# Debtors at Play:

## Gaming Behavior and Consumer Credit Risk

Shuaishuai Gong, Ross Levine, Chen Lin, and Wensi Xie†

April 2023

**Abstract**

Exploiting a unique high-frequency, individual-level database, we (1) construct individual-level, incentive-compatible proxies of impulsivity based on video gaming behavior and (2) use these proxies to evaluate predictions concerning how impulsivity shapes individuals' responses to a relaxation of credit constraints as captured by receiving a credit card. We discover that pre-card gaming intensity—as measured by the frequency and amount of game expenditures—is strongly and positively associated with (a) the probability of defaulting on credit card debt in the future, (b) post-card expenditures on luxury and addictive items, (c) surges in consumption spending immediately after receiving the credit card, and (d) rapid debt accumulation after obtaining the card. Differences in financial literacy, income, income variability, education, and demographics do not drive the results. The results are consistent with (1) neurological and psychological studies stressing that excessive gaming is associated with impulse control deficiencies and (2) behavioral theories stressing that impulsivity, i.e., time-inconsistent preferences for immediate gratification and ineffective strategies for avoiding myopic cues and temptations, substantially influence individual expenditure patterns and borrowing decisions when liquidity constraints are relaxed.

**JEL classifications**: D12, D14, D91, G41

**Keywords**: Behavioral finance, Video game, Self-control, Credit risk

† Gong: Faculty of Business Administration, the University of Macau. Email: shuaishuaigong@um.edu.mo. Levine: Haas School of Business, University of California, Berkeley. Email: rosslevine@berkeley.edu. Lin: Faculty of Business and Economics, the University of Hong Kong. Email: chenlin1@hku.hk. Xie: CUHK Business School, the Chinese University of Hong Kong. Email: wensixie@cuhk.edu.hk. We thank Kay Giesecke (the Editor), an anonymous Associate Editor, two anonymous referees, Philip Bond, Stefano DellaVigna, Xavier Giroud, Jarrad Harford, Ben Levine, Ulrike Malmendier, Terry Odean, Christopher Parsons, and seminar participants at the New York University and the University of Washington for helpful comments and suggestions. Lin acknowledges the financial support from the National Natural Science Foundation of China (Project No. 72192841) and the Research Grant Council of the Hong Kong SAR, China (Project No. T35-710/20-R).

## 1. Introduction

Influential theories predict that impulsivity, i.e., time-inconsistent tastes for immediate gratification and deficient techniques for avoiding myopic temptations, can induce individuals to make expenditure and borrowing decisions that lead to costly defaults after they experience a relaxation of credit constraints (e.g., Thaler and Shefrin 1981; Laibson, 1997; Gul and Pesendorfer 2001; Fudenberg and Levine 2006; DellaVigna 2009; Heidhues and Koszegi 2010; Hirshleifer 2015). One challenge to assessing these predictions is measuring impulsivity. Some researchers use laboratory experiments or questionnaires to gauge self-control (e.g., Ameriks et al. 2007; Meier and Sprenger 2010), but there are natural concerns about whether these proxies accurately capture individuals' impulsivity in consequential, real-world settings. Others use a revealed-preference approach to evaluate whether consumption choices are more consistent with traditional or time-inconsistent preferences (e.g., DellaVigna and Malmendier 2006), but this approach does not employ a direct measure of impulsivity.

In this paper, we exploit high-frequency data on video game activity to construct individual-level, incentive-compatible proxies of impulsivity and use these proxies to assess predictions concerning how impulsivity shapes individuals' responses to a relaxation of credit constraints. Specifically, we evaluate the hypothesis that as captured by receiving a credit card will trigger larger surges in spending, especially on luxury items (e.g., expensive dining and jewelry) and addictive products (e.g., alcohol and cigarette), debt accumulation, and credit card default rates among individuals with more impulsive traits. To test these predictions, we use transaction-level data on expenditures before and after individuals receive a card and granular data on debt choices and credit card performance. In this way, we offer new (1) individual-level measures of impulsivity based on video gaming behavior and (2) evidence on how personality traits influence consumer behavior.

Research from neuroscience, psychology, and public health motivates our use of video gaming behavior as a proxy for impulsivity. Neuroscience research finds strong similarities at the molecular and neurocircuitry levels between the brain activities of excessive gamers and individuals with substance abuse disorders, impulse control ailments, and other addiction-type problems (e.g., Gros et al. 2020; Han et al. 2011; Kuss 2013; Lee et al. 2008; Yao et al. 2012). Related research in psychology demonstrates associations between heavy video game playing and impulsivity (e.g., Millar and Navarick 1984; Gentile et al. 2012; Haghbin et al. 2013; Kim et al. 2008; 2016; Kuss and Griffiths 2012; Männikkö et al. 2020; Mehroof and Griffiths 2010), and the World Health Organization (2018) defined excessive video gaming as a health disorder belonging to a cluster of addictions that can severely impair decision-making. As a result, we use data on gaming behavior to construct proxies of impulsivity.

We exploit a unique dataset containing daily information on individuals' online gaming behavior, consumption expenditures, and credit card performance. We obtained these data from a large Chinese financial firm (the firm) for over 80,000 individuals who applied for credit cards between February 2017 and August 2017. We construct and examine several measures of the intensity of each individual's online gaming behavior. These measures include the amount, frequency, and volatility of game expenditures, the number, diversity, and types of games, and the timing of game expenditures, e.g., whether these expenditures occur during weekends or the workweek, on rainy or non-rainy days. We trace individuals' credit card payment performance for 12 months after obtaining the card. We define a default as occurring when a cardholder misses payments for more than 90 days. In addition, we trace individuals' expenditure patterns before and after they receive a credit card using transaction-level data on expenditure categories that differentiate by luxury items, addictive products, etc. Thus, we examine the response of expenditure patterns and credit card performance after individuals receive credit cards while differentiating individuals by their pre-card gaming behaviors.

We stress two features of our approach. First, our goal is to evaluate whether impulsivity predicts expenditure patterns and credit card default rates after easing credit constraints. We use gaming behavior to proxy for the underlying behavioral trait of impulsivity. We do not assess the impact of exogenous changes in gaming on consumer behavior. Second, we measure gaming during the 30 days *before* the person applies for the credit card, reducing concerns that our analyses capture the effects of receiving a credit card on gaming behavior.

We discover that individuals who spent more, and more frequently, on gaming during the month before applying for the credit card were significantly more likely to default on credit card payments during the year after obtaining the card. The results are robust to (1) using total expenditures on gaming or gaming expenditures relative to other individuals in the same income peer group and (2) conditioning on an array of demographic information (i.e., gender, age, marital status, education, income, and whether the person owns their home). The estimated relationship is economically significant. Individuals who spent money on gaming during the 30 days before applying for the credit card were, on average, 5.4 percentage points more likely to default on their credit card debts during the year after receiving the card than non-gamers. Similarly, "heavy gamers," i.e., individuals with one-standard deviation greater game spending than otherwise similar individuals, were 2.2 percentage points more likely to default than those less intensive gamers.

We also discover that changes in expenditure patterns after individuals receive credit cards are consistent with the impulsivity view of consumer behavior. First, more intensive gamers increase spending on luxury items (such as jewelry, high-amount dining, etc.) and addictive products (such as alcohol and cigarettes) much more during the year after, and not before, getting the card than less intensive gamers. Second, we observe a more immediate surge in overall consumption spending during the first month after receiving the card among more intensive gamers. This is consistent with those individuals having less self-control than otherwise similar individuals receiving credit cards.

One potential concern with interpreting these findings is that the gaming measures might capture individuals' overall spending propensity rather than impulsivity. We address this concern using three approaches. First, we repeat the analyses while controlling for overall spending propensity, which we measure as the individual's consumption rate relative to others with similar incomes. We continue to find a positive relationship between gaming in the pre-card period and purchasing luxury and addictive items afterward. Second, we use discrete measures of whether an individual buys particular goods and services since discrete measures are less likely to proxy for individuals' overall spending propensity than continuous measures. All results hold when using discrete measures. Finally, we conduct a falsification test by examining spending on non-luxury and non-addictive items ("normal" goods). Suppose overall spending propensity drives the gaming-expenditure results. In that case, we should find similar associations between gaming intensity and spending on normal goods as we do with gaming and spending on luxury and addictive items. However, we find no relationship between pre-card gaming intensity and subsequent spending on non-luxury, non-addictive items. These results are inconsistent with the spending propensity explanation and fully aligned with the impulsivity view.

We further explore mechanisms linking gaming behavior and credit risk by examining debt choices. If gaming is negatively associated with self-control, the gaming measures should also predict debt accumulation. The data allows us to construct individual-specific measures of (1) borrowing from sources other than bank-issued credit cards (such as online lending platforms), (2) the number of credit cards used by the individual, and (3) credit card balances. We find that intensive gamers borrow more from non-bank sources, have more credit cards, and quickly use greater proportions of credit card borrowing limits than otherwise similar but less intensive gamers.

Having established that gaming intensity is positively associated with surges in luxury and addictive spending borrowing after getting a credit card and credit card delinquency rates, we extend the analyses of the gaming-default nexus to draw sharper inferences about the relationship between impulsivity and credit risk. First, we differentiate between workweek and weekend gaming. Workweek gaming may involve a more costly substitution out of work and into immediate gratification than a similar amount of gaming over the weekend, which might reflect leisure tastes. From this perspective, workweek gaming provides a more accurate signal of impulsive actions than weekend gaming. Consistent with this view, workweek gaming strongly predicts credit card default, but weekend gaming does not.

Second, we differentiate between gaming on bad and good weather days. Expenditures on bad weather days may reflect a substitution out of outdoor leisure activities and into indoor gaming. This view suggests that bad-weather gaming will be less indicative of impulsivity than gaming on good-weather days. Indeed, we find that gaming on bad weather days does not predict credit card default, but game spending on good weather days does.

Third, we examine gaming volatility. Theories of self-control explain how people employ pre-commitment devices and other strategies to avoid impulsive behaviors (e.g., Thaler and Shefrin 1981; DellaVigna and Malmendier 2004). When applied to gaming, this research suggests that gamers might allocate a fixed amount of money at regular time intervals for gaming to avoid erratic and imprudent surges in gaming expenditures. From this perspective, gamers unable to adhere to such budgeting strategies would reveal behavioral traits associated with greater impulsivity and credit risk, such as more volatile gaming. Consistent with this view, gamers with more volatile gaming expenditures have higher future credit card default rates.

In a fourth and related extension, we evaluate the relationship between the number, variety, and types of gaming applications on individuals' mobile devices and future credit card default rates. This examination is motivated by research suggesting that people use strategies to avoid cues and temptations that trigger impulsive or addictive behaviors (e.g., Bernheim and Rangel 2004; Gul and Pesendorfer 2001). When applied to gaming, gamers might engage in cue and temptation avoidance by installing fewer game applications (apps) and fewer types of games (e.g., card and board, sports, strategy, role-playing, action, and leisure and puzzle games). Accordingly, individuals with fewer apps and game types might be more effective at avoiding behaviors that increase credit risk. We find evidence consistent with this cue and temptation avoidance view: individuals with a larger number and variety of games on their mobile devices are more likely to default on future credit card obligations. Moreover, these results hold when conditioning on gaming expenditures, suggesting that the positive association between default and game variety does not simply reflect more game spending. When further exploring whether the specific game types that individuals play predict credit card default, we find that the estimated relationship between *Card and Board* and credit card default is larger than for other game types. One explanation is that *Card and Board* games tend to involve gambling-related activities within the game, and gambling is closely related to self-control problems.

Furthermore, we conduct additional tests to rule out alternative explanations. First, we were concerned that heterogeneity in "financial literacy" might drive the results (e.g., Lusardi and Mitchell 2014; Fernandes, Lynch, and Netemeyer 2014; Gathergood and Weber 2017). For example, gaming activity might be correlated with the ability to assess and manage credit risk rather than impulsivity. Thus, we re-did the analyses while separately examining (a) those who attended college and (b) those working in finance-related occupations. The connection between gaming and credit card default holds across the different sub-samples, indicating that financial literacy is unlikely to account for the paper's findings.

Second, we address concerns that the gaming-default relationship reflects either (a) a negative correlation between gaming and income or (b) spending on gaming that is sufficiently large such that heavy gamers have insufficient funds to satisfy their debt obligations as follows. Concerning income, we show that the results hold when controlling for income and when comparing the relationship between gaming and default within income groups. Concerning spending on gamine, we first note that gaming expenditures typically represent a negligible proportion of household expenditures. For example, the average gamer in China spends $4 per month on video games. Second, the results hold when restricting the analyses to a subset of borrowers whose game spending accounts for an especially small proportion of income, suggesting that gaming expenditures per se are unlikely to trigger credit card delinquencies. Instead, the findings are consistent with the view that impulsivity, as captured by past gaming behavior, influences how individuals respond to a relaxation of credit constraints.

Our work contributes to research on consumer credit risk. One line of research examines how demographics, income, education, political ties, and policies influence credit risk (e.g., Agarwal et al. 2015; 2018; 2020; Agarwal and Qian 2014; Gross and Souleles 2002; Telyukova 2013; Vissing-Jorgensen 2021; and the review by Gomes, Haliassos, and Ramadorai 2021). Our work focuses on assessing the potential role of impulsivity in shaping consumer credit risk. A second line of research, and the one most directly related to our work, also examines the role of behavioral biases in shaping consumer choices. Specifically, DellaVigna and Malmendier (2004), Gabaix and Laibson (2006), Heidhues and Koszegi (2010), and Ru and Schoar (2020) show that firms successfully employ strategies designed to appeal to impulsive consumers, consistent with the view that behavioral biases influence consumer behaviors. After developing measures of impulsivity based on video gaming behavior, we discover that impulsivity is positively associated with (a) the probability of defaulting on credit card debt in the future, (b) post-card expenditures on luxury and addictive items, (c) surges in consumption spending immediately after receiving the credit card, and (d) rapid debt accumulation after obtaining the card. These findings suggest that behavioral biases materially influence consumer choices. More specifically, our findings are consistent with the view that heterogeneity in time-inconsistent tastes for immediate gratification and temptation avoidance significantly and substantially shapes individual responses to relaxing credit constraints.

The remainder of the paper proceeds as follows. Section II describes the data and empirical methodology. Section III reports and discusses our results. Section IV concludes.

## 2. Data and Variable Definitions

### 2.1 Data and sample

A large financial firm in China (hereafter "the firm"), ranked in the top ten in the Chinese credit card industry, provided us with data on individuals who applied for a credit card from November 2016 through August 2017. The data include information on (1) credit cards, including application dates, whether the application was approved, and whether the individual defaulted on credit card obligations during the 12 months after obtaining the card, (2) individuals' gender, age, education, marital status, income categories, and whether they own housing property, and (3) daily expenditures. These individual-level spending data are from one of the largest third-party online payment platforms in China and include all spending made through the online payment platform, not spending via credit cards. Thus, we have data on (a) individuals' daily spending, (b) their credit card performance, and demographic details.

For a subset of individuals who use Android systems, the firm obtains data on the types of games installed on individuals' phones and tablets from service vendors operating App Stores for Android devices in China. The firm organizes the data into six game types, *Card and Board*, *Leisure and Puzzle*, *Action*, *Sports*, *Strategy*, and *Role-playing*, which we describe below. Online Appendix Figure OA1 depicts screenshots of the most popular Apps.

Our analyses require that we match data on an individual's gaming expenditures before applying for the credit card with data on the individual's credit card payments after receiving the card. Thus, we restrict our analyses to individuals with at least 30 days of non-missing expenditure data before applying for the credit card. Our primary sample comprises 82,270 cardholders who applied for and received a credit card from February 2017 to August 2017 and includes information on individuals from 325 cities.

## 2.2 Gaming measures

We analyze four gaming measures that gauge the frequency and amount of gaming expenditures. We compute these measures during the 30 days before the credit card application date, which we define as $t = 0$. Appendix Table A1 provides detailed variable definitions.

*Game_dummy* equals one if the individual paid for game-related activities during the 30 days before applying for the credit card and zero otherwise.

*log Game_freq* equals the logarithm of one plus the cumulative frequency of game payments:

$$log\ Game\_freq = log\ (1 + \sum_{t=-1}^{-30} (number\ of\ payments\ in\ period_t)).$$

*log Game_amt* equals the logarithm of one plus the cumulative game spending (in RMB):

$$log\ Game\_amt = log\ (\ 1 + \sum_{t=-1}^{-30}(amount\ of\ spending\ in\ period_t)).$$

*log Game_amt/peer_amt* equals the logarithm of one plus the ratio of cumulative game spending of an individual to the average cumulative game spending across individuals in the same income group.[1]

We also examine the volatility of an individual's gaming expenditures. Since individuals make payments relatively infrequently, we compute volatility over the 30 days (or 90 days) before the credit card application and only include non-zero game spending days.

*log Std. (Game_amt/peer_amt)* equals the logarithm of one plus the standard deviation of the ratio of the individual's expenditures on gaming to the average expenditures on gaming across individuals in the same income group during the pre-application period.

We also analyze two measures of the number and types of game Apps on individuals' mobile devices. Compared to expenditure-based gaming measures, income is less likely to influence these game-App installation measures since it is typically free to download games.[2] Although only 18% of individuals in our sample spent money on gaming, more than 83% installed at least one game App on their mobile devices.

---

[1] Income is provided in five scales, with 5 corresponding to a range of RMB 12500-24999, 4 to RMB 8000-12499, 3 to RMB 5000-7999, 2 to RMB 3500-4999, and 1 to RMB below 3499. For each range, we use the average value of the upper and lower bound as the income level for borrowers classified in that range.

[2] See Chen et al. (2021) for an examination of the pricing of in-game ("loot box"), virtual items.

*log # of GameApps* equals the logarithm of one plus the total number of game Apps installed on the individual's mobile devices.

*# of Game types* equals the number of game types (card and board, leisure and puzzle, action, sports, strategy, and role-playing) installed on the individual's mobile devices.[3] The value of this variable ranges from 0 to 6.

The firm also provides information on the six types of games installed on each person's mobile devices. *Card and Board* is an indicator that equals one if the individual's mobile device has a card and board game. The most popular such games in China include poker, Mahjong, Chinese chess, and Go. *Leisure and Puzzle* is an indicator that equals one if the individual's mobile device has a leisure and puzzle game App. This game type focuses on logical, spatial relations, and conceptual challenges, such as manipulating shapes, colors, or symbols into specific patterns. Two of the most popular puzzle games on mobile devices in China are Crazy Match and Angry Bird. Although many action games include puzzle-solving components, game Apps within the puzzle category involve puzzle-solving as the primary activity of the game. *Action* equals one if the individual's mobile device has an action game, typically involving fighting, shooting, racing, flying, adventure, etc. Popular games include Prince of Persia, CrossFire, and We Shoot. Sports equals one if the individual's mobile device has a sports-type game App. These games mimic professional athletes, e.g., FIFA Online, NBA 2K, and Need for Speed. Strategy is an indicator that equals one if the individual's mobile device has a strategy-type game App. Such games typically involve developing and implementing a strategy to accomplish a goal, such as winning a war or creating a prosperous civilization, e.g., Civilization, Clash of Clans, and Clash of Kings.

---

[3] These six game types are broadly consistent with other categorizations of video games https://en.wikipedia.org/wiki/Video_game_genre.

*Role-playing* is an indicator that equals one if the individual's mobile device has a role-playing game in which individuals act out the role of a significant character. China's most popular role-playing games include World of Warcraft, Fantasy Westward Journey, and EverQuest.

These game-type categorizations are imperfect. Each App has unique features and may involve activities falling into many game types. For example, World of Warcraft is categorized as role-playing, but the game also requires strategy, action, and puzzle-solving. Nevertheless, the different game types provide information about the most salient features of each game App.

2.3 Credit card performance and expenditures

*Default* equals one if the credit card holder defaults within 12 months after the card is approved and zero otherwise. For each individual over the 12 months following the approval of the credit card, we have data on whether the individual (1) misses a payment for more than 90 days, (2) misses a payment for more than 30 days but less than 90 days, and (3) never misses a payment for over 30 days. Following the definition commonly employed by the Chinese banking industry, we define a credit card default as occurring when the cardholder misses a payment for more than 90 days.

We examine granular data on each individual's expenditures. Specifically, we study spending on luxury items and addictive products, including (a) large-amount dining, (b) large-amount shopping, (c) jewelry, and (d) alcohol and cigarettes. We define "large amount" as spending in a day that is above the 95th percentile of spending on that day for the expenditure category, e.g., dining. For everyone, we trace monthly spending on each item from three months before to 12 months after card application, [t-3, t+12]. With these data, we compute the growth rate in spending on each item from before until after individuals receive a credit card. That is, for each cardholder *i* who applied for a credit card in month *t* and expenditure item *j*, we compute

$\Delta$*log(Spending on item j)$_i$* as the difference between the average monthly spending on item *j* during the 12 months after the credit card application and spending over the three months before the card application:

$$\Delta\log(\text{Spending on item } j)_i = \ln\left(1 + average\ monthly\ amount\ on\ item\ j)\ _{i,[t+1,t+12]}\right) - \ln\left(1 + average\ monthly\ amount\ on\ item\ j\ _{i,[t-3,t-1]}\right).$$

We also examine each individual's change in overall spending after being approved for a credit card. Extreme increases in overall spending could reflect an impulsive surge in consumption with the relaxation of credit constraints. For individual *i* who applied for a credit card in month *t*,

$$\Delta\log(\text{Consumption})_i = \ln(1{+}monthly\ amount\ of\ consumption\ _{i,\,t+1}){-}\ln(1{+}average\ monthly\ amount\ consumption\ _{i,\,[t+1,t+12]})$$

2.4 Borrowing

Furthermore, we construct two measures of each individual's borrowing decisions over time to gauge the relationship between gaming behavior and debt choices. First, *Borrowing from sources other than banks* is an indicator variable that equals one if a person borrows from sources other than banks (such as online lending platforms or finance companies) during the 12 months after applying for the credit card. The cost of borrowing from these alternative sources is generally higher than traditional banks. We obtain data on non-bank debt from the third-party online payment platform discussed above. Second, *Number of credit cards* equals the number of credit cards on which the individual made payments during the year after submitting the credit card application. Although we do not have direct information on the number of credit cards owned by each individual, the third-party online payment platform provides information on the number of times individuals use the platform to make payments on their credit card debts every month. Assuming that people repay only once per card per month, we define *Number of credit cards* as equal to 0 if they do not repay any credit card debt via the online payment platform, 1 if they repay credit card debt once via the online payment platform, 2 if twice, 3 if three times, and 4 if four or more times. For each individual, we use the month with the maximum number of credit card repayments during the 12 months after the credit card application to create *Number of credit cards*.

### 2.5 Controls

We control for an assortment of individual characteristics. First, income and wealth could be related to both delinquencies on credit card balances and gaming behavior. For example, if income and wealth are positively associated with game expenditures and negatively related to credit card default, omitting income and wealth from the analyses would bias the results against finding a positive connection between default and spending on games. To address such omitted variable concerns, we control for income by including a series of dummy variables representing income categories, which is the form in which the firm provided that income data. For this vector of income categories, *Income*, the individual dummy variables equal zero except for the category in which the individual's monthly income falls. The five categories of income are between RMB 12500-24999, RMB 8000-12499, RMB 5000-7999, RMB 3500-4999, and below RMB 3499. We control for wealth by including a dummy variable, *House property*, which equals one if the individual owns housing property.

Second, several demographic traits, including gender, age, marital status, and education, might affect both gaming behavior and credit card default (D'Acunto et al., 2019, 2021, 2022).

For example, past work suggests that men are more likely to spend more on video games and default on their debts. We control for *Gender*, which equals one if the individual is male and zero otherwise. We also condition on *log Age*, which equals the logarithm of age, *Marital status*, which indicates whether the person is married or single, and *Education degree*, which is a set of dummy variables representing the highest degree attained.[4] In addition, following the recent literature (e.g., Ru, 2018), we include (a) city-fixed effects based on the residence of each individual to account for potential time-invariant local factors and (b) time-fixed effects based on the calendar year-month of each card application to account for the potential influences of seasonal factors on credit card applications and the types of people applying for credit cards. Our key findings are robust to including or excluding these controls.

Table 1 displays the summary statistics for the demographics. Male credit card holders account for 71% of our sample. The average age equals 32. The average income level (categorical variable) is 2, representing a monthly salary range from RMB 3500 to RMB4999, which is between US$ 500 and US$ 720 per month. Homeowners account for 17% of the sample.

[4] The *Education degree* dummy variables equal zero except for the category representing the individual's highest education degree. The categories are primary school, junior high school, senior high school, bachelor, and postgraduate and above. *Marital status* and *Education degree* include an additional category if the data are missing.

## 3. Empirical Results

*3.1 Regression specification*

We estimate the following model to evaluate the relationship between gaming behaviors and default probabilities.

$$Default_i = \alpha + \beta \times Gaming_i + \gamma' \boldsymbol{X_i} + \varepsilon_i, \tag{1}$$

where *i* indexes individual borrowers, and *Default* is an indicator of whether an individual defaults on credit card payments during the year after being approved for the card. Our key explanatory variable, *Gaming*, is one of the measures of an individuals' gaming behavior defined above and is measured during the 30 days before an individual applies for a credit card. ***X*** is a vector of control variables, which includes demographics (i.e., *Gender*, *Age*, *Income*, *House property*, *Marital status*, and *Education degree*) and fixed effects for the residential city where and the time period (year-month) when the individual applied for a credit card, i.e., there is a separate fixed effect for each time period in the sample (year-month). We estimate the model using OLS and logit regressions, with standard errors clustered at the city level. When using a logit, we report the marginal effects.

*3.2 Game and credit card default: Baseline results*

We discover that the amount and frequency of gaming expenditures during the 30 days before a person applies for a credit card are positively associated with whether the individual defaults on credit card payments during the year after receiving the card. As shown in Table 2 using a linear probability model, each *Gaming* measure enters positively and significantly at the 1% level. The results hold when conditioning on gender, age, marital status, education, income group, homeownership, and fixed effects for the city of residence and the credit card application month. The estimated coefficients on the conditioning variables are consistent with past findings.

For example, people in lower-income groups are more likely to default than those in the highest-income group. The likelihood of missing credit card payments decreases with education and whether the individual owns a house. Furthermore, as shown in Online Appendix Table OA1, the relationship between gaming behavior and default is robust to (a) excluding the demographic controls from the regressions, (b) including city-by-time fixed effects that absorb any time-varying shocks at the city level that might affect the patterns of default rates across consumers who reside in the same cities, and (c) using an alternative definition of default, which defines default as occurring when the individual misses a payment for more than 120 days.

The estimated coefficients suggest an economically meaningful relationship between gaming behavior and credit risk. For example, consider the simple indicator of whether the individual spent, or did not spend, on games during the 30 days before submitting the credit card application. The estimated coefficient in column 1 suggests that individuals who spent money on gaming are, on average, 5.4 percentage points more likely to default on their credit card debts than otherwise similar individuals with zero gaming expenditures. As a second example, consider the relationship between credit card default and total gaming expenditures, *log Game_amt*. The estimates in column 3 suggest that individuals with one-standard deviation greater cumulative game spending (1.536) are 2.2 percentage points (=1.536*0.014) more likely to default. This difference in the likelihood of default equals 17% of the sample mean default rate.

Although the Table 2 regressions condition on income, we further isolate the relationship between past gaming and future credit card delinquency from income effects by differentiating credit card holders by their gaming expenditures relative to their income peers.[5] We scale each

---

[5] In examining gaming relative to agents' peers, our work connects to recent research examining consumption, saving, and financing choices of households and consumers relative to their income peers, e.g., Maturana and Nickerson (2019), Ouimet and Tate (2020), D'Acunto, Rossi and Weber (2019), among others.

individual's total game expenditures by average game spending by other individuals in the same income group (*log Game_amt/peer_amt*). As shown in the last column, *log Game_amt/peer_amt* is positively associated with the probability of credit card default, indicating that individuals who spend more on gaming than others with similar incomes have higher credit card default probabilities. The estimated coefficients suggest an economically large relationship between income-adjusted *Gaming* and default. For example, compare an intense game player whose expenditures on games relative to income peers (*log Game_amt/peer_amt*) is one standard deviation (0.58) greater than the sample mean to an otherwise identical person who is an average gamer. The estimates indicate that the intense game player is 3.36 percentage points (=0.058*0.58) more likely to default than the average gamer.

We confirm these findings using logit regressions. As shown in Panel D of Online Appendix Table OA1, the positive relationship between credit card default and game spending remains statistically significant. When using the logit estimator, the estimated economic magnitudes are similar to, though slightly smaller than, the OLS estimates. Overall, these baseline results suggest a strong, positive relationship between gaming intensity and the probability of credit card default.

*3.3 Gaming behavior and consumption*

We next explore potential mechanisms linking gaming behavior to credit risk. To the extent that our gaming measures capture, at least partially, a person's ability to use willpower and strategies to avoid temptations and impulsive actions, these gaming measures should also predict consumption patterns after individuals receive credit cards. Thus, we examine (a) the increase in spending on luxury items (such as large-amount dining or shopping) and addictive products (such as alcohol and cigarette) during the year after individuals receive a credit card relative to those before getting the card, and (b) the increase in total consumption spending immediately after—the first month after—getting the credit card relative to spending in subsequent months. Specifically, using the same regression specification as in Table 2, Table 3 reports the results of regressions in which the dependent variable is the post-credit card growth rate in one of the five spending measures: (a) large-amount dining, (b) large-amount shopping, (c) jewelry, and (d) alcohol and cigarettes, or (e) the post-credit card changes of total spending.

The regression results are consistent with the view that intensive gaming reflects behavioral traits that manifest in many areas, including credit card delinquencies (Table 2), increases in spending on luxury and addictive items, and surges in overall consumption spending after getting a credit card (Table 3). As shown in Panel A of Table 3, gaming intensity—as measured by *log Game_amt/peer_amt*—is positively and significantly related to each of the five spending measures. That is, after getting access to the credit card, more intense gamers (1) increase spending more on luxury items, (2) boost expenditures more on addictive goods, and (3) much more rapidly engage in a surge in spending immediately than less intensive gamers.

We shed additional empirical light on the relationship between gaming and spending on luxury and addictive items by examining the pre- and post-credit card periods separately. Specifically, as just noted, the results from Table 3 Panel A indicate that spending on luxury and addictive items increased more after the credit card application among more-intensive gamers than individuals less engaged with gaming. In Panel B of Table 3, we separately examine the connection between gaming intensity and spending before (*pre*) and after (*post*) the credit card application. These analyses provide information on whether differences in luxury and addictive spending between more and less intensive gamers appear primarily when credit constraints are relaxed, e.g., through a credit card. We use the same regression specification as in Panel A of Table 3 but conduct separate analyses for pre- and post-spending.

As shown in Panel B of Table 3, differences in spending on luxury and addictive items between more and less intensive games largely appear after the easing of credit constraints. Specifically, the coefficient estimates on *log Game_amt/peer_amt* are statistically insignificant when the dependent variable is the log of spending on luxury or addictive items during the pre-application period. In contrast, the coefficient estimates on *log Game_amt/peer_amt* are positive and statistically significant when examining spending on luxury or addictive items during the post-application period. As also shown, the coefficient estimates on *log Game_amt/peer_amt* in luxury and addictive spending regressions are significantly different in the pre- and post-application period. These results suggest that intensive gamers started to spend significantly more on impulsive goods and services once financing became available.

We next employ three strategies to address a potential concern with analyses in Tables 2 and 3: our gaming measures might reflect individuals' overall spending propensity rather than impulsivity or self-control problems. First, we repeat the analyses that regress Δ*log(Spending on item j)* on gaming intensity measures but now control for each individual's overall propensity to spend. We compute *log Consumption/peer consumption* as the logarithm of one plus the ratio of total spending by an individual to the average spending across individuals in the same income group. Thus, *log Consumption/peer consumption* measures an agent's propensity to spend relative to those with similar incomes. As shown in Panel A of Online Appendix Table OA2, we continue to find a significant and positive relationship between gaming expenditures and measures of luxury and addictive spending after conditioning on individuals' overall propensity to spend.

Second, we shift from using continuous measures of how much individuals spend on gaming and luxury and addictive items to using discrete indicators of whether individuals spend on gaming and these other items at all. These discrete measures are less likely to proxy for individuals' propensity to spend than the continuous expenditure measures. In particular, we now measure game spending using *Game_dummy*, which equals one if the individual paid for game-related activities during the 30 days before applying for the credit card and zero otherwise. We measure each individual's spending on item *j* using a 0/1 dummy variable as well so that *Spending on item j or not*, as an indicator equal to one if a borrower spends on the item during the 12 months after the credit card application, and zero otherwise. The results are robust to using these dummy variables. As shown in Panel B of Online Appendix Table OA2, *Game_dummy* enters positively and significantly in three out of four columns, suggesting a positive association between gamers and individuals who ever purchase luxury or addictive products.

Third, we examine spending on non-luxury and non-addictive items as a falsification test. Suppose the gaming-spending nexus is driven by individuals' overall spending propensity rather than underlying impulsivity and self-control characteristics. In that case, we should find similar associations between gaming intensity and spending on non-luxury, non-addictive items as we do with luxury and addictive items. In this falsification test, we focus on "normal spending," i.e., spending on items other than large-amount dining, large-amount shopping, jewelry, and alcohol and cigarette. We compute and examine Δ*log(Normal spending)* as the log difference between the monthly amount of normal spending during the 12 months after the credit card application and normal spending over the three months before the card application. As shown in Panel C of Online

Appendix Table OA2, the coefficient estimate on *log Game_amt/peer_amt* is statistically insignificant, suggesting no correlation between gaming behavior and the growth rate of normal spending from before until after accessing the credit card. This non-result further suggests that individuals' overall spending propensity probably does not drive the Table 3 findings.

*3.4 Gaming behavior debt choices*

We continue to explore mechanisms linking gaming behavior and credit risk by examining debt choices. Suppose the gaming measures are negatively correlated with willpower and temptation avoidance strategies that reduce impulsive actions. In that case, the gaming measures should also predict individuals' debt choices. As described in Section 2, we measure a person's debt choices using (1) *Borrowing from sources other than banks*, which equals one if a person borrows from sources other than banks (such as online lending platforms or finance companies) and zero otherwise, and (2) *Number of credit cards*. We then assess the association between our gaming measures and these two measures of the individuals' demand for and use of credit.

The estimation results reported in Table 4 imply that individuals who play video games intensively tend to have greater debt demand and usage. As shown, *log Game_amt/peer_amt* enters positively and significantly, suggesting that more intense gamers are more likely to borrow from sources other than banks and own a larger number of credit cards.

Furthermore, we examine credit card balances. Our primary sample does not contain information on individuals' credit card balances. However, we collected a separate sample that includes 147,809 borrowers who applied for credit cards from another bank in China from June 2018 – December 2018. This new sample contains direct information on individuals' credit card balances. *Credit limit usage* equals the percentage of the credit limit used by each card holder six months after approval. Using a model specification similar to equation (1) above, we examine the linkage between gaming behavior and credit limit usage using this separate sample and report the results in Online Appendix Table OA3.[6] The results suggest a positive and statistically significant connection between gaming intensity and credit limit usage. Heavy gamers quickly use larger proportions of the limits on their credit cards.

*3.5 Gaming and default: Timing and Volatility*

So far, our analyses suggest that gaming behavior predicts credit card delinquency. Moreover, consistent with the notion that gaming behavior is negatively associated with temptation resistance and self-control, we find that gaming intensity is positively related to surges in luxury spending and addictive spending, and borrowing after getting a credit card.

In this subsection, we extend the analyses along three dimensions to draw sharper inferences about the association between gaming behavior and credit card delinquency. First, we differentiate between game expenditures during workdays and weekends. We distinguish between workweek and weekend gaming because they may offer different signals about a person's behavioral traits and credit risks. For example, suppose workweek gaming provides more precise information than weekend gaming about the willingness of the individual to substitute into immediate gratification and out of higher pecuniary return activities. We would then expect a comparatively robust and positive connection between workweek gaming and future credit card default.

Consistent with this view, we find that workweek gaming is a better predictor of credit card delinquency than weekend gaming. More specifically, we measure workweek and weekend

---

[6] Note that since the new sample is provided by a different bank company, the set of information differs slightly from our primary sample. Since we do not observe individuals' marital status, the demographic controls in Online Appendix Table OA3 do not include marital status.

gaming during the 30 days before applying for a credit using the following variables: *log Game_amt/peer_amt, workweek* equals the logarithm of one plus the ratio of workweek game expenditures to average workweek game expenditures among individuals in the same income group, and *log Game_amt/peer_amt, weekend* equals the logarithm of one plus the ratio of weekend game expenditures to average weekend game expenditures across individuals in the same income group. As shown in Panel A of Table 5, the estimated coefficient on *log Game_amt/peer_amt, workweek* is positive and significant, whereas the estimated coefficient on *log Game_amt/peer_amt, weekend* is insignificant and economically small. Furthermore, the differences are statistically significant, and the results hold when excluding (column 1) or including (column 2) public holidays for the classification of weekends.

Second, we differentiate game expenditures on bad vs. good weather days. Expenditures on video games during bad weather days might represent a substitution out of some (outdoor) leisure activities and into video gaming. From this perspective, gaming expenditures on bad weather days provide a less informative signal about behavioral traits associated with credit risk—such as a lack of self-control—than gaming on good weather days. We obtain weather data from the National Oceanic and Atmospheric Administration (NOAA), which provides hourly records at the monitor station level. We match the monitor station data from the NOAA to the cities of the individuals in our dataset. Almost 60% of our sample of individuals live in cities with monitor stations. To isolate days in which precipitation is likely to restrict outdoor activities, we classify a day as having bad weather if the 12-hour precipitation total reaches 30mm or 15mm, which the China Meteorological Administration defines as "very heavy" and "heavy" rain, respectively. In particular, *log Game_amt/peer_amt, rainy day* equals the logarithm of one plus the ratio of game expenditures during very heavy (or heavy) rain days to the average game expenditures during heavy rain days across individuals in the same income group.

We discover that intensive game expenditures during bad weather days do not predict credit card default, but game expenditures on non-rainy days are strongly and positively connected with default during the year after getting the card. Table 5 Panel B shows that *log Game_amt/peer_amt, rainy day* enters insignificantly, but *log Game_amt/peer_amt, non-rainy day* enters positively and significantly. Moreover, the difference between game expenditures during rainy and non-rainy is statistically significant when using alternative definitions of bad weather days. The results are consistent with the view that gaming expenditures on rainy days represent a substitution out of one leisure activity into another—and therefore do not reflect underlying behavioral traits associated with elevated credit risks.

Third, we evaluate the relationship between the volatility of gaming expenditures and future credit card default rates. Some behavior explanations of why intensive gaming is associated with higher credit card default rates motivate our examination of the volatility of daily gaming expenditures. In particular, some theories explain how people employ pre-commitment and other strategies to avoid myopic, impulsive actions (e.g., Thaler and Shefrin, 1981; O'Donoghue and Rabin, 2001; Ariely and Wertenbroch, 2002; DellaVigna and Malmendier, 2004; 2006). For example, gamers might adopt strategies to limit rash, imprudent, volatile gaming. From this perspective, adhering to those strategies and avoiding erratic surges in gaming would reflect behavioral traits, such as strong self-control, that reduce credit risk. Thus, we use volatility of gaming expenditures as a proxy for the extent to which an individual is less able to control myopic, impulsive actions.

To conduct this evaluation, we use the volatility of daily game spending over the 30-days or 90-days before the person applied for the credit card. The volatility measures require an individual to have multiple days with non-zero payments, shrinking the sample size. Thus, we also use a longer period, 90-days, to include a larger number of non-zero game spending days. We examine the standard deviation of the ratio of daily gaming expenditures to the average gaming expenditures by people in the same income group (*log Std. Game_amt/peer_amt*).

Table 6 shows that the volatility of game spending is positively associated with the probability of credit card default. The results hold when using either the 30-day or 90-day pre-application period to compute spending volatility. When using 90-days in column 1, the estimated coefficient suggests a one-standard-deviation increase in *log Std. Game_amt/peer_amt* is associated with an increase in the probability of credit card default of 1.7 percentage points (=0.037*0.459), corresponding to 13.5% of the sample mean default rate.

The empirical findings so far suggest that credit card default rates are higher among individuals who (a) spend more frequently on games, (b) spend larger amounts on games, (c) spend more on games during the workweek and when the weather is comparatively good, and (d) exhibit greater daily volatility in gaming expenditures. The findings highlight the value of using gaming in assessing credit.[7]

*3.6 Game Apps and credit card default*

Given that our unique data includes information on the types of games installed on individuals' mobile devices for a subset of individuals in the primary sample, we also examine the connection between credit risk and the number and variety of gaming applications on mobile devices. We examine the degree to which individuals focus on a few games or have a wide

[7] Having demonstrated that gaming behavior before an individual applies for a credit card helps predict credit card delinquency during the year after receiving the card, we also examine whether gaming behavior helps account for whether the individual's application for a credit card is approved or rejected. To conduct this evaluation, we (a) expand the sample to all applicants and (b) use an indicator of whether a credit card application is approved or rejected by the lender as the dependent variable. As shown in Online Appendix Table OA4, the gaming behavior indicators enter insignificantly in the credit card approval regression.

assortment of games. Behavioral theories by Bernheim and Rangel (2004) and Gul and Pesendorfer (2001) offer one motivation for examining the number and variety of games. These authors explain that individuals may implement techniques to avoid cues or temptations that trigger impulsive or addictive behaviors. When applied to gaming, such cue and temptation avoidance strategies might include installing fewer game applications (apps) and fewer game types. Individuals who implement such avoidance strategies effectively might also have behavioral traits that increase the probability of satisfying their credit card obligations. Thus, we extend our analyses to assess the connection between credit card default and the number and diversity of game Apps that individuals have installed on their mobile devices. We use (a) *log # of GameApps*, and (b) *# of Game types*. In several specifications, we control for game expenditures (*log Game_amt/peer_amt*) to assess whether the relationships between credit risk and measures of the number and variety of games hold independently of individuals' gaming expenditures.

Results reported in Table 7 suggest that people with a larger number and a greater variety of game Apps on their mobile devices default more on their credit card debts than others. As shown in columns 1 – 4, *log # of GameApps*, and *# of Game types* enter positively and significantly. These results hold when controlling for game-expenditures (i.e., when including *log Game_amt/peer_amt*). Regarding economic magnitudes, the estimates from column 1 indicate that a one-standard deviation increase in *log # of GameApps* would raise the default probability by 2.3 percentage points.

We next explore whether the specific games that individuals play predict credit card default after conditioning on gaming in general. For example, many games in the *Card and Board* category involve gambling, which is often linked with an assortment of addictive, self-control problems. In Appendix Table A3, we use the same regression specification as above while also including measures of whether the individual plays card and board, action, role-playing, puzzle, or other types of games. Specifically, each of the regressions includes *log Game_amt/peer_amt*. Column 1 includes *Card and Board*, which equals one if an individual's mobile device has at least one card and board game App and zero otherwise. Column 2 presents the results when including *Leisure and Puzzle*, which is defined analogously to *Card and Board*. The following four columns include *Strategy*, *Sports*, *Role-Playing*, and *Action* games, respectively, and the last column includes all of the gaming variables simultaneously.

Three findings emerge from analyzing specific games. First, *log Game_amt/peer_amt* enters positively and significantly in all specifications, and the estimated coefficient on *log Game_amt/peer_amt* changes little across the specifications. Gaming intensity is associated with higher rates of credit card default, and this result is robust to controlling for different types of games on individuals' devices. Second, the presence of each specific gaming App on an individual's device is associated with higher default probabilities after conditioning on game spending in general (*log Game_amt/peer_amt*). That is, the dummy variable for each of the six game types enters positively and significantly, suggesting an independent relationship between each type of game installed on individuals' devices and credit risk. Third, the estimated relationship between *Card and Board* and credit card default is larger than for other game types. Specifically, when examining the difference in the estimated coefficients on the six types of games in column 7, which simultaneously includes the indicator variables for game types and *log Game_amt/peer_amt*, the coefficient estimate on *Card and Board* is significantly larger than the estimates on the other indicator variables. One explanation is that *Card and Board* games tend to involve gambling-related activities within the game, e.g., poker, and existing research suggests that gambling can often reflect an assortment of self-control problems.

*3.7 Financial literacy*

There might be concerns that heterogeneity in "financial literacy," the ability to understand and effectively use financial products, accounts for the findings rather than impulsivity. For example, people with less financial literacy might systematically underestimate the interest rate on credit card debt and overestimate their ability to satisfy their debt obligations, leading to higher default rates. If gaming is negatively correlated with financial literacy, the finding that more intensive gaming is associated with higher default rates after individuals receive credit cards could reflect financial literacy and not self-control problems.

We evaluate this concern by repeating the analyses while distinguishing individuals by financial literacy. We use two proxies for a person's financial literacy: (1) whether a person has attended college and (2) whether a person works in the finance industry. Thus, we test whether the connection between gaming and credit card default holds across four subsamples of individuals: those who attended college, those who did not, those working in the finance industry, and those who are not.

Table 8 shows that results hold across subsamples of individuals that differ by proxies of their ability to understand and effectively use financial products. Specifically, the coefficient estimates on the gaming behavior measures are positive and statistically significant when examining the sub-samples of college-educated, those who did not attend college, individuals employed by the financial services industry, and those not working in finance. Moreover, the estimated coefficients on the gaming measures are similar across the subsamples, suggesting that financial literacy does not drive the strong connection between gaming and credit card risk.

These findings are consistent with the view that self-control problems adversely affect the credit decisions of many individuals, including those with and without the education and professional familiarity to understand and effectively engage with the financial services industry.

This finding implies that educating individuals about financial products alone is unlikely to prevent those with impulse control problems from making suboptimal choices.

*3.8 Alternative explanations and extensions*

We conduct three additional tests. The first two evaluate alternative explanations for the connection between gaming and credit card delinquency. The final test provides further information on the mechanisms linking gaming and default.

First, there might be concerns that spending on gaming could be so large that it leaves insufficient funds to satisfy debt obligations. However, additional information and tests suggest that this is unlikely. First, as noted above, gaming expenditures typically represent a negligible proportion of household expenditures. The average gamer in China spends $4 per month on video games, suggesting that the strong link between past gaming behavior and future credit card default rates is unlikely to reflect the amount that individuals spend on games.[8] Second, our results hold when restricting the analyses to a subset of borrowers whose game spending accounts for an especially small proportion of income such that spending on gaming per se is unlikely to influence the ability of such individuals to pay their credit card debts. Specifically, as shown in Online Appendix Table OA6, the results are robust to restricting the sample to those with below the median values of game expenditures, as measured by *Game_amt/salary*. The findings are consistent with the view that intensive gaming reflects self-control problems that manifest in increased spending on addictive and luxury items and default rates after credit cards ease financing constraints.

[8] The $4 per month figure is from the following source: https://www.scmp.com/tech/apps-gaming/article/2099180/china-driving-global-video-games-market-record-us109b-2017.

Second, a related concern is that obtaining a credit card allows intensive gamers to spend more time gaming, hurting work performance, lowering income, and increasing credit card delinquency rates. From this perspective, relaxing credit constraints triggers higher credit default rates among intensive gamers by reducing income, not by triggering a surge in spending and debt. Although we do not have time-series data on individuals' income, several tests suggest that this mechanism running from credit card approval to increased gaming to a deterioration in work performance is unlikely to drive our results. First, as just noted, spending on gaming is a negligible component of expenditures, suggesting that credit card approval is unlikely to have a material impact on the amount of time spent on gaming. Second, we examine "normal" spending, i.e., total spending minus spending on luxury and addictive items. Suppose gaming increases credit card delinquencies by lowering work productivity and income. In that case, we expect a reduction in normal spending, not simply an increase in the purchases of luxury and addictive items. However, Online Appendix Table OA2 shows that gaming is positively related to a surge in spending on luxury and addictive items but unrelated to normal spending. Third, suppose our key findings are driven by a drop in income caused by intensified gaming activities after the credit card approval. In that case, our results should not hold among individuals whose gaming intensity is insensitive to their financial conditions. To test this, we restrict the sample to individuals whose game spending accounts for a very small proportion of salary and hence unlikely to be sensitive to easing credit constraints. Specifically, we compute the ratio of game expenditure relative to income and focus on those having *Game_amt/salary* below the sample median value (0.7%). As shown in Online Appendix Table OA6, our results hold for this subsample.

Third, we extend the analyses to explore an additional implication of the view that easing credit constraints triggers especially large surges in spending on luxury and addictive items among individuals with more impulsive traits, increasing the likelihood that those individuals default on their debts. We test whether individuals more attuned to satisfying debt obligations are better able to curb their impulsive tendencies when credit constraints are eased. From this perspective, the relationship between past gaming behavior and future credit card delinquencies will be smaller among such debt-attuned individuals. We proxy for individuals' debt awareness using *House property*, i.e., whether they have a mortgage or not, under the maintained hypothesis that servicing homeownership debts, especially given the high costs of defaulting on mortgage loans in China, makes individuals more vigilant about controlling debt-financed spending and satisfying credit obligations in general. Thus, we augment our standard regression specification by adding the interaction term, *Game_dummy*House property,* and test whether the relationship between gaming and default is weaker among homeowners. Recall that we included *House property* in our standard set of demographic controls above (e.g., Table 2), finding that homeowners are less likely to default on credit card debts. We now also assess whether the impact of gaming intensity on credit card delinquencies is muted among homeowners. As reported in Online Appendix Table OA7, *Game_dummy*House property* enters negatively and significantly. These findings are consistent with the view that having a mortgage strengthens impulse control, reducing credit card delinquencies.

## 4. Conclusions

Exploiting a unique high-frequency, individual-level database, we (1) construct individual-level, incentive-compatible proxies of impulsivity based on video gaming behavior and (2) use these proxies to evaluate predictions concerning how impulsivity shapes individuals' responses to a relaxation of credit constraints as captured by receiving a credit card. We discover that pre-card gaming intensity—as measured by the frequency and amount of game expenditures—is strongly and positively associated with (a) the probability of defaulting on credit card debt in the future, (b) post-card expenditures on luxury and addictive items, (c) surges in consumption spending immediately after receiving the credit card, and (d) rapid debt accumulation after obtaining the card. The results are consistent with (1) neurological and psychological studies stressing that excessive gaming is associated with impulse control deficiencies and (2) behavioral theories stressing that impulsivity, i.e., time-inconsistent preferences for immediate gratification and ineffective strategies for avoiding myopic cues and temptations, substantially influence individual expenditure patterns and borrowing decisions after liquidity constraints are relaxed.

**References**

Agarwal, S., Chomsisengphet, S., Mahoney, N. and Stroebel, J., 2015. Regulating consumer financial products: Evidence from credit cards. *Quarterly Journal of Economics*, 130(1), pp.111-164.

Agarwal, S. and Qian, W., 2014. Consumption and debt response to unanticipated income shocks: Evidence from a natural experiment in Singapore. *American Economic Review*, 104, pp.4205-30.

Agarwal, S., Chomsisengphet, S., Liu, C., Song, C. and Souleles, N., 2018. Relationship Lending: Evidence from the Consumer Credit Market, *Journal of Monetary Economics* 96, pp. 16-32.

Agarwal, S., Qian, W., Seru, A. and Zhang, J., 2020. Disguised corruption: Evidence from consumer credit in China. *Journal of Financial Economics*, 137(2), pp.430-450.

Ameriks, J., Caplin, A., Leahy, J., Tyler, T., 2007. Measuring self-control problems. *American Economic Review* 97, 966-972.

Ariely, D. and Wertenbroch, K., 2002. Procrastination, deadlines, and performance: Self-control by precommitment. *Psychological Science*, 13(3), pp.219-224.

Bernheim, B.D. and Rangel, A., 2004. Addiction and cue-triggered decision processes. *American Economic Review*, 94, pp.1558-1590.

Chen, N., Elmachtoub, A.N., Hamilton, M.L. and Lei, X., 2021. Loot box pricing and design. *Management Science*, 67(8), pp.4809-4825.

D'Acunto, F., Hoang, D., Paloviita, M., and Weber, M., 2019. Cognitive Abilities and Inflation Expectations. *American Economic Review* 109, P&P, 562-66.

D'Acunto, F., Hoang, D., Paloviita, M., and Weber, M., 2022. IQ, Expectations, and Choice, *Review of Economic Studies*, forthcoming.

D'Acunto, F., Malmendier, U., and Weber, M., 2021. Gender Roles Produce Divergent Economic Expectations, *Proceedings of the National Academy of Sciences* (PNAS),118 (21).

D'Acunto, F., Rossi, A.G., and Weber, M., 2019. Crowdsourcing Financial Information to Change Spending Behavior. Working paper.

DellaVigna, S., 2009. Psychology and economics: Evidence from the field, *Journal of Economic Literature*, 47, pp.315-372.

DellaVigna, S. and Malmendier, U., 2004. Contract design and self-control: Theory and evidence. *Quarterly Journal of Economics*, 119, pp.353-402.

DellaVigna, S. and Malmendier, U., 2006. Paying not to go to the gym. *American Economic Review*, 96(3), pp.694-719.

Fernandes, D., Lynch Jr, J.G. and Netemeyer, R.G., 2014. Financial literacy, financial education, and downstream financial behaviors. *Management Science*, 60(8), pp.1861-1883.

Fudenberg, Drew, and David K. Levine., 2006. A Dual-Self Model of Impulse Control. *American Economic Review*, 96(5), pp.1449-1476.

Gabaix, X. and Laibson, D., 2006. Shrouded attributes, consumer myopia, and information suppression in competitive markets. *The Quarterly Journal of Economics*, *121*(2), pp.505-540.

Gathergood, J. and Weber, J., 2017. Financial literacy, present bias and alternative mortgage products. *Journal of Banking & Finance*, 78, pp.58-83.

Gentile, D.A., Swing, E.L., Lim, C.G. and Khoo, A., 2012. Video game playing, attention problems, and impulsiveness: Evidence of bidirectional causality. *Psychology of Popular Media Culture*, 1, pp.62-70.

Gomes, F., Haliassos, M. and Ramadorai, T., 2021. Household finance. *Journal of Economic Literature*, 59(3), pp.919-1000.

Gros, L., Debue, N., Lete, J. and Van De Leemput, C., 2020. Video game addiction and emotional states: possible confusion between pleasure and happiness? *Frontiers in Psychology*, 10, p.1-21.

Gross, D.B. and Souleles, N.S., 2002. Do liquidity constraints and interest rates matter for consumer behavior? Evidence from credit card data. *Quarterly Journal of Economics*, 117(1), pp.149-185.

Gul, F. and Pesendorfer, W., 2001. Temptation and self-control. *Econometrica*, 69, pp.1403-1435.

Haghbin, M., Shaterian, F., Hosseinzadeh, D. and Griffiths, M.D., 2013. A brief report on the relationship between self-control, video game addiction and academic achievement in normal and ADHD students. *Journal of Behavioral Addictions*, 2, pp.239-243.

Han, D.H., Bolo, N., Daniels, M.A., Arenella, L., Lyoo, I.K. and Renshaw, P.F., 2011. Brain activity and desire for Internet video game play. *Comprehensive Psychiatry*, 52(1), pp.88-95.

Heidhues, P. and Koszegi, B., 2010. Exploiting naïvete about self-control in the credit market. *American Economic Review* 100, 2279-2303.

Hirshleifer, D., 2015. Behavioral finance. *Annual Review of Financial Economics*, 7, pp.133-159.

Kim, E.J., Namkoong, K., Ku, T. and Kim, S.J., 2008. The relationship between online game addiction and aggression, self-control and narcissistic personality traits. *European Psychiatry*, 23(3), pp.212-218.

Kim, N.R., Hwang, S.S.H., Choi, J.S., Kim, D.J., Demetrovics, Z., Király, O., Nagygyörgy, K., Griffiths, M.D., Hyun, S.Y., Youn, H.C. and Choi, S.W., 2016. Characteristics and psychiatric symptoms of internet gaming disorder among adults using self-reported DSM-5 criteria. *Psychiatry Investigation*, 13(1), pp. 58-66.

Kuss, D.J. and Griffiths, M.D., 2012. Internet gaming addiction: A systematic review of empirical research. *International Journal of Mental Health and Addiction*, 10(2), pp.278-296.

Kuss, D.J., 2013. Internet gaming addiction: current perspectives. *Psychology Research and Behavior Management*, 6, pp.125-137.

Laibson David, 1997. Golden eggs and hyperbolic discounting. *Quarterly Journal of Economics*, 112(2), pp.443-477.

Lee, Y.S., Han, D.H., Yang, K.C., Daniels, M.A., Na, C., Kee, B.S. and Renshaw, P.F., 2008. Depression like characteristics of 5HTTLPR polymorphism and temperament in excessive internet users. *Journal of Affective Disorders*, 109(1-2), pp.165-169.

Lusardi, A. and Mitchell, O.S., 2014. The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature*, 52(1), pp.5-44.

Männikkö, N., Ruotsalainen, H., Miettunen, J., Pontes, H.M. and Kääriäinen, M., 2020. Problematic gaming behaviour and health-related outcomes: A systematic review and meta-analysis. *Journal of Health Psychology*, 25(1), pp.67-81.

Maturana, G. and Nickerson, J., 2019. Teachers teaching teachers: The role of workplace peer effects in financial decisions. *The Review of Financial Studies*, *32*(10), pp.3920-3957.

Mehroof, M. and Griffiths, M.D., 2010. Online gaming addiction: The role of sensation seeking, self-control, neuroticism, aggression, state anxiety, and trait anxiety. *Cyberpsychology, Behavior, and Social Networking*, 13(3), pp.313-316.

Meier, S. and Sprenger, C., 2010. Present-biased preferences and credit card borrowing. *American Economic Journal: Applied Economics* 2, 193-210.

Millar, A. and Navarick, D.J., 1984. Self-control and choice in humans: Effects of video game playing as a positive reinforcer. *Learning and Motivation*, 15, pp.203-218.

O'Donoghue, T. and Rabin, M., 2001. Choice and procrastination. *Quarterly Journal of Economics*, 116(1), pp.121-160.

Ouimet, P. and Tate, G., 2020. Learning from coworkers: Peer effects on individual investment decisions. *The Journal of Finance*, *75*(1), pp.133-172.

Ru, H., 2018. Government Credit, a Double-Edged Sword: Evidence from the China Development Bank. *Journal of Finance* 73, 275-316.

Ru, H. and Schoar, A., 2020. Do credit card companies screen for behavioral biases? BIS Working Paper No. 842.

Telyukova, I.A., 2013. Household need for liquidity and the credit card debt puzzle. *Review of Economic Studies*, 80(3), pp.1148-1177.

Thaler, R.H. and Shefrin, H.M., 1981. An economic theory of self-control. *Journal of Political Economy*, 89, pp.392-406.

Vissing-Jorgensen, A., 2021. Consumer Credit: Learning Your Customer's Default Risk from What (S)he Buys. Federal Reserve Board, mimeo.

World Health Organization (2018). Available at: https://www.who.int/features/qa/gaming-disorder/en/ (accessed October, 2021).

Yau, Y., Crowley, M., Mayes, L. and Potenza, M. (2012). Are Internet use and video game play addictive behaviours? Biological, clinical and public health implications for youths and adults. *Minerva Psichiatrica*, 53, pp.153–170.

**Table 1 Summary Statistics**

This table presents the summary statistics of the key variables used in our analyses. The unit of observation is at the individual borrower level. In the column headings, N designates the number of non-missing observations for the variable, Mean, Median, and Std. Dev. provide the average, median value, and standard deviation across these observations for the variable. *Education degree* uses a qualitative scale ranging from 0 to 5. In particular, 1=primary school, 2=junior high school, 3=senior high school, 4=bachelor, 5=postgraduate and above, and 0 if the data is missing.

| | N | Mean | Median | SD |
|---|---|---|---|---|
| Default | 82270 | 0.126 | 0 | 0.332 |
| *Game expenditure measures* | | | | |
| Game_dummy | 82270 | 0.183 | 0 | 0.387 |
| log Game_freq | 82270 | 0.236 | 0 | 0.607 |
| log Game_amt | 82270 | 0.652 | 0 | 1.536 |
| log Game_AMT/Peer_amt | 82270 | 0.062 | 0 | 0.281 |
| *Among game payers only* | | | | |
| log Game_freq | 15078 | 1.290 | 1.099 | 0.805 |
| log Game_amt | 15078 | 3.556 | 3.045 | 1.596 |
| log Game_AMT/Peer_amt | 15078 | 0.341 | 0.100 | 0.581 |
| log Std. Game_amt/peer_amt | 9920 | 0.307 | 0.112 | 0.458 |
| *Game Apps measures* | | | | |
| log # of GameApps | 41975 | 2.162 | 2.398 | 1.260 |
| # of Game types | 41975 | 2.249 | 2 | 1.625 |
| *Consumption measures* | | | | |
| Δlog(Spending on Large-amount Dining) | 82084 | 1.076 | 0 | 2.040 |
| Δlog(Spending on Large-amount Shopping) | 82084 | 0.332 | 0 | 1.418 |
| Δlog(Spending on Jewelry) | 82084 | 0.162 | 0 | 0.900 |
| Δlog(Spending on Alcohol and Cigarette) | 82084 | 0.360 | 0 | 1.085 |
| Δlog(Consumption) | 81278 | -2.226 | -1.981 | 2.313 |
| *Debt measures* | | | | |
| Borrowing from sources other than banks | 60655 | 0.121 | 0 | 0.326 |
| Number of credit cards | 60655 | 2.127 | 2 | 1.724 |
| *Demographic controls* | | | | |
| log Age | 82270 | 3.469 | 3.434 | 0.223 |
| Gender (male) | 82270 | 0.716 | 1 | 0.451 |
| Income | 82270 | 2.105 | 2 | 0.867 |
| House property | 82270 | 0.173 | 0 | 0.378 |
| Education degree | 82270 | 1.527 | 0 | 1.753 |
| Marital status | 82270 | 1.411 | 2 | 0.889 |

**Table 2 Gaming and default rates, baseline results**

This table reports the estimation results of default rates on individual gaming behavior. The dependent variable is an indicator that equals one if the individual defaults on his/her credit card, and zero otherwise. The key explanatory variables are game-based self-control measures, namely *Game_dummy*, *log Game_freq*, *log Game_amt*, and *log Game_amt/peer_amt*, all measured using daily expenditure during the 30 days before a person applies for a credit card. We include *Demographic controls* (gender, age, marital status, education degree, income group, house property). We also include fixed effects for the city where and the time when the individual applied for a credit card. We estimate the model using OLS. Standard errors are clustered at the city level and reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%.

| | Default or not | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Game_dummy | 0.054*** | | | |
| | (0.003) | | | |
| log Game_freq | | 0.040*** | | |
| | | (0.003) | | |
| log Game_amt | | | 0.014*** | |
| | | | (0.001) | |
| log Game_amt/peer_amt | | | | 0.058*** |
| | | | | (0.006) |
| Income (=2) | -0.024*** | -0.024*** | -0.024*** | -0.024*** |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| Income (=3) | -0.054*** | -0.053*** | -0.054*** | -0.054*** |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| Income (=4) | -0.071*** | -0.071*** | -0.071*** | -0.071*** |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| Income (=5 highest level) | -0.100*** | -0.099*** | -0.100*** | -0.100*** |
| | (0.011) | (0.011) | (0.011) | (0.011) |
| House property | -0.072*** | -0.072*** | -0.073*** | -0.073*** |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| Education (=Primary) | -0.013** | -0.013** | -0.013** | -0.013** |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| Education (=Junior high school) | -0.014* | -0.013* | -0.014* | -0.013* |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| Education (=Senior high school) | -0.038*** | -0.037*** | -0.038*** | -0.037*** |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| Education (=Undergraduate) | -0.049*** | -0.049*** | -0.049*** | -0.049*** |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| Education (=Postgraduate & above) | -0.052*** | -0.052*** | -0.052*** | -0.053*** |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| City fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Age, Gender, Marital status | Yes | Yes | Yes | Yes |
| Observations | 82,270 | 82,270 | 82,270 | 82,270 |
| # city | 325 | 325 | 325 | 325 |
| R-squared | 0.045 | 0.046 | 0.045 | 0.043 |

## Table 3 Gaming and consumption

This table reports the estimation results of luxury spending or impulsive spending on gaming behaviour. The dependent variable in columns 1-4 of Panel A is the log difference between the monthly amount of spending on a luxury item during the 12 months after the credit card application and spending over the three months before the card application. For dining and shopping, we define large-amount spending if the total amount of expenditures is above the 95th percentile. The dependent variable in column 5, Δ*log(Consumption)*, is the log difference between total consumption over the first months after the card application, and total consumption over 12 months after the application. Panel B separately examines spending before and after credit card approval. The dependent variable in Panel B is the log monthly amount of spending on a luxury item over three months before the card application (in columns with an odd number), and 12 months after the application (in columns with an even number). Other variables are defined the same as above. We include *Demographic controls* (gender, age, marital status, education degree, income group, house property), and fixed effects for the city where and the time when the individual applied for a credit card in all specifications. Standard errors are clustered at the city level and reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%.

### Panel A: Changes in spending

| | Δlog(Spending on item j), where item j= | | | | |
|---|---|---|---|---|---|
| | Large-amount Dining | Large-amount Shopping | Jewelry | Alcohol and Cigarette | Δlog(Consumption) |
| | (1) | (2) | (3) | (4) | (5) |
| log Game_amt/peer_amt | 0.127*** | 0.043** | 0.027*** | 0.053*** | 0.125*** |
| | (0.029) | (0.019) | (0.010) | (0.014) | (0.029) |
| City fixed effects | Yes | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes |
| Demographic controls | Yes | Yes | Yes | Yes | Yes |
| Observations | 82,084 | 82,084 | 82,084 | 82,084 | 81,278 |
| # city | 325 | 325 | 325 | 325 | 325 |

**Panel B: Spending before and after card approval**

| | Spending on item j, where item j= | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Large-amount Dining | | Large-amount Shopping | | Jewelry | | Alcohol and Cigarette | |
| | pre | post | pre | post | pre | post | pre | post |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| log Game_amt/peer_amt | 0.014 | 0.141*** | 0.007 | 0.051*** | 0.001 | 0.028*** | 0.008 | 0.060*** |
| | (0.009) | (0.030) | (0.007) | (0.017) | (0.004) | (0.011) | (0.006) | (0.013) |
| City fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Demographic controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| F-statistic (β_pre-β_post=0) | 19.07*** | | 5.03** | | 6.81*** | | 13.78*** | |
| Prob > chi2 | (0.000) | | (0.0249) | | (0.0091) | | (0.0002) | |
| Observations | 82,180 | 82,157 | 82,180 | 82,157 | 82,180 | 82,157 | 82,180 | 82,157 |
| # city | 325 | 325 | 325 | 325 | 325 | 325 | 325 | 325 |

## Table 4 Gaming and borrowing

This table reports the estimation results of borrowing on individual gaming behavior. The dependent variable is an indicator of whether a person borrows from sources other than banks (such as online lending platforms or finance companies) during the 12 months after the credit card application in columns 1 and 2, and the number of credit cards owned by individuals in columns 3 and 4. The key explanatory variables, *log Game_amt/peer_amt*, is defined the same as above. We include *Demographic controls* (gender, age, marital status, education degree, income group, house property), and fixed effects for the city where and the time when the individual applied for a credit card in all specifications. We estimate the model using OLS in columns 1 and 3, logit and report the marginal effects in column 2, and ordered logit in column 4. The standard errors clustered at the city level and reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%.

| | Borrowing from sources other than banks | | Number of credit cards | |
|---|---|---|---|---|
| | OLS | Logit | OLS | Ordered Logit |
| | (1) | (2) | (3) | (4) |
| log Game_amt/peer_amt | 0.067*** | 0.046*** | 0.125*** | 0.139*** |
| | (0.006) | (0.003) | (0.025) | (0.028) |
| City fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Demographic controls | Yes | Yes | Yes | Yes |
| Observations | 60,652 | 60,658 | 60,652 | 60,658 |
| # city | 322 | 328 | 322 | 328 |

## Table 5 Gaming and default rates, timing

This table reports the estimation results of default rates on individual gaming behavior, while differentiating game expenditures during workdays vs. weekends (Panel A), or during rainy vs. non-rainy days (Panel B). The key explanatory variables in Panel A *log Game_amt/peer_amt*, is defined the same as above, except that we separate expenditures by whether they occurred during workdays or weekends. Similarly, the key explanatory variables in Panel B separates expenditures by whether they occurred during very rainy days or days when it does not rain very heavily. We include *Demographic controls* (gender, age, marital status, education degree, income group, house property), and fixed effects for the city where and the time when the individual applied for a credit card in all specifications. Standard errors are clustered at the city level and reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%.

### Panel A: Workday vs. Weekends

| | Default or not | |
|---|---|---|
| | Weekend: Saturday & Sunday | Weekend: Saturday & Sunday & public holidays |
| | (1) | (2) |
| log Game_amt/peer_amt, workweek | 0.057*** | 0.054*** |
| | (0.009) | (0.009) |
| log Game_amt/peer_amt, weekend | 0.010 | 0.014 |
| | (0.010) | (0.010) |
| City fixed effects | Yes | Yes |
| Time fixed effects | Yes | Yes |
| Demographic controls | Yes | Yes |
| F-statistic (β_workweek-β_weekend=0) | 7.63*** | 5.35** |
| Prob > chi2 | (0.0061) | (0.0213) |
| Observations | 82,270 | 82,270 |
| # city | 325 | 325 |

### Panel B: Rainy vs. Non-rainy days

| | Default or not | |
|---|---|---|
| | 12h-precipitation >=30mm | 12h-precipitation >=15mm |
| | (1) | (2) |
| log Game_amt/peer_amt, rainy day | -0.003 | 0.014 |
| | (0.034) | (0.017) |
| log Game_amt/peer_amt, non-rainy day | 0.072*** | 0.070*** |
| | (0.014) | (0.014) |
| City fixed effects | Yes | Yes |
| Time fixed effects | Yes | Yes |
| Demographic controls | Yes | Yes |
| F-statistic (β_rainy-β_nonrainy=0) | 3.30* | 5.03** |
| Prob > chi2 | (0.0710) | (0.0263) |
| Observations | 46,054 | 46,054 |
| # city | 163 | 163 |

## Table 6 The volatility of gaming and default rates

This table reports the estimation results of default rates on the volatility of individual daily gaming expenditures. The dependent variable is an indicator that equals one if the individual defaults on his/her credit card, and zero otherwise. The key explanatory variables *log Std. Game_amt/peer_amt*, measures the volatility of game expenditures during 90 days (or 30 days) before an individual applies for a credit card. Thus, we require an individual to have multiple days with non-zero game expenditures in all columns. We include *Demographic controls* (gender, age, marital status, education degree, income group, house property), and fixed effects for the city where and the time when the individual applied for a credit card in all specifications. Standard errors are clustered at the city level and reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%.

| | Default or not | |
|---|---|---|
| | Pre-90 days | Pre-30 days |
| | Conditional on multiple-day game payment | |
| | (1) | (2) |
| log Std. Game_amt/peer_amt | 0.037*** | 0.039*** |
| | (0.009) | (0.010) |
| City fixed effects | Yes | Yes |
| Time fixed effects | Yes | Yes |
| Demographic controls | Yes | Yes |
| Observations | 9,920 | 6,950 |
| # city | 303 | 288 |

## Table 7 Game-apps and default rates

This table reports the estimation results of default rates on individual game-Apps usage. We use a subsample that includes individuals using Android system and with Apps information available. The dependent variable is an indicator that equals one if the individual defaults on his/her credit card, and zero otherwise. The key explanatory variables are *Log # of GameApps* (the number of game Apps), and *# of Game types* (the diversity of game Apps). We include *Demographic controls* (gender, age, marital status, education degree, income group, house property), and fixed effects for the city where and the time when the individual applied for a credit card in all specifications. Standard errors are clustered at the city level and reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%.

| | Default or not | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| log # of GameApps | 0.018*** | 0.017*** | | |
| | (0.001) | (0.001) | | |
| # of Game types | | | 0.014*** | 0.013*** |
| | | | (0.001) | (0.001) |
| log Game_amt/peer_amt | | 0.055*** | | 0.055*** |
| | | (0.008) | | (0.008) |
| City fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Demographic controls | Yes | Yes | Yes | Yes |
| Observations | 41,975 | 41,975 | 41,975 | 41,975 |
| # city | 322 | 322 | 322 | 322 |

## Table 8 Gaming and default rates, differentiate by financial literacy

This table reports the estimation results that are similar to Table 2, while differentiating individuals by education and finance occupation. We use the degree of education, and whether a person's occupation is related to finance to proxy for the person's financial literacy. Other variables are defined the same as above. We include *Demographic controls* (gender, age, marital status, education degree, income group, house property), and fixed effects for the city where and the time when the individual applied for a credit card in all specifications. Standard errors are clustered at the city level and reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%.

| | Default or not | | | |
|---|---|---|---|---|
| | college or above | high school or below | finance-related occupation | other occupation |
| | (1) | (2) | (3) | (4) |
| log Game_amt/peer_amt | 0.059*** | 0.058*** | 0.060*** | 0.049*** |
| | (0.011) | (0.009) | (0.013) | (0.007) |
| City fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Demographic controls | Yes | Yes | Yes | Yes |
| Observations | 16,707 | 22,223 | 10,750 | 42,371 |
| # city | 308 | 314 | 281 | 320 |

**Appendix**

**Table A1 Variable definitions**

| Variable | Definition |
|---|---|
| *Gaming measures* | |
| Game_dummy | A dummy variable that equals one if the individual paid for game-related activities, and zero otherwise. |
| log Game_freq | Log of one plus the cumulative frequency of game payments: $log\ Game\_freq = log\ (1 + \sum_{t=-1}^{-30}(number\ of\ payments\ in\ period_t))$, where $t$ denotes the day an individual applies for the credit card. |
| log Game_amt | Log of one plus the total amount (in RMB) of game spending: $log\ Game\_amt = log\ (1 + \sum_{t=-1}^{-30}(amount\ of\ spending\ in\ period_t))$, where $t$ denotes the day an individual applies for the credit card. |
| log Game_amt/peer_amt | Log of one plus the ratio of total expenditures on gaming to the average expenditures on gaming across individuals in the same income group. Income is provided in five scales, with 5 corresponding to a range of RMB 12500-24999, 4 RMB 8000-12499, 3 RMB 5000-7999, 2 RMB 3500-4999, and 1 RMB below 3499. |
| log Std. (Game_amt/peer_amt) | Log of one plus the standard deviation of the ratio of the individual's expenditures on gaming to the average expenditures on gaming across individuals in the same income group. |
| log # of GameApps | Log of one plus the total number of game Apps installed on the individual's mobile devices. |
| # of Game types | The number of game types (card and board, sports, strategy, role-playing, action, and leisure and puzzle). The value of this variable ranges from 0 to 6. |
| *Credit card outcomes and Demographic controls* | |
| Default | An indicator that equals one if the credit card holder defaults within 12 months after the card is approved, and zero otherwise. |
| Credit approval | An indicator that equals one if an individual application of credit card is approved and zero otherwise. |
| Income | A set of individual dummy variables representing the category in which the individual's monthly income falls. The five categories of income are between RMB 12500-24999, RMB 8000-12499, RMB 5000-7999, RMB 3500-4999, and below RMB 3499. |
| House property | An indicator that equals one if the individual owns housing property, and zero otherwise. |

| | |
|---|---|
| Gender | An indicator that equals one if the individual is male, and zero otherwise. |
| log Age | Log of an individual's age |
| Marital status | An indicator of whether the person is married or single |
| Education degree | A set of dummy variables representing the highest degree attained. For the vector Education degree, the entries equal zero for each individual except for the category representing the individual's highest education degree. The categories are primary school, junior high school, senior high school, bachelor, and postgraduate and above. |
| *Other expenditure-related measures* | |
| Δlog(Spending on Large-amount Dining) | Log difference between the average monthly spending on large-amount dining over three months before the card application and the average monthly spending over 12 months after the application, where large-amount means spending in a day is above the 95th percentile of spending. |
| Δlog(Spending on Large-amount Shopping) | Log difference between the average monthly spending on large-amount shopping over three months before the card application and the average monthly spending over 12 months after the application, where large-amount means spending in a day is above the 95th percentile of spending. |
| Δlog(Spending on Jewelry) | Log difference between the average monthly spending on jewelry over three months before the card application and the average monthly spending over 12 months after the application. |
| Δlog(Spending on Alcohol and Cigarette) | Log difference between the average monthly spending on alcohol and cigarette over three months before the card application and the average monthly spending over 12 months after the application. |
| Δlog(Consumption) | Log difference between the amount of expenditures over the first month after applying for a card and the average monthly spending over the 12 months after the application. |
| *Debt measures* | |
| Borrowing from sources other than banks | An indicator equal to one if a person borrows from sources other than banks (such as online lending platforms or finance companies) during the 12 months after the credit card application. |
| Number of credit cards | Assuming that people repay only once per card per month, we define *Number of credit cards* as equal to 0 if they do not repay any credit card debt via the online payment platform, 1 if they repay credit card debt once via the online payment platform, 2 if twice, 3 if three times, and 4 if four or more times. For each individual, we |

use the month with the maximum number of credit card repayments during the 12 months after the credit card application.