innovation.

With all these results combined, we can see how firms choose their release schedules and product characteristics: firms balance between innovation and release frequencies where high innovation is adopted in compensation for low release frequency and vice versa; in response to its competitor's more frequent releases, a firm increases its innovation, but may or may not increase its release frequency; firms with major product improvement charge higher prices.

Note that I have not identified a fixed cost associated with each product release because I only observe market outcome when $R_A = 12, R_S = 6$, and any parameter governing firms' choices of release schedules cannot be identified. But it is interesting to see that even where there is no fixed cost included, firms are still bounded from choosing too frequent releases. For example, when $R_2 = 3$, firm 1's profit decreases when R_1 shifts from 12 to 3.

One reason for this finding is that more frequent releases do not necessarily increase aggregate demand. To see this, I calculated firm 1's market share within each 12-month period, and it is averaged across all states for each combination of (R_1, R_2). These average market shares are plotted in Figure 2.5.

Figure 2.5: Firm 1's market share in each 12-month period with different release schedules



These two subfigures in Figure 2.5 correspond to $R_2 = 12$ and $R_2 = 3$, and in each graph, three lines correspond to firm 1's three choices of release frequencies: $R_1 = 3, 6, 12$. When both firms choose $R = 12$, market share slowly declines over time as time approaches for the next product release (at $t = 1$, which is after $t = 12$); if firm 1 chooses to release additionally at $T = 7$, i.e. change R_1 to 6, then there is an additional decline in its market share near $T = 6$ just as consumers expect new release in the next period. Finally with more frequent releases, firm 1's market share decreases right before every product release, with a general declining trend in each 12-month period for $R_2 = 12$.

From this figure we can also see the sales decline before each new product release, which can possibly offset sales boost brought by the additionally released products and decrease the aggregate sales. For example, when $R_2 = 12$, aggregate demand for firm 1 decreases when it speeds up its frequency from $R_1 = 12$ to $R_1 = 6$, where most of sales decline comes from consumers' purchase delay at $t = 6$ anticipating a new product to be released at $t = 7$. Another finding is that the extent of consumers' purchase delay is correlated with the number of firms releasing new products in the near future. For example, when $R_1 = 6$ and R_2 shifts from 12 to 3, firm 2 starts to release at $t = 7$ as well along with firm 1. As a result, consumers' demand at $t = 6$ becomes much lower as they expect new products introduced by both firms instead of just firm 1.

In conclusion, aggregate demand does not always increase when firms release products more frequently because consumers' demand declines significantly when they expect new products to be released soon and this decline can offset the sales boost brought by the new products. It is this property that bounds firms from choosing too frequent release schedules.

2.6.2 Release schedules in the monopoly market

When a durable good market becomes more concentrated, existing firms may alter their policies, including price, innovation, and as newly considered in this paper, product release schedules, and all of these changes will affect social surplus. GG studies a possible market structure change where AMD is no longer present in the CPU market, and finds that Intel will innovate more and charge higher prices; total surplus is lower though as gains from higher innovation is dominated by loss in consumer surplus due to higher prices. Their analysis fits R&D intensive industries where firms concentrate on innovation and release new products when they are available, but could lead to biased welfare estimates in downstream manufacturer industries, like smartphone and many other consumer electronics, where firms can alter their schedules of new product release in the new market structure.

To examine the welfare impact from market concentration with possible changes of release schedules considered, I change the market structure to monopoly and compare its outcome to the duopoly market. To make the results comparable, I set the monopolist's marginal cost and investment efficiency as Apple estimates and remove the brand preference as well. I also chose the duopoly market where $R_1 = R_2$ to be compared with the monopoly market such that the duopoly market can be seen as dividing the monopolist firm into two symmetric firms while still preserving its product release schedules. In this way, differences in market outcome between monopoly market with $R_M = R'$ and duopoly market with $R_1 = R_2 = R'$ only come from changes in market structure. For each choice of monopolist's release schedule from $R = 3, 6, 12$, I solve the model, simulate the market for 1,000 periods, and repeat the simulation process for 500 times. Results are summarized in Table 2.8.

Table 2.8: Simulated policy function: Monopoly and symmetric duopoly

		Price	Profit	Prob of τ''	Consumer Surplus	Social Welfare
Monopoly R_1	12	\$ 746.23	0.238	0.986	5.154	5.392
	6	\$ 729.64	0.189	0.989	5.194	5.383
	3	\$ 649.13	0.148	0.988	5.216	5.364
Duopoly $R_1 = R_2$	12	\$ 548.36	0.078	0.940	3.797	3.875
	6	\$ 572.20	0.085	0.912	3.866	3.950
	3	\$ 552.67	0.063	0.708	4.030	4.092

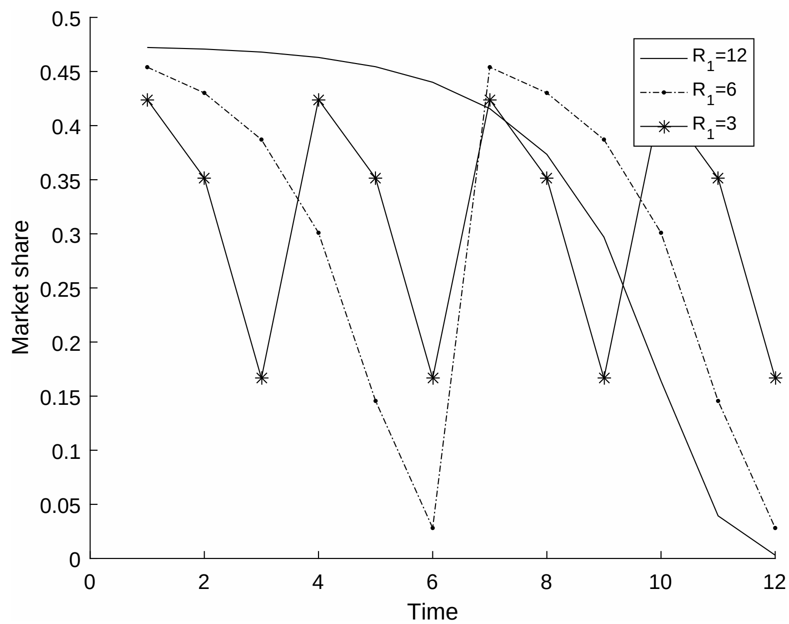
Note: Profits reported are average per-period profits in all the simulated periods, with market size set as one. Units for profits, consumer surplus and social welfare are in dollars.

From Table 2.8 we can see that, when the market becomes more concentrated, the monopolist charges higher prices but also invests more in quality improvement, which is consistent with Schumpeter's hypothesis and the findings in GG. But in this model, consumer surplus is higher in the monopoly market than in the duopoly market, which implies that gains from monopolist's higher innovation rates are only partly offset by loss from its higher price levels. Because of higher consumer surplus and higher profit levels in monopoly market, social surplus is also higher in the more concentrated market structure.

A second observation is that a monopolist prefers less frequent product releases, as profit of choosing $R = 12$ is higher than that of $R = 3, 6$. This preference towards less frequent release schedules is because the monopolist only needs to compete with consumers' holdings, and as more frequent releases actually result in less aggregate sales (as is shown in Figure 2.6), the monopolist would slow down its pace.

The monopolist's choice of higher innovation and less frequent releases also highlights the importance of separately modeling firms' choices of frequency and size of innovation. In a model where new product releases are driven by successful innovation outcome, we can only see firms with either higher innovation and implied frequent product releases, or lower innovation and rare releases, which will lead to biased estimates of social welfare.

Figure 2.6: Firm 1's market share over time



A further examination of consumers' demand over each 12-month window, as presented in Figure 2.6, suggests that consumers will still hold off purchasing products immediately before each new product releases. By comparing demand between $R_1 = 12$ and $R_1 = 6$ we can also see that speeding up release frequency will not increase total sales, which is consistent with the finding in the symmetric duopoly market.

2.7 Appendix: Algorithms for solving the model

The algorithm I implement for solving the dynamic model takes as input the model structure and parameter values, and returns firms' policies and consumers' choice probabilities. There are $n_{\Delta} \times n_q^2 \times (12/R_j)$ states in firm j's problem (that is how many possibilities for each type of consumer distribution with each possible combination of new product qualities and each possible release state),[23] and $n_{\Delta} \times n_q^2 \times 12 \times n_{C\ holding}$ states in each consumer's problem, which expands firms' states into full 12 months and also includes all possible values of consumers' holdings ($n_{Cbasic} = n_q \times 3$). For each firm, the algorithm returns its optimal price and investment, and for each consumer, the algorithm returns her purchase probabilities for the three possible choices (Apple, Samsung and "Other").

My model is solved by iterating between updating firms' and consumers' values until convergence. The outer loop checks if firms' and consumers' values have converged between two consecutive iterations, and inner loops update firms' policies and consumers' purchase probabilities. Detailed algorithm to solve this dynamic model is as follows.

[23] For example, if Samsung releases twice every year ($R_S = 6$), then holding all other state variables constant, releasing in the 1st and 7th month are in two different states.

Algorithm 1 Dynamic model algorithm

```
Set initial consumer's value V and firm's value W as zero for all states.
while max|V^k − V^{k−1}| ≥ 1e − 5 or max|W^k − W^{k−1}| ≥ 1e − 5 do
    for each firm j chooses each value on the price grid do    ▷ Solve for each firm's optimal prices
        ▷ Calculate intermediate values given preset price values, then extrapolate.
        Simulate forward for R_j periods.
        For each possible evolution path, calculate its probability Pr_m, cumulative profits Π_m and value of final state W_m^{k−1}.
        Values of choosing current price is Σ_m Pr_m(Π_m + β^{R_j} W_m^{k−1})
    end for
    Extrapolate and update firms' optimal prices.
    for each firm j do    ▷ Solve for optimal investment and value
        Simulate forward for R_j periods with optimal prices.
        Calculate values of different innovation outcomes, then solve for optimal investment.
        Given firms' optimal investment and prices, update their values to {W_j^k}_j.
    end for
    Given firms' policies, update consumers' values and purchase probabilities to {V_i^k, Pr_ij^k}_{i,j}
    Given firms' policies and consumers' purchase probabilities, update transition rules for Δ.
end while
```

Chapter 3: Managerial Implications for Durable Goods Release Schedule

3.1 Introduction

In this chapter, I adopt the model framework developed in Chapter 1, and apply it in the general durable goods market to provide managerial implications on product release schedule arrangement. As discussed in the previous chapter, product release schedule in the model introduces several additional implications for firms' strategic choices.

First, release frequencies determine the pace of materializing up-to-date innovation outcomes, where firms can release products more frequently to improve product qualities and outperform competitors for most of the time, but this frequent releases also raise consumers' awareness of new product releases in the near future and increase their value of waiting rather than buying the current products.

Second, firms can alter their relative release timing with respect to others' strategically, either capture the market with early releases, or postpone the releases to incorporate the most recent innovation outcomes.

Third, firms can also alter their format of product release schedules, like speeding up/slowing down the pace of their product introduction or even transform into irregular release schedules, which can have long term effects because consumers' expectations of future releases are also updated based on the new schedule.

The first implication has been discussed in Chapter 1 where the market outcomes under duopoly and monopoly are compared. Firms choose their release frequency by balancing between the gains of selling more products with frequent quality updates and the loss of sales due to consumers' frequent expectations of new releases. When the market becomes more competitive, firms' concern of frequent consumer expectation is alleviated and the gains from additional releases become dominant. As a result, firms introduce products more frequently with more firms present in the market.

This chapter studies the second and third implications, or more specifically, the market outcome when firms change their relative release timing or switch their release frequency along the time. Based on the simulated results, I find that a duopolist can benefit from staggering its releases relative to those of the other firm, as firms can spend the additional time increasing its product qualities and outperform other firms' new products. This result also suggests no additional value for the simultaneity in releases. I also show that it is valuable for a firm to be seen as committed to a regular release schedule, as the possibility of switching schedules in the future affects consumers' current purchases and hurts firms' values.

There is a branch of literature that studies firms' product release decisions in the presence of strategic consumers. Borkovsky [2017] studies innovators' timing decisions of their product releases in a non-durable good context and finds that firms innovate and release more aggressively when products are vertically, rather than horizontally, differentiated. Cohen et al. [1996] and Lobel et al. [2015] analyze the trade-off between release frequency and quality improvement in the monopoly market. Cohen et al. [1996] finds that more frequent releases are not necessarily profitable if the existing product has a high margin and the new product has a large market potential. Lobel et al. [2015] further compare the monopolist's profit in two scenarios, "varying schedule with fixed investment" and "varying investment with fixed schedule", concluding that the schedule commitment is valuable. My paper generalizes their discussions with more flexible release schedules and an empirical application in an oligopoly market. I show that the market structure affects firms' product release scheduling as well. Casadesus-Masanell and Yoffie [2007] examine the release decisions for complementary products and find that upstream suppliers release aggressively while downstream manufacturers delay the adoption to profit from the installed base. Paulson Gjerde et al. [2002], Balcer and Lippman [1984] and Farzin et al. [1998] study firms' technology adoption decisions given an exogenous advance of the technological frontier in a limited dynamic framework.

3.2 Staggering product releases

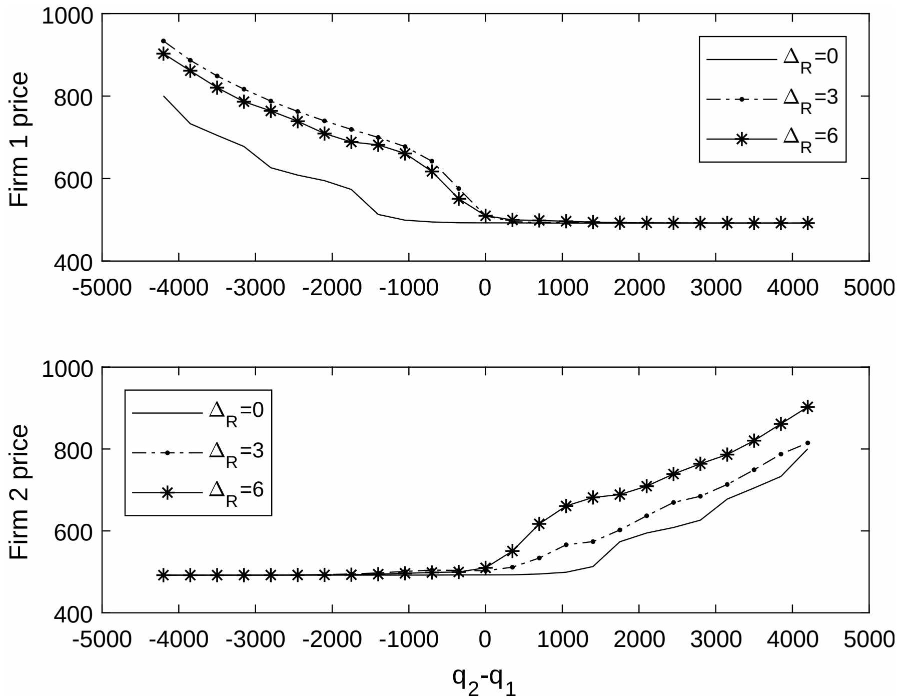
In the model I make an assumption that all firms release simultaneously in at least one period. While this assumption is helpful in sufficiently determining all future release schedules given firms' choices of release intervals $\{R_j\}_j$, it also rules out some examples of interest. For example, in a duopoly market where both firms choose $R = 12$, this assumption only allows for the schedule where both firms release new products simultaneously and repeatedly every 12 months. It is also possible, however, that these two firms still release new products every 12 months, but their releases are 6 months apart from each other (say, one in every January and the other in every July); in this case, by setting its new product release apart from its competitor, which I term as "staggering," a duopolist firm can outperform its competitor with better quality products for 6 months, at a cost of being dominated by its competitor's product for the other 6 months.

My analysis is based on the symmetric duopoly market as constructed in Section 2.6.1, and I limit both firms' release frequencies as $R_1 = R_2 = 12$. To capture the relative timing of product releases, I define a new variable, "release difference Δ_R", which is the number of periods between two firms' nearest product releases. For example, suppose firm 1 releases at $t, t+12, t+24, \ldots$, and $\Delta_R = 1$, then without loss of generality, firm 2 is assumed to release at $t-1, t+11, t+23, \ldots$, which means that firm 2 always releases products relatively earlier than, if not together with firm 1. With $R = 12$ for both firms, Δ_R takes value between 0 and 6,[1] where $\Delta_R = 0$ represents the simultaneous "conglomerate" release, and $\Delta_R = 6$ means 6-month-apart "dispersed" release.

Figure 3.1 shows how both firms' average prices vary based on their relative product qualities. A firm charges higher price when it sells higher quality products, and its price will increase with this quality advancement. We can also see that when these two firms' product releases are less concentrated (Δ_R increases from 0 to 6),

[1] $\Delta_R = 7$ for example, is equivalent to $\Delta_R = 5$ and switching two firms' moving order.

Figure 3.1: Optimal prices over quality differences in different staggering release schedules

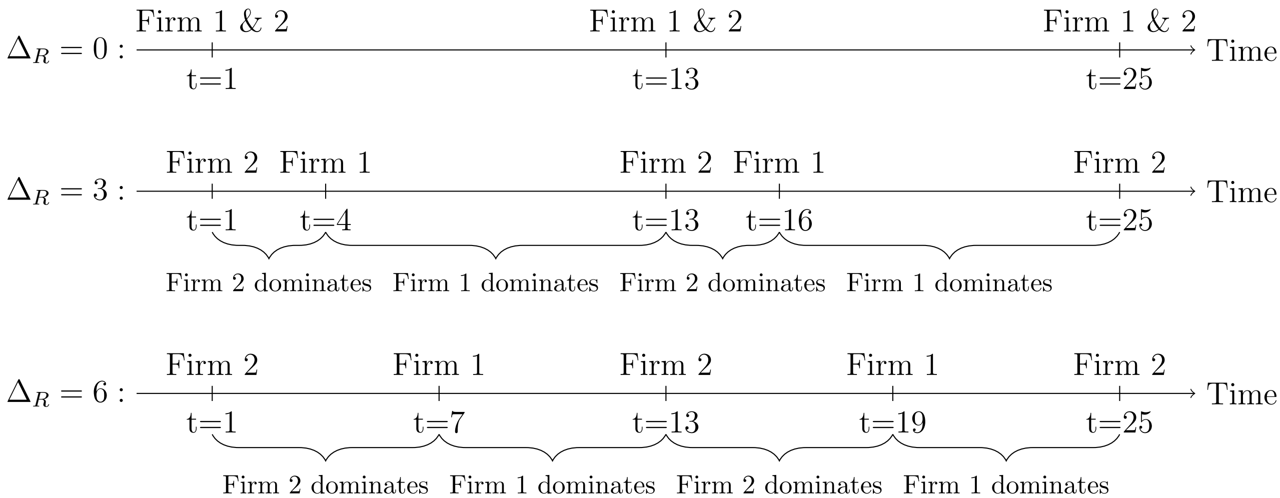


both firms charge higher prices which indicates softened market competition.

Note that these two firms are symmetric when $\Delta_R = 0$ or 6, and their corresponding price curves are also symmetric in Figure 3.1. For $\Delta_R = 3$, firm 2 releases new products 3 months ahead of firm 1. By comparing firms' price curves when Δ_R increases from 0 to 6, we can find that firm 2's prices are monotonically increasing while firm 1's prices peak at $\Delta_R = 3$. This pattern implies that when firm 2 shifts away from firm 1's product releases and introduces products earlier, both firms benefit from softened market competition and firm 1 can extract more surplus from its innovation at $\Delta_R = 3$. This is a result of the number of periods that each firm's product dominates the market, which is shown in Figure 3.2.

Figure 3.2 illustrates how release timing affects firms' market dominance. Firms have equal market dominance when $\Delta_R = 0$ or 6: when $\Delta_R = 0$, both firms

Figure 3.2: Graphic illustration of $\Delta_R = 0, 3, 6,\ R_1 = R_2 = 12$



release simultaneously across all times and no firm has any advantage/disadvantage in release timing; when $\Delta_R = 6$, each firm "dominates" the market by 6 months with its new products just released, and then becomes "dominated" by another 6 months with its competitor's even newer products. Firms' symmetric positions in these two cases guarantee that their optimal policies and value functions are also symmetric, which leads to the same shape of price curves as in Figure 3.1. When $\Delta_R = 3$, firm 2 releases new products and dominates the market for only 3 months, and then becomes dominated by firm 1 for 9 months, which gives firm 1 higher market power to extract surplus from its quality advancement and explains why firm 1's prices are the highest when $\Delta_R = 3$. To better understand the welfare implication of these three release schedules, Table 3.1 reports summary statistics of both firms' policies, including price, profit and probability of higher quality increment, and welfare impacts.

Consistent with the graph, both firms' policies are the same when $\Delta_R = 0$

Table 3.1: Simulated policy function: $R_1 = R_2 = 12$, $\Delta_R = 0, 3, 6$

		Price	Profit	$\Pr(\tau'')$	Consumer surplus	Social Welfare
$\Delta_R = 0$	Firm 1	\$ 548.36	0.0780	0.9399	3.7910	3.9461
	Firm 2	\$ 547.13	0.0771	0.9382		
$\Delta_R = 3$	Firm 1	\$ 636.53	0.1240	0.9917	3.6380	3.8469
	Firm 2	\$ 560.81	0.0849	0.9928		
$\Delta_R = 6$	Firm 1	\$ 610.58	0.1086	0.9930	3.6194	3.8350
	Firm 2	\$ 616.26	0.1070	0.9930		

and 6, and the differences in these statistics only come from simulation errors. Firm 1's price and profit are the highest at $\Delta_R = 3$. The welfare estimates suggest that consumers' surplus and social welfare are the highest at $\Delta_R = 0$ where firms' compete in simultaneous release schedules and charge lower prices.

Based on this result, we can see that firms should focus on their market dominance and try to make their products among the best choices for longer periods. For example, if no competitor firm will release new product in the next few months, and a firm can either introduce a new product now with similar quality to its competitors, or improve and release a better product in the next period, my result shows that this firm should choose the latter option.

3.3 Release schedule switching

In the previous analysis, I adopt the model assumption that firms take full commitment on their release schedules: once they have made their choices, they have to release products accordingly throughout the dynamic innovation and pricing game that follows. This assumption helps focus my discussion on firms' dynamic competition while treating firms' release schedules as exogenous, and the results provided using this framework can be interpreted as firms' strategies in the long run given their current release schedules.

Another way to approach the observed regular release schedule in the data is to assume that firms keep introducing new products regularly to build up their "reputations" of regular release schedules. In other words, firms are not bounded by any pre-set release rules; they can release new products whenever they want, but preferably they choose to maintain their regular release schedules. This alternative model setup cannot be rejected by the data either, and it can also provide insights on the regular form of firms' release schedules: by comparing market outcomes between the full commitment and the partial commitment model setup, I can evaluate both the value of maintaining uncommitted release schedules, and the cost of switching to alternative schedules. Based on the simulated market outcome, I find that firm's schedule commitment is valuable, and it is costly to switch schedules.

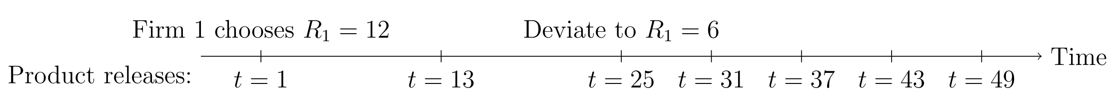
To implement this flexible choice of schedules and relax the full commitment assumption, I modify the model framework by allowing firms to deviate from their previously chosen schedules in the dynamic pricing and innovation game for at most once, then be committed to their new schedules. The feasibility of this "deviate-then-commit" setup, which I term as "partial commitment", is still restrictive considering that firms could deviate regardless of their past histories, but it is flexible enough to capture the two features of interest: the value of maintaining regular release schedules comes from the difference between full-commitment case and firms' strategies before their deviations; the cost of switching can be evaluated from firms' delaying deviations. Without much modification from the previous framework, this new model setup is also computationally feasible.

This subsection proceeds as follows. First, the new model setup is described in details to show how I modify the model to accommodate the partial commitment setup; next, with the new model setup applied in the monopoly market, I evaluate the value of maintaining the uncommitted release schedules by studying how the monopolist keeps its favorite schedule without deviating to others; finally I evaluate the cost of switching schedules by studying how the monopolist delays its deviation to its favorite schedule.

3.3.1 Model setup

To accommodate firms' flexibility in adjusting their release schedules, I adopt partial commitment to release schedules where I allow for a firm to deviate from its initial schedule at most once. For example, firm 1 first chooses to release once every 12 months, then after 2 years, switches to and commits to releasing once every 6 months, as is illustrated in Figure 3.3.

Figure 3.3: Partial commitment: example



To be more specific, I adopt the monopoly model as in Section 2.6.2 where the monopolist's innovation efficiency and marginal cost are the same with Apple parameter estimates, and consumers' preferences over brand are removed (with only quality and price preferences left).[2] The model timing under this framework is as follows:

1. At the very beginning, the monopolist chooses its temporary release frequency $R_1 = R_1^T$. (T for temporary)

2. **STAGE 1:** Given R_1, the monopolist becomes active if it is scheduled to release new products and remains inactive otherwise.

   - In each period, if the monopolist is active:

     (a) If the monopolist has never deviated, it decides whether to deviate and commit to a new release schedule $R_1 = R_1^C \neq R_1^T$ (C for commitment) or not. After deviation, the game enters **STAGE 2**.

     (b) The monopolist invests to improve the quality of its new product, and conditional on the investment outcome, sets price for this new product.

     (c) Every consumer observes the updated product offering and decides whether to buy it or keep using her current phone.

   - If the monopolist is inactive:

     (a) The monopolist's product offering remains unchanged from the previous period.

     (b) Every consumer observes the updated product offering and decides whether to buy it or keep using her current phone.

[2]This monopoly setup is to remove market competition's impact, and only focus on firms' management over its product life cycles. I will evaluate how rival competitors' strategies affect a firm's release schedules in future research.

It is worth noting that the monopolist is restricted to change its release schedule when it is active rather than in every period. This restriction on the timing of deviation helps simplify the monopolist's strategy space and consumers' beliefs, and reduce the computational burden. Another assumption is that $R_1^C \neq R_1^T$, which indicates that the monopolist cannot commit to its current temporary release schedule. This is to avoid the degenerate case where the monopolist commits to the new schedule right at the beginning, which is equivalent to the full commitment problem. This forced schedule switching setup is also necessary to learn the importance of commitment in two ways. First, if $R_1^T = 12$, which is also the monopolist's most preferred release schedule in the full commitment case, how would the monopolist maintain this preferred schedule without commitment? Second, if $R_1^T \neq 12$, then the monopolist would want to switch to $R_1^C = 12$, but is there any cost associated with the schedule switching that delays the change?

I use backward induction to solve this partial commitment game. First, I calculate the monopolist's payoff after deviation (Stage 2) by solving the full commitment game with the newly committed release schedules. Next, given the payoff of deviating, the monopolist's innovation and pricing decisions before the deviation (Stage 1) are solved through iteration. Consumers' beliefs about possible deviations are also updated.

STAGE 2: After deviation

When the monopolist deviates and commits to an alternative release schedule,[3] the whole game is the same as in the full commitment. Denote the industry state is (q, Δ, r) when the monopolist deviates, where q and Δ represent the product quality and consumer distribution, respectively, and r is the number of periods before the monopolist's next release. Based on the model timing, q represents the product quality *before* the new product release in the current period, and r takes the value of R_1^C, the newly committed release frequency. Given the new release schedule R_1^C, I can solve the optimal pricing and innovation decisions as well as consumers' purchase decisions, and the monopolist's payoff of deviation, represented by its value in the corresponding industry state, can be written as $W^D(q, \Delta, r = R_1^C)$ (D for deviation).

STAGE 1: Before deviation – General

Before the deviation, the monopolist makes innovation and pricing decisions as well, but during each product release, it also decides on whether to change its product release schedules. To facilitate the expression, denote the monopolist's payoff *after deciding not to deviate* as $W^{ND}(q, \Delta, r = R_1^T)$, where r takes value of R_1^T, the current temporary release schedule. Set $d(q, \Delta, r = R_1^T) = 1$ if the monopolist deviates at state $(q, \Delta, r = R_1^T)$, and zero otherwise, then

[3]Consistent with the previous model, release frequency R still takes value from $\{3, 6, 12\}$.

$$d(q, \Delta, r = R_1^T) = 1 \Leftrightarrow W^{ND}(q, \Delta, r = R_1^T) \leq \max_{R_1^C \neq R_1^T} W^D(q, \Delta, r = R_1^C), \qquad (3.1)$$

and the monopolist's value before deviation decisions is defined as

$$W(q, \Delta, r = R_1^T) = \underbrace{\big(1 - d(q, \Delta, r = R_1^T)\big)\, W^{ND}(q, \Delta, r = R_1^T)}_{\text{Value of no deviation}} + \underbrace{d(q, \Delta, r = R_1^T) \max_{R_1^C \neq R_1^T} W^D(q, \Delta, r}_{\text{Value of deviation}} \qquad (3.2)$$

$W^{ND}(q, \Delta, r = R_1^T)$ is computed in two steps: first, compute consumers' value with their beliefs of future deviations included; second, given updated demand, iterate and update W^{ND} until convergence.

STAGE 1: Before deviation – Consumer's problem

Iteration on consumer's value function is the same with the main model, except in periods right before each product release. In these periods, consumers form expectations on the monopolist's deviation decisions as well alongside with its pricing and innovation decisions. Similar with the notation for the firms, denote consumer's value under deviation and no-deviation as $V^D(q, \Delta, r, \mathcal{I})$ and $V^{ND}(q, \Delta, r, \mathcal{I})$, and their beliefs of the monopolist's deviation decision as $d^c(q, \Delta, r = R_1^T)$,[4] then their

[4] R_1^T is consumers' believed optimal deviation. For simplicity I use the same notation as the monopolist's choice.

value function before the monopolist's deviation decision is calculated as

$$V(q,\Delta,r,\mathcal{I}) = d^c(q,\Delta,r=R_1^T)V^D(q,\Delta,r,\mathcal{I})+(1-d^c(q,\Delta,r=R_1^T))V^{ND}(q,\Delta,r,\mathcal{I}), \tag{3.3}$$

which completes updating the iteration over consumers' values.

STAGE 1: Before deviation – The monopolist's problem

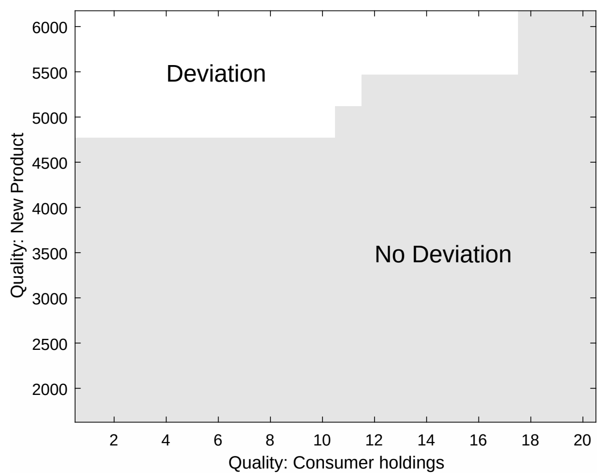
As is in the main model, I use backward induction by first solving the monopolist's optimal investment decisions, and then its optimal pricing decisions. What is different here is that the value function achieved with these two decisions only gives $W^{ND}(q,\Delta,r=R_1^T)$, i.e. the payoff without deviation, and the monopolist's value function used in future iterations, $W(q,\Delta,r=R_1^T)$, needs an additional round of calculation based on (3.2).

With iterations on updating consumers' and the monopolist's value functions, as well as their policy functions, conditional on consumers' beliefs of deviation are rational, i.e. $d^c(q,\Delta,r=R_1^T) = d(q,\Delta,r=R_1^T)$, I can then solve for the equilibrium of this STAGE 1 game.

3.3.2 The value of commitment

To study how the monopolist maintains reputation over its current release schedule without making any commitment, I set the monopolist to choose $R = 12$ first, which is its most preferred release schedule in the full commitment case, and only allow it to deviate/commit to $R = 3$ or $R = 6$ later. Intuitively, one might expect that the monopolist should, on average, keep its $R = 12$ schedule and earn more profits without any deviation, but based on the model outcome, I find that it does deviate in some states, which is depicted in Figure 3.4.

Figure 3.4: Deviation decisions by new product quality and consumers' holdings

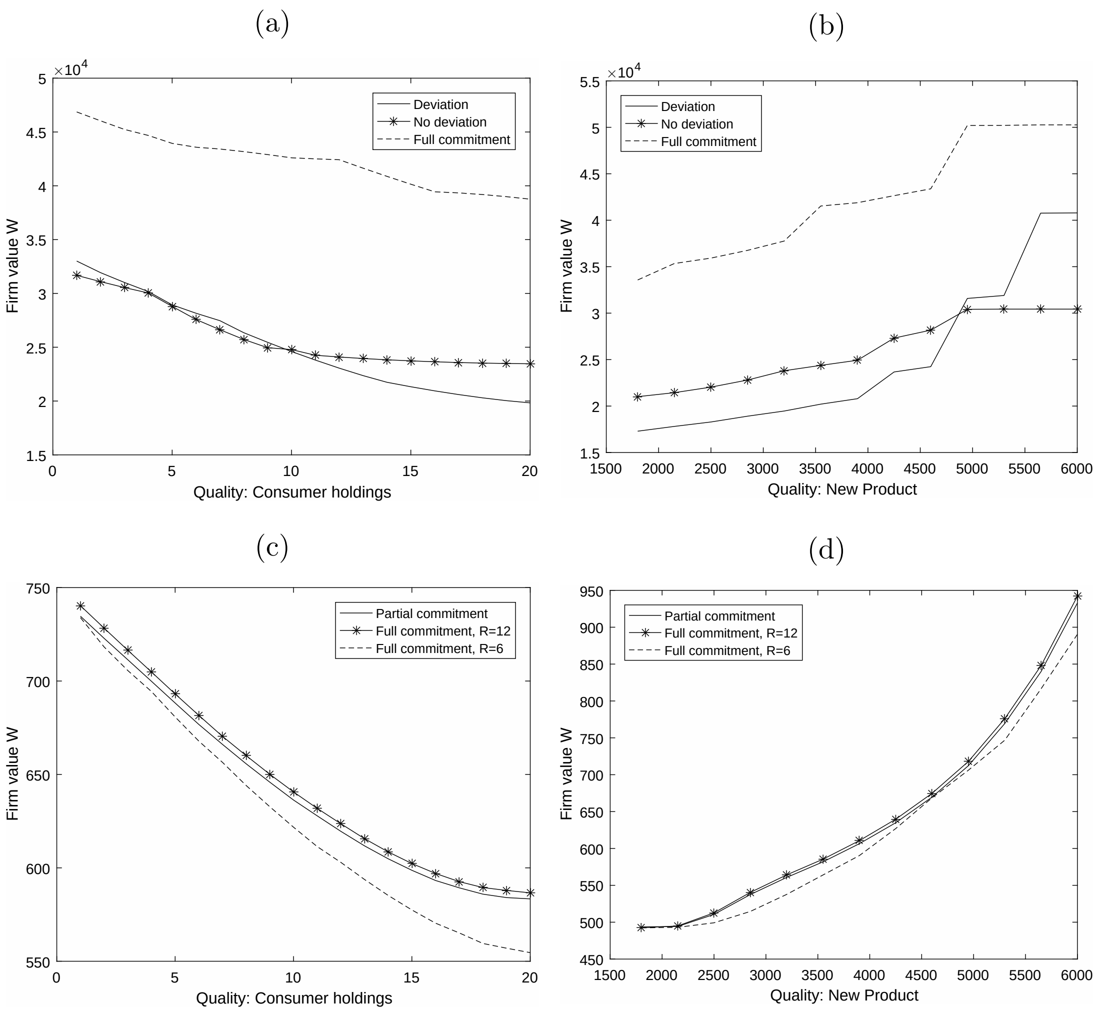


From Figure 3.4 we can see that, when the new product quality is high, and consumer holdings are of low quality, the monopolist would prefer to deviate from $R = 12$.[5] This is even more interesting when one considers how the market evolves: the monopolist improves its product quality until it reaches $\bar{q}$, then stays at $\bar{q}$ with decreasing consumers' holding quality to enlarge the relative quality difference between new products and consumer holdings. Based on this evolution model, the deviation *always* happens after a sufficiently long period where $q_j = \bar{q}$ and consumer holding qualities are pushed down by new releases, which contrasts the intuition that the monopolist wants to maintain $R = 12$ schedule.

To see why this happens, in Figure 3.5, (a) and (b) present the monopolist's payoff in three cases: (1) deviation to one of the other two schedules ($R = 3, 6$),

[5] In this outcome, the monopolist only deviates to $R = 6$ if possible so I suppress the expression of solving for optimal deviation schedules.

Figure 3.5: Firm's payoff and average price across new product quality and consumers' holdings



(2) no deviation with current $R = 12$ schedule, and (3) full commitment model without possibility of deviation. We can see that the monopolist's incentive to deviate (represented by the relative difference between (1) and (2)) is larger when consumers are using lower quality products and new product qualities are high, which is consistent with Figure 3.4. But we can also see that with possible deviations in the future, the monopolist's payoff becomes flatter: it is not so low in "bad situations" like higher quality holding or low quality new product to sell, and not so high in "good situations" either. In this sense, the ability to deviate in the future serves as partial insurance. By further comparing (1), (2) with (3), the removal of the commitment device still hurts the monopolist so it is no longer able to extract that much surplus from its sales, which shows that the full commitment assumption does provide the monopolist additional market power.

By further comparing the monopolist's average prices, as is shown in (c) and (d), we can see that the price before deviation lies between $R = 12$, its current release schedule, and $R = 6$ its target deviation schedule. In other words, the monopolist charges lower prices when it no longer has commitment power, to be closer to the schedule it is likely to deviate to.

3.3.3 The cost of switching

An alternative aspect of the commitment decisions is whether there is any cost associated with the deviation from a firm's previously uncommitted release schedules. To see this, I assume that the monopolist chooses $R = 3$ or 6 at first, and can deviate to one of the other two release schedules later. Given that $R = 12$ is the monopolist's most preferred schedule, the monopolist should deviate it as early as possible, and any deferral will be explained by costs of this schedule switching.

Figure 3.6 reported the monopolist's deviation decisions for each combination of new product qualities and consumers' holdings.[6] In these two cases, the monopolist's deviation decisions are more randomized than $R = 12$, but we can still see that the deviation occurs more frequently when the firm's new product is of high quality; for some low quality states, the monopolist would rather continue with its current release schedule for the moment and postpone the deviation.

To better understand the occurrence of this "deviation delay," Figure 3.7 plots the monopolist's payoff and prices over its new product qualities for $R = 3$ and $R = 6$. In (a) and (b), the payoff of deviation and no-deviation intertwines which leads to the irregular deviation decisions, but as the monopolist's product is of higher quality, deviation dominates in both cases. By comparing these payoffs with their counterpart in full commitment, we can see that the possibility of deviation to better release schedules significantly increases the firm's payoffs. In (c) and (d), the monopolist's price choices are not much different from the full-commitment choices under the same release schedule.

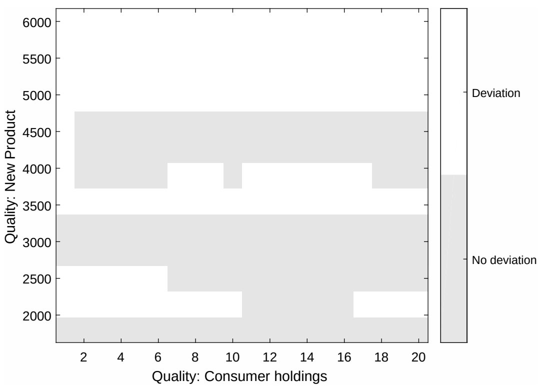
3.4 Appendix: Commitment vs. no-commitment in product releases

In the durable goods market, the manufacturer's ability to commit to future prices and quality improvement is influential on consumers' demand. Without com-

[6] For both $R = 3$ and $R = 6$, the monopolist only deviates to $R = 12$ if possible.

Figure 3.6: Deviation decisions by new product quality and consumers' holdings

(a) $R = 3$



(b) $R = 6$

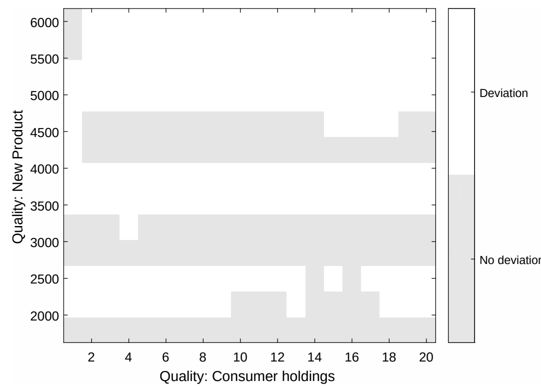
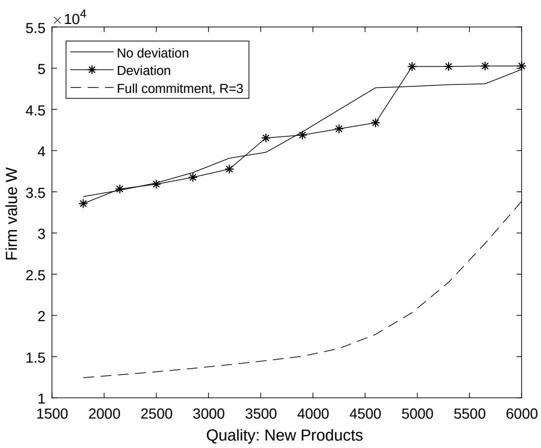
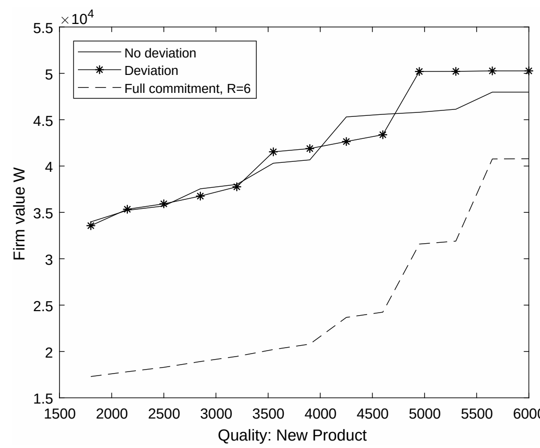


Figure 3.7: The monopolist's value and prices across new product quality for $R = 3$ and $R = 6$

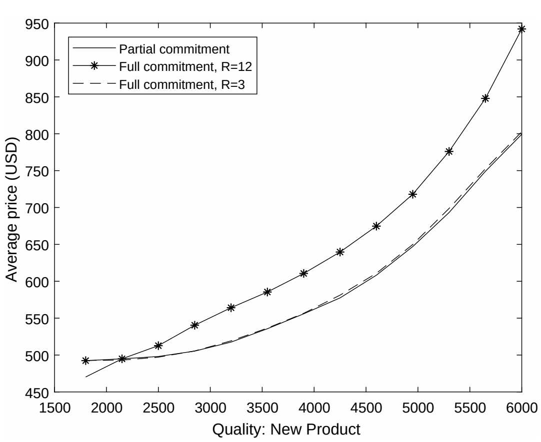
(a) Firm's value: $R = 3$



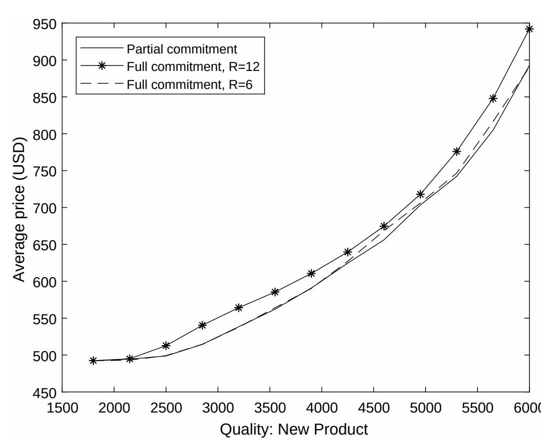
(b) Firm's value: $R = 6$



(c) Average price: $R = 3$



(d) Average price: $R = 6$



mitment, durable goods firms have the incentive to charge lower prices or improve product qualities to cater to the rest of the market after consumers with higher willingness to pay have made the purchase. If consumers are rational and forward-looking, they can expect firms' such behavior and postpone their purchase, which in turn hurts firms' sales. This problem can be alleviated when firms have a commitment device: firms can commit to their future prices and qualities which could totally be different from their ex post optimal choices, but consumers' beliefs in this commitment can increase their demand and may increase firms' total revenue as a result.

This paper modifies the framework in Ericson and Pakes [1995] and Goettler and Gordon [2011] by assuming that firms commit to their product release schedules and release new products when they are scheduled to, rather than may or may not release new products depending on the innovation outcome. This framework allows me to study the role of product release frequency explicitly, but it also endows these durable goods firms the ability to commit, which is a strong assumption considering that there is hardly any firm making promises on how often it will release new products in the future. Take Apple for example: new iPhone models are released every year in September after iPhone 4S,[7] so it is natural for people to believe that new iPhone models will be released like this in the future as well. But Apple is not bounded by this pattern; it can definitely skip one year, or release its new models "irregularly" in August or November. Even though this irregular release is not highly

[7]Excluding iPhone SE which was released in March 2016, because it is not considered as a flagship model.

likely, consumers can still expect it and adjust their purchase behavior accordingly, e.g. someone bought an iPhone in August rather than waiting for another month because she did not believe a new iPhone to be introduced in the next month. So it remains a question whether this assumption of full commitment is too strong and leads to biased welfare analysis.

In this section, I studies the role of firms' commitment to their release schedules in my model and examines its impact on the market outcome. To see this, I adopt the monopoly model used in 2.6.2 and modify it as follows.

1. In this model, the monopolist's new product release is represented by the increase in relative quality of its product to consumers' holdings. Therefore to allow the monopolist not to release any new product even if it is scheduled to, I set the lower possible quality increment (τ') as zero for "no-committed release" cases.

2. To make the market outcome comparable when the monopolist chooses different release schedules, I adjust the higher possible quality increment (τ'') to equalize the upper bounds of quality increment per year.

3. The control group, "committed release" is constructed by setting τ' to δ, so the monopolist always release new products when it is scheduled to.

In total there are five cases to be considered: three no-commitment cases and two commitment cases. Setup details are summarized in table 3.2.

Case 2 and 4, as well as case 3 and 5, are designed to compare firms' policies and market response when new product releases are committed or stochastic. In

Table 3.2: Model specifications with or without committed product releases

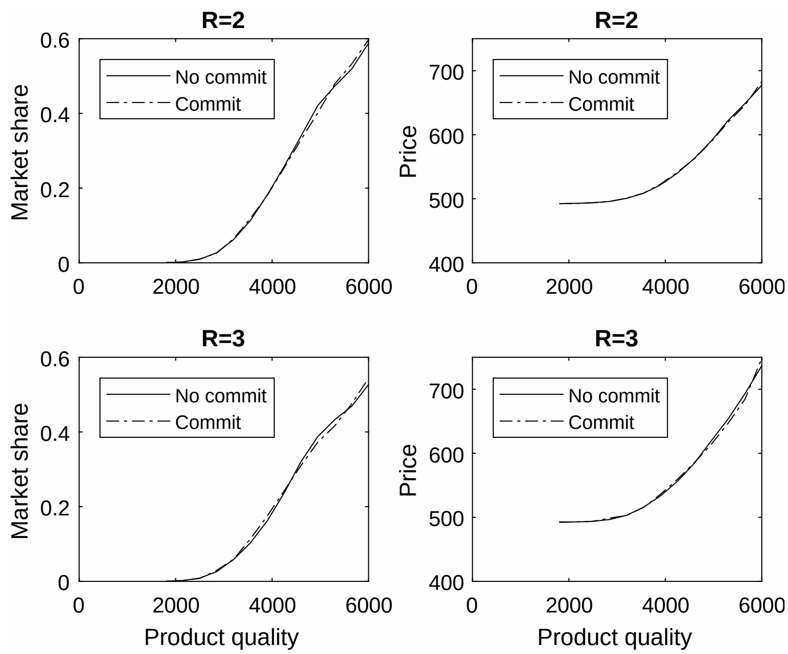
			Possible quality increment		Range of Q increase per year	
		R	τ'	τ''	Lower bound	Upper bound
Case 1	No commit	1	0	δ	0	12δ
Case 2		2	0	2δ	0	12δ
Case 3		3	0	3δ	0	12δ
Case 4	Commit	2	δ	2δ	6δ	12δ
Case 5		3	δ	3δ	4δ	12δ

case 4 and 5, the monopolist is guaranteed to release a new product every time it is scheduled to with at least δ increase in its product quality, while in case 2 and 3, the monopolist's product quality might be unchanged. Other model components, including the upper bound of quality increment per year, and the distribution of consumers' holdings are not different, so discrepancies in the market outcome will mostly result from firms' commitment of new product releases.[8]

Figure 3.8 shows how the monopolist's market share and price changes over its product quality in both committed and non-committed case, where the top two subfigures correspond to case 2 and 4, and the bottom two figures correspond to case 3 and 5. From the graph, for both average price and average market share, they are almost the same with or without commitment to product releases and the minor discrepancy comes from changes in the monopolist's innovation problem as illustrated in footnote 8. This suggests that both consumers and firms are not affected by firms' commitment to product releases, what they care about is the

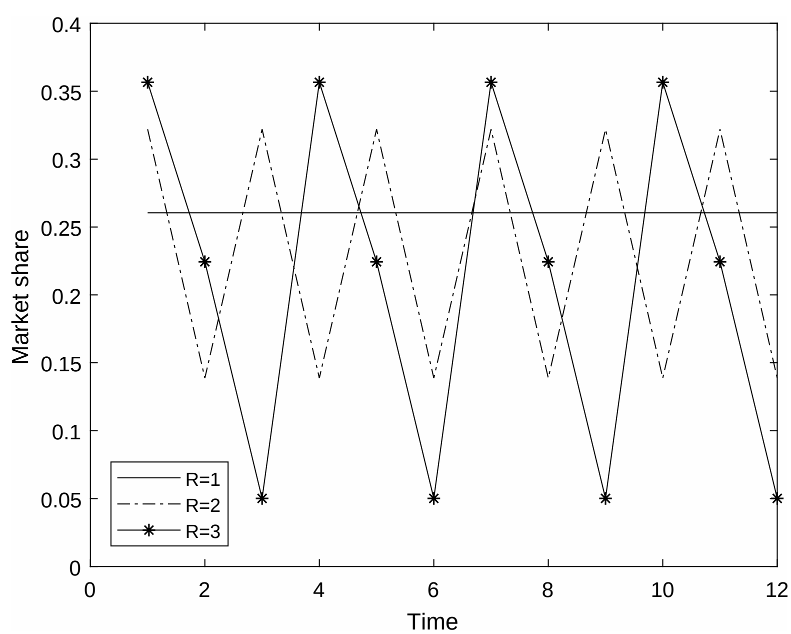
[8] The other source of the possible discrepancy comes from the changes in the monopolist's innovation. By increasing τ', the lower possible quality increment from 0 to δ, the monopolist's gain by switching from τ' to τ'' decreases so it will invest less in quality improvement. This changes in investment cost then affects firms' value functions and price choices, and furthermore, consumers' demand. Based on the results, the impact from this mechanism is of limited scale.

Figure 3.8: Average price and market share over product qualities: with or without commitment of release



possibility of product releases. To see this, I plot the consumers' demand within each 12-month period in case 1 through 3 and it is presented in figure 3.9.

Figure 3.9: Consumers' demand within each 12-month for $R = 1, 2, 3$



Note that in case 1, new product releases are not committed; in each period firms may or may not release new products depending on the investment outcome, which is the same setup as the innovation structure. Given this setup, the monopolist's market share averaged across other state variables (product quality and consumer distribution) is the same over time and results in a horizontal line.

When case 2 and 3 are added where new product releases are still not committed at any time, but for some periods new products are guaranteed not to be introduced, consumers' demand starts to fluctuate where they buy more right after the new product is released, and hold up their purchase before each new release. When the new product is potentially of higher quality ($R = 3$ as compared to $R = 2$ or 1), more consumers choose to wait.

This pattern suggests that if the new products differ from the current products only in qualities, firms' commitment of product release does not have any effect on consumers' and firms' problem.[9] Instead, it is the expectation of possible quality increase in the future that induces consumers' purchase delays. This is an interesting result as it implies that in the innovation model where firms make investment and may or may not increase its product quality in every period, consumers' demand are both boosted by the innovation outcome (if successful) and weakened by their expectation of possible quality increase in the future at the same time. So it is necessary to separate these two effects to better evaluate firms' innovation strategies.

[9]If consumers' value new products in other dimensions, like fashion or advertisement exposure, this result will no longer hold.

Chapter 4: A Tale of Old and New: Multi-Version Consumption in the Video Game Industry

(Co-authored with Andrew Sweeting)

4.1 Introduction

Empirical models of demand for durable goods typically assume that consumers use and derive utility from the most recent version of the product that they own. While this assumption is sensible for some products, like large appliances, it is inaccurate for products which are almost costless to store and where older versions may offer a different and not necessarily inferior user experiences. In this paper, we establish the empirical evidence for multi-product consumption in a video game franchise, where video game players may continue to play the old games after buying the new versions, and provide a framework to analyze their optimal time allocation decisions among their game portfolios.

There are various reasons that consumers may continue to use their old units after buying the upgraded ones. For example, the old product may include certain features that consumers value but removed in the new products, or the old and new products may be complementary in usage. In our empirical setting, we assume that players develop their product-specific preferences through usage, and their relatively high preferences towards the old games, as compared to the new ones, incentivize the continuing usage of the old games. This assumption is supported by two empirical findings.

First, players spend relatively more time in "serially-featured modes," like the career mode, when they play the old game after new purchases. In these modes, players develop their game progress through consecutive matches and their game progress cannot be transferred to other game versions. These non-transferrable game progresses result in individual specific preference towards the old game versions relative to the new games.

Second, players more likely to play old games after new purchases are also less likely to buy future game versions. Players make their purchase decisions based on the additional value brought by the new game, so if they enjoy their old versions and will spend much time on it regardless of their purchase decisions, they will not value their new games much.

Based on these empirical evidence, we develop a framework where players allocate playing time within their game portfolios and across different game modes, based on a latent variable, "game preference." Players' game preferences include common components across individuals like game-specific and mode-specific preferences, and heterogeneous components as well including individual effects and each player's past gaming preferences in the same game mode. We show that incorporating individual heterogeneity is important to fit this detailed usage data and capture the variations.

We estimate the model parameters using a proprietary dataset provided by Wharton Consumer Analytic Initiative, which documents players' play and purchase activities in a major sports video game franchise from 2011 to 2016. In the data we focus on three types of player strategies: game purchase decisions, choices of game versions and modes to play, and game play duration. Given the parameter estimates, we show how the model fits the data in these three dimensions.

Product development and updates are among the most important marketing questions [Norton and Bass, 1987]. Past research on product innovation focus on consumer purchase decisions [Mahajan et al., 1991, Rogers, 2010], where the dependent variables are the timing and the rate of consumer adoption decisions rather than consumers' product usage patterns. As more detailed usage data is made available, recent studies show that post-purchase behavior is important to understand consumers' incentives of upgrade purchase and evaluate the impact on long-term purchasing and usage patterns [Golder and Tellis, 2004]. This paper utilizes the observed video game activities to impute their real-time game preferences and their purchase intentions for the future game releases.

Consumers' product usage patterns are determined by their endogenous product preferences, and previous research focus on how consumer involvement with the products and learning process motivate their continued product usage [Westbrook and Oliver, 1991, Holt, 1995]. Albuquerque and Nevskaya [2012] and Nevskaya and Albuquerque [2012] use data on players' game activities in a multiplayer game and evaluate players' responses to introduction of new game contents. They find that the success of game version updates depends on consumer heterogeneity, rate of content consumption and social interaction. This paper further allows players to allocate their playing time in multiple game versions in their portfolios, and develop version-specific game preferences.

The rest of this paper is structured as follows. Section 2 describes the data and provide empirical evidence on players' multi-game consumption behavior. Section 3 sets up the model and Section 4 provides details about the estimation strategy, with estimation result and model fit presented in Section 5. Section 6 presents the counterfactual analysis, and Section 7 concludes the chapter.

4.2 Data and empirical summaries

This section describes the data format and the game franchise we study, and also provide empirical support on key model setup, including players' multi-product consumption and persistent gaming preferences.

4.2.1 Data Description

Our data is provided by Wharton Consumer Analytic Initiative and it documents game players' play activities in a major sports video game franchise.[1] The publisher of this game franchise releases a new game version every summer and is named after the following year to distinguish from previous game versions. To facilitate the expression without revealing the game identity, we rename the game version named after year 201X as game GX. For example, game $G5$ was released

[1]To comply with the data usage agreement, we will not reveal the game title or the identity of its publisher. All relevant information that could potentially reveal the entity is also anonymized in this paper.

in 2014 summer with 2015 in its name.

Players in our data are randomly selected from the population as follows: around 20,000 players are selected from those whose first observe game version is $G2$ or earlier version; for each game from $G3$ to $G6$, around 10,000 players are selected from those who purchased the game as their first game versions in the franchise. Once a player is selected, all his future game session activities until summer 2016 are included.[2] Since we do not observe players' actual date of purchases directly, we take each player's initial observed game play date for each game version as his purchase date.

For each game session, we observe its date, game mode, game version and the session duration. Given that the original game mode descriptions might reveal the identity of the game, we combine similar game modes into major categories and rename them in more general terms that still reflect the game mode features but could apply for general sports video games as follows:

- "Career" mode: players act as athletes to improve their skills or act as a manager to run a team. Players can save their current game progress and resume later.

- "Instant Play" mode: players choose their teams and compete with the CPU for a single match. Match results have no cumulative effects.

- "Ultimate Mode": players trade cards of professionals with each other or buy them from the system, and use them to form their teams. Their purchased

[2] Since we do not observe the total sales of each game version, in this paper we focus on players' individual behavior rather than making inference on the aggregate level statistics like market share.

cards may be valid for a short time.

- "Occasional Play" mode: players initiate a match series like a championship cup, which requires playing for several matches until winning the final or being eliminated. Players play fewer games than in the career mode, and they can save game progress and continue later.

Table 4.1 provides summaries on player count and average total duration across players. Career mode, ultimate mode and occasional play mode are the three most popular game modes in terms of game session count and session duration. Career mode is consistently popular among all game versions in terms of game duration, whereas the Ultimate Mode gains popularity starting from $G5$. The ultimate mode's significantly higher standard deviations suggests that game time in this mode is more concentrated into a smaller group of players.

Figure 4.1 plots the number of new game activation in each month based on the buyers' initial game version observed in the data. When a new version is released, there will be two peaks in purchases: right after the new game release, and during the holiday seasons. If we further look into the composition of game buyers, those who buy the new games are most likely the existing players who have played previous game versions, while new comers who are new to the franchise are more likely to buy the game during holidays. Based on this difference, we define "pre-holiday" periods as dates after release and before November 15 each year, and "holiday" periods as the rest of the annual cycle. The different types of buyers in these two periods will be captured by their time-specific purchase costs.

Table 4.1: Summary statistics: by players

(a) Player count

		Game Version				
		G2	G3	G4	G5	G6
Game Mode	Career	7,953	13,090	12,652	15,056	16,476
	Instant Play	11,303	14,291	16,960	23,449	22,526
	Ultimate Mode	3,012	6,900	10,785	12,812	13,517
	Occasional Play	7,633	13,754	9,852	11,157	16,849

(b) Average total duration across players (seconds)

		Game Version				
		G2	G3	G4	G5	G6
Game Mode	Career	59869	86484	105212	105288	91754
	Instant Play	13227	21172	24067	24358	17489
	Ultimate Mode	24006	45403	67618	136819	106507
	Occasional Play	58616	61938	79388	80065	68273

(c) Standard deviation of total duration across players (seconds)

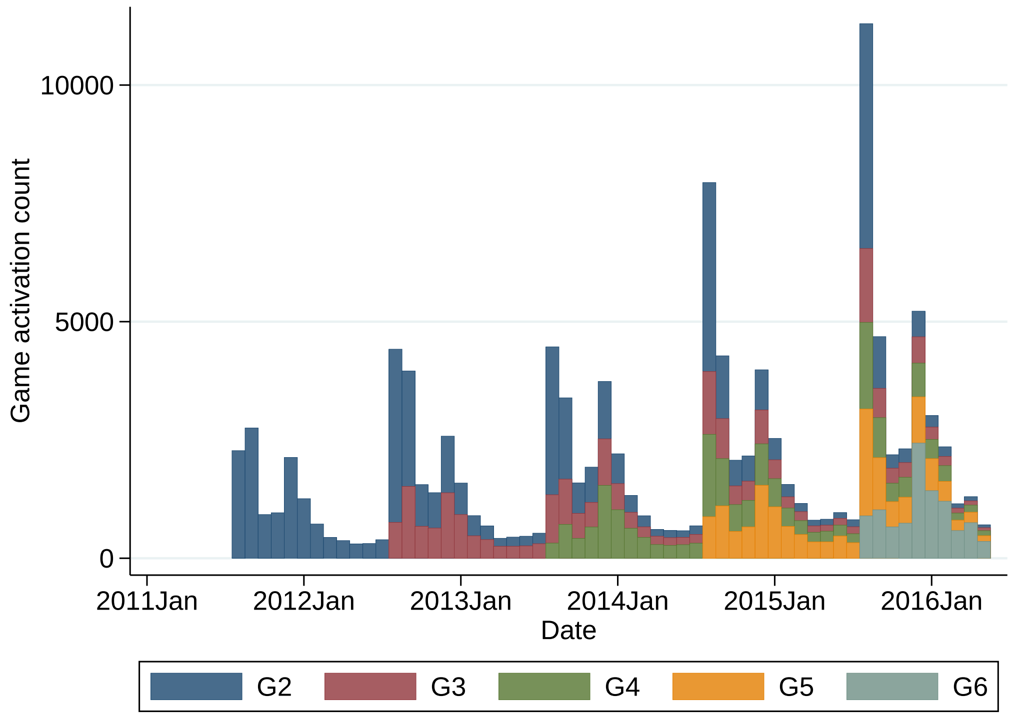
		Game Version				
		G2	G3	G4	G5	G6
Game Mode	Career	157387	195829	198001	193502	153279
	Instant Play	32888	49280	56784	63507	38868
	Ultimate Mode	70578	139855	215969	312891	228893
	Occasional Play	167403	196234	206518	213324	146489

Notes: All players who have played at least one game session in any game are included.

4.2.2 Multiproduct consumption

In the durable good literature, it is commonly assumed that consumers' outside options are completely represented by their more recent purchases. In the video game industry, this would predict that a player should completely shift his playing time to the new game version after purchase and discontinue his game play in the old games. While this prediction is intuitive as the new game has better graphics

Figure 4.1: Game activation over time



performance, in data we observed that some players still play their old games after buying the new game versions, which we term as "port-back." The formal definition of "port-back" is as follows.

Definition 1 (Porting Back in Video Game) *Player A is defined as porting back in game version x if*

1. *Game version x is player A's most recent purchase in his game portfolio X.*

2. *There exists a version x', where $x' \neq x, x \in X$, such that player A played version x' after buying version x.*

There are several implications from this definition. First, a player needs at least two game versions to be eligible, as he needs an old game version to port back to, and this requirement excludes players' initial versions. Second, porting back behavior is player-version specific, so it is possible that player A ported back in $G4$ but not in $G5$ because he stopped playing old games (including $G4$) after buying $G5$. To facilitate the expression, we denote porting back players as PB players, and non-porting back players as NPB players. Similarly we define game sessions when players port back as PB sessions, and others as NPB sessions.

Table 4.3: Summaries on PB player count

		Player count			PB %
		NPB player	PB player	Total	
Current game	G3	6,027	1,414	7,441	19.00%
	G4	8,192	1,935	10,127	19.11%
	G5	10,959	2,868	13,827	20.74%
	G6	14,389	2,237	16,626	13.45%

Notes: "Current game" denotes players' most recent game versions in terms of purchase date. For each game version, define a player to be PB player if he ported back to earlier versions when this version is his current version. Discrepancy in the player count between this table and player purchase statistics comes from players with no active game sessions observed.

Table 4.4: Summaries on PB percentage across initial and current games

		Current game			
		G3	G4	G5	G6
Initial game	G2	19.00%	17.75%	18.51%	11.49%
	G3		21.44%	19.86%	12.30%
	G4			25.01%	16.27%
	G5				14.64%

Notes: "Initial game" is defined as the first game a player bought. For each combination of initial game and current game, the number reported is the percentage of PB players among total players.

Table 4.3 provides summaries on the distribution of PB players across different game versions. Approximately 13% to 20% of players ported back in our example, which is a large base considering the popularity of this sports game franchise. But we can also see that game $G6$ has a significantly lower portion of PB players than other games, and this portion is unanimously lower regardless of their initial game versions. Therefore it is necessary to incorporate game version specific fixed effect when modeling players' PB choices. Table 4.4 further disentangles the percentage of PB players based on the current game version and players' initial game version. On average, less players would port back when their current versions are more recent as compared to their initial versions, which could be potentially explained as players buying multiple game versions are more likely those who appreciate the game features brought by the new game versions.

4.2.3 Persistent gaming preferences

All game versions in the game franchise we study here are similar in design, where game versions only differ in graphics, up-to-date sports information and certain game contents, so we assume that each player has correlated game preferences over time and across different versions he has played. Given that players' purchase intentions are determined by the additional values of the new game, which is also affected by players' values of the old game in the portfolio, this assumption establishes correlations between players' purchase activities and past playing activities as well.

To validate this assumption, we regress players' purchase probabilities and playing hours for the next game over their current game session duration. Several data patterns can be found in Table 4.5.

Table 4.5: Regression of players' future purchase probabilities on current playing time and PB behavior

	If buy next	Dur in next ver	If buy next	Dur in next ver
If PB	-0.251***	-1.965***		
	(-5.75)	(-9.60)		
Log(duration) in current ver	0.0809***	0.494***	0.113***	0.667***
	(97.78)	(109.66)	(29.82)	(42.01)
If PB $\times$ Log(duration) in current ver	0.0179***	0.160***		
	(4.78)	(9.44)		
Duration in PB session			-0.0263***	-0.0210
			(-8.00)	(-1.65)
Current game FE	Yes	Yes	Yes	Yes
Initial game FE	Yes	Yes	Yes	Yes
Observations	79236	39870	6225	4049
R^2	0.201	0.278	0.141	0.318

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

First, for any game version, if a player ports back, he will play less in the next new game version purchased. Players' port-back behavior indicates their higher preferences towards the old game relative to the new game, so this pattern can be explained if these port-back players' higher preferences towards the old games are persistent over time.

Second, longer playing time is associated with higher purchase probabilities. To incorporate this pattern, we associate both players' playing time and purchase intentions with their game preferences γ.

Third, longer playing time in PB sessions is linked to lower purchase probabilities. In our model, PB players have higher game preferences towards the old game, so the lower purchase intentions can be explained as lower additional value brought by the new game relative to their current game portfolios.

Table 4.6 also describes the average duration each player spent across different modes. The statistics are categorized between PB and NPB players, and for PB players, the average duration in PB and NPB sessions. As is in the last column, which reports the ratio of PB and NPB sessions for the PB players, we can see that PB players spend more in Career Mode, as compared to others.

Table 4.6: Average total duration across players (seconds)

		NPB Players	PB Players		PB/NPB ratio
			NPB Sessions	PB sessions	
G3	Career	103458	76566	14699	0.19
	Instant Play	21743	21455	2762	0.13
	Ultimate Team	24321	35921	1250	0.03
	Occasional Play	75842	59326	4735	0.08
G4	Career	100662	74728	12946	0.17
	Instant Play	22471	28845	4034	0.14
	Ultimate Team	42454	82601	3265	0.04
	Occasional Play	56481	49693	7222	0.15
G5	Career	91797	71836	12550	0.17
	Instant Play	26451	35541	5585	0.16
	Ultimate Team	82614	145385	5323	0.04
	Occasional Play	48246	47471	5748	0.12
G6	Career	77739	68949	8442	0.12
	Instant Play	17254	23019	4336	0.19
	Ultimate Team	69001	125796	5769	0.05
	Occasional Play	55924	76922	2778	0.04

Finally, to see how game durations within each player is correlated over time and within each game mode, we run two regressions on game duration and a dummy variable that equals one if the play plays the corresponding mode in a period over past game activities, as in Table 4.7.

Both game duration and game play dummy are positively correlated with

Table 4.7: Regression on game duration and game play dummy over past duration in the same mode

	(1) Total duration	(2) If play (1=play, 0=no play)
Past duration	0.365***	0.00000336***
	(13.78)	(15.30)
Instant Play × Past duration	-0.397***	0.00000434***
	(-5.59)	(7.39)
Ultimate × Past duration	0.0277	-0.00000142***
	(0.58)	(-3.68)
Occasional Play × Past duration	-0.158***	-0.000000562
	(-3.91)	(-1.66)
Time FE	Yes	Yes
Player FE	Yes	Yes
Observations	2853	5815
R^2	0.281	0.206

Notes: t statistics in parentheses. * $p < .05$, ** $p < .01$, *** $p < .001$. Observation unit is user-mode-period level. "Past dur" is each player's duration in the same mode in the previous period (zero if not played). In the first regression, only observations with positive duration are included.

players' past game duration in the career mode (the base level) and the ultimate mode. For example if a play plays a lot in Career mode at t, he is also predicted to play the Career mode at $t + 1$ and spend more time on the mode as well. Duration in Occasional mode is less predictive for future duration, and for Instant Play mode, players' game duration is almost uncorrelated (=.365-.397). Such differences across different modes motivate our model setup that players' preferences are correlated over time, and such correlations are mode-specific.

In regards to predicting whether a player would play a mode, as reported in the second column, the instant play mode is the most predictable among others as it has the highest correlation with past game duration activities. The relatively low R^2 may indicate, however, that game play dummies could be hard to fit.

4.2.4 Data processing

Data is processed into player-mode-version-period level observations. For each group of players defined by their initial game versions played, we drop the top 10% players in terms of their total playing time in their initial and subsequent versions.[3] In each period, assume each player has 500 hours to allocate across different game modes and the outside option.

There are two periods defined between each two consecutive releases: "pre-holiday", defined as between the release and November 15 each year, and "holiday" for the rest of the annual cycle. After dropping the top 10% players, there are 53,076 players remaining in the sample. In estimation, we take a 2% random sample, which includes 1087 players, to facilitate the computation while maintaining enough player heterogeneity.

4.3 Model

In this section, we develop a model framework that incorporates both players' game purchase decisions and game play activities. Players observe the newest game version in each period, and decide whether to buy it to be included in their game portfolios for all of the future periods; conditional on their updated game portfolios,

[3] The cumulative playing time thresholds are 2654.48 hours, 1275.68 hours, 1247.08 hours, 906.79 hours, 297.88 hours for players initially played in G2 through G6, respectively.

they allocate their playing time across different game modes and game versions.

Denote player as i, game mode as m, game version as v and period as t. At the beginning of period t, denote player i's game portfolio as $\mathcal{V}_{i,t-1}$. In each period, the model proceeds as follows.

1. For all the games $v \in \mathcal{V}_{i,t-1}$, players observe their realized preferences in period t, $\{\gamma_{imvt}\}_{m\in\mathcal{M},v\in\mathcal{V}_{i,t-1}}$.

2. If a player is eligible to purchase in period t (defined below), he receives a signal of his preference towards the game modes in the new game version $\bar{v}_t$, and decide whether to buy the new game ($\mathcal{V}_{it} \triangleq \mathcal{V}_{i,t-1} \cup \{\bar{v}_t\}$) or continue to play his current game portfolio ($\mathcal{V}_{it} \triangleq \mathcal{V}_{i,t-1}$).

3. If the player buys the new game, his preference towards the new game is realized as $\{\gamma_{imvt}\}_{m\in\mathcal{M},v=\bar{v}_t}$.

4. Based on the realized game preferences, the player allocates his playing time.

A player is defined as "eligible to purchase in period t" if (1) he has not purchased $\bar{v}_t$ yet; (2) he has purchased an earlier version before period t. The first requirement rules out repeated purchases of the same game version. The second requirement rules out players potentially buying the new game as their first game versions. As will be illustrated in the data section, we do not observe the market size of all potential game buyers; therefore we only model players' upgrade purchase decisions when they already play the game franchise for at least one period.

In the rest of this section, we first present players' utility function from playing the game conditional on their game portfolios and realized gaming preferences; then given the utility specification, we solve for players' game purchase decisions.

4.3.1 Utility from game play

We follow Crawford and Yurukoglu [2012] and assume that players' maximize their utilities by allocating their time across all the modes and versions they have access to, in the form, [4]

$$\max_{\{d_{imvt}\}} = \sum_{m\in\mathcal{M},v\in\mathcal{V}_{it},d_{imvt}>0} \gamma_{imvt} \log d_{imvt}, \quad \text{s.t.} \sum_{m\in\mathcal{M},v\in\mathcal{V}_{it}} d_{imvt} \leq D. \tag{4.1}$$

Players' outside options, i.e. other entertainment activities, are included in all players' choice sets as $v_0 \in \mathcal{V}_{it}$. $d_{imvt} \geq 0$ denotes the time spent in the corresponding mode, version and period. D represents the total time spent in all forms of entertainment in each period. Player preference γ_{imvt} takes the form

$$\gamma_{imvt} = \begin{cases} \chi_{imvt} \circ (\tilde{\gamma}_{imvt})^{1-\alpha_m} (\bar{\gamma}_{im,t-1})^{\alpha_m}, & \text{if } \#(\mathcal{V}_{i,t-1}) \geq 1 \\ \chi_{imvt} \circ \tilde{\gamma}_{imvt}, & \text{if } \#(\mathcal{V}_{i,t-1}) = 0 \end{cases} \tag{4.2}$$

where

$$\tilde{\gamma}_{imvt} = \exp\left(\eta_i + \xi_m + \xi_v + \xi_t + \zeta_{imvt}\right), \quad \bar{\gamma}_{im,t-1} = \gamma_{imv',t-1|v'=\bar{v}_{i,t-1}}. \tag{4.3}$$

[4] Players' game duration is in the units of second. In our data, there is no observation with $d_{imvt} \in (0, 1)$.

$\tilde{\gamma}_{imvt}$ represents the "contemporary component" of the game preference, which includes mode-specific preference ξ_m, game-specific preference ξ_v, period-specific preference ξ_t and individual random effect $\eta_i \sim N(\mu_\eta, \sigma_\eta^2)$. $\zeta_{imvt} \sim N(0, \sigma_\zeta^2)$ represents other unobserved utility components that are independent across modes, versions, time and individuals. $\bar{\gamma}_{im,t-1}$ represents players' game preferences in the most recent game version in the previous period. $\chi_{imvt} \in \{0, 1\}$ is a random process to fit the data patterns that players only play certain game modes and game versions, with the probability form constructed as

$$Pr(\chi_{imvt} = 1) = \begin{cases} \dfrac{\exp(a_{0m} + a_{1m}\gamma_{imv,t-1})}{1 + \exp(a_{0m} + a_{1m}\gamma_{imv,t-1})}, & \text{for newest game in the portfolio} \\ \dfrac{\exp(a_{0m} + a_{1m}\gamma_{imv,t-1} + a_{2m})}{1 + \exp(a_{0m} + a_{1m}\gamma_{imv,t-1} + a_{2m})}, & \text{for other games} \end{cases} \tag{4.4}$$

The presence of player's game preference in the previous period in this functional form captures the empirical pattern that longer playing time is associated with higher future play probabilities. We allow such correlation to vary across game modes, and also between PB and NPB sessions as captured by a_{2m}.

Players' optimal time allocation $\{d^*_{imvt}\}$ solves (4.1), and by normalizing players' preferences towards the outside option as $\gamma_{i0t} = 1$, it takes the form

$$d^*_{imvt} = \begin{cases} 0, & \text{if } \gamma_{imvt} = 0 \\ \dfrac{\gamma_{imvt}}{1 + \sum_{m' \in \mathcal{M}, v' \in \mathcal{V}_{it}} \gamma_{im'v't}} D, & \text{if } \gamma_{imvt} > 0 \end{cases}, \tag{4.5}$$

This solution form can be interpreted as if a player plays individual sessions repeatedly, and for each session the player only chooses one version-mode combination. In this way, players' playing time for each mode-version is determined by its relative game preference with respect to others.

With the optimal time allocations, players' indirect utilities conditional on the game portfolio $\mathcal{V}_{it}$ and game preference $\boldsymbol{\gamma}_{it} = \{\gamma_{imvt}\}_{m\in\mathcal{M},v\in\mathcal{V}_{it}}$, are

$$u(\mathcal{V}_{it}, \boldsymbol{\gamma}_{it}) = \sum_{m\in\mathcal{M},v\in\mathcal{V}_{it},\gamma_{imvt}>0} \gamma_{imvt} \log\left(\frac{\gamma_{imvt}}{1+\sum_{m'\in\mathcal{M},v'\in\mathcal{V}_{it}}\gamma_{im'v't}} D\right), \tag{4.6}$$

which is used to facilitate the computation of players' values under different game purchase decisions.

4.3.2 Game purchase decision

In the game franchise that we study, new versions are released every year, and players keep buying new game versions to be added to their portfolios. There are two periods between each two consecutive gam4e releases: "pre-holiday" which starts from the game release and ends at Nov 15th, and "holiday" which covers the rest of annual cycle until the next game release.

From this piont, we denote the most recent game available for purchase as "new game", and all the other games as "old game." When a new game is released, a player chooses from the following options: (1) pay the full retail price p to buy the game in pre-holiday period; (2) pay the discounted price δp to buy the game in post-holiday period; (3) not buy the game. To simplify the computation, assume that players only evaluate the purchase decisions based on their value in the current period, or in another word, players' lifetime value of buying the new game is proportional to the value in the current period.

To formalize the discussion of purchase decisions, we make the following assumptions.

Assumption 1 *Players keep at most two game versions at any time; when a player already has two versions in his portfolio and buys another game, the oldest version is automatically removed.*

Assumption 2 *A player has access to all the game modes, denoted as $\mathcal{M}$, for all the games in his portfolio.*

Assumption 3 *Players can only buy the most recent game version in each period.*

For the newest version in period t, denoted as $\bar{v}_t$, a player who is eligible to buy the game compares his value of buying and not buying the new game and make his purchase decision accordingly.

Since a player knows his game preferences towards the owned games $\mathcal{V}_{i,t-1}$ at the time of purchase decision, his value of "no-purchase" is deterministic and takes the form

$$u_{it}^{\text{No-Buy}} = u(\mathcal{V}_{i,t-1}, \boldsymbol{\gamma}_{it} = \{\gamma_{imvt}\}_{m\in\mathcal{M},v\in\mathcal{V}_{i,t-1}}) \tag{4.7}$$

To evaluate the utility of buying the new game, assume that a player receives a random shock $\tilde{\zeta}_{imvt} \sim N(0, \sigma_\zeta^2)$ for the new game when he decides on the new game purchase, and this random shock is not observable to the econometrician. With this shock, the player can calculate his preference for the new game, and his value of "purchase" is (denote $\mathcal{V}_{it}$ as the updated game portfolio after purchase)

$$u_{it}^{\text{Buy}} = u(\mathcal{V}_{it}, \{\gamma_{imvt}\}_{m\in\mathcal{M},v\in\mathcal{V}_{it}}) \tag{4.8}$$

The player will buy the game if the additional value brought by the new game is larger than a time-specific threshold p_t. Denote players' purchase behavior as $s_{it} \in \{0, 1\}$, the player's purchase probability is

$$Pr(s_{it} = 1) = Pr\left(u_{it}^{\text{Buy}} - u_{it}^{\text{No-Buy}} \geq p_t \middle| \mathcal{V}_{i,t-1}, \{\gamma_{imvt}\}_{m\in\mathcal{M},v\in\mathcal{V}_{i,t-1}}\right) \tag{4.9}$$

which completes the model setup of players' purchase and play decisions.

4.4 Estimation

Our model parameters, as summarized in Table 4.8, are estimated using maximum likelihood function over players' observed play and purchase activities. In the rest of this section, we provide detailed description on how the likelihood function for players' game play activities and game purchase decisions, as well as the estimation algorithm imposed in the estimation.

4.4.1 Likelihood function of game play

Denote the set of parameters to be estimated as Θ, and the set of a player's state variable *after the purchase decision and before time allocation decision* at period t as $X_{it}^1 = \{\mathcal{V}_{it}, \boldsymbol{\gamma}_{it}, \boldsymbol{\gamma}_{i,t-1}\}$. For each mode and version in the portfolio,

Table 4.8: List of parameters to be estimated

	Function	Count
A. Utility function		
a_{0m}, a_{1m}, a_{2m}	$Pr(s_{imvt} = 1)$	12
B. Specification of γ_{imvt}		
ξ_m	Mode FE	4 (1 default)
ξ_v	Version FE	5 (1 default)
ξ_t	Time FE	2 (1 default)
u_η, σ_η	Distribution of η_i	2
C. Specification of ε_{imvt}		
α_m	Correlation within game modes	4
σ_ζ	Distribution of ζ_i	1
α_p	Value threshold for purchase	2

conditional on the value of individual random effect η_i, the log likelihood function of observed playing time, d_{imvt} is

$$\begin{aligned} f^d(d_{imvt} = d|\Theta, X^1_{it}, \eta_i) &= Y(d=0)\log\left(Pr(d=0|X^1_{it}, \Theta)\right) \\ &+ Y(d>0)\log\left((Pr(d>0|X^1_{it}, \Theta) f(d|X^1_{it}, \Theta, \eta_i, d>0)\right), \end{aligned} \tag{4.10}$$

where $f(\cdot)$ is the probability density function for d_{imvt}, and $Y(\cdot)$ is the indicator function which equals one if the condition is met, and zero otherwise.

Given the parameter value $\{a_{0m}, a_{1m}, a_{2m}\}_{m\in\mathcal{M}}$, and game preference in the last period $\boldsymbol{\gamma}_{i,t-1}$, $Pr(d>0|X_{it}, \Theta)$ can be calculated based on (4.4). To calculate the probability density function $f(d|X_{it}, \Theta, d>0)$, first impute players game preference as $\tilde{\gamma}_{imvt} = d^*_{imvt}/d^*_0$, then the imputed random term ζ takes the form

$$\tilde{\zeta}_{imvt} = \log(\tilde{\gamma}_{imvt}) - \eta_i - \xi_m - \xi_v - \xi_t - \alpha_m \gamma_{imv',t-1|v'=\bar{v}_{i,t-1}} \tag{4.11}$$

From this expression we can see that probability density of positive game duration is equal to $\phi(\tilde{\zeta}_{imvt}|X_{it}, \Theta, \eta_i)$ where $\phi(\cdot)$ is the density function for normal distribution with mean zero and standard deviation of σ_ζ.

4.4.2 Likelihood function of game purchase

Denote players' state variables before making purchase decisions as $X_{it}^0 = \{\mathcal{V}_{i,t-1}, \{\gamma_{imvt}\}_{m\in\mathcal{M}, v\in\mathcal{V}_{i,t-1}}\}$, which differs from X_{it}^1 in that, if the player buys the new game $\bar{v}_t$, X_{it}^0 does not include players' realized game preference towards the new game. In each period, the log likelihood function for the observed game purchases, $s_{it} \in \{0, 1\}$, and game play activities, $\{d_{imvt}\}$, is

$$\begin{aligned} f(s_{it} \quad , \quad & \boldsymbol{d}_{it} = \{d_{imvt}\}_{m\in\mathcal{M}, v\in\mathcal{V}_{it}}|\Theta, X_{it}^0, \eta_i) = \\ & Y(s_{it} = 1)\left[\log\left(Pr(s_{it} = 1|\Theta, X_{it}^0)\right) + \mathbb{E}\sum_{m,v} f^d(d_{imvt} = d|\Theta, X_{it}^1, \eta_i, s_{it} = 1)\right] \\ & + Y(s_{it} = 0)\left[\log\left(Pr(s_{it} = 0|\Theta, X_{it}^0)\right) + \sum_{m,v} f^d(d_{imvt} = d|\Theta, X_{it}^1 = X_{it}^0, \eta_i, s_{it} = 0)\right] \end{aligned} \tag{4.12}$$

where the expectation is taken over preferences in the new game.

To effectively calculate players' game purchase probabilities, note that players' indirect utilities take the analytic form (as in (4.6)) of

$$U_{it}^{buy} = \mathbb{E}\sum_{m\in\mathcal{M}, v\in\mathcal{V}_{it}\cup\{\bar{v}_t\}} \gamma_{imvt} \log\left(\frac{\gamma_{imvt}}{1 + \sum_{m'\in\mathcal{M}, v'\in\mathcal{V}_{it}\cup\{\bar{v}_t\}} \gamma_{im'v't}} D\right). \tag{4.13}$$

To empirically evaluate this expectation, we take n_r random draws of game preferences in the new game, based on the current parameter trial in the estimation, as

$\{\gamma^r_{imvt}\}_{m\in\mathcal{M},v=\bar{v}_t}$ where $r = 1, 2, \ldots, n_r$. Then players' value of buying new games can be calculated as ($\gamma^r_{imvt} = \gamma_{imvt}$ for preferences of old games)

$$U^{buy}_{it} = \frac{1}{n_r}\sum_{r=1}^{n_r}\sum_{m\in\mathcal{M},v\in\mathcal{V}_{it}\cup\{\bar{v}_t\}}\gamma^r_{imvt}\log\left(\frac{\gamma^r_{imvt}}{1+\sum_{m'\in\mathcal{M},v'\in\mathcal{V}_{it}\cup\{\bar{v}_t\}}\gamma^r_{im'v't}}D\right). \tag{4.14}$$

Players' values of no-purchase are deterministic as players observe their realized game preferences for all their available games before making the purchase decisions. Denote the value of no purchase as U^{no-buy}_{it}, then players' purchase probabilities are

$$Pr(s_{it} = 1|\Theta) = Pr(U^{buy}_{it} - U^{no-buy}_{it} \geq p_t). \tag{4.15}$$

Finally, the aggregate likelihood function sums up individual likelihood of purchase and play behaviors, and is integrated over individual random effect as

$$\mathcal{L}(\Theta) = \sum_i \int \sum_t f(s_{it}, \boldsymbol{d}_{it}|\eta_i, \Theta)dF(\eta_i|\Theta) \tag{4.16}$$

Our estimation proceeds as follows: for each player and each period, first impute the game preference and calculate the likelihood for the observed game duration; then given the imputed preference value, simulate and calculate players' purchase probabilities. The detailed algorithm is as follows.

Algorithm 2 Calculate likelihood function for parameter estimation

Generate a vector of the random effect η_i candidate values, chosen as 1% to 99% quantiles with 1% increment.
for Each η_i value, each player and each period **do**
    Impute players' preferences for the games they played based on observed game duration
    Impute ζ from players' preferences. Calculate its density as the likelihood for players' game duration.
    Impute probabilities of game play, and calculate likelihood function for observed game play choices.
    For players eligible to buy new games, calculate their values of "buy" and "no-buy" choices and impute their purchase probabilities.
end for
For each η_i value, calculate the aggregate likelihood function, then integrate over all η_i based on distribution parameters.

4.5 Estimation result

4.5.1 Parameter estimates

This section reports estimation results based on 1078 players, a 2% random sample selected from the original dataset. For each selected player, we include all of his game sessions for all game versions and modes observed in the original data. Parameter estimates are reported in Table 4.9.

For common utility components, which are homogeneous across all individuals, the fixed effect estimates suggest that players' favorite modes are career mode (as the base) and Occasional Play Mode, and favorite game version is G2 (as the base) and G6. Differences in estimates across modes are higher than across game versions. On average, players play mode in the pre-holiday season, and within-player heterogeneity (measured by σ_ζ) dominates cross player heterogeneity (measured by σ_η).

Table 4.9: Parameter estimates

Parameter description			Param Est.	Std. Err.
A. Common utility components				
Fixed Effect	ξ_m	Career	-	-
		Instant Play	-1.5556	0.0020
		Ultimate Mode	-1.5300	0.0020
		Occasional Play	-0.8361	0.0005
	ξ_v	G2	-	-
		G3	-0.0963	0.0003
		G4	-0.1057	0.0008
		G5	-0.0752	0.0012
		G6	-0.0445	0.0015
	ξ_t	Pre-holiday	-	-
		Post-holiday	-0.0360	0.0015
Random Effect	μ_η		-4.0516	0.0001
	σ_η		0.0239	0.0060
ζ	σ_ζ		2.1896	0.0005
B. Correlation with past game experiences				
Correlation with γ_{t-1}	α_m	Career	0.0967	0.0001
		Instant Play	0.1196	0.0001
		Ultimate Mode	0.0373	0.0003
		Occasional Play	0.0769	0.0007
$Pr(d > 0)$	a_{0m}	Career	0.7592	0.0006
		Instant Play	0.6113	0.0003
		Ultimate Mode	0.2676	0.0118
		Occasional Play	0.2275	0.0004
	a_{1m}	Career	1.3037	0.8341
		Instant Play	1.5743	0.0004
		Ultimate Mode	0.2657	0.3597
		Occasional Play	2.1730	0.5820
	a_{2m}	Career	0.5240	0.0604
		Instant Play	0.6559	0.0653
		Ultimate Mode	0.2225	0.0409
		Occasional Play	0.5154	0.0505
C. Monetary preference				
Price coefficient	Pre-holiday		0.1685	0.0003
	Holiday		0.2199	0.0003

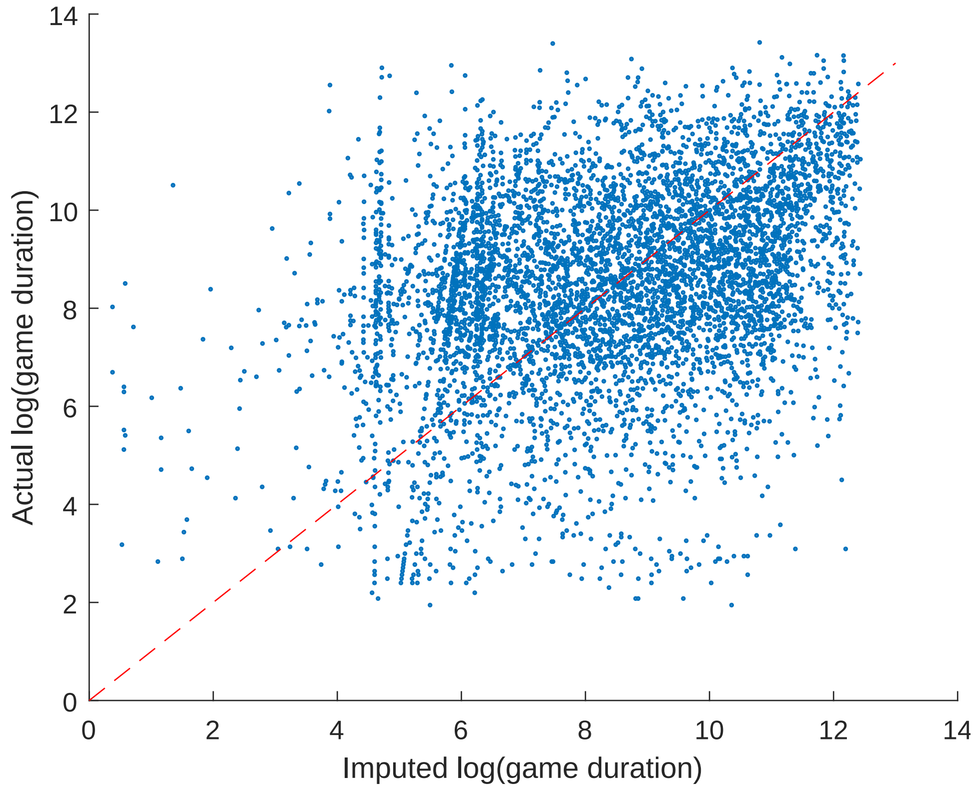
The second part reports estimates that determines the probability of play and correlation with past gaming activities. Players' playing time is correlated the Ultimate Mode and Career Mode, and given the fact that players spend the most time in Career Mode, we can say that it is the most correlated game mode in game play. By comparing the estimates of a_{0m}, we can see that players are more likely to play in their initial game versions.

The third part reports players' value threshold of buying the new game in each period. In general, the additional value required for new purchase is higher during the holiday season, mostly because of player selection: those who would wait until holiday seasons to buy the game are less enthusiastic about the game franchise, and the higher value threshold reflect their lower willingness to play.

4.5.2 Model fit

This paper focuses on players' individual behavior, rather than aggregate market level statistics. The additional data details provide more variations in identification, but also levels up the difficulty for model fit: each individual player could be affected by various factors not captured by the model, and exhibit higher variations than the market average. In this section, we provide measures on how our model structure fits the data in players' three major decision categories: game duration, game play probability, and game purchase probabilities.

Figure 4.2: Correspondence between imputed and actual game duration



Game duration

Based on our model parameter estimates, we first calculate the imputed game preference as

$$\tilde{\gamma}_{imvt} = \exp\left(\eta_i + \xi_m + \xi_t + \alpha_m \gamma_{imv',t-1|v'=\bar{v}_{i,t-1}}\right), \tag{4.17}$$

which differs from the model structure in ζ_{imvt} as it is assumed to be mean zero.[5] Figure 4.2 plots the correspondence between predicted and actual game duration for observations with $d_{imvt} > 0$.

Based on the figure, the imputed and actual duration coordinates are clustered around the 45 degree line, but with a high degree of variance. This suggests

[5]Another interpretation is that $\tilde{\gamma}$ measures the "predicted" component of player preference, and ζ_{imvt} measures the unpredictable component.

that the model captures the average duration level but there are still factors not captured by the model, and these factors could potentially affect players' game play decisions. To further check the model fit for the duration, Table 4.10 reports the average imputed and actual game duration across periods, versions and modes, as well as their standard deviations. On average, game duration fits better across periods and games than across modes, which is mostly driven by certain mode-version combinations. More details can be found in the appendix.

Play probabilities

Given the parameter estimates, we also calculate the imputed probability of players playing each game mode and game version in each period, and the comparison in this imputed probability between no-play and play observations are reported in Table 4.11. While the predicted play probabilities are higher in the play observations than no-play observations, the differences are small compared to their standard deviation which suggests the model cannot predict which mode and version a player would play. To overcome this difficulty, we hold fixed the versions and game each player actually played in the counterfactual analysis.

Purchase probabilities

Finally, we also impute players' purchase probabilities and report them across periods in Table 4.12. Note that in our model, players are only allowed to buy the newest game version, so the reported imputed purchase probabilities across periods

Table 4.10: Imputed and actual game session durations (in seconds)

	Imputed		Observed	
	Mean	Std. Dev.	Mean	Std. Dev.
A. By period				
2012 Holiday	19869	18993	27940	62653
2013 Pre-holiday	22841	21220	25203	46054
2013 Holiday	18545	17294	22961	50306
2014 Pre-holiday	20728	19292	19730	34878
2014 Holiday	17273	17892	23618	55269
2015 Pre-holiday	21005	19643	23763	46971
2015 Holiday	17611	17462	24392	53382
2016 Pre-holiday	21754	20334	23648	45961
2016 Holiday	18198	18333	21138	43681
B. By game				
G2	16326	35613	18034	45465
G3	18801	38909	19915	43984
G4	24752	43435	21866	51007
G5	21253	35682	23066	47398
G6	32365	47787	26437	49874
C. By mode				
Career	52474	66080	37948	61992
Instant Play	16937	24272	11374	21000
Ultimate Mode	16534	25481	26276	64432
Non-game	2293.7	3601.2	6372	19118
Occasional Play	9809.4	12724	23761	47279

Note: Observation units are player-game-mode-time specific. Only observations with positive game play are included.

are also across different game versions as indicated in the first column.

In general the model predicts the purchase instances well as the predicted purchase probabilities for non-buyers are around 0.2 and for buyers are around 0.9.

Table 4.11: Imputed probabilities of game play between play and no-play observations in players' most recent version

	Play observations		No-play observations	
	Mean	Std. Dev.	Mean	Std. Dev.
A. By period				
2012 Holiday	0.3286	0.1029	0.2787	0.1027
2013 Pre-holiday	0.3426	0.1146	0.2921	0.1041
2013 Holiday	0.3383	0.1134	0.2948	0.1051
2014 Pre-holiday	0.3454	0.1103	0.2982	0.1064
2014 Holiday	0.3426	0.1106	0.2945	0.1061
2015 Pre-holiday	0.3529	0.1075	0.2953	0.1063
2015 Holiday	0.3497	0.1109	0.2939	0.1064
2016 Pre-holiday	0.3472	0.1140	0.2974	0.1062
2016 Holiday	0.3389	0.1115	0.2976	0.1063
B. By mode				
Career	0.4921	0.0230	0.4882	0.0190
Instant Play	0.5608	0.0367	0.5568	0.0374
Ultimate Mode	0.2911	0.2427	0.2809	0.2394
Non-game	0.4709	0.0669	0.4677	0.0674
Occasional Play	0.5347	0.0064	0.5333	0.0040

Table 4.12: Imputed purchase probabilities between buyers and non-buyers

New game	Period	Buyers		Non-buyers	
		Mean	Std. Dev.	Mean	Std. Dev.
G3	2013 Pre-holiday	0.2521	0.0622	0.8302	0.0683
	2013 Holiday	0.1640	0.0648	0.8760	0.0746
G4	2014 Pre-holiday	0.2351	0.0782	0.8536	0.0765
	2014 Holiday	0.1430	0.0502	0.9058	0.0544
G5	2015 Pre-holiday	0.2392	0.0773	0.8653	0.0761
	2015 Holiday	0.1633	0.0555	0.9088	0.0593
G6	2016 Pre-holiday	0.2445	0.0810	0.8716	0.0675
	2016 Holiday	0.1652	0.0599	0.9155	0.0491

4.6 Counterfactual analayasis

In this section, we simulate players' game play activities based on two potential game mechanism changes that could be of interest for the video game publishers:

restriction of game access to new game version only, and removal of past game preferences.

Single-game restriction

As is illustrated in the data section, around 13% to 20% of players continue to play their old games after buying the new games, which makes it natural for firms to wonder what would happen if these players are restricted to play their newest game version only. After all, when these players have no access to their old games, they should spend more time in their new games, and higher playing time in the new game can facilitate even higher game duration in the future through correlation in the game preferences.

To see how players would reallocate their playing time in the new games, we simulate players game duration by restricting them playing in the newest game version in their portfolios. We hold the mode-version each player actually played and players' purchase decisions fixed as the same with the actual observations. The results are reported in Table 4.13.

From the table we can see that, players play more in the new game, but the extent of such game play increase is very limited to the scale of 0.3%. This suggests very weak substitution in players' game duration between the old and the new game, and removing players' access to their old games will significantly reduce their playing time.

Table 4.13: Comparison of game duration with and without the single-game restriction

Period	Original		Single-game restriction
	New game	Old game	New game
2013 Pre-holiday	9934	3019	9985
2013 Holiday	5975	1917	5996
2014 Pre-holiday	4385	1064	4384
2014 Holiday	4595	1692	4606
2015 Pre-holiday	4688	1183	4691
2015 Holiday	4435	1441	4452
2016 Pre-holiday	4899	1313	4922
2016 Holiday	4079	976	4083
Average	5374	1576	5390

Note: numbers reported are average duration (in seconds) in each version-mode-period that players played.

Correlation in intertemporal game preferences

One of the data patterns in the data is that players spend consistently high or low time in certain game modes over time, and this persistence cannot be explained by common utility factors like game mode fixed effect and individual random effect. To evaluate how these correlated game preference in the past affect players' current game play activities, we change players' game preferences, originally in the form of

$$\gamma_{imvt} = \begin{cases} \chi_{imvt} \circ (\tilde{\gamma}_{imvt})^{1-\alpha_m} (\bar{\gamma}_{im,t-1})^{\alpha_m}, & \text{if } \#(\mathcal{V}_{i,t-1}) \geq 1 \\ \chi_{imvt} \circ \tilde{\gamma}_{imvt}, & \text{if } \#(\mathcal{V}_{i,t-1}) = 0 \end{cases} \tag{4.18}$$

to

$$\gamma_{imvt} = \chi_{imvt} \circ \tilde{\gamma}_{imvt} \tag{4.19}$$

In another word, players are treated as if they have no prior playing experiences, although their game purchase records and game portfolios in each period are unaffected. Table 4.14 compares players' game duration with and without the previous game preferences.

Table 4.14: Comparison of game duration with and without game preferences

Period	Original		With no previous preference	
	New game	Old game	New game	Old game
2013 Pre-holiday	9934	3019	7970	2852
2013 Holiday	5975	1917	5597	1751
2014 Pre-holiday	4385	1064	3507	985
2014 Holiday	4595	1692	4350	1619
2015 Pre-holiday	4688	1183	3831	1118
2015 Holiday	4435	1441	4100	1307
2016 Pre-holiday	4899	1313	3903	1225
2016 Holiday	4079	976	3746	882
Average	5374	1576	4625	1467

From the table, when players' game preferences are only determined by contemporary component $\tilde{\gamma}_{imvt}$, players on average spend 13.9% less time (from 5374 to 4625) in their new games, and 6.9% less time (from 1576 to 1467) in their old games.

4.7 Conclusion

This paper provides a framework to analyze video game players' multi-version consumption behavior in the video game industry. In this framework, players allocate their playing time across game versions and game modes in their portfolios, and their purchase decisions of new game versions are also endogenously determined by the additional value brought by players' portfolios. This framework is developed to fit two patterns found in the data, where players are observed to continue to play their old games after buying the new versions, and they spend consistently higher time in certain game modes over time.

Given the parameter estimates, we conduct two sets of counterfactual analysis by simulating players' game activities under two alternative model alternative. When players are restricted to play their newest game only in the portfolio, players spend on average 0.3% more time in their new game while they completely stop playing the old game, which suggests very weak substitutions across game versions in players' portfolios. When we remove players' past game experiences from their current game preferences, players spend on average 14% less time in the new game, and 7% less time in the old game, which suggests strong intertemporal correlation in players' game preferences.

In the next step, we will further relax players' choices in the counterfactual analysis by allowing them to change their purchase decisions from the data, and re-evaluate the impacts of alternative game designs, like the single-game restriction, on players' play activities through their purchase changes. It is also worthwhile to study how players' purchase intentions for the new game would vary across their past game experiences, and examine how common marketing strategies like targeted discount would change players' play and purchase activities.

4.8 Appendix: Supplemental summary statistics

Table 4.15 reports statistics based on game session level, as compared to player level in Table 4.1. One significant difference from the player level statistics is that number of sessions and average session duration in the Ultimate mode is higher than career mode, while the session count and session average duration are not. This suggests that ultimate mode is played by relatively less players with each player, which is also consistent with the high standard deviation for the ultimate mode.

Table 4.15: Summary statistics: by game sessions

(a) Game session count

		Game Version				
		G2	G3	G4	G5	G6
Game Mode	Career	95,876	305,131	339,275	379,602	376,141
	Instant Play	57,890	87,438	126,465	184,970	147,041
	Ultimate Mode	18,882	95,928	209,438	492,554	464,937
	Non-game	56,180	14,954	16,700	12,600	
	Occasional Play	96,474	222,748	165,973	173,936	318,249

(b) Average session duration (seconds)

		Game Version				
		G2	G3	G4	G5	G6
Game Mode	Career	4966.20	3710.15	3923.51	4175.99	4019.06
	Instant Play	2582.54	3460.45	3227.59	3087.91	2679.24
	Ultimate Mode	3829.36	3265.80	3482.00	3558.84	3096.44
	Non-game	1762.77	1467.86	873.89	1348.55	
	Occasional Play	4637.72	3824.48	4712.42	5135.74	3614.58

(c) Standard deviation of game duration (seconds)

		Game Version				
		G2	G3	G4	G5	G6
Game Mode	Career	5278.83	4550.10	4693.03	4986.39	4124.25
	Instant Play	3796.91	4097.38	4426.34	6035.28	4210.36
	Ultimate Mode	3815.01	3622.08	4101.47	4887.49	3875.17
	Non-game	2957.91	2271.58	2170.36	4629.76	
	Occasional Play	4669.90	4556.51	5090.76	7061.29	4946.02

Notes: All players who have played at least one game session in any game are included.

Table 4.17: Imputed and actual game duration by game mode and version

		Imputed	Actual	Difference
Career	G2	40944.41	27900.76	13044
	G3	43257.92	34744.04	8514
	G4	55510.35	40208.36	15302
	G5	48213.91	41084.46	7129
	G6	71162.91	42013.31	29150
Instant Play	G2	13443.12	7822.75	5620
	G3	13398.06	11342.42	2056
	G4	18931.81	12225.94	6706
	G5	15416.23	12295.3	3121
	G6	22237.7	11508.45	10729
Ultimate Mode	G2	12597.58	27109.37	14512
	G3	12001.79	15840.33	3839
	G4	14170.85	20018.06	5847
	G5	16649.87	29564.68	12915
	G6	22686.89	35258.37	12571
Non-game	G2	2758.367	11350.73	8592
	G3	2698.665	4202.941	1504
	G4	1900.088	1727.875	172
	G5	1334.252	2961.453	1627
	G6	-	-	-
Occasional Play	G2	7835.61	27043.21	19208
	G3	8116.8	20728.86	12612
	G4	11069.44	24846.95	13778
	G5	8294.879	23630.92	15336
	G6	13173.69	24879.55	11706

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