Welfare Impacts of Subscriptions for Digital Goods: The Case of Video Games

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Abstract

Offering content via bundle-based subscription services has become a prevalent business strategy for media platforms. Despite its popularity, there is limited empirical evidence on whether the subscription model can generate better outcomes for customers and content providers than the traditional à la carte sales model. We answer this question using a novel proprietary dataset from the Xbox video game platform. We develop and estimate a model of demand and supply for individual games and the subscription service Game Pass. We find consumer surplus increases by 16% when Game Pass is introduced. The decomposition analysis shows that the bundling and renting features of the subscription service contribute almost equally to the surplus change. We further simulate subscription-only models that are widely used by streaming video and music platforms. We find that if the Xbox platform only offers one subscription bundle, consumer surplus is lower than its level under the traditional à la carte sales model, but it can be increased if the platform offers multiple tiers of subscription bundles. Based on our assumptions on the contract structures, we find content providers are better off with the subscription-only model when the platform shares greater than 70% of the subscription revenue with them.

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1 Introduction

Over the past decade, an increasing number of media platforms began offering their products via a bundle-based subscription service, which grants customers access to a large catalog of content for a fixed monthly fee. Prominent examples are Netflix for streaming videos, Spotify for music, Apple Arcade for video games, and Kindle Unlimited for ebooks. Despite the popularity of the subscription model, observers have been raising concerns over its sustainability due to platforms' struggle to achieve profitability,[1] low payments to content providers,[2] and recent price hikes for customers.[3] It is unclear whether this fast-growing business model can indeed benefit market participants more than the traditional à la carte sales model.

In this paper, we answer this question using a novel proprietary dataset from the Xbox video game platform. Traditionally, customers purchase games on Xbox and are perpetually entitled to them. In 2017, Xbox launched a subscription service called *Game Pass*, which allows customers to play a bundle of more than 100 games by paying $9.99 a month.[4] Game Pass subscribers can still purchase any individual game as before. The nice feature of our data is that we can simultaneously observe customers' game purchases and subscription enrollments. This enables us to estimate a realistic demand model for both options, which forms the backbone of our counterfactual analysis, where we simulate the welfare outcomes of different business models by removing either the purchase or subscription option.

We characterize the Game Pass subscription service as a business strategy of *bundling* and *renting*. First, it offers customers a large bundle of zero marginal cost content. Bundling offers the platform the possibility of raising profits by reducing variation in customers' valuations of games. It may also increase consumer surplus by turning customers' positive valuation of games that does not lead to à la carte sales into willingness to pay for the bundled offering (Stigler 1963, Adams and Yellen 1976, McAfee et al. 1989).

Second, Game Pass resembles a renting mechanism: subscribers do not own the content in the bundle and lose access to it if they unsubscribe. The renting feature allows customers to enjoy

[1] Lucy Handley, 2019. "Streaming services like Disney+ aren't likely to make money 'anytime soon,' analyst says", CNBC. `https://www.cnbc.com/2019/12/09/streaming-services-arent-likely-to-make-money-anytime-soon.html`

[2] Ben Sisario, 2021. "Musicians Say Streaming Doesn't Pay. Can the Industry Change?", New York Times. `https://www.nytimes.com/2021/05/07/arts/music/streaming-music-payments.html`

[3] Barry Collins, 2021. "Netflix Price Rises Are Just About To Bite", Forbes. `https://www.forbes.com/sites/barrycollins/2021/01/05/netflix-price-rises-are-just-about-to-bite.html`

[4] For a detailed description of Game Pass, see `https://en.wikipedia.org/wiki/Xbox_Game_Pass`.

games that are completed quickly at a lower price than the purchase cost. However, at the same time, game developers might use the subscription service as a price discrimination device (Varian 2000, Rao 2015).[5] By setting higher purchase prices, they could extract more profits from customers who get satiated with games slowly and thus are willing to pay more to own them.

In addition, both the bundling and renting features generate the possibility that Game Pass cannibalizes games sales. The increased product offering intensifies competition on the platform and could lead to decreased game prices. When we take all these considerations together, the welfare impacts of introducing a subscription service on both the demand and supply sides are ex-ante ambiguous and therefore an empirical question.

Our paper combines reduced-form analyses with a structural model of supply and demand for games to assess the impacts of adopting subscription models. First, we find that all platform participants benefit from the introduction of Game Pass because it successfully turns the deadweight loss from à la carte sales into surplus gain: customers play more games through subscription, and the subscription revenue outweighs the cannibalized sales in the long term. We then investigate whether the subscription model can completely replace the traditional à la carte sales model. Counterfactual analysis suggests that offering all games only through a subscription bundle makes both sides of the market strictly worse off than they are under the à la carte sales model. The negative impact is more pronounced for customers who spend little time playing or stick to the same game for a long time, and for game developers that have more sales. Finally, we find that this welfare result can be improved if multiple tiers of subscription bundles are offered for different segments of customers.

We leverage a rich sample of de-identified Xbox console gamers in a single US county to conduct the empirical analysis. Our data covers the first two years of the Game Pass offering. The purchase dataset contains customer-level game purchases and subscription enrollments. The usage dataset records the number of hours that a customer spends playing each game each day. Combined with the purchase panel, this usage panel helps us estimate customers' initial valuation for games and how it decays over time, which we find to be important determinants of the subscription impacts. On the supply side, we observe the dynamic list of games offered through Game Pass and the characteristics of all games on the platform.

We start our analysis by showing which customers are most likely to subscribe. We find that subscribers tend to play more games *before* they subscribe than non-subscribers. Also, they finish

[5] We use the terms game developers and content providers interchangeably throughout the paper.

a game more quickly on average. Thus, by revealed preferences, subscription is more appealing to those with higher usage intensity and faster satiation in gaming, in line with the benefits of bundling and renting, respectively.

We then document how customers' behavior change *after* they subscribe using the difference-in-differences method. We find that subscribers spend more hours gaming and play more low-sales games. Meanwhile, they purchase fewer games that are included in Game Pass than non-subscribers, suggesting that the subscription service may displace game sales. On the supply side, game developers are less likely to decrease prices if their games are included in Game Pass, implying a certain degree of price discrimination.

The reduced-form evidence motivates us to develop an equilibrium model of supply and demand for individual games and the subscription bundle. Our demand model has two stages. In the first stage, customers make purchase and/or subscription choices based on their expected usage utility and the observed price menu. In the second stage, they allocate time across games that they possess (or that are accessible in Game Pass) and the non-gaming activity to maximize usage utility. We allow two key parameters in the usage model to vary heterogeneously across customers: baseline game valuation and satiation rate (i.e., the speed at which the baseline valuation decays). The former affects the choice between à la cart games vs a bundle of games; the latter affects the choice between purchasing vs subscribing (renting). In the supply model, game developers set game prices and the platform sets the subscription price to maximize revenue, conditional on the observed bundle content.[6]

We jointly estimate two stages of the demand model to recover customers' unconditional valuations. Our estimates show rich heterogeneity in customer preferences. For example, gamers who live in areas with higher median income are more sensitive to usage utility but less sensitive to price changes. Male gamers have a higher valuation for shooter and sports games but a lower valuation for casual and platform games. They are also satiated with a game more quickly than women. Our supply estimates show that the platform aims to optimize long-term revenue by putting roughly equal weight on short-term revenue and consumer surplus when it sets the Game Pass price.

We then use our model to quantify the welfare impacts of Game Pass. We find that the introduction of the observed subscription bundle increases consumer surplus by 16%. The bundling and renting features explain 47% and 53% of the gains, respectively. On the supply side, Game

[6] In practice, bundle content is determined through bilateral negotiations between these two parties. However, due to the lack of Game Pass contract data, we do not model this process and take the bundle as given.

Pass games are less likely to decrease prices compared to non-Game Pass games, indicating that game developers may use the subscription service as a price discrimination device. Total long-term revenue increases by 12% because the expected revenue stream from the subscription service outweighs the modest reduction in sales.

Finally, we evaluate subscription-only models that are widely used by other media platforms. We start from the counterfactual of offering all games only via a grand bundle subscription service. Consumer surplus decreases by 38% from its level under the à la cart sales model. Low-usage and slow-satiation customers would be more negatively affected: they either stop gaming activity entirely on the platform or have to pay more than before to obtain the same level of gaming utility. Meanwhile, total revenue decreases by 12%. High-sales games experience more loss because subscription increases the probability of playing low-sales games, reducing the market concentration to some extent.

We further simulate another popular business model where the platform offers a menu of subscriptions to cater to different segments of customers. In our simulation, two tiers of subscription bundles are offered: a premium version that includes all games and a basic version that includes a subset of games. We find that offering tiered subscriptions generates welfare outcomes similar to those under the à la carte sales model. However, the tiered subscription model still performs worse than the hybrid model that Xbox currently uses, suggesting that in contrast to the case for other types of media, the subscription-only model may not be well suited for video games.

Our paper contributes to several strands of the literature. First, it adds to a growing empirical literature that studies the impacts of offering media content via bundled subscriptions. Earlier works have examined whether the emergence of subscription services generates more usage and revenue for the music industry and found mixed results (Aguiar and Martens 2016, Wlömert and Papies 2016, Aguiar and Waldfogel 2018, Datta et al. 2018). Our paper is the first to study subscriptions for video games and provides a more holistic understanding of the subscription effects. Unlike previous literature that focuses only on the change in platforms' short-term profits, we also study the distributional effects on customers and content providers, which are crucial for the long-term growth of platforms. Furthermore, we break down the value of subscriptions into the value associated with the bundling and renting components of the offering, shedding light on the mechanism underlying the popularity of subscriptions.

Second, our study bridges the bundling and renting literature. The theoretical literature has long understood that multi-product monopolists can use bundling as a price discrimination device

(Stigler 1963, Adams and Yellen 1976, McAfee et al. 1989). Our paper is closest to the works that compare à la carte selling, pure bundling, and mixed bundling for zero marginal cost goods (Bakos and Brynjolfsson 1999, Geng et al. 2005, Abdallah 2019, Ghili 2021, Haghpanah and Hartline 2021). On the empirical side, some studies have compared selling products à la carte vs. in bundles for theater tickets (Chu et al. 2011), a console and games (Derdenger and Kumar 2013), and songs in albums (Danaher et al. 2014). Others have compared renting products à la carte vs in bundles for TV channels (Crawford 2008, Crawford and Yurukoglu 2012, Crawford et al. 2018). Our paper combines the two by comparing selling products à la carte vs renting products in the bundle.

Varian (2000) and Rao (2015) are the most related to our paper with respect to the renting of digital content. They show that firms can indirectly price discriminate against customers with heterogeneous diminishing returns to consumption by operating both purchase and rental markets. Notably, Rao (2015) studies the purchase and rental model of single movies and calls for future empirical work to study bundled subscriptions, which requires knowledge of the distribution of customers' preferences for all goods on the platform. With rich individual-level customer purchase and usage data, our paper fills this gap in the literature.

Third, our paper is related to an expanding literature on the design of subscription services. Existing literature has studied the strategy of offering different tiers of subscriptions based on the amount of ads in the content (DeValve and Pekeč 2022, Sato 2019, Lin 2020, Goli 2020). This product "versioning" strategy (Shapiro et al. 1998) is used to implement second-degree price discrimination. Our counterfactual analysis that offers two tiers of subscription bundles shares the same idea, but we vary the tiers by bundle size instead of ads level. In addition, some other works have studied revenue-allocation rule for content in the subscription bundle theoretically (Shiller and Waldfogel 2013, Lei and Swinney 2018, Alaei et al. 2022). Though it is not the main focus of our paper, we empirically assess the effects of different payment rules on game developers' profits.

Finally, our paper contributes to the literature on the economics of video games. Earlier studies have examined inter-temporal price discrimination strategies (Nair 2007), exclusive games (Lee 2013, Derdenger 2014), used goods markets (Shiller 2013, Ishihara and Ching 2019), bundling of consoles and games (Derdenger and Kumar 2013), and inter-temporal demand spillover effects (Haviv et al. 2020). Our paper complements these works by studying a new and fast-growing business model in the video game industry.

The rest of the paper proceeds as follows. Section 2 provides background information on the Xbox platform and describes our data. Section 3 shows reduced-form evidence on the impacts of

Game Pass. In Sections 4–5, we build and estimate a demand and supply model of games and the subscription bundle. Section 6 shows our counterfactual exercises. Section 7 concludes.

2 Setting and Data

Our study uses proprietary data from Microsoft Xbox, one of the most popular video game platforms in the United States. In 2020, the platform had more than 100 million monthly active users and generated over $10 billion in revenue, including sales of hardware (consoles), software (games), and other services.

On June 1, 2017, Xbox launched the Game Pass subscription service, which grants users access to a rotating catalog of 100+ games from a range of publishers for a single monthly subscription price. The media has described Game Pass as "Netflix for video games", but the Xbox platform offers multiple entitlement options, including purchasing any game à la carte and subscribing to the bundle.

Our data contains rich demand and supply information for Xbox covering June 1, 2017 to April 30, 2019. During these first two years of the subscription offering, Game Pass was available only for consoles.[7] Thus, our main dataset contains a random sample of console gamers from a large US county with broad demographics representative of all Xbox console gamers.

On the demand side, we observe panel data on de-identified customers' purchase, subscription, and playing decisions. The purchase panel records transaction dates, game titles, and retail prices. The subscription panel records Game Pass subscription and unsubscription dates and the subscription fees paid. The usage panel records daily gaming activity on the console, i.e., the number of hours that customers spend playing each game. We also observe some customer demographics, such as self-reported gender, age group, Xbox enrollment date, and account zip code. We supplement this data by merging with census zip code-level income. In addition, we observe a snapshot of customers' Xbox Live and EA Play subscription status in the last month of the sample period.[8]

We do some light trimming of the sample to avoid edge cases in the data. We focus on active customers who purchased at least one game and played for more than five hours over the two-year sample period. We drop professional or extremely heavy gamers who play for more than 240 hours

[7] During this period, there was no cloud gaming (streaming) option in Game Pass. Instead, subscribers downloaded games to their consoles before playing.

[8] Xbox Live is an online multiplayer gaming and digital media delivery service. It lets users play games against other people online and network with other players. Signing up to Xbox Live is free. EA Play is a subscription service similar to Game Pass, but it offers access only to selected games published by Electronic Arts. It was launched on Xbox One in August 2014 and costs $4.99 a month.

per month. These restrictions leave us with 26,838 unique customers (83% of the raw sample). A median gamer in our sample is a male in the 25- to 34-year-old age group who lives in a zip code area with a median annual income of $75,000.

On the supply side, we observe games available for purchase on Xbox and the dynamic list of games offered in Game Pass (titles enter and exit the library over time). For each game, we observe its daily price, genre, publisher, release date, add-on purchase option, and customer ratings.

Below, we describe the Game Pass subscription and à la carte purchase options in more detail, using the combined demand and supply data.

2.1 Game Pass Subscription

Price The retail price of Game Pass for console is $9.99 a month (see the subscription plan in Figure A.1), along with price discounts for the first month of subscription.[9] Figure A.2 shows the distribution of fees paid by first-time subscribers in each month. The most common offer over our sample is a first-month-free or one-dollar trial subscription. Conversations with the Xbox marketing team indicate that because this was a new service during our sample period, discounts were not targeted to individual customers but rather extended through a variety of "blunt" campaigns. Thus, this quasi-random variation in prices can help us identify customers' price sensitivity. After the introductory discount period, subscribers pay the full price. The subscription renews automatically and can be canceled at any time.

Content The Game Pass bundle is composed of first-party games from Xbox Game Studios and third-party games from a wide range of publishers. The homepage on the Xbox console user interface lets subscribers browse titles offered as part of the Game Pass catalog, shown in Figure A.3. There are no material personalized recommendations in the service during our sample period.

Titles move in and out of the bundle at a monthly cadence. When Game Pass was first launched, 116 games were included in the catalog. Since then, the platform has constantly added and removed approximately 10–15 games every month (see Figure A.4). First-party titles are added to the bundle the same day that they are released and are rarely removed, while third-party titles are usually added sometime after release and are subject to removal.[10] Bundle content is determined through

[9] We also observe price discounts for three-month, six-month, and one-year subscriptions, but these are much less common, so we focus on the first-month discount in our data.

[10] As long as a game remains in the catalog, it is available for unlimited download and play by subscribers. If the player ends her subscription, access is suspended until the player purchases the game or renews the subscription, but her in-game progress will be saved.

bilateral bargaining between the platform and third party game studios. During our sample period, the payment contracts range from a lump-sum payment based on a perceived value to covering a share of development cost to a usage-based royalty approach.[11] Since we do not observe the contract data, we take the bundle content as given in our analysis.

Demand A total of 32.5% of customers in our sample subscribed to Game Pass at least once during the observation window. The average utilization rate of the subscription service is 76%, which means that if a customer subscribes for 10 months, she plays at least some games in Game Pass during 7.6 of those months. In addition, the total price of games played by customers in Game Pass is higher than the subscription fee paid. This evidence suggests that the demand for subscription does not primarily come from inertia or irrationality leading customers to subscribe without using the content or underusing it (DellaVigna and Malmendier 2006, Handel 2013, Miller et al. 2022).

2.2 À la carte Purchases

Xbox offers more than a thousand games on the platform. Customers can purchase any title in the Xbox store (Figure A.5). If a game is included in Game Pass, such as Minecraft displayed in Figure 1, customers can play the game by subscribing monthly or purchasing it.

Price Game prices are primarily determined by developers and publishers. There is big variation in game prices. The median price of games offered on the platform is $14.99. Large AAA titles often sell for $59.99, with deluxe editions selling for more. Game prices vary over a title's life through a combination of temporary sales and permanent price drops. When a transaction occurred in our sample period, game developers paid a royalty fee (30% of the price) to Xbox.

Demand In the purchase data, we observe transactions made via the Xbox store but not those made via a third-party retailer such as Target or GameStop. Therefore, we use the date on which the respective user first plays the game as a proxy for the purchase date. We use the sale price of the title in the Xbox store on that date as a proxy for the purchase price.[12]

[11] Alex Calvin, 2020. "Xbox's Spencer details how Game Pass developers are compensated", `https://www.pcgamesinsider.biz/news/71723/heres-how-xbox-game-pass-developers-are-compensated`

[12] We can observe customers' game-playing behavior on the console regardless of whether the games were purchased through the Xbox store.

2.3 Game-playing Behavior

An observation in the usage data records the number of hours that a customer spent playing a game on a day. The panel structure provides information on customers' initial engagement with games and how the engagement decays over time. In Figure 2, we show descriptive statistics on these two aspects of the gaming behavior.

First, we use first-month play time on a game as a proxy for customers' initial engagement. We define a game as the customer's favorite if it has highest first-month play time among all the games that she has played. We then rank games based on their popularity—the proportion of customers who see the game as their favorite. Panel A of Figure 2 shows the ranking distribution: customers' favorite games are very different from each other; even the "top" game is only 2.75% of customers' favorite.

Second, we use the number of months between the first and last time that a customer plays a game to measure how quickly her engagement decays.[13] Panel B in Figure 2 shows the distribution of this measure. In 51.37% of the cases, a game is finished within a month, but there is also a nontrivial proportion of games played for long periods.[14]

Our descriptive analysis shows that there is rich heterogeneity in customers' gaming preferences. Combined with the variation in game prices and subscription fees, the variation in their initial engagement allows us to identify customers' baseline game valuation, and the changes in the engagement over time allows us to identify their satiation rate in gaming in our structural model later on.

3 Descriptive Evidence

In this section, we provide model-free evidence on the impacts of offering Game Pass on customers and game developers. On the demand side, we study what types of customers are more likely to subscribe to Game Pass and how their behavior change after they subscribe. This informs us about the factors we need to capture when modeling customers' subscription choices. On the

[13] We assume that a customer is fully satiated with a game if she has stopped playing it over six months. A faster gaming satiation rate indicates that a customer takes fewer months to finish a game. However, we do not distinguish the reasons why she spends fewer months finishing it—e.g., whether she completes/beats a game quickly, gives up a game halfway because of its increasing difficulty, or feels satiated with a game and does not want to play it any more.

[14] Ishihara and Ching (2019) also find that game owners' consumption value deteriorates quickly. Using weekly aggregated new and used-copy purchase data, they estimate that the game value decays by 23%–58% after the first week of ownership.

supply side, we study how the addition of games into the Game Pass bundle affects game developers' pricing decisions. This informs us about whether we need a supply model to simulate the equilibrium outcomes when Game Pass is introduced.

3.1 Demand Side Response

We employ a difference-in-differences design to estimate the effects of subscribing to Game Pass on subscribers' game purchase and playing behavior. Customers who subscribed at least once during our sample period serve as the treated group (subscribers). Customers who never subscribed during our sample period serve as the control group (non-subscribers).

As a first step, we assess whether subscribers' pre-subscription gaming behavior is similar to non-subscribers'. For each subscriber, we calculate her average gaming activity over all periods prior to her first subscription date. For each non-subscriber, we calculate her average gaming activity over the whole sample period. Table 1 shows the comparison results. Prior to subscription, subscribers play 52% more hours, 77% more unique titles, and 23% more genres each month than non-subscribers on average. They also finish playing a game more quickly in terms of both hours and months of playing time. Overall, subscribers have a higher usage intensity and faster satiation rate. In addition, customers who are male, have longer tenure on the platform, and live in areas with lower median income are more likely to become Game Pass subscribers. Hence, to guarantee that non-subscribers serve as a suitable control group against which to estimate subscribers' counterfactual behavior outcomes, we implement a matching procedure to isolate non-subscribers who resemble subscribers on every observed aspect except their subscription decisions.

We execute our matching procedure in the following steps. For each subscriber, we first identify all non-subscribers whose activity can be observed for three months prior to the focal subscriber's first subscription date and six months after it. This ensures that the matched pair have the same observational window. We further restrict the sample to non-subscribers who share the same gender, age group, income level, and year joining the platform as the focal subscriber. Next, we calculate the Mahalanobis distance between the subscriber and each eligible non-subscriber, in terms of average gaming hours, number of games played, and number of games purchased across the three months prior to the first subscription date. Finally, we use the one-nearest-neighbor (with replacement) algorithm to match each subscriber to her closest non-subscriber. We also impose a caliper that puts an absolute maximum on the Mahalanobis distance to avoid bad matches. After this procedure, 3,448 subscribers are matched to 3,011 unique non-subscribers. Figure A.7 shows that the covariates are well balanced between the treated and control groups after matching.

Next, we compare the average outcomes of subscribers to the matched non-subscribers to estimate the impacts of subscription on customers' behavior. We run the following difference-in-differences regression:

$$y_{it} = \sum_{\tau=-3}^{5} \beta_\tau (s_i \times \gamma_\tau) + \omega_\tau \gamma_\tau + \xi_i + \eta_t + \varepsilon_{it}, \tag{1}$$

where y_{it} is the monthly activity outcome for customer i at time t. s_i is an indicator variable equal to 1 for subscribers. γ_τ is an indicator of τth month since subscription. β_τ is our coefficient of interest. It represents the treatment effect in the τth month since subscription. We look at customers' activity three months before and six months after the first subscription date. ξ_i are customer fixed effects. η_t are the calendar year-month fixed effects.[15]

Figure 3 shows our main estimation results. We focus on customers who remain active subscribers for at least six months in the treatment group. The coefficients are normalized by the sample mean of dependent variables one month prior to subscription, as suggested in Freyaldenhoven et al. (2021). In all four panels, we observe clear increases in customers' gaming activity after they subscribe to Game Pass. After the spike in the first month of subscription, the increase becomes remarkably stable and persists for five months. On average, customers spend 29.0% more hours on 28.6% more games and 14.7% more genres after they subscribe. They also play 55.1% more non-top 50 games,[16] which means niche and indie games are more likely to be played through subscription. Our estimation results are consistent with the theoretical prediction that offering a subscription service helps turn the deadweight loss from à la carte pricing strategies, especially of low-valuation products, into surplus.

In addition to the change in the usage behavior, we find that customers purchase fewer games included in Game Pass after they subscribe.[17] However, we find no significant change in sales of games not included in Game Pass. This finding suggests that the subscription service displaces sales of its own content but has little impact on other content on the platform.[18]

Our results are robust to different choices of data samples. We find similar subscription effects

[15]If the subscription month crosses two calendar months, we use the one with more subscription days in the regression. For example, if the subscription month is from July 5 to August 4, we use the July fixed effect for η_t.

[16]We use purchases by non-subscribers to determine the rank/popularity of games.

[17]We do not show the plots of estimates on game purchases due to data confidentiality.

[18]The fact that customers purchase fewer instead of more Game Pass games after they subscribe rules out the hypothesis that customers primarily use subscription to explore and try out games to figure out which games they would like to buy.

across different subscriber cohorts and across customers who subscribe for less than six months. The effects also hold when we construct the sample using the propensity score matching method. We discuss the detailed robustness analysis in Appendix B.

There are two caveats to our results. First, customers' subscription choices may be endogenous. In particular, customers are more likely to self-select into subscriptions when they expect to spend more time on gaming, which would bias our estimates upwards. To investigate this concern, we look at the change in intensity of gaming inside and outside of Game Pass (GP). Figure 4 shows that in the first month of subscription, customers play more of both GP and non-GP games. This suggests that customers may indeed choose to subscribe when they have a sudden craving for gaming. However, from the second month of subscription, their activity on non-GP games return to normal, indicating that the unobserved spike in their interest in gaming decays and thus the estimates from the second month onward come closer to capturing the real effects of subscription. Second, our estimates measure a treatment-on-treated effect. Because subscribers in our sample are early adopters of Game Pass and consist of more active gamers, our estimated subscription effect may be larger than the population average effect.

3.2 Supply Side Response

In this section, we use the same framework to study how the addition of games into the Game Pass bundle affects game developers' pricing decisions.

We first examine the characteristics of 328 games added into Game Pass during our sample period. Their average launch price is \$21, and none of them are free-to-play games. Among all these 328 titles, 11% are AAA games, 16% belong to first-party studios, and 37% have in-game purchase features. If we rank the GP titles with all 1,580 active non-GP titles based on sales, the GP games are ranked at 338th on average, with the highest at 6th and the lowest at 831st. Since the average GP game is more popular than the average non-GP game, we use matching methods to construct a suitable comparison group before studying the impacts of a game being added to Game Pass on pricing.

To pair GP games with the most similar non-GP games, we first match them on genre, release month, price range (e.g., \$10–20, \$20–30), AAA game status, and in-game purchase options. If multiple non-GP games satisfy these conditions, we choose the one with the smallest Mahalanobis distance in release date, price, and pre-GP sales. We also restrict the sample to games whose prices can be observed for three months prior to their addition to Game Pass. Eventually, 138 GP titles are matched to 124 unique non-GP titles.

Next, we use Equation 1 to estimate the effects of a game's addition to Game Pass on its price. Panel A in Figure 5 shows the raw price trend of GP games. As a typical durable good, average game price decreases over time. Although both GP and non-GP games display gradual declines in their prices, Panel B shows that games that stay in Game Pass for at least six months see price decreases of a smaller magnitude than those for non-GP games. More specifically, the price of these GP games is 10% higher than that of their non-GP counterparts on average. The estimates of the difference are borderline significant at the 95% confidence level. In contrast, Panel C shows that the price effects become less significant over time among games that were removed from Game Pass sometime before the sixth month. This means that when a game is removed from Game Pass, its price trajectory becomes similar to that of the non-GP games, suggesting that the change in prices is indeed a response to the game's addition to Game Pass. This finding is consistent with the theoretical prediction from Varian (2000) that customers who chose to purchase GP games over playing them through subscription tend to have a higher valuation for owning games, which gives game developers an opportunity to charge relatively higher à la carte prices.[19,20]

We are less concerned about the endogeneity of game entry timing in this event study. As Game Pass was in its infancy stage during our sample period, most of the first-party games were added as an overall strategy to source Game Pass titles. Also, to figure out the best content configuration in Game Pass's early days, the platform experimented with various games, introducing an element of randomness in the content selection.

It is worth noting that all games and customers were affected by the introduction of Game Pass in general equilibrium. Non-GP games may have faced more competition on the platform and reduced their prices. Non-subscribers may have behaved differently in the face of the adjusted game prices due to Game Pass. Thus, they do not constitute a perfect/pure control group for studying the equilibrium effects of introducing the subscription service. To take into account the endogenous responses of all platform participants, we build a structural model of demand and supply for individual games and the subscription bundle in the next section.

[19] Anecdotally, since 2020, the standard price for some video games has increased from \$60 to \$70, coinciding with a pronounced movement toward subscription services (Ringer 2020).

[20] Another possible explanation for the price change is intertemporal price discrimination (Coase 1972, Stokey 1979, 1981, Bulow 1982). The subscription service functions as a renting mechanism, which enables game developers to be more committed to purchase prices. However, we do not consider this the main reason for the higher prices of GP games. First, Panel A of Figure 5 shows that GP game prices continue to decline after the games are added Game Pass. Second, if GP game developers are more committed to the purchase price because of the subscription option, we should expect the differences between GP and non-GP prices to widen over time. However, we find in Panel B that they remain stable.

4 Structural Model

Three key findings emerge from our descriptive analysis. First, customers who have higher usage intensity and customers who exhaust their gaming stock more quickly are more likely to subscribe. Second, subscribers spend more time gaming and purchase fewer GP titles after signing up. Third, prices for titles in GP decrease at a smaller magnitude than non-GP games over time. These results inform our construction of a demand model that captures customers' selection into Game Pass by accounting for heterogeneous game valuations and their decay over time. Also, we need to model the substitution between the usage choice of gaming vs non-gaming activities and the choice of subscribing vs purchasing titles directly. Finally, we need a supply model that allows game developers to adjust their prices in the equilibrium. Using the structure from our model, we can simulate demand and supply side response to the introduction of the subscription service and other business models.

4.1 Demand

We define a market at the platform–month level and index it by t. The model proceeds in two stages. In stage 1, customer i makes her purchase and subscription choice $k \in K_{it}$, where K_{it} is the choice set that includes any combination of a game purchase choice $j \in J_t \setminus I_{it}$ and subscription choice $s \in \{0,1\}$. J_t is a set of games offered on the platform at time t plus an outside good. I_{it} is the customer's game inventory at the beginning of month t. We assume that customers can purchase at most one game and can subscribe at the same time each month.[21] The size of the choice set K_{it} is therefore $2|J_t \setminus I_{it}|$. In addition, we assume the customer subscribed to Game Pass in month t as long as she subscribed for at least one day in that month in the data.

After choice k is made in stage 1, in stage 2 the customer allocates time across games in her game set $G_{it}(k)$. $G_{it}(k)$ includes customer i's inventory I_{it}, the game purchased in month t if any, all games in the Game Pass bundle if she subscribes, and the outside option (a non-gaming numeraire activity). Since the purchase decision depends on expected usage utility, we introduce the usage model first and then the purchase model.

Usage Decision We model customers' gaming decisions using a variation of the multiple discrete-continuous utility function formulated in Kim et al. (2002), Bhat (2008), and Crawford et al. (2018).

[21] In our data, 88% of the time, customers purchase no more than one game a month. When a customer purchases more than one game in a given month, we choose the most expensive game as the one purchased.

The unique feature of our model is that a customer's usage utility from a game can change as a function of her prior experience playing it and that customers vary in how quickly they grow tired with the game. Thus there are two key parameters in the usage model: one that dictates preferences for a title at the beginning of each month but can vary based upon experience with the title in earlier months (aggregate stock of usage). The other that dictates how quickly a consumer tires of playing a specific title within a given month and thus implicitly defines preferences for variety. We introduce the usage model below.

In each month t, customer i allocates her time $\boldsymbol{x_{it}} \equiv \{x_{ijt}\}_{j \in G_{it}(k)}$, where x_{ijt} is the time spent on game j (or a non-gaming activity if $j = 0$), to maximize her usage utility:

$$\begin{aligned} v_{ikt} = \max_{\boldsymbol{x_{it}}} \quad & \sum_{G_{it}(k)} \frac{\theta_{ijt}}{\gamma_{ij}} log(x_{ijt}\gamma_{ij} + 1) \\ & \sum_{G_{it}(k)} x_{ijt} = T, \quad x_{ijt} \geq 0, \end{aligned} \tag{2}$$

with

$$\theta_{ijt} = exp(d_{ij} + h_{ijt} + \eta_t^u + e_{ijt}). \tag{3}$$

θ_{ijt} and γ_{ij} govern the customer's taste for each game. θ_{ijt} measures customer i's marginal utility from game j at the beginning of month t. γ_{ij} controls how fast the marginal utility decays with additional playing within a month, measuring the *within-month* satiation rate.[22] T sets the total time available to the customer in a month. v_{ikt} is the indirect usage utility from the optimal playing decisions.

Equation 3 shows the parametrization of θ_{ijt}. d_{ij} captures a customer's baseline valuation for game j that does not change with time. Explanatory variables in d_{ij} include game fixed effects, customer demographics, and the interaction terms between the demographics and game characteristics. h_{ijt} is a function of playing history variables, capturing a customer's state-dependent preference. If playing a game last month decreases a customer's probability of playing it this month, then h_{ijt} captures her *cross-month* satiation rate. More specifically, h_{ijt} includes cumulative hours and months the customer has spent on game j prior to t and their quadratic terms to capture the (possibly) non-monotonic preference. It also includes interaction terms between playing history variables, customer demographics, and game genres to account for heterogeneous

[22] A larger value of γ_{ij} represents faster decay. We normalize the utility function by dividing it by γ_{ij} to ensure that the marginal utility at the point of zero consumption is equal to θ_{ijt} and does not depend on γ_{ij}. To see this clearly, the marginal utility from gaming is $\theta_{ijt}/(x_{ijt}\gamma_{ij} + 1)$. It is equal to θ_{ijt} when $x_{ijt} = 0$.

cross-month satiation rates.

h_{ijt} and γ_{ij} together govern the customer's satiation preferences. The cross-month satiation rate directly determines the customer's probability of playing the same game in the next month while the within-month satiation rate indirectly affects the probability through changing the playing history variables. For example, if two customers have the same h_{ijt} but different γ_{ij}, then their probability of playing the game this month is the same but hours spent on the game within this month are different, which leads to different $h_{ij,t+1}$ and thus different playing probability in the next month. Throughout the paper, when we mention only the satiation rate, we refer to the cross-month satiation rate h_{ijt} because this is a more direct determinant of the purchase vs monthly subscription choice.

In addition, η_t^u controls for seasonality in gaming. e_{ijt} is an idiosyncratic taste shock that is observed by the customer at the usage stage but not at the purchase stage. We impose an exponential function form to ensure that θ_{ijt} stays positive. In this section, we set the parameters to be customer–game specific. Discussions of the observed and unobserved heterogeneity, parameter specifications and identifications are delayed till Section 5.

Purchase and Subscription Decision Now, we introduce stage 1. Customers make purchase and subscription decisions based on their expected usage utility from the choice and the price that they need to pay. The indirect utility from choice $k \in K_{it}$ to customer i is therefore

$$u_{ikt} = \beta_i^u \tilde{v}_{ikt} + \beta_i^p p_{ikt} + \xi_k + \eta_t^p + \epsilon_{ikt}, \tag{4}$$

with

$$\tilde{v}_{ikt} = \sum_{m=t}^{\bar{t}_k} \delta^{m-t}(\mathbb{E}[v_{ikm}] - \mathbb{E}[v_{i0m}]). \tag{5}$$

$\tilde{v}_{ikt}$ is customer i's expected usage utility of choice k. β_i^u measures the customer's preference for gaming utility. p_{ikt} is the price of the choice. If the customer purchases a game, p_{ikt} is the game price; if she subscribes, it is the cost of a one-month subscription fee; if she chooses both, it is the sum of the two prices.[23] β_i^p measures the price sensitivity. ξ_k are choice fixed effects. η_t^p are year–month fixed effects to control for seasonality in demand. ϵ_{ikt} is an idiosyncratic preference shock.

Equation 5 shows the specification of $\tilde{v}_{ikt}$. $\mathbb{E}[v_{ikm}]$ is customer i's expected one-month usage

[23] We exclude the choice of subscribing and purchasing a GP game at the same time, as this is rarely seen in the data.

utility from choice k. $\mathbb{E}[v_{i0m}]$ is the expected usage utility if she chooses outside goods. The difference between these two terms is the net benefit from choice k for one month. δ is the discount factor. The customer then calculates the discounted usage utility from future $\bar{t}_k$ periods when making the choice.

For a fully forward-looking customer, her purchase, subscription and usage choices are intertemporally linked. All actions in this period will affect the probability of purchasing, subscribing and playing in the next period via changing the state variables of game inventory and playing history. Ideally, a fully dynamic model is needed (see Appendix C.1), but it cannot be estimated due to the curse of dimensionality — it is computationally impossible to keep track of the playing history of each game for each customer.

To make the model tractable, we impose two main assumptions. First, we assume that customers only consider the impact of today's decision on next month's usage decisions, and not on purchase and subscription decisions. Thus, when they calculate the utility from future periods they treat the inventory as fixed.[24] Second, customers have limited foresight. In our main model specification, we assume that if the customer purchases a game, she considers a flow of discounted usage utility from this game until $\bar{t}_k$, the month when she becomes fully satiated with it. If she subscribes, then she considers only one-month usage utility from the subscription bundle, i.e., $\bar{t}_k = t$. With this assumption, we can still capture a customer's trade-off between purchasing a game vs playing a game for a month via subscription. This is an important and a relatively common trade-off that the customers may encounter because, in our data, for more than 51.37% of the time, a game is finished within a month (see Panel B of Figure 2).

The limitation of our main model is that it cannot capture the trade-off between purchasing a game vs playing a game for two or more months via subscription. Thus in the robust analysis, we estimate a model where customers consider three months of utility from the subscription service instead of just one month. We choose "three months" because customers' average subscription length is 3.8 months in the data. We find that estimates from this model are close to the estimates from our main model (see Appendix D.1 for details and other robustness analyses). We choose the "one month" specification as our main model because it is more consistent with the payment structure of the subscription service and we do not need to extrapolate the "three months" subscription length assumption obtained from data to our counterfactual analysis when we simulate new subscription bundles.

[24] We describe how customers calculate their usage utility from future periods in detail in Appendix C.2.

Finally, we define $U_{ikt} = u_{ikt} - \epsilon_t$ and C_t as the set of all console gamers on the platform in month t. Assume ϵ_{ikt} has an extreme value type I distribution. The predicted demand for choice k in month t is then given by

$$Q_{kt} = \sum_{i \in \mathcal{C}_t} \frac{exp(U_{ikt})}{\sum_{g \in K_{it}} exp(U_{igt})}. \tag{6}$$

Q_{jt} is the demand for game j. It is calculated as the sum of Q_{kt} when choice k includes purchasing game j. Similarly, the demand for subscription Q_{st} is the sum of Q_{kt} when choice k includes subscribing to Game Pass.

$$Q_{jt} = \sum_{j(k)>0} Q_{kt}, \quad Q_{st} = \sum_{s(k)>0} Q_{kt}. \tag{7}$$

4.2 Supply

We assume that game developers set à la carte game prices and that the platform sets the subscription price for Game Pass following a Nash–Bertrand model with differentiated products.

In each month, the developer of game j chooses price p_{jt} to maximize the following profit function, taking the prices of other games and the Game Pass bundle content as given.

$$\max_{p_{jt}} \quad Q_{jt}(\boldsymbol{p_t}, \boldsymbol{L_t})(1-\tau)p_{jt} + l_{jt}r_{jt} \tag{8}$$

τ is the royalty rate paid to the platform on each sale. We set $\tau = 30\%$ according to the corresponding industry report (Peters 2021). Although video games can be sold in both digital and physical form, we assume that the marginal cost of games is zero in our main estimation and discuss the implication of this assumption in next section. l_{jt} is a dummy variable indicating whether the game is in the subscription bundle. r_{jt} is a lump-sum payment from the platform if the game is in the bundle. $\boldsymbol{p_t}$ is a vector of prices of all products. $\boldsymbol{L_t}$ is a vector representing Game Pass content. We allow game developers to revise their prices periodically to reflect the fact that prices of games decrease as they age and when they are added to (or removed from) Game Pass as shown in Figure 5.

Notably, we model the pricing decisions conditional on the observed bundle content of Game Pass. We do not model the negotiations between game developers and the platform over game inclusion due to the lack of contract data on revenue-sharing. We assume that developers receive a lump-sum payment when the game is added because this is the most common approach, according to the head of Xbox (Patel 2020). And since r_{jt} is not a function of game prices, it is not estimated in our model.

The platform chooses the monthly subscription price p_{st} to maximize the following objective function:

$$\max_{p_{st}} \quad \lambda_t[Q_{st}(\boldsymbol{p_t}, \boldsymbol{L_t})p_{st} + \sum_{J_t} \tau Q_{jt}(\boldsymbol{p_t}, \boldsymbol{L_t})p_{jt} - \sum_{J_t} l_{jt}r_{jt}] + (1-\lambda_t)CS_t(\boldsymbol{p_t}, \boldsymbol{L_t}). \tag{9}$$

We assume that the platform aims to maximize a convex combination of profits and consumer surplus. An interview with the Xbox team in 2020 reveals that, over our sample period, Microsoft was not maximizing short run profits from Game Pass and planned to play the long game by delivering more value to customers (Makuch 2020).[25] λ_t is the weight on short-term profits. We allow the weight to change along the life-cycle of the subscription offering to reflect the change in GP promotion intensity each month. The marginal cost of the subscription service is set to zero as it is a pure digital product. The total consumer surplus is computed as follows. It measures customers' ex-ante utility (before they make their purchase choices).

$$CS_t = \sum_i \frac{1}{\beta_i^p} E_\epsilon \left[u_{ikt}\right] \tag{10}$$

In the equilibrium, the timing of our model is as follows: (1) The platform and game developers simultaneously choose prices for products, taking bundle composition as given. We assume that they also observe customers' game inventory and playing history in this stage. (2) Purchase shock ϵ_{ikt} is realized; customers make a purchase decision based on their expected usage utility. (3) Game-playing shock e_{ijt} is realized, and customers play games. We discuss the limitations of our demand and supply model in Appendix C.3.

5 Estimation

This section introduces our parametric assumptions, identification, estimation strategy and results.

[25] Dinerstein et al. (2018), Castillo (2020) and Rosaia (2020) also find that tech firms like eBay and Uber maximize the weighted sum of profits and consumer surplus. Such an objective function might capture platforms' incentive to keep prices lower in the short run to expand the market in the long run.

5.1 Parametrization

In the usage model (Equation 2), θ_{ijt} varies across customers and games to account for heterogeneous tastes. Explanatory variables include customer demographics such as gender, age, income, tenure on the platform, and Xbox Live and EA Play subscription status,[26] and game characteristics such as release year, genre, add-on purchase feature, and customer rating.

We assume that the usage shock e_{ijt} follows a normal distribution $N(0, \sigma_e^g)$ and is independently distributed across months, games and customers. We allow σ_e^g to be different across genres. Figure A.8 shows the usage correlation matrix between games. We can see that hours spent on games within a genre are more positively correlated than those spent on games across genres. Usage between games in different genres is also largely independent. Thus, we believe that genre variables in d_{ij} can take care of the positive within-genre valuation correlation and that it is reasonable to assume independent error structures across games.

We restrict the within-month satiation rate γ_{ij} to vary only across genres; that is, $\gamma_{ij} = \gamma_j = \gamma^g$ if j belongs to genre g. To ensure that γ^g is positive, we model it using the exponential function of the genre dummies. We set T, the total time spent on gaming and a non-gaming activity, at 240 hours and keep it constant across all customers. This number is above the largest number of monthly gaming hours that we observe in the data.

In the purchase model (Equation 4), β_i^p is parameterized as $\beta^{p_0} + \beta^{p_1} y_i$, where y_i is customer i's zip code–level annual income. β_i^u is specified in the same way. The choice fixed effect ξ_k is the sum of the game fixed effect $\xi_{j(k)}$ (if $j(k) > 0$) and the subscription fixed effect $\xi_{s(k)}$ (if $s(k) = 1$). It represents the product quality perceived by customers that is unobserved to the econometrician. Finally, we set the discount factor δ at 0.99, as is commonly done in the literature.

5.2 Estimation Strategy

We jointly estimate parameters in the usage and purchase models using maximum simulated likelihood to recover customers' unconditional preferences for games. Then, we use the demand estimates and first-order conditions with respect to prices to back out the supply-side parameters in equilibrium.

[26]We include the Xbox Live and EA Play subscription status variables in the estimation even though we observe them only for the month of April 2019 because we find that they are good predictors of purchase and GP subscription choices.

Demand Estimation Customer i makes two decisions in month t: her purchase and game-playing decisions. Let k^*_{it} be the observed purchase choice, $\boldsymbol{x_{it}}^*$ be the observed time spent on games, and Θ be the parameters. Then, the likelihood function is

$$\mathcal{L}_{it}(\boldsymbol{x_{it}}^*, k^*_{it}|\Theta) = Pr(\boldsymbol{x_{it}}^*|k^*_{it}, \Theta)Pr(k^*_{it}|\Theta), \tag{11}$$

where the first term is the usage probability conditional on the purchase choice and the second term is the purchase probability. We describe the expression of these two terms below.

In the usage stage, the customer maximizes her utility subject to the time constraint. The Karush–Kuhn–Tucker (KKT) conditions for this optimization problem (Equation 2) are

$$\begin{aligned} &\bar{v}_{i0t} - \bar{v}_{ijt} = e_{ijt} - e_{i0t}, \text{ if } x_{ijt} > 0 \\ &\bar{v}_{i0t} - \bar{v}_{ijt} \geq e_{ijt} - e_{i0t}, \text{ if } x_{ijt} = 0 \\ \text{where} \quad &\bar{v}_{ijt} = d_{ij} + h_{ijt} + \eta^u_t - log(x_{ijt}\gamma_j + 1), \quad j \in G_{it}(k). \end{aligned} \tag{12}$$

Because only the difference between errors matters under the time budget constraint, we normalize e_{i0t}, the benchmark non-gaming activity, to zero, following Akchurina and Albuquerque (2019). We also normalize θ_{i0t} and γ_{i0t} to one, so $\bar{v}_{i0t} = -log(x_{i0t} + 1)$.

From the KKT conditions, we can see that the distribution of optimal gaming hours is mixed discrete-continuous: the interior solution ($x_{ijt} > 0$) creates a continuous component, while a corner solution ($x_{ijt} = 0$) creates a discrete component. When an interior solution is observed, the observed optimal time is mapped to usage shocks through an equality. When a corner solution is observed, the mapping is formed through an inequality. Thus, the probability that customer i makes $\boldsymbol{x}^*_{it}$ game-playing decision given her purchase choice is

$$Pr(\boldsymbol{x_{it}}^*|k^*_{it}, \Theta) = \prod_{j \in \{x_{ijt}=0\}} \Phi_g(\Delta\bar{v}_{ijt}) \prod_{j \in \{x_{ijt}>0\}} \phi_g(\Delta\bar{v}_{ijt})|\mathcal{J}|, \tag{13}$$

where $\Delta\bar{v}_{ijt}$ is equal to $\bar{v}_{i0t} - \bar{v}_{ijt}$, $\phi_g(\cdot)$ is a normal density function with a mean of zero and a standard deviation of σ^g_e, $\Phi_g(\cdot)$ is a cumulative normal distribution function, and $\mathcal{J}$ is the Jacobian for interior solutions.

Given the parameters from the usage model, we simulate customers' expected usage utility from purchase/subscription choice k_{it}. We generate nd draws of usage shocks from $N(0, \sigma^g_e)$ for each game. d denotes the simulation draw, $d = 1, ..., nd$. For each draw, we calculate the optimal usage utility from choice k_{it}. The simulated expected usage utility is therefore

$$\widehat{\tilde{v}_{ikt}} = \frac{1}{nd} \sum_{d=1}^{nd} [\sum_{m=t}^{\widehat{t}_k} \delta^{m-t} (\hat{v}_{ikm} - \hat{v}_{i0m})], \tag{14}$$

where $nd = 50$. We also set the usage shock of a game to be the same in future periods, i.e., $e_{ikt} = e_{ik,t+1} = ... = e_{ik,\widehat{t}_k}$.

Now, we have the indirect purchase utility $\widehat{U_{ikt}} = \beta_i^u \widehat{\tilde{v}_{ikt}} + \beta_i^p p_{ikm} + \xi_k + \eta_t^p$. The probability of making choice k_{it}^* is

$$Pr(k_{it}^* | \Theta) = \frac{exp(\widehat{U_{ik^*t}})}{\sum_{l \in \mathcal{K}_{it}} exp(\widehat{U_{ilt}})}. \tag{15}$$

Supply Estimation Recall that in Section 4.2 we assume a zero marginal cost of games and the subscription service, so we do not need to back out the marginal costs of products in equilibrium as is usually done in the IO literature. The only unknown parameter is λ_t, the weight that the platform puts on short-term profits, which is recovered using the first-order condition:

$$p_{st}^* = \frac{\partial Q_{st}}{\partial p_{st}}^{-1} (\frac{\lambda - 1}{\lambda} \frac{\partial CS_t}{\partial p_{st}} - \tau \sum_{J_t} \frac{\partial Q_{jt}}{\partial p_{st}} p_{jt}^* - Q_{st}), \tag{16}$$

where p_{st}^* is the observed subscription price and p_{jt}^* is the observed game price. Using our demand estimates, we solve for the equilibrium at current prices conditional on the observed bundle content.

5.3 Identification

Identification of the demand model relies on the rich panel structure of our data. In the usage model, variation in customers' probability of playing a game identifies θ_{ijt}, the marginal utility at the first moment of play in a month. For example, θ_{ijt} includes game fixed effects, customer demographics, and playing history. A game played with lower probability across all customers would have a lower game fixed effect estimate. The difference between women's and men's overall likelihood of playing games identifies the coefficient of gender in θ_{ijt}. Variation in a customer's probability of playing the same game over time identify her cross-month satiation rate—the coefficients of cumulative playing hours and months.

Conditional on θ_{ijt}, the distribution of time spent on a game within a month identifies the within-month satiation rate γ_j. To be more concrete, suppose two games of different genres are played with the same probability in each month, i.e., θ_{ijt} is the same. The difference in total time spent on these two games within a month identifies the coefficient of the genre dummy in γ_j.

In the purchase model, we exploit the residual variation in prices after controlling for game, Game Pass and year-month fixed effects to identify price coefficient β_i^p. We use three types of residual variation for identification: (1) cross-month variation in the price of the same game that arises from temporal promotions and permanent price drops; (2) cross-month variation in the subscription price that arises from promotion campaigns on the service;[27] (3) within-customer variation in the subscription price, e.g., subscribing at discount in the first month and full price afterwards. The preference for gaming utility β_i^u can be identified through the variation in games in the game playing set. For example, the content in Game Pass varies each month, which leads to a variation in expected usage utility from the subscription choice.

We run Monte-Carlo simulations to assess the recovery of parameters in the two-stage demand model and report the results in Appendix D.5. We find that parameters are well recovered.

5.4 Estimation Data

We use a selected sample of games and customers over a one-year period to do the model estimation. We construct the data as follows.

First, we use only the second half of our data (May 2018–April 2019) for estimation. There are several benefits to doing so. Game Pass in its early stage consisted mainly of old first-party games. The content offered in the second year was closer to the titles that have more recently become available in Game Pass, containing a combination of first- and third-party games and newer games. In addition, customers are more likely to be aware of this service one year after its introduction, so we can assume that all customers know about the existence of Game Pass in the model, without considering the information friction. Also, we can use the first-year data to determine customers' inventory and game-playing history more accurately. Although we cannot observe customers' initial inventory in the data directly, we can use the first-year data on customers' purchased and played games to determine their initial inventory for the second year.[28]

Second, we only keep customers who joined the platform before May 2018, who account for 88% of the full sample. We impose this restriction because we do not explicitly model customers'

[27] As mentioned above, the periodic price cuts to the subscription price of the Game Pass were "blunt" and not very strategic over our sample as it was early in Game Pass's life-cycle as a product. We discuss the construction of the monthly subscription price in Section 5.4.

[28] We assume that games in a customer's inventory set are obsolete if they were never played in the first year.

platform entry and console purchase choice. Thus, our model captures customers' demand for games and the subscription service only once they are already on the platform, not the extensive margin of these products.

Third, to make the demand model estimation computationally feasible, we keep a selected sample of games. We first drop games played by fewer than 1% of the customers in our sample, which leaves us with 280 games. We then drop 32 free games because they have a different monetization strategy from the standard games. We also drop games released before 2014. These restrictions finally leave us with 153 non-GP games and 80 GP games.

Lastly, we describe the construction of product prices for estimation. For games, we observe daily retail prices and discounts in the data. We use the average price within a month as a proxy for the monthly price because we model choices on a monthly basis. We assume all customers face the same price for a game. For subscriptions, we observe the price paid at transactions and use the average transaction prices in a month as a proxy for the subscription price. Although this is not a perfect measure of the actual subscription price that customers face, its variation across months could reflect the change in promotion intensity for first-time subscribers. We assume that all customers face the same subscription price in a month if they have never subscribed before. If they have already signed up before, we use $9.99 as the subscription price.

5.5 Estimation Results

Now we present the estimates of selected key parameters of our demand and supply model.

Usage Estimates We first look at the estimated game fixed effects in usage that capture the average baseline valuation for each game across customers. Instead of plotting fixed effects for all 233 games, we display their summary statistics by group in Figure 6. Panel A shows the estimates by genre.[29] Shooter is the most popular, followed by sports and role-playing, with casual, strategy and platform games being least popular. The average difference between the shooter and casual game fixed effects is 0.76, equivalent to a 5-hour usage difference. As the usage utility function is non-linear, we provide details on interpreting the coefficients in Appendix D.3. In Panel B, we group games by release year. Games that came out in 2018 and 2019 are the most played, reflecting customers' strong preference for product recency. Panel C shows that customers are more likely to play non-GP games than GP games on average. This does not mean that GP games are less

[29] Casual includes puzzle, classic, and family and kids games. Fighting also includes racing and flying games.

popular than an average game on the platform. Here we are comparing them to only the top 153 selected games on the platform.

Next, we show customers' heterogeneous baseline game valuation. We report the coefficients of interaction terms between customer demographics and game characteristics in Table 2. Male customers are more likely to play games on average and play more shooter and sports games. Customers in the middle-age group tend to spend more time on games with add-on purchases. Higher-income customers are less likely to play games. They prefer strategy, casual, and platform games and games with higher ratings. There is no clear difference between customers who joined the platform at different times. Xbox Live subscribers play shooter games the most, consistent with the fact that one of the greatest benefits of Xbox Live is that it offers access to multiplayer games. Not surprisingly, EA Play subscribers play more fighting and sports games, as these are the main offerings on that service.

Finally, we show customers' heterogeneous satiation rate in Table 3. This rate is an important determinant of the customer' decision of playing a game via purchase or subscriptions. Panel A shows that customers' value from a game deteriorates as the game ages. Heavy users care more about the recency of games. Panels B–D show customers' cross-month satiation rate. Customers' interest in the same game strictly decays across months. For example, if a median customer played a shooter game last month, she would spend 2.6 fewer hours on this game this month. However, there is a bliss point in playing the same game in terms of cumulative playing hours: the estimate of the linear term is positive and the squared term negative. The average bliss point in a game is 12 hours, with platform, shooter, and sports on the higher end and strategy and role-playing on the lower end. In addition, most coefficients of the interaction terms between customer demographics and playing history are significantly different from zero, showing rich heterogeneity in the satiation rates. Customers who are more likely to play games are also more quickly satiated across months but have a higher bliss point in playing hours. Panel D reports the estimates for the within-month satiation rate. The positive intercept shows that the satiation rate is faster for gaming than for non-gaming activity. Customers become satiated fastest with platform games and slowest with sports and role-playing games.

Purchase Estimates Estimates of selected key parameters in the purchase model are presented in Table 4. Higher expected usage utility increases customers' purchase utility, while higher prices decreases their utility. Moreover, customers with higher income are more sensitive to usage utility change and less sensitive to price change. The average own-price elasticity of games is -1.225, on par with estimates from the previous literature (e.g., Nair 2007 and Lee 2013). The own-price elasticity of the subscription service is -0.467, showing that demand for the subscription bundle is less elastic than that for an average game. This might arise from early adopters of Game Pass being less price sensitive. Our point estimates are fairly robust to alternative specifications of the purchase model. Appendix D.1 details the other models that we tried, including controlling for customer inertia in subscription decisions and making different assumptions on the number of future periods that customers consider.

In Figure 7, we plot the estimated game fixed effects from customer's purchase model against those from customer's usage model. As expected, these two sets of estimates are positively correlated: games played for longer also tend to have a higher unobserved quality in the purchase model. The correlation is not perfect though, indicating that some games may be highly valued but played for only a short period of time.

Supply Estimates The average estimated weight that the platform puts on short-term profits is 0.52. There is limited literature estimating such a parameter using data from media platforms. For a broader comparison, Castillo (2020) and Rosaia (2020) find a profit maximization weight of 0.48 and 0.38 for ride-sharing platforms, respectively. A similar weight for a new subscription service in a tremendous growth phase makes intuitive sense though, since data from ride sharing apps in these papers was from a similar pre-IPO growth phase.

In the supply model (Equation 8), we assume that games compete in a Nash–Bertrand equilibrium and that their marginal costs are zero. With the demand estimates and these assumptions, we can actually solve out game prices in the equilibrium. We find that our simulated game price is \$21.34 on average, lower than the average price of \$25.12 observed in the data. This discrepancy may arise from our inappropriate assumptions on pricing behavior and marginal cost.

In Appendix D.2, we estimate the marginal costs of games under Nash–Bertrand competition using observed prices. We find that the average cost of a game is \$3.40, on par with the number from the industry report (Takahashi 2002). Thus, this estimation result gives us some confidence in the assumption of the game developers' conduct.

Although there may be some marginal costs for selling games such as packaging and distribution, for the rest of our paper, we stick to the zero marginal cost assumption because (1) in 2018, only

17% of video games were sold in physical form,[30] and (2) the subscription service is digital in nature and should have zero marginal cost. If we set a positive marginal cost of selling games à la carte, we create an asymmetry between the two business models. Since the difference in marginal costs is not the focus of our paper when we compare welfare outcomes, we assume zero marginal costs for both to avoid this asymmetry.

5.6 Model Fit

Finally, we test the performance of our demand model. We find that the level of fit of the purchase model is good, with an R^2 statistic of 81.49% when we look at the monthly market share predictions for games and Game Pass. We further visualize some selected moments in Figure 8 to show that our model appropriately fits the usage data. Panel A displays predicted and observed monthly gaming hours for subscribers (solid line) and non-subscribers (dashed line). Panel B displays the average number of months taken to finish a game. Our model prediction is able to recover the same patterns observed in our reduced-form results: subscribers are heavier users and tend to grow satiated with a game faster. Panels C and D show the predicted and observed gaming hours and months by genre. We can see that our model closely follows the data. In addition, it is worth noting that although shooter games have larger estimated fixed effects (i.e., a higher baseline marginal utility) than sports games in the usage model, customers actually spend more hours on sports than on shooter games in total due to the fact that sports games have a slower satiation rate and so are played for more months.

6 Counterfactual Analysis

In this section, we use our structural model to assess the welfare impacts of offering video games under different business models. We first quantify the welfare effects of introducing the Game Pass subscription service and decompose them into different economic forces. We then simulate subscription-only models to see if they can outperform the traditional à la carte sales model. Finally, we discuss the distributional consequences across customers and game developers. Details about the simulation method are provided in Appendix E.

[30] https://www.statista.com/statistics/190225/digital-and-physical-game-sales-in-the-us-since-2009/

6.1 The Impacts of Game Pass

In this section, we estimate the welfare impacts of introducing Game Pass and conduct two decomposition analyses to understand the drivers of these impacts. In the first exercise, we study the equilibrium effects of Game Pass by decomposing the impacts into demand and supply side responses. In the second exercise, we study the economic properties of Game Pass by decomposing the impacts into the bundling and renting components.

We simulate a counterfactual of only selling à la carte games as the benchmark. This scenario corresponds to the platform's original business model before Game Pass was introduced. Same as the estimation data, we assume that there are 233 games on the platform. In the benchmark scenario, all these games are sold à la carte. When Game Pass is introduced, the platform offers a subscription bundle of 88 games in addition to the purchase option. In each counterfactual, we simulate customers' monthly purchase and usage choices and supply side's pricing decisions when needed. We use Equation 10 to calculate average consumer surplus.

Decomposing the Demand and Supply Response We simulate three counterfactuals to disentangle the roles of demand and supply in the Game Pass impacts. Counterfactual (1) is our benchmark: customers can only purchase à la carte games. Game Pass is added in counterfactual (2), but we only allow the demand side to respond to it. Game developers are forced to keep game prices the same as in the benchmark scenario. We compare these two counterfactuals to isolate the demand forces, i.e., the level of the welfare change from offering Game Pass driven by the demand side response. We then compute counterfactual (3), where we also allow game developers to optimally choose their game prices when GP is introduced. The difference in consumer surplus between (2) and (3) captures the supply forces, i.e., the level of the welfare change from offering Game Pass driven by the supply side response. The direction of the change is ex-ante ambiguous: while game developers may decrease their prices due to the new competition from GP, they might also utilize GP as a price discrimination device to segment customers and thus increase their prices.

Table 5 presents our simulation results. Comparing counterfactuals (1) and (2), we find that when GP is introduced, customers shift part of their demand from à la carte games to GP and their average surplus increases by \$2.60 per month, or 16.73% in comparison to the benchmark, in the absence of the supply-side response. When we allow game developers to optimally adjust their prices in counterfactual (3), we find that 79% of game prices increase while the rest decrease, indicating that the effect of price discrimination outweighs the force of the price competition on the platform. Overall, prices increase by 2.69% on average, and thus, the gain in consumer surplus is 2% lower than in counterfactual (2), but still materially higher than the benchmark senario.

On the supply side, because the platform is currently underpricing GP to reap future benefits, the revenue from GP is smaller than the decreased sales of titles in GP, resulting in a 3.85% decrease in short-term profits in comparison to the benchmark. However, the total expected long-term profits could increase by 12.28% when consumer surplus is taken into consideration. It is unclear how game developers' profits change since we do not observe their revenue sharing contract with the platform.

Decomposing the Bundling and Renting Effects To assess which aspect of the subscription service (i.e., bundling vs renting) has a greater impact on consumer surplus change, we conduct another decomposition analysis shown in Table 6.

Again, counterfactual (1) is our benchmark scenario where games are sold à la carte. In counterfactual (4), the same bundle of 88 GP games is offered, but customers can access it only by purchase not subscription. Thus the difference in consumer surplus in (1) and (4) captures the pure impacts from the bundling aspect of GP. Counterfactual (5) corresponds to the scenario where the GP bundle is offered through a monthly subscription, so the difference in consumer surplus in (4) and (5) shows the extra impacts that come from the renting aspect. When simulating these counterfactuals, we allow both the demand and supply sides to respond in the equilibrium.

Notably, in counterfactual (4), we assume that the platform sets the bundle purchase price to maximize short-term profits instead of the weighted average of profits and consumer surplus. In doing so, we ensure that the difference between (1) and (4) captures the pure bundling effect. Otherwise, it would reflect the combination of the bundling effect and the long-term benefits of subscription. Under this assumption, the simulated optimal purchase price of the GP bundle is \$38.15. To be consistent, we also assume that the platform sets the GP subscription price to maximize its short-term profits in counterfactual (5), so the difference between (5) and (4) captures the pure renting effect. The simulated monthly subscription price is \$15.20. This price is higher than the actual subscription price because that is set to maximize weighted average of profits and consumer surplus.

Figure 9 summarizes the decomposition results. Comparing counterfactuals (1) and (4), we find that through bundling, consumers play 4 more games on average and consumer surplus increases by \$0.79 per month over the benchmark. Comparing (4) and (5), we find that the additional renting feature lets consumers play 6 more games and increases consumer surplus by \$0.88 per month. Combining the two, the bundling property contributes to 47% of the consumer surplus increase from the introduction of GP, while the rest of the increase comes from the opportunity to access games at an even lower price through renting than through purchasing.

Finally, we explain why customers play fewer games when they purchase the bundle than when they subscribe to it. GP updates approximately 10% of its content every month, and since the subscription price is much lower, customers are more likely to subscribe to the updated bundle multiple times than to purchase it multiple times. Hence, on average, they can benefit more from the renting aspect of the subscription service. The difference in consumer surplus change between bundling and renting is smaller than that in the number of games played though, because customers also pay more if they subscribe several times to play more games.

6.2 Alternative Subscription Models

In this section, we explore alternative business model designs in which all content is offered through monthly subscription services and no purchase/ownership option is available. This is a prevalent business strategy used by market-leading media platforms. We compare these counterfactuals with the benchmark scenario to see if the subscription-only model could completely replace the traditional à la carte selling mechanism. We further explore the distributional consequences across customers and game developers.

Grand Bundle Subscription In counterfactual (6), we assume that all 233 games are offered in a grand subscription bundle and that customers cannot purchase any individual games. Table 7 shows our main simulation results. The optimal simulated subscription price to maximize long-term profits is \$27.97 per month. At this equilibrium price, 96% of customers subscribe at least once during the one-year period and they subscribe for a total of 4.8 months on average.

Consumer surplus decreases by more than 38% on average relative to the benchmark, but the change varies widely across customers. We focus on two key parameters in our model to show the heterogeneous impacts. One parameter is customers' baseline game valuation (intercept terms in Table 2). The other is customers' cross-month satiation rate (the coefficient of cumulative playing months shown in Panel B of Table 3). We plot a heatmap of the change in consumer surplus against these two parameters in Panel A of Figure 10. We can see that 20.6% of customers benefit from the grand bundle subscription service and that most of them have a high game valuation and fast satiation rate. On the contrary, casual gamers who spend little time playing and focused gamers who stick to playing the same games for a long period of time benefit less from the subscription service.

This finding is consistent with our reduced form results (Table 1) that subscribers are a group of gamers who spend more hours gaming and fewer months on the same game. This is also in line with results from a gaming survey conducted by Simon-Kucher & Partners (Figure A.9). They asked customers the reasons why they do not choose gaming subscriptions. The top reason from casual gamers was they do not play much and from serious gamers was they want to own the games instead of renting them.

On the supply side, profits decrease by 12% from the benchmark. Panel A of Figure 11 shows the change in customers' spending against their spending level under the benchmark scenario. Low-spending customers under the benchmark scenario now spend more on average because they have to pay at least one month's subscription fee to play a single game. Median-spending customers pay approximately the same or less under the subscription model. For example, suppose that a median customer purchases six twenty-dollar games a year in the benchmark scenario. Under the subscription model, if she plays a great deal each month and is satiated quickly, she can finish all the games within four months and obtain similar utilities. However, if she becomes satiated slowly and plays only a little bit every month throughout the whole year, she might stop subscribing before reaching the fourth month when the extra benefit is lower than the fee. In this case, she obtains lower playing utility and pays less than in the benchmark. Finally, the subscription service offers a good deal for heavy-spending customers as they can obtain the same level of gaming utility but pay less.

Tiered Subscriptions In the section above, we find that offering only one subscription bundle makes both customers and the platform worse off because it fails to satisfy the needs of different types of customers. To increase profits and reduce dead-weight loss, we evaluate a "versioning" strategy (Shapiro et al. 1998) where the seller offers a menu of options for customers to self-select. In counterfactual (7), we simulate a scenario where two tiers of subscription bundles are offered: one is a basic version of 50 games, and the other is a premium version of all 233 games. This helps us segment customers based on their game valuation (or gaming intensity).

Table 7 shows the simulation results. The optimal price for the basic bundle is $15. A total of 93.5% of customers subscribe at least once to this bundle and subscribe for 3.9 months on average.

The optimal price for the premium bundle is \$33, higher than when only one bundle is offered. Average consumer surplus is still somewhat lower than the benchmark but 50.4% higher than in the one-bundle scenario. Panel B of Figure 10 shows the distributional consequences: more than 56% of customers are better off with two-tier subscriptions. Similar to counterfactual (6), customers with higher gaming intensity and faster satiation rate benefit more. On the supply side, total profits are 1.14% higher than in the benchmark. Panel B of Figure 11 shows that the profit increase mainly comes from low- and median-spending customers in the benchmark.

Note that our results do not represent the optimal outcome of offering tiered subscriptions. In our simulation, we randomly select 50 games for the basic bundle and simulate the price conditional on the content to maximize weighted profits. To obtain the actual optimal outcome of this business model, we would also need to maximize over the number of tiers and bundle size and content for each tier. This is a rather computationally expensive process, so here, we offer one example for heuristic purposes, hoping to show that tiered subscriptions could achieve similar profits and consumer surplus to those under the traditional à la carte sales model in our setting.

Impacts on Game Developers Finally, we discuss the impact of adopting subscription business models on game developers (content providers). In the benchmark scenario, where games are sold à la carte, game developers obtain 70% of the sales revenue, which is \$8.55 per customer per month. In counterfactual (6), where the platform offers a grand bundle subscription, the total revenue is \$10.74, which means game developers would need to be compensated with 79.6% of the subscription revenue to be as well off as in the benchmark. In counterfactual (7), with tiered subscriptions, they would need to be paid with 69.2% of the subscription revenue. There is limited information available on the payout rate between video game platforms and game developers in the industry. However, for a broader comparison, content providers on Apple Music receive 53% of the subscription revenue (Steele 2021) and those on Spotify receive 62%–67% (Ingham 2020).

After determining the overall sharing rate, the platform needs to further distribute the revenue among game developers. The primary revenue-allocation rule used by music streaming platforms is *pro-rata*: content providers are paid proportionally to their share in the overall streaming volume. Because songs are of similar length, the number of streams is proportional to hours played. In contrast, games vary in the length. Thus, we explore and compare the pro-rata revenue allocation rules based on the number of times a game is played (pay-by-play) vs the number of hours played (pay-by-hour).

We conduct the revenue allocation analysis under counterfactual (7), the tiered subscription model. We assume that the platform takes 30% of the subscription revenue, the same rate as that imposed on à la carte sales. Figure 12 shows the change in game developers' revenue. The y-axis represents the difference in revenue between counterfactual (1) and (7) for each game. The x-axis represents the game sales rank in the benchmark scenario. A lower rank means higher sales. The left panel shows the change when subscription revenue is allocated based on the number of times that customers play the game, while the right panel is based on number of hours spent on the game. In both plots, high-sales games experience greater losses while low-sales games gain from the subscription model. This is because customers play more low-value games that they would not purchase in the benchmark scenario in the subscription service.

Furthermore, pay-by-play is more beneficial for less popular games than pay-by-hour. This is because a popular game is both more likely to be played and more likely to be played for longer. Pay-by-hour could further increase the concentration in game revenue. To be more specific, the Herfindahl–Hirschman index is 227 in terms of game sales, 138 in terms of subscription revenue under pay-by-play, and 339 under pay-by-hour.

In addition to the pro-rata allocation rule, a growing number of studies and industry reports (Igroove 2021, Alaei et al. 2022, Muikku 2017) suggest using a *user-centric* rule to allocate revenue, applying the proportionality principle at the user level: each individual user's subscription fee is divided proportionally among content providers based on the consumption of that user. We find that this rule generates similar outcomes as the pro-rata rule in our setting, so we leave the details to Appendix E.2.

6.3 Discussion

In all of our simulations, we make assumptions in line with a short-term analysis. On the demand side, we assume that customers' gaming preferences are invariant under different business models. For example, they do not play a game faster when they have a subscription than when they purchase it. They do not experience choice overload problem when faced with a larger subscription bundle. In addition, no customers enter or exit the platform, so the market is the same across all counterfactuals.

On the supply side, we assume that no game enters or exits the platform when there is a change in the business model and that the design and quality of games do not change. For example, game developers do not add more in-game purchase features or make the game shorter when it is offered in the subscription service.[31] Finally, we do not consider the competition from other platforms, e.g., the PlayStation Now subscription service from Sony. Thus the optimal subscription prices may be lower than those obtained in our current results if we take competition into consideration. At the same time, the benefit of offering an attractive subscription service might be larger in order to increase market share.

7 Conclusion

In this paper, we study the impacts of adopting different types of bundle-based subscription business models on the Xbox video game platform. We first show that the equilibrium consequences of introducing the current Game Pass subscription service are ambiguous. The bundling and renting aspects of the subscription service may raise revenue, consumer surplus, or both, depending on the distribution of customers' game valuations and the rate at which this valuation decays over time.

To quantify the effects of Game Pass, we develop and estimate a model of supply and demand for individual games and the subscription bundle. We find that consumer surplus increases by 16% on average when Game Pass is introduced. Through a decomposition analysis, we find that the bundling aspect of the offering contributes to 47% of the consumer surplus increase, as it helps turn the deadweight loss from à la carte sales into gains. The rest of the increase comes from the opportunity to access games at a lower price by renting instead of purchasing them.

We then use our model to study subscription-only business strategies to see if subscriptions can completely replace the traditional sales model. In the counterfactual analysis, we find that offering all games via a subscription bundle decreases consumer surplus by 38% from the level under the à la carte sales model. This adverse effect is more pronounced for casual gamers who play only a few games and focused gamers who stick to one game for a long period of time. On the supply side, total revenue decreases by 12%, with high-valuation games being more affected, because subscription increases customers' probability of playing low-valuation games.

To extract more surplus from customers of heterogeneous gaming preferences, we further simulate a tired-subscription model, which is commonly used by market-leading media platforms. We find consumer surplus and revenue outcomes are greatly improved compared to the grand bundle subscription. Our results suggest that the subscription-only business model might generate similar outcomes as the sales model if tiers of bundles are carefully designed for different segments of

[31] It is suggested that the economics of streaming is making songs shorter. See `https://qz.com/1519823/is-spotify-making-songs-shorter`.

customers.

Our paper is the first to empirically study the welfare incidence of bundle-based subscription services across all agents on a media platform. We acknowledge that gaming is in some ways different from streaming videos, music and reading subscriptions since there is an upfront cost to gaming: purchasing a console. That said, the two might not be all that dissimilar since customers must bring their own devices to those other offerings. Hence the portability of our findings to other contexts is an empirical question in our view. While the results are specifically tied to video games, our analysis framework and the structural model can be used to study subscriptions for other media products.

We note that our data cover only the first two years after the launch of Game Pass, so the results that we display here might not persist over the full life cycle of the service and are possibly skewed by early adopters. In addition, some interesting questions are left unanswered in our paper. First, we abstract from competition between platforms when assessing the effects of launching a subscription service. Second, we take the status quo bundle content instead of the optimal content when comparing models. Finally, measuring the long-term effects on customer behavior and product design is also important for understanding the effects of adopting subscription business models.

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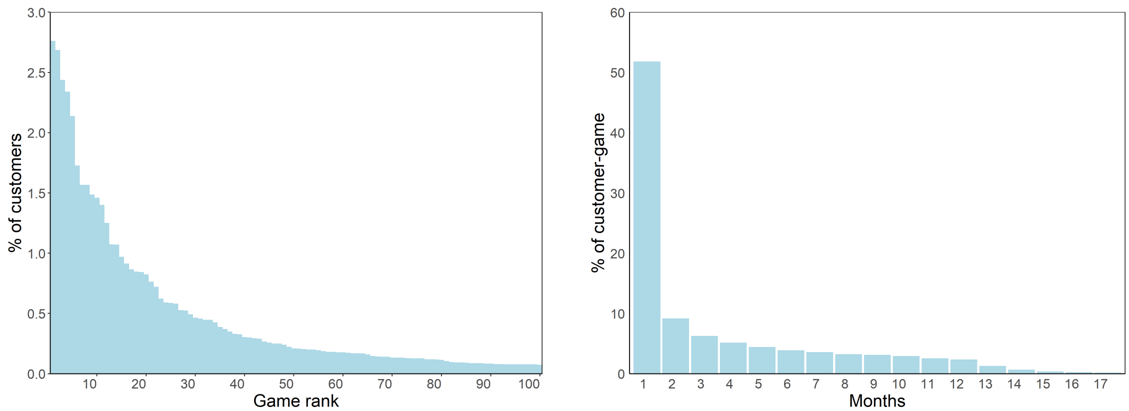
Figures and Tables

Figure 1: Subscription vs À la carte Purchase

Notes: This figure shows a screenshot from the Xbox game store for Minecraft. Customers can choose to play Minecraft by subscribing to Game Pass on a monthly basis or by purchasing the game for $19.99.

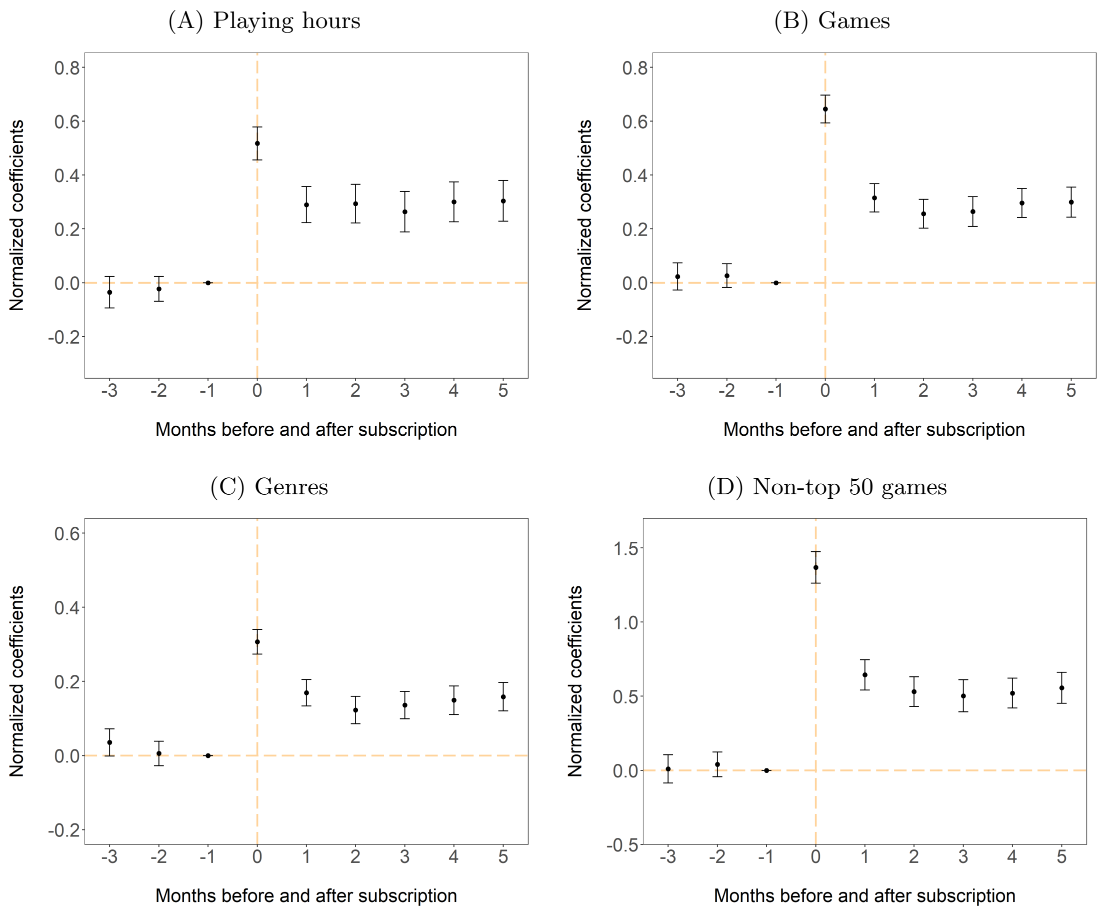
Figure 2: Customers' Heterogeneous Gaming Preferences

(A) Distribution of Customers' Favorite Games (B) Distribution of Months Spent on a Game



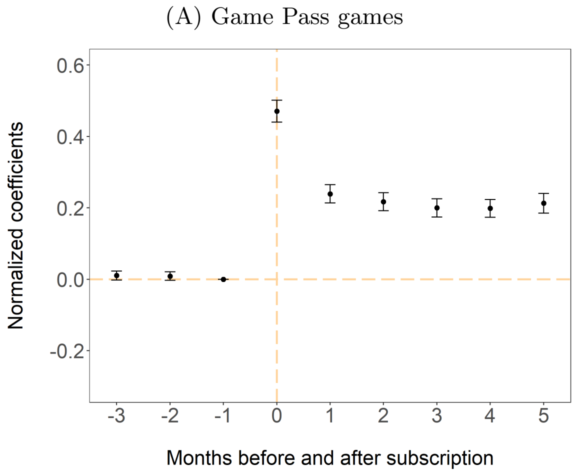
Notes: This figure shows customers' heterogeneous gaming preferences. Panel A shows the distribution of customers' favorite games. An observation is at the game level. The y-axis represents the percentage of customers who spent the most hours on the game in the first month of play among all the games that they played. The x-axis represents the rank of the top 100 games. We restrict the sample to games that were released after May 1, 2017. We also exclude Fortnite (a phenomenally popular game) from the analysis. Panel B shows the distribution of customers' total months spent on each game. An observation is at the customer–game level. We restrict the sample to games released six months before the end of the sample period.

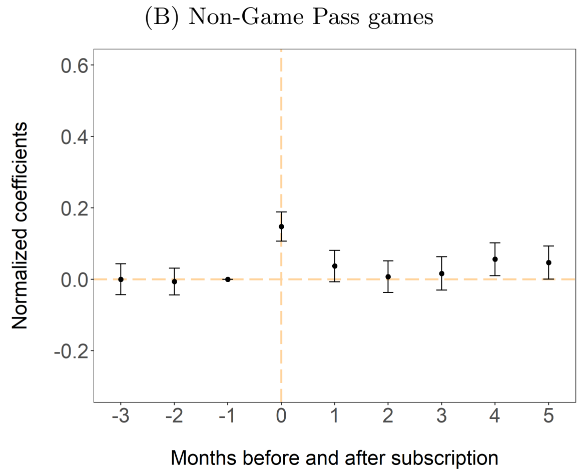
Figure 3: Demand Side Response



Notes: This figure plots the estimated effects of subscription on customers' gaming hours, games played, genres played, and non-top 50 games played. We use customers who remain active subscribers for at least six months as the treatment group. We use one month before subscription ($\tau = -1$) as the benchmark. The coefficients are normalized by the sample mean of dependent variables one month prior to subscription. 95% confidence intervals of the normalized coefficients are displayed. Robust standard errors are clustered at the customer level.

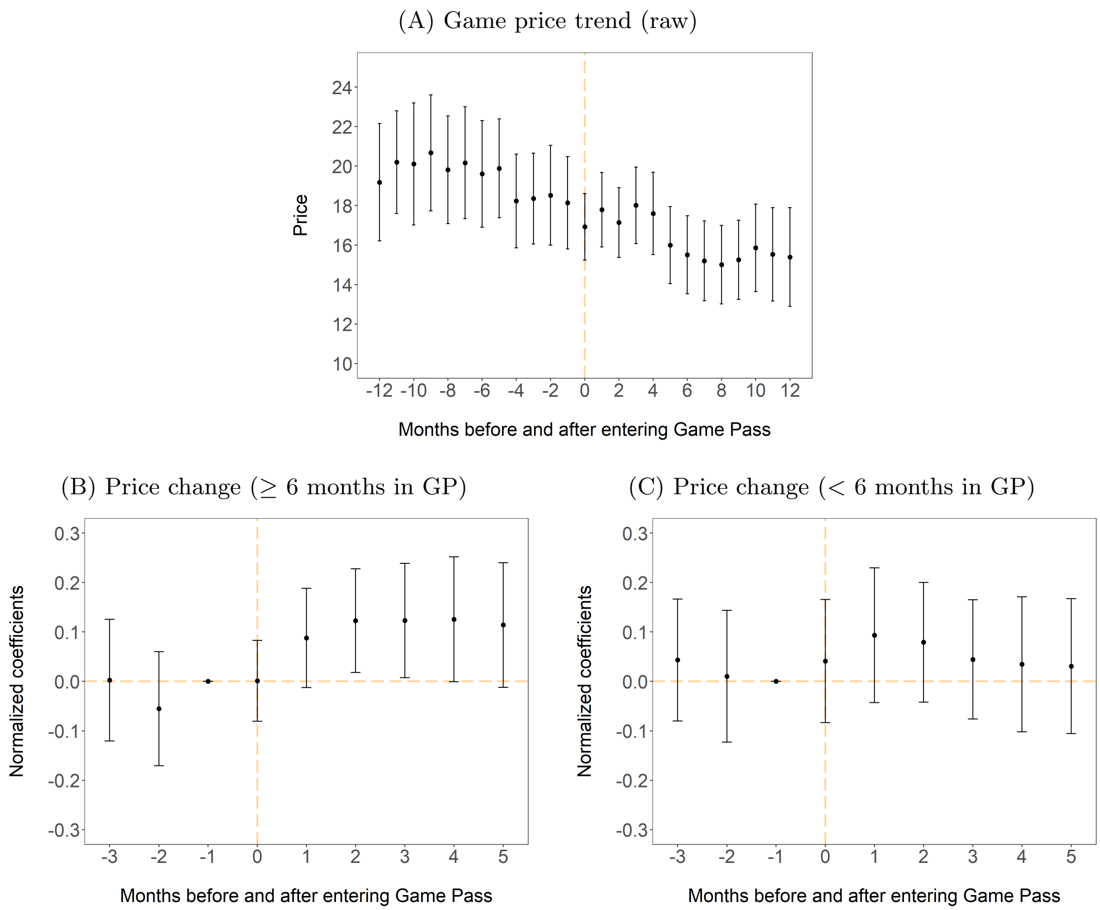
Figure 4: Demand Side Response (Decomposition)





Notes: This figure plots the estimated effects of subscription on the number of GP games played and non-GP games played. We use customers who remain active subscribers for at least six months as the treatment group. We use one month before subscription ($\tau = -1$) as the benchmark. The coefficients are normalized by the sample mean of dependent variables one month prior to subscription. 95% confidence intervals of the normalized coefficients are displayed. Standard errors are clustered at the customer level.

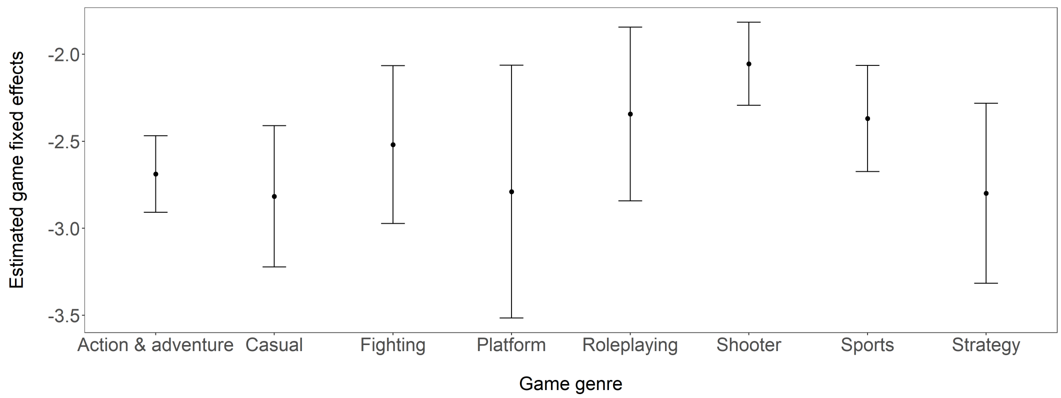
Figure 5: Supply Side Response



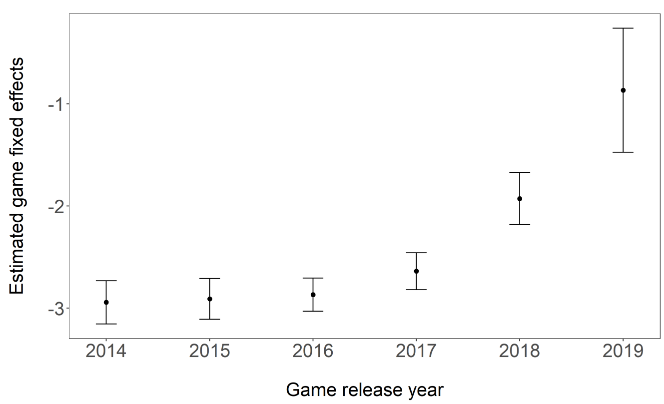
Notes: This figure plots the estimated effects of a game's addition to Game Pass on the game price. Panel A shows the raw price trend of Game Pass games. Panel B shows the estimated price change of games that stayed in Game Pass for at least 6 months. Panel C shows the estimated price change of games that stayed in Game Pass for less than 6 months. We use one month before the addition to Game Pass as the benchmark. 95% confidence intervals constructed using standard errors clustered at the game level are also displayed.

Figure 6: Usage estimates: Game fixed effects

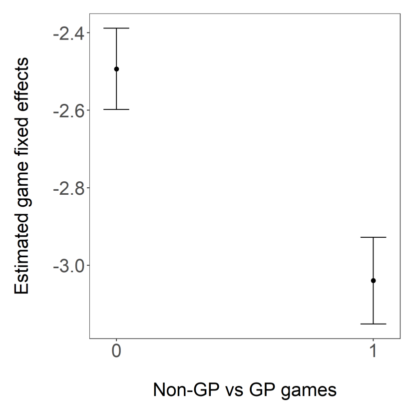
(A) Average game fixed effects by genre



(B) Average game fixed effects by release year

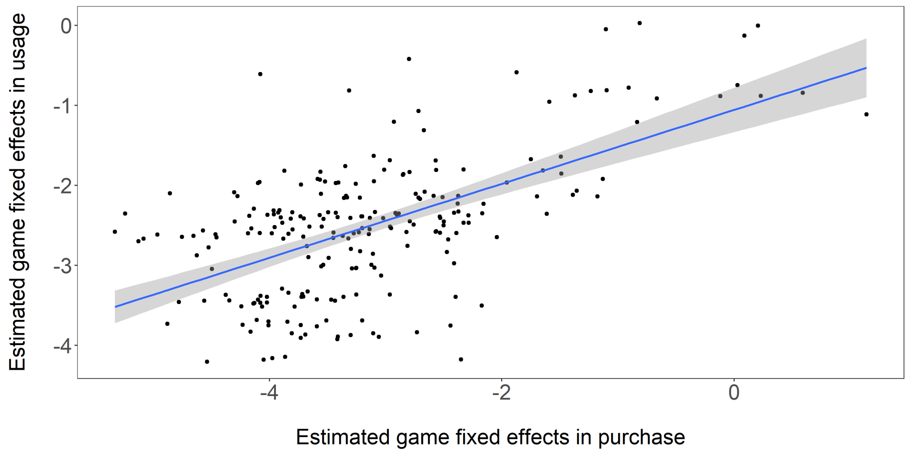


(C) Average game fixed effects by GP status



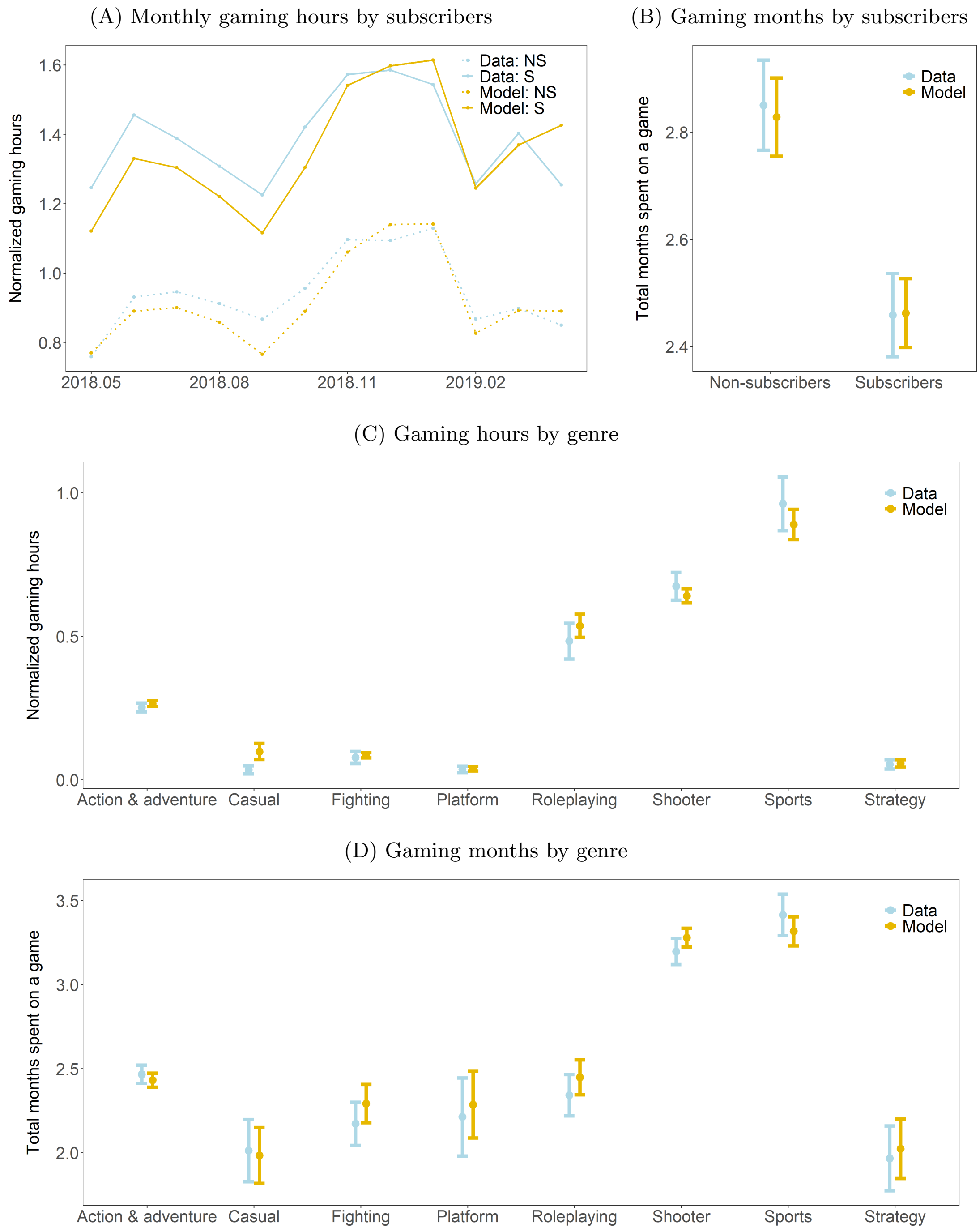
Notes: This figure plots the estimated game fixed effects in the usage model. Instead of plotting fixed effects for all 233 games, we show their average estimates in different groups. In Panel A, we group games by genre. In Panel B, we group games by release year. In Panel C, we group games by whether they belong to Game Pass. The y-axis shows the average fixed effects of the games in each group. 95% confidence intervals are also displaced around the mean estimates.

Figure 7: Estimated Game Fixed Effects from the Usage model vs Purchase Model



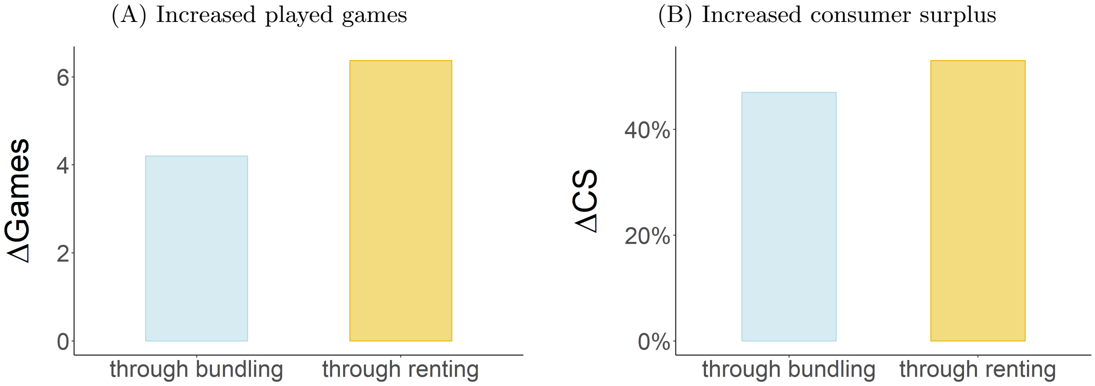
Notes: This figure compares estimated game fixed effects from the usage model and the purchase model. Each point in this figure represents a game. The y-axis shows the estimated game fixed effects from the usage model. The x-axis shows the estimated game fixed effects from the purchase model. The correlation between these two estimates is 0.62.

Figure 8: Model Fit



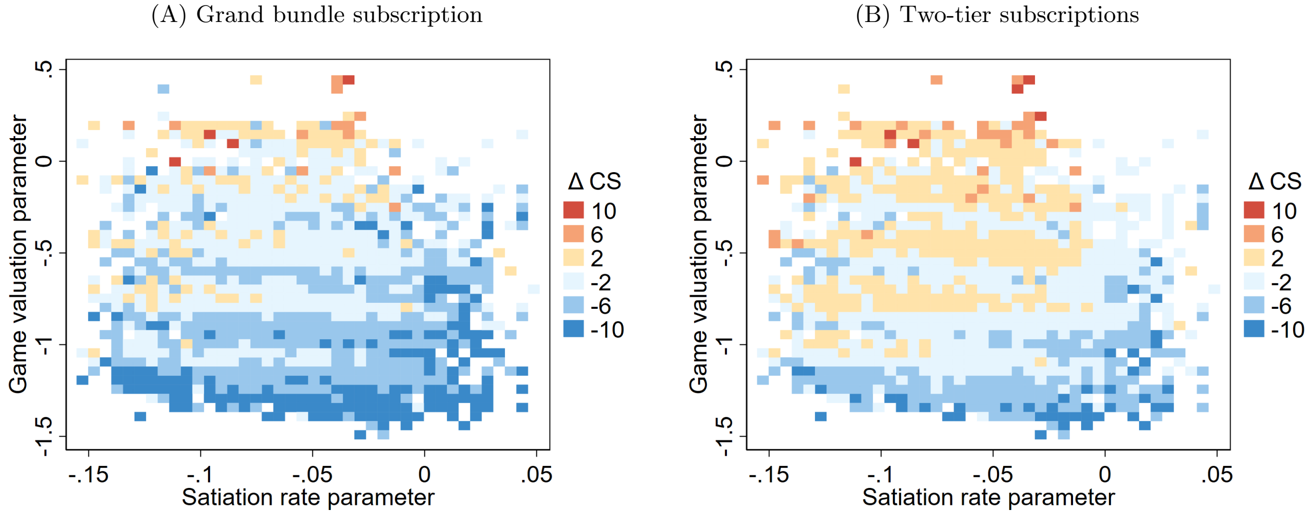
Notes: This figure plots the model fit. Panel A shows the predicted and observed monthly gaming hours for subscribers (solid line) and non-subscribers (dashed line). We define a customer as a subscriber if she subscribed at least once during May 2018 – April 2019. The gaming hours are normalized to preserve data confidentiality. Panel B shows the average number of months that customers take to finish a game. Panel C shows the average total number of normalized hours customers spend on a game by genre. Panel D shows the average total number of months that customers spend on a game by genre.

Figure 9: Decompose the Benefit from Subscription to Bundling and Renting Channels



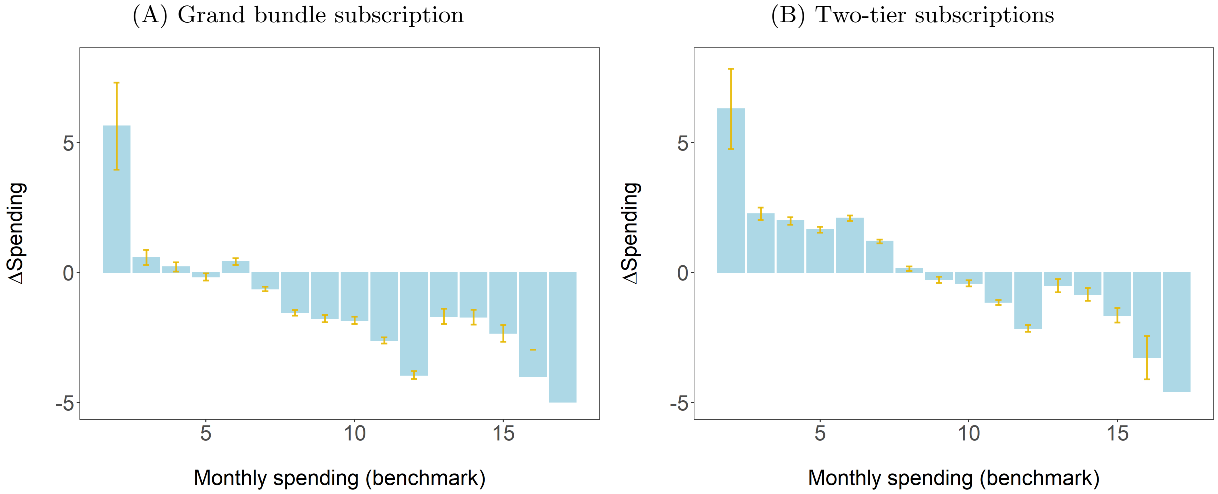
Notes: By comparing counterfactuals (1) and (4), we obtain the pure benefits from bundling. By comparing counterfactuals (4) and (5), we obtain the extra benefits from renting. The left panel shows that the bundling feature of the subscription service allows consumers to play 4 more games than in the benchmark. The renting feature of the subscription service allows consumers to play 6 more games. The right panel shows that the bundling feature contributes to 47% of the consumer surplus increase and that the rest is from renting.

Figure 10: Heterogeneous Consumer Surplus Change under Different Subscription Models



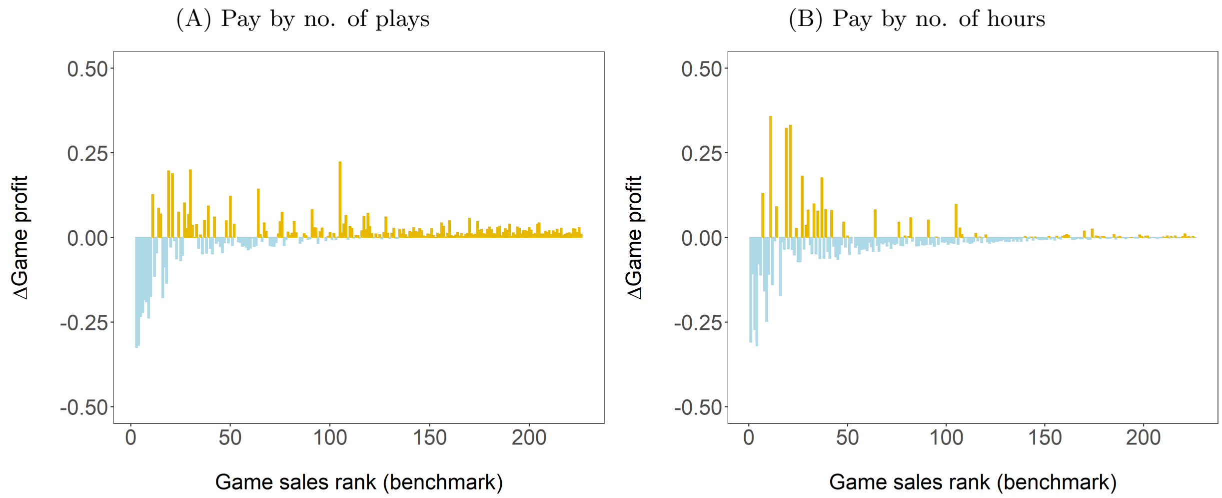
Notes: This figure shows a heatmap that represents the differences in consumer surplus between subscription models and the benchmark. The y-axis represents the gaming intensity parameter (intercept terms in Table 2). A higher number means a greater love of gaming. The x-axis represents the satiation speed parameter (coefficients in the left column in Panel B of Table 3). A lower number means a higher satiation speed. Panel A shows the difference between the grand bundle subscription model and benchmark ($CS(6) - CS(1)$). Panel B shows the difference between the tiered subscription model and benchmark ($CS(7) - CS(1)$). Appendix Figure A.10 shows the results of regressing the consumer surplus change on these two parameters separately.

Figure 11: Change in Customer Spending under Different Subscription Models



Notes: This figure shows the change in customer spending under different subscription models. The y-axis of Panel A represents the difference in customer spending between the grand bundle subscription model and benchmark $(S(6) - S(1))$. The y-axis of Panel B plots the difference in customer spending between the tiered subscription model and benchmark $(S(7) - S(1))$. The x-axis represents customer spending in the benchmark scenario. The unit of the bars is one dollar. 95% confidence intervals of each bar are also displayed.

Figure 12: Change in Game Revenue (Pro-rata Allocation)



Notes: This figure shows the change in game developers' revenue under the pro-rata allocation rule. The y-axis represents the difference in revenue between counterfactuals (1) and (7) for each game ($R(7) - R(1)$). Yellow represents a positive change. Blue represents a negative change. The x-axis represents the game sales rank in the benchmark scenario. Sales are measured in dollars. A lower rank means higher sales. The left panel shows the change when subscription revenue is allocated based on the number of times that customers play the game, while the right panel shows the change when the revenue allocation is based on the number of hours spent on the game.

Table 1: Comparison of Non-subscribers and Subscribers prior to Subscription

	Control	Treatment	p-value
Demographics			
Gender (Male = 1)	1.00	1.04	0.00
Age Group	1.00	1.00	0.39
Income	1.00	0.97	0.00
Tenure	1.00	1.08	0.00
Month Level Activity			
Gaming Hours	1.00	1.52	0.00
No. Games Played	1.00	1.77	0.00
No. Genres Played	1.00	1.23	0.00
No. Games purchased	1.00	1.79	0.00
Game level activity			
Total hours spent on a game	1.00	0.71	0.00
Total months spent on a game	1.00	0.76	0.00
Observations	18,115	8,723	

Notes: This table shows that subscribers and non-subscribers are significantly different on a set of key demographics and gaming behavior variables. We use non-subscribers as a benchmark and show the relative numbers for subscribers due to data confidentiality. To calculate pre-subscription gaming activity variables, we keep observations up to each subscriber's first subscription date. For non-subscribers, we keep their observations over the whole sample period. In the last column, we report p-values of paired t-tests of differences in variable means. All variables except age differ significantly between the treatment and control groups at the 0.01 level of confidence.

Table 2: Usage Estimates: Baseline Game Valuation

	Estimate	SE		Estimate	SE
Gender (male=1)			Tenure (years)		
Intercept	0.048	0.025	Intercept	0.029	0.007
Casual	-0.083	0.055	Casual	0.006	0.005
Fighting	0.079	0.037	Fighting	-0.017	0.004
Platform	-0.099	0.061	Platform	-0.001	0.006
Roleplaying	-0.093	0.045	Roleplaying	0.008	0.004
Shooter	0.090	0.021	Shooter	0.002	0.002
Sports	0.114	0.028	Sports	-0.006	0.003
Strategy	-0.243	0.065	Strategy	-0.029	0.007
Add on	-0.021	0.029	Add on	0.004	0.003
Rating	-0.012	0.005	Rating	-0.007	0.001
Age group (25-49 = 1)			Xbox Live (subscriber=1)		
Intercept	0.346	0.045	Intercept	0.406	0.060
Casual	-0.054	0.037	Casual	0.046	0.052
Fighting	-0.050	0.024	Fighting	0.125	0.032
Platform	-0.002	0.041	Platform	-0.024	0.054
Roleplaying	0.043	0.028	Roleplaying	0.035	0.039
Shooter	0.012	0.014	Shooter	0.180	0.019
Sports	0.004	0.018	Sports	0.157	0.024
Strategy	-0.103	0.045	Strategy	-0.042	0.061
Add on	0.053	0.020	Add on	0.004	0.027
Rating	-0.006	0.003	Rating	0.055	0.004
Income (/$70k)			EA play (subscriber=1)		
Intercept	-0.125	0.057	Intercept	0.097	0.060
Casual	0.131	0.047	Casual	-0.090	0.047
Fighting	0.080	0.032	Fighting	0.152	0.031
Platform	0.144	0.053	Platform	-0.047	0.055
Roleplaying	-0.141	0.036	Roleplaying	0.082	0.036
Shooter	-0.026	0.018	Shooter	0.043	0.018
Sports	0.083	0.023	Sports	0.095	0.023
Strategy	0.132	0.055	Strategy	-0.109	0.056
Add on	-0.010	0.025	Add on	-0.028	0.026
Rating	0.017	0.004	Rating	-0.001	0.005

Notes: This table shows estimation results for time-invariant game taste in the usage model. It reports the estimates of interaction terms between customer demographics and game characteristics.

Table 3: Usage Estimates: Satiation Rate

	Estimate	SE		Estimate	SE
A. Game Age					
Intercept	-0.281	0.004			
Gender	-0.006	0.007	Tenure	-0.013	0.001
Age group	-0.022	0.005	Xbox Live	0.041	0.006
Income	0.032	0.006	EA play	-0.038	0.006
B. Cross-month satiation (cum months)					
Intercept	-0.248	0.020	Casual	-0.064	0.012
Gender	-0.016	0.005	Fighting	-0.025	0.007
Age	0.004	0.003	Platform	-0.036	0.012
Income	-0.001	0.004	Roleplaying	-0.013	0.008
Tenure	-0.002	0.000	Shooter	0.059	0.004
Xbox Live	-0.012	0.005	Sports	0.082	0.005
EA play	0.014	0.003	Strategy	0.031	0.015
C. Cross-month satiation (cum hours)					
Intercept	1.560	0.327	Casual	-0.211	0.272
Gender	-0.159	0.063	Fighting	0.279	0.130
Age	-0.128	0.050	Platform	1.091	0.273
Income	0.004	0.060	Roleplaying	-0.514	0.125
Tenure	0.029	0.005	Shooter	-0.038	0.059
Xbox Live	0.089	0.071	Sports	0.099	0.050
EA play	0.184	0.045	Strategy	-0.322	0.247
D. Cross-month satiation (cum hours^2)					
Intercept	-1.490	0.161	Casual	0.268	0.178
Gender	0.057	0.043	Fighting	-0.119	0.051
Age	0.058	0.017	Platform	-0.509	0.157
Income	-0.005	0.029	Roleplaying	0.279	0.062
Tenure	0.008	0.003	Shooter	0.204	0.028
Xbox Live	0.034	0.035	Sports	0.098	0.024
EA play	0.050	0.022	Strategy	0.140	0.124
E. Within-month satiation (γ_j)					
Intercept	2.166	0.063	Roleplaying	-0.250	0.073
Casual	0.147	0.095	Shooter	-0.084	0.035
Fighting	0.187	0.064	Sports	-0.277	0.049
Platform	0.319	0.099	Strategy	-0.141	0.098

Notes: This table shows estimation results for time-variant game taste in the usage model. Panel A reports the estimates for interaction terms between game age and customer demographic variables. Panel B reports the estimates for interaction terms between cumulative playing months and customer demographic variables and game characteristic variables. Panels C–D report the estimates for interaction terms between cumulative playing hours (and its squared term) and customer demographic variables and game characteristic variables. Panel D reports the within-month satiation rate.

Table 4: Purchase Estimates

Parameter	Coefficient	SE	Key statistics	Mean	SD
Playing utility	0.311	0.027	Own-price elasticity	-1.225	0.658
Playing utility*Income	0.097	0.024	(game purchase)		
Price	-0.066	0.003	Own-price elasticity	-0.467	
Price*income	0.011	0.003	(subscription)		

Notes: This tables shows estimation results for selected parameters in the purchase model.

Table 5: Impacts of Game Pass: Decomposition into demand and supply responses

Counterfactuals	(1) Selling ALC	(2) Hybrid (demand only)	Δ%	(3) Hybrid (demand + supply)	Δ%
Demand					
# Games purchased	0.56	0.49	-13.22%	0.49	-13.52%
Pr(subscribe at least once)		37.60%		37.61%	
Total subscribed months		4.28		4.29	
Supply					
Average game price	20.78	20.78		21.34	2.69%
Subscription price		8.37		8.37	
Welfare					
Consumer surplus	15.54	18.14	16.73%	18.09	16.40%
Game profits	12.21	10.60	-13.15%	10.63	-12.94%
Subscription profits		1.11		1.11	
Total profits	12.21	11.71	-4.08%	11.74	-3.85%
Platform long-term profits	9.37	10.54	12.50%	10.52	12.28%

Notes: This table shows counterfactual results from the decomposition of GP effects into demand and supply responses. Column (1) reports our benchmark outcomes of only selling à la carte games on the platform. Column (2) reports the outcomes of the addition of a GP subscription bundle option when only customers are allowed to respond. Columns (3) reports the outcomes of the addition of a GP subscription bundle option when game developers are also allowed to respond by optimally setting game prices. In the Demand panel, we report the average number of games purchased per customer per month, the probability of a customer subscribing to GP at least once over a year, and the total subscription months conditional on subscribing at least once over a year. In the Supply panel, the average game price and subscription price are reported in dollars. In the Welfare panel, consumer surplus and profits are reported in dollars per customer per month. Platform long-term profits are calculated using Equation 9: a weighted average of short-term profits and consumer surplus. All the percentage differences are calculated with counterfactual (1) as the baseline.

Table 6: Impacts of Game Pass: Decomposition into Bundling and Renting Effects

Counterfactuals	(1) Selling ALC	(4) Hybrid (buy bundle)	Δ%	(5) Hybrid (subscribe bundle)	Δ%
Demand					
# Games purchased	0.56	0.53	-5.69%	0.51	-9.79%
Pr(buy/subscribe bundle)		34.01%		32.04%	
Total subscribed months				3.56	
Supply					
Average game price	20.78	21.35	2.74%	21.34	2.69%
Bundle price		38.15		15.20	
Welfare					
Consumer surplus	15.54	16.33	5.07%	17.21	10.73%
Game profits	12.21	11.65	-4.59%	11.08	-9.26%
Bundle profits		1.07		1.45	
Total profits	12.21	12.72	4.19%	12.53	2.62%
Platform long-term profits	9.37	9.82	4.89%	10.22	9.08%

Notes: This table shows counterfactual results from the decomposition of the GP effect into its bundling and renting channels. Column (1) reports our benchmark outcomes of only selling à la carte games on the platform. Column (4) reports outcomes of selling à la carte games and a bundle of 88 GP games. Column (5) reports outcomes of selling à la carte games and offering a bundle of 88 GP games through subscription. In the Demand panel, we report the average number of games purchased per consumer per month, the probability of a customer purchasing or subscribing to GP bundle at least once over a year, and the total subscription months conditional on subscribing at least once over a year. In the Supply panel, the average game price and subscription price are reported in dollars. In the Welfare panel, consumer surplus and profits are reported in dollars per consumer per month. All the percentage differences are calculated with counterfactual (1) as the baseline.

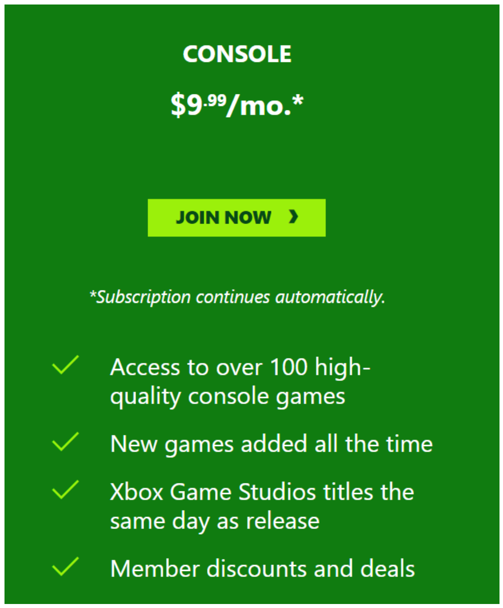
Table 7: Counterfactual Results of Different Subscription Models

Counterfactuals	(1) Selling ALC	(6) Grand bundle Subscription	Δ%	(7) Two-tier Subscriptions	Δ%
Demand					
# Games purchased	0.56				
Pr(subscribe at least once)		96.00%		100% (93.5%, 86%)	
Total subscribed months		4.80		3.9, 3.1	
Supply					
Average game price	20.78				
Subscription price		27.97		15.43, 33.45	
Welfare					
Consumer surplus	15.54	9.59	-38.30%	14.42	-7.22%
Game profits	12.21				
Subscription profits		10.74		12.35	
Total profits	12.21	10.74	-12.04%	12.35	1.14%
Platform long-term profits	9.37	6.28	-32.96%	8.85	-5.52%

Notes: This tables shows the simulation results for the benchmark scenario and two different subscription models. Column (1) reports our benchmark outcomes of only selling à la carte games on the platform. Column (6) reports the outcomes when only a subscription service with a grand bundle of all 223 games is offered. Column (7) reports the outcomes when a basic subscription bundle of 50 randomly selected games and a premium subscription bundle of all 233 games are offered. In the Demand panel, the first number corresponds to the outcome for the basic bundle, and the second number corresponds to that for the premium bundle. Consumer surplus and profits are reported in dollars per customer per month. All the percentage differences are calculated with counterfactual (1) as the baseline.

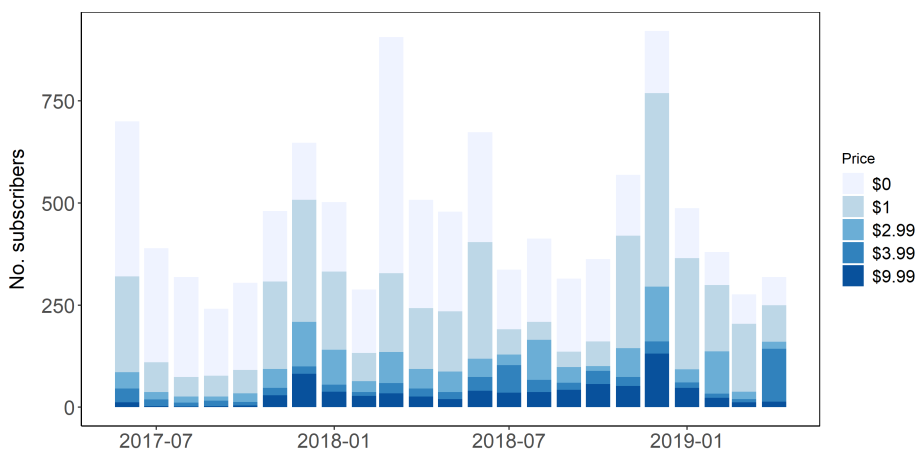
A Additional Figures

Figure A.1: Subscription Plan



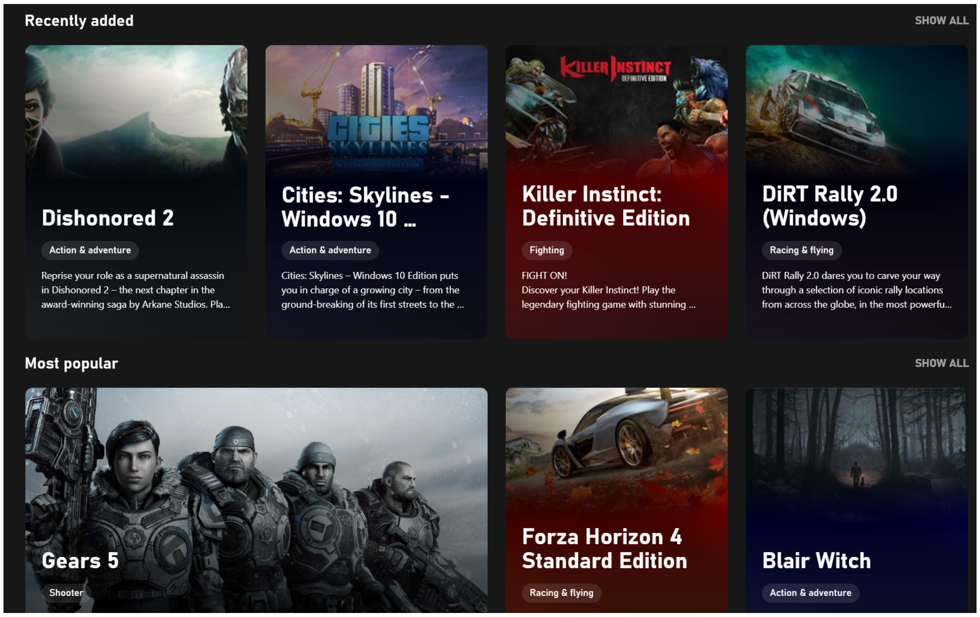
Notes: This figure shows the description of the Game Pass subscription service on the Xbox website.

Figure A.2: Subscription Prices



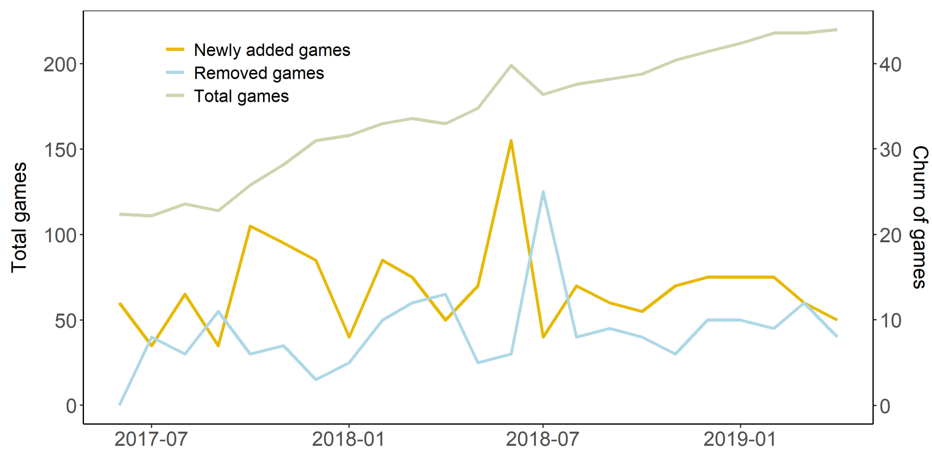
Notes: This figure shows the distribution of customers' first-month subscription fees from June 2017 to May 2019. The height of the bars shows the total number of new subscribers in each month. Each color represents one type of promotion that subscribers received.

Figure A.3: Console Interface for Game Pass



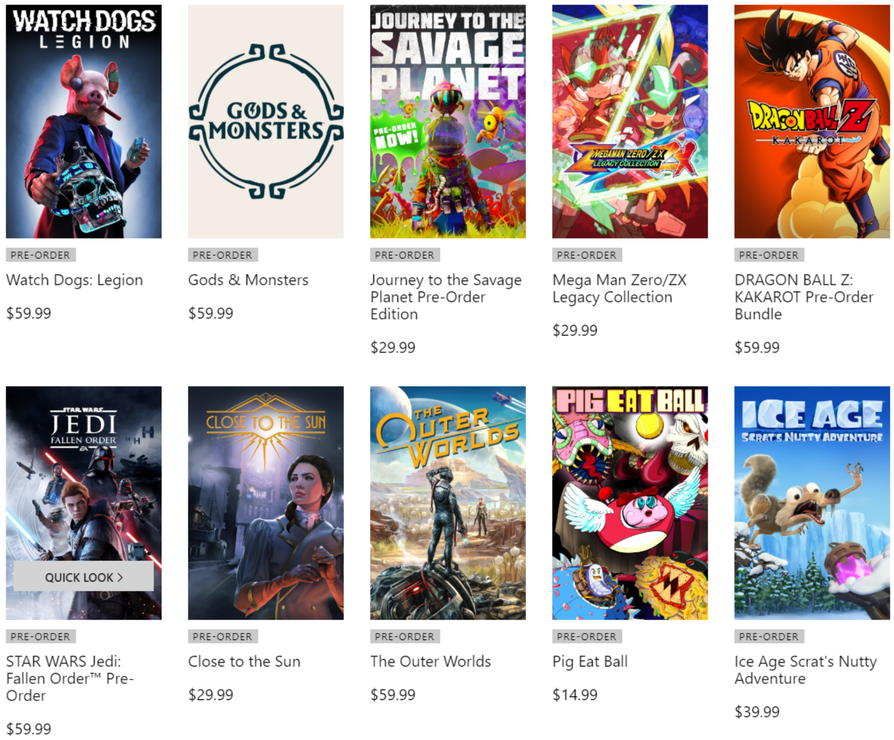
Notes: This figure shows a screen shot of the console interface for Game Pass.

Figure A.4: No. Games in Game Pass



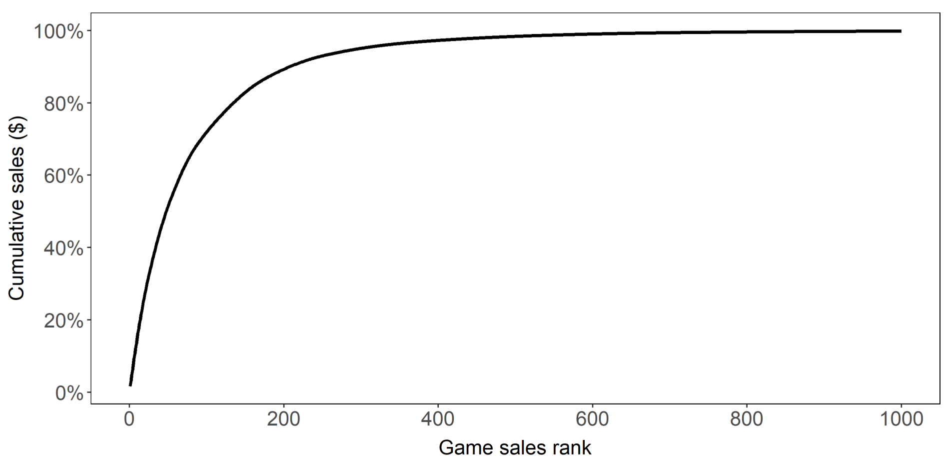
Notes: This figure shows the number of games in the Game Pass library in each month. The left y-axis represents the total number of games in the bundle. The right y-axis represents the number of newly added and removed games.

Figure A.5: Website Interface for Game Purchases



Notes: This figure shows a screen shot of the website interface for game purchases.

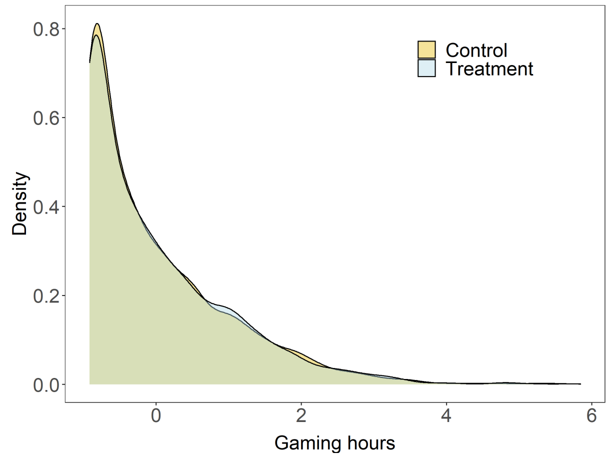
Figure A.6: Cumulative Sales



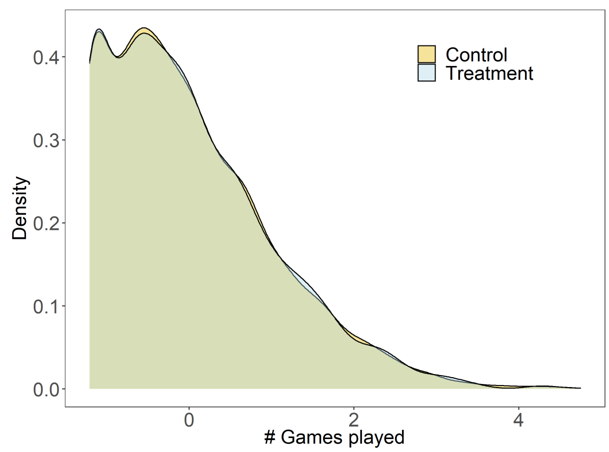
Notes: This figure shows the cumulative distribution of game sales (in dollars) on the platform over the sample period.

Figure A.7: Distribution of Customer Behavior Variables after Matching

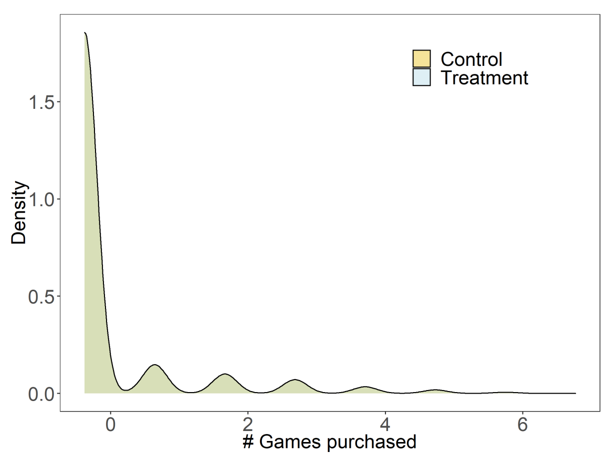
(A) Gaming Hours



(B) Games Played

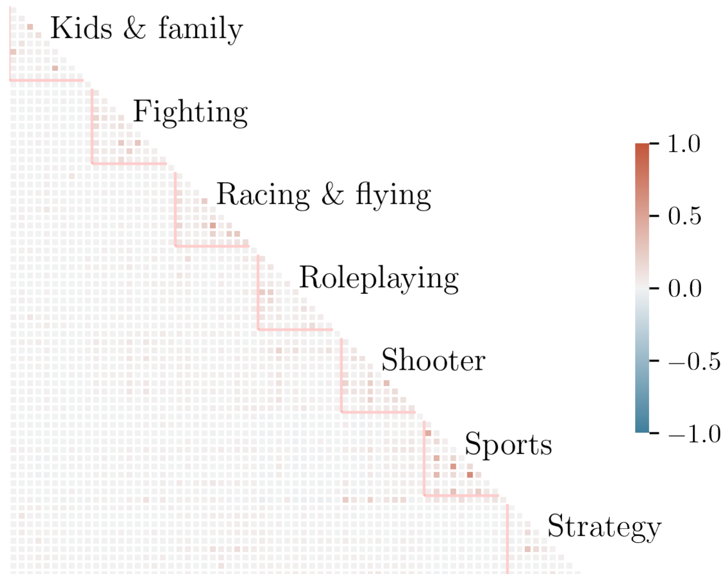


(C) Games Purchased



Notes: This figure plots the distributions of customer behavior variables for treatment and control groups after matching.

Figure A.8: Game Usage Correlation Matrix among the Top 100 Games



Notes: This figure shows the correlation matrix of gaming hours among the top 10 best-selling games in each genre. We first calculate the total hours that each customer spent on each of the top 100 games. We then compute the correlation of hours between games. The triangles along the diagonal show the correlation of game usage within the same genre. Areas outside triangles show the correlation of games across the genre. The average correlation between two games is 0.0203. Seventy-six percent of game pairs are positively correlated, and the rest are negatively correlated. Ninety-seven percent of the correlation elements in the matrix are within the range of -0.1 to 0.1. The average correlation of usage is larger within a genre than across genres.

Figure A.9: Survey

Perception of high gaming subscription prices are keeping gamers from subscribing

SIMON • KUCHER & PARTNERS
Strategy & Marketing Consultants

The second most prevalent reason is the desire to own, rather than to stream, games

		Reasons for gamers not subscribing to gaming subscriptions		
	Ranking	Casual Gamers (<5 hrs/week)	Moderate Gamers (6-20 hrs/week)	Serious Gamers (>20hrs/week)
Most important reason	1	**Price**	**Price**	**Price**
	2	I don't play much	Other	I want to own the game
	3	I want to own the game	I want to own the game	Other
	4	Prefer status quo (standalone purchases)	Prefer status quo (standalone purchases)	I don't play much
	5	Quality of games	I don't play much	Quality of games
	6	Other	Quality of games	Prefer status quo (standalone purchases)
	7	Too much choice	Too much choice	Too much choice
	8	I don't have access to an available payment method	Limited Internet access	Limited Internet access
Least important reason	9	Limited Internet access	I don't have access to an available payment method	I don't have access to an available payment method

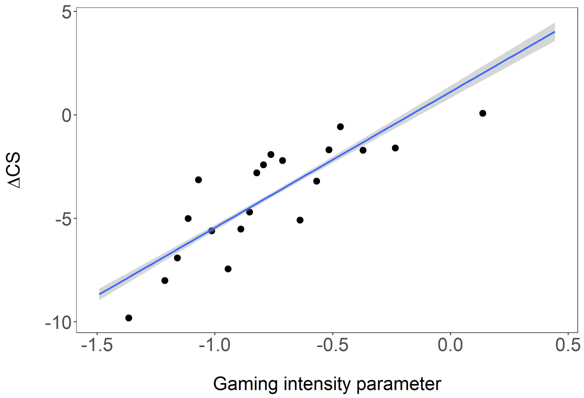
Source: Simon-Kucher & Partners; Gaming Monetization Quant Survey | Please rank the reasons why you subscribe to a gaming service (N = 4579)

Simon-Kucher & Partners | The Global Gaming Study: Video Game Subscriptions 15

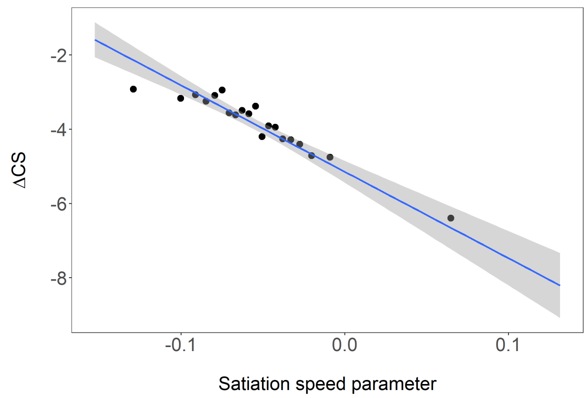
Notes: This figure shows a gaming survey conducted by Simon-Kucher & Partners. The survey asked customers the reasons why they do not take out gaming subscriptions. The top reason among casual gamers is that they do not play much, and the top reason among serious gamers is that they want to own games instead of renting them.

Figure A.10: Heterogeneous Consumer Surplus Change under Different Subscription Models

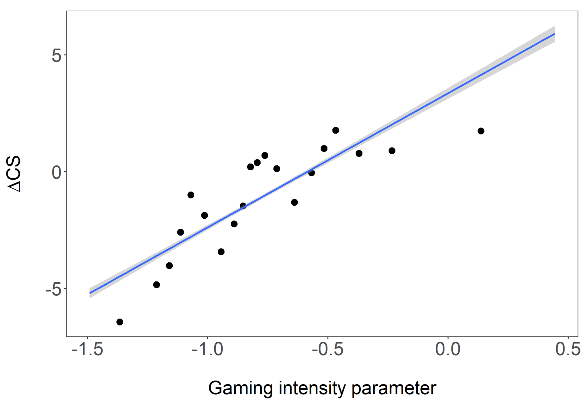
(A) Grand bundle subscription (gaming intensity)



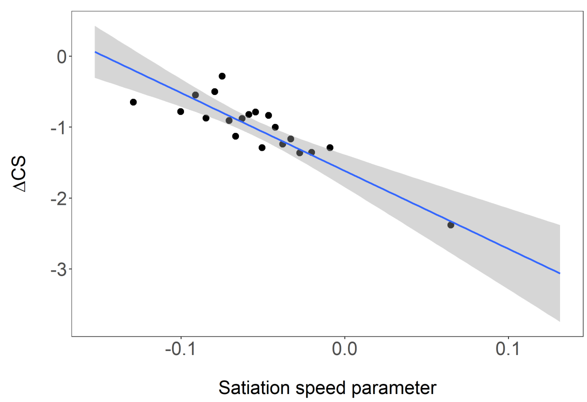
(B) Grand bundle subscription (satiation rate)



(C) Two-tier subscriptions (gaming intensity)



(D) Two-tier subscriptions (satiation rate)



Notes: This figure shows heterogeneous impacts of the adoption of subscription models on consumer surplus. In Panels A and B, the y-axis is the difference in individual consumer surplus between counterfactuals (1) and (6) ($CS(6) - CS(1)$). In Panels C and D, the y-axis is the difference in individual consumer surplus between counterfactuals (1) and (7) ($CS(7) - CS(1)$). In the left panels, the x-axis represents the gaming intensity parameter (the intercept terms in Table 2). A higher number means a greater love of gaming. In the right panels, the x-axis represents the satiation speed parameter (the coefficients in the left column in Panel B of Table 3). A lower number means a higher satiation speed. All panels show the regression of the surplus change on these two parameters. The solid line shows the best linear fit. 95% confidence intervals and the binned scatter plot are also displayed.

B Additional Descriptive Analyses

We show in Section 3.1 that customers' gaming intensity increases after they subscribe. In this section, we provide several robustness analyses for our event study.

- Propensity Score Matching.

  We use the Mahalanobis distance to match subscribers with non-subscribers in the main text. Here we match them using propensity scores. Similar to the main specification, we first match customers on their gender, age group, middle income, platform joining year, and Xbox Live subscription status. We then estimate subscribers' and eligible non-subscribers' adoption propensity as a function of their average gaming hours, number of games played, and number of games purchased three months prior to the subscription date. Each non-subscriber may appear in the data for multiple times because she may be matched to subscribers who have different first subscription dates. Thus, we weight each control observation by one over the number of control units matched to the corresponding treated individual. Finally, we use the one-nearest-neighbor (with replacement) algorithm to match each subscriber to her closest non-subscriber. We also impose a caliper (one standard deviation of the propensity) that puts an absolute maximum on the distance to avoid bad matches. After this procedure, 2,956 subscribers are matched to 2,638 unique non-subscribers. Figure B.1 shows the estimation results using PSM matching in red and the results using Mahalanobis distance matching in black for comparison.

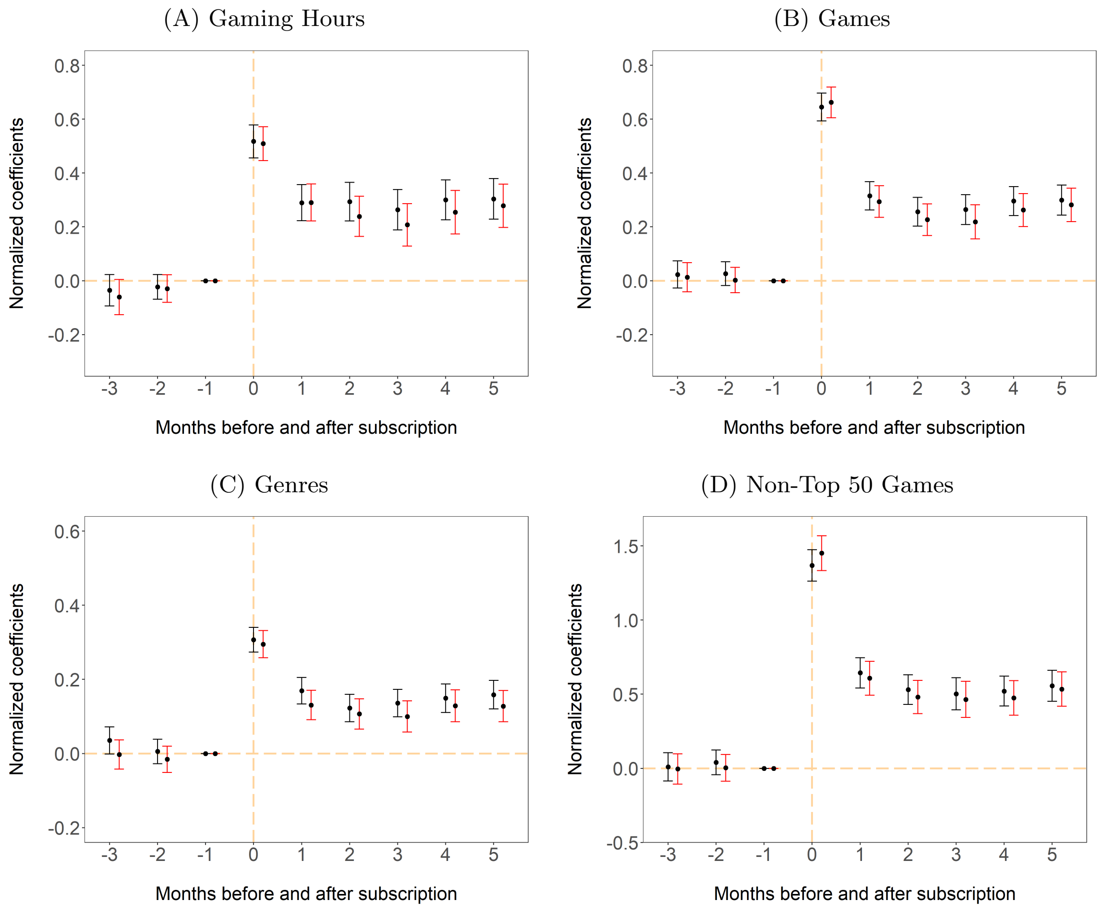
- Event study across subscriber cohorts.

  We estimate Equation 1 on four subscriber cohorts. The cohorts are determined by the time of subscription enrollment—the fourth quarter of 2017 or one of the first three quarters of 2018. Figure B.2 shows the estimated change in the number of games played by subscribers. The estimates are close to those using the main sample and have the same trend across all cohorts. We also find similar results when the dependent variables are gaming hours, genres and non-top 50 games. The robustness of the results across adoption cohorts alleviates concerns over customers endogenously selecting into subscription due to a common time-related shock, e.g., the occurrence of winter/summer break.

- Event study on one-month and three-month subscribers.

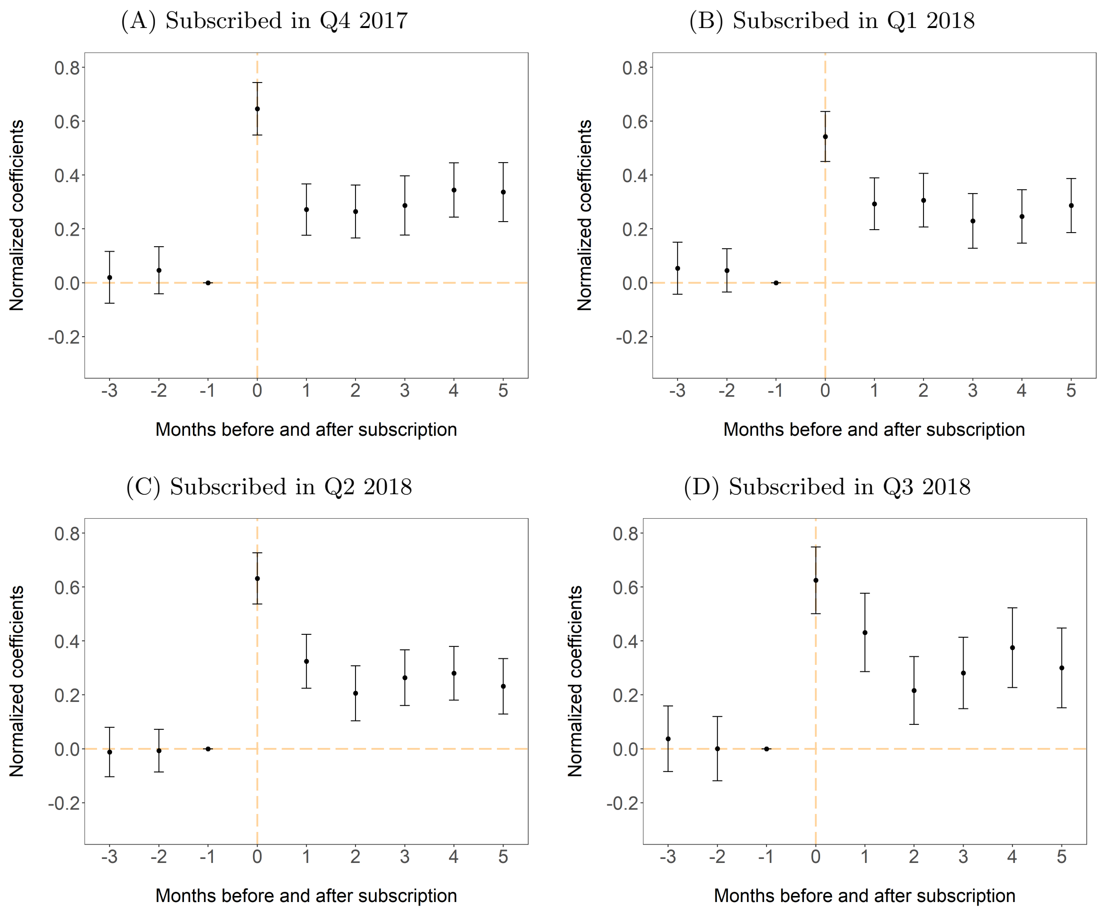
In Section 3.1, we show the results for customers who continuously subscribe for at least six months. Figures B.3 and B.4 show the results for one-month and three-month subscribers, respectively. We can see that short-term subscribers' gaming activity level increases when they subscribe, similarly to that of the long-term users shown in the main text. Also similarly, there is a slight increase in non-GP usage in the first month of subscription, and it vanishes quickly in the second month for both short-term and long-term users. This suggests that although there is some unobserved endogeneity in first-month subscription, the estimates from the second month should come close to capturing the real effects.

Figure B.1: Demand Side Response (PSM)



Notes: This figure plots the effects of subscribing to Game Pass on customers' gaming behavior. The red error bars show the estimation results from propensity score matching. Each point is an estimate of the subscription effect β_τ in the τth month. The black error bars show the result from Mahalanobis distance matching. 95% confidence intervals are constructed using standard errors clustered at the customer level.

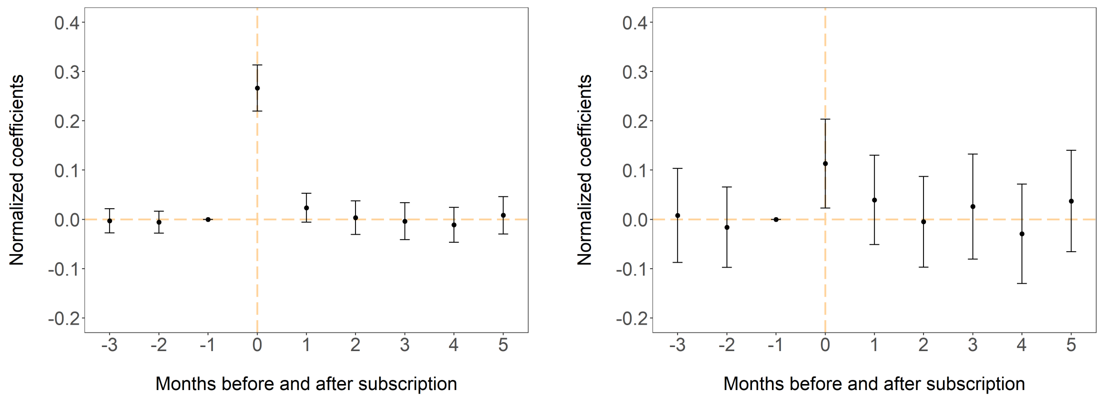
Figure B.2: Change in No. of Games Played across Subscriber Cohorts



Notes: This figure plots the effects of subscribing to Game Pass on the number of games played across four subscriber cohorts. The cohorts are determined by time of subscription enrollment—the fourth quarter of 2017 or one of the first three quarters of 2018. Each point is an estimate of the subscription effect β_τ in the τ th month. We use one month before subscription ($\tau = -1$) as the benchmark. 95% confidence intervals are constructed using standard errors clustered at the customer level.

Figure B.3: Demand Response from One-month Subscribers

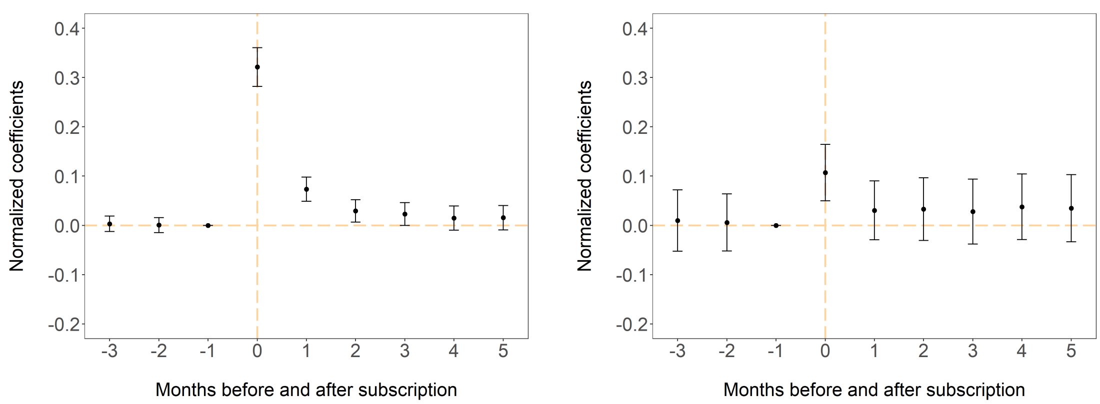
(A) No. GP Games Played | (B) No. Non-GP Games Played



Notes: This figure plots the effects of a Game Pass subscription on the number of GP games and non-GP games played by one-month subscribers. Each point is an estimate of subscription effect β_τ in the τth month. We use one month before subscription ($\tau = -1$) as the benchmark. 95% confidence intervals are constructed using standard errors clustered at the customer level.

Figure B.4: Demand Response from Three-month Subscribers

(A) No. GP Games Played | (B) No. Non-GP Games Played



Notes: This figure plots the effects of a Game Pass subscription on the number of GP games and non-GP games played by three-month subscribers. Each point is an estimate of subscription effect β_τ in the τth month. We use one month before subscription ($\tau = -1$) as the benchmark. 95% confidence intervals are constructed using standard errors clustered at the customer level.

C Additional Details on the Structural Models

C.1 Dynamic Model

Our purchase model departs from a standard dynamic model. In this section, we first build a fully dynamic model and then describe the assumptions that we make to simplify it.

The per-period indirect utility from choice $k \in K_{it}$ in month t is

$$u_{ikt} = \beta_i^u \mathbb{E}(v_{ikt}) + \beta_i^p p_{ikt} + \xi_k + \eta_t^p + \epsilon_{ikt}. \tag{1}$$

$\mathbb{E}(v_{ikt})$ is customer i's expected usage utility from choosing k in month t. p_{ikt} is the price of the choice. If the customer purchases a game, p_{ikt} is the game price; if she subscribes, it is a one-month subscription fee; if she chooses both, it is the sum of the two prices. ξ_k are choice fixed effects. η_t^p are year–month fixed effects to control for seasonality in demand. ϵ_{ikt} is an idiosyncratic preference shock.

Customers' purchase, subscription and usage choices are inter-temporally linked. All actions in this period will affect the probability of purchasing, subscribing and playing in the next period through changing inventory and playing history. For example, playing a game in this period affects the probability of playing the same game in the next period, subscribing in this period decreases the probability of purchasing the played games in the bundle in the next period, and purchasing a game in this period decreases the probability of subscribing in the next period if this game is offered in the bundle. Thus, a dynamic model of forward-looking customers is needed to accommodate these inter-temporal trade-offs.

The state vector W_{it} consists of customer i's inventory I_{it}, playing history H_{it} and market information M_t. M_t includes any other variables in customer i's information set in month t that affects her utility, e.g., bundle content, new releases, and game prices. We drop i for simplicity of notation hereafter.

There are four types of choice-specific value functions: only purchase a game $V_{j(k)\neq 0,s(k)=0}$ or V_p for notation simplicity; only subscribe $V_{j(k)=0,s(k)=1}$ or V_s; both purchase and subscribe $V_{j(k)\neq 0,s(k)=1}$ or V_{ps}; and choose outside goods $V_{j(k)=0,s(k)=0}$ or V_o. The value function associated with only purchasing a game in month t is

$$V_p(w_t) = u_p(w_t) + \delta E \max_{\epsilon_{t+1}} \{V_p(w_{t+1}), V_s(w_{t+1}), V_{ps}(w_{t+1}), V_o(w_{t+1}) | w_t, p\}. \tag{2}$$

The evolution of state variables is $I_{t+1} = \{I_t \cup j(p)\}$, $H_{t+1} = \{H_t + \boldsymbol{x_t}\}$. The newly purchased game is added to the inventory, and customers' playing history is updated for all games in the game set. The value function associated with only subscribing in month t is

$$V_s(w_t) = u_s(w_t) + \delta E \max_{\epsilon_{t+1}} \{V_p(w_{t+1}), V_s(w_{t+1}), V_{ps}(w_{t+1}), V_o(w_{t+1}) | w_t, s\}. \tag{3}$$

The evolution of state variables is $I_{t+1} = \{I_t\}$, $H_{t+1} = \{H_t + \boldsymbol{x_t}\}$. Although the value functions look similar for both choices, the state evolution is different. After a game is purchased in this period, the game enters the inventory, so even if the customer chooses outside goods in the next period, she can still play this purchased game and obtain usage utility. However, subscribing to a bundle only changes game playing history states, not inventory, so the customer cannot obtain utility from the bundle in the next period if she chooses outside goods.

This dynamic model suffers from the curse of dimensionality problem because we need to keep track of each customer's inventory and her playing history for each game. In addition, there are hundreds of games available for purchase on the platform. We therefore need to calculate hundreds of value functions. We impose several assumptions to make this model tractable. First, we assume that customers do not consider the impact of today's decision on next month's purchase and subscription decisions. Hence, the value function of purchase becomes

$$V_p(w_t) = u_p(w_t) + \delta \mathbb{E}\{V_o(w_{t+1}) | w_t, p\}. \tag{4}$$

The value function of subscription becomes

$$V_s(w_t) = u_s(w_t) + \delta \mathbb{E}\{V_o(w_{t+1}) | w_t, s\}. \tag{5}$$

Second, we assume that customers have limited foresight, which makes the model a finite-horizon one. In our main model (Equations 4 and 5), for the purchase choice, we assume that the customer considers the usage utility from future periods until she becomes satiated with it. For the subscription choice, we assume that the customer considers only one month pf usage utility as this is the direct utility associated with the one-month subscription fee.

We relax the second assumption in the robustness analysis. In the first analysis, we assume that customers consider three months of utility from the subscription service instead of just one month. We choose this number because we find that the average subscription length is 3.8 months in the data. In the second analysis, we assume that customers consider three months of utility for both the purchase and subscription choice. The data shows that it takes customers 2.7 months on average to finish a purchased game, which is close to the subscription length. Thus, it may be reasonable to assume that the customer is forward looking for the same period of time for both choices. We report the estimation results of these two alternative models in Appendix D.1.

C.2 Updating Inventory and Playing History

We explain how we update the inventory and playing history when calculating the expected usage utility.

For the purchase option, we assume that the customer does not consider the possibility of purchasing other games or subscribing in future periods. In other words, she considers her inventory to be fixed for all future periods when calculating the expected usage utility from the purchase. However, she updates the playing history of all games in her game set accordingly in each period to capture the decreasing valuation of games. Table C.1 shows an example. Suppose that game A is her inventory at the beginning of period t and that she is considering purchasing game B. In each period, she maximizes her expected utility by allocating time to these two games given their taste shocks. We assume that the shocks are the same across all periods. In period t, she spends 0.5 hours on game A and 2 hours on game B. In period $t+1$, she updates the playing history for both games and make playing decisions. In period $t+2$, she is fully satiated with game B and spends no time on it. Since the customer knows the distribution of taste shocks, she can eventually obtain the expected usage utility from purchasing game B.

For the subscription option, we assume that customers do not consider the possibility of future purchase and believe that the games in the subscription bundle will stay the same in subsequent periods. Beyond this, the expected usage utility is calculated in the same way as the purchase option.

Table C.1: An Example on the Calculation of Future Usage Utility

	Game A	Game B
t		
Cumu hours	1	0
Cumu months	2	0
Hours this period	0.5	2
t+1		
Cumu hours	1.5	2
Cumu months	3	1
Hours this period	0.3	0.5
t+2		
Cumu hours	1.8	2.5
Cumu months	4	2
Hours this period	0.1	0

Notes: This table shows an example of how customers update their playing history when calculating the expected usage utility from a purchase option.

C.3 Model Discussion

Our model provides a unified framework to study business models for media products on a two-sided platform. It is flexible enough to capture the important trade-off between offering products à la carte vs in a bundle by estimating the empirical distribution of customers' game valuations and the trade-off between purchasing vs renting by estimating the empirical distribution of customers' satiation rate. It also accommodates several key pieces of reduced-form evidence on how both sides of the market respond to the introduction of a subscription service.

For parsimony, our model abstracts from reality in several ways. First, our purchase model departs from standard dynamic models of fully rational agents. We assume that the customer considers only one period of usage utility from subscribing, while in reality, customers may consider subscription utility for several months when making decisions. In Appendix D.1, we estimate alternative models where we relax this assumption and find that the estimates are close to those from our main model, suggesting that our main estimation results are robust to this assumption.

Second, we do not explicitly model customer inertia in the subscription choice. Although we find that inertia is not the main driver of subscription demand in our data, we do find cases where customers subscribe but do not play. In Appendix D.1, we include the state dependence term of the subscription choice in the model and find that the coefficient of this term is positive and significantly different from zero, suggesting that inertia indeed exists in our setting and that failing to control for it will lead to underestimation of customers' sensitivity to price change. However, we decide not to include this term in the main model because (1) the difference in estimates is not large enough to change our counterfactual results qualitatively; (2) we cannot clearly identify the source of the inertia, that is, whether it is structural or spurious state dependence (Dubé et al. 2010); and (3) most of the time, inertia is harmful to customers as it increases the probability that customers continue buying a product even when superior options exist. However, it would have the opposite effect when we calculate consumer surplus because of the positive coefficient. Thus, we would end up overestimating the consumer surplus arising from the introduction of a subscription service.

Third, our model captures only the extensive margin of change from the introduction of a subscription service. Lacking console purchase data, we do not model customers' platform entry decision. Thus, our analysis captures mainly the benefits from the introduction of Game Pass for existing customers. However, since we assume that the platform optimizes over both short-term profits and consumer surplus, we could potentially be capturing the benefits of underpricing the service now and attracting more customers to the platform in the future even if we do not explicitly model these in the demand model.

Fourth, we do not model a fully endogenous supply side. We do not build a model of bargaining between game studios and Xbox over what titles are part of the Game Pass portfolio due to a lack of contract data. This is an interesting problem in its own right, and we leave it for future research. In addition, our model does not allow for endogenous entry and exit of products or changes in product design. Because we look at only the first two years after the launch of the Game Pass offering, it is unlikely that gaming studios had time to adjust the attributes of games to make them more appealing to play in subscription. Finally, we focus on the business strategy on a single video game platform and do not model the competition among platforms.

D Additional Details on Estimation

D.1 Alternative Purchase Models

In this section, we report the estimation results associated with alternative purchase models.

D.1.1 Inertia in Subscription In this subsection, we test for the existence of inertia in our data. A simple way of capturing inertia in our model is by letting the previous subscription choice affect customers' decision utility this period

$$u_{ikt} = \beta_i^u \tilde{v}_{ikt} + \beta_i^p p_{ikt} + \zeta \mathbb{1}\{state_{it} = s(k)\} + \xi_k + \eta_t^p + \epsilon_{ikt}, \tag{6}$$

where the state variable $state_{it}$ represents whether the customer subscribes in the last period. $s(k) = 1$ represents that the current choice k includes a subscription choice. All other variables are as in Equation 4 in the main text. The estimation results of this purchase model are displayed in Table **??** below. The coefficient of the state variable is positive and significantly different from zero, suggesting that inertia indeed exists in our data. Customers are willing to pay about \$3 more to keep subscribing in this period. Customers are on average more sensitive to price changes when we control for inertia because in the main model, we confound the subscription inertia effects and price sensitivity. Applying this new estimation result, we find that demand is more elastic for individual games and less elastic for the subscription service than in the main model results.

D.1.2 Forward-looking Behavior in the Subscription Choice In the main article, we assume that customers consider only one period of usage utility from the subscription service. Here, we relax this assumption and assume that they account for utilities from continued subscription for three months. We choose this number based on the empirical distribution of the subscription length. The purchase model then becomes

$$u_{ikt} = \beta_i^u \sum_{m=t}^{\bar{t}_k} \delta^{m-t}(\mathbb{E}(v_{ikm}) - \mathbb{E}(v_{i0m})) + \beta_i^p \sum_{m=t}^{\bar{t}_k} \delta^{m-t} p_{ikm} + \xi_k + \eta_t^p + \epsilon_{ikt}, \tag{7}$$

where $\mathbb{E}(v_{ikm})$ is customer i's expected one-month usage utility. For the purchase choice, the customer considers the expected utility from future periods until she becomes completely satiated with it. For the subscription choice, the customer considers the expected utility from the next two periods (i.e., $\bar{t}_k = t + 2$). p_{ikm} is the price of choice k. If the customer purchases a game, p_{ikm} is the game price in the first month, and it becomes zero afterwards—i.e., she pays the price only in month t. If she subscribes, p_{ikm} is equal to the subscription price in all periods. If she both purchases and subscribes, p_{ikm} is the sum of the prices from the two scenarios above. Table D.1 below shows the estimation results for this model. We find that the estimates are very similar to those from the main model. This is because although customers consider three periods of usage utility from subscription in this model, they also need to pay three periods of subscription fees, consistent with the payment structure in our main model.

Table D.1: Estimates from Alternative Purchase Models: Forward-looking in Subscription

Parameter	Coefficient	SE	Key statistics	Mean	SD
Playing utility	0.283	0.026	Own-price elasticity	-1.131	0.608
Playing utility*Income	0.071	0.022	(game purchase)		
Price	-0.062	0.003	Own-price elasticity	-0.413	
Price*income	0.011	0.003	(subscription)		

Notes: This table shows estimation results for an alternative purchase model where we assume that the customer considers utility for three periods when making subscription decisions.

D.1.3 Same Forward-looking Periods for both Purchase and Subscription Choices In this subsection, we use the same purchase model (Equation 7) as in the previous section except that we set $\bar{t}_k = t+2$ for both the purchase and subscription choices. In the data, it takes customers 2.7 months on average to finish a purchased game, and their average subscription length is 3.8 months. Thus, it might be reasonable to assume that customers are forward-looking for the same period in both choices. Table D.2 shows the estimation results. The estimates are almost identical to those from Table D.1. In the previous section, we allow $\bar{t}_k$ to be different across customers and games. In this section, we use the average number of $\bar{t}_k$ in estimation, so this is an aggregate version of the previous model, making the estimates similar to each other.

Table D.2: Estimates from Alternative Purchase Models: Same Forward-looking Periods for Both Choices

Parameter	Coefficient	SE	Key statistics	Mean	SD
Playing utility	0.283	0.025	Own-price elasticity	-1.130	0.607
Playing utility*Income	0.071	0.021	(game purchase)		
Price	-0.062	0.003	Own-price elasticity	-0.413	
Price*income	0.011	0.003	(subscription)		

Notes: This table shows estimation results for an alternative purchase model where we assume that the customer considers utility for three periods when making both the subscription and purchase choices.

D.2 Marginal Costs

In our main model, we assume that the marginal costs of games and Game Pass are zero. In an alternative supply model, we include and estimate marginal costs for both. We still assume that sellers compete in Nash–Bertrand equilibrium. Game developers set prices to maximize profits:

$$\max_{p_{jt}} \quad Q_{jt}(\boldsymbol{p_t}, \boldsymbol{L_t})((1-\tau)p_{jt} - mc_{jt}) + l_{jt}r_{jt}, \tag{8}$$

where mc_{jt} is the marginal cost of offering one copy of the game (including production and distribution costs, etc.).

Meanwhile, the platform chooses the subscription service price to maximize profits in each month:

$$\max_{p_{st}} \quad Q_{st}(\boldsymbol{p_t}, \boldsymbol{L_t})(p_{st} - mc_{st}) + \sum_{J_t} \tau Q_{jt}(\boldsymbol{p_t}, \boldsymbol{L_t})p_{jt} - \sum_{J_t} l_{jt}r_{jt}. \tag{9}$$

We denote mc_{st} as the marginal cost of offering Game Pass although it is not restricted to being positive and could be an marginal benefit. In other words, if the marginal cost is negative, it means the platform is currently underpricing Game Pass to gain more profits in the future, consistent with our main model, which assumes that the platform aims to maximize both short-term profits and consumer surplus. Furthermore, we assume that developers do not internalize the marginal costs/benefits of the subscription. In the equilibrium, the game developer chooses p^*_{jt}, and the platform chooses p^*_{st}:

$$p^*_{jt} = \frac{mc_{jt}}{1-\tau} - \frac{\partial Q_{jt}}{\partial p_{jt}}^{-1} Q_{jt}, \tag{10}$$

$$p^*_{st} = mc_{st} - \frac{\partial Q_{st}}{\partial p_{st}}^{-1} (Q_{st} + \tau \sum_{\mathcal{J}_t} \frac{\partial Q_{jt}}{\partial p_{st}} p^*_{jt}). \tag{11}$$

Using the equations above, we find that the estimated marginal cost of games is \$3.40 on average. We do not find literature that directly estimates the marginal cost of producing video games. Instead, prior works use the cost information from industry reports (Nair 2007, Lee 2013, Ishihara and Ching 2019). The cost usually includes the costs of packaging and distributing physical copies of games. Our estimates are on par with the numbers that these works use, supporting our assumption of Nash–Bertrand competition.

The estimated marginal cost for the subscription bundle is -\$7.80. This negative number indicates that there are some implied benefits from offering the subscription bundle at the current price that we do not capture in the model. For example, at the extensive margin, more new customers may be attracted to the platform by the low price of the subscription service, and the platform could acquire even more customers through "word of mouth" marketing, indirect network effects, etc. At the intensive margin, as customers spend more time playing games through Game Pass, their loyalty/stickiness to the platform might increase. In addition, due to some level of inertia, customers may be less likely to unsubscribe once they sign up, enabling the platform to obtain a steadier stream of revenue.

The negative marginal cost results are consistent with our main model, where we find that the platform cares about not only short-term profits but also consumer surplus (which could turn into long-term profits).

D.3 Interpretation of the Usage Coefficients

The effects of a unit change in a variable depends on the level of other variables in this nonlinear utility function. Here, we interpret the estimated usage coefficients for the median customer (i.e., a man in the 25–49 age group who joined the platform in June 2015 with an annual income of \$75,000 and who has an Xbox Live subscription and no EA Play subscription) in April 2019. We assume that the customer has only an average shooter game in his game set. He maximizes his usage utility v_1 by allocating time across the game ($j = 1$) and a non-gaming activity ($j = 0$). To simplify the notation, we drop the subscript i and t in what follows.

$$\begin{aligned} v_1 = &\max_{x0,x1} \quad \frac{\theta_1}{\gamma_1} log(x_1\gamma_1 + 1) + \frac{\theta_0}{\gamma_0} log(x_0\gamma_0 + 1), \\ &x_1 + x_0 = T. \end{aligned} \tag{12}$$

$\theta_0 = \gamma_0 = 1$ for the non-gaming activity. θ_1 includes the fixed effect of the game, the interaction term between demographic and game characteristic variables, the playing history, the time fixed effect and the taste shock. We assume that the game is not played before and that the taste shocks for both activities are zero. $\theta_1 = exp(-1.083) = 0.34$ for an average shooter game in the dataset in April 2019. We set $\gamma_1 = exp(2.082) = 8.02$: this is the within-month satiation rate for the median customer on an average shooter game.

With these parameters, the optimal time spent on the shooter game is 7.82 hours. If the game fixed effect decreases by 0.76 (the difference between average shooter and casual games) and all the other variables stay fixed, $\theta_1 = exp(-1.083 - 0.76)$ and $x_1 = 2.18$ hours. The customer would spend 5.6 fewer hours on this game.

If the shooter game is played for one month before (and we ignore the cumulative hours played), then θ_1 decreases to $exp(-1.367)$. The customer would spend 2.6 fewer hours in the current month.

D.4 Additional Estimates from the Usage Model

The table below reports the estimation results for the standard deviation of game taste shocks. Games of the same genre share the same standard deviation parameters.

Table D.3: Usage Estimates – Standard Deviation

	Estimate	SE		Estimate	SE
Action & Adventure	1.818	0.021	Roleplaying	1.953	0.060
Casual	1.477	0.075	Shooter	1.653	0.019
Fighting	1.486	0.048	Sports	1.455	0.028
Platform	1.568	0.080	Strategy	1.921	0.111

Notes: This table shows estimation results for the standard deviation of the taste shock distribution by genre in the usage model.

D.5 Monte Carlo Simulation

We run Monte-Carlo simulations to assess the recovery of parameters in the two-stage demand model. We generate the purchase and gaming decisions of 2,000 customers over 30 games for six months. We restrict θ_{ijt} to be a function of game fixed effects, customer gender, and cumulative playing months. γ_j is a function of two genre dummies. We also assume that standard deviations of the taste shock distribution vary across genres. In the purchase model, customers consider their usage utility and game prices.

Customer gender and game prices are drawn with replacement from the empirical distribution observed in the data. We repeat the data generation process 10 times and report the mean estimates in Table D.4. Most parameters are recovered well.

Table D.4: Monte Carlo Simulation Results

	True value	Mean estimate		True value	Mean estimate
		Usage: θ			
Game FE1	-1.320	-1.016	Game FE16	-2.748	-2.756
Game FE2	-1.353	-1.345	Game FE17	-2.780	-2.949
Game FE3	-2.649	-2.209	Game FE18	-2.713	-2.673
Game FE4	-1.645	-1.729	Game FE19	-2.386	-2.311
Game FE5	-1.089	-0.783	Game FE20	-1.912	-1.828
Game FE6	-1.072	-0.897	Game FE21	-2.208	-2.199
Game FE7	-2.294	-1.931	Game FE22	-2.867	-3.026
Game FE8	-2.267	-2.342	Game FE23	-2.468	-2.499
Game FE9	-1.908	-1.826	Game FE24	-2.751	-2.668
Game FE10	-2.006	-2.315	Game FE25	-1.488	-1.495
Game FE11	-2.631	-2.348	Game FE26	-1.344	-1.278
Game FE12	-1.183	-1.106	Game FE27	-1.198	-1.321
Game FE13	-2.908	-3.366	Game FE28	-1.251	-1.223
Game FE14	-2.702	-2.757	Game FE29	-2.407	-2.346
Game FE15	-2.816	-2.806	Game FE30	-2.002	-1.978
Age	0.500	0.508	σ^1	1.048	0.993
Cumu months	-0.010	-0.009	σ^2	1.907	1.897
	Usage: γ			Purchase	
Intercept	2.631	2.548	Usage utility	2.000	1.978
Genre 2	1.183	1.166	Price	-0.0900	-0.091

Notes: This table shows the Monte-Carlo simulation results.

E Additional Details on Counterfactuals

E.1 Simulation Details

In Section 6, we present outcomes under different business models. We describe the simulation procedures below.

Counterfactual (3) We start from the counterfactual where customers can purchase games and subscribe to GP. We simulate each pseudoconsumer's monthly purchase, subscription and playing decisions from May 2018 to April 2019.

1. Each customer starts from zero game inventory in the first month.
2. For each customer–game, we randomly draw 50 usage shocks e_{ijt} from a normal distribution $N(0, \sigma_e^g)$ to form the expected usage utility of the game. Customers consider all future usage utility from the purchase option and the one-month utility from the subscription option.
3. For each purchase/subscription choice, we draw a taste shock from a type 1 extreme value distribution. We calculate the utility from each choice and identify the most preferred purchase/subscription choice.
4. We randomly draw a usage shock from $N(0, \sigma_e^g)$ for the game that the customer purchases or shocks for all games in GP if she subscribes. We solve the optimal time allocation problem given the shocks to obtain the hours spent on each game in the current month.
5. In the next month, we repeat steps (2)–(4), taking the playing history and inventory from the last month into consideration when calculating the expected usage utility.
6. We solve for game prices (zero marginal cost) and the subscription price ($\lambda = 0.52$ for all months) in the equilibrium.
7. We repeat the procedure above 100 times (soon!).

Counterfactual (1) In the benchmark scenario, we remove the subscription choice and repeat the procedure above to simulate.

Counterfactual (2) In this counterfactual, we take the prices from counterfactual (1) as given and add the GP subscription option. We only use steps (1)–(5) and do not solve the equilibrium price.

Counterfactual (4) We add the choice to purchase a bundle of GP games to the benchmark scenario. The platform sets the bundle price to optimize profits (i.e., $\lambda = 1$).

Counterfactual (5) We add the choice to subscribe to GP to the benchmark scenario. The platform sets the subscription price to optimize profits (i.e., $\lambda = 1$).

Counterfactual (6) In this counterfactual, there is only a grand bundle subscription choice. The platform sets the subscription price to optimize weighted profits (i.e., $\lambda = 0.52$).

Counterfactual (7) In this counterfactual, there are two subscription tiers. The platform sets the two subscription prices to optimize weighted profits (i.e., $\lambda = 0.52$). Table E.1 shows the number of games in the bundle in each month. We take the GP content as given in the simulation. The changing number of games in GP reflects the actual churn of content. For the basic bundle, we randomly draw 50 games from the full sample. The bundle size keeps increasing because newly released games are added.

Table E.1: Impacts of Game Pass: Decomposition into Demand and Supply Responses

Month	GP	Basic bundle	Grand bundle
1	34	42	195
2	41	44	201
3	41	45	204
4	45	45	205
5	46	47	212
6	49	47	217
7	52	47	219
8	56	47	220
9	62	47	222
10	66	49	227
11	68	50	231
12	73	50	233

Notes: This table displays the number of games in each bundle each month.

Assumptions We make several more assumptions in addition to those in Section 6.3.

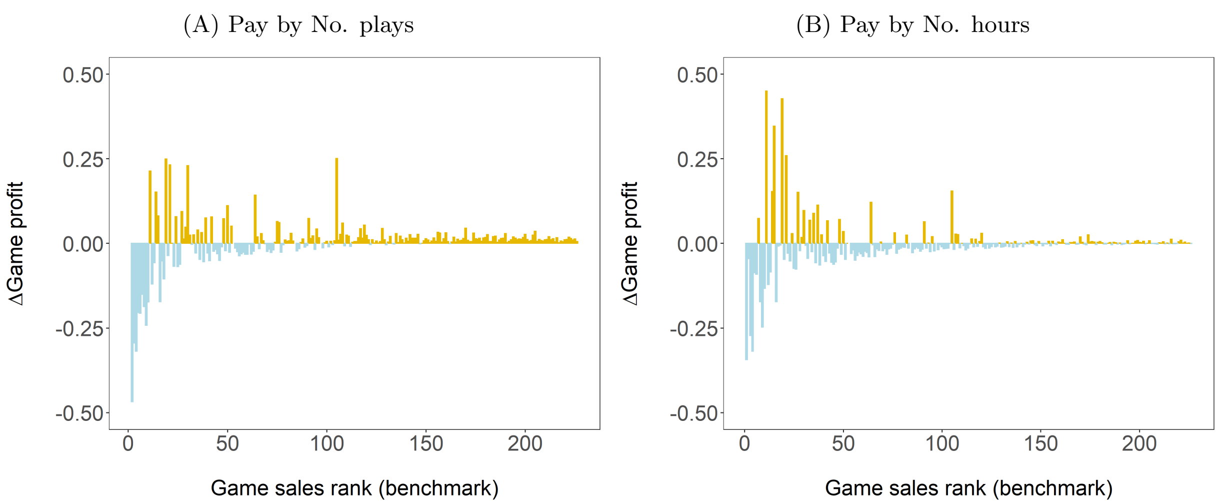
1. We assume that the fixed effects for the GP purchase bundle, basic subscription bundle and grand subscription bundle are the same as the estimated fixed effects for the GP subscription.

2. Even though we do not model the subscription choice for Xbox Live and EA Play, we use these variables when simulating customers' choices in all simulations.

E.2 Allocation Rules

When consumption differs among users, pro-rata payments do not proportionally allocate revenues generated by users who subscribe to the platform to predominantly play a particular game. This property of pro-rata allocation results in a cross-subsidization between heavy users and light users and introduces a fundamental inequity between the compensation and the revenue that each game brings to the platform by attracting more subscribers. Thus, we test another allocation rule to assess the impacts of subscriptions on game developers. The so-called *User-centric* rule is used to allocate revenue at the user level: each individual user's subscription fee is divided proportionally among content providers based on the consumption of that user. From Table E.2, we can see that the user-centric rule slightly reduces the concentration of game revenues.

Figure E.1: Change in Game Revenue (User-centric Allocation)



Notes: This figure shows the change in game developers' revenue under the user-centric allocation rule. The y-axis represents the difference in revenue between counterfactuals (1) and (7) for each game ($R(7)-R(1)$). Yellow represents a positive change. Blue represents a negative change. The X-axis represents the game sales rank in the benchmark scenario. Sales are measured in dollars. A lower rank means higher sales. The left panel shows the change when subscription revenue is allocated based on the number of times that customers play the game, while the right panel shows the results when revenue is allocated based on the number of hours spent on the game.

Table E.2: Herfindahl–Hirschman Index of Game Revenue under Different Allocation Rules

HHI	Pro-rata	User-centric
Pay by # plays	138	114
Pay by # hours	339	308

Notes: This table shows the Herfindahl–Hirschman index of game revenue under different allocation rules.

F Toy Model

We use a simple two-period model to illustrate some key elements that will be the focus of our empirical exercise.

Consider two games ($J = \{A, B\}$) and a subscription bundle (S) consisting of these two games on the platform. In each period t, customer i makes a purchase choice $k \in K_{it}$, where K_{it} is a choice set that includes purchasing a game $j \in J \setminus I_{it}$ that is not owned yet, subscribing, or outside goods. I_{it} is the customer's inventory of games at the beginning of period t. After making the purchase decision k, customer i decides how to play the games in her game set $G_{it}(k)$. $G_{it}(k)$ includes customer i's inventory I_{it}, the game purchased in period t if any, games in the bundle if she subscribes and a non-gaming activity. We start from modeling the usage stage and then the purchase stage.

In the usage stage, customer i solves a time allocation problem to maximize her utility:

$$v_{ikt} = \max_{\boldsymbol{x_{it}}} \quad \sum_{G_{it}(k)} \frac{\theta_{ijt}}{\gamma_i} \log\left(x_{ijt}\gamma_i + 1\right) \tag{13}$$

$$\sum_{G_{it}(k)} x_{ijt} = T, \quad x_{ijt} \geq 0, \tag{14}$$

$$\theta_{ijt} = \exp(\alpha_i - \lambda_i h_{ijt}). \tag{15}$$

v_{ikt} is the indirect utility from optimal playing decisions. x_{ijt} is the time spent on game j in period t by customer i. The marginal utility from an extra hour of gaming is $\frac{\theta_{ijt}}{x_{ijt}\gamma_i+1}$. With this functional form, θ_{ijt} measures the marginal utility when the customer just starts to play game j in period t (i.e., $x_{ijt} = 0$). α_i represents customer i's baseline valuation for game j. h_{ijt} includes customer i's total periods spent on game j before period t. Its coefficient λ_i captures the customer's cross-period satiation rate, e.g., her likelihood of playing the same game in the next period. γ_i is a translation parameter that measures customer i's within-period satiation rate. A larger value of γ_i represents a higher satiation speed.

At the purchase stage, the per-period utility from choice k at t is

$$u_{ikt} = \beta^u v_{ikt} - \beta^p p_{kt} + \epsilon_{ikt} \tag{16}$$

v_{ikt} is customer i's playing utility from choosing k as described before. p_{ikt} is the price of choice k.

All purchase and usage decisions are inter-temporally linked. Actions in this period will affect purchase/subscription/usage decisions in the next period through the changing inventory and playing history. Therefore, we introduce a dynamic model of forward-looking customers. The state vector W_{it} consists of customer i's inventory I_{it} and playing history H_{it} and market information M_t.We assume that customers have complete information about the market conditions (price and available products).

In this two-period model, we assume that the products offered and their prices are the same in both periods (i.e., $M = \{p_A, p_B, p_S\}$). The state variable is $w_1 = \{I = \{\emptyset\}, H = \{0, 0\}\}$ in the first period. To simplify the notation, we drop M since it is the same in both periods and drop i and t in what follows. The value function for purchasing game A in the first period is

$$V_A(w_1) = u_A(w_1) + \delta E \max_{\epsilon_2} \{u_B(w_2), u_S(w_2), u_O(w_2)|w_1, A\}.$$

The state variable is $w_2 = \{I = \{A\}, H = \{1, 0\}\}$ in the second period. The value function for subscribing in the first period is

$$V_S(w_1) = u_S(w_1) + \delta E \max_{\epsilon_2} \{u_A(w_2), u_B(w_2), u_S(w_2), u_O(w_2)|w_1, S\}.$$

The state variable is $w_2 = \{I = \{\emptyset\}, H = \{1, 1\}\}$ in the second period if the customer plays both games in the bundle. The value function for choosing outside goods in the first period is

$$V_O(w_1) = u_O(w_1) + \delta E \max_{\epsilon_2} \{u_A(w_2), u_B(w_2), u_S(w_2), u_O(w_2)|w_1, O\}.$$

The state variable is $w_2 = \{I = \{\emptyset\}, H = \{0, 0\}\}$, the same as in the first period. We assume that the unobserved shocks follow a Type 1 extreme value distribution. The probability of choosing $k \in \{A, B, S, O\}$ in the first period can be written as

$$P_k = \frac{exp(\bar{V}_k)}{\sum_{l \in K} exp(\bar{V}_l)}, \tag{17}$$

where $\bar{V}_k = V_k - \epsilon_k$. We obtain the purchase probability in the second period after ϵ_k in the first period is realized. The calculation procedure is similar to that for the first period except that there is no future utility flow.

On the supply side, we assume that game developers set game prices to maximize revenue from game sales and the subscription service from two periods. The platform sets the subscription price to maximize the royalty fee from game sales and the subscription service. $\tau = 0.3$ is the royalty rate. We assume zero marginal costs for products. Games A and B shares the subscription revenue equally.

$$\text{Game developers:} \quad \max_{p_j} \quad (1-\tau)p_j Q_j(\boldsymbol{p}) + \frac{1}{2}(1-\tau)p_s Q_s(\boldsymbol{p}) \tag{18}$$

$$\text{The platform:} \quad \max_{p_s} \quad \tau \sum_J p_j Q_j(\boldsymbol{p}) + \tau p_s Q_s(\boldsymbol{p}) \tag{19}$$

We simulate 1,000 customers' choices in two periods. We assume that customers' baseline game valuations are uniformly distributed, $\alpha_j \sim [0, 4]$, and that their valuations for both games are uncorrelated, i.e., $\alpha_A \alpha_B$. Their within-period satiation rate is uniformly distributed between 0 and 1, $\gamma_i \sim [0, 1]$, and that their cross-period satiation rate is $\lambda_i \sim [0, 4]$. We set $\beta^u = 0.1, \beta^p = -0.05, T = 1$.

Table F.1 shows the results of our simulation analysis under three different business models. In the first scenario, customers can only purchase games A and B on the platform. This setup corresponds to Xbox's original business model, and we use it as a benchmark. The optimal price of game A is \$27.1. Game B shares the same price because the two games' valuation distributions are the same. The total demand for games is 0.52 per person.

In the second scenario, we add a bundle of games A and B that can be purchased. The difference between business models (1) and (2) shows the effects of bundling. The optimal bundle price is \$36.4, lower than the sum of the two game prices. Sellers increase à la carte game prices to extract more surplus from customers who value only one game.

In the third scenario, we add a subscription bundle of games A and B (the current business model on Xbox). The difference between business models (1) and (3) shows the total effects of introducing a subscription bundle. The difference between business models (2) and (3) shows the effects of the renting feature of the subscription service. The monthly subscription fee is lower than the sale price of the bundle. With the existence of the subscription option, sellers can set even higher selling prices to extract surplus from customers who prefer to own the game. Subscription brings a new stream of revenue but at the same time cannibalizes game sales. Customers benefit from playing more games at a lower price through subscription, but at the same time, some may have to pay more than before to purchase a game. The total welfare impact of offering a subscription option is thus ambiguous and an empirical question.

Figure F.1 shows the distributional effects of the introduction of a subscription bundle on customers. We find that customers with a higher total game valuation $\alpha_A + \alpha_B$ and a higher within-month and cross-month satiation speed are more likely to subscribe. These customers also benefit more from subscription. Some low-intensity and slowly satiated customers may be worse off since they have to pay a higher price to purchase games. This simulation exercise illustrates that estimating customers' heterogeneous game valuation (α) and the rate at which it decays (γ, λ) is the key to analyzing the welfare impacts of subscription. We estimate these parameters using detailed usage and purchase data from the platform in our paper.

Table F.1: Simulation Results for the Toy Model

Business Model	(1) sell ALC only	(2) sell ALC + sell bundle	(3) sell ALC + subscription
Game price	27.1	28.2	28.8
# Games purchased	0.52	0.45	0.40
Bundle/sub price		36.4	27.8
Bundle/sub demand		0.10	0.21
# Games played	0.52	0.65	0.75

Notes: This tables shows the simulation results under different business models. The first column shows the scenario where only à la carte games are offered. The second column shows the scenario where both à la carte games and a bundle of games are offered for purchase. The third column shows the scenario where a bundle of games are offered through subscription instead of for purchase. Games purchased and played are reported at the customer level.

Figure F.1: Simulated Distributional Effects of Introducing a Subscription Bundle on Customers

Notes: The first two panels show customers' heterogeneous subscription probability against their total game valuation $\alpha = \alpha_A + \alpha_B$, within-month satiation rate γ, and cross-month satiation rate λ. The last two panels show the consumer surplus difference between scenarios (1) and (3) (CS(3)–CS(1)) for customers with heterogeneous gaming preferences.