Rational Addiction and Video Games

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Abstract

As video games become more popular the extent to which they can and should be considered addictive has become controversial. I adapt the classic Becker-Murphy model of rational addiction for video games and apply it to a micro-data panel collected from the online video game Team Fortress 2. I find evidence of significant rational addiction; past and future consumption are important in determining the amount an individual plays today. These data also allow for the identification of individual potential addicts in a way consistent with the rational addiction model. Finally, including learning-by-doing provides evidence of a feedback loop: playing improves the skill of an individual which reinforces his decision to play in the future.

*JEL classification: D11, D12, I10

*Keywords: rational addiction, video games

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1 Introduction

In 2007 the American Medical Association was called upon to consider “video game addiction” as a condition for formal diagnosis in the 2012 Diagnostic and Statistical Manual of Mental Disorders (DSM-V). Their followup report acknowledged possible connections between video games and addictive behavior but concluded that “more research is needed in this area.”

Their focus on potential addiction in video games reflects both the rise in use of video games and controversy over their effects. A 2008 Survey by the Pew Institute found that 97% of teens play video games (Lenhart et al., 2008) and the Entertainment Software Association (ESA) reports that 72% of American households play video games. Perhaps surprisingly 82% percent of gamers are 18 years of age or older, the average game player is 37 years old, and 42% of game players are female (ESA 2011).

There is not yet a consensus over the long-term effects of video games and the topic is controversial. Some studies find that video games lead to greater aggression and violence in the real world, while others find a positive correlation between playing video games and creativity, productivity and increased mental health. Ultimately, as with any consumption good, too much can be harmful and there are several cases in which playing video games has lead to death. In 2010 a South Korean couple was arrested for neglecting and starving their baby while playing an online video game. Section 1.1 provides a number of examples of the side effects of gaming. As video games become more ubiquitous in everyday life it is important to understand their effects, and if and when they should be classified as addictive.

In economics addiction is frequently studied in the context of a rational addiction model, originally formalized by Becker and Murphy (1988). In their model of rational addiction, the
value of consuming an addictive good depends on past consumption. The more an individual consumed in the past, the greater value from consuming today. Individuals are also fully rational and forward looking; they make consumption choices based on the knowledge of how their decision today will affect the value of consumption in the future. The degree a good is considered addictive depends on the extent to which past and future consumption influence current consumption. For a more detailed explanation of how addiction has been approached with economics in the past see Becker (1996).

I analyze addiction in video games using a rational addiction model in a manner similar to how Becker et al. (1994) study cigarettes. A video game differs from traditional consumption goods (e.g. cigarettes), in a number of significant ways. First, unlike the purchase of a pack of cigarettes, time spent playing a video game typically does not have an explicit monetary cost. Once an individual has purchased the game, the relevant cost of playing for an hour is the opportunity cost or the value of what that hour of entertainment could have been spent on instead. Second, the value an individual receives from playing a video game is dynamic and may depend on his performance in that game. If he does poorly at the game he may enjoy it less. While my main focus is addiction, I also consider some aspects of learning-by-doing and investigate how changing performance may feed back into the decision to play.

In section 2 I develop a model of rational addiction for video game consumption. I apply this model to unique panel data collected from an online video game called Team Fortress 2 (TF2) and provide evidence of significant rational addiction. The value an individual gets from playing today depends on the amount an individual played in the past, while the amount the individual plays today affects the amount he chooses to play in the future. The size of this effect is similar in magnitude to what Becker et al. (1994) find for cigarettes.

My dataset is rich enough in the time dimension that I can go beyond analyzing addiction at the game level and estimate the rational addiction model at an individual level. This estimation allows me to identify and characterize individual addicts in a way that is consistent with rational addiction. The set of individuals I identify in this way differs significantly
from those identified as addicts using a simple metric, such as the average amount of time spent playing. Using a simple cut-off, such as playing two hours or more per day, to define addiction does not take into consideration differences in the marginal value of time between individuals. An individual who plays a lot but also has a lot of free time for entertainment may not necessarily be addicted. Applying the rational addiction at the individual level provides a method to identify addicts that allows for differences in the marginal value of time between individuals.

One of the results that arises from the estimation of the rational addiction model is evidence that future consumption, even with discounting, may play a larger role in current consumption than past consumption. This is unusual in the rational addiction literature and suggests there may be something different about the future consumption of video games than traditional goods like cigarettes. One possible explanation is that the underlying skill and subsequent performance of an individual in video games improves with time and experience. In section 4.4 I modify the model to allow for learning-by-doing. When time spent playing affects an individual's underlying skill there is evidence of a feedback loop: By playing today an individual improves his skill and subsequent performance in the future which in turn reinforces his decision to play in the future. Learning-by-doing affects the value of playing in the future which contribute to rational addiction.

My results provide evidence in support of rational addiction in video games. Because I estimate the model for a single game, these results should be interpreted as a lower bound on possible addiction, or they may understate the degree of addiction. Individuals likely play more than one game and with my data I do not observe other games that may contribute to addiction. Even so, I provide evidence of rational addiction in video games. In addition, these results show that addiction may depend as much or more on the individual than the nature of a specific game.
1.1 Related literature

The literature in psychology on the effects of video games tends to fall in one of two groups based on their results. One group finds a significant link between violent and aggressive video games and violence and aggression in the real world. For example, Fischer et al. (2007) provides evidence of a link between playing virtual driving video games and aggressive driving behavior. For a review of the literature in this group see Anderson et al. (2004) and Anderson and Bushman (2001). The second subset of the literature finds beneficial effects from playing video games. Jackson et al. (2012) provides evidence that playing video games is strongly linked to creativity. Video games have also been shown to have strong educational benefits (Griffiths, 2002) as well as improve cognitive ability in older adults (Whitlock et al., 2012). While these results may appear diametrically opposed, Gentile (2011) argues that video games affect children and adolescents in multiple dimensions and we need a more nuanced approach rather than simply labeling video games “good” or “bad.”

In economics, addiction was first approached as non-rational habit formation. The theory behind the economics of habit formation was initially investigated by Pollak (1970) and Pollak (1976). More recently the standard approach to modeling addiction is with the theory of rational addiction proposed by Becker and Murphy (1988). While rational addiction is controversial, it remains popular primarily for two reasons: First, it is the most successful method so far at explaining addiction in a way that is consistent with rational forward-looking behavior. Second, the model provides clear empirical implications that can be easily tested. The rational addiction model has been applied to a variety of goods including cigarettes in Becker et al. (1994) and Chaloupka (1991), cocaine in Grossman et al. (1999), and gambling in Mobilia (1993).

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2 Model

To analyze addiction in video games I use a model of rational addiction adapted for video games. In a rational addiction model, forward-looking agents have utility that depends on current and past consumption. The degree to which past and future consumption influence current consumption is the main parameter of interest and the measure of the addictiveness of the good.

In the case of a traditional good like cigarettes, an individual has an income from which he can purchase the good. Once the good is consumed it must be repurchased in order to be consumed again. Demand, therefore, depends on an individual’s income, the current price of the good, and the current prices of other goods. In the case of a video game, however, once an individual has paid the fixed cost to acquire the game there is no direct monetary cost associated with playing the game. Instead, the cost of playing the game will take the form of an opportunity cost, i.e. the value of what an individual could have been doing during this time. Because of this difference from a traditional consumption good with a market price, I adapt the Becker and Murphy (1988) model of rational addiction so that an individual has a fixed endowment of entertainment or leisure time that can be allocated between playing a video game and some other entertainment activity. The value derived from playing a video game depends on the expected performance of an individual in the game. In addition, the value of the other entertainment options may change over time.

At the beginning of each period $t$ an individual chooses how to allocate his fixed entertainment time endowment between time spent playing video games, $y_t$, and time spent consuming some other outside entertainment option, $z_t$. Instantaneous utility in period $t$ is given by the concave utility function:

$$U(y_t, y_{t-1}, p_t, z_t, e_t),$$  \hspace{1cm} (1)

$^5$Note that this is not true for games that continue to have associated monthly fees such as many massively multiplayer online role playing games (MMORPGs) that are traditionally considered to have strong addictive features.
where \( p_t \) represents the performance of the individual in period \( t \) in the video game and \( e_t \) is an unobservable shock to the marginal value of the outside option, \( e_t \sim F_e(0, \sigma_e^2) \). The performance of an individual in period \( t \) is a random variable and is unknown to the individual at the start of the period when he chooses to allocate his time for playing. However, \( p_t \) is based on the skill of the individual (which is known to the individual but not the econometrician) as well as a random shock:

\[
p_t = s + \eta_t, \tag{2}
\]

where \( s \) is the skill of an individual and \( \eta_t \sim F_\eta(\eta_{t-1}, \sigma_\eta^2) \) is a Markov process shock to performance. While an individual’s performance depends on his underlying skill, uncertainty arises because performance is a relative measure and depends on the skill of his teammates and opponents. For example, an individual may realize higher performance when playing against low skill opponents than against high skill opponents. The shocks to performance follow a Markov process to allow for persistence in who you play with or against, which is not observed.\(^6\)

A rational forward-looking consumer, therefore, solves the problem:

\[
\max_{\{y_t, z_t\}_{t=1}^{\infty}} E_{p_t} \left[ \sum_{t=1}^{\infty} \beta^{t-1} U(y_t, y_{t-1}, s_t, z_t, e_t) \right] \tag{3}
\]

\[
\text{s.t. } \begin{align*}
(i) & \quad y_t + z_t = H \\
(ii) & \quad p_t = s + \eta_t,
\end{align*}
\]

where \( H \) is the fixed endowment of entertainment time in each period an individual is able to allocate between playing the video game and another outside entertainment option. The expectation is taken with respect to \( p_t \) given the past history up to point \( t \). Eliminating \( z_t \)

\(^6\)In section 4.4 I consider the case where the skill of an individual evolves endogenously over time based on past playtime.
through the budget constraint, the first order condition is:

\[
E_{pt} [U_1(y_t, y_{t-1}, p_t, H - y_t, e_t) - U_4(y_t, y_{t-1}, p_t, H - y_t, e_t) + \beta U_2(y_{t+1}, y_t, p_t, H - y_{t+1}, e_{t+1})] = 0 \tag{4}
\]

Similar to Becker et al. (1994) I assume the utility function is quadratic in \( y_t, y_{t-1}, z_t \) and \( e_t \). I also assume that performance \( p_t \) interacts only with playtime \( y_t \) but may do so in a non-linear way. This structure of performance implies that the expected value of performance today is the same as the observed value of performance yesterday. This structure allows us to substitute performance in the previous period, \( p_{t-1} \), for the expected value of performance today. We can then write the first order condition as the following demand equation:

\[
y_t = \theta y_{t-1} + \beta \theta y_{t+1} + \theta_1 p_{t-1} + \theta_2 (p_{t-1})^2 + \theta_3 e_t + \theta_4 e_{t+1} + K, \tag{5}
\]

where \( \theta \) and each \( \theta_i \) are constant utility parameters. This is the main equation used for estimation with forward-looking rational individuals. See appendix A.1 for more details on the derivation of equation 5.

The model predicts that an individual’s demand for playing a video game today is a function of playtime yesterday, playtime tomorrow, performance yesterday, and unobservable shocks to the value of the outside option. One implication is that the coefficient on \( y_{t-1} \) and \( y_{t+1} \) both share the same \( \theta \) which represents the marginal effect of future and past playtime on playtime today. \( \theta \) is the parameter of interest and represents the degree of addiction in a rational addiction model. A significant and positive \( \theta \) suggests that past and future consumption play an important role in determining consumption today. Larger values of \( \theta \) suggest stronger rational addiction.

\footnote{That is, performance affects the marginal utility of playtime (in possibly a non-linear way) but does not directly affect the marginal utility of the outside option. For a more complete explanation of functional forms and derivation of the estimation equation see appendix A.1.}
2.1 Estimation strategy

An implication of equation 5 is that an OLS estimate attempting to explain playtime would be biased. There is positive autocorrelation in the shocks to the marginal value of the outside option $e_t$. Even if $\theta$ is actually zero, an OLS regression would suggest it is positive. In addition, even if the term $e_{t+1}$ was not present in equation 5 estimates would still be biased due to its dynamic nature.

To deal with this endogeneity and autocorrelation I use the playtime of friends as an instrument for the playtime of an individual. Becker et al. (1994) uses the price of cigarettes in the previous period as an instrument for consumption of cigarettes in the previous period. The analogue in my model would be to use lagged performance as an instrument for lagged playtime. However, because of the persistence of shocks to performance, any shock to performance will affect future performance and this instrumental variable strategy is not feasible.

Associated with the game of TF2 is a online social community in which players can form friendship links with other players. These links provide benefits including making it easier to communicate and play together. For a description of this community see appendix B. In addition to observing individual characteristics I also observe the identity of an individual’s friends and can determine their characteristics. If an individual chooses friends who are similar to himself in terms of playing time, then the average playtime and performance of friends will be correlated with an individual’s own playtime but independent of earlier playtime and performance. This makes the average playtime and skill of friends valid instruments for an individual’s own playtime. For more on the the validity of these variables as instruments see appendix A.3. Instrumental variable estimation is done using the panel data IV methods of Balestra and Varadharajan-Krishnakumar (1987).

Finally, the constant $K$ in equation 5 includes the individual specific quantity of time available for entertainment $H$. Including individual fixed effects can be interpreted as either allowing the total entertainment time endowment $H$ to differ for each individual or allowing
differences by individual in the marginal value of the other outside entertainment activity.

2.2 Myopic model

The rational addiction model can also easily accommodate individuals who are not forward-looking, but who exhibit non-rational or myopic addiction in their playing. This would be consistent with earlier models of habit formation such as in Pollak (1970) and Pollak (1976). In the case of myopic addiction, past playtime affects the marginal utility from playing today, but individuals are myopic and do not consider how their decision today may affect their future utility. The first order condition equation is the same as equation 4 except that all forward-looking terms are zero and not present. In this case we have demand time spent playing video games as:

\[ y_t = \theta y_{t-1} + \theta_1 p_{t-1} + \theta_2 (p_{t-1})^2 + \theta_3 e_t + K \]  

This is the main equation used for estimation of myopic addiction. As with forward-looking individuals, the main parameter of interest is \( \theta \). A significant and positive \( \theta \) suggests that past consumption plays an important role in consumption today. Larger values of \( \theta \) suggest stronger habit formation and addiction in the myopic sense.

3 Data

The majority of empirical research on addiction in both psychology and economics faces severe data limitations. Research in the field of Psychology tends to use either survey or experimental data. In both cases the sample size is usually small, there are potential selection issues and estimation is based on a single or small number of cross-sections. With survey data, individuals may not have incentives to report truthfully. Economics literature also relies on both survey and experimental data, as well as aggregate data at the national, state, or county level. While aggregate data allows multiple cross-sections over time (usually by
month or year), the aggregate nature of the data gives rise to a significant problem.

Using aggregate data to estimate the rational addiction model leads to misleading results. For a detailed explanation of potential problems using aggregate data to estimate rational addiction see Auld and Grootendorst (2004). For a simple explanation of why aggregate data can be misleading, imagine an example where every 18 year old consumes one cigarette as soon as they are legally able to do so and subsequently never smokes again. Clearly in this example there is no addiction present. However, if there is a combination of population growth and any data aggregation, even at the city level, an estimation would conclude that cigarettes are highly addictive. The persistence of consumption in aggregate data, which may not come from the same individuals, leads to a predisposition to identify rational addiction. While there are some exceptions that take advantage of micro-data to estimate rational addiction, such as Chaloupka (1991) and Labeaga (1999), even in these cases either the individual or time dimension is usually small.

My data does not have such weaknesses. I use a very large unbalanced panel dataset collected from publicly available information for the online video game Team Fortress 2 (TF2), developed by Valve Corporation. TF2 is a first-person-shooter game in which individual players play as one of nine different classes (such as soldier, medic, spy, et cetera) to work together as a team and compete against an opposing team of other players to complete an objective. For more information about the game see appendix B.

TF2 was originally released in October 2007 as part of a package of five games called the Orange Box which sold over 3 million copies within the first year (Remo, 2008). Since its release TF2 has been primarily distributed through Valve Corporation’s online digital distribution and multiplayer system called Steam. Despite being almost five years old, today TF2 is the second most-played game, with an average of over 50,000 users playing at any

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This particular game was chosen due to the high quality and availability of data. There is no reason for this particular game to be any more “addictive” than any other video game. TF2 is likely to be less addictive than other games, particularly massively multiplayer online role-playing games (MMORPGs) which have progressive elements that are often cited as contributing to addiction.
given time, on the Steam system which distributes over 8,000 games.\footnote{See \url{http://www.steampowered.com} and \url{http://www.valvesoftware.com/} for additional information about the Steam system. The popularity of TF2 determined from \url{http://store.steampowered.com/stats/}, and number of games available on steam determined from \url{http://store.steampowered.com/search/} on 10/20/2013.} Associated with the Steam system is an online community which publicly reports extensive gameplay statistics for individuals by game. The Steam community also allows individuals to form bi-lateral friendship links, which are also reported. Through friendship links individuals are notified when a friend plays, they can easily communicate with friends, and they can join and play with a friend with a single click. My dataset consists of individual and friend statistics collected from this online Steam community.

Weekly cross-sections of all individual members in the “Team Fortress 2 Official Game Group” on Steam were collected over a period of approximately 18 months from February 1st, 2010 until June 22nd 2011. By extrapolation, this “Official Group” represented approximately 70-80\% of all active TF2 players at the time.\footnote{Extrapolated using server statistics in November 2010.} Using these data, I construct an unbalanced panel dataset of 160,810 individuals who are active in at least one cross-section. An individual is considered active in a particular cross-section if they played at least 30 minutes\footnote{30 minutes was the average length of one round on a team-based map in November of 2010.} in that week. The average user is active for 14 weeks with 2.8 gaps in their play-time.\footnote{A gap is defined as a week in which an individual does not play consecutively, excluding when they initially enter or exit the panel.} One feature of TF2 is individuals play as one of nine distinct “classes.” These classes are divided into three distinct roles: offense, defense and support. Each class has particular strengths and weaknesses designed to complement their teammates in different ways. At any time during a game individuals are free to change which class they are playing. The data I collect is reported at the class-level which I then aggregate by class for each individual.

For each individual in each week I observe the amount of time they play (hours per week) and the average number of points they earn per hour (if active), which is a measure of performance. For each individual I observe the set of their friends, which allows me to determine the characteristics of friends. The final result is a panel dataset of 160,810
individuals with 66 cross-sections and with a total of 2,247,239 individual-time observations. Table I presents a list of the important variables with descriptions and summary statistics for active individuals. The summary statistics are first averaged across cross-sections by individual and represent the mean and median individual.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>SD</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$y_t$</td>
<td>4.73</td>
<td>3.71</td>
<td>3.86</td>
<td>Total amount of time an individual plays in week $t$ measured in hours.</td>
</tr>
<tr>
<td>$p_t$</td>
<td>93.8</td>
<td>87.4</td>
<td>55.8</td>
<td>Performance of an individual in week $t$ measured by the average number of accumulated points per hour of playtime in the previous week.</td>
</tr>
<tr>
<td>$F_t$</td>
<td>4.31</td>
<td>1.67</td>
<td>6.88</td>
<td>Number of friends an individual has in week $t$.</td>
</tr>
<tr>
<td>$y_t^F$</td>
<td>7.10</td>
<td>6.85</td>
<td>3.75</td>
<td>Average playtime of an individual’s friends in week $t$.</td>
</tr>
<tr>
<td>$s_t^F$</td>
<td>95.4</td>
<td>94.2</td>
<td>34.9</td>
<td>Average performance of an individual’s friends in week $t$.</td>
</tr>
<tr>
<td>$m_t$</td>
<td>0.338</td>
<td>0.299</td>
<td>0.149</td>
<td>An index that measures the degree an individual specializes among classes. See appendix B for details.</td>
</tr>
</tbody>
</table>

While the average total playtime of 4.73 hours per week is perhaps not particularly high (approximately 40 minutes per day), the distribution is heavily skewed to the right. For example, in an average cross-section 90% of individuals play 14 hours or less and these individuals average 4.57 hours per week. The remaining 10% that play more than 14 hours per week average 21 hours per week. In an average week 50% of active individuals contribute 85% of all the time spent playing.

4 Results

In this section I present the main empirical results. I start by estimating the myopic model and then consider the rational model with forward-looking individuals. Next, I estimate the
rational addiction model at the individual level to identify and characterize what it means to be an addict. Finally, I consider a modification to the model to allow for learning, or endogenous skill formation.

4.1 Myopic model

Before estimating the model of rational addiction with forward-looking individuals I estimate the myopic model from section 2.2. Table 2 presents the estimation results of the myopic model. Each column of this table is estimated using a panel regression with fixed effects. The fixed effects capture individual differences in the endowment of time. The first four columns are estimated with instrumental variables to correct for the endogeneity of playtime. Columns (i)a and (i)b use the same period average playtime of friends as an instrument for an individual’s playtime, while columns (ii)a and (ii)b add lagged average performance of friends as an instrument. The final column (iv) is estimated without instruments. Each of the instrumental variable regressions include the $\chi^2$ test statistic from a Hausman test to check if the non-IV estimate is consistent. Since this hypothesis is rejected in each case, I focus on the instrumental variable estimates in the first four columns. Also included in the regression are individual fixed effects. Columns (i)a and (ii)a estimate equation 6 with individual fixed effects and some date fixed effects as explanatory variables. Columns (i)b and (ii)b add as additional explanatory variables non-linear specialization and number of friends.

The main estimates of interest are $\theta$, the coefficient on lagged playtime $y_{t-1}$, as well as $\theta_1$ and $\theta_2$, the coefficient on lagged performance $p_{t-1}$ and lagged performance squared, $p_{t-1}^2$. $\theta$ represents the persistence of playtime, or the degree to which past playtime affects current playtime. In each specification $\theta$ is positive and significant, ranging from 0.441 to 0.47 depending on instruments and specification. This coefficient represents the degree of

13 The date fixed effects included are for the month of July (summer holiday), the last two weeks in December (winter holiday), and a number of weeks in which a major patch or update to the game was added.
Table 2 – Estimates of Myopic Models of Addiction, Dependent Variable $y_t$

<table>
<thead>
<tr>
<th></th>
<th>Fixed effects with IV</th>
<th>Non-IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(i)a</td>
<td>(ii)a</td>
</tr>
<tr>
<td>$y_{t-1}$</td>
<td>0.47***</td>
<td>0.47***</td>
</tr>
<tr>
<td></td>
<td>(84.2)</td>
<td>(73.7)</td>
</tr>
<tr>
<td>$p_{t-1}$</td>
<td>0.00266***</td>
<td>0.0035***</td>
</tr>
<tr>
<td></td>
<td>(12.3)</td>
<td>(9.74)</td>
</tr>
<tr>
<td>$p^2_{t-1}$</td>
<td>-0.000003***</td>
<td>-0.000404***</td>
</tr>
<tr>
<td></td>
<td>(-9.66)</td>
<td>(-8.80)</td>
</tr>
<tr>
<td>$m_{t-1}$</td>
<td>-1.21***</td>
<td>1.18***</td>
</tr>
<tr>
<td></td>
<td>(-8.5)</td>
<td>(7.1)</td>
</tr>
<tr>
<td>$m^2_{t-1}$</td>
<td>-0.987***</td>
<td>-0.967***</td>
</tr>
<tr>
<td></td>
<td>(-8)</td>
<td>(-6.67)</td>
</tr>
<tr>
<td>$F_{t-1}$</td>
<td>-0.0877***</td>
<td>-0.0847***</td>
</tr>
<tr>
<td></td>
<td>(-84.1)</td>
<td>(-73.4)</td>
</tr>
<tr>
<td>summer</td>
<td>3.36***</td>
<td>3.47***</td>
</tr>
<tr>
<td>holiday</td>
<td>(122)</td>
<td>(109)</td>
</tr>
<tr>
<td>winter</td>
<td>1.3***</td>
<td>1.46***</td>
</tr>
<tr>
<td>holiday</td>
<td>(34.8)</td>
<td>(35)</td>
</tr>
<tr>
<td>major patch</td>
<td>2.22***</td>
<td>2.41***</td>
</tr>
<tr>
<td></td>
<td>(109)</td>
<td>(100)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.147</td>
<td>0.152</td>
</tr>
<tr>
<td>$\chi^2$</td>
<td>1326</td>
<td>1402</td>
</tr>
<tr>
<td>$n$</td>
<td>108276</td>
<td>87415</td>
</tr>
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<td>64</td>
<td>63</td>
</tr>
<tr>
<td>$N$</td>
<td>1358745</td>
<td>1056907</td>
</tr>
</tbody>
</table>

Significance levels: * = 10%, ** = 5%, *** = 1%, t-statistics in parentheses.
habit formation or addiction when utility today depends on past playtime. For example, a value of $\theta = 0.4$ would imply that every hour that an individual played in the previous week contributes 24 minutes to the amount he plays this week. These estimates are slightly smaller but similar in magnitude to those found in Becker et al. (1994) where they found estimates of $\theta$ for cigarettes ranging from 0.478 to 0.602 in a myopic model of addiction using instruments.

Greater performance in the previous period also contributes to greater playtime this period. The estimates of the coefficients on lagged performance, $\theta_1$ and $\theta_2$, represents the effect of performance last period on playtime this period. In each of the instrumental variable estimations $\theta_1$ and $\theta_2$ are significant. $\theta_1$ is positive and captures the first order effect of an increase in performance on playtime. $\theta_2$ is negative and captures the diminishing marginal returns of performance on playtime. Evaluated at the median performance, a one standard deviation increase in skill increases the playtime of an individual by between 5 and 9 minutes per week.

The estimates of the remaining coefficients are also useful in explaining playtime. The estimates of the coefficients on specialization, $m_{t-1}$ and $m_{t-1}^2$, are significant. The values of the specialization variable $m_t$ range from complete diversification at $m_t = 1/9$ to complete specialization at $m_t = 1$. Going from complete diversification to a value of $m_t = 0.61$ increases an individual’s playtime by 15 minutes per week, while continuing on to complete specialization reduces his playtime from this peak by 9 minutes. Each friend decreases an individual’s playtime by 5 minutes per week. Finally, the date fixed effects are all positive. A summer or winter holiday increases the amount an individual plays by around 3.3 hours and 1.3 hours per week respectively, while the release of a major patch increases playtime by 2.3 hours per week.
4.2 Rational model

Estimating the myopic model provides evidence of habit formation or addiction in a myopic sense. However, the real focus is on rational addiction with forward looking individuals. To determine if there is evidence of rational addiction, I estimate equation 5 for the significance of the coefficient on leading playtime $y_{t+1}$. A criterion for rejecting a model of rational addiction in favor of myopic addition is if the coefficient on leading playtime is not significant. Table 3 presents the estimation results of the rational model and shows that this coefficient is significant.

As in the estimation of the myopic model, each column of table 3 is estimated using a panel regression with fixed effects. The fixed effects capture individual differences in the endowment of time. The first four columns are estimated with instrumental variables to correct for the endogeneity of playtime. Columns (i)a and (i)b use the same period average playtime of friends as an instrument for an individual’s playtime, while columns (ii)a and (ii)b add lagged average performance of friends as an instrument. The final column (iv) is estimated without instruments. Each of the instrumental variable regressions include the $\chi^2$ test statistic from a Hausman test to check if the non-IV estimate is consistent. Since this hypothesis is rejected in each case, I focus on the instrumental variable estimates in the first four columns. Columns (i)a and (ii)a estimate equation 5 with individual fixed effects and some date fixed effects as explanatory variables. Columns (i)b and (ii)b add as additional explanatory variables non-linear specialization and number of friends.

In each specification the coefficient on leading playtime $y_{t+1}$ is significant and positive which provides evidence of rational addiction. The estimates of $\theta$, the coefficient on lagged playtime $y_{t-1}$, range from 0.347 to 0.361 in the specifications using instruments. These estimates are slightly smaller but similar in magnitude to those of Becker et al. (1994) for cigarettes where they find estimates ranging from 0.373 to 0.481 in their specifications using instruments. The estimates for the coefficient on $y_{t+1}$ are all significant and range from 0.353 to 0.371 in the specifications using instruments. This is significantly higher than the
Table 3 – Estimates of Rational Models of Addiction, Dependent Variable $y_t$

<table>
<thead>
<tr>
<th></th>
<th>Fixed effects with IV</th>
<th>Non-IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(i)a</td>
<td>(ii)a</td>
</tr>
<tr>
<td>$y_{t-1}$</td>
<td>0.361***</td>
<td>0.359***</td>
</tr>
<tr>
<td></td>
<td>(53.2)</td>
<td>(48.1)</td>
</tr>
<tr>
<td>$y_{t+1}$</td>
<td>0.371***</td>
<td>0.364***</td>
</tr>
<tr>
<td></td>
<td>(50.2)</td>
<td>(46)</td>
</tr>
<tr>
<td>$p_{t-1}$</td>
<td>0.00131***</td>
<td>0.00183***</td>
</tr>
<tr>
<td></td>
<td>(5.03)</td>
<td>(5.94)</td>
</tr>
<tr>
<td>$p_{t-1}^2$</td>
<td>-0.000002***</td>
<td>-0.000002***</td>
</tr>
<tr>
<td></td>
<td>(-3.77)</td>
<td>(-4.34)</td>
</tr>
<tr>
<td>$m_{t-1}$</td>
<td>-</td>
<td>1.17***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(7.18)</td>
</tr>
<tr>
<td>$m_{t-1}^2$</td>
<td>-</td>
<td>-0.913***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-6.46)</td>
</tr>
<tr>
<td>$F_{t-1}$</td>
<td>-</td>
<td>-0.042***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-29.2)</td>
</tr>
<tr>
<td>summer holiday</td>
<td>2.32***</td>
<td>2.3***</td>
</tr>
<tr>
<td></td>
<td>(65.2)</td>
<td>(61.1)</td>
</tr>
<tr>
<td>winter holiday</td>
<td>1.53***</td>
<td>1.49***</td>
</tr>
<tr>
<td></td>
<td>(37.9)</td>
<td>(38)</td>
</tr>
<tr>
<td>major patch</td>
<td>2.23***</td>
<td>2.25***</td>
</tr>
<tr>
<td></td>
<td>(99.7)</td>
<td>(92.4)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.222</td>
<td>0.219</td>
</tr>
<tr>
<td>$\chi^2$</td>
<td>974</td>
<td>687</td>
</tr>
<tr>
<td>$n$</td>
<td>86535</td>
<td>86535</td>
</tr>
<tr>
<td>$T$</td>
<td>63</td>
<td>63</td>
</tr>
<tr>
<td>$N$</td>
<td>1049626</td>
<td>1049626</td>
</tr>
</tbody>
</table>

Significance levels: * = 10%, ** = 5%, *** = 1%, t-statistics in parentheses.
estimates in Becker et al. (1994) which range from 0.135 to 0.236.

One reason the estimates of the coefficient on $y_{t+1}$ are much closer to the estimates of the coefficients on $y_{t-1}$ is that these data are weekly and reflect weekly, rather than annual, discount rates. For example, a weekly discount rate of $\beta = 0.99$ is equal to an annual discount rate of $0.99^{52} \approx 0.59$. While this explains why the estimates for the coefficient on $y_{t+1}$ are closer in value it does not explain why the estimate of the coefficient on $y_{t-1}$ appears to be consistently larger. Pairwise tests of the coefficients on $y_{t-1}$ and $y_{t+1}$ show that the second is statistically larger than the first in all specifications. One possible explanation is learning-by-doing and improvement in skill. If by playing an individual improves his skill and subsequently his future performance, then there is an additional benefit to playing today that will be realized in future periods. In section 4.4 I investigate effects of learning-by-doing and show that this provides some explanation for these results.

Greater performance in the previous period also contributes to greater playtime this period. The estimates of the coefficients on lagged performance, $\theta_1$ and $\theta_2$, represents the effect of performance last period on playtime this period. In each of the instrumental variable estimations $\theta_1$ and $\theta_2$ are significant. $\theta_1$ is positive and captures the first order effect of an increase in performance on playtime. $\theta_2$ is negative captures the diminishing marginal returns of performance on playtime. Evaluated at the median performance, a one standard deviation increase in skill increases the playtime of an individual by between 3 and 5 minutes per week.

The estimates of the remaining coefficients are also useful in explaining playtime. The estimates of the coefficients on specialization, $m_{t-1}$ and $m_{t-1}^2$, are significant. The values of the specialization variable $m_t$ range from complete diversification at $m_t = 1/9$ to complete specialization at $m_t = 1$. Going from complete diversification to a value of $m_t = 0.64$ increases an individual’s playtime by 15 minutes per week, while continuing on to complete specialization reduces his playtime from this peak by 7 minutes. Each friend decreases an individual’s playtime by 2.5 minutes per week. Finally, the date fixed effects are all positive. A summer or winter holiday increases the amount an individual plays by around 2.35 hours.
and 1.6 hours per week respectively while the release of a major patch increases playtime by 2.3 hours per week.

Since the coefficient on leading playtime, \( y_{t+1} \) is positive and significant this provides evidence in support of rational addiction in this video game. The estimates of \( \theta \) are large, similar in magnitude to the estimates in Becker et al. (1994) for cigarettes, suggesting a strong addictive component to the game.

### 4.3 Identifying addicts

While the results above provide evidence of rational addiction in this game, a natural question that follows is how can we identify and characterize individual addicts? While the game exhibits evidence of rational addiction, this does not mean that all individuals who play the game are addicted. The rational addiction model coupled with individual data over time suggests a natural way to identify individual addicts.

I apply the rational addiction model at the individual level and estimate equation 5 separately for each individual. This allows me to identify an individual-specific measure of the degree of addiction, \( \theta_i \). Estimating individual specific \( \theta_i \) in this way does not introduce bias since all parameters are individual-specific (i.e. there are no common parameters), but the estimates may be imprecise. By estimating equation 5 separately for each individual using as instruments the playtime and skill of friends, I am able to identify the individuals with significant and positive \( \theta_i \), hereafter called “addicts”.

This approach is related to Fernandez-Val and Lee (2010) in which they develop a GMM method to estimate panel data with nonadditive unobserved heterogeneity. They then apply this method to the original Becker et al. (1994) model and data to show there is significant State-specific heterogeneity in the price effect. In their case some parameters are not individual-specific, since the addictiveness of cigarettes should not depend on the State. Because of this, a separate OLS regression for each state would lead to severely biased estimates due to an incidental parameter problem. To address this problem, they develop
a method to correct the bias in mean and variance. In my case, however, all parameters are individual-specific which allows me to effectively treat each individual with a separate regression.

Since the dataset is an unbalanced panel, some individuals have a small number of observations, due either to the individual leaving the dataset early or entering late. Among the 42,103 individuals with sufficient data to make estimation possible\textsuperscript{14} I identify 5,626 or 13.4% as addicts with significant and positive \( \theta \). This addiction rate is significantly larger than found in Gentile (2009) who using a national survey data show that 8% of youths aged 8 to 18 had symptoms of video game addiction. Among the these addicts there are 677 (or 7.3% of addicts) who also have a positive and significant estimate for the coefficient on \( y_{t+1} \), which is evidence of rational forward-looking addiction.

Table 4 presents the mean and median values for variables and estimates of coefficients when individuals are divided into subgroups of non-addicts, myopic addicts and rational addicts. These three subgroups are surprisingly similar in characteristics. Myopic addicts play slightly more (about 20%) than non-addicts and have slightly higher performance\textsuperscript{15} Both myopic and rational addicts tend to have more friends than non-addicts, and these friends tend to play more. Myopic addicts also tend to have friends that have higher performance than non-addicts.

The similarity between these groups (in particular in terms of playtime) suggests that using a simple metric to determine addiction, such as a cut-off rule in playtime of 14 hours or more per week, may lead to very different set of addicts than predicted by the rational

\textsuperscript{14}Limiting the estimation to only individuals with a large number of observations may lead to a selection problem since addiction should be correlated with remaining in the dataset longer. Most of the individuals dropped however are dropped based on when they entered the dataset. By design each observation for estimation requires a lagged and leading observation. The minimum requirements for estimating an individual is therefore seven three-consecutive period observations in the data. Those that cannot be estimated are primarily those that entered the dataset late or have gaps in their consecutive playtime. I also show later on that there is no evidence of selection problems.

\textsuperscript{15}In the case of drug and alcohol abuse, typically one of the features of addiction is less social participation. In this case, since an online video game involves social interactions addiction leads to greater rather than less social interaction. While the quality of interactions may not be the same, this is possibly a positive side effect of online video game addiction.
addiction model. A cut-off rule identifies addicts based on the absolute amount of time spent playing rather than the relative amount to available hours. Estimating rational addiction at the individual level captures persistence in playing as well as allowing for differences in the amount of time available for entertainment across individuals.

Among myopic and rational addicts the mean estimates for $\theta_i$ is 0.93 and 0.842 respectively. This estimate is much higher than in the panel data specifications and suggests very strong addiction. A value of $\theta_i = 0.8$ implies that every hour an individual plays in the previous week contributes 48 minutes to the amount he plays this week. Among rational addicts the mean estimate for $\hat{\beta}\theta$ is 0.845, or that future playtime is an important factor in determining current playtime.

In order to verify that dropping individuals with too few observations for estimation does not cause a selection problem, I check the addiction rate among individuals with an arbitrary but specific number of observations (rather than those with more than a certain number). Among individuals who have exactly 20 observations the addiction rate is 14% and among these addicts 9% show evidence of rational forward-looking addiction. This addiction rate is similar to the rate using all individuals for which estimation is possible, and this suggests that dropping individuals with too few observations to estimate does not necessarily lead to over-selection of addicts.
Until a formal definition and classification of addiction in video games is adopted it is not possible to conclude whether estimating the rational addiction model at the individual level is better than a simple metric for identifying addicts. However, the rational addiction model has the advantage of allowing for different marginal value of entertainment time by individuals, even when data on this is not available. This is important if addiction and the associated negative effects depend on the value of what an individual is giving up in order to play as well as the quantity of time spent playing. For example, if an individual has more free time for entertainment than another, the negative effects of both playing the same number of hours may be less for this individual. While playing more should be associated with greater addiction for an individual, comparing the amount of time two individual spend playing may not always correctly identify the addict.

Estimating the rational addiction model at the individual level also provides evidence that using micro data rather than aggregate data helps prevent spurious results. One of the main criticisms of Becker et al. (1994) is that aggregate data tends generate spurious evidence in favor of the rational addiction model. To understand why this is the case see Auld and Grootendorst (2004) as well as my simple example in section 3. Auld and Grootendorst (2004) also state that this particular problem of spurious results may not apply to micro data. These individual estimation results support their statement. If the results in section 4 were spurious, then it should follow that the addiction rate when estimating the model separately for each individual should be very high. Since the addiction rate is low, only 13.4%, and not an artifact of selection problems, this supports the argument that micro significantly reduces the risk of spurious results in the rational addiction model.

Finally, the results from the individual estimations suggest that there is very strong heterogeneity in the data. Estimating the model separately for each individual suggests that there is only a small proportion of individuals who are addicted. This heterogeneity may mean that it is not a characteristic of the game which leads to addiction, but rather some characteristic of an individual that determines addiction. This suggests an approach for
looking at addiction that is individual-based: what is it about an individual that causes him to become addicted to different goods? Rather than a good-focused approach: what is it about this product that makes it addictive?

4.4 Learning-by-doing

The demand equation 5, which follows from the rational addiction model, predicts that the estimate of the coefficient on $y_{t+1}$ should represent $\beta \theta$ while the estimate of the coefficient on $y_t$ should represent $\theta$. Since $\beta \leq 1$, it follows that $\beta \theta \leq \theta$. Since the discount rate $\beta$ is a weekly discount factor and may be very small (for example $\beta = 0.999$), the estimates of these two coefficients may not be significantly different from each other. For the purpose of rejecting the myopic model in favor of the rational model, the significance rather than the value of the coefficient on $y_{t+1}$ is important. However, in a number of the instrumental variable specifications in table 3, the coefficient on $y_{t+1}$ is statistically larger than the coefficient on $y_{t-1}$. A significantly larger coefficient on $y_{t+1}$ is not consistent with the model. In this section I will consider learning, which provides one possible explanation for this inconsistency.

One significant difference between playing video games and consuming a good, such as cigarettes, is that video games may involve significant learning-by-doing. When an individual first begins to play a video game they may not be familiar with some aspects of the game, such as the game mechanics or layout of the maps. Playing the game over time may lead to higher level of skill, which then is reflected in performance. In the context of human capital development, learning means that investment by playing today increases the stock level of skill, which then affects future decisions. In this case the choice of action today affects all future decisions and introduces significant dynamic complications. One attractive features of the rational addiction model is that even though the assumption of additive separable utility in time is relaxed, the model can be reduced to a simple demand equation that depends only on your consumption in the previous and next future period. No dynamic programming is required to solve the rational addition model. Adding learning, however, changes this. If
skill is a stock variable that persists each period, improvements to this stock level affect decisions not just tomorrow but in all future periods.

I introduce a modified version of the model from section 2 that allows an individual’s skill, $s_t$, to evolve endogenously over time based on the past playtime decisions of that individual without requiring dynamic programming techniques to solve the model. In contrast to the earlier model, I assume that the marginal utility of playing in period $t$ depends on an individual’s performance at the start of period, $p_t$, rather than the performance realized during period. At the start of period $t$, performance $p_t$ is realized based on the underlying skill of an individual at the start of the period, $s_t$, and a random shock:

$$p_t = s_t + \eta_t,$$  \hspace{1cm} (7)

where $\eta_t \sim F_{\eta}(0, \sigma^2_{\eta})$. Performance $p_t$ is observed by individuals and the econometrician and known when an individual chooses $y_t$. Skill $s_t$ is known by the individual, but not the econometrician. At the end of each period (after utility for that period is realized) skill $s_t$ transitions based on the amount an individual played during that period and some noise:

$$s_{t+1} = \delta s_t + b_1 y_t + \mu_t,$$  \hspace{1cm} (8)

where $\mu_t \sim F_{\mu}(0, \sigma^2_{\mu})$. While skill is not observable by the econometrician, observing only performance and playtime in period $t$ is sufficient to determine the expected value of performance for the next period. Equations 7 and 8 imply that performance $p_t$ transitions according to:

$$p_{t+1} = \delta p_t + b_1 y_t + \eta_{t+1} - \delta \eta_t + \mu_t,$$  \hspace{1cm} (9)

so that in period $t$:

$$E[p_{t+1}|p_t, y_t] = \delta p_t + b_1 y_t.$$  \hspace{1cm} (10)

The individual faces the same problem as before, except now $p_t$ is known in each period and
the expectation is taken with respect to performance in future periods:

$$\max_{\{y_t, z_t\}_{t=1}^{\infty}} \mathbb{E} \left[ \sum_{t=1}^{\infty} \beta^{t-1} U(y_t, y_{t-1}, p_t, z_t, e_t) \right]$$

s.t. (i) $p_t = s_t + \eta_t$

(ii) $s_{t+1} = \delta s_t + b_1 y_t + \mu_t$

(iii) $z_t + y_t = H.$

While this problem is similar to the original specification of equation 3 there is an important difference. In the original specification any inter-temporal decisions entered the utility function directly, linking each period with the immediately preceding and subsequent period. This, combined with the assumption of quadratic utility allows us to nicely reduce the infinite time horizon dynamic programming problem to one in which only the previous, current and next period are relevant for decision making. The addition of learning, even in the simplest form, links the decision in each period with the decision in EVERY future period and the dynamic programming problem can no longer be reduced to yield a simple demand function.

In order to keep the problem tractable and remain consistent to the idea that while an individual is fully rational, his decision in each period only depends on the previous and next future period and not all future periods, I assume that while individuals are forward-looking they only consider the benefits of improving skill through learning in the immediately following period. This assumption can also be thought of as a first-order empirical approximation to the problem of the consumer in order to allow estimation. See appendix A.2 for a more detailed description and discussion of the implications of this assumption.

Under this assumption the problem can be solved and written as the linear demand function:

$$y_t = \theta y_{t-1} + \beta(\theta + \alpha)y_{t+1} + \theta_1 p_{t-1} + \theta_2 e_t + \theta_3 e_{t+1} + K,$$

where the additional term $\alpha$ represents the value of learning-by-doing.
Equation 12 is a first order approximation of the true solution to the problem in 11 and there are two ways to interpret this demand function. The first is that it represents demand when individuals are forward-looking but only consider how playtime affects their skill in the immediately following period (rather than all future periods). This semi-myopic approach eliminates the longer-term effects of learning and collapses the problem back to the same horizon as the rational addiction model. Ultimately however, this interpretation is inconsistent with rational behavior. A second interpretation is that equation 11 represents a numerical approximation of the true demand function.

If $\alpha$ is positive then an individual considers how his playing today affects his skill tomorrow which in turn affects the utility from playing tomorrow. Larger values of $\alpha$ imply stronger learning-by-doing effects. With this specification it is not possible to separate and directly estimate $\alpha$, however, with the estimate of $\theta$ it is possible to calculate an implied estimate of $\alpha$ for different values of $\beta$. Using the results in table 3 of section 4 we can calculate implied estimates for $\alpha$.\footnote{The change in notation for performance means that $p_t$ in problem 11 is actually $p_{t-1}$ in the model in section 2. This means that we can directly apply the results in table 3. While these results also include the term $p_{t-1}$, re-estimating without this term does not significantly change the coefficients of interest on $y_{t-1}$ and $y_{t+1}$.} Table 5 presents the implied estimates of $\alpha$ for a given discount rate $\beta$.

\begin{table}[h]
\centering
\begin{tabular}{cccccc}
$\beta$ & (i)a & (i)b & (ii)a & (ii)b & (iii) \\
\hline
0.999 & 0.011* & 0.009 & 0.005 & 0.0066 & 0.011*** \\
0.995 & 0.012** & 0.01* & 0.0065 & 0.008 & 0.012*** \\
0.99 & 0.014** & 0.012* & 0.0083 & 0.0098 & 0.013*** \\
0.98 & 0.018*** & 0.016** & 0.012* & 0.013* & 0.016*** \\
0.95 & 0.03*** & 0.028*** & 0.024*** & 0.025*** & 0.025*** \\
0.9 & 0.051*** & 0.049*** & 0.045*** & 0.045*** & 0.042*** \\
\end{tabular}
\caption{Implied estimates of parameter $\alpha$ for different discount rates $\beta$}
\end{table}

While the significance and magnitude of the implied $\alpha$ is directly tied to the assumed value of $\beta$, the imputed estimate for $\alpha$ is significant and positive for many discount factor values. $\alpha$ can be interpreted as the degree to which learning affects an individual’s decision
to play today. For example, an individual with a weekly discount rate of $\beta = 0.98$ (which corresponds to an annual discount rate of 0.35) and a value of $\alpha = 0.017$ will play an additional minute this week for each hour he anticipates playing next week in order to improve his skill and increase the value of playing next week.

5 Conclusion

I analyze and provide evidence in support of addiction in video games. I adapt the Becker and Murphy (1988) model of rational addiction for video games and estimate this model using unique panel data I collected from the online video game Team Fortress 2.

The empirical results provide evidence in support of rational addiction in video games. Past and future consumption of this game play a significant role in determining the amount an individual plays today. The degree to which past consumption affects current consumption is similar in magnitude to what Becker et al. (1994) find for cigarettes.

By using data collected at the individual rather than aggregate level, I am able to avoid some empirical problems with estimating the rational addiction model. Auld and Grootendijst (2004) show that when aggregate data with strong auto-correlation is used to estimate rational addiction it leads to spurious results in favor of addiction. The data are also rich enough to allow me to estimate the model separately for each individual. When I do this, I find an addiction rate of approximately 13.4%, and of these addicts 7.3% show evidence of rational addiction. In this case both myopic and rational addicts show much stronger addiction than when estimated as a whole population. Estimating the rational addiction model separately for individuals allows me to identify addicts in a way that is consistent with the rational addiction model.

The results of the individual estimations suggests that the addiction trends identified in the full data may be driven primarily by a small number of addicted individuals rather than a particular feature of the game. At the same time, these estimates of addiction for
this particular video game represent a lower bound on the addictiveness of video games in general.

Finally, I present a simplified model that allows for learning-by-doing and endogenous skill. Using this model I provide evidence of a skill-playtime feedback loop: By playing today an individual improves his future skill which in turn reinforces his decision to play in the future. Learning affects the value of playing in the future, and this can contribute to rational addiction. This model provides the first step to looking at learning in more depth.
Appendix A  Estimation details

A.1 Derivation of demand

Assume the utility function has the following quadratic form:

\[ U(y_t, y_{t-1}, p_t, z_t, e_t) = (a_1 + a_{13}p_t + a_{331}p_t^2)y_t + a_{11}y_t^2 + a_{2}y_{t-1} + a_{22}y_{t-1}^2 + a_3p_t + a_{33}p_t^2 + a_4z_t + a_{44}z_t^2 + a_5e_t + a_{55}e_t^2 + a_{12}y_{t-1} + a_{14}y_t z_t + a_{15}y_t e_t + a_{24}y_{t-1} z_t + a_{25}y_{t-1} e_t + a_{45}z_t e_t, \]

where each \( a_i, a_{ii}, a_{iii} \) represent a scalar. In the notation each number in the subscript of a scalar represents a variable in the term that the scalar is multiplied by. For example, \( a_{331} \) is the coefficient on \( p_t^2 y_t \) or the third variable of the function squared times the first. The first line above represents the way in which current playtime \( y_t \) enters and how lagged performance \( p_{t-1} \) affects the marginal utility of playing. The second line includes the first and second power terms of the remaining variables and the third line includes the interactions of variables.

Returning to the individual’s maximization problem:

\[
\max_{\{y_t\}_{t=1}^{\infty}} E \left[ \sum_{t=1}^{\infty} \beta^{t-1} U(y_t, y_{t-1}, p_t, H - y_t, e_t) \right]
\]

By expanding the summation we can see in what terms \( y_t \) appears:

\[
\max_{\{y_t\}_{t=1}^{\infty}} \ldots + \beta^{t-1} E_{pt} [U(y_t, y_{t-1}, p_t, H - y_t, e_t)] + \beta^t E_{pt+1} [U(y_{t+1}, y_t, p_{t+1}, H - y_{t+1}, e_{t+1})] + \ldots
\]

The first order condition is:

\[
E_{pt} [U_1(y_t, y_{t-1}, p_t, H - y_t, e_t)] - E_{pt} [U_4(y_t, y_{t-1}, p_t, H - y_t, e_t)] + \beta E_{pt+1} [U_2(y_{t+1}, y_t, p_{t+1}, H - y_{t+1}, e_{t+1})] = 0. \tag{13}
\]

Because performance today only affects the marginal utility of playing today, performance only shows up in the first term in the first order condition. Consider the first term of equation \(13\):

\[
E_{pt} [U_1(y_t, y_{t-1}, p_t, H - y_t, e_t)] = a_1 + a_{13}E_{pt} [p_t] + a_{331}E_{pt} [p_t^2] + 2a_{11}y_t + a_{12}y_{t-1} + a_{14}(H - y_t) + a_{15}e_t.
\]

Since \( E_{pt} [p_t] = p_{t-1} \) and \( E_{pt} [p_t^2] = (p_{t-1})^2 + \sigma^2_\eta \) we can rewrite:

\[ E_{pt} [U_1(y_t, y_{t-1}, p_t, H - y_t, e_t)] = a_1 + a_{13}p_{t-1} + a_{331}(p_{t-1})^2 + a_{331}\sigma^2_\eta + 2a_{11}y_t + a_{12}y_{t-1} + a_{14}(H - y_t) + a_{15}e_t.
\]

The expectation is degenerate over the second and third term in the equation \(13\) and these terms are:

\[ U_4(y_t, y_{t-1}, p_{t-1}, H - y_t, e_t) = a_4 + 2a_{14}(H - y_t) + a_{14}y_t + a_{24}y_{t-1} + a_{45}e_t \]

\[ U_2(y_{t+1}, y_t, p_t, H - y_{t+1}, e_{t+1}) = a_2 + 2a_{22}y_t + a_{12}y_{t+1} + a_{24}(H - y_{t+1}) + a_{25}e_{t+1}.
\]
Putting the terms together in the first order condition and collecting like terms we have:

\[
2 \left[ a_{11} - a_{14} + \beta a_{22} + a_{44} \right] y_t + \left[ a_{12} - a_{24} \right] y_{t-1} + \left[ \beta a_{12} - \beta a_{24} \right] y_{t+1} + a_{13} p_t - a_{33} p_{t-1} + a_{33} p_{t+1} + \left[ a_{15} - a_{44} \right] e_t + \beta a_{25} e_{t+1} + a_1 - a_4 + a_{33} \sigma_y^2 + \beta a_2 + \left[ a_{14} + \beta a_{24} - 2a_{44} \right] H = 0.
\]

Solving for \( y_t \) we get the following demand function:

\[
y_t = \theta y_{t-1} + \beta \theta y_{t+1} + \theta_1 p_{t-1} + \theta_2 p_{t+1}^2 + \theta_3 e_t + \theta_4 e_{t+1} + K, \tag{14}
\]

where the coefficients are

\[
\theta = \frac{a_{12} - a_{24}}{A}, \quad \theta_1 = \frac{a_{13}}{A}, \quad \theta_2 = \frac{a_{33}}{A}, \quad \theta_3 = \frac{a_{15} - a_{44}}{A}, \quad \theta_4 = \frac{\beta a_{25}}{A},
\]

with constants \( A = 2 \left( a_{14} - a_{11} - \beta a_{22} - a_{44} \right) > 0 \) and \( K = a_1 - a_4 + a_{33} \sigma_y^2 + \beta a_2 + (a_{14} + \beta a_{24} - 2a_{44}) H \).

### A.2 Derivation of demand with learning-by-doing

To simplify the problem suppose there are no quadratic terms of \( p_t \) in utility function. Or that one period quadratic utility can be written as:

\[
U(y_t, y_{t-1}, p_t, z_t, e_t) = (a_1 + a_{13} p_t) y_t + a_{11} y_{t-1}^2 + a_{22} y_{t-1}^2 + a_3 p_t + a_4 z_t + a_{44} z_t^2 + a_5 e_t + a_{55} e_t^2 + a_1 y_t y_{t-1} + a_{14} y_t z_t + a_{15} y_t e_t + a_{24} y_{t-1} z_t + a_{25} y_{t-1} e_t + a_{45} z_t e_t.
\]

Under the functional form assumed above the first order condition with respect to \( y_t \) of the problem in (11) is:

\[
U_1^{(t)} + U_4^{(t)} + \beta U_2^{(t+1)} + \sum_{i=t+1}^{\infty} (\beta b_1)^{i-t} U_3^{(i)} = 0, \tag{15}
\]

where \( U(t) = U(y_t, y_{t-1}, p_t, H - y_t, e_t) \). The first three terms are similar to what we had in the equation (13) of the main model. The addition of the the infinite sum as a fourth term represents the effect of playing today on performance in every future period (because playing today affects performance tomorrow and performance persist). Solving equation (15) for \( y_t \) we have:

\[
y_t = \theta y_{t-1} + \beta \theta y_{t+1} + \theta_1 p_{t-1} + \theta_2 p_{t+1}^2 + \theta_3 e_t + \theta_4 e_{t+1} + K + \sum_{i=t+1}^{\infty} \beta^{i-t} \alpha y_i, \tag{16}
\]

where \( \beta^{i-t} \alpha > 0 \) captures the marginal effect of playing in period \( t \) on future period \( i \) through learning. Note that the coefficients in this equation are not the same as the coefficients in the regular model, equation (14). To estimate equation (16) we would need to include as explanatory variables playtime in each and every future period. Including all future values of playtime is not feasible, and so I consider two possible approximations of this final term that will allow me to estimate demand.

The first approximation method assumes \( y_i = y_{i+1} \) for all \( i > t + 1 \). This reduces the final term in equation (16) to \( \frac{\beta^t}{1 - \beta} y_{t+1} \). There are two drawbacks with this approach. Since \( y_t \) is generally increasing over time this will on average underestimate the value of learning for individuals who
continue to play. At the same time, for individuals who completely stop playing in some future period, this approach may overestimate the value of learning. The second approximation method assumes \( y_i = 0 \) for all \( i > t + 1 \). This reduces the final term in equation (16) to \( \alpha \beta y_{t+1} \). This approach will consistently underestimate the value of learning for all individuals who play beyond the next period.

Both approximation methods lead to the same demand equation with slightly different interpretations of \( \alpha \):

\[
y_t = \theta y_{t-1} + \beta (\theta + \alpha) y_{t+1} + \theta_1 p_{t-1} + \theta_2 p_{t-1}^2 + \theta_3 e_t + \theta_4 e_{t+1} + K
\]

This demand function is also consistent (i.e. not an approximation) with the above model if individuals are forward-looking but only consider the benefits of learning in the immediately following period.

The main advantage of equation (17) is that by comparing the estimated coefficients on \( y_{t-1} \) and \( y_{t+1} \) for a fixed discount rate \( \beta \) it is possible to impute an estimate of the value of learning.

### A.3 Instrumental variables

In section 4 I am able to reject the hypothesis that a non-IV panel regression is consistent. To deal with the endogeneity of the model I use the average playtime and skill of friends as instruments for an individual’s own playtime. Table 6 shows the results of the first stage of a 2SLS estimation. Friend playtime in the current period and performance in the previous period are significant in explaining an individual’s playtime.

**Table 6 – First stage of 2SLS, Dependent Variable \( y_t \)**

<table>
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<th>Fixed effects</th>
<th>Pooling</th>
</tr>
</thead>
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<tr>
<td></td>
<td>(i)</td>
<td>(ii)</td>
</tr>
<tr>
<td>( y_t )^F</td>
<td>0.205*** (191)</td>
<td>0.228*** (164)</td>
</tr>
<tr>
<td>( p_t )^F</td>
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<td>0.00045*** (5.76)</td>
</tr>
<tr>
<td>( R^2 )</td>
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<td>0.0218</td>
</tr>
<tr>
<td>( F )</td>
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</tr>
<tr>
<td>( n )</td>
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<td>104406</td>
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<tr>
<td>( T )</td>
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<td>64</td>
</tr>
<tr>
<td>( N )</td>
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</tr>
</tbody>
</table>

Significance levels: * = 10%, ** = 5%, *** = 1%, t-statistics in parentheses.

### Appendix B Game background information

Team fortress 2 (TF2) was originally released on October 10, 2007 as part of a bundle called the Orange Box which cost $49.99. In the first year alone the Orange Box sold over 3 million retail copies (Remo (2008)). On April 9, 2008 it was released as a stand alone game for $29.99. In 2009 the price of TF2 was reduced to $19.99. Beginning on June 23, 2011 TF2 became “Free-to-play”,

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meaning the game became freely available to anyone and ongoing development is supported by in-game microtransactions, or the purchasing of in-game items for money (victory hats, weapons, etc).

In TF2 there are a number of modes of play. In most modes players work together as a team versus other players on an opposing team to achieve a particular set of goals. For example, in *capture the flag* both teams simultaneously attempt to capture a flag from the enemy team’s base and return it to their own base while preventing the opposing team from doing the same. Players may also freely change between nine distinct classes during the game. The classes are designed to have strategic complementarities and encourage teamwork. For example, the heavy and medic classes are weak on their own but very strong when combined. Classes are also designed to have a comparative advantage against each other in a non-transitive, or “rock-paper-scissors” way: each class has strengths versus some classes and weaknesses versus others. This structure prevents any one class from dominating the others and gives an advantage to a team that plays a mix of classes rather than all playing the same class. To capture a measure of the classes an individual plays I define an index of heterogeneity for specialization as:

\[
m = \sum_{k=1}^{9} \left( \frac{\text{playtime for class } k}{\text{total playtime}} \right)^2
\]

This index will take values from \( p = 1/9 \) to \( p = 1 \). A value of \( p = 1 \) represents complete specialization or that the individual played only one class the entire week. A value of \( p = 1/9 \approx 0.111 \) represents complete diversification, or that the individual played all classes equally.
References


