Essays on Addiction and Drivers of Excessive Consumption in Digital Media

by

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DEDICATION

To Margarida.

In loving memory of Lorraine.

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ABSTRACT

This dissertation investigates the mechanisms behind the pathological consumption of digital media, particularly focusing on impulsivity and addiction. With digital media's rise as a major form of entertainment, issues such as addiction and lack of self-control have become prominent, leading to significant mental and physical health concerns. Video games, especially popular among children and adolescents, exacerbate these issues due to their immersive nature and the use of manipulative design elements known as dark patterns, which exploit psychological vulnerabilities and drive excessive consumption. Utilizing data from a leading video game distribution platform, scraped daily over a year, this research comprises two essays. The first essay integrates psychological insights into a dynamic structural model to differentiate between stable, forward-looking consumption plans and impulsive, emotion-driven behaviors. The second essay employs a hierarchical Bayes approach to estimate individual addiction parameters, distinguishing addicts from regular players and examining behaviors such as game purchasing and playtime. This dissertation provides a nuanced understanding of how impulsive behavior and addiction impact digital media consumption, highlighting the threats to consumer agency and well-being.

CHAPTER 1

Hot Triggers vs Cold Preferences: Consumption Patterns in Digital Media

1.1 Introduction

Digital media has drastically changed the way we consume and interact with information and entertainment, many times in positive ways. However, excessive consumption of digital media has become a widespread issue and the mental and physical problems associated with it are increasingly common (Wongkoblap 2017; Lissak 2018; Neophytou et al. 2021; Braghieri et al. 2022). A fundamental issue when studying overconsumption is how to determine to what extent the observed consumption levels are truly excessive or simply the result of consumers making choices according to their preferences. This is because even though consuming digital media all day long would probably be qualified as excessive by most people, it is still possible that some individuals derive such high utility from this activity that it is still optimal to do so despite the negative consequences. In this context, however, multiple survey results suggest that high consumption levels are not simply the result of individuals' preferences, but that there may be other mechanisms at play. For example, in one survey,[1] 41% of teenage boys in the U.S. have reported spending "too much" time playing video games, suggesting that according to their own judgement they are overconsuming and 59% of gamers across different age groups in the U.S. and U.K. have acknowledged that they would continue gaming even in situations where doing so would be detrimental to their daily responsibilities.[2] Similarly, Burr et al. (2018) shows that up to 61% of social media users experience regret regarding the daily time spent on these apps, and yet do not cut down their usage.

Rational and forward-looking customers should not systematically make consumption choices that go against their preferences – that is, since they have agency over their consumption choices, there should be not regret. Thus, when consumers report that they are

[1] https://www.pewresearch.org/short-reads/2018/09/17/5-facts-about-americans-and-video-games/
[2] https://www.expressvpn.com/blog/who-spends-the-most-time-gaming/

consuming excessively as in the cases above, that indicates incongruence between their stated long-term goals and short-term decisions. This issue is known as *time inconsistency* and can arise for multiple reasons, including cases where it is triggered by environmental cues (Laibson 2001; Pennesi 2021). Interestingly, previous research has shown that digital media provide experiences that cause individuals to consume excessively by appealing to their "non-rational" side. For example, Koepp et al. (1998) show that video games can cause a release of dopamine in amounts similar to those observed with the use of amphetamine drugs and contain elaborate reinforcement mechanisms and reward schedules that maximize motivation (Green and Bavelier 2012). Video-on-demand platforms such as *YouTube* and *Netflix* have been shown to undermine users' sense of agency and induce them to spend more time consuming content (Lukoff et al. 2021, Schaffer et al. 2023), and social media apps employ variable interval reward schedules to keep users engaged (Burhan and Moradzadeh 2020). In fact, public health and industry experts have claimed that tech companies purposefully include design features in their products aiming at increasing engagement by exploiting vulnerabilities in customers' psychology.[3] [4]

In this paper, we focus on the case of video games to show that overconsumption of digital media can be explained by impulsive decisions triggered by experiences encountered during consumption. We estimate a dynamic model in which players decide how long to play each day while respecting leisure time constraints. When they play, however, individuals may encounter specific in-game experiences that trigger a hot process impulse that changes the expected utility of playing again in the present, making it more challenging to resist the urge to play more. As a consequence, they tend to consume more in the present than what they had originally planned, which causes deviations from their optimal long-term paths of consumption and may impact profits for the focal game and the platform offering multiple games.

Our approach is based on dual-processing theories, which propose that human behavior results from the interplay between two systems: one is "cold" deliberative, forward-looking, analytical and capable of planning, and the other is "hot", affective, myopic, and responsible for processing emotions and motivational states. We integrate insights from dual-processing decision theory into a dynamic structural model and take it to data. By doing so, we seek to understand the long-term distortions caused by cue-triggered time inconsistency generated by the myopic influence of the hot system (i.e. impulsivity). While previous literature has focused on the immediate impact of affect and other hot processes on decision-making, our structural model allows us to simulate decisions to study the long-term impact of impulsivity.

[3] https://www.bbc.com/news/technology-44640959
[4] https://www.nytimes.com/2022/10/02/opinion/video-game-addiction.html

Our counterfactual simulation shows that, in our context, impulsivity is responsible for 15.9% of monthly consumption. In addition, impulsivity leads to a more "lumpy" consumption pattern, where individuals tend to indulge in binge episodes and subsequent abstinence due to time constraints on their total hours available for leisure. We also discuss the implications to revenues for both the focal game and the platform offering multiple games.

Trading off long-term goals and short-term gratifications plays a crucial role in a variety of contexts. For example, when managing their personal finances, individuals often face the dilemma of saving for retirement versus indulging in purchases for immediate pleasure. The choice between maintaining a nutritious diet with attention to calorie intake or succumbing to unhealthy cravings confronts many every day. Therefore, a deep understanding of the mechanisms underlying self-control, temptation, and cue-triggered behavior is relevant not only for scholars in the field of marketing but to adjacent fields studying decision-making more generally as well. By studying the processes through which individuals make decisions and how psychological biases interact with the context (the influence of environmental cues), we contribute to a deeper understanding of human behavior and provide valuable insights that can have real-world implications.

The results of our study are relevant to policymakers around the world who have considered regulations aiming at curbing excessive video gaming by the underage population. For example, in 2021, China introduced new rules limiting gaming time for children under 18 years old to only public holidays or Fridays to Sundays from 8 pm to 9 pm. Similarly, South Korea had the *Shutdown Law* in effect between 2011 and 2021, which impeded the use of online games from midnight to 6 am for those under the age of 16. In the United States, there are currently no laws regulating video gaming time, but there is growing concern of excessive use of digital media among teenagers. According to a 2020 survey conducted by the University of Michigan's C.S. Mott Children's Hospital, almost nine in 10 parents believe that teenagers spend too much time playing video games,[5] and in Canada the game *Fortnite* faces a class action lawsuit from parents who claim that it was designed to be "as addictive as possible." We contribute to this debate by providing evidence that video games contain elements that appeal to the myopic side of players, potentially leading them to consume more than they would consider optimal.

From the point of view of practitioners, our study underscores two key points. First, if we can identify the specific situations and better understand the degree to which consumers are influenced to make decisions contrary to their goals, we can gain insight into when ethical concerns should be given special attention by professionals involved in designing and distributing such products. Our main contribution with respect to that is to show that such

[5] https://mottpoll.org/reports/game-teens-and-video-games-idUSKBN1ZJ25M

mechanism is present in digital media and to quantify the distortions caused in the context of video games. Second, it is possible that, over time, a share of customers become aware of the negative impact that consumption of certain products may have on their ability to self-control, and thus may decide to entirely abstain from consuming. If that happens, it is possible that demand may drop in the long run as has also been argued by previous literature (Nevskaya and Albuquerque 2019). Even though we do not look into this specific issue, it is a natural consequence of our findings as deviations from optimal consumption trajectories become more pronounced and consumers need to forego consumption after binge episodes in order to avoid indefinitely increasing the time they allocate to leisure.

1.2 Related Literature

Because time inconsistency leads to preferences that change over time, the topic is relevant to a variety of economic outcomes that involve long-term planning, such as mortgage decisions, credit card borrowing, smoking cessation, job search, gym attendance, and consumption of digital media (Strotz 1995; DellaVigna and Paserman 2005; DellaVigna and Malmendier 2006; Machado and Sinha 2007; Meier and Sprenger 2010; Atlas, et al. 2017; Zhang et al. 2022). Theory suggests that such time inconsistency could arise from present-biased preferences (Laibson 1997; O'Donoghue and Rabin 1999), temptation from certain goods (Wertenbroch 1998; Gul and Pesendorfer 2001), or impulsive decisions triggered by environmental cues and affective states (Laibson 2001; Loewenstein et al. 2015; Pennesi 2021). Our study is closely related to this last body of work, which investigate situations where individuals plan their consumption but are susceptible to changes in its marginal utility (or its expected utility) due to the influence of hot processes generated by environmental cues – which, in turn, leads to systematic mistakes in intertemporal decisions.

A related stream of literature has studied the impact of hot processes and environmental cues on decision-making (Loewenstein 1996; Forgas 2008; Berger and Fitzsimons 2008). However, most of these studies have been either exclusively theoretical or focused on the direct and immediate impacts observed in lab experiments. Some of this work has applied dual processing theories to explain the mechanism through which the hot system influences decision-making (Shiv and Fedorikhin 1999). Loewenstein et al. (2015) use the dual-processing framework to explain how the myopic influence of the hot system leads to present bias, and how such a model provides a reinterpretation of more traditional approaches to present bias such as quasi-hyperbolic discounting (Laibson 1997). We add to this literature by modeling present bias as the result of a hot system that responds to experiences during consumption, which allows us to study the compound consequences of a series of impulsive decisions over time and quantify the distortions with respect to the optimal consumption path.

Such framework has received support from research in psychology and neuroscience (Damasio 1994; LeDoux 1996; Panksepp 1998; Metcalfe and Mischel 1999; Kahneman and Frederick 2002; Lieberman 2003; Strack and Deutsch 2004) and gained popularity in other fields. For example, in economics, dual-processing theories are useful to explain departures from rationality, such as time-inconsistent preferences, Rabin's paradox of risk aversion (Fudenberg and Levine 2006; Rabin 2000), addiction and consumption despite harmful consequences (Bernheim and Rangel 2004), and other classic questions of economic interest such as savings decisions and individual discount rates (Thaler and Shefrin 1981). We add to this literature by applying this framework to understand the determinants of consumption in digital media.

This paper is also related to the literature on excessive consumption management (Nevskaya and Albuquerque 2019; Jo et al. 2020; Allcott et al. 2022). Substantively, this paper is closer to Nevskaya and Albuquerque (2019), who study how the frequency of rewards and notifications impact video game play time. Our approach is different from theirs in a couple of key aspects: first, they investigate the influence of in-game rewards, most of them virtual items that have cosmetic value or help players' progression. In this paper, we study hedonic experiences that have no cosmetic or functional use, in a match-based game where there is no stage progression or storyline. Therefore, rewards (in their case) and experiences (in our case) impact the decision to continue playing via different mechanisms. Furthermore, the impact of experiences in consumption is likely more generalizable to other situations. Second, while they study the impact of in-game rewards on the probability of implicit engagement states, we explicitly model the underlying mechanism that links in-game experiences to behavior.

Our approach is closer to Zhao et al. (2022), in that both papers study player behavior with a dynamic model where consumers have bounded rationality. However, the mechanism we study in this paper is fundamentally different. While they investigate players' prediction errors due to an intrinsic behavioral bias (overconfidence), our mechanism of interest is based on a hot impulse that depends on external stimuli (in-game experiences). Their context is a single-player game where individuals learn while progressing through increasingly challenging stages, and because each stage is unknown before played, overconfidence and prediction errors regarding own-success are an appropriate mechanism. In our context, players are divided into two teams by a matchmaker algorithm that aims at arranging matches in which teams have an equal chance to win. In other words, the matchmaker tailors the challenge level to each player, trying to offer always a similar experience. As players become more proficient, they are matched to play with better players. Thus, the matchmaker ensures that the expected chance to win is always 50% and player confidence on success should not be affected by previous outcomes. Furthermore, success is not individual, as it depends on the skills and interactions between other players in the same and opposing team. Our context is also considerably different in other dimensions: while their data comes from a 24-stage cooking game where revenue is generated by display ads, our data comes from a popular multiplayer game distributed on a platform that offers over 50,000 titles. This allows us to study how the mechanism impacts game revenues via microtransactions and the platform's revenue via the purchase of new games.

In the context of experiential consumption and entertainment, research has studied a variety of economic and marketing-relevant outcomes, such as pricing and advertising policies (Liu 2010; Mai and Hu 2022), network effects (Dubé et al. 2010), the impact of online reviews on sales and brand strength (Zhu and Zhang 2010; Ho-Dac et al. 2013), the impact of used goods on the sales of new goods (Ishihara and Ching, 2019), user engagement (Huang et al. 2019; Zhao et al. 2022), and state dependence (Etkin and Sela 2015; Woolley and Sharif 2022). In their theoretical work, Ely, Frankel, and Kamenica (2015) propose that suspense and surprise is the source of utility for entertainment products and can be calculated with observational data by assuming that individuals have expectations over outcomes. They show how to apply their model to mystery novels, political primaries, casinos, game shows, auctions, and sports. The framework has also been applied to study viewership in tournaments of the popular video game *Counter-Strike: Global Offensive* on the streaming platform *Twitch* (Simonov, Ursu, and Zheng 2022).

Specifically in the case of playing (as opposed to watching via streaming) video games, previous work has found that they are associated with satisfying psychological needs, which leads to engagement due to well-being effect (Przybylski et al. 2010). Video games also provide an optimal level of challenge that is conducive of a flow state and high levels of engagement (Sharek and Wiebe 2014). Still, most of this research has been based on surveys and self-reported data. Because we observe detailed data on in-game events and subsequent player behavior, we are able to use observational data to link experiences during consumption of a popular online game to managerially relevant outcomes, such as session continuation, switching to other games on the same platform, and purchase of new games. In the same manner, our paper also contributes to the growing literature on the video game industry.

1.3 Background and Data

With nearly 3.2 billion users worldwide and revenues forecasted to hit $220 billion in 2023, the video game industry is one of the most popular types of digital media today. In 2018, in a letter to its shareholders, *Netflix* stated that they more often compete with the bestselling game *Fortnite* than with *Hulu* and *HBO* – and since 2021, the company has started *Netflix Games*, their own video game platform. Another remarkable example of the industry's magnitude is *Grand Theft Auto V*, a game considered to be the fastest entertainment product to generate $1 billion in stores sales ever and the most successful entertainment product of all time with 170 million units sold for almost $8 billions in revenue since its release in 2013.

The game for which we observe in-game experiences is *Defense of the Ancients 2 (Dota 2)*, a popular game launched in 2013. As shown in Table 1.1, Dota 2 is currently one of the most popular esports worldwide by both viewership and prize pool. Dota 2 has an average number of monthly active users in the excess of 7.5 millions and can be accessed exclusively through *Steam*, the leading digital platform for video game distribution. Steam was founded over 20 years ago and currently offers over 50,000 titles for purchase and download. As of 2021, it has reached a billion registered accounts and 130 million monthly active users.

Figure 1.1: Number of users for digital media categories worldwide over the years (Statista.com)

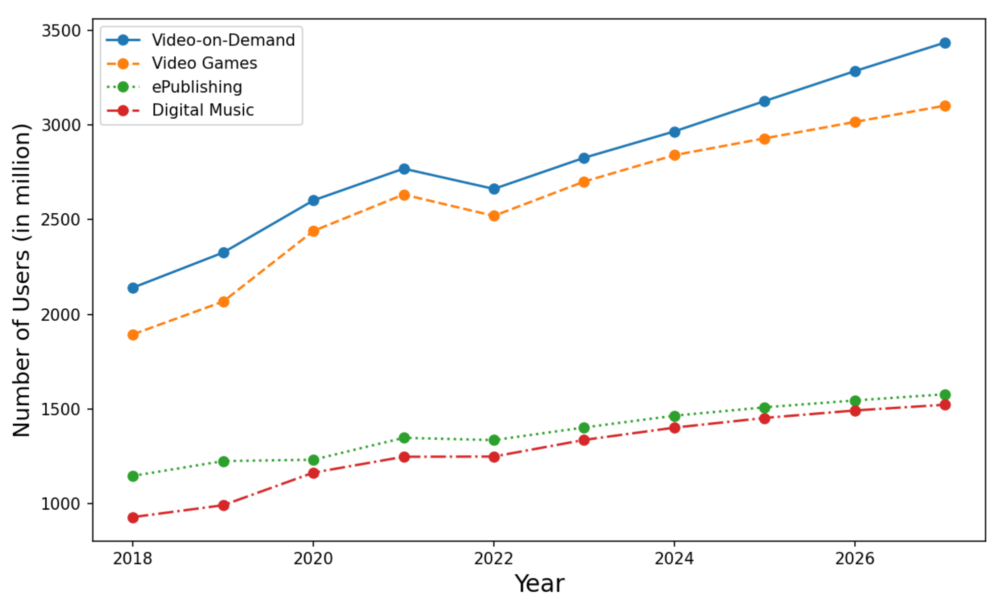


Figure 1.2: Revenue for digital media categories worldwide over the years (Statista.com)

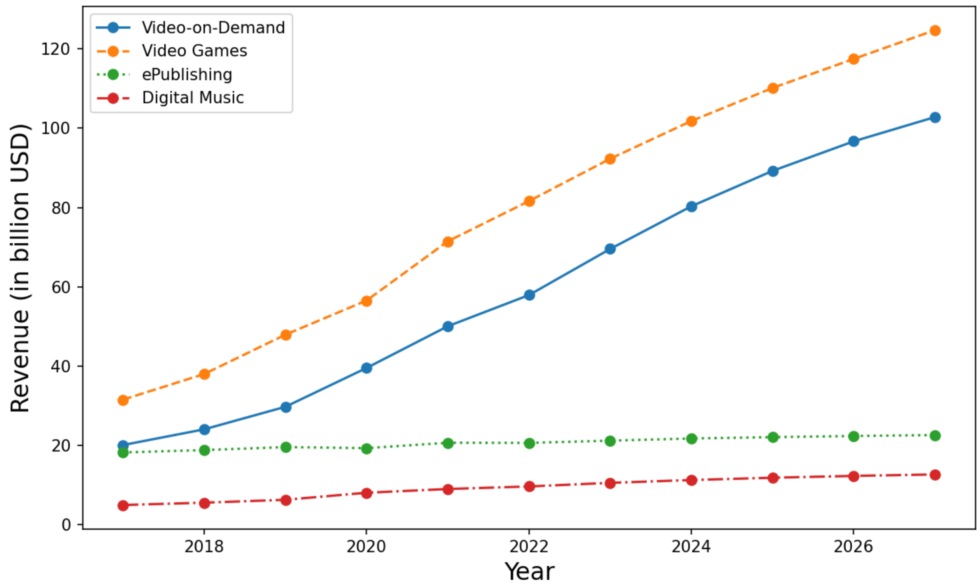


Table 1.1: Most popular esports in 2022 by peak viewers and prize pool (escharts.com)

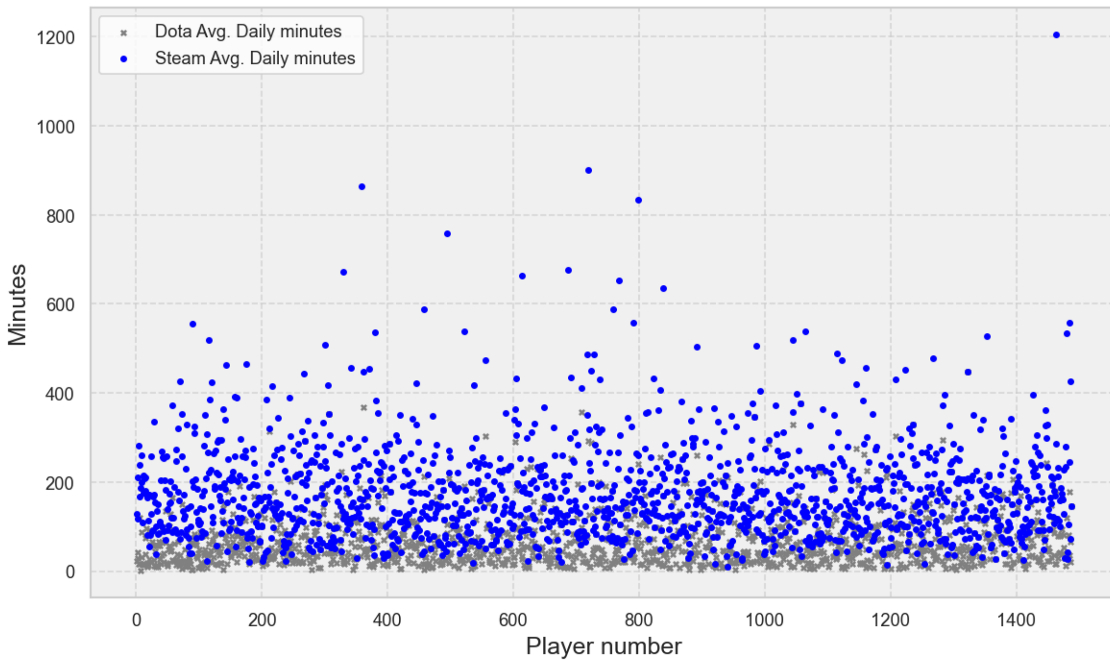
By peak viewers (#viewers)	**By prize pool (million dollars)**
League of Legends (5,147,701)	Dota 2 (32.5)
Mobile Legends: Bang Bang (2,845,364)	PUBG Mobile (24.7)
Counter-Strike: Global Offensive (2,113,610)	Arena of Valor (22.5)
Dota 2 (1,751,086)	PUBG: Battlegrounds (16.3)
Valorant (1,505,804)	Counter-Strike: Global Offensive (15.8)
Free Fire (1,477,545)	Fortnite (12.6)
PUBG Mobile (903,011)	Tom Clancy's Rainbow Six Siege (8.8)
Apex Legends (676,653)	Rocket League (8.7)
Arena of Valor (644,383)	League of Legends (7.8)
Fortnite (557,722)	Valorant (7.3)

1.3.1 Steam and Dota 2

Steam provides access to public user profiles data via their API. Users are identified by a 17-digit ID number, but there is no directory of user IDs. We generate random 17-digit numbers and store them after checking whether they correspond to a Steam user ID with a public profile. We also check whether the ID has an account on the website *OpenDota.com*, an open-source project that provides comprehensive statistics and data analysis for Dota 2. OpenDota also provides access to their data via their API, which allows us to observe matches by a given player and extract detailed match information. Lastly, we also use the website *SteamApis.com* to track prices and quantities for microtransactions taking place on Steam.

Because Steam API only provides a snapshot of players' accounts at a given time, we systematically webscrape data for 4,500 players every two hours from September 2022 to March 2023 and compute changes to obtain a final data set where we observe all games played or purchased for each player. We also observe when the account was created, number of friends and games downloaded, the total number of minutes each user played each game, user geographic information, and how many times they have been temporarily banned from the platform for cheating or other forms of misconduct. We focus on players with some experience in Dota 2 because for them the expected utility of playing one match should be stable, and select those who have played at least 50 matches (about 33 hours of gameplay.) We are interested in frequent players as hour model assumes that they have Dota 2 in their choice set for daily leisure. We further restrict the sample to those individuals who played at least once a month during the period in analysis. Our final data set comprises 1,490 players and 274,367 matches.

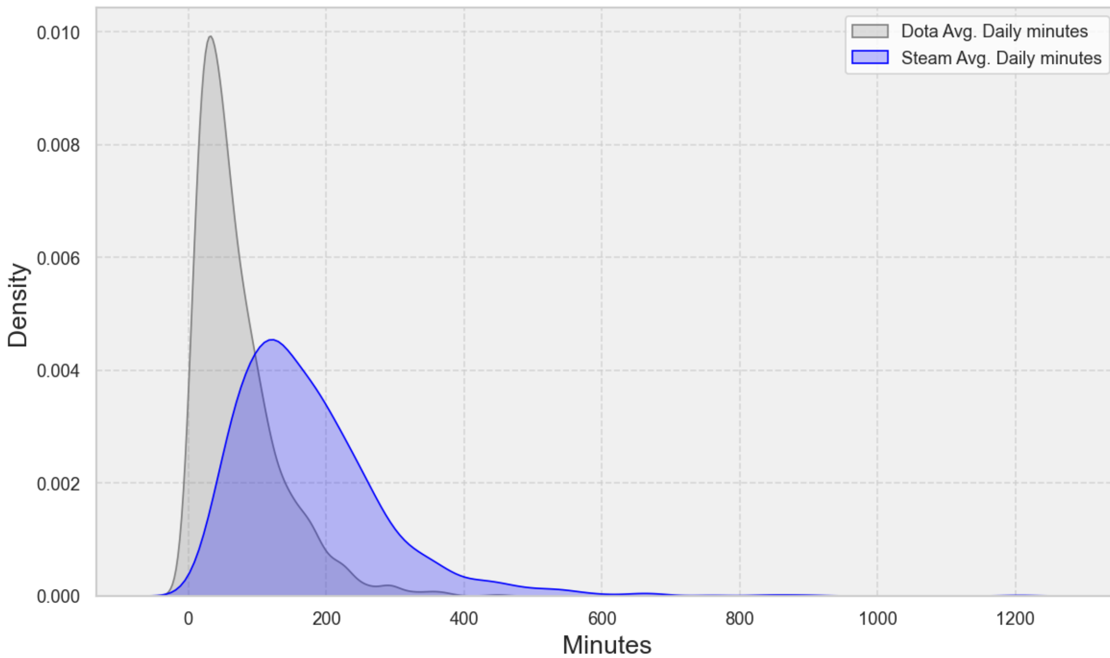
Figure 1.3: Scatter plot for playtimes: players (x-axis) and their respective playtimes for Dota 2 and all games on Steam (y axis.)



A possible concern regards players' self-selection into making their profile public. It is possible that more hardcore gamers could be more engaged with the game and more prone to making their profiles public, or it could be the case that more hardcore gamers are more likely to hide their profiles to avoid judgment. It is interesting to notice that almost all players in our data set are not exclusively playing Dota 2, but play other games regularly as well. In Figure 1.3, for each player, we plot the average daily playtime in minutes for Dota 2 and all other games on Steam. Similarly, Figure 1.4 shows the density of playtimes for Dota 2 and all other games on the platform. We can also observe the skill distribution and find no evidence to support the notion that our sample is skewed towards better players. In Dota 2, players are assigned ranks according to their skill level.

In the data, each rank is represented by a two digit number: the first digit (from 1 to 8) represents the rank and the second digit represent the number of stars (from 1 to 5). In Figure 1.5 we plot the histogram of rank distribution, where it becomes clear that most of the players in the data set are just regular players who do not achieve skill levels comparable to professionals who could play with the purpose of training and following a specific schedule.

Figure 1.4: Density plot for the average playtimes for Dota 2 (dark grey) and all other games on Steam (purple).



Third, we compare the weekly playtime observed in our sample with the results of a survey conducted in 2021 in the Dota 2 subreddit[6] and verify that our sample is actually less active on the game than the survey respondents. The results presented in Figure 1.6 show that our sample is more concentrated in the group of "4 to 8" weekly hours and has a much lower share playing 16 hours or more when compared to the survey results. The Reddit survey also asked participants what other esport games they watched or played. The results, reported in Table 1.3, show that 72.4% of the top 15 most mentioned games are also available on Steam, which means we can observe their time played in case they switch to one of those games. Lastly, we do not have access to players' demographics, but the survey may provide some insight. The age breakdown can be found in Table 1.4 and shows that only a small share (2.2%) of the participants are underage. Additionally, 93.5% are male, 3.5% are female, and 2.9% are non-binary, transgender, or declined to answer.

[6]https://www.reddit.com/r/TrueDoTA2/comments/lyb94u/rdota_2021_demographic_survey_results/

Figure 1.5: Rank Medals Distribution.

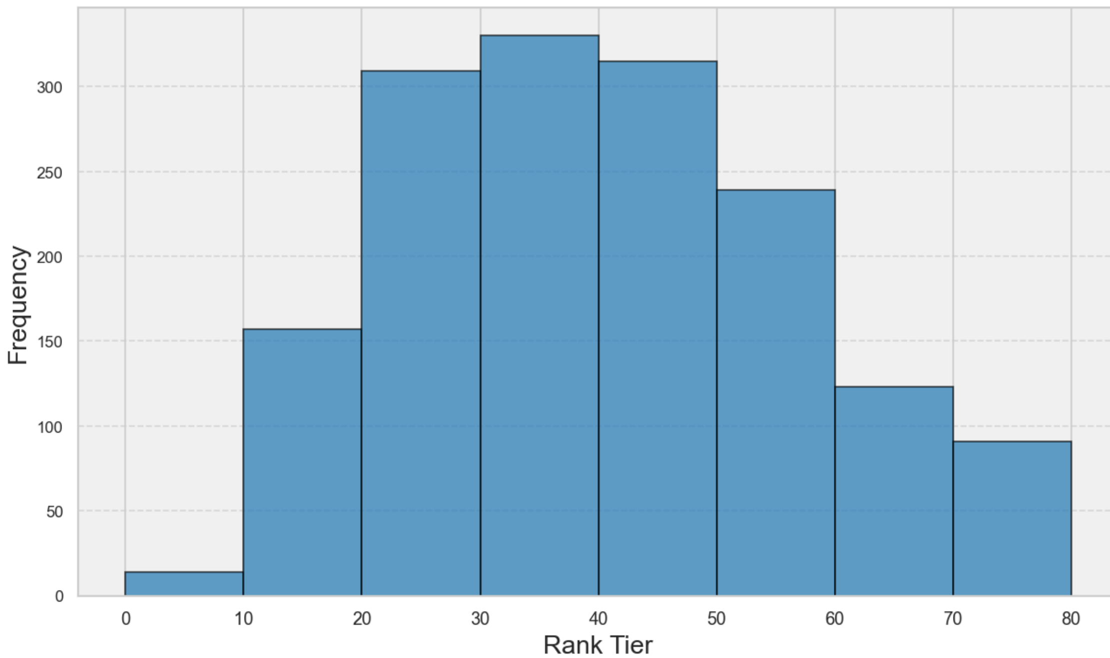


Figure 1.6: Playtime comparison between our sample and a Reddit survey.

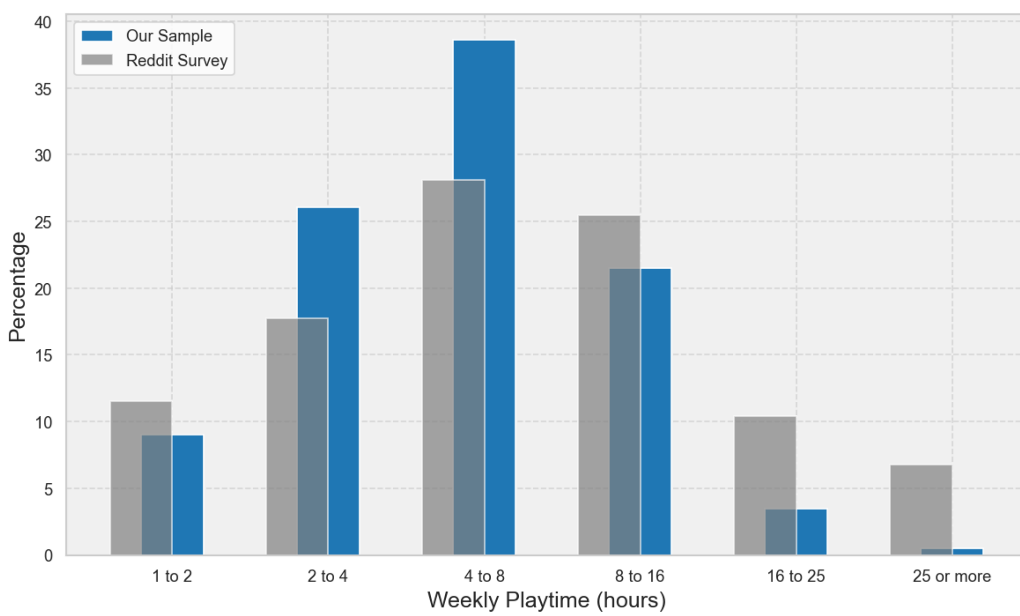


Table 1.2: Age distribution for Dota 2 players (Reddit survey).

Age group	**Percentage**
10 to 13	0.2%
14 to 17	2%
18 to 21	18.7%
22 to 25	32.8%
26 to 30	31.2%
31 to 35	11.9%
36+	3%

Table 1.3: Most commonly played esport games among Dota 2 players (Reddit survey). Asterisk indicates availability on Steam.

Game	**Percentage**
CS:GO*	24.6%
SuperSmash Bros	10.6%
Apex Legends*	9.4%
Rocket League*	7.4%
Starcraft II	7.3%
League of Legends	7%
Call of Duty*	6.7%
Valorant*	6.4%
Overwatch*	5.9%
Hearthstone	5.9%
Rainbow Six Siege*	5.6%
PUBG*	4.9%
Heroes of the Storm	2.1%
Smite*	1.5%
Fortnite	1.1%
Other	47%

1.3.2 Game Structure

We are able to isolate the impact of hot processes due to particularities of Dota 2's structure. First, from the perspective of the player, Dota 2 matches are independent as in more traditional games such as chess or checkers. Any items bought by a player or skills unlocked by experience points earned during a match disappear after that match ends. Every match starts in the same conditions, which makes match $m+1$ essentially a repeat of match m, except with new players picked by the matchmaker algorithm from a pool of players with comparable skill levels. The one aspect that can be changed is the combination of characters picked by players, but those are determined only after the decision to play has been made. This means that, *ceteris paribus*, the expected utility from playing a match does not depend on when it happens. Even if inexperienced players are still learning and updating their priors regarding the expected utility from playing, that should not change the optimal intertemporal allocation of playtime. For a simple illustration, consider the case of a player allocating T minutes between two periods:

$$\max \;\; V = u(c_1) + \delta u(c_2)$$
$$s.t. c_1 + c_2 \leq T$$

where $0 < \delta < 1$ is a discount factor and c_1 and c_2 are consumption allocations (in minutes) on periods one and two, respectively. For well-behaved utility functions $u()$, the first order condition is such that the marginal utility of playing is the same for both periods:

$$\frac{\partial V}{\partial c_1} = \frac{\partial V}{\partial c_2}$$

$$\frac{\partial u}{\partial c_1} = \delta \frac{\partial u}{\partial c_2}$$

Utility functions are defined up to a positive affine transformation, thus a learning process where u is updated would not change optimal allocations unless the update involves a radically different expected utility where playing is now perceived as harmful and undesirable (a negative affine transformation). For concreteness, assume that $u(c) = \log(c)$ and solve for the optimal quantities: $c_1^* = \frac{T*\delta}{\delta+1}$ and $c_2^* = \frac{T}{\delta+1}$. If the utility is updated to $\tilde{u}(c) = a.u(c) + b$ where $a > 0$ and b is a constant, the solutions c_1^* and c_2^* would remain unchanged.

A relevant case where allocations would change is when there is time sensitivity, for example, if $u_{t=1}(c) > u_{t=2}(c)$. In Dota 2, such situations generally do not happen because from the players' perspectives matches are independent. This means that, right after playing match m, the player is faced with the decision to continue the gaming session and play match $m+1$ immediately (continue the gaming session) or quit and play the next match in the future. The expected utility of playing match $m+1$ is the same in both cases. In Dota 2, the one situation where an exclusively rational, forward-looking player would binge is when playing with friends in the presence of a coordination issue – that is, if players derive great utility from playing with friends and they have the opportunity to do that on the current period and not in the foreseeable future.

In summary, to isolate the hot process mechanism that we propose to investigate, it is important that players' binge episodes cannot be rationalized by forward-looking individuals with preference for consumption smoothing. Notice that when matches actually happen, the uncertainty regarding the experiences is realized and players experience different levels of utility, but the decision to play is based on expected utility. Therefore, for an exclusively rational and forward-looking player, events experienced in match m should not impact the intertemporal allocation of match $m+1$.

1.3.3 Exogeneity of in-game experiences

First, the exogeneity of in-game events may depend on players' motivations when playing. For example, more motivated players could be more likely to play more matches in the same gaming session and also behave differently when playing, thus experiencing certain events more frequently. We argue that, in our context, players' ex-ante motivations do not vary significantly due to the highly competitive nature of the game, which provides strong incentives for players to always do their best to win. Dota 2 is an *esport* with frequent tournaments that in 2022 reached a total prize pool close to 33 million dollars, and competition is a big part of the game. Players are constantly watching each other and making sure that all team members are performing their roles correctly to the point that the developers actively try to make the game more friendly to new players.[7] For related reasons, Dota 2's community has been voted as one of the most toxic gaming communities several times,[8] which shows the strong peer pressure for each player to always do their best. This super competitive nature also eliminates concerns regarding players pursuing self-assigned goals instead of those proposed by the game. Because competition is such a big part of Dota 2, at any point during a match players can report each other for not playing their assigned roles by clicking an embedded "report" button – doing one's best to achieve victory is expected and they are punished for not doing so. The goal is always clearly defined and

[7] https://www.engadget.com/2017-07-29-dota-2-update-protects-newcomers.html
[8] https://www.theesportslore.com/post/why-dota-2-is-the-most-toxic-game

the way to achieve it is by maximizing the number of enemies killed and minimizing own deaths.

Furthermore, Dota 2 can be played in a *ranked* mode, which is even more competitive and rewards players with badges and medals that are displayed on their online profiles to represent their skill level. We restrict our sample to the ranked matches. We also restrict our sample to experienced players (at least 300 matches played) to ensure that they are a part of the game's community, understand it, and act accordingly. Lastly, we restrict our sample to frequent players, defined as those who play at least once a month. This mitigates possible variations in eagerness to play, which could happen for players who enjoy the game but were not able played for a long time.

Figure 1.7: Rank Medals from Dota2.com.

Second, even though players' intentions and objectives are always to win the match, they can still play in different ways (e.g. choosing to help their team by assisting allies instead of killing enemies), which could be correlated with different distributions of experienced in-game events. In Dota 2, players choose a character (called "heroes") before the start of each match. Each hero has distinct strengths, weaknesses, and roles to perform on the team, which means that they reflect different play styles. For example, heroes with supporting roles can be associated with fewer "kills" since they have abilities that focus on supporting their teammates and to killing enemies. We observe the hero chosen on each match, and thus we are able to control for different play styles as well. Conditional on play style, in-game experiences such as the the match result, the number of enemies killed, amount of gold collected, and number of deaths, can be considered exogenous as players have very well defined way to interact with the game: always trying achieve victory by maximizing gold and kills and minimizing deaths. Thus, conditional on our controls, the variations observed in experiences are caused by the actions of other players or computer controlled units.

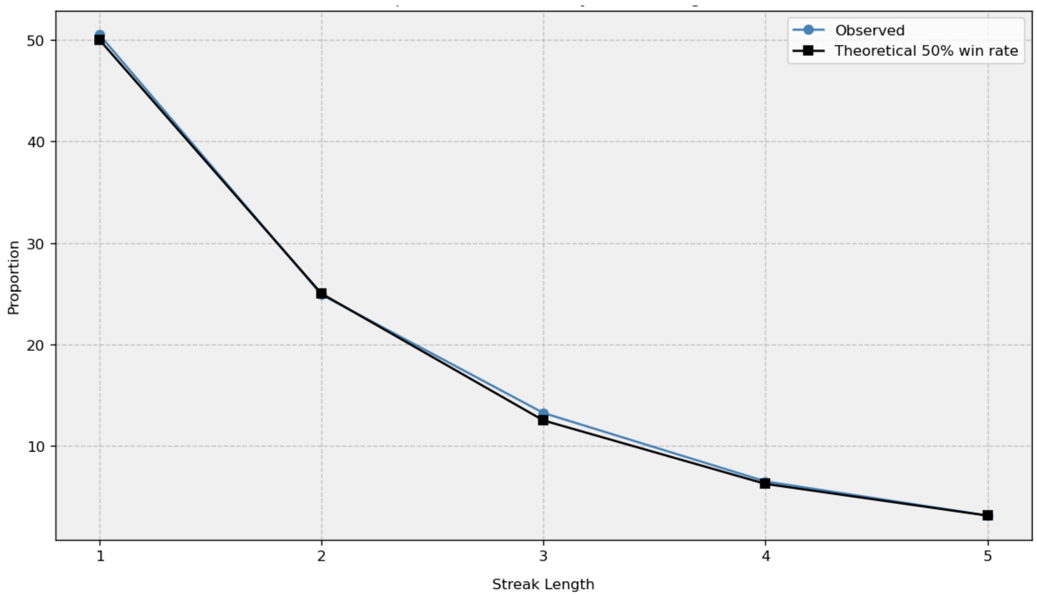
1.3.4 The Matchmaker Algorithm

Dota 2 developers claim that the matchmaker algorithm aims at providing challenging matches in which each team has an equal chance to win, and chooses the combination of individuals who will provide such experience to each other when they play together.[9] The first thing to notice is that the most important factor in the determination of how challenging a match will be to a given player is their *matchmaking rating* (MMR), which increases when players win a match and decreasing when they lose. This suggests that the algorithm adapts sequentially (and not temporally), as it learns from how players behave in game. Thus, it does not create windows of opportunity that induce time sensitivity.

Still, there is the possibility that players experience a "hot hand", where they are able to perform better due to feeling especially focused or confident for a relatively short time. We investigate whether momentum leads to winning streaks by comparing the probability to win conditional on streak length. If winning streaks are caused by momentum, players could take advantage of this time-sensitive opportunity where their chance to win is higher and play longer sessions. If players derive higher utility from winning, binging to take advantage of a hot hand could be considered rational and forward-looking. However, this possibility is not supported by the data. Figure 1.8 shows the proportion of observed streaks by length and compares them with the theoretical case where players have exactly 50% win rate. The proportion of winning streaks of each length is remarkably close to what we would expect if win rates were perfectly set at 50%, thus suggesting that the average winning streak is not caused by a hot hand, but a product of small sample bias (the number of matches in a session).

[9] https://win.gg/news/valve-dev-debunks-dota-2-players-forced-50-win-rate-theory/

Figure 1.8: Proportions streaks by length: observed and theoretical 50% win rate.



The slightly higher proportion of observed streaks may be at least partially explained by survival bias: players do not have to commit to a number of matches before they start a session, and once a match ends they can decide whether to quit or play one additional match. Because of that, players on a winning streak (even if that happened by chance) could be more likely to continue – which is also in accordance with our proposed impulsive mechanism. This is also supported by the winning probabilities in Table 1.4. The aggregate win rate is 50% and the winning probabilities conditional on streak length differ from that by at most 1.7 percentage point.

Table 1.4: Winning probabilities.

Pr(win)	0.505
Pr(win — 1-win streak)	0.506
Pr(win — 2-win streak)	0.515
Pr(win — 3-win streak)	0.483
Pr(win — 4-win streak)	0.505

Figure 1.9: Evolution of win rates for 20 randomly sampled players.

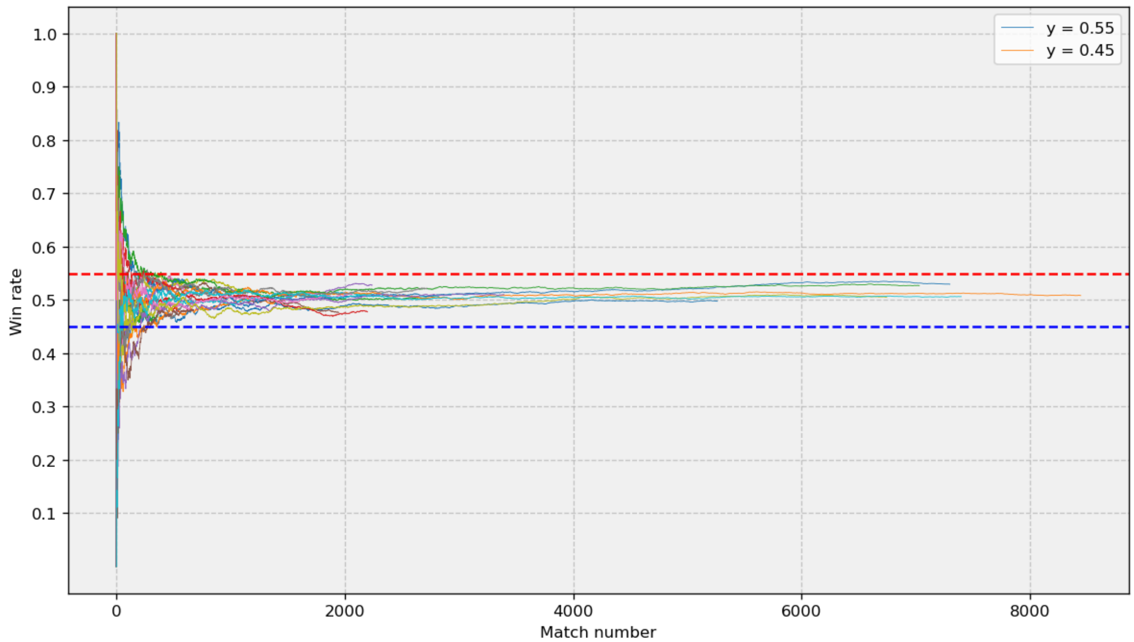


Figure 1.9 shows the quick convergence of individual win rates to 50% for 20 randomly sampled players. Notice that a 50% win rate is not required to study the mechanism of interest; the only requirement is that there are no time-sensitive situations, which could happen if the matchmaker offers players matches in which they have higher expected win rates for short periods. Still, Figure 1.9 is evidence that the matchmaker works as intended by the developers, since arranging matches where each team has an equal chance to win would result in a 50% individual win rate in the long run. A second reason why a 50% win rate is relevant is that it provides the right incentives to avoid binging: even in the occasion of a time-sensitive opportunity to obtain a higher win rate, indulging may not be optimal since the long-term win rate converges to 50%. Winning due to luck or any other aspects unrelated to skills would just lead the matchmaker to assign the individual to matches where other players are more skilled, thus leading to a subsequent lower win rate.

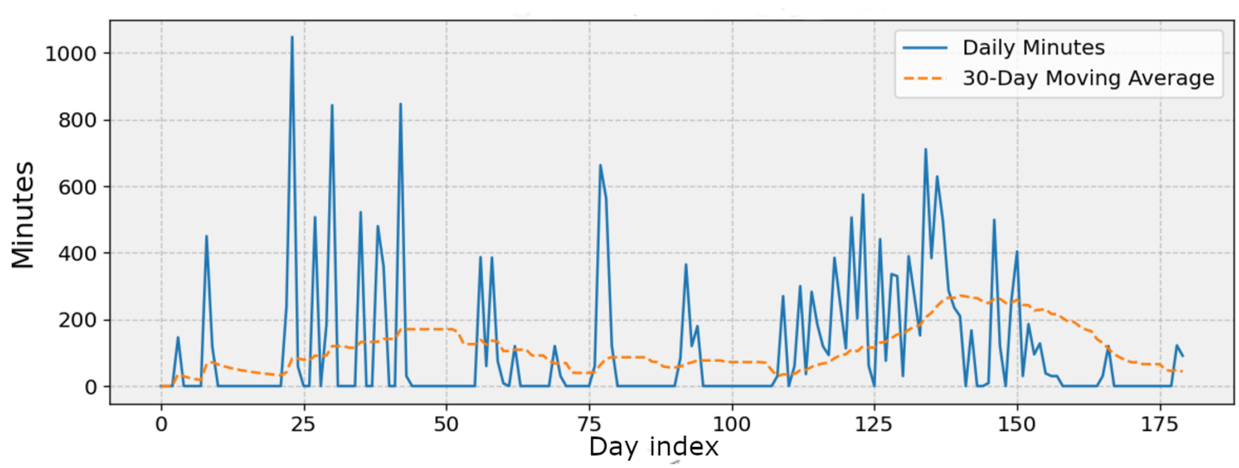
1.4 Theory and Model-Free Analysis

Our objective is to study the distortions caused by impulsivity to the optimal consumption path over time. In order to do that, we need a notion of optimality, which involves the key assumption that players have a preference for consumption smoothing. Once that has been established, we can interpret deviations from a smooth consumption trajectory caused by in-game experiences as the influence of hot processes. In this section, we discuss this assumption and the cases in which a rational, forward-looking agent could choose to violate it. We also lay out the theoretical basis for the impact of experiences during consumption on the subsequent decision to continue or quit the gaming session.

1.4.1 Consumption Smoothing

To study the patterns of consumption, we start with an informal visual analysis of video gaming patterns for illustration. We randomly draw a player and plot their total video game consumption on the platform as daily minutes on each of the days for the period under study. Figure 1.10 shows total minutes spent on Steam (that is, for any video games, including Dota 2). The graph displays high variation in daily playtime, with spikes that go past 1,000 minutes (16 hours) and days where playtime goes all the way down to zero. Notice that despite what seems to be long-term trends shown by the 30-day moving average, these variations occur within very short periods as well, from one day to the next.

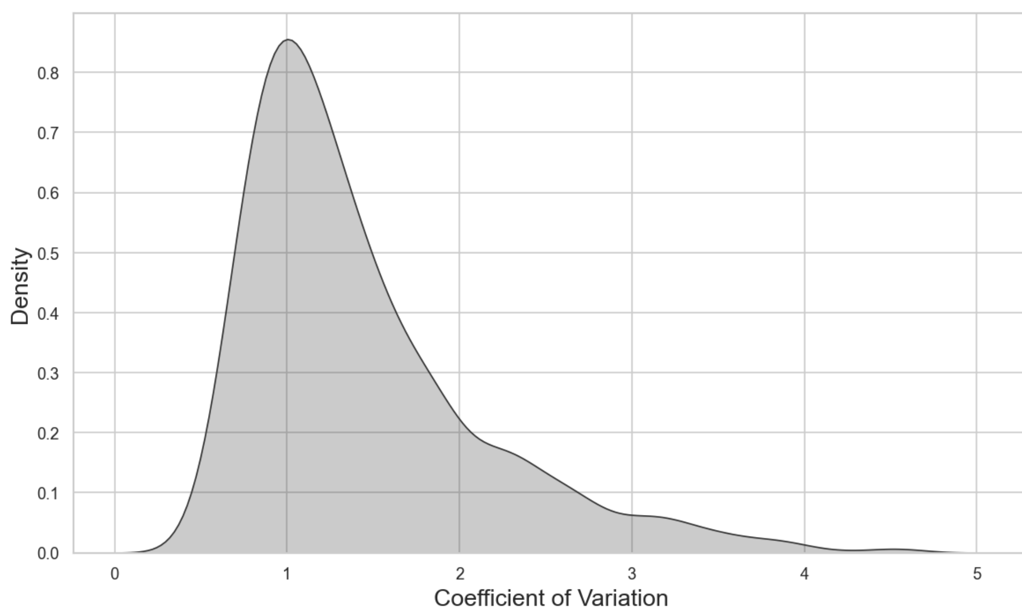
Figure 1.10: Minutes played on Steam for randomly sampled player.



In order to provide an aggregate measure of dispersion in consumption, we compute for each player the *coefficient of variation* for the playtime for each day of the week, defined as $CV = \frac{Std.Deviation}{Mean}$. This gives us a notion of how much each player's playtime varies on each day of the week. We then average that across days of the week for each player to get individual-specific measures of playtime dispersions. Notice that if players are perfectly smoothing consumption, their CV should be close to zero. In our data set, we find that the average CV is 1.4, thus indicating a significant level of variation in playtimes as the standard deviation is on average 1.4 times larger than the mean. Notice also that since we first compute the CVs for each day of the week and then average them, they are robust to weekly variations, that is, an individual who does not play during weekdays but spends a long time playing on weekends could still get a very low CV as long as this pattern is consistent. In Figure 1.11 below, we plot the density for the computed player-specific CVs.

Such patterns of consumption are intriguing because they are at odds with what we would expect from theory. Consumption smoothing is a standard concept in economic theory and dates back to the life cycle-permanent income hypothesis (Friedman 1957), which posits that individuals base their current consumption decisions on their expected lifetime income rather than their current income. Preference for leisure smoothing, specifically, is also a standard assumption in economic models (Anderson and Dogonowski 2004; Lentz and Tranaes 2005) and is a consequence of decreasing marginal utility of consumption: given a limited number of leisure hours, distributing playtime over many days yields higher utility than doing one single binge episode and then abstaining from playing later.

Figure 1.11: Density Plot of individual Coefficients of Variation for daily minutes of Dota 2.



Research has documented situations in which preference for consumption smoothing is violated, and liquidity constraints have been suggested as the most likely explanation (Parker

1999). That is, individuals will not smooth consumption when they are unable to borrow from their future income to mitigate present exogenous fluctuations. In our context, that would be equivalent to individuals who are not able to manage their free time and whose leisure depend on exogenous variations. We argue that such tight time constraints are unlikely for the majority of individuals, especially considering that the duration of a Dota 2 match is only 40 minutes, which represents only 2.7% of the total time available on a 24-hour day.

Table 1.5 shows data from the *2021 American Time Use Survey* (ATUS), and provides evidence that individuals do not significantly change how they allocate their leisure time even in situations where there are clear differences in time constraints (weekdays vs weekends). Moreover, ATUS breaks down time use by subgroups of the population according to employment, age, race, gender, and other characteristics. The group with less free time is that of individuals with at least one child under six years old in the household. Even for this group, the average free time per day is 2.96 hours, of which 30 minutes are spent in the category "Playing games and computer use for leisure." Therefore, it is unlikely that a significant share of players in our sample are so severely constrained in terms of their free time that smoothing becomes impossible.

Table 1.5: Average hours per day, all individuals above 15 years old (2021 American Time Use Survey.)

Hours per day (%)	**Weekdays**	**Weekends**
Total Leisure	4.72 (100%)	6.57 (100%)
Sports, exercises, recreation	0.31 (6.5%)	0.34 (5.1%)
Socializing and Communicating	0.43 (9.1%)	0.89 (13.5%)
Watching TV	2.57 (54.5%)	3.55 (54.0%)
Reading	0.26 (5.5%)	0.31 (4.7%)
Relaxing/Thinking	0.34 (7.2%)	0.35 (5.3%)
Playing games and computer use for leisure	0.53 (11.2%)	0.61 (9.2%)
Other leisure including travel	0.28 (5.9%)	0.52 (7.9%)

Another important observation is that time-sensitive situations that provide higher utility could explain a forward-looking agent choosing to concentrate their use of leisure hours on a few days instead of smoothing consumption. We argue that, in Dota 2, that only happens when playing with friends, which could involve both a higher expected utility of playing and a coordination problem to play together in the foreseeable future that creates time-sensitivity. For example, a player with 10 hours of free time to distribute throughout a week may choose to spend all those hours on a single day if their friends can only play together on that day, provided that they get a high enough increase in utility from playing with friends. For this reason, we do not use matches in which individuals played with friends in the estimation, but we still take into account the time they spent doing that or playing other games on the platform. Although it is true that the decision to play on a given day may depend on the availability of friends to play with, this exclusion is necessary to isolate the effects of interest.

Dota 2's structure is such that once we rule out learning effects by selecting experienced players, the decision to play an additional match does not depend on the in-game events recently experienced, since they do not provide new information about the utility of playing – and even if for some reason that happens, it would still be required that it does so in a time-sensitive manner in order to affect intertemporal allocations of playtime.

In summary, literature has identified liquidity constraints as an explanation for lack of consumption smoothing even when consumers are rational and forward-looking, but this is unlikely in our context. In addition to that, we identified that time-sensitivity in utility of playing could also explain deviations from a smooth trajectory, but we are able to exclude decisions potentially made under such circumstances. Thus, deviations from a smooth trajectory must be explained by a different mechanism. Moreover, notice that even though these two alternative mechanisms explain deviations from smoothing, they do not explain the influence of in-game events when matches are independent.

We conclude that the most likely channel through which experiences during consumption impact decisions is via the influence of hot processes. Because of that, we take an approach more closely related to the stream of literature that suggests that bounded rationality and behavioral biases such as limited attention, lack of planning and self-control as explanations for lack of consumption smoothing (Caballero 1995; Reis 2006; Gul and Pesendorfer 2004; Ameriks et al. 2003). In our model, experiences during consumption generate impulsivity, which temporarily changes the flow utility, thus leading to time inconsistency. It is interesting to note that Dota 2 is a *Multiplayer Battle Online Arena*, a type of video game for which past research has shown evidence that players experience strong affect during gameplay (Johnson et al. 2015; Tyack et al. 2016) and where excessive consumption has been linked to measures of impulsivity (Nuyens et al. 2016).

1.4.2 Impulsivity and Dual-Processing

In our context, decreasing marginal utility should lead to consumption smoothing by a rational, forward-looking players as that would maximize utility over time. However, our data suggests the opposite and players seem to indulge in binge episodes and subsequent abstinence. This happens even without evidence of time constraints that could impair smoothing or the presence of time-sensitive situations that would rationalize a forward-looking agent behaving this way . Given this context, we hypothesize that players may not behave rationally and in a perfectly forward-looking way all the time. Instead, they may give in to their impulsivity at times, which would explain: (a) the binge episodes observed in the data, (b) surveys where consumers report consuming excessively, even though they have agency over their own consumption, and (c) evidence presented by previous research and industry experts that digital media – and video games, in particular – take advantage of vulnerabilities in the brain to stimulate impulsive consumption.

Impulsivity is the tendency for actions with limited foresight and without consideration for its consequences, often made without hesitation and resulting in undesirable consequences (Grassi, Cecchelli, and Vigozzi 2021). The concept is intimately related to temptation and self-control: impulsive individuals have little self-control, which refers to the capacity to resist temptation or desires by overriding incipient patterns of response with a more thoughtful course of action (Baumeister 2002). Impulsivity can be viewed through the lens of a two-system model that explains social behavior as a joint function of reflective and impulsive processes (Strack and Deutsch 2004), which posits that decision-making is under the influence of two distinct systems. The first one, often referred to in the literature as the "cold" system, is reflective, deliberative, and based on knowledge and value assessment. In contrast, the second system – often called the "hot" system – is impulsive and influences behavior through associative links, affective responses, and motivational states, and is often driven by immediate desires and temptations. The interaction between the two systems, whether cooperative or conflicting, collectively determines behavior.

More closely related to our application, impulsivity may also be triggered by environmental cues that cause temptation and, more generally, hot processes can influence decision-making in a variety of contexts, including consumption decisions. Specifically in the case of video games, research has shown that individuals experience intense affect when playing (Johnson et al. 2015; Tyack et al. 2016) and that video games use reinforcement mechanisms to maximize motivation (Green and Bavelier 2012). In addition, Koepp et al. (1998) use tomography scans to show that video games can lead to the production of high amounts of dopamine, which is responsible for reinforcement behavior and released in an anticipatory stage, when players respond to environmental stimuli associated with positive outcomes. All of these findings support the notion that video games can impact decision-making via hot processes.

Notice that the extreme form of this mechanism characterizes addiction, when impulsivity progresses to the point of becoming compulsion and is typically characterized by a cycle of three stages: anticipation or craving, binge, and withdrawal (Koob 2012). Although making claims of addiction requires formal diagnosis as per the Diagnostic and Statistical Manual of Mental Illnesses (DSM-5), it is interesting to notice that the consumption patterns shown in the last session resemble the addiction cycle. Relatedly, Bernheim and Rangel (2004) use a dual-processing framework to model addiction as the switching from a cold to a hot mode in the presence of environmental cues that cause exaggerated responses by the hot system and hence an irresistible impulse to pursue the object of addiction.

A similar, but less extreme version of this mechanism can be found in decision-making models that take into account the influence of environmental cues (Pennesi 2020, Loewestein, O'Donoghue, and Bhatia 2015). Such models have found support in neuroscience, which suggests a mechanism where otherwise dormant areas of the brain are activated by external signals in a way that is proportional to the strength of the signal – the stronger it is, the more difficult it is for the cold system to override the hot one (Berridge and Aldridge 2009). We follow this literature and model the influence of the hot system on the decision to continue a gaming session as a function of the stimuli it has received during gameplay, that is, the in-game experiences working as external signals or cues.

1.4.3 In-game Experiences

The in-game experiences studied are: (a) an indicator variable for the final outcome of the match (*win*), which is the most salient feedback received by the player and their team and the most important measure of team performance; (b) the kill and assists to deaths ratio (*kda*), which is a measure of player performance specifically at killing enemies and avoiding being killed, commonly used in the video gaming community; (c) the gold obtained per minute by the focal player, which is a measure of player performance that takes into account other objectives such as defeating computer controlled units or defense structures; (d) the difference between the player's gold per minute and the average gold per minute by the player's team (*playerdiff_gpm*) as a measure of relative performance of the player with respect to their team; (e) the difference between the player's team average gold per minute and the rival teams average gold per minute (*teamdiff_gpm*) as a measure of relative performance of the player's team with respect to the rival team; (f) an indicator variable for whether the player obtained an upgrade in their rank badge (*rank up*); and (g) an indicator variable for whether the player was downgraded in their rank badge (*rank* down).

Table 1.6: In-game experiences.

Variable	**Description**
win	Number of kills and assists divided by number of deaths
kda	Player's kills + assists divided by deaths
gold per minute (gpm)	Player's gold per minute
playerdiff_gpm	(Player's gold per minute) - (Team's gold per minute)
teamdiff_gpm	(Player's team's gold per minute) - (Rival team's gold per minute)
rank up	Rank medal upgrade
rank down	Rank medal downgrade

In Dota 2, players choose a character (called *heroes* in the game) to play with in each match. Each hero has characteristics that describe their strengths, weaknesses and their play style. More generally, heroes can be described along nine dimensions: carry, support, nuker, disabler, jungler, durable, escape, pusher, and initiator. "Carry" heroes evolve into powerful late-game damage dealers, while "Support" heroes prioritize assisting teammates. "Nukers" excel in burst damage and are ideal for killing other heroes, "Disablers" can impair the abilities of enemies, "Junglers" excel at wandering alone across the map, "Durables" absorb damage and are more resilient to damage, "Escape" heroes evade threats, "Pushers" damage structures that need to be destroyed in order to win, and "Initiators" start team fights. Figure 1.12 below shows an example of hero characteristics.

Figure 1.12: Example of hero characteristics available at dota2.com.

Because different play styles could lead to different in-game experiences or reflect different ex-ante intentions that players may have (e.g. more risk-taking), we control for heroes characteristics and complexity by clustering heroes and including cluster assignment fixed effects. In our subsequent analyses, we also include the control variables in Table 1.7 below: The number of matches in the current session (*session matches*), the log of the total number of matches ever played ($log(matches\_ever)$), the duration of the match in minutes, and player fixed effects.

Table 1.7: Control variables.

Variable	**Description**
session matches	Total number of matches played in the session
minutes	Duration of the match in minutes
player FE	Player fixed effect
hero cluster FE	Indicator variables for cluster assignment of hero played

1.4.4 Gaming Sessions

In order to study the impact of in-game experiences on playing pattern, we need to understand the duration of hot processes and define gaming sessions accordingly. Notice that while full-blown emotions do not last more than a few seconds (Levenson 1994, Mauss et al. 2005), affect and hot processes in general are much broader concepts and include associative links and motivational states that can last considerably longer. For example, the *affect infusion model* (Forgas 1995), considers cases where affective states can modulate encoding, retrieval, and selective use of information for extended periods of time and thereby influence subsequent decisions, which has also been shown in experimental settings (Forgas and Bowler 1987). Similarly, the *emotion-imbued choice model* (Lerner et al. 2015) considers the carryover of incidental emotions and how what is experienced in a situation can influence judgement in a different and unrelated situation later.

Because theory does not offer definitive guidance on the duration of hot processes (which may be context-specific), we adopt a data-drive approach. In our setting, once individuals play one Dota 2 match, they are confronted with the choice of playing an additional match ($d_m = 1$) or quitting the gaming session ($d_m = 0$). We would like to determine the length ℓ that defines a gaming session according to the presence of the influence of in-game experiences that happened in the previous match: experiences in match m impact the decision to play match $m+1$ if both matches are in the same session. The task is to determine how long after match m the influence of experiences still exists when deciding whether to play match $m+1$.

We start by choosing $\ell = 1$, in which case matches m and $m+1$ are considered in the same session if they happened within one hour. This means that if the decision that happened following match m was to continue, which we represent by $d_m = 1$, otherwise $d_m = 0$. The binary nature of the problem allows us to model the decision with a simple logistic regression and, following that, we can apply the likelihood ratio test to evaluate the influence of in-game experiences. The test compares the full model that includes both controls (Table 1.7) and in-game experiences (Table 1.6) with a reduced model that only includes the controls. If the full model fits the data better than a the reduced model, we re-do the procedure to test for the case where $\ell = 2$. In the negative case, we increase ℓ. Our results show that the in-game experiences improve fit when deciding whether to continue playing up to two hours ($\ell = 2$). For $\ell > 2$, the full model does not improve fit over the reduced model, which we interpret as lack of evidence that a hot process is exerting influence over this decision. Therefore, in our application, we say that matches m and $m+1$ are in the session if the end of match m ended within two hours of the start of match $m+1$.

Algorithm 1 Finding the maximum duration of impulsiveness generated by in-game experiences.

For ℓ **in** $\{2, 3, 4, 5, 6, ...\}$**:**

  Define $d_m = 1$ if match $m+1$ started between ℓ and $\ell - 1$, otherwise $d_m = 0$

  Estimate full model (DV: d_m , Regressors: experiences and controls) and save its likelihood $\mathcal{L}_1$

  Estimate reduced model (DV: d_m, Regressors: only controls) and save its likelihood $\mathcal{L}_2$

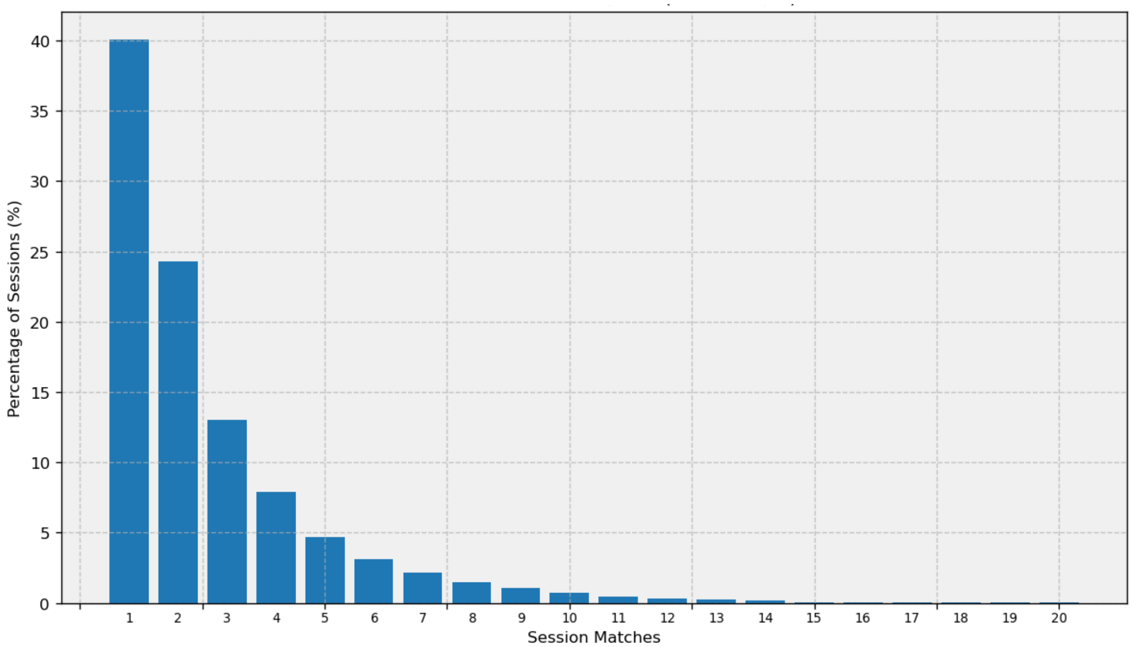
  Compute the likelihood ratio statistic $\lambda_{LR} = 2\left[\mathcal{L}_1 - \mathcal{L}_2\right]$ and the associated $p-value$.

  if H_0 **not rejected** ($p - value > 0.05$) **then**

    return $\ell - 1$

Given our definition of gaming session (matches that happened within two hours), we plot a histogram of session length in Figure 1.13, where we can see that most sessions consist of only one or two matches. Since the average match duration of 40 minutes, this corresponds to something between 40 and 80 minutes of playtime per session. The histogram of session lengths also reveals that longer sessions, spanning from 4 to 8 matches (equivalent to 2.6 to 5.3 hours), are not uncommon. Furthermore, a long tail is observed where a few extreme

Figure 1.13: Dota 2 Session Length (number of matches)



cases involve 10 or more matches in a single session. Our analysis focuses on these instances of longer sessions, aiming to determine whether we can attribute these occurrences to the influence of hot processes triggered by in-game experiences.

1.4.5 Preliminary Analysis

Table 1.8 presents the coefficient estimates of a logistic regression for the session continuation decision and the influence of in-game experiences, where the dependent variable is the decision to continue a gaming session ($y = 1$ if continue, $y = 0$ otherwise). These preliminary results suggest that individual performance has a positive impact on the probability of session continuation, as measured by gold per minute (*gold_per_min)* but negative as measured by the kill-death-assist ratio. The first captures overall performance better as it is related to not only killing enemies and surviving, but also killing enemy structures and neutral computer-controlled creatures, while the latter could capture other aspects as well – for example, an uneventful match could result in a high *kda* but a high *gold_per_min* only happens if the player achieves success in pursuing goals. When players are upgraded or downgraded by the matchmaker to the next or prior skill rank tier, they are also more likely to keep playing (*rank_up* and rank_down). Lastly, players have a preference for balanced matches as evidenced by the coefficients on *player_dif_gpm* (which measure the difference between the focal player's gold per minute) and *team_dif_gpm* (which measures the difference between the two team's gold per minute).

Table 1.8: Results for session continuation logistic regression. Player and month fixed effects omitted for conciseness.

	Dependent variable:
	Continue Session
win	0.013
	(0.021)
kda	-0.020^{***}
	(0.006)
player_dif_gpm	-0.181^{***}
	(0.024)
gold_per_min	0.266^{***}
	(0.027)
team_dif_gpm	-0.163^{***}
	(0.016)
rank_up	0.546^{***}
	(0.044)
rank_down	0.400^{***}
	(0.046)
session_matches	0.050^{***}
	(0.002)
minutes	-0.300^{***}
	(0.009)
Observations	177,493
Note:	*p<0.1; **p<0.05; ***p<0.01

The main takeaway is that players respond to in-game experiences even though they provide no information regarding the utility obtained in the next time they play. Thus, this should not happen for a rational, forward-looking player and suggests that other, "non-rational" mechanisms are at play. Notice also that the existence of an impact of in-game events on the decision to continue a gaming session is also evidence that such decisions are not simply determined by exogenous changes in free time. Interestingly, notice that the "win" indicator variable is not significant, which is evidence against the possibility of the hot hand as a mechanism driving continuation decision.

It is noteworthy that the most significant in-game events influencing a player's decision to continue playing are the upgrading and downgrading of player ranks. Our computation of the average marginal effects reveals that a rank downgrade (*rank_down*) increases the likelihood of continuing to play by 9.3%, while a rank upgrade (*rank_up*) boosts this probability by 12.7%. From a policy and business perspective, it is interesting to highlight that these elements are not inherently integral parts of the game itself, but are introduced to increase engagement by providing virtual rewards in the form of medals and badges that represent skills. It is also interesting that both the positive (rank upgrade) and negative (rank downgrade) feedbacks from the game have positive impact on players' decision to continue a gaming session.

1.5 Dynamic Structural Model

Dota 2 is based on matches with a well-defined beginning and end, thus session continuation is a discrete choice. In addition, because time for leisure is limited, the decision to continue a gaming session is also well described by a dynamic optimization problem, where current session continuation impacts leisure time available for more consumption of video games in the future. On each day t, players decide whether to play the first match, $m_t = 0$. When they play, we say that they started a gaming session, and once match $m = 0$ ends, they decide whether to continue and play $m_t = 1$ or quit the session. In every decision, they take into account that they are consuming their available leisure time in the current period and will have less leisure time in the future. Let $d_m \in \{0, 1\}$ represent the decision to play match m. When exclusively forward-looking ("cold" system only), players choose the sequence $\{d_1, d_2, ..., d_m, d_{m+1}, ...\}$ that maximizes the discounted expected utility stream:

$$\max_{\{d_m\}_{t=1}^{\infty}} \mathbb{E}\left[\sum_{t=0}^{\infty} \delta^t u(d_m, X_m, W_m, f_m, \varepsilon_m; \theta)\right] \tag{1.1}$$

$$s.t.\ f_{m,t+1} = f_{m,t} - y_{m,t} + \tilde{f}_t \tag{1.2}$$

where X_m is a vector of controls and θ are the associated parameters, f_m is the free time available when decision m happens, and $\varepsilon_m, \varepsilon_{m+1}, ...\varepsilon_{m+n}$ are i.i.d. structural errors. The free time f_m is an unobservable state variable with law of motion given by $f_{m,t+1} = f_{m,t} - y_{m,t} + \tilde{f}_t$, where $y_{m,t}$ is the duration of match m on day t and $\tilde{f}_t$ is an exogenous daily endowment of free time. The exogenous daily free time endowment assumes that, before the period under consideration, individuals decided to include Dota 2 in their choice set for daily leisure activities. Because of that, there is a certain number of minutes every day that they expect to use for video gaming.

When there is an opportunity to play a match, individuals take into account expected changes in state variables for future days, but without consideration for subsequent decisions within the same day – these are then only linked by changes in the state variables such as the number of matches in that same session and free time, etc. In other words, we model them as forward-looking across days, but not within days. While this assumption is useful because it limits model complexity, it ignores a first stage decision where individuals choose at which time of the day to play (e.g. whether to forego playing in the morning in order to play at night). Since we do not observe situations where individuals had an opportunity to play but chose not to do so, we need an assumption regarding such opportunities. The assumption that individuals have multiple opportunities to play throughout the day introduces more complexity into the model compared to our current framework, which requires individuals to have only one such opportunity per day and thus allows us to abstract from the first stage decision.

Players can also "borrow" free time from the future to use in the current period, as well as accumulate free time in the current period to use in the future. Players display some level of sophistication and understand that they have a tendency to get carried away during a gaming session. However, they are not sophisticated enough to predict exactly in which way that can happen. This means that when estimating the expected values of future states, they account for the fact that if they choose to play a match, the time commitment will reflect the average length of an entire gaming session rather than just a single match. The payoff associated with the first decision of a session $m = 1$ considers only the "cold" system and is given by:

$$u_{C,m}(d, X, f, \varepsilon) = \alpha + \theta X_m + \lambda_1 \mathbb{I}[f_m < 0] + \lambda_2 \mathbb{I}[f_m > 0] + \varepsilon_m$$

where λ_1 and λ_2 are parameters associated with time management. In other words, both systems derive utility from playing, but the hot system is myopic and does not take into account the intertemporal consequences of playing on the current period – that is, given the time constraints, more playtime now means less playtime in the future.

However, once players start a gaming session, their decisions are potentially under the influence of "hot" processes caused by in-game experiences (excitement, frustration, anger, etc.) For decisions $m > 1$ in a gaming session (whether to continue and play one additional match or quit), relevant payoff is:

$$u(d, X, f, \varepsilon) = \alpha + \theta X_m + \lambda_1 \mathbb{I}[f_m < 0] + \lambda_2 \mathbb{I}[f_m > 0] + \phi(\pi W) d_{H,m} + \varepsilon_m$$

Where $d_{H,m}$ is the decision generated by hot system's utility, which is the same as the cold system's, except it is myopic:

$$u_{H,m}(d, X, f, \varepsilon) = \alpha + \theta X_m + \varepsilon_m$$

The hot impulse function is represented by $\phi()$, and moderates the influence that the hot system has over an individual's final decision, as in Loewenstein, O'Donoghue, and Bhatia (2015). The intensity of the hot process and its impact on decision-making varies based on the different experiences described in Table 1.6.

$$\begin{aligned}\phi(\pi W) = \pi_1 \text{win} + \pi_2 \text{kda} + \pi_3 \text{gpm} + \pi_4 \text{gpm\_playerdiff} \\ + \pi_5 \text{gpm\_teamdiff} + \pi_6 \text{rank\_up} + \pi_7 \text{rank\_down}\end{aligned}$$

Notice that the connection with quasi-hyperbolic discounting models (Phelps and Pollak 1968, Laibson 1997) is intuitive. In such models, individuals' have a preference for current rewards that is consistent and decreases at a constant rate over time (the exponential discounting δ). However, in addition to that, individuals are impatient and discount all future periods with respect to the current one by β:

$$\begin{aligned}V &= u_0 + \beta\delta u_1 + \beta\delta^2 u_2 + ... + \beta\delta^n u_n \\ V &= u_0 + \beta\left(\delta u_1 + \delta^2 u_2 + ... + \delta^n u_n\right)\end{aligned}$$

This type of preference is time-inconsistent: on period t, individuals decide how to allocate playtime on all future periods such as $t + 1$ and $t + 2$. But since consumption allocation decisions are made again on every period, when $t + 1$ becomes the current period, the discount is only applied to the payoffs on periods $t + 2$ onwards, which increases the relative utility of the current payoff on $t + 1$. As a result, individuals with such preferences tend to change their minds about intertemporal allocation, consistently placing more weight on present consumption. Time inconsistency arises due to this systematic present bias, where the allocations for periods $t > 1$, that were planned on period t, keep changing as time passes. Our model works in a similar way, but time inconsistency is caused by a temporary increase in the expected utility of consumption in the current period instead of a relative decrease in the utility of consumption in future periods. This is in accordance with dopaminergic reward and prediction error models (Bernheim and Rangel 2007; Caplin and Dean 2008), where environmental cues lead individuals to overestimate the utility they will get from consumption on the current period.

Lastly, heterogeneity is allowed in the model by using individual-specific daily free time endowments based on the each player's average time played on each day of the week in each month. This accommodates changes in free time over the 6-month period under analysis and implies multiple transition probability matrices that depend on which player is making a choice and in which day of the week and month. We also include player fixed effects to capture different individual-specific baseline propensities to play Dota 2. Econometrically, the model explains how in-game experiences influence variations in time played around a time trend over a 6-month period.

1.5.1 Estimation

Using Bellman's equation, we can rewrite the optimization problem in (1) as an infinite sequence of two-period decisions:

$$\begin{aligned} V(X_m, f_m, \varepsilon_m) &= \max_{d_m, f_{m+1}} \left\{ u(d_m, X_m, f_m, \varepsilon_m; \theta) + \delta \mathbb{E}\left[\sum_{m=0}^{\infty} u(d_{m+1}, X_{m+1}, f_{m+1}, \varepsilon_{m+1}; \theta) \right] \right\} \\ &= \max_{d_m, f_{m+1}} \left\{ u(d_m, X_m, f_m, \varepsilon_m; \theta) + \delta \mathbb{E}\left[V(d_m, X_{m+1}, f_{m+1}, \varepsilon_{m+1}; \theta) \right] \right\} \\ s.t. \quad f_{m,t+1} &= f_{m,t} - y_{m,t} + \tilde{f}_t \end{aligned}$$

We can also define the choice-specific value function:

$$\tilde{V}(d_m, X_m, f_m, \varepsilon_m) = \begin{cases} u(1, X_m, f_m, \varepsilon_m; \theta) + \beta V(1, X_{m+1}, f_{m+1}, \varepsilon_{m+1}) & if\ d_m = 1 \\ u(0, X_m, f_m, \varepsilon_m; \theta) + \beta V(0, X_{m+1}, f_{m+1}, \varepsilon_{m+1}) & if\ d_m = 0 \end{cases}$$

Let $d^*()$ be the optimal decision rule, and we can write it as:

$$d^*_m(X_m, f_m, \varepsilon_m) = \arg \max_{d_m \in \{0,1\}} \left\{ \tilde{V}(1, X_m, f_m, \varepsilon), \tilde{V}(0, X_m, f_m, \varepsilon) \right\}$$

And to estimate the model, we can integrate out ε to obtain conditional choice probabilities. Assuming that the errors $\varepsilon$are distributed according to an *Extreme Value Type I* and are i.i.d. across matches, the probability to play a match is:

$$\Pr\left(d^{*}=1|X,f\right)=\frac{\exp\left(u(1,X,f)+\beta\mathbb{E}\left[\tilde{V}(f'(1),X')\right]\right)}{\sum_{d=0,1}\exp\left(u(d,X,f)+\beta\mathbb{E}\left[\tilde{V}(f'(d),X')\right]\right)}$$

Given the conditional choice probabilities, we can write the log-likelihood as the sum of the log conditional probabilities given observed data. Estimation is then carried out with a nested fixed point approach. The *inner loop* iterates the value function to find the fixed point EV and simulate the decisions $(d_{C,m}, d_{H,m})$. The *outer loop* maximizes the likelihood function and updates the parameters to estimate to estimate the parameters after the inner loop converges.

Because the free time f is unobservable, we follow the same method applied by Gordon and Sun (2015) to manage unobserved inventories: First, we set all initial free time to zero and estimate the model's parameters and initial condition parameters. Second, we use the resulting estimates to simulate the model 100 times for 2×180 periods to generate a distribution of initial free times for each player. Third, for each player, we draw an initial free time value from the pooled set of free time distributions across the 100 run and use these draws as our initial distribution of free times in the final estimation. Lastly, we use the average daily time spent on the video game platform – playing Dota 2 or any other games – as the exogenous free time endowment.

1.5.2 Identification

Our identification strategy is similar to that of Yao et al. (2012). In their paper, they estimate discount rates by taking advantage of a field experiment that allowed them to observe customers making choices in two distinct situations, when the choices were static and when decisions in a period would impact their decisions in the future. The first situation allows them to estimate the utility parameters and, since these are considered unchanged, the difference in choices when comparing static and dynamic settings can be explained with the inclusion of a discount factor.

Following a similar strategy, we use only situations where individuals make decisions while "cold to estimate the parameters of the utility. Because we observe that players choose differently in situations where they are under the influence of recently experienced in-game events, we can rationalize the difference in behavior with the influence of the hot impulse function and estimate its parameters. In the first case, choices only reflect players' intertemporal preferences, but in the second case they also reflect the influence of the myopic system. Since we are able to clearly assign each observation to one of the two situations, we can separate the impact of the hot impulse. Furthermore, even though the different types of experiences (in-game events) may be correlated with each other, they do appear separately in the data, which provides us with variation to estimate parameters and evaluate the impact of each of them.

For example, every day individuals have the opportunity to decide whether to start a gaming session. Since that decision is the first on a given day, there is no influence from a hot process generated by previous in-game experiences. When individuals choose to play one match and start a gaming session, they also need to decide whether to quit the session or play one additional match. According to the results we obtained in section 1.4.4, when they play again within two hours, we know this decision was made potentially under the influence of experiences they had in the last match. Similarly for the case they choose to quit. Thus, we can identify the parameters of the utility using the observations where players decided without the influence of the impulse. Conditional on that, the remaining observations are used to identify the parameters of the hot impulse function, π. As usual in dynamic structural models, the discount factor is not identified and we need to fix a value based on estimates obtained in previous literature. Yao et al. (2012) finds a weekly discount rate of 0.91 using the identification strategy outlined above. Since our context involves daily decisions, we convert the 0.91 weekly discount rate to a daily discount, which corresponds to 0.987.

1.6 Results and Counterfactuals

Table 1.9 below shows parameter estimates. The time management parameters λ_1 and λ_2 indicate how much more likely to play individuals become when they have extra free time. Because players can borrow or save hours to use in the future, $\lambda_1 > 0$ means that they are less likely to play when their current balance of hours is negative (i.e., time constrained) and $\lambda_2 > 0$ indicates a higher probability of playing when there is extra free time (i.e., free time for leisure is available). Players also respond to winning a match (*win*), performing well as measured by their kills-deaths-assists ratio (*kda*) and amount of gold obtained per minute. Players become less likely to play when their team performs relatively worse than they do individually, as measure by *gpm_playerdiff* and when their team is superior to the rival team (conditional on winning) as measured by *gpm_teamdiff*, which may suggest a preference for competitive matches. Notice that there are two different "time" variables in the model. The first one is the total video game time. It is represented by y and goes in the free time law of motion. It takes into account time spent playing any video games on Steam, including Dota

2 with or without friends. The other "time" is the "session time" that appears as a control variable in the decision to play one additional match. Figure 3 below shows daily measures for each of these, where we can verify that they are different. The correlation between the two time variables is 0.18.

Econometrically, the structural model differs from the logistic regression model from session 4.5 in that it estimates the impact of in-game experiences only when the decision cannot be explained by the preferences alone – since the impact of experiences in the dynamic model only appears when the cold and the hot systems decide differently. In addition, it takes into account an unobservable variable (the free time at the moment of each decision) and how players are forward-looking when managing it, taking into account that they will act rationally when making future decisions as well. Furthermore, the in-game experiences are only allowed to impact the decision when the lack of free time leads to a reversal in the decision. Thus, these are two distinct models estimated under different assumptions.

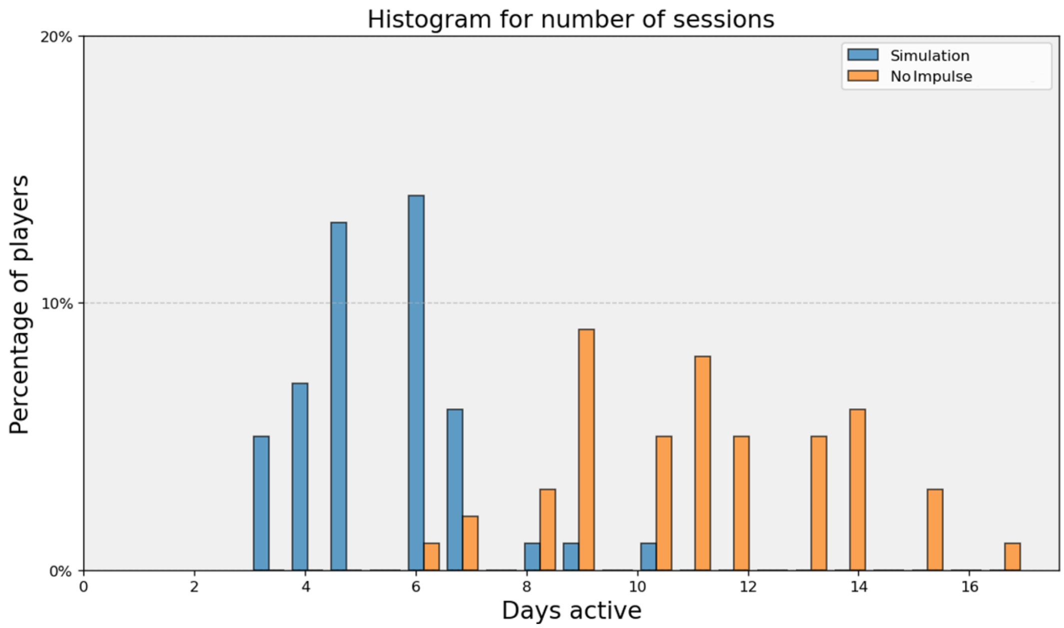
Because experiences may be correlated, we cannot randomly simulated them separately. Instead, we draw from the distribution of observed matches and their associated in-game experiences. The no-impulse counterfactual suggests that in-game experiences cause individuals to play more via impulsivity: while the baseline simulation using the estimated parameters results in an average of 23.18 matches played in a month (approximately 15.4 hours in total or around 31 minutes a day), the counterfactual where there is no impulsivity results in an average of 20 matches in a month (approximately 13.3 hours in total or 26.4 minutes a day). Thus, in the time frame of one month, the impulsivity triggered by in-game experience leads to an average increase of 3.18 matches (around 2.12 hours) over the baseline simulation. Notice that this increase refers to the playtime of Dota 2 only, but if the same underlying mechanism applies to other forms of digital media with effects of similar magnitude, the total number of hours of consumption due to impulsivity is likely much higher. In percentage terms, impulsivity leads to an increase of 15.9% in consumption of Dota 2.

Table 1.9: Parameter estimates. Individual fixed effects omitted for conciseness.

Variable	**Estimate (Std. Error)**
λ_1	0.71 (0.08)
λ_2	0.0007 (0.003)
session matches	-0.09 (0.038)
win	0.04 (0.24)
kda	0.24 (0.05)
gold per minute	0.82 (0.08)
gpm_playerdiff	-0.83 (0.08)
gpm_teamdiff	-0.40 (0.05)
rank up	-1.29 (0.83)
rank down	0.41 (0.72)
minutes	0.06 (0.05)

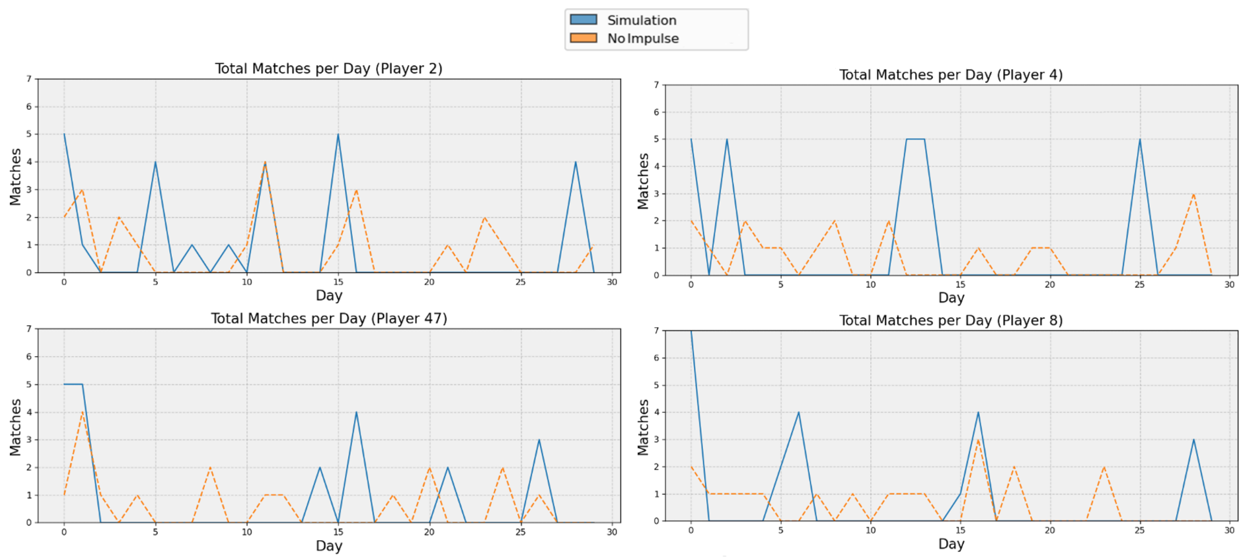
The patterns of consumption are also different when there is no impulsive decisions, as individuals would play more often and shorter sessions. Defining as “active” on a given day those individuals who played at least one match, Figure 1.14 shows histograms for the active players according to the number of days in the 30 simulated days. Comparing both histograms, we can see that when there is no impulsivity players tend to be active on more days (x-axis) as they spread out the Dota 2 matches instead of concentrating them in fewer and longer sessions driven by impulsive decisions. The duration of a gaming session (conditional on playing at least one match) is 3.6 matches (or around 2.4 hours) in the baseline simulation, but only 1.9 matches (or around 1.2 hour) in the counterfactual without impulsivity. In addition, because each gaming session is shorter, players are less time-constrained on each day and thus are active on more days per month: 6.44 active days in the baseline simulation and 10.5 without impulsivity.

Figure 1.14: Share of players who were active (played at least one match) during a simulation of 30 days. Baseline simulation (blue) and no impulsivity counterfactual.



To better illustrate how impulsive decisions affect consumption patterns, we randomly draw eight players and plot their daily decisions for the baseline model and the counterfactual without impulsivity in Figure 1.15. The blue continuous lines show the consumption for the baseline simulation and the presence of spikes of consumption representing days in which many matches were played, usually followed by valleys where there is no consumption. The orange dotted lines plot the corresponding counterfactual simulation where there is no impulsivity. Consumption becomes more regular, with more frequent and shorter gaming sessions.

Figure 1.15: Number of matches played per day for five randomly sampled players. Baseline simulation (blue continuous line) compared to no impulsivity counterfactual (orange dotted line).



From a policy perspective, our findings emphasize the importance of implementing mechanisms to assist consumers with self-control challenges. Prior research by Zhang et al. (2022) reveals that customers use commitment mechanisms effectively to resist temptations in the context of e-books. However, such mechanisms are not universally available across all digital media platforms. In such instances, software designed to promote digital well-being (e.g., app blockers, screen management tools, app usage trackers) may offer viable solutions. Nonetheless, awareness of these software options remains limited, hindering their potential widespread adoption and usefulness. Drawing a parallel with the debates surrounding the regulation of potentially harmful products like tobacco and sugary drinks, our results support the consideration of digital media in this category.[10] In several countries, regulations require clear disclosure of sugar content on sugary drink labels due to health concerns. Similarly, cigarette packages are required to display explicit warning labels about their addictive potential and health risks.

Other digital platforms such as Instagram, TikTok, and streaming services also contain elements that appeal to the "hot" system and influence the decision to continue or stop consumption, such as infinite scrolling, cliffhangers, interaction buttons ("like", "share", etc.) that deliver dopamine hits or impact self-control through other similar hot processes.

[10] https://www.huffpost.com/entry/smartphone-warning-label_n_56152dc6e4b0cf9984d7c43a

In this sense, they are similar to video games, which also contain this type of elements and takes advantage of the same mechanism. However, the magnitude of the impact could be different even if the mechanism is the same. The paper does not really investigate other types of digital media so what we can say in terms of extrapolation is very limited and mostly about the shared mechanism. Recreational screen time in the US is currently around 4 hours a day (120 hours a month) and our counterfactuals suggest that without impulsivity, it would go down to 100 hours a month, which means 20 extra hours that are misallocated.

These results also hold implications for the platform offering multiple games. On Steam, players see game recommendations when they log in to the platform or switch games, but not during gameplay. In a scenario where players adopt the counterfactual behavior of shorter, more frequent gaming sessions, they would receive more exposure to game recommendations, which could lead to discovering a wider array of games and therefore more sales for the platform. In the longer term, the data generating process could change as players move away from Dota 2 more often. Conversely, a new influx of new players to Dota 2 could also happen as they switch from their current favorite games. Interestingly, Steam offers over 50,000 games but is a winner-takes-all environment: according to the third-party website *Steamdb.com*, the game with the highest all-time peak players if *PUBG: Battlegrounds* with 3.2 million players and the 5,000th game is *Defense Grid 2* with a little over one thousand players (for comparison, Dota 2 is 4th place with 1.3 million.) Thus, for Dota 2 and other "winners" in the current scenario, keeping a high player base could become more challenging if the only way to keep players engaged were by appealing to their "cold preferences.

Another aspect to consider is that over time, a share of the customers may realize the how video games negatively impact their self-control and the consequent harmful effects in other aspects of their lives. Consequently, they may choose to completely stop playing altogether. This shift in consumer behavior could lead to a decrease in demand in the long term, as previous studies have also suggested (Acland and Chow 2018; Nevskaya and Albuquerque 2019). Over the past decades, we have seen a shift in customers' preferences toward more healthy and sustainable products, with a growing share avoiding products such as cigarettes, sugary food, or products that contain PFAs chemicals, and the increase in demand for eco-friendly products such as solar panels and electric vehicles. Therefore, even without ethical considerations, it may be in developers' best interest to avoid creating video games that exploit customers' psychological biases.

1.7 Conclusion

In this paper, we focus on the case of video games to investigate the long-term impact of impulsivity on consumption levels. We study the underlying mechanism by enriching a dynamic structural model of consumption with theories of dual-processing decision-making, in which decisions result from the interplay between a cold, forward-looking system and a hot, myopic system. The latter responds to experiences during gameplay and causes players to make "mistakes" and deviate from their optimal consumption plans. A natural next step for our work is to leverage microtransaction data for Dota 2 and sales figures for Steam, which would allow us to perform counterfactual simulations where we vary the type and frequency of in-game experiences and evaluate the consequent changes in total play time and revenues for the focal game and the platform offering multiple games. We argue that even though we leverage the structure of our empirical context to identify the impulsivity on consumption of video games, this same fundamental mechanism is present in the consumption of other forms of digital media.

Our work has important policy and managerial implications. The widespread adoption of smartphones, social media platforms, video streaming services, online gaming, and other digital technologies has led to increased screen time and potential addictive behaviors, thus sparking great interest in public health experts. While the deceptive aspects of "dark patterns" have received most of the attention from researchers and regulators, manipulative design can also be used to tempt users with short-term satisfaction and thereby lead to overconsumption, binge behavior, regret, and even addiction (Burr et al. 2018, Chaudhary et al. 2022; Roffarello, et al. 2023). For example, Facebook's founding president has stated that their goal was to consume as much of people's time and attention as possible by appealing to the brain's reward system. While we cannot support the claims that such mechanisms are implemented intentionally by product designers and developers, we show evidence that they are present in the case of a popular online video game and indeed influence the decision to continue consumption. We also quantify the long-term distortions to consumption patterns and total monthly consumption and find that impulsive decisions are responsible for 15.9% of digital media consumption. Thus, our results highlight the need to raise awareness about excessive consumption of digital media and the application of devices that help users enforce their commitment to their optimal levels of consumption.

Academically, our paper is relevant to multiple fields that study decision-making, as it contributes to the enduring interest in bounded rationality and psychological biases. From the perspective of marketing scholars, our work is relevant as it studies the role of impulsivity on the consumption of digital media, which is one of the most important industries of our time. It also contributes to bridging the gap between work in psychology and quantitative modeling. Finally, understanding the extent to which consumption is due to impulsivity also underscores the importance of ethical considerations in product design and promotion. As such, our findings draw attention to the need for responsible marketing practices.

CHAPTER 2

Is Video Gaming Addictive?: An Empirical Analysis

2.1 Introduction

In recent decades, the video game industry has experienced an explosive growth that outpaces traditional entertainment industries like film and television. With projected industry revenues of $282 billion in 2024,[1] video games are an important and ubiquitous form of entertainment. Their availability on dedicated consoles, laptop computers, and smartphones makes them accessible to consumers of all ages and backgrounds anywhere and at any time. Iconic games such as *Grand Theft Auto V* and *Minecraft* exemplify the magnitude of the industry: the former is considered the most profitable entertainment product of all time[2] and the latter has sold over 300 million units worldwide. Such remarkable figures are possible due to a robust market in which over one billion individuals currently participate[3], with over 200 million participating in the United States alone.[4]

This exponential growth, however, has resulted in increased scrutiny, especially due to the popularity of video games among children and adolescents. Excessive video gaming has been associated with an array of physical and mental health issues, such as obesity, sleep problems (Robinson et al. 2018), increase in ADHD-related behaviors (Bavelier et al. 2011; Turel, Romashkin, and Morrison 2016), anxiety, depression (Hoge, Bickham, and Cantor 2018), aggressiveness, and higher consumption of cigarettes and drugs (Desai et al. 2010.) Furthermore, the frequent inclusion of elements that take advantage of consumers' psychology to increase engagement has prompted the debate about the ethical issues involved in such practices (Søraker 2016). As seen in the case of more traditional addictive goods such

[1] https://www.statista.com/outlook/dmo/digital-media/video-games/worldwide
[2] https://www.gamesindustry.biz/gta-v-is-the-most-profitable-entertainment-product-of-all-time
[3] https://www.statista.com/statistics/748044/number-video-gamers-world/
[4] https://www.statista.com/forecasts/1277728/physical-or-digital-core-gamers-in-the-us

as cigarettes, gaming also overstimulates the brain's *reward system*, thereby leading to behavior reinforcement and repeated consumption. Currently, the World Health Organization considers video game addiction as a mental disorder,[5] and in their recently published book *Technological Addictions* (2021), the American Psychiatric Association called for greater awareness of the addictive potential of technology – including video games – and the need for preventative measures.[6] In this paper, we try and shed light on this issue by leveraging a rich data set of actual gaming behavior sourced from *Steam*, the leading worldwide video game digital distribution platform. This is one of the first studies of video game addiction that uses a very rich data set, comprising real-life behavior of thousands of consumers playing a large number of games. To the best of our knowledge, these two aspects combine in what is probably the first study on video gaming addiction using observational data. In order to build the data set required to study this phenomenon, we need to observe the playtime for each individual on each day, the games they purchase, along with other decisions and choices that they make on the video game platform. To that end, we systematically track 50,000 users for 11 months via their *Steam* accounts. This allows us to take advantage of the panel structure to infer addiction patterns using observational data. Specifically, we use the reduced form empirical test for addiction - a positive coefficient on past consumption - that is well established in the economics (e.g., Becker, Grossman and Murphy 1994) and marketing (e.g., Gordon and Sun 2015) literatures.

We first provide evidence of video game addiction based on aggregate estimates and show that the effect is present even after ruling out alternative mechanisms, such as consumer learning and serial correlation. We then investigate carry out a disaggregate level analysis, adopting a Hierarchical Bayes approach, that allows us to recover individual-level addiction coefficients. Based on these coefficients, our main finding is that video gaming addiction exists, with 18.3% of gamers exhibiting patterns consistent with addiction. The granularity of our data allows us to perform robustness tests that consider video game consumption from different perspectives (e.g., video gaming as a single product or each video game considered as a different product) - these show that the percentage of addicted gamers can go down to 14.6%. This range (14.6% to 18.3%) can be seen as a starting point for both policymakers and for future research using secondary data (in contrast to most of the past literature that has used primary data (surveys, interviews etc.)).

The estimation of individual-level addiction parameters and the richness of the data also offer us the opportunity to document differences between addicted and non-addicted gamers. We find that addicted gamers, on average, play longer daily sessions, have larger gaming

[5] https://www.who.int/features/qa/gaming-disorder/en/

[6] https://www.psychiatry.org/patients-families/internet-gaming

friend networks, and are more likely to purchase new games. We also investigate issues typically associated with addiction, such as whether it is driven by the existence of "addictive personalities" or caused by product-specific characteristics. We do not find any strong association between game characteristics and addiction, which we interpret as support for the idea that addiction is primarily driven by individual-specific personality traits or predispositions.

This research and its findings become even more relevant in the current context due to three reasons.[7] First, the emergence and rapid growth of *esports*, which brings large-scale tournaments, significant prize pools, associated video streamers and influencers, and dedicated fan bases. All these characteristics of *esports*, along with competitive and immersive environment in which they are played, represent fertile ground for addictive behavior. Second, the COVID-19 pandemic led to the deterioration of mental health and a consequent increase in internet-based addictive behaviors,[8] including gaming (Massaeli and Farhadi 2021). Third, the development and popularization of technologies such as Virtual Reality (VR) and Artificial Intelligence (AI) have contributed to the increase in immersion and attractiveness of video games via the creation of tailored gaming experiences and will continue to do so even more in the future.[9]

These concerns have led policymakers around the world to enact regulations aiming at curbing excessive video gaming. For example, China heavily regulates the industry in a variety of ways, including which games can be distributed and the amount of money spent on them.[10] In 2021, it also introduced new rules restricting video gaming hours for gamers 18 years or younger.[11] Similarly, South Korea enforced the Shutdown Law between 2011 and 2020, which prohibited online gaming from midnight to 6 am for those under the age of 16. In Canada, the game Fortnite motivated a class action lawsuit, where a group of parents claim that the video game made their children addicted and damaged their lives.[12] In the United States, although multiple issues involving video games have been targeted by lawmakers and debated in the public sphere (e.g., gambling and privacy violations), there are currently no laws regulating their excessive use. However, in 2020, a survey by the University of Michigan's C.S. Mott Children's Hospital found that nine out of ten parents in the US believe that teenagers spend too much time playing video games.[13] Interestingly, to the best of our knowledge, these concerns as well as the enacted policies are rarely based

[7] While video game addiction has been a subject of concern for a while (e.g., Soper and Miller 1983; Fisher 1994), their usage and prevalence was a tiny fraction compared to today.

[8] https://www.ft.com/content/14ba3a5a-8d3b-49bb-bddd-d157d09c9863

[9] https://www.cnn.com/world/generative-ai-video-games-spc-intl-hnk

[10] https://www.bbc.com/news/technology-67801091

[11] Gamers are only allowed to play 8 pm to 9 pm Friday to Sunday and on public holidays.

[12] https://www.cbc.ca/news/canada/british-columbia/bc-supreme-court-class-action-epic-games

[13] https://mottpoll.org/reports/game-teens-and-video-games

on patterns of behavior of real gamers. Our study takes the first step in terms of addressing this big limitation.

For marketing scholars in particular, the study of addiction is important as it is intimately linked to consumer purchase choices and subsequent consumption. Specifically, the study of addiction offers a unique opportunity to understand the determinants of consumption on a deeper (neurobiological) level. Such an understanding can be a powerful tool, in both a positive or negative manner, for designing targeted and effective marketing strategies that resonate with consumer's underlying desires and needs. Moreover, the potential for addiction underscores the need for consideration of ethical concerns and responsible marketing practices that take into account consumer well-being. Without an understanding of the mechanisms and prevalence of problematic consumption, marketers may unknowingly induce unhealthy behaviors. This is especially relevant in the era of digital marketing and targeted advertising, where artificial intelligence systems whose objectives are to increase user engagement may "learn" how to exploit behavioral vulnerabilities even when they were not purposefully programmed to do so.

Overall, this paper makes the following contributions. First, it looks at consumer behavior in a large (and still growing) entertainment domain - video gaming - that has seen scant research in marketing. Second, the question it focuses on is one that policymakers, consumers (including gamers and parents of gamers) and game designers are all grappling with i.e., do we see addiction patterns in gaming? Third, it does so by using secondary (as opposed to primary) data leveraging the game play behavior of thousands of gamers playing hundreds of games on one of the world's largest gaming platforms. Fourth, it sheds light on the extent and prevalence of gaming addiction. To the best of our knowledge, this is first documentation of this estimate using behavioral data. Fifth, it shows that more addicted gamers not only play more, but also own more games, have more friends on the platform, play longer sessions, and are more likely to purchase new games. Finally, it sheds light on the longstanding debate about the nature of behavioral addictions i.e., whether they are symptomatic of underlying individual-specific disorders or induced by product or activity-specific characteristics. As a result, we hope that the paper deepens the understanding of gaming addiction, helping policymakers, consumers and game designers to all work together to promote healthier gaming behaviors.

The rest of the paper is organized as follows. We present an overview of the previous literature and the theories/paradigms that that we draw upon in section §2. Next, we describe and analyze our data in §3. Then, we introduce our empirical approach in §4 and report our main findings in §5. Finally, we present and discuss our findings in §6 and conclude in §7.

2.2 Related Literature

Traditionally, addiction has been studied as a form of compulsive behavior caused by the effect of certain substances on the brain's reward system, which regulates pleasure, motivation, and leads to behavioral reinforcement (Grassi, Cecchelli, and Vignozzi 2021). Because such substances provide great short-term satisfaction, they can lead to persistent behavior despite the potentially devastating long-term consequences of continued use. More recently, the idea that certain activities may trigger similar mechanisms even without the present of psychoactive substances has gained recognition. Individuals who suffer from *behavioral addictions* report experiencing similar symptoms as those addicted to substances, such as reduced ability of self-control, a strong urge to engage in certain activities, and positive feelings after it happens (de Castro et al. 2007).

While behavioral addictions may not involve chemical dependence, they are deeply ingrained and difficult to overcome since the underlying mechanisms also involves the deregulation of the brain's reward pathways, thus resulting in persistent behavioral patterns. Over time, the brain becomes less responsive to the usual stimuli and prompts the individual to engage in the addictive behavior more frequently to achieve the same level of satisfaction – hence the association of addiction and excessive consumption. Furthermore, behavioral addictions often involve psychological and emotional dependence on the rewarding experience. Because of that, the anticipation of engaging in the activity becomes a significant motivator even in the absence of immediate pleasure caused by performing the activity itself (Bernheim and Rangel 2004).

The addiction literature has also considered the existence of "addictive personalities" – certain personality traits that are linked to a person's susceptibility to becoming addicted. In their theoretical work, Becker and Murphy (1988) propose that addiction is caused by the interaction of individuals and the products they consume. They argue that even though empirical observation indicates that some products are more likely to cause addiction than others, it is also true that individual traits such as higher intertemporal discount rates could influence one's likelihood of developing addiction. Research in psychology has shown that individuals with behavioral addiction tend to exhibit impulsivity, sensation-seeking, and low risk-avoidance, similar to those suffering from substance addiction (Kim and Grant 2001; Raymond, Coleman, and Miner 2002; Grant and Kim 2002). Closer to our context, Takao, Takahashi, and Kitamura (2009) identify that gender, self-monitoring, and approval motivation are predictive of addiction to mobile phones. Similarly, Shaffer, Hall, and Vander Bilt (2000) study computer addiction and suggest that it is symptomatic of other primary disorders rather than a disorder of its own.

While individuals consuming addictive substances are more likely to develop a chemical type of addiction, those with addictive personalities could be especially prone to a psychological type of addiction when consuming other substances, products, or activities that are not usually regarded as highly-addictive, such as exercising (Landolfi 2012; Lichtestein and Hinze 2020) and going to the cinema (Sisto and Zanola 2010). The most recent edition of the *Diagnostic and Statistical Manual of Mental Disorders* (DSM-5) currently has video gaming, gambling, shopping, sex, and exercising under consideration as behavioral disorders (Potenza 2014).Specifically, it includes *internet gaming disorder* as a condition separate from other internet disorders and recommends further study on the topic.

In marketing, one stream of literature has studied addiction from a psychological perspective. For instance, Hirschman (1992) interview drug users who self-declared as "addicts" or "non-addicts" and study their responses in the light of different theoretical backgrounds, interpreting the many potential causes for drug addiction as forms of compulsive behavior. Similarly, O'Guinn and Faber (1989) conduct a mail survey among compulsive and regular shoppers and argue that individuals with a general compulsive behavior in other aspects of life are more prone to developing some form of addiction. We follow a second stream of research that draws on economic theory, wherein addiction is defined as the positive dependence of current consumption on past consumption. Stigler and Becker (1977) discuss how this intertemporal dependence in the consumption of addictive goods emerges from the effect that the accumulated consumption capital has on the marginal utility of current consumption. Because the marginal utility is decreasing on the accumulated consumption capital, addictive goods require increasing consumption to keep utility at the same level over time.

Taking a step further, Becker and Murphy (1988) propose that this intertemporal adjacent complementarity holds not only for the past, but also for the future. In their *Rational Addiction* framework, addicts are agents with perfect foresight that are constantly trading off the short-term gains and the long-term costs of consuming addictive goods. Becoming addicted to a certain product or substance changes the utility that individuals obtain from consumption, but they understand that process and take it into account in the dynamic optimization of their consumption trajectories. Building on the Becker-Murphy theoretical framework, Chaloupka (1991) and Becker, Murphy, and Grossman (1994) derive a reduced-form empirical test for addiction by regressing current consumption on past consumption. A positive coefficient on past consumption is interpreted as evidence of addiction, and the magnitude of the coefficient reflects its intensity. Similar notions of addiction have been used to study and derive policy recommendations for various goods, such as cigarettes (Becker, Grossman, and Murphy 1994; Machado and Sinha 2007; Chen, Sun, and Singh 2008; Gordon and Sun 2015), cocaine (Grossman and Chaloupka 1998), e-cigarettes (Tuchman 2019), and casino gambling (Narayanan and Manchanda 2012).

Our paper is more closely related to recent research that has focused on addictions associated with digital media. In economics and marketing, such studies have focused on the habit formation properties and mental health effects of social media apps. For example, Hoong (2021) finds that individuals spend more time on Facebook than they claim to desire and that such overconsumption could be attributed to a lack of self-control. Also studying Facebook, Braghieri, Levy, and Makarin (2022) find that the introduction of the social media had a negative impact on mental health and led to impairment of academic performance in college students. The literature has also uncovered evidence suggesting that not only is social media habit-forming, but people are also often unaware of this tendency and a significant portion of its consumption derives from self-control issues (Alcott, Gentzkow, and Song 2023). Furthermore, it has been shown that there is substantial variation in both addictiveness and forward-looking behavior across demographics in social media consumption, which is also moderated by the type of social media app (Kwon et al. 2016).

A few studies have also looked into self-control and excessive consumption of other digital products. Zhang et al. (2022) show that some consumers of e-books have time-inconsistent preferences and are willing to pay a premium for mechanisms that help with self-control. In the context of video games, Nevskaya and Albuquerque (2019) study how in-game reward schedules and time limits can be used to effectively manage excessive consumption and still lead to longer subscriptions. Similarly, Acland and Chow (2018) show evidence that those who play more tend to have a preference for commitment devices to curb playtime, which suggests self-identified lack of control. We contribute to this literature by employing the classic economic model of addiction to the broader domain of digital consumption, focusing on video games – one of the biggest industries in this domain.

2.3 Data

Our data comes from *Steam*, the largest digital distribution platform for video games. Founded over 20 years ago (2003), it provides users with a digital ecosystem where they can purchase and access games, in-game items and other downloadable content (DLCs), as well as build and manage friend networks. As of 2023, the platform has about a billion registered accounts and over 130 million monthly active users. It is estimated to sell around 400 million units annually from a menu of over 50,000 games.[14] Originally a distributor of computer games, *Steam* launched its handheld dedicated device in 2022, offering full compatibility with its website.

[14] https://www.statista.com/topics/4282/steam/

2.3.1 Data Collection

On *Steam*, user accounts can be accessed given their 17-digit user ID number. To obtain an extensive list of user IDs, we generate random numbers and verify whether they correspond to real Steam IDs. When they do, we check if the associated profile is publicly visible [15] and include the user in our sample if so. We then download it the player's profile and activity via the platform's Application Programming Interface (API).

The original data is a snapshot of players' accounts at a given time, thus building a panel data set requires us to first systematically webscrape players accounts daily and then compute changes such as playtime for each game, new purchases, etc. We follow this procedure for 50,000 players from May 2022 to April 2023. We also observe when the account was created, how many friends each player has on the platform, how many games they own, the total number of minutes they have played each game since the moment they downloaded them, their country of residence, and if and when they have been banned for cheating or community-related forms of misconduct. Because it is not possible to determine whether each account is currently active, we store information for all accounts and drop the ones that did not play for three full months since since the first day we started tracking them. When we drop accounts, we include new ones to keep the number of players being tracked at 50,000 every day.

From this panel, we retain the accounts that we observe for at least 250 days. A few of these accounts played multiple games for 24 hours a day during several weeks. This may be due to users logging in to games without actually playing, shared accounts, or accounts that belong to esports gaming centers. To deal with this issue, we drop observations of accounts/users who played more than 20 hours a day at some point. Our goal is to study addiction among "gamers", which requires us to determine a cut-off for the minimum activity necessary for a user to be considered as such. We drop accounts/users whose activity is less frequent than playing any game for at least one minute once a month. Lastly, there are 10,142 different games being played at least once in our sample. However, in 85% of all observations the game played is in the the top 1,000 most popular. To keep our analysis restricted to the most relevant games, we retain only these observations Our final data set is an (unbalanced) panel of 13,400 users, resulting in 3,418,105 user-day observations.

[15] The platform's default privacy setting is to let players keep their information private. Players have an option to make their profile and data publicly visible.

2.3.2 Sample Description

As mentioned above, we are only able to randomly sample players among those who chose to make their profile public. We acknowledge that his may introduce a selection bias as the choice to set the profile as public could be associated with more engaged and enthusiastic players, who could potentially care more about showing which games they own, their achievements, hours played, etc. Ideally, we should compare the characteristics of our sample with those of the population on the platform but, unfortunately, *Steam* does not publish official statistics for all their games and player base. As an alternative approach, we leverage data from the third-party website *SteamSpy.com*, which regularly scraped data from *Steam* using a procedure similar to ours up to April 2018, before *Steam* changed the default account setting from "public" to "private."

An important observation is that a random sample of accounts is not ideal either if our goal is to study gamers. *Steam* currently has over 1 billion registered accounts and 130 million monthly active users, which suggests that most accounts are inactive. A random sample would include mostly inactive accounts since many individuals may only use the platform for a short period due to a variety of reasons: (a) signing up but never actually playing games on the platform; (b) trying a few games for a short period and dropping out; or (c) creating an account in order to play a specific game distributed exclusively by *Steam* and abandon the account once the gameplay is over. Because of that, some statistics reported by *SteamSpy.com*, such as the average time played or number of games owned are likely biased in the opposite direction when compared to ours (i.e. less active users).

Table 2.1: Summary statistics for our main variables.

Variable	**Mean**	**St. Dev.**	**Max**	**Min**
Sum minutes focal daily	69.9	134.7	1,080	0
Sum minutes non-focal daily	9.6	50.5	1,072	0
Number of friends	47.1	57.5	486	0
Years on steam	7.8	3.7	20	1
Number of games played in a day	0.5	0.8	14	0
Number of games owned	115.5	250.5	7720	1
Total hours ever played on steam	3,284.4	3,082.0	51,078.1	0.5
Number of times banned	0.05	0.24	3	0

The countries of origin are similar in both our sample and *SteamSpy*'s sample, with the notable exception of China. Historically, *Steam* was not allowed to officially operate in China due to strict government requirements. Since 2021, a restricted version of *Steam* containing only 53 games has been officially launched as *Steam China*, which likely explains the significant increase in Chinese users from 2018 (*SteamSpy*'s data) to 2023 (our data). From *Steam*'s official website,[16] we also obtained the most common languages in which the *Steam* software was installed. Taking into account the countries where those languages are natively spoken, the ordering is very close to what we find in our sample.

Table 2.2: Top 10 most common countries of origin in our sample (left) and according to 2018 estimates from Steamspy.com (right)

Sample (2022)		**Steam (2018 estimates)**	
China	29.5%	United States	14.4%
United States	19.7%	China	11.6%
Russia	14.2%	Russia	9.6%
Brazil	7.3%	Brazil	4.8%
Germany	5.9%	Germany	4.1%
Poland	5.5%	Canada	3.1%
United Kingdom	4.9%	France	3.0%
Canada	4.5%	United Kingdom	3.0%
France	4.3%	Poland	2.6%
Turkey	4.0%	Turkey	2.4%

Official statistics on number of owners for each game are also not available. However, specialized websites often rank the top games according to the peak number of concurrent players available on *Steam*'s website. We use one of these statistics for March 2023. Our data was collected daily, and hence we can only observe which games each users played on a given day, but not if they were online at the same time of the day – that is, we cannot estimate the number of concurrent players. We can, however, count the number of times each game was played and use that as a metric of frequency. We list in Table 2.4 below our top 10 most popular games and the top 10 as published by the leading media outlet for video game content, IGN.com, both for March 2023. Seven of them are present in both lists,

[16] https://store.steampowered.com/hwsurvey

indicating a reasonable level of similarity. Figures 2.2 shows the distribution of average daily time played, with mean of 78.7 minutes and standard deviation of 80.5. Figure 2.3 shows the histogram of consecutive days playing, with mean of 2.7 and standard deviation of 5.6. Additionally, the average account in our sample is 7.8 years old and owns 115.6 games.

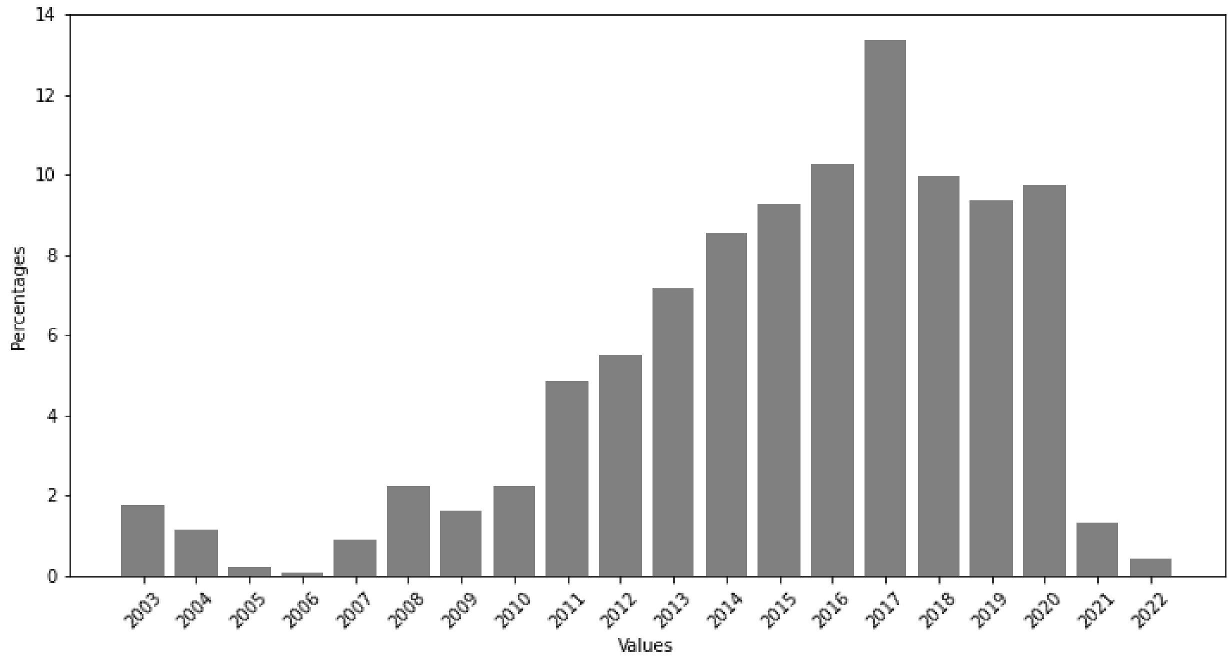
Table 2.3: Top 10 languages in which Steam launcher was installed.

Most Common Languages on Steam (% users in 2023)	
Chinese	51.63%
English	22.83%
Russian	6.94%
Spanish	3.50%
Portuguese-Brazil	2.65%
German	2.06%
French	1.58%
Polish	1.35%
Japanese	1.13%
Turkish	1.12%

Table 2.4: Top 10 most played games in our sample in 2023 (left) and top 10 games by peak players in 2023 (IGN.com).

Our sample	**Steam Estimates (IGN.com)**
Counter-Strike: Global Offensive	Counter-Strike: Global Offensive
Apex Legends	Dota 2
Dota 2	Apex Legends
PUBG: Battlegrounds	PUBG: Battlegrounds
Grand Theft Auto V	Destiny 2
Rocket League	Goose Goose Duck
Call of Duty: Modern Warfare II	Grand Theft Auto V
Destiny 2	Lost Ark
War Thunder	Naraka: Bladepoint
Rust	Rust

Figure 2.1: Number of accounts by year of creation.



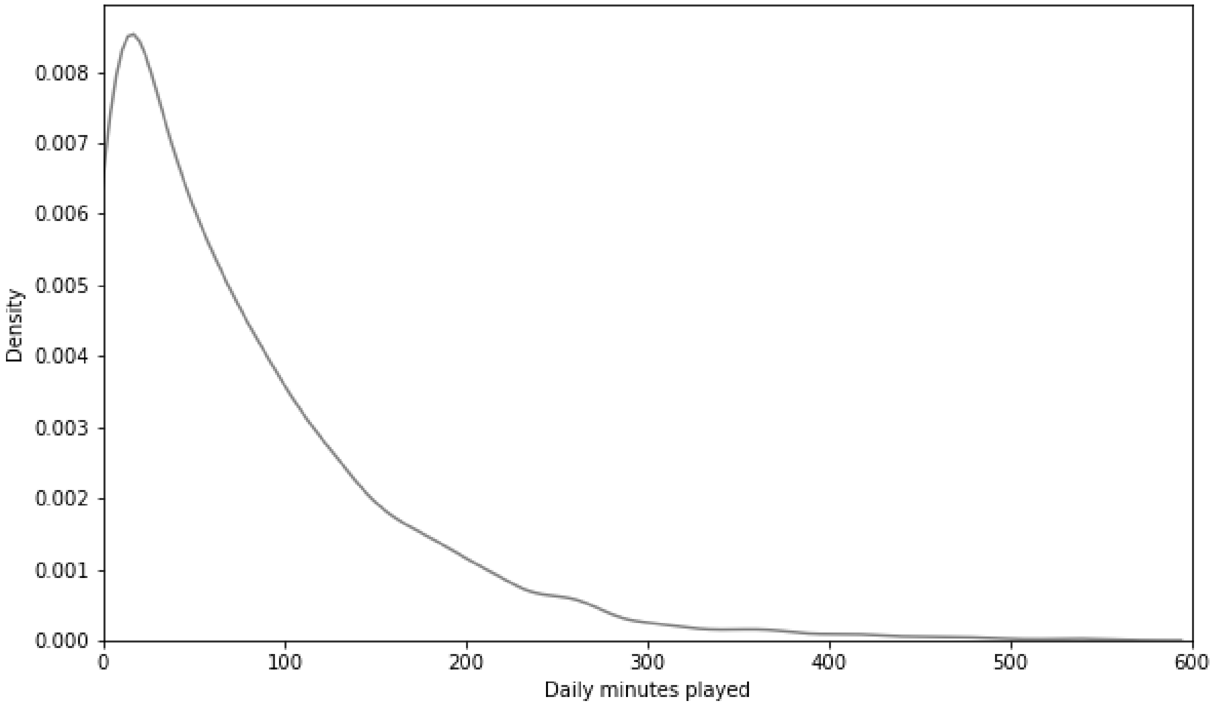
2.4 Empirical Approach

As noted earlier, our approach follows the economics literature, in which the empirical test for addiction is equivalent to testing for the positive intertemporal dependence of consumption. In the case of addictive behavior, this pattern is generated by two key properties (Becker and Murphy 1988): (i) *reinforcement*, which means that greater past consumption increases the desire for present consumption and (ii) *tolerance*, meaning that, for a given quantity consumed, the utility derived will be lower when past consumption is greater. Both these properties lead to a consumption pattern in which higher past consumption causes higher current consumption. Thus, the panel data structure provides an opportunity to test the hypothesis of addiction by regressing y_t on y_{t-1}.

Most of past literature on video game addiction has used questionnaires to identify symptoms and classify addiction based on their presence. For example, in their Diagnostic and Statistical Manual of Mental Disorders (DSM-5), the American Psychiatric Association outlines nine symptoms of gaming disorder.[17] A few observations are relevant when contrasting

[17] https://www.psychiatry.org/patients-families/internet-gaming

Figure 2.2: Density of average daily minutes played per day.



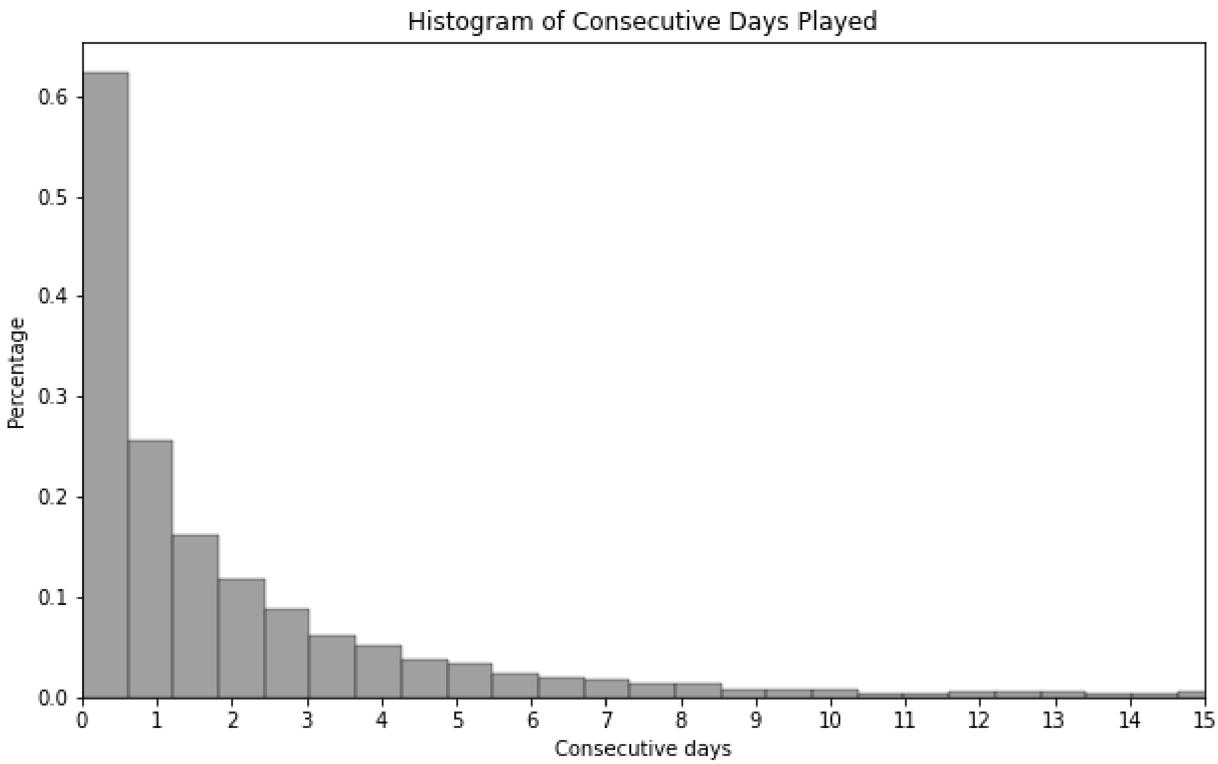
that approach with ours. First, the DSM-5 provides a theoretical foundation that allows us to interpret positive state dependence as addiction, which is necessary when applying this empirical test, as pointed out by Auld and Grootendorst (2002). Second, while the economics approach to studying addiction may not align perfectly with that of the American Psychiatric Association, it offers an opportunity to study a much larger sample of players making decisions in real life situations over an extended period of time. Third, although the economics definition of addiction is based only on consumption patterns, it describes the consumption cycle observed in addictive goods: a stage of intense craving and use, remission and abstinence, then relapse and heavy use again.[18] It also allows us to leverage rich observational data, as opposed to (retrospective) survey based data. We specify the baseline model as follows:

$$y_{igt} = \delta y_{igt-1} + \mathbf{X}'_{igt}\beta + P_i + G_{igt} + \mathbf{t}\eta_i + \varepsilon_{igt} \tag{2.1}$$

Here, y represents the sum of minutes played for all focal games in each period. X is a vector of control variables: the number of friends, years on steam, number of focal and non-focal games played in the current period, number of games owned, total number of hours

[18] https://www.asam.org/docs/default-source/public-policy-statements/1definition_of_addiction_long_4-11

Figure 2.3: Distribution of consecutive days with positive time played.



ever played on steam, indicators for new focal and new non-focal games purchased in the previous week, number of temporary bans for cheating, number of hours ever spent on the focal games played in the current period, and indicator for weekend. We also include fixed effects for players (P_i), games (G_{igj}), and an individual-specific quadratic time trend ($\mathbf{t}\eta_i$), and ε_{igt} represents an exogenous i.i.d. error.

Our coefficient of interest is δ, which measures the dependence of current consumption y_t on previous period's consumption, y_{t-1}. A positive and significant δ is considered evidence of addiction. Note that this approach tests for a myopic version of addiction and is silent about whether such behavior is considered rational.[19] Our context and the granularity of our data allows us to avoid some common econometric difficulties in the estimation of δ that we should mention for the purpose of clarification. First, data available is typically on purchases instead of actual consumption (Gruber and Koszegi 2001), which can potentially

[19]In contrast, the Becker-Murphy rational addiction model posits that players are aware of the addicting process and plan current consumption taking into account the impact it has on the marginal utility they will derive from future consumption. It also assumes that addicts understand the consequences of their actions and are pursuing optimal consumption strategies, even though their behavior may seem suboptimal to others (non-addicts). However, because video games are popular among children and adolescents, whether their actions are rational or not is less relevant as they are still in their formative years and thus are not yet considered fully responsible for the consequences of their choices.

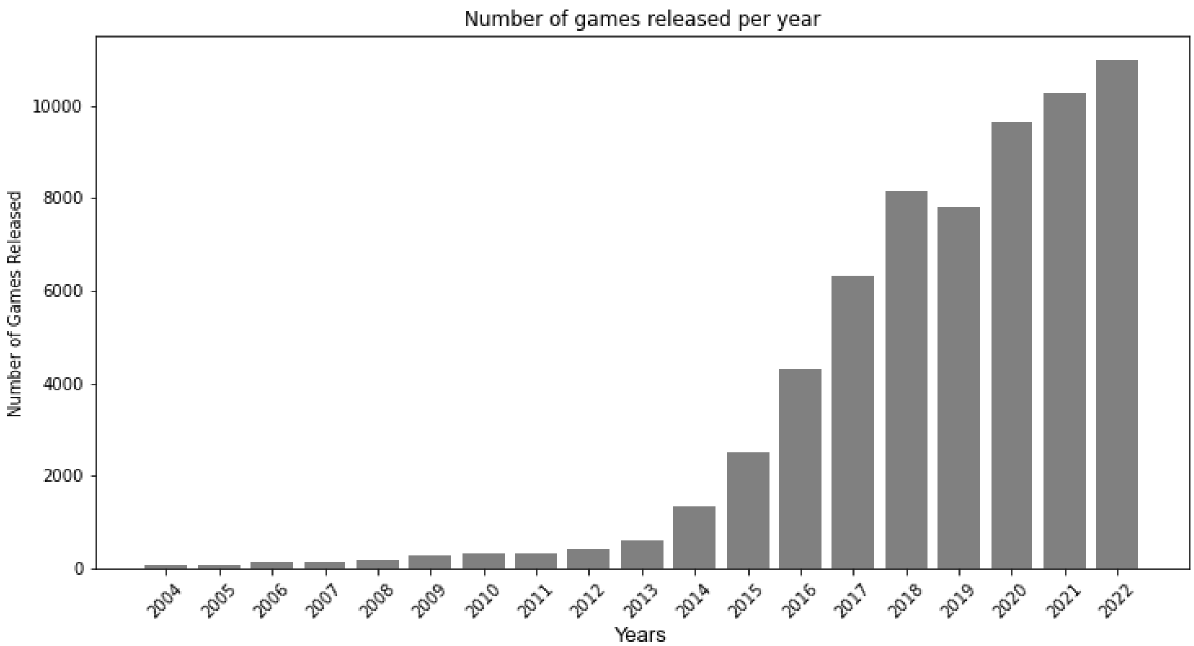
introduce measurement error and lead to biased estimates. While some studies approach this issue by modeling stockpiling behavior (e.g., Gordon and Sun 2015), that requires additional assumptions. In our case, we observe actual consumption and thus entirely avoid the issue.

Second, identifying state dependence is usually problematic because it involves separating situations where consumers made the observed choices because of their preferences or due to having made the same choice in the past (Roy, Chintagunta, and Haldar 1996; Dubé, Histch, and Rossi 2010). Typically, researchers use exogenous shocks affecting choices (e.g., temporary price changes) to obtain identification. In this paper, however, we are interested in the intensive margin of consumption: the effect that the duration of the previous gaming session has on the duration of the current gaming session. If tastes are constant over time, unobserved preference heterogeneity can explain game choice, but not the pattern of increasing consumption that describes addiction – this is especially true if we consider video game consumption as a single product irrespective of game title. Moreover, notice that even if individuals play several hours a day, they will not necessarily be considered addicted according to our definition, as it requires a pattern of consumption that is, *ceteris paribus*, increasing on the time played on the previous days.

Third, the errors in $t-1$ and t can be autocorrelated due to unobserved shocks affecting both t and $t-1$, thus leading to correlated choices even if such unobserved shock does not affect the choice in t directly (Keane 1997, Chamberlain 1985). Including fixed effects in the model allows us to control for unobserved factors that are constant in time, but some shocks could be periodical, for example, and lead to "clumpiness" in consumption, which we could misidentify as an addiction pattern. To address this issue, we adopt an instrumental variable approach with three sets of instruments. We compute, for each player, the average number of hours played on each day of the week to proxy for how much free time they have on each of those days of the week and use the lag of this variable as instrument for the lag of time played.

Fourth, consumer learning could be present as an alternative mechanism causing state dependence. It is possible that, immediately after buying a new game, players do not have as much fun when playing it as they do when they become more advanced players. The more they play, the more they learn how to use the game mechanics and become more competitive, thus achieving more success and having more fun, which causes them to play longer daily sessions. The case of consumer learning is interesting because the platform has released around 10,000 new games per year in the last few years (see Figure 2.4), which creates opportunity for virtually endless learning if consumers keep switching games. Table 2.2 shows that some players do in fact own thousands of games. In one of our specifications we try to rule out learning by using only games for which the focal player has played more than the median time for that game. Because many players download games and never play them, when taking the median play time we use as reference only players who played a positive number of minutes. If learning does in fact play a role in state dependence, we should see a difference in the estimates since most of the learning happens in the first few days of gameplay.

Figure 2.4: Number of games released on Steam worldwide from 2004 to 2022 (Source: Statista.com)



2.5 Results

Our context involves several modeling decisions that can impact the results and how to interpret them. In this paper, our purpose is not to argue in favor of a specific way to approach the question, but to provide a comprehensive empirical analysis that contributes to the discussion on a relatively new behavioral disorder that affects an increasing number of individuals. We start by showing evidence of addiction when data is taken in aggregate and then proceed to investigate heterogeneity with individual-specific addiction coefficients. Next, we investigate whether results change when we consider video game a single product compared to the case where each game is a considered a different product. Following that, we investigate persistence of addiction and whether certain game types are more strongly associated with addictive behavior. Lastly, we study how our definition of addiction translates into other behavior on the platform, such as total play time and game purchase behavior. In this section, we report results for different models that try and tackle these issues.

Our regression results are presented in Table 2.5. The first column reports the results from an OLS model. These results shows the presence of considerable state dependence with $\delta = 0.36$. For comparison, Becker, Grossman, and Murphy (1994) estimate that the coefficient on the lagged consumption of cigarettes is between 0.48 and 0.75 depending on the specification. Table 2.6 shows the estimated coefficients for the lagged consumption when performing similar regressions for different goods.

To provide a baseline, the second column reports a specification without the lagged consumption. The third column shows the estimates adjusted for the exclusion of learning effects, where we only use games for which the player had total time played higher than the median for that game. Our coefficient of interest ("Focal minutes played$_{t-1}$") slightly drop from 0.367 to 0.359, thus suggesting that learning does not seem to be driving state dependence. The fourth and last column reports 2SLS results, and we observe a steep drop in the addiction parameter to 0.194. Across all specifications, we see a positive and significant addiction parameter.

The other variables are controls, but the signs are mostly what we would expect. Among the statistically significant coefficients, there is a negative effect of playing non-focal games ("Non-focal minutes played$_t$"); negative effect for the number of years on the platform and positive for its squared form, perhaps suggesting survival bias ("Years on steam"¡ 0 and "Years on Steam^2" ¿ 0); a positive sign for the number of focal games played on the current day ("No. focal games played$_t$") and negative for the number of non-focal games played in the current day ("No. non-focal games played$_t$"); positive sign for the weekend indicator ("weekend"). The number of hours played for the focal games display an inverted "U" shape ("total hours played focal ($\div$100)"¿0 and "total hours played focal^2 ($\div$100)"¡ 0), as expected for entertainment products that display a period of increasing returns to consumption as the player becomes more familiar with the game or the storyline develops, until satiation starts and utility from playing decreases.

Table 2.5: Regression results

	Baseline	No lag	No learning	2SLS
Focal minutes played$_{t-1}$	0.367***		0.359***	0.194***
	(0.003)		(0.004)	(0.012)
Non-focal minutes played$_t$	-0.033***	-0.043***	0.585***	-0.037***
	(0.002)	(0.003)	(0.010)	(0.003)
No. Friends	0.013	0.026	0.007	0.019
	(0.021)	(0.032)	(0.025)	(0.026)
No. focal games played$_t$	87.707***	111.330***	84.579***	98.844***
	(0.552)	(0.722)	(0.731)	(0.951)
No. non-focal games played$_t$	-7.946***	-12.265***	-12.436***	-9.982***
	(0.376)	(0.474)	(0.723)	(0.437)
Years on Steam	-8.269***	-10.320***	-7.326**	-9.236***
	(2.735)	(3.915)	(3.067)	(3.261)
Years on Steam^2	0.235**	0.379**	0.267**	0.303**
	(0.103)	(0.160)	(0.120)	(0.129)
No. games owned (÷10)	0.032	0.066	0.010	0.048
	(0.047)	(0.074)	(0.036)	(0.059)
Hours played on Steam (÷100)	-0.503**	-0.347	-0.529*	-0.430
	(0.256)	(0.398)	(0.294)	(0.321)
Hours played on Steam^2 (÷100)	0.001	0.001	0.003	0.001
	(0.002)	(0.003)	(0.002)	(0.002)
New focal game previous week	0.279	0.233	-0.928	0.257
	(0.917)	(1.329)	(0.992)	(1.101)
New non-focal game previous week	4.777***	6.124***	3.221***	5.412***
	(0.292)	(0.418)	(0.372)	(0.352)
No. Anti-Cheat Bans	-1.037	-2.020	-5.898	-1.500
	(4.212)	(6.174)	(4.319)	(5.111)
Total hours focal games (÷100)	0.861***	1.564***	1.119***	1.192***
	(0.087)	(0.133)	(0.115)	(0.111)
Total hours focal games^2 (÷100)	-0.003**	-0.007***	-0.006**	-0.005**
	(0.002)	(0.003)	(0.002)	(0.002)
Weekend	7.396***	6.728***	6.251***	7.081***
	(0.292)	(0.306)	(0.272)	(0.304)
Adjusted R^2	0.591	0.522	0.585	0.475

Standard errors in parentheses; fixed effects omitted

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: Previous studies on addiction for selected products.

Study	**Product**	**Addiction coefficient**
Becker et al. (1994)	Cigarettes	0.48
Olekalns and Bardsley (1996)	Coffee	0.52
Grossman and Chaloupka (1998)	Cocaine	0.38
Labeaga (1998)	Cigarettes (individual data)	0.19
Bentzen et al. (1999)	Alcohol	0.49
Sisto and Zanola (2010)	Cinema attendance	0.33

2.5.1 Heterogeneity

In this section, we cast our model into a hierarchical Bayes framework, which allows us to recover individual addiction parameters and thereby estimate the share of addicted players by performing individual hypothesis test for the presence of positive state dependence. Investigating heterogeneity also provides additional insight over the aggregate analysis from the previous section because it informs us on the main drivers of the aggregate results, for example, whether a few individuals with severe addiction are driving the findings or if, instead, we have a higher share of individuals with mild addiction.

We use the following system of equations to take advantage of the exogenous variation provided by the instruments z_i. We compute the average time played for each day of the week for each player, and use it to proxy for the free time available for each person on each day. The lag of this variable provides some exogenous variation to the lagged consumption:

$$y_{igt} = \delta_i y_{igt-1} + \mathbf{X}'_{igt}\beta + P_i + G_{igt} + \mathbf{t}\eta_i + \varepsilon_{igt} \tag{2.2}$$

$$y_{igt-1} = z_i \pi_i + \mathbf{X}'_{igt}\tilde{\beta} + \tilde{P}_i + \tilde{G}_{igt} + \mathbf{t}\tilde{\eta}_i + \tilde{\varepsilon}_{igt} \tag{2.3}$$

$$\begin{pmatrix} \varepsilon_{igt} \\ \tilde{\varepsilon}_{igt} \end{pmatrix} \sim MVN\left(0, \Sigma\right) \tag{2.4}$$

Addiction parameter and regressors coefficients follow Normal distributions:

$$\delta_i \sim \mathrm{N}\left(\bar{\delta},\ \sigma_\delta\right) \tag{2.5}$$

$$\beta_k \sim \mathrm{N}\left(0,\ 1000\right) \tag{2.6}$$

As well as fixed effects for players and games:

$$P_i \sim \mathrm{N}\left(\bar{\mathrm{P}},\ \sigma_{\mathrm{P}}\right) \tag{2.7}$$

$$G_g \sim \mathrm{N}\left(\bar{\mathrm{G}},\ \sigma_{\mathrm{G}}\right) \tag{2.8}$$

The quadratic individual time trend:

$$\tilde{\eta}_{i1} \sim N(0,\ 1000)\ \tilde{\eta}_{i2} \sim N(0,\ 1000) \tag{2.9}$$

For the hyperpriors, the means follow Normal distributions and the variances are follow half-Cauchy taking only positive values:

$$\bar{\delta} \sim N(0, 1000) \tag{2.10}$$

$$\sigma_\delta \sim Half - Cauchy(0, 10) \tag{2.11}$$

$$\bar{P} \sim N(0, 1000) \tag{2.12}$$

$$\sigma_P \sim Half - Cauchy(0, 10) \tag{2.13}$$

$$\bar{G} \sim N(0, 1000) \tag{2.14}$$

$$\sigma_G \sim Half - Cauchy(0, 10) \tag{2.15}$$

The priors and hyperpriors for the second equation are analogous, with the addition of the extra coefficient π necessary for the instrument and its priors:

$$\pi_i \sim \mathrm{N}\left(\bar{\pi},\ \sigma_\pi\right) \tag{2.16}$$

$$\bar{\pi} \sim N(0, 1000) \tag{2.17}$$

$$\sigma_\pi \sim Half - Cauchy(0, 10) \tag{2.18}$$

We report the posterior means in Table 2.7. To estimate the share of addicts, we need a way to determine significance for each individual coefficient. Similar to Narayanan and Manchanda (2011), we use the ratio of the posterior mean and standard deviation and the 1.96 threshold (95% confidence level for a two-tailed test) and find that state dependence is present for 18.2% of players, who could be considered addicted according to our definition. The distribution of the estimated coefficients is plotted in Figure 2.5, and we can see that most individuals present only a mild addiction (between 0 and 0.1).

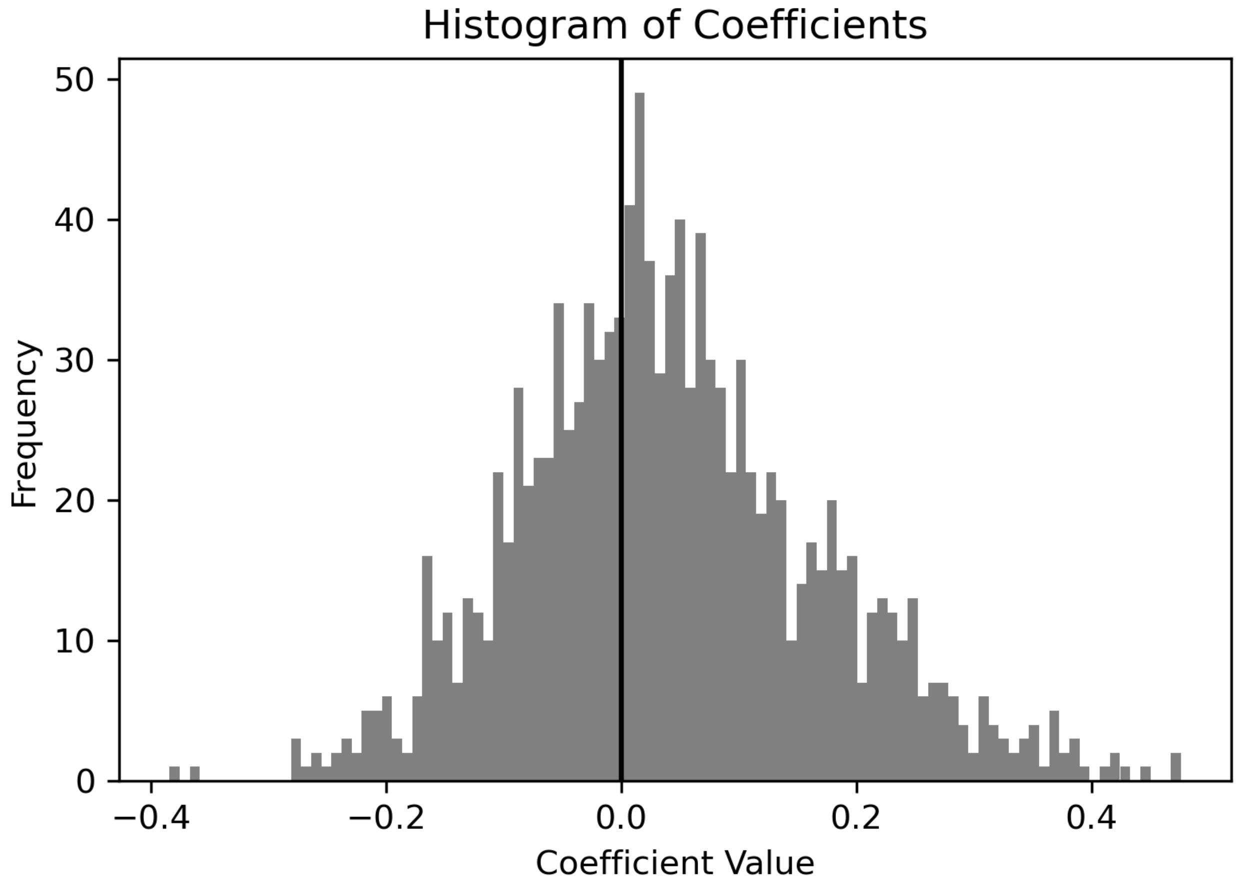
Table 2.7: Posterior means for the individual-coefficient models. Fixed effects and time trends omitted for brevity.

Variable	**Posterior mean (st. dev)**
Focal minutes played$_{t-1}$	0.17 (0.21)
Non-focal minutes played$_t$	−0.05 (0.01)
No. friends	−0.002 (0.05)
Years on Steam	−0.35 (0.13)
Years on Steam^2	0.03 (0.1)
No. focal games played$_t$	12.1 (0.74)
No. non-focal games played$_t$	2.27 (1.7)
No. games owned (÷10)	0.002 (0.06)
Total hours played platform (÷100)	0.17 (0.05)
Total hours played platform^2 (÷100)	0.006 (0.001)
New focal game previous week	4.9 (0.35)
New non-focal game previous week	8.0 (0.18)
No. Anti-Cheat Bans	1.1 (2.1)
Total hours played focal (÷100)	4.75 (0.15)
Total hours played focal^2 (÷100)	−0.025 (0.002)
Weekend	5.4 (0.39)
Average time played for day of the week$_{t-1}$	0.19 (9.2)

Revisiting the discussion in the previous section, our estimates may depend on whether video gaming addiction is studied as addiction to each game separately or addiction to video games in general. On the one hand, there are some core aspects that unify all games in the "video game" category, such as audiovisual elements, interactivity, and a set of rules and that provide feedback to one's actions in the game. Broadly speaking, games are enjoyable because they provide players with a sense of accomplishment, competence, autonomy, and relatedness (Przybylski, Rigby, and Ryan 2010). Moreover, video game addiction could be the manifestation of other underlying disorders and thus it is possible that individuals affected by this condition could switch the target game (Shaffer, Hall, and Vander Bilt 2000), which suggests that we should consider video games as one single category.

On the other hand, video games can be widely different. While some games work as ultra realistic simulators where the graphics and laws of physics closely resemble the real world, others make no attempt to provide a realistic experience and, instead, are just virtual representations of board games (e.g., checkers or chess). In addition, some games are relaxing and conducive to immersion and a flow state (Jennett et. al 2008; Kaye et. al 2018) in which individuals experience enjoyable concentration and sense of control provided by an optimal

Figure 2.5: Distribution of values for the individual addiction coefficients.



level of challenge (Csikszentmihalyi 1990), while others provide the thrilling experience of fighting a war or surviving a events in a "horror" setting.

We try both specifications. Our baseline model considers consumption of video games as the sum of all games played on each period, without distinction between the different games. In another specification, we do not sum all video gaming time but, instead, we consider different games as if they were different activities, while keeping the same addiction parameter for all games (but different for each individual). For example, if an individual played only *Counter-Strike: Global Offensive* on day t, the relevant time played in $t-1$ is the time spent playing this same game. If, instead, the person only played *Dota 2* in $t-1$, we consider $y_{t-1} = 0$. In order to consider games separately, the model needs to take into account that multiple games can be played on each period. For example, if an individual plays three games, we have:

$$y_{1,igt} = \delta_i y_{igt-1} + \mathbf{X}'_{igt}\beta + P_i + G_{igt} + \mathbf{t}\eta_i + \varepsilon_{1,igt} \tag{2.19}$$
$$y_{2,igt} = \delta_i y_{igt-1} + \mathbf{X}'_{igt}\beta + P_i + G_{igt} + \mathbf{t}\eta_i + \varepsilon_{2,igt} \tag{2.20}$$
$$y_{3,igt} = \delta_i y_{igt-1} + \mathbf{X}'_{igt}\beta + P_i + G_{igt} + \mathbf{t}\eta_i + \varepsilon_{3,igt} \tag{2.21}$$
$$y_{1,igt-1} = z_i\pi_i + \mathbf{X}'_{igt}\tilde{\beta} + \tilde{P}_i + \tilde{G}_{igt} + \mathbf{t}\tilde{\eta}_i + \tilde{\varepsilon}_{1,igt} \tag{2.22}$$
$$y_{2,igt-1} = z_i\pi_i + \mathbf{X}'_{igt}\tilde{\beta} + \tilde{P}_i + \tilde{G}_{igt} + \mathbf{t}\tilde{\eta}_i + \tilde{\varepsilon}_{2,igt} \tag{2.23}$$
$$y_{3,igt-1} = z_i\pi_i + \mathbf{X}'_{igt}\tilde{\beta} + \tilde{P}_i + \tilde{G}_{igt} + \mathbf{t}\tilde{\eta}_i + \tilde{\varepsilon}_{3,igt} \tag{2.24}$$

$$\begin{pmatrix} \varepsilon_{1,igt} \\ \varepsilon_{2,igt} \\ \varepsilon_{3,igt} \\ \tilde{\varepsilon}_{1,igt} \\ \tilde{\varepsilon}_{2,igt} \\ \tilde{\varepsilon}_{3,igt} \end{pmatrix} \sim MVN\left(0, \Sigma\right) \tag{2.25}$$

One issue with this modeling approach is that in a few periods we observe individuals playing up to 10 games on the same day. Because we are using an instrumental variable approach, we would need two equations per game, which would lead to a 20-variate normal distribution. In our sample, users played at most three games in 96.6% of observations in which they played at least one game. We keep only the three most played games on each day to avoid having to estimate a high number of correlation parameters without enough observations for times when users played four games or more.

For the model that considers each game separately, we obtain very similar coefficient estimates and a share of 20.4% of addicts. The coefficient estimates are also stable across both specifications. As shown in Table 2.8, addicts do not switch games significantly more often ("Avg. No. games per session"), and thus a modeling approach that considers each game separately does not result in dramatically different estimates.

2.5.2 Persistence

While economic theory defines addiction as the presence of positive state dependence without consideration for the time frame over which this condition should hold, one could argue that addiction is less of a problem if short-lived. Furthermore, research has shown that addiction is at least partially determined by genetics, and it is possible that parsimonious consumption by some individuals is not a possibility due to how their brains respond to the object of addiction (Duci and Goldman 2008, Nesler 2000). In such cases, addiction could be a permanent condition as long as consumption is present, and one could argue that individuals who behave as addicts only temporarily are not truly addicted.

We observe users on the platform playing video games for almost a full year (330 days), and it is possible that some players displayed a pattern of consumption consistent with addiction only for a few months and were still classified as addicts due to a very strong state dependence during that short period. We divide the data into two halves of 150 days each, and re-estimate the model separately for each half. The results are very similar for both halves, with a share of 23.6% for the first and 26.1% for the second one. We find that 14.6% of players are considered addicted in both halves. Since the latter is a a share of players with more persisting addictive behavior that is robust to the period under analysis, this number provides us with a more conservative estimate for the share of addicts in the sample.

These findings suggest the existence of additional mechanisms contributing to positive state dependence. Habit formation, for example, is an alternative mechanism that could be present in our context and would be picked up by the parameter measuring addiction. It is also more likely to be transitory and disappear, at least to some extent, when we consider different portions of the period under analysis.

2.5.3 Associated Behaviors

Given the individual coefficients estimated in the previous section, we can identify the addicts in the sample and study how they compare to the non-addicted players regarding other behavior on the platform. Summary statistics for addicted and non-addicted player populations are presented in Table 2.8. On average, addicts have longer playing sessions conditional on playing (227.9 vs 167.8 minutes), own more games (12,7 vs 8.5), purchased more games over the period studied (13.9 vs 7.9), play more often (4.1 sessions per week vs 2.6), have more friends on the platform (47 vs 35), had have been on the platform for longer (83.5 months vs 75).

Table 2.9 shows ordered lists of the most popular games of choice for addicts and non-addicts. Both lists are roughly the same, in agreement with the idea that behavioral addictions are not so much about activities that are addictive per se, but a match between personality type and how the individual expresses the behavioral disorder.

Table 2.8: Descriptive statistics for the addicted and non-addicted player population.

Variable	**Addicts**	**Non-Addicts**
Avg. session length (minutes)	227.9	167.8
Avg. No. games owned	12.7	8.5
Avg. No. games purchased	13.9	7.9
Avg. No. sessions per week	4.1	2.6
Avg. No. games per session	1.4	1.3
Avg. No. friends	47	35
Avg. account age (months)	83.5	75.0

Table 2.9: Most played games (by frequency) among addicts and non-addicts.

Addicts	**Non-Addicts**
1. Counter-Strike: Global Offensive	1. Counter-Strike: Global Offensive
2. Apex Legends	2. Apex Legends
3. Dota 2	3. Dota 2
4. PUBG: Battlegrounds	4. PUBG: Battlegrounds
5. Call of Duty: Modern Warfare II	5. Grand Theft Auto V
6. Destiny 2	6. Call of Duty: Modern Warfare II
7. War Thunder	7. Rocket League
8. Grand Theft Auto V	8. Naraka: Bladepoint
9. Rainbow Six Siege	9. Rainbow Six Siege
10. Rocket League	10. Euro Truck Simulator

Our definition of addiction is depends on the presence of positive state dependence on daily time played, but is silent about an increase in play time, which is ultimately the main issue with video game addiction. We study the association of addiction with higher consumption levels with the regression below:

$$y_i = \alpha_1 \mathbb{I}[addicted_i] + \alpha_2 \mathbb{I}[addicted_i].\tilde{\delta}_i + \mathbf{X}_i \beta + \varepsilon_i$$

where y_i is the number of minutes played daily; $\tilde{\delta}_i$ captures the relative addiction intensity for player i and is the standardized addiction coefficient, that is $\tilde{\delta}_i = {}^{(\delta_i - \mu_\delta)}/_{\sigma_\delta}$, and

$\mathbb{I}[addicted_i]$ is an indicator variable for the presence of addiction, $\mathbf{X}$ is a vector of controls and ε_i are i.i.d. error terms. The coefficient α_1 provides and estimate of the average effect of being an addict on daily minutes played and α_2 captures the effect of displaying an addiction intensity one standard deviation greater than the average. Results are reported in Table 2.10.

The presence of addiction is associated with playing 36.6 extra minutes per day, but a one-standard-deviation change in addiction intensity is associated with an 4.5 decrease in daily minutes played. It is important to note that our definition of addiction focuses on a specific pattern of consumption that displays positive state dependence, but does not inform us about consumption levels. If correctly specified, the model only informs us that consumption on a given period causes more consumption on the next period. Still, addicts in our sample do spend more time playing, in accordance with a more commonly understood concept of addiction that is linked to excessive consumption.

The results also suggest that addiction is more severe for lower levels of daily time played. This is expected due to hard constraints on daily available time, which makes individuals more likely to proportionally increase daily playtime from one day to the next when the levels are lower. An increasing pattern in the daily time played will eventually reach a plateau, and thus lead to reduction in the estimated addiction coefficient. For example, it is impossible for an individual who played 24 hours on a given day to increase their playtime on the following day.

Table 2.10: Regression results

	y = playtime (minutes)
α_1	36.638***
	(0.364)
α_2	-4.565***
	(0.218)
Non-focal minutes played$_t$	-0.004
	(0.003)
No. friends	-0.054***
	(0.001)
No. focal games played$_t$	104.783***
	(0.113)
No. non-focal games played$_t$	-20.838***
	(0.428)
Years on Steam	-1.119***
	(0.075)
Years on Steam^2	0.058***
	(0.004)
No. games (÷10)	-0.085***
	(0.005)
Hours played on Steam (÷100)	0.247***
	(0.004)
Hours played on Steam^2 (÷100)	-0.000***
	(0.000)
New focal game previous week	-1.217***
	(0.333)
New non-focal game previous week	6.710***
	(0.205)
No. Anti-Cheating Bans	2.518***
	(0.282)
Total hours focal game (÷100)	2.239***
	(0.015)
Total hours focal game^2 (÷100)	-0.014***
	(0.000)
Weekend Indicator	6.996***
	(0.153)
Adjusted R^2	0.486

Standard errors in parentheses
* p¡0.10, ** p¡0.05, *** p¡0.01

Another relevant empirical question is whether addicts are more likely to purchase new games. Since that would make them more profitable for the platform than regular players, it could work as an incentive for the platform to offer more addictive games. Results from logistic regressions (Table 2.11) show that the presence of addiction is associated with an increased probability of purchasing a new game over the period studied. The regression also confirms some expected patterns in game purchasing behavior: individuals who bought more games in the past and those who played a larger number of different games (both focal and non-focal) are also more likely to make new purchases. Conversely, older accounts could be more informed about their own preferences and thus less likely to explore new games.

Table 2.11: Logistic Regression Results

	y = Purchased New Game
α_1	0.409***
	(0.014)
α_2	-0.058***
	(0.008)
Non-focal Minutes played$_t$	0.001***
	(0.000)
No. friends	-0.001***
	(0.000)
No. focal games played	0.641***
	(0.004)
No. non-focal games played	0.541***
	(0.012)
Years on Steam	-0.026***
	(0.003)
Years on Steam^2	-0.001***
	(0.000)
No. games (÷10)	0.024***
	(0.000)
Total hours on Steam (÷100)	0.004***
	(0.000)
Total hours focal game (÷100)	-0.000***
	(0.000)
No. Anti-Cheating Bans	-0.025*
	(0.013)
Total hours focal game (÷100)	-0.053***
	(0.001)
Total hours focal game^2 (÷100)	0.000***
	(0.000)
Weekend Indicator	-0.027***
	(0.007)

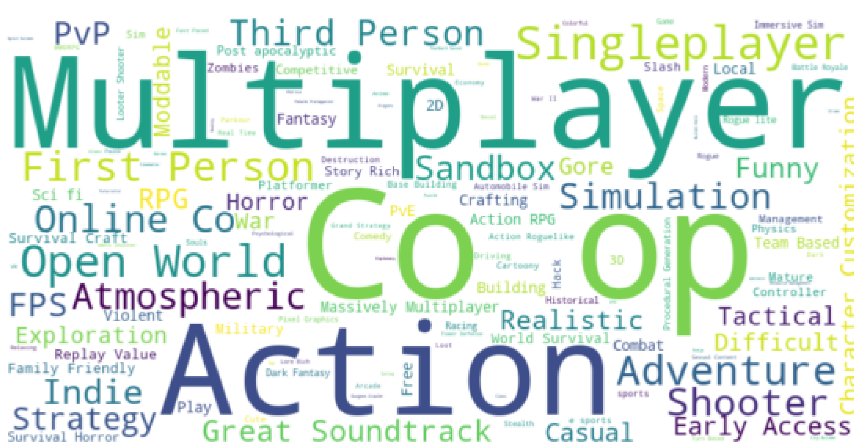
Standard errors in parentheses
* p¡0.10, ** p¡0.05, *** p¡0.01

2.5.4 Cross-game Comparison

Recently, the question whether video games are addictive by design has been a subject of public debate. For example, concerned parents launched a class action lawsuit against Fortnite's creator Epic Games in Canada, based on allegations that Fortnite is designed to be as addictive as possible and, consequently, upended their children's lives.[20] Similar class action lawsuits are currently being considered in Australia.

We contribute to this debate by investigating whether certain video games characteristics are indeed associated with addiction. On Steam's website, users can assign "tags" to each game or vote for tags previously suggested by other users. These are labels that offer insight into the key characteristics of a video game, as they serve as a collective categorization system and capture the most evident characteristics according to users themselves. Some examples of tags are "action," "adventure," "first-person shooter," "open world," and "platform." For each game, Steam provides the 20 most-voted tags. Notice that these crowdsourced tags go beyond traditional genre categorization and offer a more comprehensive representation of a game's qualities, encompassing aspects such as gameplay mechanics, thematic, and player other aspects that players may deem relevant for their experiences. Previous research has identified key aspects that are present in video games and can increase engagement, such as providing a sense of achievement, control, opportunity for social interactions, and enjoyment (Eisingerich, et al. 2019). If the tags are capable of capturing relevant game characteristics and addiction can be induced by products and activities, then it is possible that a relationship between the tags and categorization into "addicted" or "not addicted" exists.

Figure 2.6: Most common tags used to describe games. Words displayed in different sizes according to their frequency.



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[20] https://www.washingtonpost.com/nation/2022/12/14/fortnite-epic-games-lawsuit-addictive/

Ideally, we would integrate the game characteristics directly into the Bayesian hierarchical model, allowing the addiction parameters to depend on game characteristics. However, due to the high dimensionality of the video game feature space, the computational burden of the Bayesian estimation becomes computationally excessive, especially if we consider non-linear models that allow the flexibility that the task requires. As an alternative, we take a two-step approach described below.

For each player, we observe which games were played on each day and their respective descriptive tags, and we can count how many times each individual experienced each of the characteristics present in each game over the period in analysis. From last section, we also estimated addiction coefficients (δ_i) for each player, which allows us to determine whether they are considered addicted. Thus, can investigate the association between game characteristics and addiction status. The intuition behind this exercise is to find potential associations between being addicted and the aspects experienced by players during the period that led to the estimated coefficients.

To reduce the dimensionality of the feature space, we first keep only the tags that appear in at least 3 different games. We then train a Random Forest classifier to determine the tags associated with addiction and use cross-validation to tune the hyperparameters. Since our goal is to correctly discriminate between addicts and non-addicts, the hyperparameters are tuned with the goal of obtaining the best ROC-AUC (Receiver Operating Characteristic - Area Under the Curve) possible. We then evaluate the model's accuracy in a 20% hold-out sample and obtain a ROC-AUC of 0.59. Since a ROC-AUC of 0.50 indicates random guessing, the result obtained suggests that our model is able to extract signal from the data, although it also indicates that game characteristics explain a low percentage of its variance. In other words, the determinants of addiction are mostly not associated with game characteristics, and thus support the idea of addiction as symptomatic of other underlying mental disorders.

Next, we order the characteristics according to their feature importance and keep the 20 most relevant ones (Table 2.12). We use these characteristics as independent variables in a logistic regression (Table 2.13) that shows that "Singleplayer", "RPG" (Role-playing Game), "Survival", "PvE" (Player versus Environment), "Crafting", "Shooter", and "World Survival" are statistically significant as predictors of addiction status. While we refrain from making definitive causal claims, these findings highlight specific types of games and could inform future research aiming at establishing or rejecting causal relationships.

Table 2.12: Random Forest 20 most important features.

Action	Co-op	Singleplayer	Multiplayer	Atmospheric
RPG	Adventure	Open World	Online Co-Op	Survival
First-Person	PvE	Sandbox	Crafting	Third Person
Shooter	Team-Based	PvP	Open World Survival Craft	Great Soundtrack

Table 2.13: Logistic Reg. using game type as predictors of addiction status.)

	y = addiction status
Singleplayer	0.1278***
	(0.042)
RPG	0.1932***
	(0.033)
Survival	0.1108***
	(0.036)
PvE	0.0854***
	(0.029)
Crafting	-0.1094***
	(0.037)
Shooter	0.1859***
	(0.065)
World Survival	0.2030***
	(0.036)

Standard errors in parentheses

* p¡0.10, ** p¡0.05, *** p¡0.01

2.5.5 Discussion

Across our different specifications, we found that the prevalence of video game addiction ranges from 14.6% to 18.3% of gamers in our sample. To the best of our knowledge, there are no other studies on video game addiction using similar data or methodologies for comparison (as noted earlier, there is a rich literature on video game addiction that uses primary data). Table 2.14 is adapted from Griffiths et al. (2012), who performed a systematic review of the video game addiction literature from 1994 to 2012. It shows the results of various studies that investigate the prevalence of video game addiction or similar disorders (e.g. pathological video gaming) across different populations, years, and using different criteria for classification. The estimated proportions of problematic gamers range from 0.6% to 44.5%. In a more recent study, Coyne et al. (2020) examine video game addiction by following 385 adolescents during six years and estimate that approximately 10% of adolescents showed moderate levels of pathological gaming that increased over time, while 18% showed moderate levels that did not evolve during the period in analysis.

The large variation in the estimated proportions of pathological gamers in the Table 2.14 suggests the need for a careful interpretation of each study and consideration of its sample and classification criteria. Notice also that the resulting binary classification is not necessarily aligned with the views that gamers may hold about their own dependence on video gaming. For example, Gentile (2009) conduct a national survey among U.S. residents aged 8 through 18 and find that even though 8.5% satisfy their criteria for being considered pathological gamers, close to 25% of them report having felt addicted — 21.1% among those who were not categorized as pathological gamers and 65.4% among those who were. This also suggests that studies that found relatively low prevalence of pathological gaming may be at least partially explained due to more strict criteria required to categorize players as such.

In contrast to our approach, all of the papers listed in Table 2.14 used primary data collection methods (questionnaires or interviews). For example, the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), describes the following symptoms of gaming disorder:[21] (1) preoccupation with internet gaming, (2) withdrawal symptoms when not gaming, (3) needing to spend more time gaming to feel the same thrill, (4) unable to cut down or stop gaming, (5) loss of interest in other hobbies and activities, (6) continuing to game even when it causes problems, (7) lying to friends and family about the amount of time spent gaming, (8) using gaming to relieve negative feelings, and (9) having jeopardized a relationship or lost a career or education opportunity due to gaming.

As noted before, our study is one of the first to investigate video game addiction with observational data, and thus offers a new perspective. While the results of most studies typically depend on discretionary decisions made by researchers and their interpretations, this issue is less pronounced when observational data is used. In our context, we are able these decisions e.g., choosing which times to characterize addiction or which scales to use. In our study, we rely on a well established theoretical framework that supports the interpretation of positive state dependence as evidence of addiction and provide estimates of its prevalence. In addition, we are able rule out alternative mechanisms via a battery of robustness checks.

[21] https://www.psychiatry.org/patients-families/internet-gaming

We also investigate the relationship between video game addiction and certain types of games. We do not find any evidence suggestion the idea that developers, can "induce" addiction via game design. This indicates that video game addiction is primarily driven by individual predispositions, as also suggested by past literature. For example, Kuss, Pontes, and Griffiths (2018) review the literature on how neurobiological measures correlate with internet gaming disorder and argue that this disorder is caused by underlying factors that also overlap with those that lead to both substance-related addictions and other behavioral disorders. Their review finds notable neurobiological distinctions between individuals with and without internet gaming addiction: weaker response inhibition and emotion regulation, compromised functioning of the prefrontal cortex and cognitive control, diminished working memory and decision-making abilities, reduced visual and auditory functioning, and a deficiency in their neuronal reward system.

Table 2.14: Prevalence of Gaming Disorder in Various Studies (Adapted from Griffiths et al. 2012)

Study	**Location**	**Sample**	**Age (years)**	**Prevalence (%)**
Fisher (1994)	England	467	11-16	6.0
Griffiths & Hunt (1998)	England	387	12-16	19.9
Grüsser et al. (2005)	Germany	323	11-12	9.3
Grüsser et al. (2007)	Germany	7,069	15+	11.9
Lee & Han (2007)	Korea	2,584	5th/6th grade	2.5
Wan & Chiou (2007)	Taiwan	416	17-24	34.0
Xu & Yuan (2008)	China	623	13-18	21.5
Gentile et al. (2009)	U.S.	1,178	8-18	8.5
Batthyány et al. (2009)	Austria	1,068	13-18	2.7
Lemmens et al. (2009)	Holland	721	12-18	1.4-9.4
Arnesen (2010)	Norway	2,500	16-40	0.6-4.0
Choo et al. (2010)	Singapore	2,998	9-13	8.7
Rehbein et al. (2010)	Germany	15,168	14-16	1.7
Thomas & Martin (2010)	Australia	1,326	15-54	5.0
Porter et al. (2010)	Australia	1,945	14-40+	8.0
Van Rooij et al. (2010)	Holland	3,048	13-16	3.0
Wölfling et al. (2010)	Germany	1,710	13-18	7.5-8.4
Zamani et al. (2010)	Iran	564	"Students"	17.1
Jeong & Kim (2011)	South Korea	600	12-18	2.2
Lemmens et al. (2011)	Holland	851	11-17	4.0-6.0
Mentzoni et al. (2011)	Norway	2,500	15-40	0.6
Gentile et al. (2011)	Singapore	3,034	12-18	9.0
Hussain et al. (2012)	England	1,420	12-62	3.6-44.5

An issue when studying the prevalence of addiction is how to define the population of interest. We could, for example, simply use a random sample of Steam users irrespective of their actual video gaming activities (i.e., potentially including inactive accounts). The main issue with this approach is that individuals with very short sequences of active days on the platform who display state dependence would become increasingly likely to be classified as addicted, especially if they only play for a few weeks and then quit the platform for the subsequent 11 observed months. As the panel becomes longer and the number of observations where y=0 increases, the estimation of the addiction parameter increasingly relies on the few observations where y¿0, which biases the value of the addiction parameter upward. At the same time, a longer panel decreases standard errors, which makes the addiction parameter more likely to become significant. As a result, this approach would classify as addicts those individuals who only played for a few weeks in the year. This result invites criticism regarding the meaning of the parameter of interest and our categorization.

The approach we adopted consists of first determining a minimum frequency for an individual to be considered a gamer. We use the frequency of once a month since this is a metric tracked in the industry (monthly active users – MAU), including Steam. Since this frequency is commonly used in market surveys, we can leverage their results to generalize our findings to the broader population. We complement our study with the results of a 2017 survey by the leading video game market intelligence firm Newzoo[22], conducted among the population between 10 and 65 years old in 13 countries. They find that 48% of men and 35% of women report playing PC games at least once month, which matches our "gamer" criterion as explained above. Assuming a 50% division between men and women in the population, we can use the survey results to calculate the percentage of the population who plays PC games as 41.5%. Now recall that our analysis finds that the prevalence of addiction among PC gamers is between 14.6% and 18.3%. We can then adjust the prevalence found in our study among this subpopulation who plays PC games at least once a month to reflect the prevalence of video game addiction in the general population, which gives us a range between 6% and 7.5%.

2.6 Conclusion

Video games have evolved from a niche pastime into a form of digital entertainment that offers complex and immersive experiences enjoyed by millions of people worldwide. This surge in popularity has caught the attention of public health experts and legislators concerned with the potentially negative consequences of gaming addiction on physical and mental health.

[22]https://shorturl.at/W8MpM

However, most of the debate around this issue is not informed by behavioral data. Our study seeks to be one of the early studies to contribute to this debate by estimating the prevalence of addiction using (gamer) behavioral data from the leading PC video gaming platform. Our results are relevant to policymakers around the world who have considered regulations aiming at curbing excessive video gaming, the video gaming industry and marketing scholars interested in the design and consumption of addictive (digital) products.

As an enduring topic, the causes and consequences of addiction have been studied under different definitions in several fields, such as medicine and social sciences. We adopt the definition most used in economics, where addiction is captured as positive state dependence in consumption. We apply a hierarchical Bayes approach to recover individual coefficients and provide insight into the distribution and intensity of individual addiction. In our sample, the share of users who behaved as addicts over the period studied is 18.3%. However, we show that if addiction is not a transitory condition, then only 14.6% of users can be considered addicted since this is the share that behaves as such in both halves of the one year period in analysis. We also find that being identified as an addict is associated with higher daily play times, having more friends on the platform, playing more often, staying for longer sessions, and a higher likelihood to purchase new games.

As a behavioral disorder, video game addiction could arise from matching personality types and psychological needs to the elements that each game has to offer. Although theory predicts that there could be aspects of each game that attract certain types of individuals prone to addictive behavior, we do not find any association between game characteristics and addiction. Similarly, we do not find evidence that most popular games have a higher share of addicts in their player base, which suggests that their popularity is due to consumer preferences despite claims and beliefs that such games are "designed" to be addictive.

Our study has some limitations. First, we can only observe players who chose to make their profiles public, which may introduce selection bias towards those who are more enthusiastic and engaged with the gaming community. Second, *Steam* is primarily a distributor of PC games, whose consumers are often associated with esports and more hardcore gamers – in contrast with mobile, for example, which caters to a more casual audience. Third, video games can be a social activity, and some individuals may play to make new friends or keep in touch with old ones. In our data, we observe the total number of friends for each player, but not the interactions among them. We hope that further research can address these limitations and, indeed, build on our research.

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