Content Viewership and Customer Engagement: An Empirical Investigation into the Causal Effects of Esports Viewership on Customer Usage and Expenditures

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Abstract

The video game industry is increasingly invested in competitive gaming (esports) and content distribution via streaming. For game producers, the hope is that esports content may increase consumer interest and engagement. However, esports content is freely distributed and return on these investments is indirect and difficult to measure. In this study, we examine the effect of esports viewing on playing rates and purchasing activity. To execute the research, we construct a dataset that matches individual player's in-game activities and spending, with their esports viewing histories. Our analysis uses a recently developed machine learning method designed for causal inference. We find that watching esports leads to an increase in consumer playtime of about ten hour and an increase in spending of $5 over an eight-week post period. We also observe that there is substantial heterogeneity in individual level effects. Furthermore, we consider consumer learning as an explanatory mechanism. We find that viewing esports leads to improvement in in-game performance as measured by the number of kills and wins. This improvement provides an explanation for the increased player engagement. Our findings provide implications for managerial decisions related to targeting players with promotions designed to motivate esports streaming trial.

Keywords: Esports; Video Game; Consumer Learning; Causal Inference; Machine Learning; Causal Forest; Random Forest.

1. Introduction

The video game industry is rapidly growing and has become a significant element of the global entertainment sector. With global revenues in the range of $140 billion, the video game industry has surpassed the revenues of the global film industry box office ($40 billion) and far out paces major American professional sports leagues such as the NFL ($14 billion) (Ell 2018, Ingraham 2018, McNary 2019). The growth of the industry has been driven by a variety of digital technology advances. Networking, mobile and streaming technologies all facilitate interaction between gamers, game producers the gaming communities. In addition, competitive gaming or esports is also thought to be a driver of industry growth (Syracuse University 2019).

Esports is particularly interesting from a consumer behavior perspective as it creates new opportunities for players to engage with games and associated communities. Video games are different from most entertainment products in that consumers (players) are active participants in the entertainment. In addition, network and streaming technologies allow for significant interactions with other gamers. Streamed content on platforms such as Twitch, YouTube Live, or Mixer has helped create significant fan communities and esports stars. Current estimates are that over 250 million people watch esports via streaming services (Syracuse University 2019). Individual streamers have also been able to create substantial fan communities. For example, Tyler Blevins, also known as Ninja, has amassed a following of over 12 million followers and he generates $300,000 per month in streaming revenues (Syracuse University 2019). In terms of consumer benefits, streamed content and online communities may provide entertainment experiences and expert guidance that may help players improve their gaming performance.

However, due to the newness of esports, relatively little is known about the effects of such programming on customer engagement with the underlying games. This is a salient marketing issue because esports content and events require significant investments and many esports oriented games use freemium business models that rely on voluntary consumer expenditures (Wu et al. 2013). Game producers are, therefore, interested in questions related to how much of customers' in-game purchases or playing time are attributable to exposure to esports content. The goal of our research is to investigate the causal effects of esports viewership on subsequent game play and in-game spending.

The competitive nature of esports complicates the use of freemium business models. There are sub-categories within the freemium category of games. Pay-to-win games allow players to accelerate progress through purchases of in-game currencies while “esports” oriented games emphasize fair competition across players. Given that esports titles are often “free” at the point of acquisition and emphasize competitive fairness, esports titles typically produce revenue from paid in-game items that only alter the player’s appearance in the game rather than by providing competitive advantages. This is a challenging business model because the typical percentage of players that make any purchase is in the range of 5 to 10% of the total population of players (Hanner and Zarnekow 2015, Shi et al. 2015). Consumer engagement is therefore critical since publishers need to create sufficient interest to motivate what are essentially voluntary purchases of aesthetic items.

More generally, the question of whether and how free content can stimulate subsequent paid activity is an important marketing topic. The literature related to freemium business models (Bapna and Umyarov 2015, Chica and Rand 2017, Gu et al. 2018) has emphasized the transition from complimentary but constrained versions of a product to paid versions of a premium product. “Freemium” like business models are also common in the entertainment sector. For example, sports are frequently distributed via free channels such as television with a goal of motivating consumers to spend on tickets or the purchase of a pay-per-view broadcast. Esports content provides a similar marketing intervention for video game makers.

The purpose of our research is to investigate the relationship between free content and consumer engagement. Our basic conjecture is that esports content may potentially increase the appeal of a game, foster fan communities and provide insights that improve player’s game performance. Specifically, we investigate the effects of viewing esports on subsequent consumer spending and product usage using video game industry data. The data on playing rates and spending is provided by a leading Multiplayer Online Battle Arena (MOBA) game producer. This game maker also produces and distributes esports content via a prominent streaming service. We also investigate the relationships between observable customer traits and the effects of esports viewing. Given the richness of data related to video game consumption, observable customer heterogeneity is especially important. For example, game producers can monitor and target based on data such as playing rates, game performance or metrics related to in-game character selection.

Our empirical analysis uses the causal forest (CF) algorithm (Athey et al. 2019, Wager and Athey 2018). The CF algorithm can estimate heterogeneous treatment effects for usage and spending for each individual consumer. The analysis is more granular than conventional forms of causal inference analysis, in that we model individual-level treatment effects. The analysis yields strategic and managerially meaningful results because it allows us to explore the heterogeneity in treatment effects based on customer's individual-level covariates. Individual level estimates may improve a game operator's future ability to identify the most profitable segments to target with esports related promotional offers.

Our results suggest that watching esports content significantly increases customer engagement in terms of both participation rates and spending. For example, watching esports leads to roughly a 10 hour increase in gamer's playtime during an 8 week post-period. In terms of in-game spend, we observe that there is an average effect of about a $5 increase during the post-period for esports viewers. We also find that the magnitudes of the treatment effects vary depending on customer's in-game behavior. We find that more experienced players and players who exhibit variety seeking in character choice tend to spend and play more if exposed to esports.

In addition to the overall findings related to esports viewing, we also conduct analyses related to the underlying mechanisms that drive the main effects. In particular, we consider a mechanism related to the learning that takes place from watching content. We speculate that consuming esports content may increase player knowledge and in-game skills. We operationalize this speculation by evaluating how esports viewership effects in-game performance. We find that compared to non-viewers, esports viewers have more in-game success. This finding is consistent with the idea that esports content improves customer engagement by increasing gamer knowledge related to effective strategies.

The paper is organized as follows. We begin with a background section that provides context and positions our research relative to the literatures on gaming, sponsorship and freemium business models. We then present a data section that includes descriptive statistics and model free evidence that highlights trends and empirical challenges. Following the data section, we describe the causal forest algorithm and present our main results. We then present supplemental analyses that explore the underlying mechanisms and the robustness of the findings. We conclude with a discussion of limitations and future research directions.

2. Background

Our research examines how esports viewership affects subsequent consumer behavior. While our research context is the novel setting of esports, the research is relevant to the larger topics of entertainment and sports marketing. For instance, the brand equity of stars has been cited as an important diver of the success of films (Eliashberg et al. 2006). Brand equity may also be relevant to esports, since esports competitions provide a tool for growing the awareness and highlighting the excitement of a game. In terms of sports, research has emphasized the importance of competition (Lewis 2008) and fan communities (Zagnoli and Radicchi 2010). Esports content highlights the competitive aspects of specific video games and may provide awareness of the accompanying fan communities (Hamari and Sjöblom 2017).

In this section, we provide background material that positions our research and our intended contributions. We begin with a brief review of the literature on gaming and esports that provides context. Next, we consider two aspects of the marketing literature that are especially related to the use of esports as a tool for increasing interest in a video game. First, we consider research related to sponsorship. Sponsorship is relevant because esports leagues are increasingly sponsored by the producers of the games. Second, we discuss research related to freemium business models. Freemium business models are critical because esports titles and content, are often freely distributed and rely on voluntary transactions.

2.1. Gaming and Esports

Gaming is an increasingly important part of the entertainment industry and an accompanying academic literature has developed. The early literature largely focused on firm-level strategies in the gaming industry. Studies have focused on oligopolistic and two-sided market characteristics of the game industry and examined strategies for hardware (i.e., consoles) and software (i.e., game titles) producers (Binken and

Stremersch 2009, Derdenger 2014, Landsman and Stremersch 2011, Liu 2010, Nair 2007, Zhou 2016). For example, Binken and Stremersch (2009) showed that console manufacturers should focus on blockbuster game titles as they create positive externalities that increase demand for hardware consoles. In addition, several researchers also proposed structural models for game system pricing that incorporate indirect network effect and consumer heterogeneity (Liu 2010, Nair 2007, Zhou 2016).

There has been relatively limited empirical research that has examined individual players' game expenditures and consumption. Historically, it has been difficult to assemble individual level panel data on game purchases and to collect data on post-purchase game usage (Huang et al. 2019, Jo et al. 2019). There are a few notable exceptions (Huang, et al. 2019, Jo, et al. 2019, Nevskaya and Albuquerque 2019, Park et al. 2018). For example, Park, et al. (2018) studied peer influence effects of game item usage in online games. They found that gamers' spending is positively affected by peers' spending. These peer effects were positively moderated by game experience for functional items but negatively moderated for decorative items. Huang, et al. (2019) studied customers' game play behaviors using a Hidden Markov model and suggested an optimized matching algorithm to maximize overall game play volume. They found that gamers with high-, medium-, and low-engagement react differently to several motivational factors such as feelings of curiosity about the game.

There are also experimental and behavioral studies that have examined more general gaming behaviors and the implications of gaming features (Holbrook et al. 1984, Müller-Stewens et al. 2017). For example, Müller-Stewens, et al. (2017) showed that use of games in information delivery increased consumers' the rates of compliance (i.e., innovative feature adoptions). They also showed that these behaviors are mediated by consumer playfulness and perceived vividness of information. Research by Holbrook, et al. (1984) discussed several components of consumer's playful consumption such as perceived complexity, performance, emotions, and personality−game congruity. They found that positive emotions are aroused when consumers' preferred cognitive style and game format is matched, and that positive affect increases with the mastery of the game.

A relatively recent but increasingly important component of the video game industry is competitive gaming or esports.[1] For example, the 2018 League of Legends World Championship generated over 200 million concurrent viewers during the finals. In terms of scale, this was roughly twice as many viewers as the most watched NFL Super Bowl (Genova 2018). Market research firms have projected that the esports sector will soon generate more than $1 billion in revenue (Carpenter 2019, Yahoo 2019).

While esports has become a culturally and economically important phenomenon, it has received limited attention from academic researchers. There has been some survey research that has explored the psychological drivers of esports viewing (Hamari and Sjöblom 2017, Lee et al. 2018, Sjöblom et al. 2018). Hamari and Sjöblom (2017) found that escapism, game knowledge, game skills, novelty, and esport athlete's aggressiveness influence esports spectating frequency. In addition, cultural studies researchers have discussed esports (Seo and Jung 2014). For example, in a conceptual paper, Seo and Jung (2014) highlighted that consumers can concurrently play multiple roles such as being both players and observers.

The extant literatures on video games and esports suggests several interesting avenues for consumer behavior research. For instance, Seo and Jung's conceptualization highlights an increasingly common marketing issue. Specifically, it is increasingly common in digital environments that consumers can be both participants and observers. Social media researchers (Moe and Schweidel 2011, Toubia and Stephen 2013) have also considered the dual roles of creators and consumers. However, the esports context of both playing a game and being a watcher of others playing, is different than the social media environment since the consumption experience is competitive in nature. This may be a key differentiator if concurrent watching and playing are connected through active learning during watching that results in improved play when participating. The existence of multiple elements of playful consumption (Holbrook et al. 1984) also raises interesting questions related to esports. For example, Holbrook, et al. (1984) find that playful consumption is affected by performance and emotions. Esports programming may motivate increased consumption if incremental knowledge from viewing affects future performance.

[1] Esports refers to '… *a form of sports where the primary aspects of the sport are facilitated by electronic systems* …' Hamari J, Sjöblom M (2017) What is eSports and why do people watch it? *Internet Research*. 27(2):211-232..

2.2. Sponsorship

While esports is a relatively new phenomenon, the esports aspect of video game business models shares similarities with existing marketing practices. For example, esports provides a communications function that increases awareness of specific games. Specifically, esports represents a form of sponsorship since title producers explicitly sponsor esports events and leagues. The production and distribution of free esports content with the goal of increasing interest in the sponsoring game is a fairly new marketing practice but the general issue of sponsorship is well known to marketing academics (Agrawal and Kamakura 1995, McCracken 1989). Notably, the esports environment, which allows a linkage between sponsorship exposure and subsequent consumption, provides a unique opportunity to study sponsorship effects at the level of the individual consumer.

The sponsorship literature has yielded mixed findings. Agrawal and Kamakura (1995) studied 110 celebrity endorsement contracts and found that deal announcements create positive abnormal returns. However, relatively recent studies by Cobbs et al. (2012) and Mazodier and Rezaee (2013) showed that sponsorship announcements result in negative abnormal returns for many firms. This inconclusive set of results may give game makers pause given the expenses involved in sponsoring esports already exceed over $500 million as of 2017 (Newzoo 2017). The traditional sports industry has significant sponsorship activity ranging from product endorsements (Chung et al. 2013) to stadium naming deals. Chung et al. (2013) showed that Nike’s Tiger Wood endorsement generated over $103 million in golf ball sales over ten years.

The celebrity endorsement literature has emphasized the roles of endorser attractiveness (McGuire 1985) and credibility (Hovland and Weiss 1951, Sternthal et al. 1978). McCracken (1985) suggested that endorsers are effective because a celebrity’s cultural meaning is transferred to the product. In the case of sports sponsorships such as stadium naming deals, this transference model may be appropriate. While endorsements such as Tiger Woods advocacy for a product may be based on inferences about the celebrity’s expertise, many sponsorships in the sports category such a stadium naming deals are driven by firms’ desires to attach their brands to teams’ brands.

The idea of transferring cultural meaning may be relevant for esports. Similar to traditional sports

(Zagnoli and Radicchi 2010) esports has distinctive fan cultures (Wolf 2019) and elements of community (Influencer Marketing Hub 2019). Esports programming highlights the excitement and community surrounding each title by showing engaged crowds and intense competition. Esports may benefit a game through association transfer or meaning transfer (McCracken 1985).

2.3. Freemium Business Models

The Free-to-Play (FTP) systems used by many video game producers involved in esports are forms of freemium business models. In general, "freemium" refers to business operations that provide free basic services but require a payment for accessing additional features or premium add-ons (Chica and Rand 2017, Niculescu and Wu 2014, Pauwels and Weiss 2008, Wu et al. 2013). In the case of esports oriented video games, the games themselves are often free but add-on aesthetic items are offered for a fee.

Customer retention strategy is one of the most critical issues for firms that employ freemium models because "churn" is difficult to define (Ascarza et al. 2018, Datta et al. 2015). For example, Ascarza, et al. (2018) used a hidden Markov model (HMM) to study two types of customer churn ('overt' and 'silent' churn) and found that overt churners interact with firms more often in the period before churn. Gu, et al. (2018) conducted a randomized field experiment and analyzed the effect of adding premium options to a free ebook platform. They found that adding premium options (i.e., ebooks or hardcover) generates more sales than adding a simple paperback option. Relevant insights from these papers are that consumer behavior in freemium environments is often a function of individual differences in activity levels and the nature of the pay based add-on services offered.

There are also analytical studies that have investigated the acquisition aspects of freemium models (Shi et al. 2019, Wu, et al. 2013). For example, Wu, et al. (2013) discussed the role of network effects in freemium models. They suggested that the revenue for game operators is maximized if the positive network effect of the game itself is high and the negative network effect of game items is low.

2.4. Summary

The preceding discussion highlights several research opportunities. From a substantive perspective, the video game industry is large, growing and has already become a key part of the global entertainment industry. Furthermore, the video game industry has already invested significant resources in using esports as a vehicle to spur consumer interest. However, there is extremely limited empirical research that examines the economic impact of this free content on consumers.

The esports and video game industries also provide a data context that allows for new investigations into more general consumer behavior issues. Gaming and play are fundamental types of human behavior and the esports-video game environment provides an opportunity to study the interplay between participation and observation by consumers. For example, watching a game may provide incremental knowledge or reveal new possibilities that may inspire incremental play. It remains an open question how observation or watching influences subsequent participation and spending.

The esports context also provides a valuable context for studying established marketing topics such as sponsorship and freemium business models. These are increasingly important marketing tactics, but these topics are often difficult to study with traditional datasets. The ability to link viewing, playing and spending decisions in the esports-video game context provides valuable new data for researchers.

3. Data

3.1. Data and Research Design

To investigate the influence of esports watching on playing rates and spending, we assemble a dataset that includes information on esports watching from a streaming platform and game usage data from a Multiplayer Online Battle Arena title. Individual level consumption activities are from the game logs of a major U.S. based game publisher. The game under study was launched post 2010 and is one of the most popular MOBA games.

In game play, two teams are created for every session with gamers usually being randomly assigned to one of the competing teams. Gamers choose their personal character from a set of available characters.

In this case, the characters are mythological characters from a range of cultures. As of summer 2019 there were over 100 playable characters. The set of available characters varies across players. There is a core group of characters available to all players, but players may earn or purchase access to additional characters. While each character has different skills, the overall level of power is balanced across characters.

The goal of each match is to defeat the opposing team. To accomplish the goal, gamers attack enemies and try to destroy the enemy team's home base. Based on game play there are several observable in-game statistics for individual players. For instance, if a player is on the victorious side, the player earns a win for a session. In addition to team performance, the game tracks instances where a player's character "kills" or is killed by another player's character.

The game uses a FTP business model. This allows for game play without spending but provides options for the purchase of elective items. Players may purchase access to additional characters and aesthetic items (character costumes referred to as "skins"). In this category of games, the purchasable content does not provide a competitive advantage. This is an important element of gaming culture because there is an emphasis on fair competition. As such, incremental characters may provide different abilities, but the abilities are balanced to eliminate advantages. Aesthetic items or skins are essentially costumes for characters that alter appearance but do not change character ability.

The game producer created a professional sports league about a year after the game's launch. The official channel for the esports league was hosted on the dominant esports streaming platform. The platform is an online streaming service that hosts a variety of content related to video games. The online streaming platform is an important aspect of our environment. Consumer have the ability to link viewing accounts with game accounts. During our data collection window, the firm only streamed its esports events through this platform (i.e., no alternative source of watching the title's official esports professional events was available). For our analysis, we examine the effects of the title's 8 week-long 2017 summer league. The summer league content provides the core intervention or treatment for our analyses.

We focus on registered users of the game who are active players before and during the game's professional esports league in the summer of 2017. We construct a sample of 56,400 gamers who physically reside in the U.S., play the game through a PC (not console), and who are active in the eight weeks prior to and during the professional league season. We also tracked this group of gamers for an eight week post-period following the esports season. We label the 8 weeks prior to the season as the pre-period, the 8 weeks of the season as the esports viewing period and the 8 weeks following the season as the post-period.

We rely on two major sources of data for the analyses. The first data source is player transaction and usage data collected directly from the game producer. This data includes individual player-level histories of all gaming sessions played, choice of virtual character for each session, expenditures on paid items or extra features, and in-game performance statistics such as win rates, kills, and deaths. This data also includes account related information such as sign-up date, account identifier, and geographic region. The second data source on esports viewing has three key aspects. This data includes account identifiers for viewers, time stamps for viewing activity and information on the streamer viewed. For our purposes, we limit the analysis to the streaming account for the game producer's official account.

Of the 54,600 players in the overall sample, 5,564 watched the official esports channel during the 8 week pro league season. The connection of gamers' play and spending activity, to viewing activity is possible when gamers link the two accounts. Historically, there has been no incentive provided for customers to link accounts. However, this limitation likely results in a more conservative analysis because some viewing of streamed content may occur in the non-watching segment. This will result in a conservative bias if watching streamed content increases purchases and playing rates.

3.2. Descriptive Statistics and Model-free Evidence

Table 1 presents descriptive statistics and definitions for relevant variables. On average, gamers in our sample played about 235 game sessions during the 24-week period that encompasses the pre, pro-league and post periods. The 235 game sessions represent about 4,100 minutes or 68 hours of game play. In terms of expenditures, players made on average about 1.5 purchases worth about $40. The average tenure of gamers is 63 weeks since sign-up at the start of the pro-league window. Approximately 10% viewed esports.

In terms of in-game statistics, players in the sample won about half of game sessions played and the average kills per player was about 1,100. The ratio of kills to the sum of kills and player deaths is also about .50. In addition, the game includes a leveling system based on players experience points. On average, gamers accumulated about six million reward points during the observation window. These types of data provide insight into player's skill and experience levels (Alba and Hutchinson 1987, Mehta et al. 2011) . These may be relevant characteristics in terms of response to esports programming. For example, the Elaboration Likelihood Model (ELM) of Petty and Cacioppo (1986) suggests that expertise will allow for detail oriented central route processing. If this is the case, then we might expect that players with greater experience with the game would learn more and therefore experience a greater increase in engagement from exposure to esports.

We are also able to observe players' character selections. A preference for character variety may be a salient element of consumer behavior if a tendency towards variety seeking is related to responsiveness to esports content (McAlister and Pessemier 1982, Ratner et al. 1999). In addition to obtaining transaction utility from change and variety, variety seeking has been found to be correlated with underlying psychological traits. For example, variety seeking has been explained in terms of impression management goals (Ratner, et al. 1999) or as a tool used to foster sense of control (Yoon and Kim 2017). Both of these theories suggest that increased character variety selection may be related to consumer interest levels.

To operationalize variety seeking, we construct a Herfindahl index like measure based on the variety of a player's character choices. Specifically, we take the sum of the squares of character choice shares (i.e., proportions of character choice) $\sum s_{ij}^2$ where s_{ij} is the gamer i's choice share of character j. The character variety value therefore ranges from zero to one. For example, if 100 characters were available, a player that always chose the same character would have a character variety index of 1 while a player that used each character equally would have an index of .01. The average value of character variety in our sample is .164.

--- Insert Table 1 here ---

Our analysis is predicated on the notion that esports viewing represents a treatment. Under this assumption, players who watch esports are treated and non-watchers represent a control group. For the remainder of the paper we use treatment group and control group to refer esports viewers and non-viewers, respectively. As an initial step, we divide our data into two groups (i.e., treatment and control groups) based on esports watching status (i.e., an exposure to treatment) and report summary statistics for several variables in the post-period. Table 2 reveals a substantial difference between viewers and non-viewers of esports. In the 8-week post-period, esports viewers play about 80 more sessions than non-viewers. This represents an incremental 25 hours of playtime. In terms of purchases, esports viewers make .46 more purchases than non-viewers. This difference results in an incremental $10 in spending for the treated (esports watching) group. In addition, we also see substantial differences in game performance metrics such as winning and killing. On average, esports viewers have about 15% higher kill and win rates compared to non-viewers. The combination of increased playing and performance also results in a greater accumulation of rewards points for the esports viewers.

--- Insert Table 2 here ---

While the data in Table 2 suggest substantial differences between viewers and non-viewers of esports, the results do not control for potential confounding factors. In particular, the group differences in the post-period may be due to group level differences that existed prior to the exposure to esports (the treatment). To highlight group level differences prior to the pro-league period we report covariate imbalances in the pre-period in Figure 1. Figure 1 shows the distribution of playing time (log scaled) for esports viewers and non-viewers. The figure shows that the mean of playing time is much greater for the esports viewers. We also compare the viewers and non-viewers in terms of proportion of paid gamers. In the esports viewing group about 39% of players make a purchase in the 8 week pre-period compared to 19.5% of non-viewers. Similar behavioral differences exist for several other pre-period covariates. These differences are reported in Section A of the Web Appendix. These group differences highlight the need for a more sophisticated approach than the simple group comparisons reported in Table 2.

--- Insert Figure 1 here ---

4. Method

4.1. Conventional Identification Strategy

Our purpose is to measure the causal effect of watching esports on customer's in-game behaviors. Our foundational assumption is that viewing esports is a type of experimental treatment to which only a subset of players are exposed. A conventional empirical strategy adopted by researchers for this type of data is to use a difference-in-differences (DD) approach with a propensity score adjustment (Angrist and Pischke 2008, Imbens and Wooldridge 2009). By definition, a propensity score is the probability of assignment to a treatment versus remaining untreated conditional on observed covariates. Recent marketing studies have used propensity scores in the estimation of treatment effects (Bell et al. 2017, Wang and Goldfarb 2017).

However, propensity score methods suffer from several limitations. First, the use of standard parametric models may not always guarantee the robust estimation of treatment effect. While common practice is to use binary models such as the logit or probit (Bell, et al. 2017, DeFond et al. 2016), little attention has been paid to the statistical efficiency of such logit or probit based propensity scores. In simulation studies, it has been found that the logit or probit model based propensity scores are suboptimal for the estimation of correct treatment effects (Burgette et al. 2016, Lee et al. 2009). Second, parametric models rely on certain distribution and likelihood structures and these assumptions may not be valid for some settings. Failure to satisfy assumptions may lead to biased effect estimation (Drake 1993). Finally, conventional causal models only allow researchers to examine group level average treatment effects.

The emphasis on group level effects is a significant limitation in many marketing applications. The impact of many managerial decisions or promotions (i.e., treatments) may vary across segments of consumers. For example, an exposure to esports program may influence in-game spending for some gamers but may have little effect on others. Fortunately, recently developed machine learning methods provide a means for estimating individual level treatment effects.

4.2. Advanced Identification Strategy Using the Causal Forest

In recent years, researchers have used machine learning methods to estimate heterogeneous causal effects in settings that involve many covariates. One popular method is the causal forest (CF) algorithm (Athey and Imbens 2016, Wager and Athey 2018). The CF method is computationally efficient, consistent, and asymptotically Gaussian (Wager and Athey 2018). The method relies on the potential outcomes framework proposed by Rubin (1974) and offers a valid estimator with asymptotic normality and consistency. The method is free from key shortcomings of the random forest method (Breiman 2001) such as a lack of asymptotic properties for valid statistical or causal inference.

The CF method also produces individual level point estimates of treatment effects and variance. This allows researchers to obtain confidence intervals for estimates (Wager and Athey 2018). CF models are especially useful for exploring the sources of treatment heterogeneity since the researcher may examine the relationship between individual treatment effects and individual characteristics.

The basic idea of the CF method is to find and classify nearest neighbors for each observation unit in the data. The method is similar, in some respects, to the conventional *k-nearest neighbor* algorithm which operates by finding the *k* closest observations in a covariate space. The CF constructs subsamples in a different way by using tree-based measures (e.g. squared error loss or impurity) and clusters similar observations into the same leaf which is a terminal node of the classification (Athey and Imbens 2016, Wager and Athey 2018). The leaf (i.e., terminal node) is constructed so that units within leaves become more homogenous, while different leaves become more heterogeneous. Athey and Imbens (2016) developed the Causal Tree algorithm to estimate the within-leaf treatment effect by taking the difference between the means of treated and untreated pairs from the leaves of the tree. The bagging of such trees generates the Causal Forest and produces asymptotically Gaussian and consistent estimates of treatment effects for each individual (Wager and Athey 2018).

The CF algorithm involves three steps (Wager and Athey 2018). First, a random subsample is drawn from the data without replacement. This sample is the input for a classification and regression tree (CART) model that constructs several leaves. The classification of observations is based on finding splits that optimize some criteria such as minimum loss in squared errors (Breiman 2001). The squared error loss is a function that measures the deviation of realized outcome values from the average outcome value in each leaf. Equation (1) describes the loss function used in our analysis.

$$\sum_{i \in J} (\hat{\mu}(X_i) - Y_i)^2 = \sum_{i \in J} Y_i^2 - \sum_{i \in J} \hat{\mu}(X_i)^2 \tag{1}$$

Second, following the completion of the tree-based classification, it is possible to estimate a local treatment effect for each leaf using equation (2):

$$\hat{\tau}(x) = \frac{1}{|\{i: W_i = 1, X_i \in L\}|} \sum_{\{i: W_i = 1,\, X_i \in L\}} \Delta Outcome_i - \frac{1}{|\{i: W_i = 0, X_i \in L\}|} \sum_{\{i: W_i = 0,\, X_i \in L\}} \Delta Outcome_i \tag{2}$$

where W_i denotes the treatment group indicator and X_i is a set of pre-period covariates used to construct the tree model. In addition, $\Delta Outcome_i$ is the difference in the outcome variable between the post- and pre-periods. Taking the difference between post and pre-periods removes any unobserved and permanent heterogeneity for each subject. Econometrically, this is consistent with controlling for individual-level fixed effects in conventional panel data analysis. In our case, we use minutes played and customer expenditures as outcome variables. Taking the difference between two differences leads to conceptually the same estimator as in the standard difference-in-differences method. However, the CF method employs an additional step called *honesty* building in the estimation of local treatment effects. Specifically, we establish honesty by using a double-sample tree suggested by Wager and Athey (2018). For illustrative purpose, we provide a visual representation of the first two steps of the algorithm in Section B of the Web Appendix.

In the third step, the CF algorithm produces an ensemble of B trees, each of which repeats the first two steps and generates point estimates for each observation. In practice, researchers may have difficulties in determining the "optimal" tree (Breiman 2001, Wager and Athey 2018). Bagging of multiple trees into a forest using the ensemble method provides better predictions for the treatment effect as in equation (3).

$$\hat{\tau}(x) = \frac{1}{B} \sum_{b=1}^{B} \hat{\tau}_b(x) \tag{3}$$

To compute the asymptotic variance of the estimated treatment effect we use equation (4),

$$\widehat{Var}\big(\hat{\tau}(x)\big) = \frac{n-1}{n} \left(\frac{n}{n-s}\right)^2 \sum_{i=1}^{n} Cov_*[\hat{\tau}_b^*(x), N_{ib}^*] \tag{4}$$

where $\hat{\tau}_b^*(x)$ is the estimated treatment effect from the b^{th} tree and N_{ib}^* indicates whether the i^{th} training example was used for constructing the b^{th} tree (Efron 2014). $n(n-1)/(n-s)^2$ is the term for correcting finite-sample for forests grown by step 1 of forest building (i.e., subsampling without replacement).

In terms of covariates, we consider nine variables from the pre-period to characterize customers. The player level variables include 1) player's tenure (in weeks) since sign up, 2) total play time in minutes, 3) total spending amount, 4) the character variety index defined as in section 3, 5) average win rate, 6) total rewards points obtained, and 7) the three key in-game performance statistics (total kills, deaths, and assists). Using these variables, the CF algorithm constructs several leaves that contain individual players with similar behavioral patterns prior to the pro league programming. To avoid overfitting, we use a 10-fold cross validation with 20,000 trees in each iteration. This entails randomly dividing the sample into ten groups and constructing the CF model on nine groups (90%) (i.e., training set) and estimating the effects on the remaining one group (10%) (i.e., test set). We repeat the same process ten times on each subgroup.

5. Results

5.1. Overall Treatment Effects

One advantage of the CF method is that the method generates point estimates of individual level treatment effects for each consumer. We plot the distributions of the estimated treatment effects for each dependent variable in Figure 2. The top panel in Figure 2 shows the distribution for playtime and the bottom shows the distribution for expenditures. The average treatment effect for playtime is about 590 minutes. The average effect for expenditures is about $5. These effects are for an 8 week period.

--- Insert Figure 2 about here ---

Table 3 provides summary statistics for the distribution of treatment effects. In terms of notation, we use tau ($\hat{\tau}$) to represent the estimated treatment effect. The estimated average effect of viewing esports of 591 minutes is directionally consistent with the raw data reported in Table 2. However, the magnitude of the effect is reduced. The effect reported in Table 3 controls for observable and unobservable differences in the populations of players. We also find that about 96% of players show a significant increase in playing at a 95% significance level. The conditional effect of esports viewing for those with significant effects is about 613 minutes. In terms of expenditures, we estimate an average esports viewing effect of $5 in incremental spending. However, for spending only about 52% of players have significant effects. The increase in purchase amount is about $4.7 among gamers with positive and significant effects.

--- Insert Table 3 about here ---

5.2. Effect Heterogeneity

The estimation of individual level treatment effects provides opportunities to investigate the relationship between the magnitude of effects and each gamer's pre-period characteristics. We next illustrate this point by investigating how esports viewing effects vary based on previous player experience and character variety choices. These investigations attempt to link response heterogeneity to underlying behavioral traits. We also show how multiple sources of heterogeneity may be used simultaneously to construct targeting strategies that are based on observable usage data.

5.2.1. Heterogeneous effects by consumer expertise and variety seeking. Two potentially important player characteristics are expertise (Alba and Hutchinson 1987, Hong and Sternthal 2010, Mehta, et al. 2011) and variety seeking (McAlister and Pessemier 1982, Ratner, et al. 1999, Yoon and Kim 2017). These traits are related to consumer understanding and exploration of the game. Given our conjecture that esports watching involves opportunities to learn about the game and associated communities, these types of traits may be particularly relevant. For our investigation of expertise, we use each customer's lifetime (i.e., cumulative) play sessions through the pre-period as a proxy for consumer expertise (Toker-Yildiz et al. 2017). To examine the relationship between expertise and player response, we divide customers into five decile groups (20% each) based on this cumulative playing variable. In terms of variety seeking, we also create five segments (20% each) based on character variety index in the pre-period.

Figures 3 and 4 show the mean values and standard errors of the treatment effects for each quantile. The left panel of Figure 3 shows that the treatment effects on playtime increase with greater customer expertise. This may occur because gamers with more expertise require less cognitive efforts to process the information (or knowledge) from esports contents, and thus gain more from the esports viewing (Alba and Hutchinson 1987, Bettman 1986). Theoretically, this observation is consistent with the differences in message processing routes for experts and novices suggested by the Elaboration Likelihood Model (Petty and Cacioppo 1986). Gamers with more contextual knowledge and experience may use central route processing rather than peripheral route processing, and may therefore acquire more detailed and valuable information from viewing esports. The right panel of Figure 3 shows a similar pattern for expenditure treatment effects. However, this figure shows that the increase in effects diminishes for quantiles 3, 4, and 5. There are a variety of potential explanations for the different patterns for playing time and expenditures. For instance, it is possible that more experienced players have already purchased the voluntary items they are interested in or that the motivation for signaling through aesthetic items levels off with experience.

--- Insert Figure 3 about here ---

In Figure 4, we report a similar analysis based on player's variety seeking tendencies. Figure 4 shows a clear relationship between variety seeking and both playing and spending treatment effects. This pattern is consistent with findings from previous studies on variety seeking (McAlister and Pessemier 1982, Raju 1980, Steenkamp and Baumgartner 1992). For example, Raju (1980) suggests that there is a positive correlation between variety seeking tendencies and optimum stimulation level (OSL). OSL is an individual level tendency that refers to the level of stimulation which satisfies a consumer (Raju 1980). The theory suggests that if the current level of stimulation is below (above) the optimum level, an individual seeks to have more (less) stimulation (Raju 1980). In our context, we speculate that variety seeking gamers are prone to have higher OSL (McAlister and Pessemier 1982, Raju 1980, Steenkamp and Baumgartner 1992), and this leads to greater tendency to engage with the game.

We also repeat the preceding analyses using alternative measures for consumer expertise and variety seeking. Specifically, we use cumulative play minutes as an alternative for expertise and the number of characters used as another measure of variety seeking. These alternative measures yield similar results. We report these results in Section C of Web Appendix.

--- Insert Figure 4 about here ---

5.2.2. Heterogeneous effects by multiple traits. The estimated treatment effects can also be used to explore differences in response across multi-dimensional segments. This type of analysis may provide significant value for targeting segments with esports oriented promotions. Tables 4 and 5 show the mean treatment effects for customer segments based on pre-period rates of game usage, game performance and spending. Specifically, we construct segments based on play minutes, purchase incidence, kill rate, and character variety seeking. Gamers are divided into three equal subgroups based on these variables except for purchase amount. For purchase amount, we divide gamers into non-spenders and spenders based on pre-period activity. To highlight differences each cell is colored to indicate the extent of treatment effect. The redder (greener) the cell is, the bigger (smaller) the magnitude.

Table 4 shows the effect of esports viewing on playing time. Several trends are observable. For example, playing time increases as the level of previous usage increases. In other words, the effect of esports watching is greater for heavy gamers compared to light gamers after controlling for observable covariates. In addition, treatment effects are the smallest for light gamers that use a narrow range of characters. Lower variety seeking character choice may represent a lower engagement as it reflects a lack of interest in exploring the game. Interestingly, pre-period spending is not a predictor of playing time effects.

--- Insert Table 4 about here ---

Table 5 shows the heterogeneity of treatment effects for player expenditures. The first observation from this table is that the treatment effects are stronger (i.e., redder in color) and more pronounced for the spender group than the non-spender group. This implies that watching esports results in spenders increasing expenditures but that it is difficult to change the behavior of non-spenders. The effects for pre period spenders show significant heterogeneity based on player performance (kill rate) and character variety seeking. Specifically, spenders with diverse character choices show greater treatment effects. However, the magnitude of this spending effect diminishes as game performance improves. Among the non-spenders, the effect of viewing esports is greatest for gamers with moderate usage and limited character choice. The customers with these traits show about a $4.4 to $5.8 increase in expenditures.

--- Insert Table 5 about here ---

5.3. Robustness Checks

In our main analysis, we discuss the overall treatment effects and effect heterogeneity based on pre-period covariates. To ensure the validity of our results, we complement the main results with a battery of robustness checks. First, we perform a simple difference-in-differences (DD) regression. Second, we investigate the possibility of self-selection bias based on unobservables. Third, we estimate a relative time trend model to evaluate the validity of the parallel trend assumption during the pre-period.

5.3.1. Difference-in-differences. The CF model provides substantial benefits through the estimation of individual level treatment effects. However, analysis of group-level treatment effects (i.e., ATE: Average Treatment Effect) (Angrist and Pischke 2008, Imbens and Wooldridge 2009) also provides insights and provides a robustness check to our results. We employ a difference-in-differences (DD) regression framework based on a propensity score weighting technique (Bell, et al. 2017, Hirano et al. 2003, Janakiraman et al. 2018, McCaffrey et al. 2004). In this technique, we utilize the pre-period covariates to estimate the probability of being treated ($\hat{e}(x)$: propensity score to watch esports). Then, we use the propensity scores as sampling weights to balance the groups (esports viewers and non-viewers) in terms of their observable characteristics. We report the propensity score estimation in Section D of Web Appendix.

To execute the difference-in-differences analysis (Manchanda et al. 2015), we run the following regression specification given in equation (5) as

$$Outcome_{it} = \beta_0 + \beta_1 EsportsViewer_i + \beta_2 Post_t + \beta_3 EsportsViewer_i \times Post_t + \varepsilon_{it} \quad (5)$$

where β_1 captures the group-level difference between esports viewers and non-viewers in their outcome and β_2 captures the mean difference in the post-period relative to the pre-period outcomes for all individuals. β_3 estimates the effect of esports watching on the outcome variable. To account for unobserved heterogeneity across customers, we include individual fixed effects. Our identification strategy is driven by within-player changes in esports watching and in-game behaviors over time, and not by permanent unobserved differences across players. We report the result of the model with propensity score weights in

Table 6. Table 6 shows that there is a positive effect of esports watching on customer engagement in terms of play and spending. The treatment effect on the play metric is 631 minutes and the effect on expenditures is \$3.67. The results show that our findings are qualitatively consistent across different methodologies.

--- Insert Table 6 about here ---

5.3.2. Self-selection bias due to unobservables. While the main CF based analysis provides advantages in terms of causal inference, the CF method only accounts for observable characteristics and permanent unobservable heterogeneity (i.e., individual fixed effects) across subjects. A potential concern is that the researcher does not have visibility of all factors that motivate esports viewing. This potentially creates a selection bias issue (Boyd et al. 2019, Gill et al. 2017, Heckman 1979). To resolve this, we also estimate a Heckman two-stage regression model (i.e., sample selection model) where error terms in selection and outcome equations are correlated (Gill, et al. 2017, Heckman 1979). Specifically, we obtain the inverse Mills ratio (IMR) from a first stage regression of the decision to watch and include it in our outcome equation to absorb unobservable heterogeneity. We implement this approach using equation (6),

$$Outcome_{it} = \beta_0 + \beta_1 EsportsViewer_i + \beta_2 Post_t + \beta_3 EsportsViewer_i \times Post_t + \boldsymbol{\beta_4}\mathbf{X_{it}} \quad (6)$$
$$+\beta_5 IMR_i + \varepsilon_{it}$$

where $\mathbf{X_{it}}$ is a set of observable covariates and IMR_i is the inverse Mills ratio.

The first stage model (selection model) requires at least one instrumental variable which affects the decision to watch esports (i.e., relevance) but is not be correlated with the outcome variables (i.e., exclusion) (Heckman 1979). We use an instrumental variable derived from the focal firm's second most popular game (Game2, hereafter). We construct this variable from the streaming log of each player and assign the value of one if the gamer watched streamed content about Game2 before he watches the primary game's esports programming (or if the gamer only ever watched Game2 programs) in the pre-period and zero otherwise.

If the player watches streamed content about Game2, it implies that the gamer is familiar with the streaming platform. This familiarity increases the probability that the player encounters or is aware of the focal game's esports content. However, there is no reason to expect that players who watch Game2 programing to have greater propensity to play or spend in the focal game. We estimate a gamer's intention to watch esports using various covariates and an instrument (i.e., watched Game2) based on a probit model and obtain the IMR.

We report estimation results in Table 7. In the first stage regression we find that watching Game2 is a positive and significant predictor of watching the focal game's esports channel. The results also show that lagged play minutes, lagged kill rate, and user tenure are significant. This provides justification for their use in the IMR calculation. In the second stage regression, we use a difference-in-difference regression framework and find that esports watching still exerts significant and positive effects on both outcome variables. These results imply that our main results do not change even after controlling for potential self-selection bias.

--- Insert Table 7 about here ---

5.3.3. Parallel trend assumption in pre-period. Causal inference research relies on a parallel trend assumption. The assumption is that the treatment and control groups show similar trends in their outcomes during any pre-treatment period (Angrist and Pischke 2008, Janakiraman, et al. 2018, Ozturk et al. 2016). To confirm this, we use the relative time model suggested by (Greenwood and Wattal 2017) to determine whether there are meaningful differences in behavioral trends between the viewing and non-viewing groups. To perform this robustness check, we reformulate the data into a panel structure with weekly time periods (Greenwood and Wattal 2017). We also create interaction terms between the treatment group indicator and the time dummies. We then estimate a panel regression with individual and time fixed effects. This model also uses propensity score weights as in Table 6. Econometrically, this model allows the researcher to examine how the treated group changes their behavior (as represented by coefficients of the time dummies × group indicators) over time. We plot the difference between the two groups in their outcome variables in the eight weeks of the pre-period and find that the two groups show no significant difference in pre-period trends. We provide the figure in Section E of Web Appendix.

6. Mechanism

The CF based analysis and the series of robust checks suggest that esports viewing has a positive effect on consumer engagement. These results have significant face validity as we expect that programming that provides opportunities to interact with a brand and associated community will enhance the brand-consumer relationship (Fournier 1998). In this section we consider a potential mechanism that may drive our results. We begin from the premise that exposure to esports content provides an opportunity for consumers to learn more about the game (e.g., skills and strategies).

One possible mechanism for the observed relationship between esports viewing and subsequent customer engagement is consumer learning (Churchill and Moschis 1979, Suh and Lee 2005). Consumer learning refers to information processing through which consumers attain knowledge, skills, information, and attitudes towards products and services (Churchill and Moschis 1979, Suh and Lee 2005). Consumer learning may occur when individuals learn salient information from stimulus events (Higgins 1996) or exposure to sensory-rich IT devices (Li et al. 2003, Suh and Lee 2005). In the esports viewing context, we expect consumer learning occurs because viewers are exposed to rich information about a specific game.

Esports programming is similar to traditional sports programming as matches are streamed live with professional commentary from “esportscasters.” Esports personalities direct viewers to highlights of the match, provide background information such as performance history, and comment on gaming strategies. This content may play an educational role as esports viewers are exposed to effective tactics and strategies. Game knowledge may be especially relevant to esports enjoyment because viewers are also typically participants. Therefore, consumer learning in esports viewership may increase knowledge that increases in-game performance which then enhances the overall enjoyment of the game (Chung 2015).

To investigate the role of consumer learning, we conduct three additional analyses. First, we rerun the CF and obtain the distribution of treatment effects in terms of gaming performances (i.e., number of kills and wins). Second, we estimate the standard DD model on the game performance metrics. Finally, we conduct a mediation analysis and confirm whether in-game performances significantly mediate the effect of esports. If consumer learning is present, watching esports should lead to an increase in customers’ gaming performance and it should mediate the effect of esports watching on customer play minutes and purchase amount. We use number of kills and wins as game performance metrics. Both measures capture customer's performance level, but they are different in that killing depends primarily on individual performance while winning depends on both individual and teammates' performance.

Figure 5 and Table 8 reveal the effects of esports viewing on gaming performance. Figure 5 shows the distribution of treatment effects for both metrics. In general, esports viewing has a positive impact on in-game performance. These results are consistent with previous findings from the literature. For example, Müller-Stewens, et al. (2017) showed that consumers adoption of innovations is increased when information is delivered using games. Table 8 reports that the mean improvement in number of kills is about 190 and the mean improvement in number of wins is about 17. We also estimate a standard DD model with propensity score weighting and report the results in Table 9. The DD analysis also yields positive and significant effects for each performance metric. The ATEs are estimated as 204 additional kills and 17 additional wins due to esports watching. To ensure robustness of our analyses, we replicate the analyses using kill and win rates as alternative definitions of gaming performances. All findings remain qualitatively consistent and the results are available in Section F of the Web Appendix.

--- Insert Figure 5 about here ---

--- Insert Table 8 and 9 about here ---

Finally, we estimate a mediation model (PROCESS, model 4 by Hayes (2017)) to investigate whether changes in gaming performance significantly mediate the effect of esports viewing. To control for group level differences, we first construct a one-to-one propensity score matched set (5,564 treated and 5,564 untreated gamers) and then conduct the mediation analysis. We report the result using the number of kills as a proxy for gaming performance. Section G of Web Appendix reports an alternative model that uses the number of wins as a proxy for game performance.

We report estimates of the mediation analyses in Figure 6. We find that changes in game performance (number of kills) significantly mediate the effect of esports viewing. First, the direct effect of esports on both play minutes (-5.483, p>.10) and purchase (+2.964, p>.10) are not statistically different from zero when the change in kills is considered as a mediator. However, the bootstrapped confidence intervals (at 95% level, for 20,000 bootstrapped samples) for the indirect effect all exclude zero (701.905 to 921.699 and 4.909 and 8.282, respectively) implying significant mediation based on in-game performance. Specifically, the estimates and bootstrapped standard errors of the indirect effects are $\beta = 813.123$ and $S.E. = 56.462$ for play minutes and $\beta = 6.435$ and $S.E. = .866$ for purchase amount. The results suggest that watching esports indirectly increases customer engagement through improving gamers' performances. This result is consistent with speculation from Holbrook et al. (1984) that playful consumption is affected by performance and emotions. In this case, viewing esport seems to provide competitive advantages that result in increased playing and spending. Collectively, our results provide preliminary evidence that consumer learning operates as the underlying mechanism.

--- Insert Figure 6 about here ---

7. Discussion

In this study, we empirically identify the effect of content viewership on customer engagement in the context of esports and video games. Methodologically, we use the causal forest algorithm in order to obtain individual level treatment effects. In our main analysis, we find that viewing esports increases product usage and incremental expenditures. We find that the causal effect of watching esports is an increase in playing time of about 600 minutes and an increase in voluntary expenditures of about $5 over an 8 week period.

We also find that there is substantial heterogeneity in terms of effect size and that the heterogeneity in treatment effects is related to various pre-period covariates. Specifically, we find that the treatment effects are larger for more experienced and variety seeking customers. These relationships have potential value to managers interested in targeting. In terms of potential underlying mechanisms, we find preliminary evidence for consumer learning. Gamers seem to learn game specific knowledge, skills, and strategies by watching esports content, and that leads to enhanced customer engagement in terms of usage and spending. We also conduct a battery of robustness checks and show that the key results are robust to alternative functional forms and potential self-selection bias. We also show that a parallel trend assumption in pre-treatment period holds.

7.1. Implications

Our research provides important contributions to both practitioners and academics. First, we empirically show that investment in 'free content' can have an important relationship building effect on customers. Given that the previous literature on freemium business models has recognized the importance of building and retaining a relationship with customers (Ascarza, et al. 2018, Bapna and Umyarov 2015, Pauwels and Weiss 2008) the current study complements the existing literature by showing an example of managing customer engagement using digital content. Our results also highlight the importance of consumer response heterogeneity in freemium business models. Tables 4 and 5 show how the individual level effects are applicable to decision support.

Our study also adds to the literature on gaming and esports. The video game industry has experienced substantial market growth in recent years and has become a major element of the entertainment sector (Ell 2018, Ingraham 2018). However, empirical research on customer behavior in the gaming industry is relatively rare (Huang, et al. 2019). Our findings should provide meaningful guidance to video game producers and digital content streamers who are engaged in customer relationship building and customer equity management.

Methodologically, the study details the application of the causal forest model to a critical business issue. The study adds to the growing literature on machine learning methods that estimate heterogeneous treatment effects (Wager and Athey 2018). While machine learning techniques are increasingly prevalent in industry, there are relatively few application of such machine learning based causal inference in the marketing literature (Ascarza 2018, Fong et al. 2019).

7.2. Limitations and Guidance for Future Research

We also acknowledge several limitations of our study and suggest avenues for future research. First, the current analysis was designed to demonstrate the effect of esports viewing on customer engagement over a limited timeframe. It may be desirable to consider the long-run impact of esports watching using metrics such as customer lifetime value (CLV). This type of analysis would provide insights in terms of setting esports investment levels.

Second, we acknowledge that esports streaming services provide not only the official esports content but also other video content from independent streamers. In the current study, we only focus on the game's official channel. It may also be interesting to see if there is any difference between watching the official esports content versus watching non-official streams. Third, as noted in the data section, the identification of esports viewers and their corresponding gaming activity is available through gamers' voluntary linkage of game and streaming accounts. We recognize this as a limitation. However, we believe that this may lead to a downward bias in effect estimation because some of non-viewer group gamers may be viewing esports.

We also note that the current research does not capture the role of spending activity within the streaming platforms (i.e., donation to streamers). This type of data is not currently available. While spending activity within the streaming platform is not a primary topic for our study, we acknowledge that spending on streamers may be related to within game spending. Streamers may be an important part of the game community and gamer's may wish to support independent content generators. It remains an open question as to whether this type of spending leads to an increase or decrease in in-game spending.

Finally, there may be additional opportunities to investigate potential explanatory mechanisms. While the esports viewing and video game playing context provides rich data on consumption behaviors, researchers are still limited in terms of data related to player's psychological states. We find correlational evidence that learning results in improved game performance that increases engagement. However, our investigation does not consider alternative explanations. Future researchers may investigate whether constructs related to relationship interactivity (Fournier 1998) or players achieving a state of flow (Hoffman and Novak 1996) might also provide explanations for increases in player activity. These types of inquiries would require the collection of individual level psychological variables through survey methods.

Tables and Figures

Table 1- Summary Statistics

Variable	*Description*	*Mean*	*Std. Dev.*
Play sessions	The number of sessions (matches) played	235.332	311.224
Play minutes	Total play minutes in total	4,111.548	5,598.132
Purchase frequency	The number of purchases made	1.549	3.935
Purchase amount	Total amount of purchase	40.029	327.953
Win sessions	The number of sessions (matches) won	120.232	161.142
Win rate	The ratio of sessions won to total sessions played	.523	.152
Kills	The number of kills made	1,176.245	1,666.125
Deaths	The number of death taken	1,056.756	1,428.443
Kill rate	The ratio of kills to kills and deaths	.506	.152
Reward points	The reward points (gold) attained (scaled in 1,000)	6,105.090	14,210.241
Character variety	Herfindahl index-like measure on the character choice	.164	.188
User tenure	The number of weeks since sign-up	63.948	33.253
Esports viewer ratio	1: if esports viewer; 0: non-viewer	.102	.303

Note: N=54,600. All values are aggregated over entire observation period (24-week period) except for user tenure. User tenure is based on the last week of pre-period.

Table 2: Model-free Evidence: Naïve Effects Observed in Post- period

Variable	*Esports viewers (Treatment group; N=5,564)*		*Non-viewers (Control group; N=49,036)*		*Difference*
	Mean	*Std. Dev.*	*Mean*	*Std. Dev.*	
Play sessions	129.618	140.649	50.688	96.738	+78.930**
Play minutes	2,485.540	2,740.240	917.228	1,767.820	+1,568.312**
Purchase frequency	.774	1.770	.317	1.282	+.458**
Purchase amount	17.843	52.294	7.801	74.426	+10.041**
Win sessions	68.914	76.779	26.012	50.569	+42.902**
Win rate	.451	.225	.311	.294	+.140**
Kills	729.819	859.713	275.745	559.283	+454.074**
Kill rate	.458	.215	.307	.271	+.151**
Reward points	3,409.060	6,602.690	1,350.960	4,345.970	+2,058.100**

Note: Difference is tested based on paired t-test. Reward points are scaled in 1,000. *p<.05; **p<.01.

Table 3: Causal Forest Results Summary on Main Dependent Variables

Treatment effects	*N*	*Mean*	*Std. Dev.*	*25%*	*50%*	*75%*
$\hat{\tau}_i^{Play\ min.}$	54,600	591.960	243.871	466.254	560.037	722.278
$\hat{\tau}_i^{Play\ min.} \mid \hat{\tau}_i^{Play\ min.}$ >0 at 95% level	52,279	613.475	226.056	482.447	568.379	731.503
$\hat{\tau}_i^{Purchase\ (\$)}$	54,600	4.997	8.674	2.750	3.845	5.440
$\hat{\tau}_i^{Purchase\ (\$)} \mid \hat{\tau}_i^{Purchase\ (\$)}$ >0 at 95% level	28,513	4.729	2.322	3.335	4.213	5.513

Table 4: Estimated Treatment Effects on Play Minutes by Pre-period Traits

Game usage	*Game performance*	*Spenders*			*Non-spenders*		
		Narrow Choice	*Balanced Choice*	*Diverse Choice*	*Narrow Choice*	*Balanced Choice*	*Diverse Choice*
Light	Low	421.748	514.853	556.753	335.507	531.364	527.817
	Middle	445.546	525.490	542.701	392.143	533.107	571.376
	High	392.394	507.791	520.134	301.943	500.968	532.891
Moderate	Low	535.429	547.379	587.203	507.581	531.826	582.027
	Middle	530.502	547.335	600.061	517.885	537.704	585.528
	High	536.403	564.674	610.677	518.670	551.361	593.628
Heavy	Low	801.406	829.945	851.914	784.147	799.451	823.450
	Middle	801.869	832.475	889.765	755.708	794.432	832.329
	High	822.404	849.626	913.023	760.627	799.181	844.467

Note: Color is available in electronic version.

Table 5: Estimated Treatment Effects on Purchase Amount ($) by Pre-period Traits

Game usage	*Game performance*	*Spenders*			*Non-spenders*		
		Narrow Choice	*Balanced Choice*	*Diverse Choice*	*Narrow Choice*	*Balanced Choice*	*Diverse Choice*
Light	Low	$ 4.156	$ 6.797	$ 6.296	$ 3.175	$ 4.506	$ 4.281
	Middle	$ 4.157	$ 5.108	$ 3.439	$ 3.705	$ 4.592	$ 5.413
	High	$ 3.895	$ 5.542	$ 4.373	$ 3.381	$ 4.265	$ 4.565
Moderate	Low	$ 5.672	$ 5.860	$ 7.132	$ 5.748	$ 5.798	$ 4.403
	Middle	$ 4.626	$ 5.857	$ 7.005	$ 4.839	$ 4.766	$ 3.969
	High	$ 4.615	$ 5.621	$ 8.494	$ 4.616	$ 4.432	$ 3.981
Heavy	Low	$ 8.365	$ 9.182	$ 12.793	$ 3.011	$ 3.283	$ 3.070
	Middle	$ 7.613	$ 8.241	$ 11.005	$ 3.350	$ 3.222	$ 2.935
	High	$ 6.498	$ 9.337	$ 10.416	$ 3.713	$ 3.982	$ 3.457

Note: Color is available in electronic version.

Table 6: Estimation Result Using Difference-in-Differences and Propensity Score Weights

Dependent Variable	*Play Minutes*	*Purchase Amount*
Model	*(1)*	*(2)*
$\text{EsportsViewer}_i \times \text{Post}_t$	631.769**	3.667**
	(32.743)	(1.324)
95% C.I.	[567.592, 695.945]	[1.071, 6.263]
Individual Fixed Effects	Included	Included
Time Fixed Effect	Included	Included
Adjusted R^2	.577	.172

Note: Robust standard errors are used. N=109,200. **p<.01.

Table 7: Estimation Result Using Difference-in-Differences and Heckman Correction

Dependent Variable	*Esports watch*		*Play Minutes*		*Purchase Amount*	
Model	*First stage*		*Second stage*			
Variables	*Estimate*	*S.E.*	*Estimate*	*S.E.*	*Estimate*	*S.E.*
EsportsViewer_i			-836.413^{**}	57.355	-8.891^{**}	2.653
Post_t			-613.403^{**}	20.169	-5.380^{**}	1.180
$\text{EsportsViewer}_i \times \text{Post}_t$: (Treatment effect)			933.625^{**}	41.224	6.303^{**}	1.426
$\text{Play minutes}_{it-1}$	$.0001^{**}$	.0000	$.538^{**}$	.009	$.002^{**}$	.000
$\text{Purchase amount}_{it-1}$	.0001	.0000	$-.201^{**}$	.063	$.118^{*}$	.047
Kill rate_{it-1}	$.801^{**}$	.079	-66.220	39.078	-.417	1.163
$\text{User tenure}_{it-1}$	$.004^{**}$	.000	.328	.281	-.008	.012
$\text{Character variety}_{it-1}$			-485.855^{**}	43.170	-8.001^{**}	1.364
Inverse Mills Ratio			-252.975^{**}	21.860	-3.732^{**}	.856
$\text{Game2 watched}_i^{+}$	3.211^{**}	.026				
Intercept	-3.077^{**}	.056	1,548.066	71.870	21.680^{**}	3.811
Pseudo/Adjusted R^2	.691		.421		.030	

Note: N=54,600 in the 1st stage while N=109,200 in the 2nd stage. Robust standard errors are used in 2nd stage models. Propensity scores are adjusted as in Table 6. +Instrumental variables for exclusion restriction. *p<.05; **p<.01.

Table 8: Causal Forest Results Summary on Gaming Performances

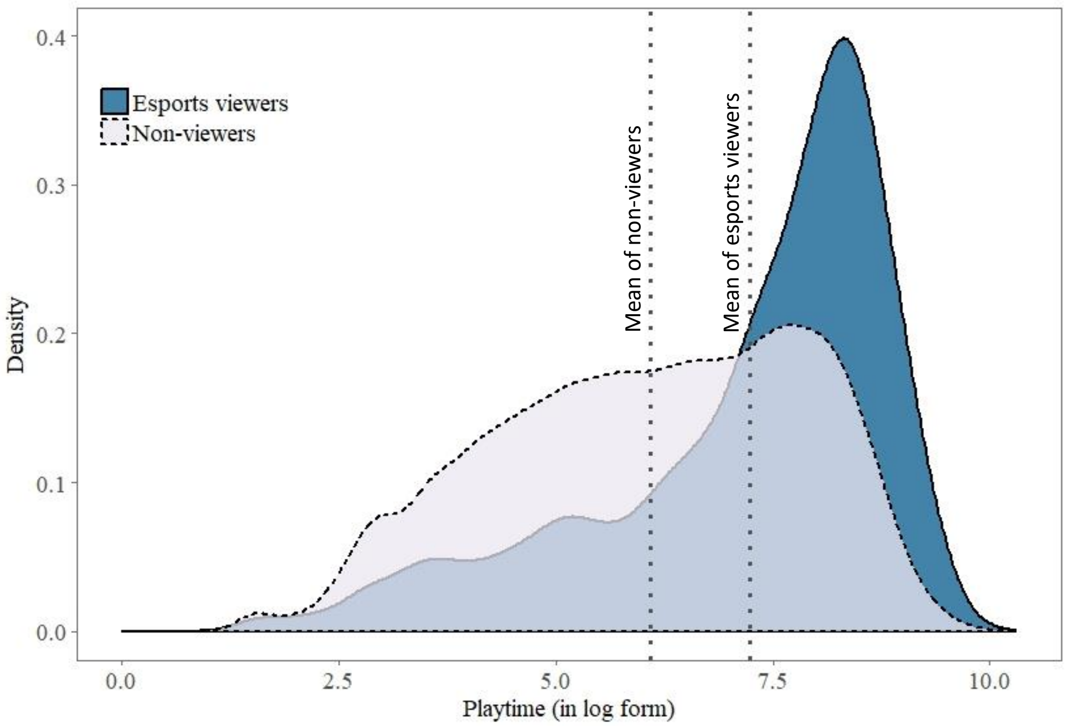
Treatment effects	*N*	*Mean*	*Std. Dev.*	*25%*	*50%*	*75%*
$\hat{\tau}_i^{Kills}$	54,600	187.281	78.999	144.869	182.811	223.476
$\hat{\tau}_i^{Kills} \mid \hat{\tau}_i^{Kills}$ >0 at 95% level	51,802	194.952	72.343	151.728	186.336	226.305
$\hat{\tau}_i^{Wins}$	54,600	17.241	7.282	13.397	16.704	21.434
$\hat{\tau}_i^{Wins} \mid \hat{\tau}_i^{Wins}$ >0 at 95% level	51,547	18.088	6.567	14.092	17.088	21.761

Table 9: Estimation Result Using Difference-in-Differences on Gaming Performances

Dependent Variable	*Number of Kills*	*Number of Wins*
Model	*(1)*	*(2)*
$\text{EsportsViewer}_i \times \text{Post}_t$	204.909^{**} (9.986)	17.514^{**} (.951)
95% C.I.	[185.337, 224.482]	[15.651, 19.378]
Individual Fixed Effects	Included	Included
Time Fixed Effect	Included	Included
Adjusted R^2	.537	.555

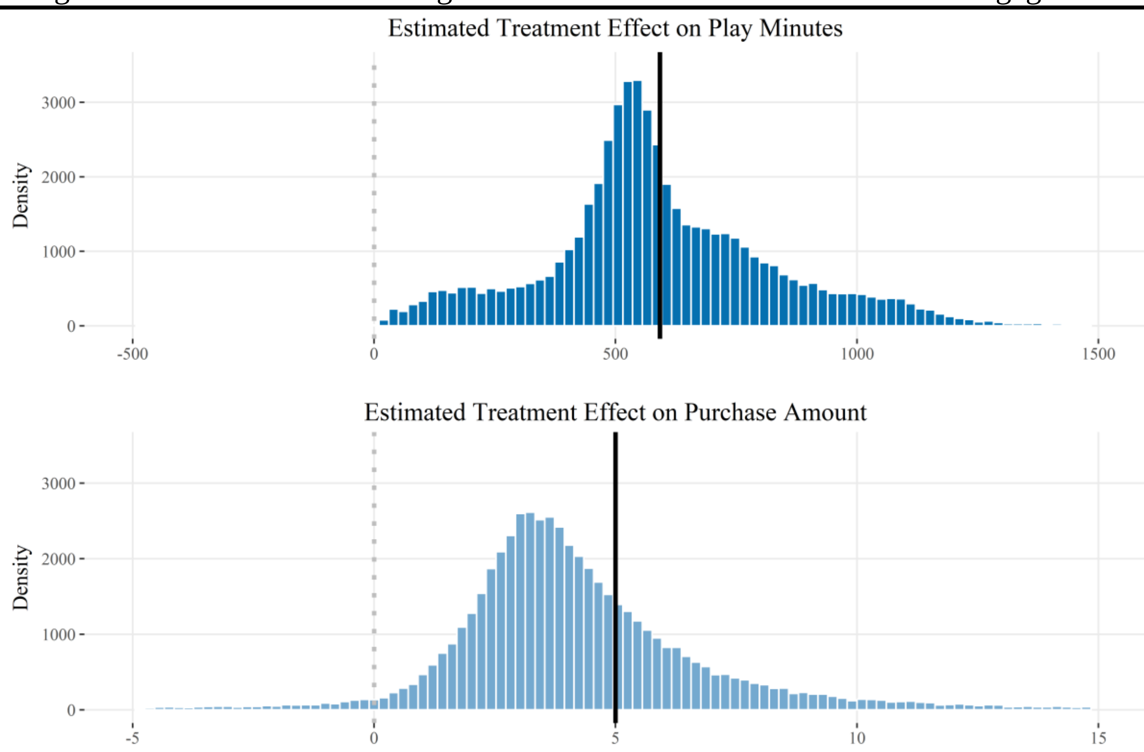
Note: Robust standard errors are used. Propensity scores are adjusted as in Table 6. N=109,200. **p<.01.

Figure 1: Covariate Imbalance in Pre-period (Distribution of Play minutes)



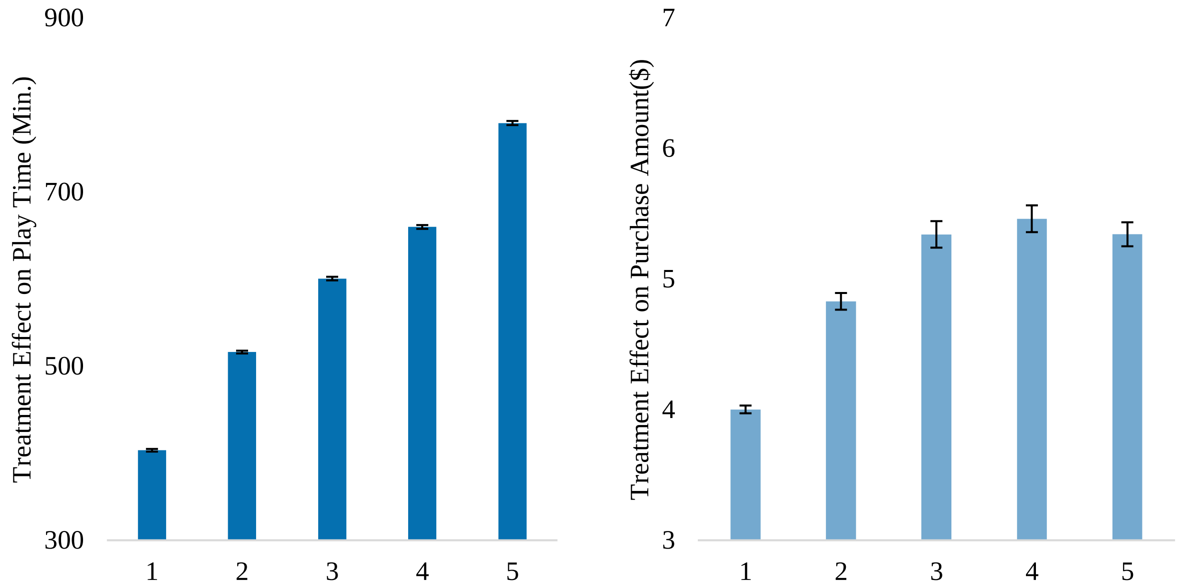
Note: Grey dotted lines indicate positions of mean values of two groups. Color is available in electronic version.

Figure 2: Distribution of Heterogeneous Treatment Effects on Customer Engagements



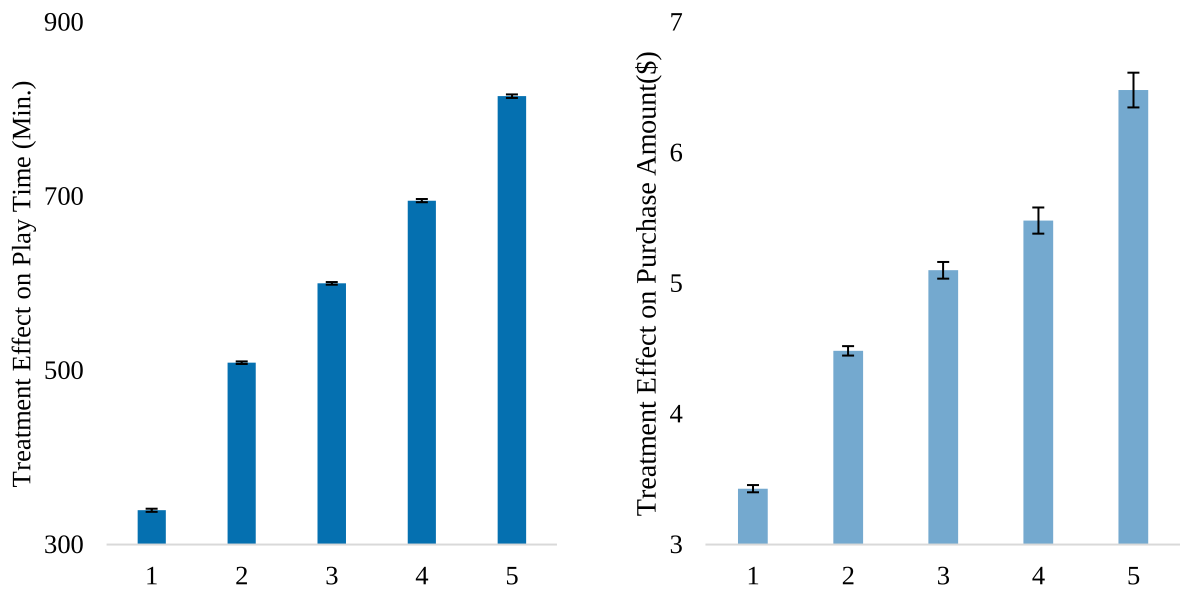
Note: Vertical lines denote the positions of mean for each distribution. Color is available in electronic version.

Figure 3: Estimated Treatment Effects by Consumer Expertise



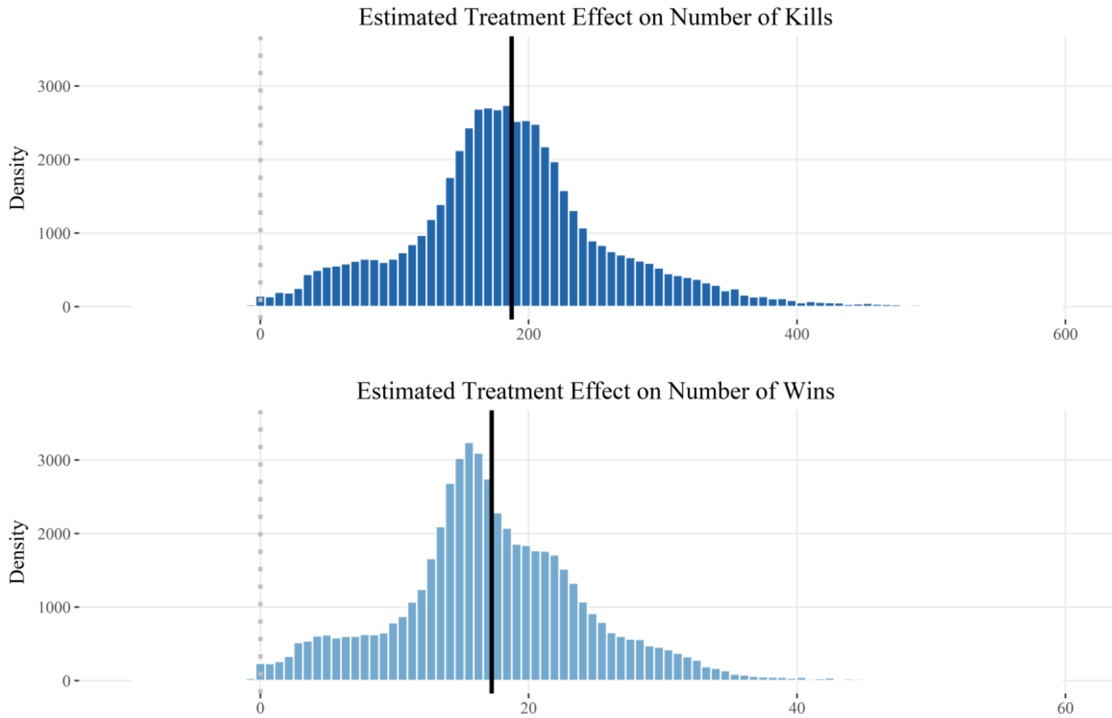
Note: Color is available in electric version. Group is ordered from the least experienced group (1) to the most experienced group (5). Error bars denote standard errors.

Figure 4: Estimated Treatment Effects by Variety Seeking



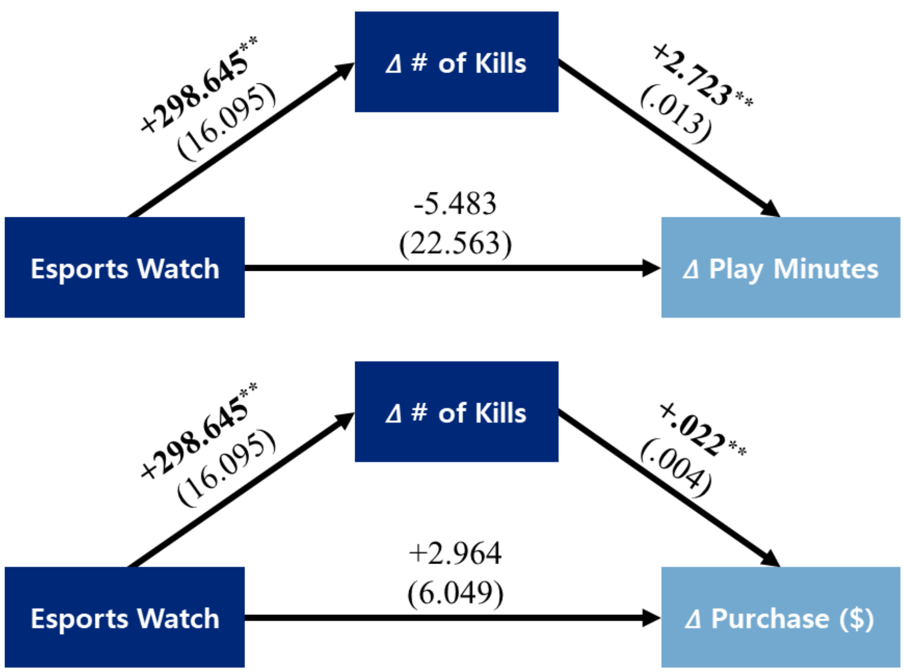
Note: Color is available in electric version. Group is ordered from the group with least variety seeking (1) to the group with most variety seeking (5). Error bars denote standard errors.

Figure 5: Distribution of Heterogeneous Treatment Effects on Gaming Performances



Note: Vertical lines denote the positions of mean for each distribution. Color is available in electronic version.

Figure 6: Mediation Analysis: Role of Gaming Performance as a Mediator



Note: Δ(delta) represents a change between pre and post periods. Standard errors are reported in parentheses. Color is available in electronic version. **p<.01.

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Content Viewership and Customer Engagement:
An Empirical Investigation into the Causal Effects of
Esports Viewership on Customer Usage and Expenditures

WEB APPENDIX

A. Group difference in pre-period

B. Details about Causal Forest

C. Robustness check: Alternative measures for consumer expertise and variety seeking

D. Details on propensity score estimation

E. Robustness check: Parallel trend assumption in pre-period

F. Robustness check: Alternative definitions of gaming performances

G. Robustness check: Supplementary result for mediation analysis

A. Group difference in pre-period

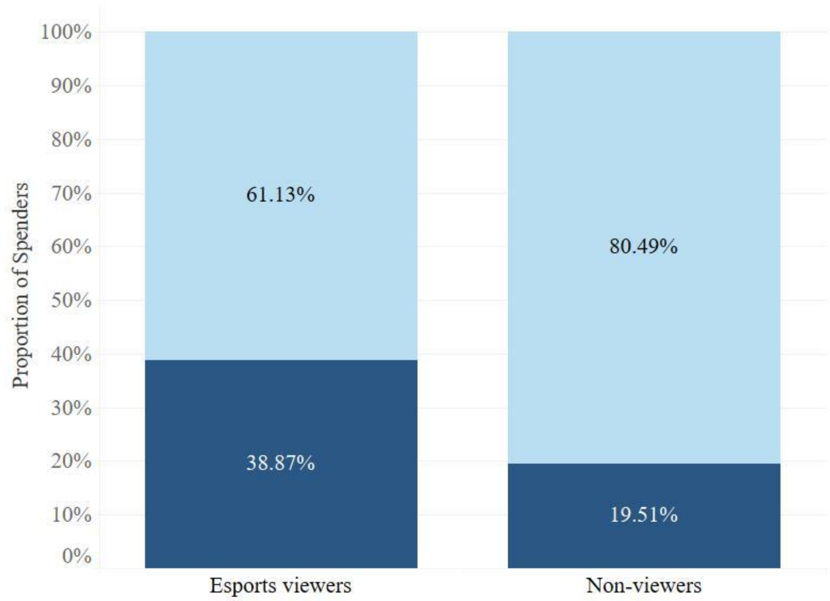
Table A and Figure A report the additional information on covariate imbalance in pre-period. As we discussed in the manuscript, two groups show a large discrepancy in gaming behaviors even before they are exposed to treatment (i.e., esports watching). Thus, the results further underscore the importance of empirical methods to resolve such group level difference in pre-period.

Table A: Covariate Imbalance in Pre-period

Variable	*Esports viewers (Treatment group; N=5,564)*		*Non-viewers (Control group; N=49,036)*		*Group Difference*
	Mean	*Std. Dev.*	*Mean*	*Std. Dev.*	
Play sessions	167.156	154.952	80.760	114.286	+86.396**
Play minutes	3,072.190	2,939.490	1,410.600	2,053.630	+1,661.590**
Purchase frequency	1.169	2.541	.535	1.717	+.635**
Purchase amount	27.044	111.974	12.722	175.734	+14.323**
Win sessions	92.547	87.652	43.178	61.040	+49.369**
Win rate	.567	.154	.558	.213	+.009**
Kills	860.427	905.911	420.811	637.478	+439.616**
Kill rate	.541	.139	.500	.182	+.041**
Reward points	4,556.760	10,116.630	2,101.400	5,976.950	+2,455.360**
Character variety	.135	.202	.271	.276	-.136**
User tenure	74.505	29.907	62.750	33.402	+11.755**

Note: Group difference is tested based on paired t-test. Reward points are scaled in 1,000. **p<.01.

Figure A: Covariate Imbalance in Pre-period (Spender Proportion Across Two Groups)



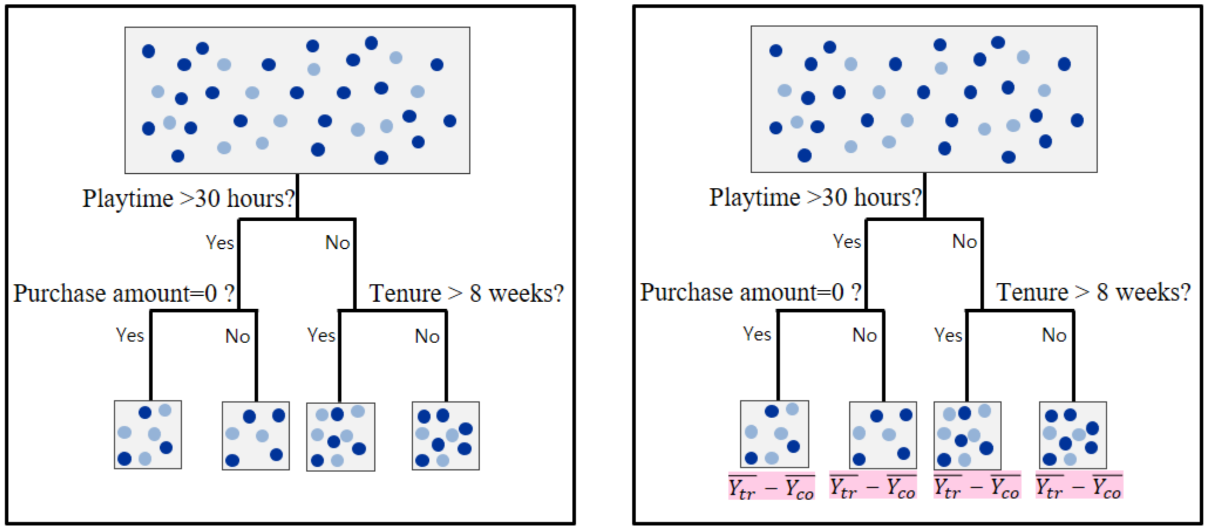
Note: Dark blue cell represents the proportion of spenders while Light blue cell denotes that of non-spenders. Color is available in electronic version.

B. Details about Causal Forest

As noted in the manuscript, our analyses mainly focus on Causal Forest suggested by Wager and Athey (2018). For illustrative purpose, we provide additional information regarding the first two steps of forest building in Figure B. Please refer to our discussion in section *4.2. Advanced Identification Strategy* in the main manuscript.

Figure B: Causal Forest Algorithm Illustration

Step 1: Tree Building	Step 2: Local Treatment Effect Estimation

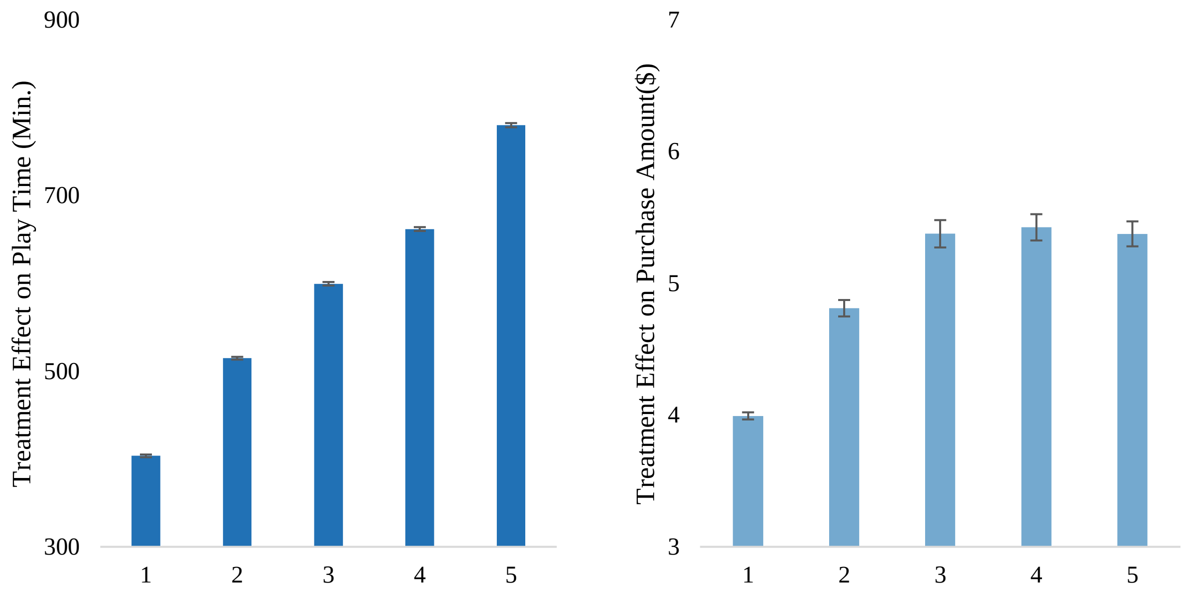


Note: The tree is simplified for illustrative purpose, the actual tree used in our model is different. Each dot implies observation (i.e., gamer). $\overline{Y_{tr}}$: mean value of outcomes for treated pairs (esports viewers); $\overline{Y_{co}}$: mean value of outcomes for untreated pairs (non-viewers). Color is available in electronic version.

C. Robustness check: Alternative measures for consumer expertise and variety seeking

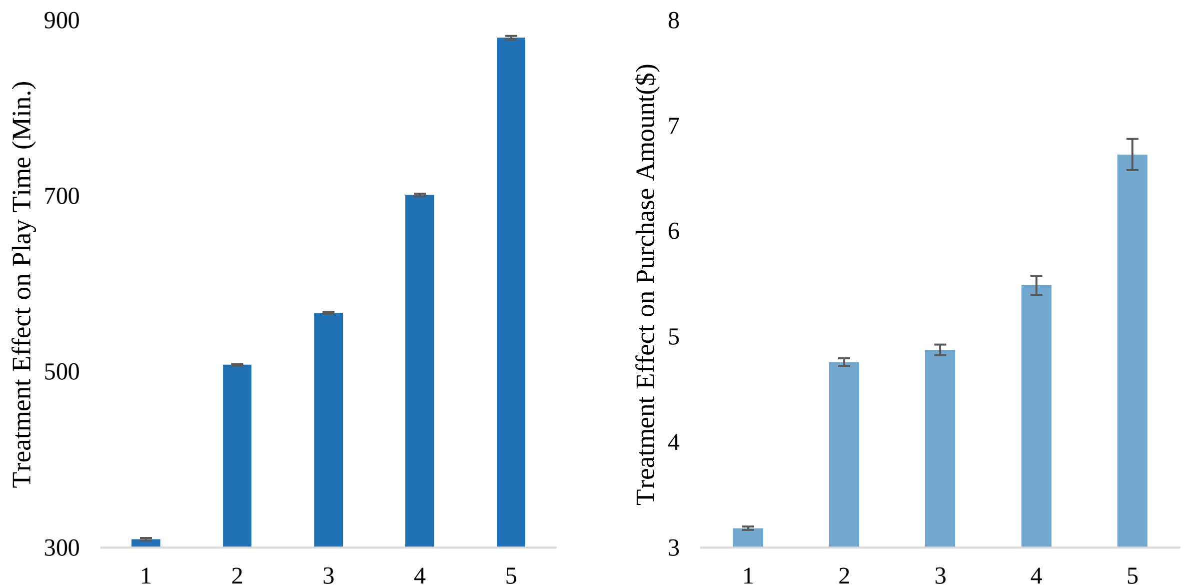
To ensure robustness of the results in effect heterogeneity, we replicate the model using alternative measures for *consumer expertise* and *variety seeking*. We use cumulative play minutes (instead of cumulative play sessions) for customer expertise and the number of unique characters chosen (instead of character variety) for variety seeking. All results remain qualitatively consistent.

Figure C-1: Estimated Treatment Effects by Customer Experience (Cumulative play minutes)



Note: Color is available in electric version. Group is ordered from the least experienced group (1) to the most experienced group (5). Error bars denote standard errors.

Figure C-2: Estimated Treatment Effects by Variety Seeking (the number of unique characters chosen)



Note: Color is available in electric version. Group is ordered from the group with least variety seeking (1) to the group with most variety seeking (5). Error bars denote standard errors.

D. *Details on propensity score estimation*

To attain the propensity score for a standard difference-in-differences regression, we estimate the indicator for the treatment group as a function of pre-period covariates using logistic regression (see Table C) (Chan and Ghose 2014, Dehejia and Wahba 1999, Rishika et al. 2013, Rosenbaum and Rubin 1983). We employ an *almost* similar set of covariates we used in Causal Forest method. That is, covariates used in propensity score estimation are not exactly the same as ones used for Causal Forest because some of them are highly correlated. Note that the tree based machine learning algorithm allows high correlation between covariates.

In Table C, One can see that as gamers play more, win more and kill more the likelihood of watching esports gets greater. The result also reveals that gamers with more tenure and variety in character choice are more likely to watch esports.

Table D: Propensity Score Estimation Result (Logit model)

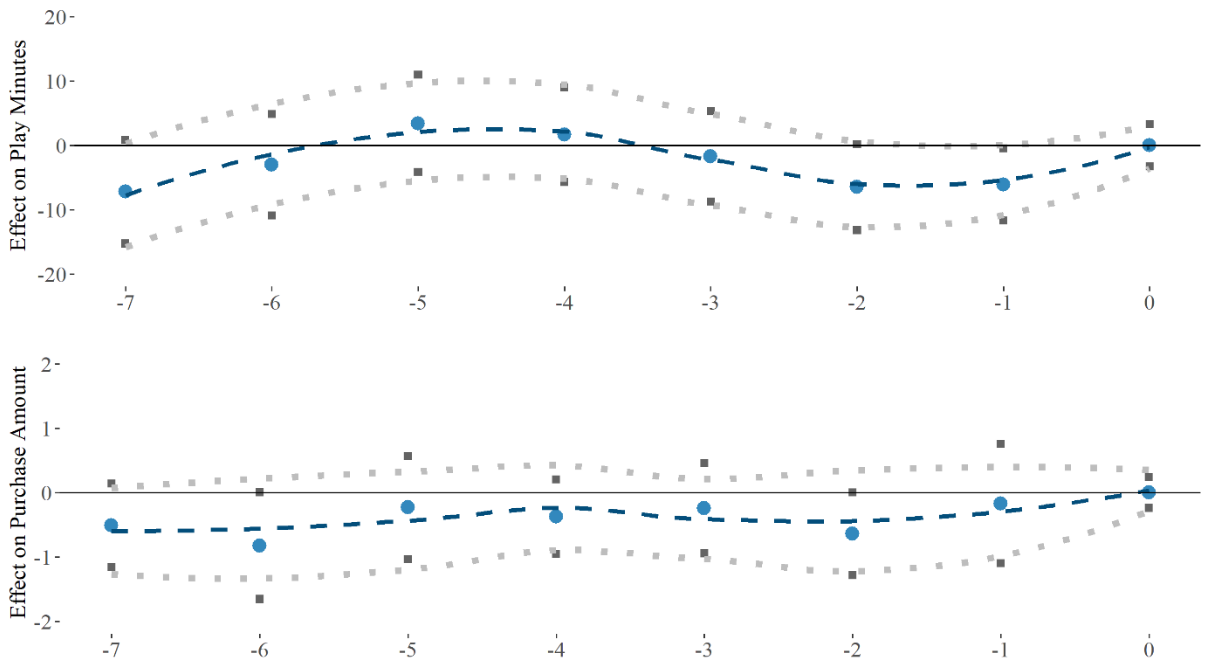
Variable	*Estimate*	*S.E.*
Play minutes	.184**	.006
Purchase amount	.039	.057
Win rate	.524**	.117
Kill rate	1.239**	.122
Rewards points	.291	1.821
User Tenure	.010**	.000
Character variety	-1.909**	.098
Intercept	-3.833**	.079
-2LL	32,500.692	
Pseudo R^2	.096	

Note: Play minutes and purchase amount are scaled in 1,000.
Rewards points is scaled in billion unit.

E. Robustness check: Parallel trend assumption in pre-period

We rely on the relative-time model suggested by (Greenwood and Agarwal 2015, Greenwood and Wattal 2017) and report the result of group level difference in pre-period in Figure E. We add trend lines to the estimates as well as confidence intervals to better highlight the time patterns. Figure E shows no significant differences in pre-treatment time trends across the treatment and control groups. This result further ensures the validity of our main results as well as the results presented in the preceding robustness checks.

Figure E: Pre-treatment Time Trend using Relative Time model

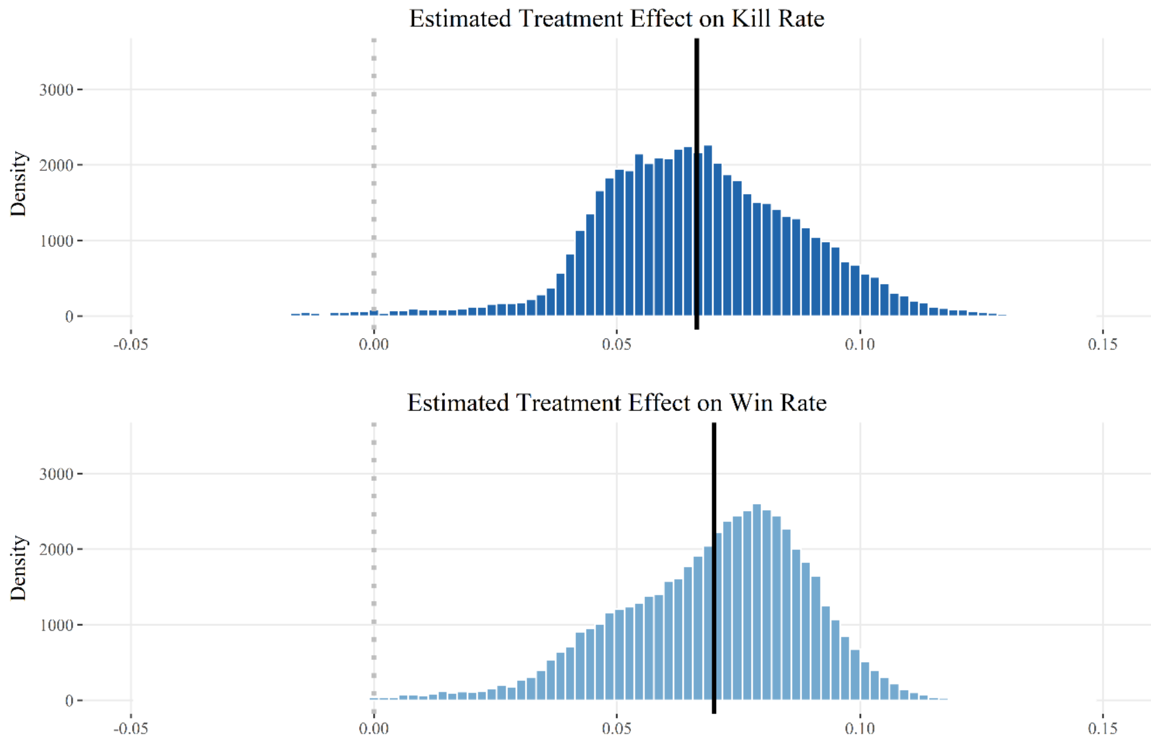


Note: Round dots denote the mean difference between esports viewers and non-viewers. Square shape dots represent 95% confidence intervals of differences. For illustrative purpose, we additionally plot the trajectories of differences and confidence interval based on loess smoothing technique. Color is available in electronic version.

F. Robustness check: Alternative definitions of gaming performances

To confirm whether our results are robust to alternative definitions of gaming performances, we replicate the first two analyses in '*6. Mechanism'* section using alternative forms of performance measures: *Kill rates* $\left(\frac{Kills}{Kills+Deaths}\right)$ and *Win rates* $\left(\frac{Win\ sessions}{Total\ sessions\ played}\right)$. All results remain qualitatively consistent: Increase in performance measures due to esports watching.

Figure F: Distribution of Heterogeneous Treatment Effects on Gaming Performances



Note: Vertical lines denote the positions of mean for each distribution. Color is available in electronic version.

Table F: Estimation Result Using Difference-in-Differences on Gaming Performances

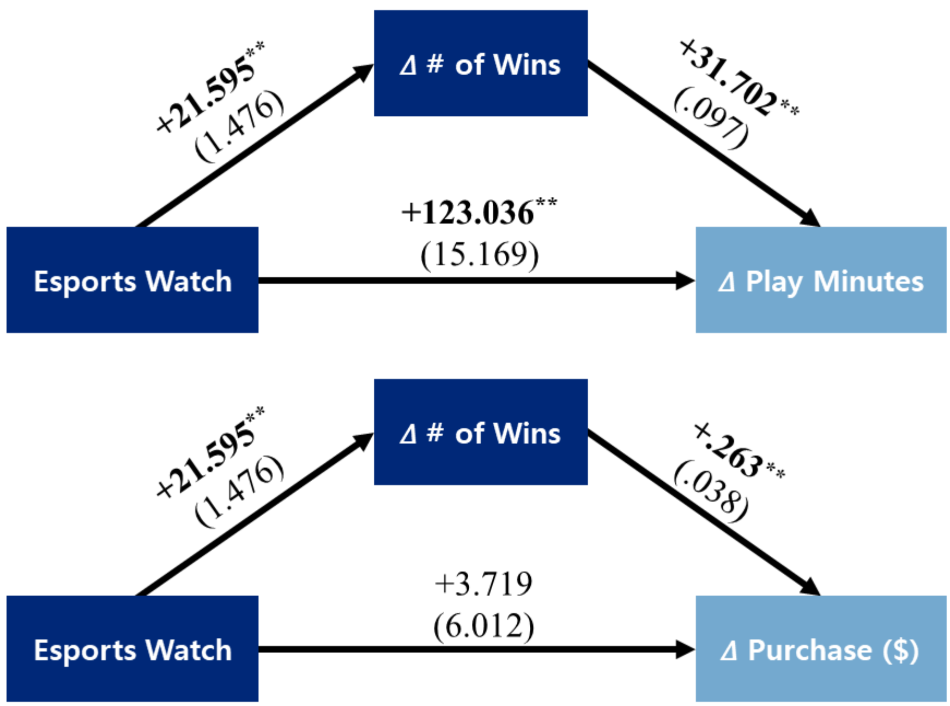
Dependent Variable	*Kill Rate*	*Win Rate*
Model	*(1)*	*(2)*
$EsportsViewer_i \times Post_t$	.085** (.009)	.078** (.003)
95% C.I.	[.067, .103]	[.053, .104]
Individual Fixed Effects	Included	Included
Time Fixed Effect	Included	Included
Adjusted R2	.265	.104

Note: Robust standard errors are used. Propensity scores are adjusted as in Table 6. N=109,200. **p<.01.

G. Robustness check: Supplementary result for mediation analysis

In addition to mediation analysis presented in Figure 6, we replicate the same analysis using the alternative measure of gaming performance: *a change in the number of wins*. The indirect effects estimates and bootstrapped standard errors are $\beta = 684.604$ and $S.E. = 48.914$ for play minutes and $\beta = 5.680$ and $S.E. = .958$ for purchase amount. Confidence intervals at 95% level also exclude zero (587.526 to 779.522 and 4.110 to 7.820, respectively) implying the result in Figure 6 is robust to alternative definition of gaming performance.

Figure G: Mediation Analysis: Role of Gaming Performance as a Mediator (a change in Wins)



Note: Δ(delta) represents a change between pre and post periods. Standard errors are reported in parentheses. Color is available in electronic version. **p<.01.

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