

Customer Management in Gaming Environments: A Dynamic Structural Analysis

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Gaming and gamified environments possess unique characteristics that influence how consumers spend time and money. The core of the customer management problem in such environments is to ensure that the challenge is difficult enough to motivate agents to exert more effort, yet not so challenging that they get discouraged and quit. In gaming, firms also monetize players' motivation to exert effort by providing them an opportunity to purchase ability-enhancing items that increase their performance; this increases player retention, while simultaneously driving future monetization as players reach higher levels – creating a two-way positive feedback loop between retention and monetization. In this paper, we develop a dynamic structural model of consumer response for gaming environments. The model accommodates key features that are common in such environments: (i) increasing levels of difficulty that result in player attrition, retaining only the most able players, and ii) opportunity to purchase in-game items that improve players' ability to win. The dilemma for game designers is to manage the retention and monetization for players with widely ranging ability levels and gameplay preferences. Counterfactual results reveal heterogeneous effects: accelerating early level progression for high ability players hurts firm profit from *premium enthusiasts* who derive enjoyment from play itself and are willing to pay, but helps retention and monetization from "*easy-progress*" and "*instant-win*" seekers who find playing the game itself costly. We highlight the added value of incorporating unobserved preference heterogeneity by designing personalized interventions at players' level frontiers, enabling firms to tap into the benefits of the positive feedback loop of retention and monetization.

Key words: gaming environments, retention, monetization, targeting, dynamic structural model

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1. Introduction

The gaming industry continues to gain in importance both in terms of share of consumer time and money. As of March 2024, an estimated 59% of consumers spend more than an hour a day on video games, with 32% claiming to spend more than 5 hours a day.¹ Worldwide revenues for the video games market in 2023 is estimated at \$250 billion and projected to grow over 8% a year. Revenue per user for mobile games is estimated at \$53 in 2023.² The advancement of virtual and augmented reality technologies is expected to further accelerate consumer spending and time in virtual environments.

Despite its massive size in ongoing revenue and user growth, there has been relatively limited research on engagement and monetization strategies for gaming environments. The context of gaming environments we study is particularly interesting because firms often monetize players' motivation to exert effort by providing them an opportunity to purchase in-game items that enhance players' ability to win, so that players can endogenously adjust their level of difficulty at a monetary cost. The ability to buy ability enhancers helps players perform better, thus increasing their retention, while simultaneously driving future monetization as the player is able to reach higher levels. This positive feedback loop is particularly strong for players who are willing to pay. This positive feedback dynamic challenges the standard notion that retention primarily drives monetization (e.g., Gupta et al. 2004), but without reciprocal effects. Our paper is the first to recognize a unique aspect of the retention-monetization dynamics in the context of gaming environment—the two-way positive feedback between retention and monetization.

This conceptual framework allows us to raise novel questions around managing the dynamic interaction between customer retention and monetization. Should higher ability players be promoted faster through levels below their frontiers? How can the firm better retain and monetize players who have already reached their frontier levels? The dilemma for game designers is to manage the retention and monetization in creating an engaging game experience real-time for players

¹ <https://www.statista.com/forecasts/997154/hours-spent-on-playing-video-games-per-week-in-the-us>

² <https://www.statista.com/outlook/dmo/digital-media/video-games/worldwide>

with widely ranging ability levels and gameplay preferences. Namely, the design of interventions should dynamically accomodate players with different levels of ability and gameplay preferences in response to changing game environments.

This paper develops a dynamic structural model of consumer response for gaming environments, in which a player decides between three choices: continue playing, purchase in-game items before continuing to play, or exit the game platform permanently. The model captures key aspects that are common in such environments: (i) the level promotion design that increases in difficulty, resulting in player attrition and retaining only the high-performing players, (ii) the option to purchase in-game items that enhance players' effective win probabilities, so that players can endogenously balance their level of challenge at a cost depending on their ability levels, and (iii) short-term rewards for immediate success that sustains interest in the game even as they seek long-term rewards of reaching the next level. Building such a structural model allows us to investigate a range of questions relating to the design of game environments.

We estimate the model using data from individual play and purchase choices in a free-to-play single-player mobile golf game. Our comprehensive dataset includes detailed match-level information on players' actions, environments, rewards, and progression throughout their entire gaming experience. We also obtain detailed records of players' in-game item purchase transactions, which allows us to examine the relationship between the timing of in-game purchases and their impact on player performance. In most settings, individual ability is considered an unobserved variable. Our game environment context and detailed data enable us to treat player ability as an observed variable by estimating it from the player lifetime gameplay records. This allows us to account for wide varying heterogeneity in player ability and design personalized interventions for player retention and monetization.

Our estimation strategy extends and adapts the two-step estimation framework in Chung et al. (2014). First, we estimate the player production function to obtain player ability estimates and incorporate player ability heterogeneity in the first stage estimation of the conditional choice probability (CCP). We accomodate latent class heterogeneity and use the expectation-maximization

(EM) algorithm within the two-step framework, following the approach in [Arcidiacono and Miller \(2011\)](#). We estimate the structural parameters in the second stage estimating the value function for each ability and latent segment type. Estimates reveal three latent segments of players: (i) *premium enthusiasts* who derive enjoyment from the play itself and incur lower costs of purchase to enhance their performance, (ii) “*instant win*” *seekers* who prefer immediate wins more than long-term level-up rewards but finds the game itself costly to play, and (iii) “*easy progress*” *seekers* who also find playing the game itself costly to play but receive higher utility from level-up rewards.

Counterfactual results reveal the value of incorporating ability and preference heterogeneity in designing targeted interventions for improving monetization of the game. Overall, accelerating early level progression for high ability players increases firm revenue, but we find heterogeneous effects across latent segments, even among the players with the same ability level. We find that the firm gains in profit by expediting level-ups by effectively lowering difficulty level at early stages from players who find playing the game itself more costly (“*easy progress*” *seekers* and “*instant win*” *seekers*), but loses in profit from players who find playing the game itself more enjoyable (*premium enthusiasts*). The biggest improvement in profit comes from the achiever segment, who likes to win and values long-term level-up rewards more, resulting in an 11% increase in profit. While expediting early level-ups boosts retention across all segments, it does not necessarily enhance monetization for *premium enthusiasts*. This demonstrates the nuanced relationship between retention and monetization in gaming environments.

Our second counterfactual further emphasizes the added value of incorporating unobserved preference heterogeneity when designing the timing of difficulty adjustments for players who have reached their frontier levels in the game. To assess the incremental impact of incorporating player ability and gameplay preference heterogeneity in designing timing of interventions, we compare three different frontier level targeting strategies: (i) ability-based targeting, (ii) gameplay preference-based targeting, and (iii) targeting using both ability and gameplay preferences. We find that using only unobserved preference heterogeneity for targeting is more effective in increasing

firm profit than considering ability alone. Because the high-spending enjoyer segment has significantly later points of exit than the other two segments, not accounting for such fact and intervening too early can cannibalize early level profit from this group. The fully personalized policy, which utilizes both ability and gameplay preferences for targeting, yields the highest profit increase by 1.05%. By extending player retention at their frontier levels, the firm can further reap profit from players on the brink of leaving the game with a costless intervention, creating a positive feedback loop from retention to monetization.

2. Related Literature

Our paper contributes to several streams of literature. First, we contribute to the growing literature on the video games market. The first stream of papers in this literature studies consumer demand for console video games (e.g., Clements and Ohashi 2005, Nair 2007, Derdenger and Kumar 2013, Derdenger 2014, Haviv et al. 2020). The shift in consumer focus to the online and mobile gaming landscape has enabled researchers to collect and utilize detailed usage records. This has given rise to the second stream of empirical papers that studies user engagement and gameplay behavior (e.g., Huang et al. 2019, Nevskaia and Albuquerque 2019, Rutz et al. 2019, Zhao et al. 2022, Castelo-Branco and Manchanda 2023, Chen 2023), monetization strategy and welfare (Appel et al. 2020, Huang et al. 2021, Runge et al. 2022, Amano and Simonov 2023, Ascarza et al. 2023, Haenlein et al. 2023, Joo and Chiong 2023, Wang et al. 2023), and analytical papers studying game and in-game product design (e.g., Guo et al. 2019, Jiao et al. 2021, Chen et al. 2021, Li et al. 2023a, Li et al. 2023b, Mai and Hu 2023, Miao and Jain 2024, Sheng et al. 2024). Despite of the significant and growing market size of the gaming industry, there is a lack of research documenting consumer spending behavior on in-game items, which are the most common and major driving source of revenue in the gaming market. Thus, it is surprising that only a handful of papers have empirically studied in-game monetization design involving in-app purchases (e.g., Huang et al. 2021, Runge et al. 2022, Amano and Simonov 2023, Ascarza et al. 2023, Joo and Chiong 2023, Wang et al. 2023). Our research aims to fill this gap.

Compared to standard retail environments, gaming and gamified environments enable the collection of more detailed data on the ongoing engagement and monetization of users. While other digital and freemium products such as Dropbox also have consumer usage data, the difference in gaming and gamified online environments is the dynamic modification of the product (game). Within this class of products in digital environments, firms have the opportunity dynamically redesign engagement in a personalized manner. The personalization principles developed in the context of gamified systems claim that accounting for individual heterogeneity can increase engagement and task outcomes (Liu et al. 2017). Such has been documented in settings such as e-training and online learning environments (e.g., Santhanam et al. 2016, Leung et al. 2023). Ascarza et al. (2023) is the closest marketing paper that studies this in a gaming context. Using a field experiment, the authors suggest evidence consistent in showing the value of designing personalized difficulty interventions.

While one approach to personalizing the redesign is through experimental variations, changing the game and conducting experiments across the large state space of potential variations is costly in terms of revenue implications and may hurt game balance. Additionally, the presence of unobserved heterogeneity at the player level (e.g., price sensitivity, motivation sensitivity) complicates the implementation of personalized interventions based solely on observables. Structural models can be extremely helpful in gaining a theoretical understanding of the dynamics and in cost-effectively assessing which sets of design interventions are likely to yield the best payoffs. Our model framework allows us to dynamically redesign consumer engagement and monetization in a personalized manner.

Our paper also contributes broadly to existing work in CRM literature. Traditionally, marketers designing CRM strategies have focused on the value of retention on monetization (e.g., Gupta et al. 2004, Ascarza et al. 2018). Our paper is the first to recognize a unique aspect of the retention-monetization dynamics in the context of gaming environment—the two-way positive feedback between retention and monetization. Additionally, our research extends the CRM literature by demonstrating how personalized interventions can be effectively designed to optimize

both retention and monetization in dynamic and heterogeneous gaming contexts. Additionally, our research extends the CRM literature on personalization by demonstrating how interventions can be effectively designed to create a positive feedback loop between retention and monetization in a personalized manner.

Finally, our work extends to empirical settings in which a gaming layer has been added to motivate individuals with preference for game-like features. For instance, the design of goals and rewards and its impact on agent performance and selection has been extensively explored in settings including but not limited to salesforce (e.g., Misra and Nair 2011, Chung et al. 2014, Chung et al. 2021b, Chung et al. 2021a, Kim et al. 2022), digital health (e.g., Allcott et al. 2022, Uetake and Yang 2022), online education (e.g., Huang et al. 2023, Leung et al. 2023), and mobile marketing (e.g., Hofacker et al. 2016).

3. Data and Empirical Setting

3.1. Description of the Game

Our empirical setting is a popular free-to-play single-player mobile golf game with over 2 million registered users. In this game, players engage in one-hole game matches, where the objective is to complete the hole with fewer shots than the opponent. Each game lasts around three to five minutes, and players are assigned matches by the game platform once entering the game. Players accumulate points from winning the match (and lose points from losing), and collection of these points is required to unlock higher levels in the game. The game design ensures a sequential progression where higher levels demand the accumulation of more points to be unlocked. The game has a total of 11 levels.

The level-progression system of the game is designed to increase difficulty through several design features. We report the points system of the game in Table 1. The expected points for each game given a player’s win probability are calculated based on the game’s win-loss points schedule, which varies by level. We illustrate the level difficulty system embedded within this points system using levels 6 to 11 as examples in Figure 1. In the figure, each line represents a different level, demonstrating that as players advance to higher levels, the expected points for a given win probability

generally decrease under the same win rate. Figure 2a helps further illustrates this point by highlighting that as the level increases, the win probability required to at least break even (i.e., zero expected points) also increases, requiring players to have higher win rates at subsequent levels. Finally, higher levels require higher points accumulation criterion to level up, making progression increasingly demanding, as shown in Figure 2b. Overall, the points system of the game is designed to discriminate on player ability, ensuring that only the most able players progress to the top levels.

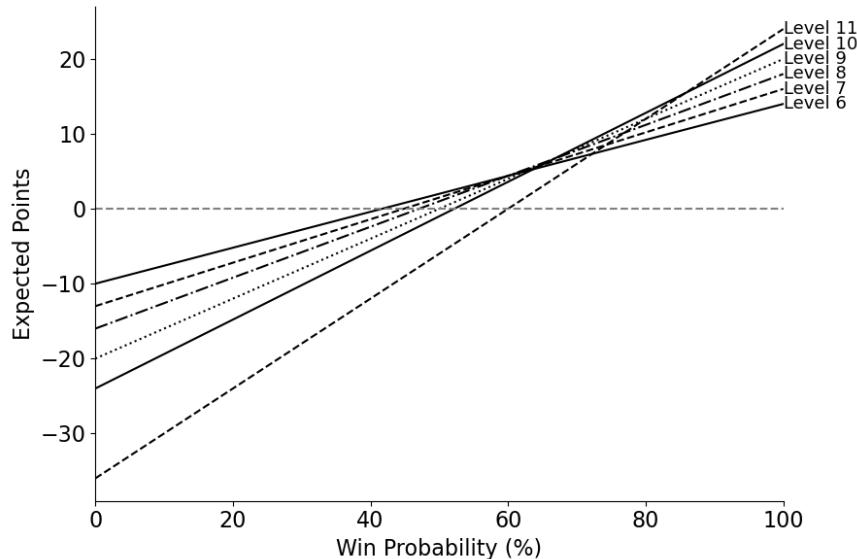
Table 1 Points and Level Progression Design of the Game

Level	Win	Lose	Total Available Points	Cumulative Points Collection
1	+4	-1	25	-
2	+6	-2	75	25
3	+8	-3	125	100
4	+10	-4	175	225
5	+12	-7	225	400
6	+14	-10	300	625
7	+16	-13	375	925
8	+18	-16	450	1300
9	+20	-20	550	1750
10	+22	-24	700	2300
11	+24	-36	900	3000
Final Lvl Clear				3900

Players can enhance their win rates by purchasing in-game items. The in-app purchases consist of durable ability-enhancers (i.e., golf clubs) that allow players to improve their win rates. For example, a paid golf club enables greater range and ball guide precision when taking a shot. By incurring a monetary cost, players can increase their chances of progressing through the levels that they might not have had otherwise. By allowing players to self-select the balance between the need to win and the cost of purchasing ability enhancers, the firm can effectively monetize across different player segments of different abilities and price sensitivity. The most popular in-game item offerings cost \$9.99 (generating around 60% of revenue), and around 90% of total durable item transactions are generated from product offerings between \$9.99 and \$19.99. Higher-priced offerings provide more quantities of golf clubs that can help enhance player win rates. While the game also features in-app advertising, the firm primarily generates revenue through in-app purchases.

The game offers a suitable setting for a single-agent model. From the player perspective, it is primarily a single-player experience, in that players do not strategically select which opponent to play against, but rather get assigned by the platform.³ The progression system of the game incentivizes players to continually improve their skills to maintain or increase their win rates and progress through the levels, inducing a dynamic and forward-looking behavior.

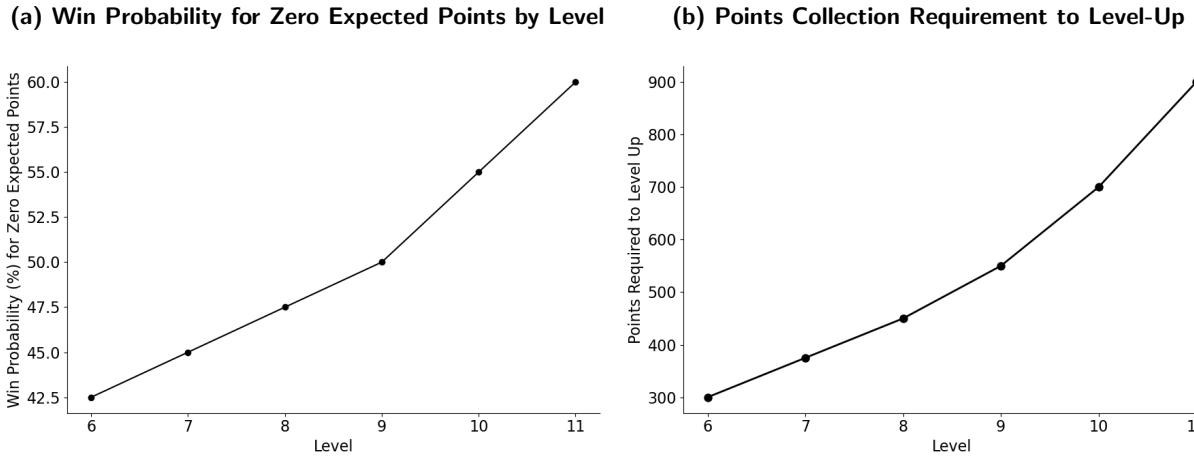
Figure 1 Game Points Design: Expected points by Win Probability by Level



3.2. Data

We leverage a unique dataset that consists of granular match-level information about players' actions, environment, rewards, and progression throughout the player's lifetime from initiation to exit. This includes detailed observations of players' play and exit decisions, in-game item usage, and the gaming environments they encounter, including the opponents they face. We also obtain detailed records of players' in-game item purchase transactions (\$), which allows us to examine the relationship between the timing of in-game purchases and player performance.

³ In the game, around 40% of gameplay matches consist of bots. To ensure the game is neither too easy nor too difficult, players are typically matched with opponents whose Elo scores are slightly below their own. In our model, we control out the effect of the opponent and focus on the player's actions and decisions as a single agent.

Figure 2 Game Points and Level-Progression Design

Our analysis focuses on a random sample of 4163 players spanning a 15-month period, from October 2021 to January 2023. We construct the sample as follows. First, we take a random 10% sample of players who meet the criteria of having valid play records in the data period. Second, players who have completed at least level 5 (i.e., collected at least 15% of total points available) are retained. This criterion ensures that our analysis focuses on individuals who exhibit a sufficient level of engagement within the game environment, while excluding less committed players who frequently download the game but discontinue usage shortly thereafter. Finally, we exclude outliers with within-level gameplays above 1.5 times the interquartile range. The final dataset for analysis includes around 750,000 match records.

Table 2 contains summary statistics of our player sample. A median player engages in 274 games throughout their lifetime, and the median exit level is 7.⁴ The average game play duration, measured by the number of days from first play to exit, is 106.21 days. Finally, given our sample, which includes players with a minimum progression to level 6, 22.36% have purchased in-game items at least once. While the median player makes no purchases, there is significant heterogeneity in the player purchase behavior at the higher end of the distribution, with total transactions ranging between 14 and 41 for players in the 99th percentile and above.

⁴ To define player exit during our data period, we apply the two-week churn condition.

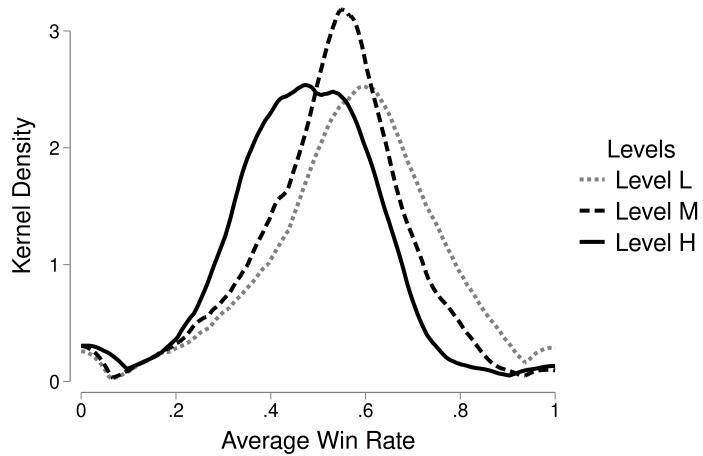
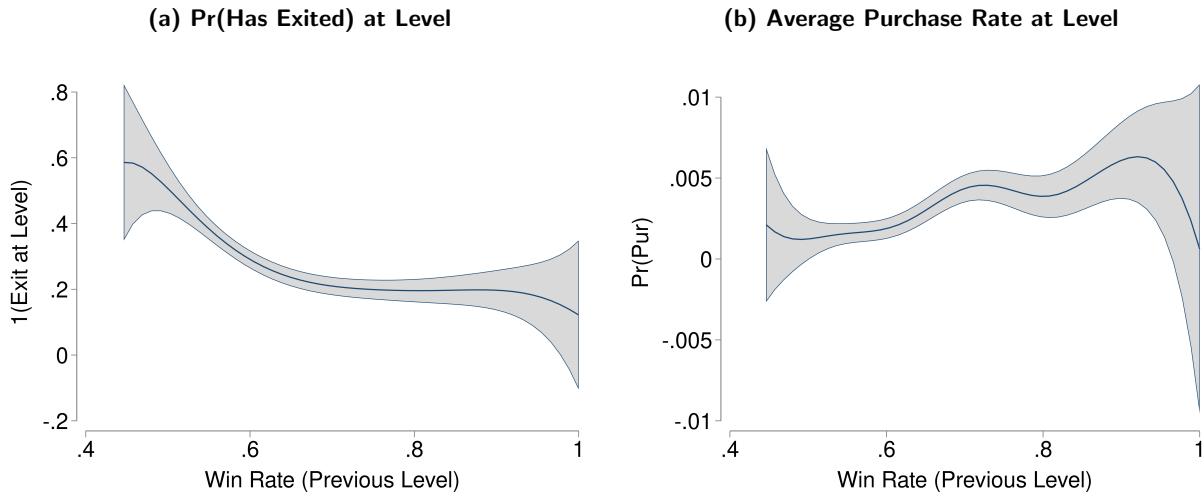
Table 2 Descriptive Statistics of Players

	Mean	SD	Median	75th	90th	99th	Max
<i>Engagement</i>							
Total Number of Games Played	331.57	225.18	274	406	583	1203	3211
Maximum Level Reached	7.41	1.54	7	9	10	11	11
Game Duration (<i>Days from First Play to Exit</i>)	106.21	98.55	73	151	259	405	454
<i>Monetization</i>							
In-app Purchase Player Share	22.36%						
Total Number of Purchase	0.88	2.69	0	0	3	13	41

3.3. Model-Free Evidence

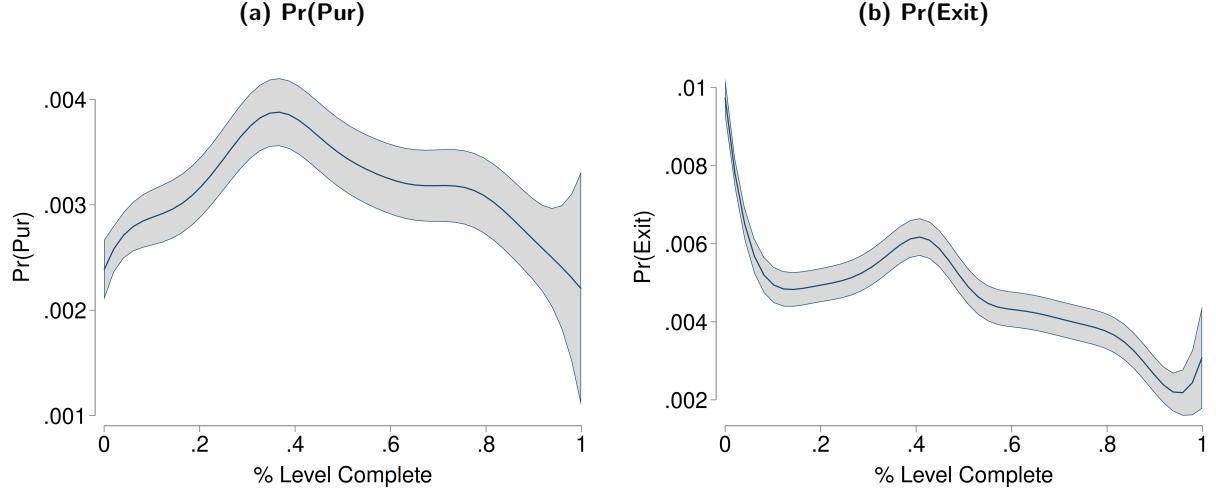
We present three key features of the data that inform our model development. First, we provide evidence of substantial heterogeneity in player win probability within and across levels. Second, we show the relationship between players' production rate (win probability) and their purchase and exit decisions. Third, we demonstrate the dynamics in the timing of players' purchase and exit decisions relative to their level completion status.

In the gaming environment, there exists substantial heterogeneity in the player rate of production, indicating their ability to progress through the game levels. We present the player differences in average win rate across levels in Figure 3. First, players have generally lower win rates at higher levels, reflecting the increased level difficulty designed into the game. Within each level, there exists significant differences in player win probabilities, providing suggestive evidence of the varied abilities of players even at the same level. We next examine the relationship between players' win probability and their purchase and exit decisions, as illustrated in the best-fitting nonparametric smoothed polynomial in Figure 4. Within each level, we find that players with higher win probabilities are more likely to continue playing and make in-game purchases as they gain positive continuation value in the gaming experience. Conversely, players with lower win probabilities are more likely to exit the game and purchase less, as their lower production rates can reduce their engagement and the perceived value of the game. This relationship underscores the importance of maintaining a balance in game difficulty to retain players and encourage in-game spending.

Figure 3 Average Win Rate Distribution of Players By Levels**Figure 4 Player Exit and Purchase by Win Rate**

Note: Level 7 Example

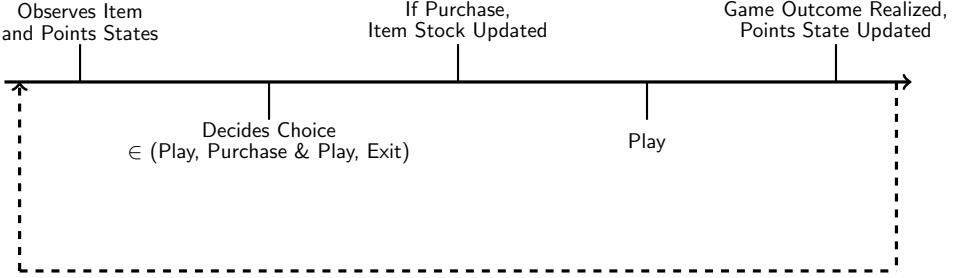
Finally, we show the relationship between the timing of players' purchase and exit decisions and their level completion status. Player exits are more likely to occur at the beginning of a level when players face increased difficulty after level-up. The durable nature of items encourages upfront purchases, typically around 20-30% into a level, when players believe they have a chance to progress. This suggests that within a level, players are more likely to purchase in-game items early on to enhance their rate of progression. Overall, these patterns highlight the importance of timing and player heterogeneity in ability when designing interventions for player retention and monetization.

Figure 5 Player Exit and Purchase by % Level Complete

4. Model

Based on the model-free evidence, we develop a dynamic model of player action in the gaming environment. Time indexed by t is discrete denoting each game. At the beginning of each period t , player i decides whether to (1) play, (2) make an in-app purchase and play, or (3) exit the game permanently. Figure 6 describes the timing of the model. Before entering a game t , player i observes the current item and progression (i.e., accumulated points) state in the game. The player decides on the action choice between playing, purchasing an item and playing, and exiting the game permanently. If the player's decision was to incur the purchase of in-game items, the item stock is updated before play. The player then enters the game, and idiosyncratic game outcome shock is realized. The realized game outcome affects the player's progression points state in the next period. The model repeats every period over an infinite horizon. After the player completes all levels, the player can continue to play the unlocked stages, which is a pattern we observe for the majority of players in the game.

The game's point system and progression design induce the player's dynamic forward-looking behavior. A player choosing the action has to be concerned not just with the current payoff but with the effect of that choice on all future rewards and play costs.

Figure 6 Model Timeline

4.1. Player Ability and State Variables

To model player progression and item purchase decisions, we assume that the player has an intrinsic baseline ability α_i . Players can improve their ability over the course of the game by making in-app purchases. To represent player states in the gaming environment, we parsimoniously track two key state variables. First is player item stock k_{it} , which tracks the number of in-app purchases a player incurred to improve their ability. It represents the vertical quality metric of the player’s in-game item state. Second is player progression points stock z_{it} . Item stock k_{it} represents the vertical quality metric of the player’s in-game item state. The points accumulation state (z_{it}) has a one-to-one mapping to the level (ℓ_{it}), given the progression design Ψ of the game, reflecting the player’s current progression state in the game.

4.2. Player Production Function

The player winning outcome $W_{it} \in \{0, 1\}$ is a function of player ability type α_i , item k_{it} , and level states ℓ_{it} , such that

$$W_{it} = \alpha_i + \delta_1 k_{it} + \ell(z_{it}) + \delta_2 k_{it} \cdot \ell(z_{it}) + \xi_{it}. \quad (1)$$

The player production function accommodates the following key characteristics to model the gameplay outcome. First, the player’s win probability increases with the player’s ability α_i . Second, items k_{it} enhance player productivity. Third, the player’s win probability decreases with increasing level difficulty ℓ_{it} , which is determined by the point accumulation state z_{it} . We allow for item and level interaction to account for the diminishing effect of items at higher levels. Finally, the idiosyncratic shock ξ_{it} affects the outcome of the game.

4.3. Flow Utility

Player i in period t receives the following per-period utility based on his or her choice of actions $d_{it} \in \{1, 2, 3\}$: whether to play the game without incurring in-app purchase ($d_{it} = 1$), whether to make in-app purchase and play the game ($d_{it} = 2$), or whether to permanently exit the game platform ($d_{it} = 3$).

$$u(S_{it}, d_{it}) = \begin{cases} \theta E[r_{it}(\alpha_i, s_{it}(d_{it}))] + c_m \cdot \mathbf{1}_{\{d_{it}=2\}} + c_p + R \cdot \mathbf{1}_{\text{LEVEL UP}(z_{it})} \cdot L_{\ell(z_{it})} + \epsilon_{it}, & \text{if } d_{it} \in \{1, 2\}, \\ 0 & \text{otherwise (exit).} \end{cases}$$

Players derive utility from immediate rewards r_{it} (i.e., expected number of points gained from the current period play), and one-time rewards R for reaching a new level ℓ at time t . The per-period player points reward r_{it} is determined by the game outcome (i.e., win or loss) and the winning and losing points reward design of the game, $(\psi_v^\ell, \psi_d^\ell) \in \Psi$, which differs by each level ℓ . That is,

$$r_{it} = W_{it} \cdot \psi_v^\ell + (1 - W_{it}) \cdot \psi_d^\ell \quad (2)$$

To model the increasing utility from leveling up at higher levels, we adjust R with respect to the level achievement criterion (i.e., the number of points required to level up), i.e., $L_{\ell(z_{it})}$. Since the level-up points criterion increases monotonically with levels in the current game design, players receive greater rewards for achieving higher levels. The idiosyncratic shock ϵ_{it} follows an extreme value distribution.

If the player decides to purchase in-game items ($d_{it} = 2$), he or she incurs a monetary cost c_m . The decision to purchase updates the player's current item stock state, which increases the chance of winning including the immediate period and all future play sequences of the game. We normalize the exit value as 0.

4.4. State Transitions

The state variables item stock k_{it} and points stock z_{it} evolves deterministically as follows:

$$k_{it} = \begin{cases} \min(k_{it} + 1, \bar{K}) & \text{if } d_{it} = 2 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

The player's item stock k_{it} increments by one with each purchase decision. Players can make multiple purchases over their lifetime. \bar{K} is the maximum item stock, representing the maximum item quality upgrade level.

$$z_{it} = \begin{cases} \min(z_{it} + \psi_v^\ell, \bar{\psi}^L) & \text{if } W_{it} = 1 \\ \max(z_{it} - \psi_d^\ell, \underline{\psi}^\ell) & \text{otherwise} \end{cases} \quad (4)$$

Upon realization of the game outcome, the player's points stock state z_{it} evolves deterministically following the game's points progression design Ψ . Here, $\bar{\psi}^L$ is the maximum points state of the game at the final level and $\underline{\psi}^\ell$ is the points criterion to unlock level ℓ . This ensures that once a player has reached a certain level by accumulating enough points, they cannot fall back below that level's threshold, ensuring that once a level is unlocked, it remains unlocked. In other words, z_{it} is incremented by ψ_v^ℓ when winning the game, but cannot exceed $\bar{\psi}^L$. Similarly, z_{it} is reduced by ψ_d^ℓ but not below the minimum threshold $\underline{\psi}^\ell$.

4.5. Bellman Equation

A player chooses action d_{it} that maximizes the expected discounted sum of utilities given the game design Ψ , the state variables and their transitions, and the idiosyncratic shock ϵ in each period. The Bellman equation can be written as

$$V(k, z, \alpha, \epsilon; \Theta, \Psi) = \max\{0, \max_{d \in \{1, 2\}} \{U(k', z, \alpha, \epsilon; \Theta, \Psi) + \beta \mathbf{E}[(V(k'', z', \alpha, \epsilon'; \Theta, \Psi) | k', z, \alpha]\}\} \quad (5)$$

where the idiosyncratic shock ϵ follows a Type-I extreme value, and the discount factor β is set to 0.9.⁵ The player continues to play the game if the expected continuation value is greater than 0, the normalized outside value of exit.

⁵ $\beta = 0.9$ gives the best fit compared to $\beta = 0.95, 0.99$, and 0.999 . In our context, setting lower discount factors greatly underestimates player exit probabilities and hence overestimates player purchase probabilities. Average inter-play time gap (in day) is around 2 days, and average lifetime play duration is 106 days.

5. Estimation

We estimate the model using two-step estimation (Hotz and Miller 1993). In the first step, we estimate the production function and the conditional choice probabilities (CCPs) of player action choice as a flexible function of state variables. The key assumption in the two-step estimation is that the first-stage CCPs represent the agent's optimal action probability given the state variables. In the second step, we estimate the structural parameters that rationalize the first stage policy estimates.

5.1. Step 1: Estimating CCPs

In the first stage CCP estimation, we estimate a flexible mapping between observable states and player action probability. The relevant state variables in our model are item and points stock states, $S_{it} = \{k_{it}, z_{it}\}$. We estimate the two-step procedure using the player state space starting from level 6, both for computational efficiency in the state space and practical reasons. The early levels 1-5 consist of beginner level tutorials and short level length, with these five levels accounting for only 15% of total points collection available in the game. We discretize the points state for each level from 6 to 11 into 10 increments and additional transition states to track level-up bonus (a total of 65), and item stock state to evolve deterministically up to 25 transactions. This leaves us with a total of 1690 state combinations.

Typically, player ability is treated as an unobserved variable. In order to incorporate rich player heterogeneity in win rates as shown in the model-free evidence, we instead treat player ability as an observed variable by estimating it from player lifetime gameplay records. Because our setting is a game, where we observe every player action, environment, and outcome, we can estimate player ability α_i as an individual fixed effects parameter from Equation 1, the player production function, controlling for the effects of items and game environments on player win rates. By incorporating player ability as an observed variable, we can directly include it in our first stage policy estimation. This enables us to account for rich observed heterogeneity in player ability levels in predicting player action. For the first stage estimation, we normalize player ability score as a continuous variable between 0 and 1, with 1 representing the highest ability level.

Given the state variables and observed ability heterogeneity of the players, we estimate the player action policy using a flexible multinomial logistic regression. We account for player unobserved heterogeneity in the first stage CCP estimation through persistent latent segments and estimate heterogeneous policy functions using the EM algorithm (Arcidiacono and Miller 2011, Chung et al. 2014). We assume that player i belongs to one of G segments $g \in \{1, \dots, G\}$ with segment probabilities $q_i = \{q_{i1}, \dots, q_{iG}\}$. Let π_g denote the population probability of being in segment g . We iteratively maximize the log likelihood in Equation 6,

$$\sum_{i=1}^N \sum_{g=1}^G \sum_{t=1}^T q_{ig} \ln[\mathcal{L}(d_{it}|S_{it}, \alpha_i, g, \beta_g)], \quad (6)$$

where

$$q_{ig} = \frac{\pi_g \prod_{t=1}^T \mathcal{L}(d_{it}|S_{it}, \alpha_i, g, \beta_g)}{\sum_{g=1}^G \pi_g \prod_{t=1}^T \mathcal{L}(d_{it}|S_{it}, \alpha_i, g, \beta_g)}, \quad (7)$$

and $\mathcal{L}(d_{it}|S_{it}, \alpha_i, g, \beta_g)$ is the choice probability of taking action $d_{it} = j$ for segment type g ,

$$\mathcal{L}(d_{it}|S_{it}, \alpha_i, g, \beta_g) = \frac{e^{\beta_g^j[S_{it}, \alpha_i]}}{\sum_j e^{\beta_g^j[S_{it}, \alpha_i]}}. \quad (8)$$

The EM algorithm begins by setting initial values for β_g , and π_g .

(a) Compute $q_{ig}^{(m+1)}$ using Equation (2) with $\beta_g^{(m)}$ and $\pi_g^{(m)}$.

(b) Update population shares

$$\pi_g^{(m+1)} = \frac{1}{N} \sum_{i=1}^N q_{ig}^{(m+1)}.$$

(c) Update $\beta_g^{(m+1)}$ for each segment g by maximizing Equation (1) with $q_{ig}^{(m+1)}$ and $\pi_g^{(m+1)}$.

We iterate steps (a)-(c) until convergence. We initialize β_g by randomly partitioning the players into G segments and maximizing the log-likelihood, and population shares to be $1/G$.

From this iterative estimation step, we obtain segment-specific policy function parameters, along with the population segment probability estimates π . We use the segment-level policy functions to obtain structural parameters of each segment, which we describe in the next section. A caveat with the two-step estimation is that the first-stage policy function estimates can be biased if the state variables in the policy function are correlated with the first-stage errors. Our approach, which leverages rich observed and unobserved player heterogeneity, helps mitigate this issue.

5.2. Step 2: Structural Parameter Estimation

The key idea of the two-step estimation is to represent the value function in terms of the policy function estimated in first stage, which reflects the player's optimal actions. That is, $V(\cdot; \theta) = h(P(\cdot; \theta), \theta)$ and $P(\cdot; \theta) = g(V(\cdot; \theta), \theta)$. Given our discrete state space, we can solve the value function as a system of linear equations,

$$V(S_{it}, \alpha_i, g; \Theta, \Psi) = (I - \beta F)^{-1} \left\{ \sum_{d_{it} \in \{1, 2, 3\}} P(S_{it}, \alpha_i, g; \Theta, \Psi) \cdot [u(S_{it}, \alpha_i, g, d_{it}; \Theta, \Psi) + E[\epsilon|d_{it}]] \right\} \quad (9)$$

where F is the matrices of transition probabilities corresponding to action d_{it} . The Type I extreme value assumption of the error term allows us to solve the value function analytically, such that $E[\epsilon|d_{it}] = \gamma - \ln(P(\cdot; \Theta))$. γ is the Euler's constant.

Furthermore, we can express the player's choice probability of action d_{it} under the structural parameters of our model in closed-form using the distribution assumption of the errors as follows:

$$\Pr(d_{it}|S'_{it}, \alpha_i, \epsilon; \Theta, \Psi) = \frac{\exp(u(d_{it}, S'_{it}, \alpha_i, \epsilon; \Theta, \Psi) + \beta E_{S''_{it}, \alpha_i, \epsilon'; \Theta, \Psi|d_{it}, \epsilon} V(S''_{it}, \alpha_i, \epsilon'))}{\sum_{\tilde{d}_{it} \in \{1, 2, 3\}} \exp(u(\tilde{d}_{it}, S'_{it}, \alpha_i, \epsilon; \Theta, \Psi) + \beta E_{S''_{it}, \alpha_i, \epsilon'; \Theta, \Psi|\tilde{d}_{it}, \epsilon} V(S''_{it}, \alpha_i, \epsilon'))}. \quad (10)$$

We construct the moment equality estimator using the following moment condition, where \hat{Pr} is the optimal policy estimated from the first stage, and \tilde{Pr} is the policy informed by the model parameters. We minimize equation 11, the distance between optimal policy and the model choice probabilities, weighted by player segment probabilities q_{ig} .

$$\begin{aligned} & \sum_{i=1}^N \sum_{t=1}^T q_{ig} \left[(\hat{Pr}(d_{it} = 2|S_{it}, \alpha_i, g, \epsilon; \beta_g) - \tilde{Pr}(d_{it} = 2|S_{it}, \alpha_i, g, \epsilon; \Theta_g, \Psi))^2 \right. \\ & \quad \left. + (\hat{Pr}(d_{it} = 3|S_{it}, \alpha_i, g, \epsilon; \beta_g) - \tilde{Pr}(d_{it} = 3|S_{it}, \alpha_i, g, \epsilon; \Theta_g, \Psi))^2 \right] \end{aligned} \quad (11)$$

For the second stage model estimation, we discretize player ability type variable into 20 bins and estimate the value function for each ability type and segment. To compute standard errors, we generated 500 bootstrap datasets following [Bajari et al. \(2007\)](#). For each bootstrapped dataset, we estimate both the first and the second stage to account for the estimation errors from the first stage policy estimation.

5.3. Identification

There are a few challenges in identifying the dynamic structural model of game playing. First, the intrinsic player ability is not observed. Our long panel of gameplay records and the variations in environments, item quality, and winning outcomes across and within players allows for the identification of player ability through player fixed effects in equation 1. The average gameplay records used for estimating the production function for each player is 171. While it is theoretically possible to identify item-ability substitutability or complementarity, doing so is practically infeasible given our individual-specific measure of ability. The trade-off we make for capturing this level of granularity in individual heterogeneity is the inability to separately identify the effects of player learning and item-ability interactions. We follow [Kasahara and Shimotsu \(2009\)](#) for the identification of unobserved finite mixture heterogeneity.

Second, the parameters in the flow utility function needs to be identified by the revealed preference argument. In particular, the mapping between the differences in conditional value functions and the conditional choice probabilities, and the normalized exit value form the basis for our model identification. With the exit value normalized to 0, the cost of play parameter c_p is identified from the two play decisions. The utility from points reward θ is identified from the play versus play and purchase decision, as the item state is updated upon purchase decision before play, changing the win probability and the expected value of points. The reward from level-up R and the cost of purchase c_m are identified from the intertemporal linkage of states, and the costs and rewards from play.

Lastly, we fix the discount factor to be 0.9.

6. Results

We discuss our results in the following order: 1) player production function and ability estimates, 2) first stage policy estimates, and 3) second stage structural parameter estimates.

6.1. Production Function and Ability Estimates

We estimate the production function using a linear probability model of player item and level states with individual fixed effects, controlling out the opponent effect.⁶ We use the estimated individual fixed effects as the measure of player ability. The production function, shown in Table 3, accommodates the following three key features. First, win probability is higher for higher ability players. Second, player win probability increases with item. Specifically, one additional item purchase at level 6 increases player win probability by around 2.6%⁷. We allow for the diminishing effect of item as levels increase. Third, player win probability decreases with level. Notably, the game becomes significantly more difficult at level 9, with win probability dropping by around 10% compared to the previous level. This increasing difficulty at higher levels is a common feature in gaming environments.

To demonstrate the reliability of our ability measure, we present the relationship between player average win probability in Figure 7a. There is a clear positive relationship, with higher ability players exhibiting higher win rates. Figure 7b displays the distribution of the player ability estimates, highlighting significant heterogeneity in our player sample.

6.2. First Stage Policy Estimates

Given the ability estimates of players, we estimate the first stage policy estimation of player action probabilities using a flexible multinomial logistic regression, accounting for both observed and unobserved heterogeneity. We find that the three-segment model best fits the data based on the AIC and BIC criterion. We report the first stage policy estimates for each segment in Table 4. Segment 1 is the smallest, comprising 7% of the players, followed by Segment 2 with 23%, and Segment 3 with 70%. We report some illustrative features of the policy with respect to player

⁶ For the second stage structural parameter estimation, we control out the effect of opponents using the median value of the opponent elo scores at each level.

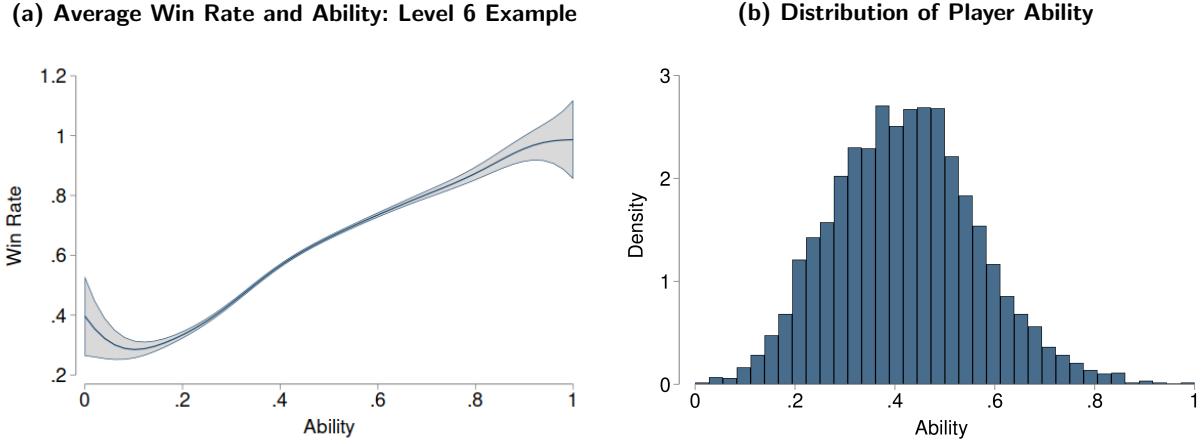
⁷ To provide additional evidence of the effect of item purchase on player win probability, we conduct a more localized before-and-after analysis of player win rates, comparing the five games before and after the purchase incident in Appendix A. The measured effect size largely aligns with the item effect measured in our production function.

Table 3 Linear Probability Model: Production Function Estimates

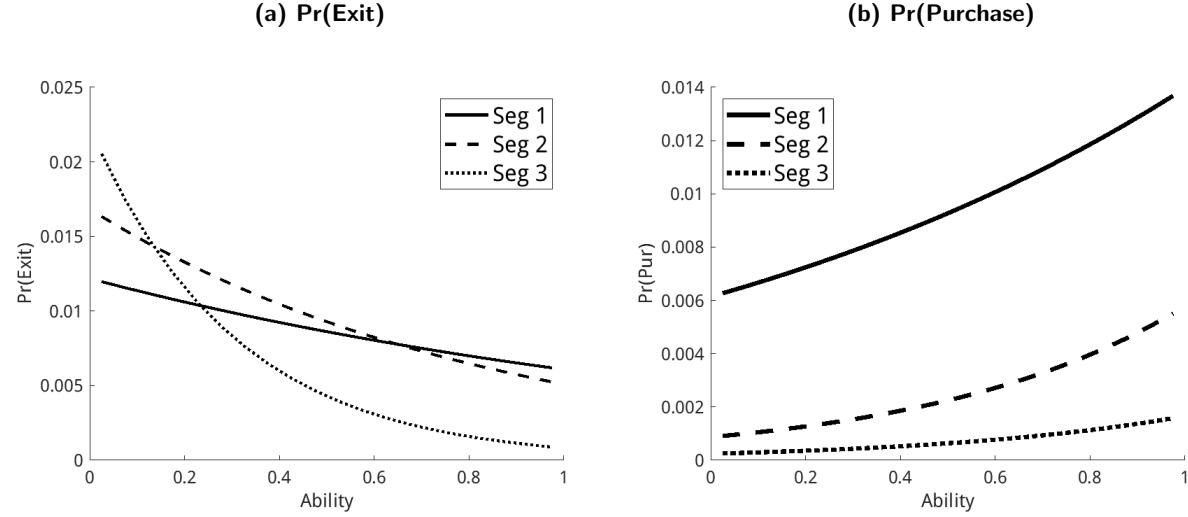
	(1)
	Win
item stock	0.02623*** (0.00157)
lvl:6	-0.08207*** (0.00146)
lvl:7	-0.06441*** (0.00187)
lvl:8	-0.07087*** (0.00199)
lvl:9	-0.17077*** (0.00228)
lvl:10	-0.17392*** (0.00296)
lvl:11	-0.23899*** (0.00384)
lvl:6 × item stock	-0.00473*** (0.00136)
lvl:7 × item stock	-0.00699*** (0.00141)
lvl:8 × item stock	-0.01082*** (0.00140)
lvl:9 × item stock	-0.01151*** (0.00143)
lvl:10 × item stock	-0.01430*** (0.00148)
lvl:11 × item stock	-0.01505*** (0.00147)
opponent elo score	-0.24202*** (0.00277)
Observations	1,168,880
Individual FE	Y
Adjusted R^2	0.049

Note: Level 5 used as baseline. Robust standard errors in parentheses;
 *** <0.01, ** p<0.05, * p<0.1

ability in Figure 8. Consistent with our model-free evidence, the probability of exit decreases with player ability, while the probability of purchase increases with ability across all segments. Segment 1 has the highest purchase rates and generally the lowest exit rates, indicating that these players are the most engaged and likely to spend money in the game. Segment 3, the largest segment,

Figure 7 Player Ability Estimates

has the lowest purchase rates. While Segment 3 shows a relatively flat decrease in exit probability across abilities, Segment 3 exhibits a steeper decline among lower ability players.

Figure 8 Player Action Policy by Ability Type

Note: Policy visualization based on example state: (Level 6, Level Completion 20-30%, and Item Stock 0)

To gain deeper insights on the segment characteristics, we report descriptive statistics in Table 5 and visualize the survival rate and the ability distribution of each segment in Figure 9. The descriptive evidence further provides support that the smallest share of players, Segment 1, comprises of high-spending individuals who also stays longer in the game and progress to higher levels, followed by Segment 2. Segment 3 has the lowest average player ability and spends the least. Because this

Table 4 First Stage Estimates: Player Action Policy Function

Choice		Seg 1 (6.92%)	Seg 2 (22.87%)	Seg 3 (70.21%)
Purchase	ability	1.0078** (0.3696)	1.8555*** (0.3389)	1.9965*** (0.3636)
	item stock	0.2119*** (0.0185)	0.4950*** (0.0163)	1.8689*** (0.0478)
	item stock^2	-0.0069*** (0.0010)	-0.0128*** (0.0007)	-0.1999*** (0.0086)
	pct lvl complete	2.6695*** (0.4361)	-0.9826** (0.4249)	1.2923*** (0.4825)
	ability × pct lvl complete	-0.7362 (0.7061)	0.1418 (0.6362)	-0.3467 (0.7756)
	pct lvl complete^2	-2.7620*** (0.4350)	0.2979 (0.4454)	-1.8515*** (0.4203)
	lvl:7	-0.0348 (0.1038)	-0.2065** (0.1016)	-0.2914*** (0.0872)
	lvl:8	0.1223 (0.1009)	-0.4376*** (0.1042)	-0.5923*** (0.0908)
	lvl:9	-0.3773*** (0.1139)	-0.6725*** (0.1089)	-0.7774*** (0.0983)
	lvl:10	-0.6498*** (0.1268)	-1.3472*** (0.1435)	-0.8373*** (0.1201)
	lvl:11	-0.9534*** (0.1431)	-1.5476*** (0.1598)	-1.0228*** (0.1534)
	cons	-5.5698*** (0.1687)	-6.8071*** (0.1457)	-8.5193*** (0.1699)
Exit	ability	0.7717** (0.3469)	-3.0300*** (0.2113)	-3.6848*** (0.1987)
	item stock	-0.1393*** (0.0286)	-0.2053*** (0.0219)	-0.0152 (0.0262)
	item stock^2	0.0056*** (0.0013)	0.0087*** (0.0009)	0.0089*** (0.0034)
	pct lvl complete	-0.9030* (0.5159)	-1.7382*** (0.2657)	-1.3912*** (0.2639)
	ability × pct lvl complete	-5.8553*** (0.9142)	7.3085*** (0.5172)	1.4232*** (0.4862)
	pct lvl complete^2	2.8489*** (0.4691)	-2.1943*** (0.2832)	-0.0362 (0.2415)
	lvl:7	-0.8087*** (0.0877)	-0.3470*** (0.0532)	-0.0847* (0.0500)
	lvl:8	-0.6385*** (0.1128)	-0.3837*** (0.0568)	0.0199 (0.0520)
	lvl:9	-0.5340*** (0.1140)	-0.1310** (0.0640)	0.3191*** (0.0549)
	lvl:10	-0.9494*** (0.1757)	0.0801 (0.1075)	0.3248*** (0.0785)
	lvl:11	-0.7838*** (0.1840)	-0.6067*** (0.1916)	0.3303*** (0.1036)
	cons	-4.3423*** (0.1257)	-3.4950*** (0.0748)	-3.4308*** (0.0701)

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

segment has greater share of low ability players, it also has higher exit rates, especially at the early levels.

Table 5 Descriptive Characteristics of Segment

Seg 1 (2.6%) N=107	Mean	Median	75Q	90Q	99Q
Avg Total No. Purchase	6.8785	5	9	14	24
Avg Purchase Rate	0.0219	0.0158	0.0260	0.0365	0.0789
Avg Level Reached	9.3364	9	11	11	11
Avg Total No. of Games Played	470.66	314	639	1021	1980
Ability Score	0.4823	0.4860	0.5912	0.6861	0.8398
Pay-to-Win Player Share			100.00%		
Seg 2 (5.2%) N=218	Mean	Median	75Q	90Q	99Q
Avg Total No. Purchase	2.7661	1	3	7	25
Avg Purchase Rate	0.0120	0	0.0120	0.0328	0.0829
Avg Level Reached	7.9725	8	9	10	11
Avg Total No. of Games Played	263.68	164	444	673	916
Ability Score	0.5330	0.5193	0.6684	0.7812	0.9282
Pay-to-Win Player Share			68.35%		
Seg 3 (92.2%) N=3,838	Mean	Median	75Q	90Q	99Q
Avg Total No. Purchase	0.2507	0	0	1	5
Avg Purchase Rate	0.0017	0	0	0.0024	0.0333
Avg Level Reached	7.3233	7	8	9	11
Avg Total No. of Games Played	166.74	112	227	387	887
Ability Score	0.4129	0.4117	0.5056	0.5882	0.7556
Pay-to-Win Player Share			10.76%		

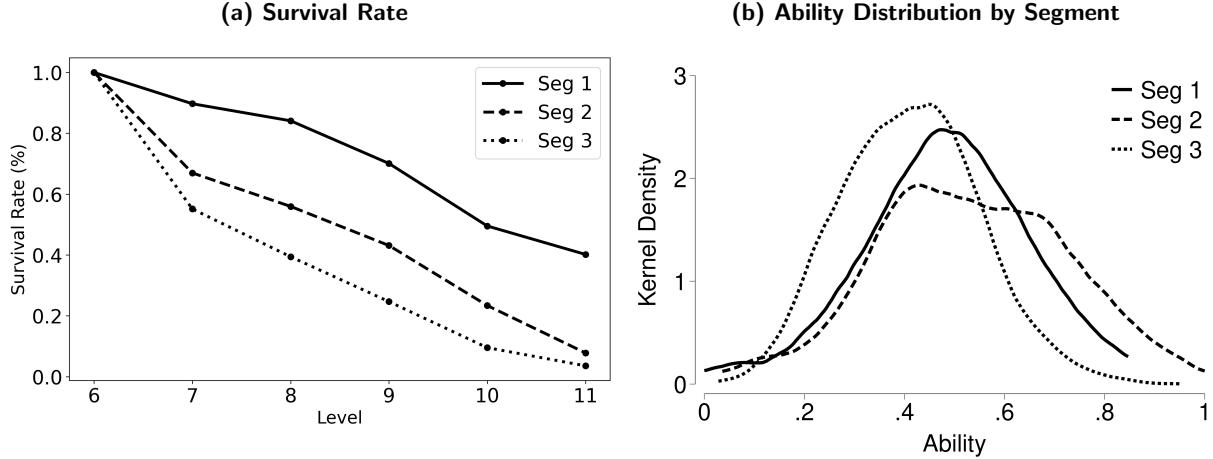
Note: The descriptive statistics are based on deterministic segment assignment (i.e., the maximum of probabilistic segment probabilities estimated in the first stage).

6.3. Structural Parameter Estimates

Table 6 reports the estimates of the structural parameters of the model, which further reveal important differences in the game play preferences among the three segments.

Segment 1 represents the smallest share of players (7%) but those who spend the most, which is reflected in their lower price sensitivity for ability enhancers (c_m).⁸ Despite their low sensitivity to immediate points rewards (θ), they derive significant utility from progressing through game levels,

⁸ Since price is invariant, we normalized the price to 1; so c_m is the disutility for paying that unit price.

Figure 9 Descriptive Characteristics of Segment: Survival Rate and Ability Distribution

as indicated by their high level-up reward (R). This segment's positive (near zero) cost of play (c_p) suggests that these players do not find playing the game costly, but rather enjoy spending time in the game. We henceforth label this group as *premium enthusiasts*.

Table 6 Structural Parameter Estimates

	Segment 1 <i>Premium Enthusiasts</i> (7.0%)	Segment 2 “Instant-Win” Seekers (23.0%)	Segment 3 “Easy Progress” Seekers (70.0%)
θ	0.0003	0.0050	0.0050
c_m	-4.4089	-5.2775	-6.4997
c_p	0.0002	-0.0395	-0.0288
R	0.0039	0.0016	0.0036

Segment 2 players, representing share of 23% of players, receive a greater utility from immediate points reward (θ) and have the second lowest price sensitivity for ability enhancers (c_m), below the *premium enthusiasts*. They however have the highest cost of play (c_p), indicating that they find playing the game more of a chore. This suggests that these players are less likely to continue playing without high enough points reward from current game, and their utility from level-up (R) is the lowest among the segments. We label this group as “instant-win” seekers.

Segment 3 constitutes the largest group with 70% of the players. These players have the same utility from immediate points reward (θ) as “*instant-win*” seekers, but their price sensitivity for enhancers (c_m) is the highest. They also find playing the game costly (c_p), but receive higher utility from level-up rewards (R) than “*instant-win*” seekers. We label them as “*easy-progress*” seekers.

We report the model fit in Table 7. In general, the model performs reasonably in matching the targeted moments, total play count (retention) and total purchase (monetization), especially well in accounting for the heterogeneity across the three latent segments. Hence, we conclude that the model can reasonably match player action and play behavior observed in data, especially with respect to different insights and predictions across the latent segments.

Table 7 Model Fit

	Real Data			Model Simulation		
	Seg 1	Seg 2	Seg 3	Seg 1	Seg 2	Seg 3
Average Lifetime Play Count	231.35	147.07	185.14	243.75	167.51	197.42
Average Level Reached	7.69	7.15	7.47	8.92	7.79	7.97
Average Total Purchase	2.77	0.70	0.29	2.95	0.90	0.31
Average Purchase Rate (per 100 plays)	0.97	0.33	0.19	1.2	0.53	0.15

7. Counterfactual

The primary challenge for game designers is balancing the retention and monetization for players with wide ranging ability and gameplay preferences (e.g., price sensitivity for ability enhancers, reward valuation, play costs). In this section, we design targeted interventions to accomodate player heterogeneity in managing retention-monetization dynamics in gaming environments. In doing so, we demonstrate the added value of incorporating player heterogeneity in ability and gameplay preferences. To perform counterfactual analysis, we generate a representative sample of 20,000 individuals from the segment, ability, and initial item stock state distribution, simulating on average 200 gameplay records for each player.

7.1. Accelerating Level Progression for High Ability Players

In the game, players progress up to their own levels of difficulty frontiers. For high ability players, such difficulty frontiers come much later in the game. In the first counterfactual analysis, we examine whether accelerating early level progression for high-ability players can improve their overall retention and monetization. This approach aims to expedite challenges for higher ability players and potentially increase in-game purchases by facilitating faster level-ups. To implement this policy, we first classify players into four ability quartiles, and target those in the highest quartile. Table 8 shows the targeted segment share of the representative players from model simulations. The average frontier level of high ability players is above level 9 across all segments. To expedite the speed of player level progression, we increase the player win probability by 5% at early levels.⁹

Table 8 Segment Share of High Ability Players

Segment	Ability	Player Share (%)	Avg Level Reached
1: <i>Premium Enthusiasts</i>	Q4	1.57	9.69
2: <i>“Instant Win” Seekers</i>	Q4	2.74	9.13
3: <i>“Instant Progress” Seekers</i>	Q4	10.55	9.26

Table 9 reports the retention and monetization results for the accelerated level progression intervention. Overall, we find that expediting early level progression for high ability players increases both total retention by 1.27% (measured by lifetime number of games played) and total profit by 2.87%. In all segments, players on average progress to higher levels and play a greater number of games.

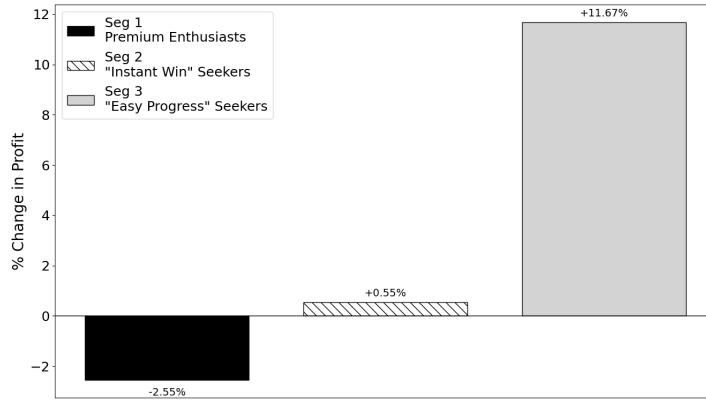
We visualize the change in profit in Figure 10. We show that the firm gains in profit by expediting level-ups by effectively lowering difficulty level at early stages from players who find playing the game itself more costly (*“easy progress” seekers* and *“instant win” seekers*), but loses in profit from players who find playing the game itself more enjoyable (*premium enthusiasts*). The increase in net total profit is largely driven by the *“easy progress” seekers* (segment 3), with their profit

⁹ This corresponds to levels 6-8 in our analysis. Practically, the firm can implement this policy by matching the player with less difficult opponents.

Table 9 Accelerating Level Progression for High Ability Players: Effect on Retention and Monetization

Ability	% Change in Avg Level Reached	Retention (% Change in Avg Play Count)	Monetization (% Change in Profit)
Total	Q4 + 1.90	+ 1.27	+ 2.87
Seg			
1: Premium Enthusiasts	Q4 + 0.36	+ 0.39	- 2.55
2: "Instant Win" Seekers	Q4 + 1.58	+ 0.75	+ 0.55
3: "Instant Progress" Seekers	Q4 + 2.22	+ 1.51	+ 11.67

increased by 11.7%. By expediting level progression to higher levels, the firm can generate more profit from the higher-ability players in the Achiever Segment who possess sufficient ability to advance through the later stages of the game. Because they gain higher utility from level-ups but incur significant play costs, expediting them to higher levels benefits firm profit by reducing the risk of early-stage attrition. While expediting early level-ups boosts retention across all segments, it does not necessarily translate to enhanced monetization. We find that retention and monetization do not necessarily align, demonstrating the nuanced nature of balancing retention-monetization in gaming environments.

Figure 10 Accelerating Level Progression for High Ability Players: Change in Profit by Segments

7.2. Value of Ability and Preference Heterogeneity in Personalized Intervention Design

In this section, we further demonstrate the value of incorporating player ability and gameplay preference heterogeneity in designing the timing of intervention. We compare three different frontier targeting strategies: (i) ability-based targeting, (ii) gameplay preference-based targeting, and

(iii) targeting using both ability and gameplay preferences. That is, we first define player frontier levels as the median exit levels of players for each ability type.¹⁰ Second, we use only the player gameplay preference information (i.e., the latent segment type) to compute the median exit level for each preference type. Third, we implement a fully personalized policy that incorporates both player ability and preference heterogeneity in computing the median exit level of the player. With the computed frontier levels, we provide targeted interventions and reduce difficulty by increasing effective win rate of 2.5% when the player reaches his or her frontier. For example, if the player's computed frontier level is 7, we adjust down the level difficulty for the player from level 7 and beyond. We summarize the computed frontier levels for targeted intervention in Table 10. For presentation purposes, we aggregate the frontier level information for ability types into four quartiles. Notably, the high-spending enjoyer segment has frontier levels at least one level higher than players with similar abilities in other segments.

Table 10 Frontier Targeting Policy for Personalized Interventions

Segment	Variable Used for Frontier Targeting			
	(1)		(2)	(3)
	Ability Only	Preference Only	Ability & Preference	Frontier Level
<i>1: Premium Enthusiasts</i>				
1	Q1	6	9	8
1	Q2	7	9	9
1	Q3	9	9	10
1	Q4	11	9	11
<i>2: "Instant Win" Seekers</i>				
2	Q1	6	7	7
2	Q2	7	7	8
2	Q3	9	7	8
2	Q4	11	7	10
<i>3: "Easy Progress" Seekers</i>				
3	Q1	6	8	7
3	Q2	7	8	8
3	Q3	9	8	9
3	Q4	11	8	10

We report the result of the targeted interventions in Table 11. Overall, retention efforts to decrease difficulty at the frontier lead to an increase in profit for all targeting policies. We highlight

¹⁰This corresponds to more granular ability types (20) used in the model estimation.

that incorporating unobserved preference heterogeneity is more effective than incorporating ability alone. This is supported by our earlier observation about differences in exit levels by segment, even within similar ability levels. We also note that the second policy, targeting the frontier with game play preferences, results in higher change in profit, even though retention and the average level reached are lower compared to the first policy (ability only). The fully personalized policy, which uses both ability and gameplay preferences for targeting, yields the largest increase in profit, at 1.05%. By increasing player retention at their frontier levels, the firm can further reap profits from players who are about to leave with a costless intervention.

Table 11 Effect of Personalized Timing of Interventions on Retention and Monetization

	Personalized Intervention Policy		
	(1)	(2)	(3)
Variable Used for Frontier Targeting	Ability	Gameplay Preferences	Ability & Gameplay Preferences
Win Probability Adjustment at Frontier	+ 2.5%	+ 2.5%	+ 2.5%
% Change in Avg Level Reached	+ 1.15	+ 1.10	+ 1.14
Retention (% Change in Avg Play Count)	+ 1.07	+ 1.06	+ 1.18
Monetization (% Change in Profit)	+ 0.43	+ 0.66	+ 1.05

8. Conclusion

This paper develops a dynamic structural model of consumer response for gaming environments to addresses novel questions that broaden the focus of empirical research in customer relationship management. In traditional customer relationship management contexts, retaining customers generally leads to increased monetization. Our paper is the first to recognize a unique aspect of the retention-monetization dynamics in the context of gaming environment—the two-way positive feedback between retention and monetization. In gaming, firms often monetize players' motivation to exert effort by providing them an opportunity to purchase in-game items that enhance players' effective skill, so that players can endogenously adjust their level of difficulty at a monetary cost.

The challenge for game designers is managing the dynamic relationship between retention and monetization for players with widely varying skill levels and preferences.

Counterfactuals reveal heterogeneous effects: accelerated early level progression scheme for high ability players hurts firm profit from *premium enthusiasts* who derive enjoyment from play itself, but helps retention and monetization from “*easy progress*” *seekers* and “*instant win*” *seekers* who find playing the game itself costly. The greatest improvement in profit comes from the “*easy progress*” *seekers* segment, who receives high utility from winning and value long-term level-up rewards more. While expediting early level progression increases retention across all player segments, it decreases monetization for *premium enthusiasts*. This highlights the nuanced retention-monetization dynamics in gaming environments.

We examine the value of incorporating ability and unobserved preference heterogeneity in designing the timing of difficulty adjustment interventions. We emphasize the role of unobserved preference heterogeneity for targeting. The fully personalized policy, which incorporates both ability and gameplay preferences for targeting, yields the highest profit increase. By prolonging player retention at their frontier levels, the firm can further gain profit from players who are nearing their exit from the game.

Gamification has become more mainstream, with gaming features incorporated into many aspects of our lives. Our framework extends broadly to settings in which a gaming layer has been added to benefit from consumer preference for game-like features. By understanding consumer response in these environments and accounting for their observed and unobserved preference heterogeneity, firms can develop targeted interventions to effectively manage consumer retention and monetization.

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Appendix

A. Effect of Item Purchase on Player Win Probability

We provide additional evidence in estimating the effect of item purchase on player win probability by conducting a localized before-and-after analysis of player win rates. This analysis focuses on player performance immediately before and after an item purchase. Specifically, we compare the win rates of players over the course of five games before and five games after they make an in-game purchase.

The after coefficient in Table A.1 captures the immediate effects of the purchased item on player win probability, controlling for ability, level, and opponent effects. We find that one in-game item transaction translates to around 3.6% increase in win probability. This effect size is largely consistent with the item effects measured in our production function, which quantifies the overall impact of in-game item purchase on player win probability across their entire match records.

Table A.1 Linear Probability Model: Before and After Purchase (5 Games)

	(1)
	Win
ability	0.52063*** (0.02648)
after	0.03554*** (0.00679)
lvl=7	0.02375** (0.01136)
lvl=8	0.02674** (0.01129)
lvl=9	-0.07839*** (0.01148)
lvl=10	-0.05936*** (0.01279)
lvl=11	-0.10529*** (0.01271)
opponent elo score	-0.14020*** (0.01811)
Constant	0.33278*** (0.01627)
Observations	20241
Adjusted R^2	0.029

Note: Robust standard errors in parentheses; *** <0.01 , ** $p<0.05$, * $p<0.1$

B. Pay-to-Win and Player Welfare

We evaluate the welfare implications of the pay-to-win business model in gaming environments. To simulate a scenario without pay-to-win, we set the cost of purchase coefficient to infinity so that no purchase occurs. Our result in Table B.1 suggest that pay-to-win models can create a win-win situation for both the firm and the player. Firm benefits from monetizing player engagement and retention. Players benefit from the option to purchase in-game items that can enhance effective win probability of the players, enabling faster progression and greater rewards. Among the three segments, the welfare gain from pay-to-win is greatest for segment 1, the *premium enthusiasts*. As shown in Figure B.1, pay-to-win options allow less able players to progress further than they otherwise would have, leveling the playing field and enhancing player experience in the game.

Table B.1 No Pay to Win and Player Welfare

	Current Design			No Pay-to-Win		
	Seg 1	Seg 2	Seg 3	Seg 1	Seg 2	Seg 3
Welfare	5.97	5.68	5.76	5.86	5.63	5.74
				(-1.95%)	(-0.86%)	(-0.25%)
Average total games played	243.75	167.51	197.42	229.51	159.07	193.94
Average level reached	8.92	7.79	7.96	8.62	7.67	7.92

Figure B.1 Ability Distribution: Current Desgin vs No Pay-to-Win

