How Do Gamblers React to Wins? Evidence from Bank Transaction Data in Japan

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Abstract

This study investigates how gamblers change their gambling and consumption behaviors after they receive gambling wins. We use novel bank transaction data in Japan, which contain information on both gambling bets and wins on public horse races with clear time flows. The estimation results show a positive marginal propensity to gamble (MPG) and consume (MPC) on impact, which however disappear in 12 weeks. While a considerable heterogeneity among gamblers exists in terms of gambling intensity, the MPG and MPC are stable, and light gamblers are insignificantly different from non-gamblers in the MPC to the government transfer in 2020. The liquidity constraint matters for the MPC, but not the MPG. Further, we find evidence against the loss chasing effect: gamblers increase bets when they win in net.

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1 Introduction

Many individuals engage in gambling,[1] where gamble wins and losses can significantly affect their behaviors. While some of windfall income may be spent on everyday expenses, large or zero gambling wins may lead to addictive behaviors and disorders, known as problem gambling (as discussed in the literature review below). The social cost of problem gambling extends beyond correctional expenses, contributing to negative externalities such as increased crime and poverty. Understanding how gambling wins affect consumption provides valuable insights into the marginal propensity to consume (MPC), which is crucial for calculating the fiscal multiplier and improving models of economic behavior, including Heterogeneous Agent New Keynesian (HANK) models. However, academic research on gambling remains underdeveloped, as Nature (2018) argues "The world of gambling research is too small and underfunded. The paucity of data available to inform policymakers and the medical profession is shocking." The primary limitation that often prevents researchers from conducting rigorous empirical studies is the difficulty of obtaining data that identify both bets and wins.

In this study, we aim to investigate how gamblers react to gambling wins by focusing on gambles of public horse races and using novel bank account transaction data in Japan.[2] The data are provided by one of Japan's major banks, Mizuho Bank, which contain information on actual transactions (not surveys) associated with bets (not just wins) on a weekly basis (not annual). We examine changes in gambling bets and consumption, which we call the marginal propensity to gamble (MPG) and the MPC, respectively, in response to a surprising component of gambling wins. We estimate the dynamic MPG and MPC in the following several weeks after the wins. Through this estimation, we provide new evidence that a gambling win can trigger repeated gambles.

The data are provided by one of the Japan's major banks (Mizuho Bank), from which we can measure inflows and outflows including gambling activities (wins and bets) at the individual and weekly level. The benefits of our data and the identification strategy

[1] Gambling includes lotteries, public races, poker, slot machines, and an array of other games. The gross revenue of gambling industry in 2019 is 78 billion U.S. dollars in Japan, according to our estimate (1 U.S. dollar $\simeq$ 130 Japanese Yen (JPY) at the end of 2022, see Section 2 for details), which is 2% of nominal GDP. In the U.S., the gross revenue of gambles, which is limited to casino games (including online iGaming), is 44 billion U.S. dollars as of 2019 according to American Gaming Association.

[2] In this study, we use the term "wins" to refer to gross earnings from bets. Net wins are defined as the profits from gambling, calculated as wins minus bets.

cannot be overstated. Observing gambling bets is important: by controlling for gambling bets, we can isolate an unexpected component of gambling wins, as bets and wins exhibit a proportional relationship. A further distinct novelty is that, combined with the data, the system of online gambling on public horse races in Japan enables us to identify an unexpected shock of gambling wins accurately. Under the system, the bank suspends gamblers' transactions temporarily during weekends when public races are taken place, and instead gamblers can use their accounts only for online gambling on public horse races. After they bet during weekends, all their gambling wins are automatically paid to their bank accounts by Monday morning. Thus, by setting the time frequency weekly where each week starts on Monday, the timing of transactions runs clearly as bets in week $t-1 \rightarrow$ wins at the beginning of week $t \rightarrow$ spending including bets in week t and thereafter. Moreover, our analysis reveals pronounced heterogeneity in their gambling intensity—the frequency and extent of their gambling activities. To investigate this heterogeneity, the observation of gambling bets serves as a fundamental prerequisite. We establish a balanced panel on a weekly basis over four years during 2019–2022 with 17,000 gamblers.

In this study, we answer mainly five questions. The first question is how gamblers change their gambling bets in response to wins (MPG). We conduct a two-way fixed effect regression, where the dependent and explanatory variables are bets and wins, respectively. Here, we control for bets in the previous weeks to make gambling wins an unexpected income shock. The estimation reveals that the on-impact MPG is 0.075, suggesting that gamble winners spend 7.5% of the unexpected component of their wins on another gamble immediately within a week. When previous bets are not included in the regression, the estimate of the on-impact MPG increases to 0.26, confirming the importance of controlling for previous bets. Gambling bet responses are significant for three months, which suggests that gambling wins can have a persistent effect on gambling for a relatively long period. Furthermore, the analysis of the extensive margin of gambling shows that gambling wins increase the likelihood of gambler participation. As their wins increase, gamblers are more likely to continue gambling.

Second, we estimate consumption responses, the MPC, where we define consumption as transaction outflows minus bets. A two-way fixed effect regression reveals that the on-impact MPC is 0.35, suggesting that gamblie winners consume 35% of wins immediately within a week. The MPC is less persistent than the MPG, disappearing in a month. This persistence is substantially shorter than that documented by Fagereng et al. (2021) and Auclert et al. (2018), that is, around three years. This low persistence suggests that simple two-agent heterogeneous models are sufficient, which echos Debortoli and Gali (2024) and Bilbiie (2024). We do not need computationally-intensive heterogeneous-agent models, although representative agent models still cannot account for a significantly large MPC.

Third, we investigate gamblers' heterogeneity. Our study documents that gamblers are heterogeneous in terms of their gambling intensity, that is, the frequency and proportion of gambling. Some engage in gambling every week and/or spend almost all of their income on gambling, while others participate in gambles to only a small extent. However, despite this large heterogeneity, we find great stability in the estimated MPG and MPC except for extremely heavy gamblers: the estimated MPG and MPC are similar among gamblers. The MPG and MPC are negatively correlated, albeit weakly, which suggests based on a simple model the importance of heterogeneity in gambling preferences. Furthermore, we confirm that liquidity matters for the MPC, in line with many empirical studies such as Fagereng et al. (2021) and Ueda (2023). However, the MPG seems unrelated to liquidity, opposed to empirical studies such as Brunk (1981) and Herskowitz (2021).

Fourth, we consider how gambling and consumption responses depend on past gambling outcomes. Our ultimate question is what bring gamblers to problem gambling. We find that net positive wins (i.e., wins exceed bets) increase gambles discontinuously, while decreasing consumption. This is opposite to the so-called loss-chasing effect, where net negative wins lead to gambles. A further finding is that when gamblers win nothing, consumption jumps up, implying a shift to another leisure such as eating and drinking. Moreover, we observe the big win (or income) effect on consumption, where the MPC increases with the size of wins, while no such effect is observed on gambling bets.

The final question we investigate is whether gamblers are special. A natural question that should arise among readers is external validity, that is, whether our study on the MPC can be generalized to non-gamblers. We compare gamblers and non-gamblers by expanding our sample in the Mizuho Bank data. A comparison shows that gamblers are aged and dominated by male. Comparing the MPC to a special cash payment (SCP) during the COVID-19 pandemic between gamblers and non-gamblers with their observed characteristics matched, we find that the MPC is not significantly different. These results suggest that gamblers are indeed special in terms of age and gender; however, once we control for observed characteristics, light gamblers and non-gamblers are hardly different in terms of the MPC.

Literature Review Problem gambling, sometimes called pathological gambling, gambling addiction, or ludomania, is "a gambling behavior that is damaging to a person or their family, often disrupting their daily life and career" (National Council on Problem Gambling). As commented in Science (1998), Science (2005), Abbott (2017) in World Health Organization, and Nature (2018), gambling and problem gambling are on increase;[3] however, as Nature (2018) argues, studies on gambling are small and underfunded.[4] It also points out a distortion of funding financed by the gamble industry.

One strand of research on gambles concerns how gambling decisions are made, in which gambling is analyzed as one type of investment under risk and uncertainty.[5] See, for example, Friedman and Savage (1948), Kwang (1965), Rosett (1965), and Hartley and Farrell (2002). According to prospect theory (Kahneman and Tversky (1979)), gambling decisions can be asymmetric around a reference point. See also Kumar (2009), Snowberg and Wolfers (2010), and Chen et al. (2021).

In view of how past gambling outcomes influence gambling decisions, the literature points out the following three types of effects: break even, big wins, and loss chasing effects. Lien and Zheng (2015) investigate reference-dependent loss aversion using slot machine gambling data and find that gamblers prefer to stop at the break-even point. Edson et al. (2023) find big-win effects, wherein large gambling wins lead to excessive gambling, by using data provided by a EU online gambling operator. Subsequently, big wins tend to be associated with future losses. Chen et al. (2022) argue loss chasing, in which gamblers intensify gambling after losing by using data collected from an online commercial game. Kainulainen (2021) show that gamblers abstain from betting when they lose by using gambling data from a Finnish horse race betting monopoly operator. It should be noted that this literature does not necessarily have strong implications

[3]Eadington (1999) examines economic characteristics of the casino industry.

[4]Nonetheless, many studies on gambling exist, covering a wide range of topics from economic, social, medical perspectives. Calado and Griffiths (2016) provide a meta analysis of problem gambling from 69 empirical studies worldwide, and argue that main issues in these studies concern the measurement of problem gambling and the determinants of problem gambling such as income, culture, types of gambles, and demographics. Consequences of problem gambling are investigated, for example, by Muggleton et al. (2021) from an economic, social, and health perspective.

[5]See Blaszczynski and Nower (2002) for a psychology model in explaining problem gambling and gambling decisions.

on problem gambling, because the time horizon of gambling decisions analyzed in the literature is relatively short (e.g., within a day), while problem gambling may entail long-term determinants and consequences. The time horizon of this study is weekly, which is intermediate, but spans over four years for the same individuals, which helps control individual fixed effects.

Conversely, there is literature in the opposite direction, that is, how gambles influence economic decisions other than gambling, such as consumption and labor supply. For example, Imbens et al. (2001) investigate the consequences of lottery wins on earnings, consumption, and savings using a lottery survey in Massachusetts. Kuhn et al. (2011) investigate interactions between lottery winners and their neighbors by analyzing a post-code lottery in Denmark using surveys conducted to lottery winners and their neighbors. Fagereng et al. (2021) examine the MPC to lottery wins using Norwegian tax-record data, finding that the effect of wins on consumption is persistent, lasting around five years. Cesarini et al. (2016) and Cesarini et al. (2017) use Swedish administrative data to study the effects of lottery wins on winners' and their children's health and on labor supply, respectively. Recently, Golosov et al. (2021a) investigate how lottery wins influence labor earnings using U.S. administrative data. These studies help formulate economic models on static and dynamic optimization including HANK.

Previous empirical studies on gambles mostly rely on three types of data: surveys, data provided by gambling agencies, and administrative data. First, according to the meta analysis of Calado and Griffiths (2016), the majority of gambling studies use surveys such as telephone or face-to-face interviews, and all are based on self-reported data.[6] Survey data provide a direct measure of gambles. However, tracking winners for a long time span is often difficult and suffers a small sample size. Self-reported numbers may be different from actual transactions. Auer et al. (2023) argue that self-reported gambling data are not reliable because of a memory bias. The second type of data are gambling agency data, which are frequently used to study gambling decisions.[7] However, there is not much study on gambling itself or problem gambling, possibly because of a distortion due to the gamble industry. Further, these data are hard to link to individuals' variables other than gambles such as consumption and labor supply. Third, administrative data, which have been extensively and increasingly employed in a wide range of studies, has an advantage in providing individuals' detailed information, compared to data provided by

[6]e.g., Imbens et al. (2001), Kuhn et al. (2011).

[7]e.g., Snowberg and Wolfers (2010), Kumar (2009), Lien and Zheng (2015), Kainulainen (2021)

gambling agencies.[8] These administrative data are valuable in highlighting relationships between gambling wins and economic behaviors at the individual level. However, none provides information on gambling bets, and a data frequency is low, often annual.

Compared from these three kinds of data, our study is distinct in using bank account transaction data. Baker (2018) uses transaction data from an online financial app to study consumption elasticity, also providing evidence for the representativeness of the transaction data. Gelman (2021) studies the causes of heterogeneity in consumption responses using a similar data. Kubota et al. (2021) and Ueda (2024) use the same dataset as ours, examining consumption responses to SCP in Japan. The advantages of using transaction data specific to our analyses are that they contain information on actual transactions associated with both bets and wins as well as other kinds of outflows (proxy for consumption) on a weekly basis. We do not rely on self-reported surveys. Our data can track a large number of gamblers continuously for approximately four years.

However, our study is not the first in the use of bank transaction data for the study of gambling. Muggleton et al. (2021) use UK bank transaction data, finding that gambling is associated with higher financial distress and adverse social and health outcomes. There are two notable differences between our study and Muggleton et al. (2021). First, a time horizon is different. While Muggleton et al. (2021) attempt to investigate consequences of gambling for social and health in the long run (7-years), our study investigates a short-run change in gambling behaviors after wins. It may be critical to investigate problem gambling for a longer time horizon such as several years, but our study mainly analyzes dynamic responses of gambling over several weeks.[9] The second difference, which is related to the first one, is a correlation or causality. Gambling decisions are endogenous: gambling can induce problem gambling, and problem gambling can induce further gambling. Further, a social and health status may influence and, at the same time, be influenced by problem gambling. Thus, what Muggleton et al. (2021) document is likely to be a correlation between gambling and problem gambling, not causality from one to the other. By contrast, we seriously attempt to estimate causal effects from gambling wins to gamblers' behaviors. In summary, our work is complementary to Muggleton et al.

[8] e.g., Cesarini et al. (2016), Cesarini et al. (2017), Fagereng et al. (2021), Golosov et al. (2021a).

[9] We can also argue that a time horizon is longer than a day, during which problem gambling may occur. Gamblers often repeat bets and wins in a single day. The past performance of gambles may heat head, leading to overspending in gambling. Lien and Zheng (2015) investigate decisions on when to quit gambles using the data of slot machine activity.

(2021) in that we make causal inferences but cannot investigate long-run consequences of problem gambling, whereas Muggleton et al. (2021) shed light on long-run associations between gambling and problem gambling.

Empirical literature on the MPC is voluminous. One prominent method to estimate the MPC is an episode identification, which uses specific events to identify income shocks and track consumption changes. Examples of income shocks are unanticipated government stimulus programs (Misra and Surico (2014a), Kueng (2018), Misra and Surico (2014b), Kubota et al. (2021)), tax rebates (Souleles (1999), Gelman et al. (2022), Baugh et al. (2021)), and inheritance.[10] Gambling (lottery) wins serve as one of windfall incomes, which help identify an unexpected, salient, and transitory income shock to estimate the MPC. Compared with other income shocks (e.g., stimulus, inheritance), gambling wins are often repeated, but this repetition is hardly explored. Fagereng et al. (2021) observe lottery wins from tax records but use the sample of only one-time winners. Imbens et al. (2001) and Kuhn et al. (2011) employ multiple-stage surveys to lottery winners but another win that can come after is not analyzed. One major reason not to analyze repeated wins is to exclude heavy gamblers, which is understandable without data on gambling bets. Our data fortunately include data on gambling bets, and thus enabling us to control for the intensity of gambling.

The size effect of unanticipated shocks to consumption responses is theoretically predicted negative by the concaveness in consumption function (Carroll and Kimball (1996)). However, empirical evidence is conflicting. The negative shock size effect is found in Fagereng et al. (2021) and Scholnick (2013), but found positive in Fuster et al. (2020) and Gelman et al. (2022). The positive correlation in Gelman et al. (2022) is theoretically explained by cash management, and such positive correlation is emphasized by Baugh et al. (2021) as evidence of mental accounting.

The remainder of this study is organized as follows. Section 2 explains the research background particularly on gambles in Japan and the bank account transaction data. Sections 3 to 7 show our estimation results, discussing gamble responses (Section 3), consumption responses (Section 4), heterogeneity (Section 5), dependence on gambling

[10]Two other types of methods are survey-based investigation and panel data decomposition. A survey-based investigation send direct inquiries to households, which usually include those on consumption and hypothesized income shocks. See, for example, Jappelli and Pistaferri (2014), Jappelli and Pistaferri (2020), Imbens et al. (2001), and Fuster et al. (2020). A panel-data decomposition requires a structural model to identify income shocks (e.g., Blundell et al. (2008) and Golosov et al. (2021b)).

wins (Section 6), and representativeness of gamblers (Section 7). Section 8 concludes.

2 Backgrounds and Data

In this section, we discuss research backgrounds on gambles. We then explain the bank account transaction data we use in this study and how we collect transactions associated with gambles and consumption. Further, we discuss data representativeness.

2.1 Gambling in Japan

The gambling industry in Japan is big, wherein total sales in 2019 amounts to approximately 2% of nominal GDP.[11] In Japan, three types of gambles are virtually legal: public races, lotteries, and pachinko. Public races are organized by governmental agencies and consist of horse, bicycle, boat, and motorcycle races, where the central horse race has the largest share (28%) as of 2019, followed by the local horse race (7%), boat race (15%), bicycle race (7%), and motorcycle race (1%). Pachinko has the largest sales share in all the gambles (34%), while lotteries have a 9% share.

While the size of gambling industry is big, how many people do engage in gambles in Japan? Although no census on gambling exists in Japan, the Problem Gambling Basic Countermeasure Act that was enforced in 2018 states that the government conduct a survey every three years to illuminate the situation of problem gambling. Based on this act, the National Hospital Organization Kurihama Medical and Addiction Center conducted the first survey in 2020, releasing a report in 2021.[12] One of their surveys was conducted to 8,223 Japanese nationals who are aged between 18 and 74 years old (the survey was sent to 17,955 persons and the percentage of valid responses was 45.8%). The report shows that 74.5% of people have the experience of gambles (male 84.1% and female 65.7%), while 33.6% (of all) participated in gambles in the latest one year. As for the types of gambles they experienced, lotteries are the top (63.7%), followed by pachinko (50.3%) and horse races (29.4%). The report also estimates the fraction of

[11] Total sales are the sum of gross gambling revenues (10.2 trillion JPY) in public races, lotteries (including toto), and pachinko. These numbers are collected from public releases from gambling administrations including Japan Racing Association (JRA), Japan Sport Council, and Pachinko Parchislot Industry Report, and the Ministry of Economy, Trade and Industry.

[12] https://www.ncasa-japan.jp/pdf/document41.pdf (in Japanese).

persons suspected to have problem gambling, obtaining the figure of 2.1% or 1.5% out of around 8,000 persons.[13]

Among many types of gambles, public races are organized mostly in weekends. Multiple races are conducted in one day, wherein seasonality exists due to high grade races (e.g., Grade I race). The return rate, that is, the fraction of gambling wins to gambling bets, is approximately 75%, although it varies depending on the type of tickets to bet (e.g., only one player (horse), a group of players, top two or three players).[14] Odds are a return rate conditional on wins. On average, the return rate equals odds times the probability of wins. Thus, odds are higher for bets with low win probability. Gamblers can choose tickets to bets by referring to as odds, and thus, the probability of wins in public races may be more affected by gamblers' skill than that in lotteries where the probability of wins is largely independent of skills. Gambling wins are not taxed at the time of reimbursements, so that winners need to report their wins on their tax return. The amount of gambling bets are from the minimum 100 JPY to a certain bet limit, which is assigned by gambling agencies to prevent problem gambling.

Nowadays, gambles can be made online.[15] Gamblers do not need to visit gambling ticket booths to bet or collect wins. Over the last decade, the internet and telephone gambling has become mainstream, explaining over the share of 80% in the 2020s. This internet transaction is the one we can observe using bank data.

In this study, we focus on the online gamble of central horse races conducted by Japan Racing Association (JRA) for the purpose of shock identification (see the next subsection).

2.2 Mizuho Bank Data

Thanks to an academic agreement between Mizuho Bank and Waseda University, we can access data provided by Mizuho Bank, one of the largest three major banks in Japan. Mizuho Bank extends a wide array of financial services to individuals and corporations

[13]Among a handful literature on problem gambling for Japan, Ino et al. (2020) investigate gambling participation and risk of problem gambling using a survey of residents in Chiba prefecture. They document facts on gambling participation and find a significant correlation between age and the risk of problem gambling. Hayano et al. (2021) show variations in problem gambling across gender and types of gambles, with significant problem gambling found in gambles in motorcycle, bicycle, and boat races.

[14]The return rate for lotteries is far lower at around 45%, while that for pachinko is said to be around $80 \sim 85\%$ although there is no official figure.

[15]Online casino and online pachinko are illegal, only online public races and lotteries are permitted.

both in Japan and abroad, with its branches covering main urban areas and holding around 24 million individual customers out of 120 million population in Japan. The data are analyzed in a setting where measures are taken to prevent the identification of individuals, such as masking and other anonymous processing.

The data contain transaction-individual-level data as well as monthly individual-level data. Transaction data record all transactions that involve Mizuho Bank, such as ATM withdrawals, payroll receipts, utility bill payments, and bank transfers. Each transaction records information on individual, date, monetary amount, inflow or outflow dummy, assigned identification code, and remarks in Japanese. The monthly individual-level data cover information on wealth, annualized income, borrowings from Mizuho Bank, and other personal information such as gender, resident area, and birth year.[16]

We explain how we construct the variables of gambling bets, wins, and consumption using Mizuho Bank data. Gambling bets and wins are measured in the following three steps. First, from remarks in Japanese in transaction data, we search for specific keywords such as "JRA" to find gambling transactions.[17] Second, we verify the transaction content. We remove non-gambling transactions that are related to public race agencies, such as transfers between horse owners and the agencies. Third, using an inflow or outflow dummy in transaction data, we divide gambling transactions into wins (inflows) and bets (outflows). In this manner, we collect gambling transactions via the internet, but not gambling via ticket booths. Consumption is defined as the sum of outflow transactions—cash withdrawals, interbank transfers, and credit card payments—with gambling bets excluded.

Timing of bets and wins matters for identification. It should be noted that the transfer of gambling wins is automatic in the central horse race. Under their system, Mizuho Bank suspends gamblers' transactions temporarily during weekends when public races are taken place, and instead gamblers can use their accounts only for internet gambling on horse races. After they bet during weekends, all their gambling wins are

[16]Wealth is defined as the balance of deposits at the Mizuho Bank, which is the sum of demand deposits, time deposits, other banking accounts, public bonds, mutual funds, and life and non-life insurance balances. The majority of deposits are demand deposits. Annualized income is calculated as the sum of salaries in the last 12 months for the individuals who receive salaries regularly at their Mizuho bank accounts. If they do not receive salaries regularly at their Mizuho bank accounts, annualized income is obtained from individuals' application forms (e.g., opening a bank account and applying loans).

[17]Specifically, the keywords we use are "JRA Haraimodoshikin", "PAT Kounyuukin", "PAT Haraimodoshikin", and "JRA Direct Furikomi."

automatically paid to their bank accounts by Monday morning. Thus, by setting the time frequency weekly where each week starts on Monday, the timing of transactions runs clearly from bets in week $t-1$, to wins at the beginning of week t, and then spending including bets in week t and thereafter.[18]

This automatic and immediate transfer of gambling wins is an advantage of using the data on public races in Japan. For example, in lotteries via the internet in Japan, wins in many types of lotteries are not automatically transferred to winners, unless the the accumulated amount of their wins exceeds 10,000 JPY. Manual transfers generate an endogeneity problem such that an increase in money demand (e.g., a desire to gamble) causes winners to collect past wins, and then, to spend later. Furthermore, even if wins exceed 10,000 JPY, their transfer takes around a week. Thus, it becomes unclear whether wins cause bets or vice versa. The same problem holds true in studies with low time frequency, such as work using administrative data on an annual basis.

After we identify gambling bets, wins, and consumption, we construct panel data at the weekly and individual level. A week starts on Monday to make the timing of gambling wins be the beginning of each week. The data range in 2019–2022 period. To be precise, data have a slightly unbalanced structure because we remove observations when gambling wins exceed 2 million JPY in order to protect privacy. The panel data also contain personal characteristics and financial information such as wealth and annual income.

Further, we construct two kinds of measures of gambling intensity at the gambler level. The first measure is the proportion of gambling, which is defined as the fraction of the sum of gambling bets to the sum of outflows including bets in our observation periods. Second is the frequency of gambling, which is defined as the fraction of the number of weeks with positive bets to the total number of weeks. If it equals one, the gambler participates in gambles every week.

The data have mainly four limitations. First, the data are based on only Mizuho Bank. Activities using other banks or cash cannot be observed. Second, because of the anonymity, we cannot integrate our individual-level data into household-level data. Third, detailed information on bets and wins within a week is unobservable. Gamblers can make bets in multiple races (approximately 10 races in each day) by buying multiple kinds of tickets (e.g., single player (horse) wins, group wins, top two or three finishes)

[18] In bicycle and motorcycle racing, a manual procedure is needed to receive gambling wins.

each weekend. However, we cannot observe their gambling records at this granular level, but only aggregated bets and wins in each week. Fourth, our measure of consumption is coarse. Unfortunately, the data do not provide detailed information on spending categories, and hence, we cannot identify true consumption. In this study, we use consumption and spending interchangeably, although some of goods purchased are durable or storable and spending does not imply consumption in the same period.

We establish a weekly balanced panel for 17,411 gamblers. The gamblers are selected out of approximately 250 thousands gamblers who have the history of online gambles in public races at least once during 2019–2022 period in the Mizuho Bank data. The sample size decreases substantially because we select gamblers' accounts that (1) contain both bets and wins for public central horse races; (2) have complete and unchanged information on gender and birth year; (3) never exceed 10 million JPY for weekly consumption (outflows minus bets); (4) record positive consumption (that excludes bets) for 20 weeks or more; and (5) register the proportion of gambling smaller than 0.5. The last two conditions are imposed to eliminate gamble-specialized bank accounts.

2.3 Descriptive Statistics

We report basic statistics for 17,411 gamblers in Table (1) at the account-week, account-month, or account level. The account-week level statistics report those for main variables related to outflows and inflows such as consumption, gambling bets, and wins, while the account-month level statistics show those for the variables that are available monthly. The account level statistics summarize personal characteristics such as age and gender. To keep anonymity, maximum and minimum values are not reported.

Both outflows and inflows contain a large share of zero-valued observations on a weekly basis, and thus, their medians are often zero at the account-week level. The mean consumption is 63 thousand JPY a week, while the mean gambling bets and wins are 7.1 thousand and 5.6 thousand JPY, respectively. Gambling participation indicates a dummy, which takes the value of one if a gambler bets in a week. The mean gambling participation is 0.52, indicating that 52% of individuals participate in gambles a week. As we discuss below, the distribution of gamblers is bimodal in terms of gambling intensity, where a large fraction of gamblers participate in gambles almost every week. The return rate, which is defined as the ratio of wins to bets, is 0.74 in its mean, which is consistent with the official figure discussed in Section 2.1. By contrast, the median return rate is much lower at 0.22, suggesting that gamble returns from public horse races have a fat right tailed distribution. The 100% loss and net win dummies take the value of one when a win is zero (positive bets and 100% loss) and when net wins are positive (wins > bets), respectively. The mean of the net win dummy is 0.2, suggesting that 80% of gamble brings a loss. Further, the fact that the mean of the loss all dummy is 0.4 suggests that 40% of gamble brings a complete loss of their bets.

At the account level, it is notable that male dominates in gambles, explaining a 94% share. The mean age is 60 years old, which suggests that gamblers in the data are more elderly than the nation-wide mean of 47 (as of 2020, National Institute of Population and Social Security Research). The proportion of gambling, which is selected to be smaller than 0.5, is 0.13 in its mean, whereas the frequency of gambling is 0.52 in its mean.

Figure 1 provides two illustrative facts on gambles. The left-hand panel shows time-series changes in the aggregated amount of gambling bets and wins over four years. It suggests seasonality, where gambles are active in Grade I races, and that gambles did not decrease but rather increase during the COVID-19 pandemic from 2020. The right-hand panel displays the distribution of the return rate. A large mass exists at the zero return, which suggests that approximately 40% of bets result in a 100% loss. Furthermore, there exists a small mass at the return rate of one, which happens when the horse that a gambler bets declares to be a non-starter.

The representativeness of the data (gamblers) is an important issue. Here we check representativeness by comparing basic characteristics between gamblers and non-gamblers. For the latter, we select residents in Chiba prefecture, neighboring prefecture to Tokyo, because original data are too large containing over 24 million individuals. We select Chiba residents who made at least one transaction at their Mizuho Bank accounts during the period from 4 March, 2019 to 25 March, 2019, and the number of individuals decreases to 3 million, which we believe still sufficient. Figure 2 illustrates the distribution for gamblers in our data and all residents in Chiba prefecture in terms of age, wealth, annual income, and weekly outflows, where we exclude the observations of zero for wealth and income.[19] The most notable difference is that gamblers in our data are more elderly than Chiba residents. The wealth of gamblers is slightly smaller than that of Chiba residents. Conversely, the income is slightly greater. The distribution of weekly

[19]The observations of zero are non-negligible. For annual income, they are 36,744 out of 47,818 for gamblers and 422,440 out of 901,268 for Chiba residents. For wealth, they are 3,668 out of 47,818 for gamblers and 37,992 out of 901,260 for Chiba residents.

outflows is similar between gamblers and Chiba residents.

3 Responses of Gambling Bets to Gambling Wins

3.1 Baseline Regression

We employ two-way fixed effects regression to estimate the causal effects of gambling wins on certain outcomes. The baseline regression equation is as follows:

$$Y_{it+\tau} = \beta_\tau win_{it} + \delta_{1\tau} bet_{it-1} + \delta_{2\tau} bet_{it-2} + \gamma_\tau Z_{it-1} + \alpha_i + \alpha_t + \varepsilon_{it}, \tag{1}$$

where Y_{it} represents an outcome variable (e.g., bets, gambling extensive and intensive margins, and consumption) for gambler i in week t; win_{it} represents gambling wins paid at the beginning of week t; bet_{it-1} represents gambling bets in week $t-1$; and Z_{it-1} represents the vector of control variables consisting of inflows minus wins, wealth, income, and borrowings, in week $t-1$. The unit is 10,000 JPY unless noted. The fixed effects are given by α_i and α_t, which represent gambler and week fixed effects, respectively. The standard errors are clustered at the individual level throughout this study.

It should be noted that gambling wins win_{it} are endogenous, depending on gambling bets in the previous week bet_{it-1}. Since the mean return rate is around 75%, win_{it} is not a purely unexpected income shock. Even a large amount of wins is not surprising to gamblers if they bet a large amount. Such endogeneity is particularly serious for gamblers who frequently participate in gambling. Therefore, it is vital to include bet_{it-1} as a control variable. Further, we add the controls of bets in week $t-2$ and inflows minus wins in week $t-1$, considering repeated gambles. Particularly, heavy gamblers often engage in repeated gambles.

Coefficient β_τ indicates the marginal propensities out of an unanticipated component in gambling wins. Further, the dynamic marginal propensities can be estimated by running the regression for each τ ($\tau = -12, -2, \cdots, 12$) using leading/lagging outcome variable, $Y_{it+\tau}$.

3.2 Estimation Results

In this subsection, we discuss the estimation results when the dependent variables are related to gambling bets. The next section discusses the estimation results when the dependent variable is related to consumption.

Column (1) in Table 2 shows the main estimation result of equation (1) for $\tau = 0$. The estimated coefficient β_0, the contemporaneous MPG, is positive and significantly different from zero at 0.075. This result suggests that gamblers spend 7.5% of the unexpected component of their gambling wins on bets in the same week. Column (2) of the table shows the estimation result when we do not control for bets (i.e., bet_{it-1}, bet_{it-2}, and inflows minus wins in week $t-1$). The adjusted R^2 decreases from 0.58 to 0.49, and the estimated coefficient of β_0 increases considerably from 0.075 to 0.26. This suggests that an endogeneity of gambling wins leads to an overestimation of the MPG, because $\delta_0^1 bet_{it-1}$ are positively correlated with win_{it} (i.e., wins are partially expected).

The dynamic MPG is estimated by estimating equation (1) for each τ. The left-hand panel of Figure 3 shows that β_τ decreases from 0.075 to zero gradually as week τ passes from 0 to 12. Thus, gambling wins have persistent effects on gambling bets over approximately three months. By contrast, β_τ tends to be insignificant when τ is negative. The figure also demonstrates that whether we control for bets makes a substantial difference in the MPG estimates. When bets are not controlled for, β_τ increases for a wide range of τ including negative τ, which suggests the possibility of highly persistent gambling and the invalidity of estimation without controlling for bets.

We run a similar regression by using different measures of gambling as the dependent variable. First, the dependent variable is a dummy of gambling participation, which takes the value of one when a gambler makes a positive bet in the week (i.e., extensive margin, EM). Column (3) of Table 2 shows that the coefficient on win_{it} is significantly positive, indicating that gamblers are more likely to participate in gambles, as their wins increase. Second, we focus particularly on gamble continuation. A dummy of gamble continuation takes the value of one when a gambler makes a positive bet this week and zero when a bet is zero this week, provided there was a positive bet in the previous week. If a bet is zero in the previous week, the value is recorded as NA. Note that this estimation gives greater weight to repeated gamblers because the data are an unbalanced panel with NA if they do not participate in gambles in the previous period. The coefficient on win_{it} in column (4) is positive, which indicates that gamblers are more likely to participate in gambles repeatedly, as their wins increase. Third, we use the change in the amount of bets from the latest one, conditional on bets being positive in both periods (i.e., intensive margin, IM). The coefficient on win_{it} in column (5) is positive at 0.07, which is similar to the estimated size of the MPG we obtained. Thus, these estimation results suggest that a larger amount of gambling wins induce gamblers to return to gambles sooner and to bet by a larger amount. The dynamic responses in the EM and IM are illustrated in the Online Appendix.

4 Responses of Consumption to Gambling Wins

Table 3 and the right-hand panel of Figure 3 show the estimation results for equation (1) when the dependent variable is now consumption, which is defined as outflows minus gambling bets. Column (1) in the table shows that the estimated coefficient β_0 for the contemporaneous MPC is positive and significantly different from zero at 0.35. Gamblers spend 35% of their gambling wins on consumption in the same week. The coefficient on bet_{it-1} is negative, and thus, coefficient β_0 decreases slightly from 0.35 to 0.33 when we do not control for bet_{it-1} as shown in column (2). In other words, an endogeneity of gambling wins leads to an underestimation of the MPC, albeit slightly.

The dynamic MPC is estimated for various τ. The right-hand panel of Figure 3 shows that gambling wins have transitory effects on consumption, in that β_τ is significant only for two weeks ($\tau = 0$ and 1). This persistence is substantially shorter than that documented by Fagereng et al. (2021) and Auclert et al. (2018), that is, around three years. The loss of persistence in the MPC has an implication for macroeconomic models, as emphasized by Auclert et al. (2018). This difference in persistence is partly attributed to whether gambling bets are controlled, because gambling wins have more persistent effects on consumption unless we control for bets. These estimation results suggest that once we control for bets, the MPC is transitory and simple two-agent heterogeneous models are sufficient to explain, which echoes Debortoli and Gali (2024) and Bilbiie (2024). We do not need computationally-intensive heterogeneous-agent models, although representative agent models cannot account for the significantly large MPC.

In columns (3) and (4) of Table 3, we provide the estimation results when we use alternative consumption measures as the dependent variable. One is cash withdrawals,[20] and the other is consumption excluding financial transactions associated with saving and investment, where we identify those financial transactions by filtering transactions whose remarks in Japanese contain specific keywords such as repayments and securities. The table shows that using cash withdrawals or consumption excluding saving-related outflows leads to the on-impact MPC at around 0.3, hardly changing our previous result.

[20] Cash withdrawals cover not only ATM withdrawals using cash and debit cards but also money transfers to cashless payment smartphone apps.

5 Heterogeneity in Responses of Gambling Bets and Consumption

Substantial heterogeneity exists among gamblers. Their gambling and consumption behaviors are likely very different between heavy and light gamblers.

5.1 Gambling Intensity

In Section 2.2, we introduced two kinds of measures of gambling intensity at the individual level: the proportion and frequency of gambling. Figure 4 shows their distributions.

For an illustrative purpose, we include heavy gamblers whose proportion of gambling is 0.5 or larger only in this section. The figure shows that the distributions are bimodal for both the proportion and frequency of gambling. On the one hand, there exist a considerable fraction of heavy gamblers who bet almost all of their income in gambling and participate in gambles almost every week. On the other hand, there are a mass of light gamblers. The distribution of the frequency of gambling hardly changes, even when we exclude heavy gamblers whose proportion of gambling is 0.5 or larger. In sum, this figure suggests that gamblers are divided into heavy and light gamblers.

5.2 Relations between MPG/MPC and Gambling Intensity

To investigate how the MPG and MPC changes depending on gambling intensity, we evenly divide gamblers by gambling intensity into several groups and run the regression of equation (1) to estimate the MPG and MPC for each group. Again, we expand our data to include heavy gamblers whose proportion of gambling is 0.5 or larger.

Figure 5 suggests the great stability of MPG and MPC estimates. The MPG and MPC are hardly different among gamblers whose gambling intensities are different. An exception is heavy gamblers whose proportion of gambling is larger than 0.75. As the proportion of gambling increases, the MPG tends to increase, while the MPC tends to decrease. However, this result is likely to be merely mechanical since these heavy gamblers use their Mizuho Bank accounts mostly for gambling.

The stable MPC is a comforting result for researchers to evaluate the MPC for non-gamblers. By construction, we cannot monitor gambling wins for non-gamblers; however, this result implies that the MPC of non-gamblers to gambling wins would be around 0.35, if they participated in gambles. When the dependent variable is the extensive margin of gambling, we find that the marginal propensity of gamble participation is substantially high for very light gamblers whose proportion of gambling is less than 0.1. This may indicate the process of novice gamblers falling into problem gambling after experiencing beginner's luck. See the Online Appendix.

5.3 Simple Model

What drives heterogeneity in the MPG and MPC? To consider the source of heterogeneity and investigate how it changes the MPG and MPC, we construct a simple model.

In the model environment, gamblers live for two periods. When young, they receive endowment y, consume c_1, and save for the future. Regarding saving, they can invest in the risk free asset by s or risky asset, which is gamble g. In addition, gamblers gain utility from gambling, denoted by $\kappa_i v(g)$. When old, they consume up all c_2. Gamblers, each denoted by i, are heterogeneous in terms of discount factor β_i and utility from gambling κ_i (and expectations on gambling wins denoted by θ_i^H or π_i^H).

A gambler i maximizes his expected utility:

$$V = u(c_1) + \kappa_i v(g) + \beta_i \mathbb{E}\left[u(c_2)\right] \tag{2}$$

subject to

$$c_1 + s + g = y \tag{3}$$

$$c_2 = Rs + \theta g \tag{4}$$

where $R \geq 1$ is risk free rate, which is deterministic, and $\theta \in [0, \infty)$ takes θ^H with the probability of π^H and θ^L with the probability of $\pi^L = 1 - \pi^H$, where $\theta^H > \theta^L \geq 0$. We assume $\theta^L/R - 1 < 0$, $\theta^H/R - 1 > 0$, and $\kappa_i \geq 0$.

Furthermore, we assume $u(c) = \log(c)$ and $v(x) = \log(x)$. Focusing on behaviors during young, we have the following properties:

1. The MPC equals $1/(1 + \beta_i + \kappa_i)$. It is decreasing in β_i and κ_i.

2. The MPG is non-negative. Specifically, the MPG is positive if $\kappa_i > 0$. Further if $\kappa_i > 0$ and the MPG $\ll 1$, then the MPG is increasing in κ and decreasing in β_i.

Note that the MPC (dc_1/dy) equals c_1/y in this simple model, whereas the MPG (dg/dy) equals g/y.

The above properties suggest the following three cases. First, suppose that heterogeneity in β_i dominates that in κ_i. Then, the MPC and the MPG are positively correlated. A gambler with high β_i (non-myopic) saves for the future, and thus, the MPC is low. The MPG is also low, because the expected return from gambling is lower than that from saving in the risk free asset. Second, suppose that heterogeneity in β_i is dominated by that in κ_i. Then, the MPC and MPG are negatively correlated. A gambler with high κ_i likes gamble, so that the MPC is low, while the MPG is high. Third, if other kinds of heterogeneity dominates, the MPC is constant. One may think a possibility that gamblers have an optimistic prospect about the possibility of gambling wins or a skill on gambling. In the model, this can be captured by heterogeneous π^H or θ^H, which changes only the MPG but not the MPC, because the MPC depends only on β_i and κ_i.

Thus, we can make a horse race on the source of heterogeneity (β_i or κ_i) by examining a correlation between the MPG and MPC. In Online Appendix, we show simulation results, where heterogeneity in β_i generates a positive correlation, whereas heterogeneity in κ_i generates a negative correlation. Further, we discuss the robustness of this result by extending the utility function from the logarithm to the constant elasticity of substitution (CES) and considering heterogeneity in β_i, κ_i, θ^H, and CES parameters.

5.4 Relations between MPG and MPC

In order to calculate a correlation between the MPG and MPC, we need a sufficient number of estimates of the MPG and MPC for different gambler groups. Thus, as in Section 5.2, we repeat the regression of equation (1) for 100 groups that are divided in terms of a bank account number (ID), the proportion of gambling, or the frequency of gambling. As in our benchmark specification, the heavy gamblers whose proportion of gambling is 0.5 or greater are excluded, and only significant estimates are shown.

Figure 6 shows the scatter plot of the estimated MPG and MPC. When grouping is based on the ID, the MPG and MPC exhibit a significantly negative correlation of -0.30 (p-value: 0.009). In other words, a gambler with a higher MPG is associated with a lower MPC. Based on the simple model, this estimation result suggests that heterogeneity in preference in gambles κ_i is key to explaining heterogeneity among gamblers, that is, gamblers are different because they have intrinsically different preferences in gambles. However, this result is not necessarily robust because, when grouping is based on the proportion and frequency of gambling, the MPG and MPC are insignificantly correlated at -0.04 and 0.09, respectively.

5.5 Relations between MPG/MPC and Liquidity

We end this subsection by examining other sources of heterogeneity than gambling intensity. Gambling literature emphasis gambling is a tool to financial constrained people (e.g., Herskowitz (2021)). The literature on the MPC points out the importance of liquidity to explain MPC heterogeneity, particularly, a large size of MPC for some liquidity-constrained individuals (e.g., HANK models, Fagereng et al. (2021), Ueda (2023)). We investigate this kind of heterogeneity by including an interaction term with wins as

$$Y_{it} = \beta_\tau win_{it} + \phi win_{it} \times X_{it-1} + \delta_1 bet_{it-1} + \delta_2 bet_{it-2} + \gamma_\tau Z_{it-1} + \alpha_i + \alpha_t + \varepsilon_{it}, \qquad (5)$$

where X_{it-1} represents that variables that can yield heterogeneous responses in the MPG and MPC, which is captured by coefficient ϕ. For X_{it-1}, we use wealth and the liquidity constraint dummy, where the latter takes the value of one when wealth is lower than monthly income.

Table 4 shows the estimation results. Starting from the MPC, columns (4) and (5) indicate significantly negative and positive coefficients ϕ when X_{it-1} is wealth and the liquidity constraint dummy, respectively. This suggests that liquidity-constrained individuals have a greater MPC in line with the existing literature. When both of the variables are included, ϕ is significant only for wealth (column (6)).

Turning to the MPG, columns (1) to (3) show that coefficient ϕ is all insignificant. In that regard, the amplitude of the MPG is irrelevant to whether gamblers are liquidity constrained or not. In Online Appendix, we find significant coefficients when the dependent variable is the extensive margin, suggesting that liquidity constrained gamblers are more likely to participate in gambles as their gambling wins increase.

6 Dependence of Bet and Consumption Responses on Past Gamble Outcomes

We have demonstrated variations in the marginal propensities in terms of individuals' heterogeneity such as gambling intensity and liquidity. In addition to this heterogeneity, the past performance of gambles (e.g., whether their net wins are positive) is likely to influence gamble and consumption decisions. In Online Appendix, we provide graphical associations between gambling bets/consumption and net wins.

6.1 Estimation with Past Gamble Outcomes

We investigate how the past performance of gambles influence gamblers' behaviors by adding several variables related to past gamble outcomes to equation (1). Specifically, we run the following regression:

$$\begin{aligned} Y_{it} &= \beta_0 win_{it} + BX_{it} \\ &\quad + \delta_{10} bet_{it-1} + \delta_{20} bet_{it-2} + \gamma_0 Z_{it-1} + \alpha_i + \alpha_t + \varepsilon_{it}, \end{aligned} \tag{6}$$

where X_{it} is the vector of variables, consisting of win_{it}^2, win_{it}^3, dummy of net wins, dummy of 100% loss, win_{it} times the dummy of net wins, and bet_{it-1} times the dummy of 100% loss. We explain the definitions and reasons of these variables.

Literature on problem gambling often concludes that gambling wins induce problem gambling through the big win effect and loss chasing effect.[21] To examine the big win effect, which may be more appropriate to call the income effect in economics, we include the higher-order terms of gambling wins: win_{it}^2 and win_{it}^3. This indicates the sensitivity of the MPG and MPC to the size of income shocks.

To capture the loss chasing effect, we distinguish whether net wins are positive or negative and also consider whether gamblers win nothing, by creating the following two dummies. First, a net win dummy takes the value of one if gambling wins exceed gambling bets ($win_{it} > bet_{it-1}$). Even if gamblers receive positive wins, they may lose in total if they bet a lot (negative net wins). Thus, investigating the difference in behaviors between the cases of positive and negative net wins is informative for analyzing the so-called loss chasing effect. Further, the case of zero net win is related to so-called the break even effect. Second, we define a 100% loss dummy, which takes the value of one if gambling bets are positive and wins are zero ($bet_{it-1} > 0$ and $win_t = 0$). By construction, we cannot calculate the MPG and MPC in this case, but how this 100% loss affects gamble and consumption in the next week is of interest.

Table 5 shows the estimation results. Because they are a little complicated, we graphically illustrate hypothetical responses of bets and consumption. We calculate a

[21] Others popular topics include hot-hand and gambler's fallacy, but our data do not allow us to analyze these topics.

change in a dependent variable (shown in the vertical axis) as follows. Suppose a certain value for net wins (shown in the horizontal axis) and bets. For bets, we set 0.01, 0.5, or 1 in 10,000 JPY. Then, we can calculate wins as net wins plus bets, and also the net win dummy and the 100% loss dummy. Note that wins must be non-negative, so that net wins must be equal to or greater than minus bets. Then, we can simulate the value of a dependent variable for each net wins and bets based on the estimation results shown in Table 5. We apply the estimated coefficients to the simulations, irrespective of whether they are significant or not; however, this hardly affects our simulation results.

Figure 7 shows the simulation results, indicating a discontinuity at the zero net win. First, let us examine gambling bets. They increase as net wins increase, when net wins are positive, consistent with the positive MPG we observed. Notably, when net wins are negative, bets do not increase even as wins (net wins) rise (although there is a negative slope, it is insignificant). When net wins marginally increase from negative to positive, bets jump discontinuously because the coefficient on $bet_{t-1}\times$net win dummy is positive. Consequently, the response of bets exhibit a U-shape, with the lowest point at zero net win. Loss chasing behavior is not observed, as negative net wins lead to decreased subsequent bets.

Second, for consumption, there is again a discontinuity at the zero net win, but in the opposite direction. Consumption increases as net wins increase, consistent with the positive MPC. This increase is observed for both positive and negative net wins. However, when net wins marginally increase from negative to positive, consumption drops discontinuously because the coefficient on the net win dummy is negative. This suggests that gamblers choose further gambling rather than consumption when they win marginally, while the opposite is true when they lose marginally, opting for consumption rather than gambling. Another interesting observation is the case where gamblers experience a 100% loss. Consumption jumps when they bet 10,000 JPY and win nothing, while a jump is not observed with smaller bets. This arises because the coefficient on $bet_{t-1}\times$100% loss dummy is positive, while the coefficient on the 100% loss dummy is negative. This result may suggest that gamblers engage in leisure (e.g., drinks) to cope with their loss when they win nothing.

For gambling bets, we examine their responses more deeply by using the extensive and intensive margins as the dependent variable. In line with the responses of bets, the extensive margin also exhibits a discontinuity at the zero net win. The likelihood of gambles jumps when net wins marginally increase from negative to positive. What is distinct from the responses of bets is a sign of loss chasing. When gamblers experience a 100% loss, the likelihood of gambles increases to almost the same level of gamblers who made positive net wins. Meanwhile, the response of the intensive margin is similar to that of bets.

The impact of large wins or income effects appears to be moderate. Figure 7 demonstrates no clear convexity or concavity with respect to net wins. According to Table 5, the coefficient on win_t^2 is significantly positive for only consumption, indicating that gamblers tend to increase the MPC as wins increase.

6.2 Sub-group Estimation

To understand gamblers' behavior from a different perspective, we run the following regression:

$$\begin{aligned} Y_{it} = \beta_0 win_{it} &+ \sum_j \beta_0^j win_{it} \times I_{jt} \\ &+ \delta_{10} bet_{it-1} + \delta_{20} bet_{it-2} + \gamma_0 Z_{it-1} + \alpha_i + \alpha_t + \varepsilon_{it}, \end{aligned} \tag{7}$$

where I_{jt} is a dummy which takes one for a specific subsample j. A subsample is selected based on the value of the amount of net wins. The number of observations for each subsample is approximately the same at 50,000. A base is set at the highest subsample for net wins, and thus, a positive β_0^j means that the MPG or MPC for subsample j is greater than that for the base. Note that we run one regression for different subsample j, rather than running separate regression, because we want to impose the same gamblers and time periods to have the same fixed effect α_i and α_t, respectively. Another note is that while this estimation reveals variations in the MPG and MPC, the previous analysis presented in Figure 7 demonstrates how the levels of bets and consumption fluctuate.

Figure 8 shows the estimation results. We find that β_0^j for the MPG becomes discontinuously negative when net wins turn from positive to negative. This suggests that the MPG jumps up when gamblers make net wins, which is consistent with the previous result and opposite to the loss chasing effect.

Regarding consumption, β_0^j for the MPC does not appear to have discontinuity around zero net wins. The MPC has a V-shaped pattern, suggesting that the smallest MPC when net wins are around zero. As net wins increase, the MPC increases, which implies a positive big win effect on the MPC.

7 Are Gamblers Special?

Our study is, by construction, limited to gamblers. A natural question that arises is to what degree our study can be generalized to non-gamblers.

Gamblers are, by no means, representative. As we saw in Section 2.3, gamblers are mostly male and tend to be elderly. However, the analysis in Section 5.2 suggests the possibility that non-gamblers, who are interpreted as the limit of individuals with gambling intensity converging to zero, are similar to light gamblers in terms of the MPC. Nonetheless, this possibility is only a conjecture. A discontinuity may exist between non-gamblers and light gamblers. Thus, we compare the MPC between gamblers and non-gamblers.

Because non-gamblers do not receive gambling wins, we need to find an alternative income shock, which is salient, transient, and unexpected. Such an ideal income shock occurs in 2020. During the COVID-19 pandemic, the government in Japan launched the SCP, providing 100,000 JPY per person. As studied in Kubota et al. (2021) and Ueda (2023), the timing of SCP is diverse across weeks and municipalities, which helps identify the SCP income shock from aggregate shocks by including week and individual fixed effects.

We focus on residents in Chiba prefecture who received the SCP. We compare the MPC between gamblers and Chiba residents (mostly non-gamblers) by estimating the following equation:

$$\begin{aligned}
Y_{it} = \beta_0 win_{it} &+ \delta_{10} bet_{it-1} + \delta_{20} bet_{it-2} \\
&+ \psi_{SCP} SCP_{it} + \chi_{SCP} SCP_{it} \times Dummy(gamblers)_i \\
&+ \gamma_0 Z_{it-1} + \alpha_i + \alpha_t + \varepsilon_{it},
\end{aligned} \tag{8}$$

where ψ_{SCP} and χ_{SCP} represent the MPC to SCP payments and its difference between gamblers and non-gamblers, respectively.

Table 6 shows the estimation results. In the first column, χ_{SCP} is significantly positive at 0.083, suggesting that the MPC of gamblers is 8.3% higher than that of non-gamblers.

However, it should be noted that the MPC is heterogeneous in many aspects. Specifically, age and wealth distributions, which are different between gamblers and non-gamblers, likely make χ_{SCP} deviate from zero. Thus, we make a propensity score matching based on age, wealth, income, and the number of active weeks during the observation period.

The second column in Table 6 shows that χ_{SCP} is insignificant, suggesting that the MPC of gamblers is of a similar size to that of non-gamblers. Thus, gamblers are not special in terms of the MPC. Furthermore, the table shows that the MPC to the SCP, ψ_{SCP}, is 0.27, whereas the MPC to gambling wins, which is estimated only for gamblers, is 0.28. Thus, the source of income shocks, either the SCP or gambling wins, does not appear to matter for the amplitude of the MPC.

Our data consist of light gamblers. If we include heavy gamblers whose proportion of gambling exceeds 0.5, the results may change. What this estimation result shows is that light gamblers are not much different from non-gamblers in terms of the MPC.

8 Concluding Remarks

We studied gamblers' bet and consumption responses to their wins and documented a number of results indicating that gamblers increase their bets and consumption significantly. In concluding this study, we would like to discuss what our estimation results imply for problem gambling. Particularly, our analysis in Section 6 suggests that gamblers are inclined to engage more in gambling as their wins increase, both in gross and net terms. This tendency reflects a pattern of easy gains and difficulty in quitting. While this could signal a potential risk for problem gambling, it is likely not a major concern since increased gambling engagement occurs predominantly when net wins are positive. Except for the extensive margin, our estimation results provide evidence against loss-chasing behavior.

One important agenda for the future work is the cause and consequence of problem gambling in a longer run. For this question, we need to expand the data to analyze more gamblers whose proportion of gambling is 0.5 or higher and who engage in gambles other than public horse races. Although a sharp causal inference is likely to be difficult, it would be valuable to document facts on problem gambling.

Another direction is to examine other gambles, particularly, a lottery and other three types of public races. How different are these gambles compared from JRA central horse racing? How do gamblers substitute or complement these different types of gambles? These questions are worth studying in the future.

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Table 1: Descriptive Statistics on Gamblers

	10%	25%	50%	75%	90%	mean	SD
			Account-Week Observations Sample size: 3,551,844				
Consumption	0	0	0.700	5.716	16.462	6.305	21
Consumption exc FT	0	0	0.300	4	12.900	5.158	20
Gambling participation dummy	0	0	1	1	1	0.518	0.500
Continue dummy	0	0	0	1	1	0.442	0.500
Stop dummy	0	0	0	0	0	0.077	0.270
Gambling bets	0	0	0.040	0.600	1.830	0.705	2.400
Gambling wins	0	0	0	0.133	1.204	0.564	4
Net Outcome	-0.900	-0.260	0	0	0.003	-0.150	2
Return ratio	0	0	0.223	0.844	1.592	0.736	4.300
Interval between bets	1	1	1	1	2	1.656	3.600
100% loss dummy	0	0	0	1	1	0.429	0.490
Net win dummy	0	0	0	0	1	0.195	0.400
			Account-Month Observations Sample size: 295,987				
Wealth	0.300	4.600	39.900	239.200	801.500	272.410	680
Borrowing	0	0	0	0	29.900	87.780	410
Annual income	0	0	116	441.500	618.500	248.764	880
LC	0	0	0	0	0	0.077	0.270
			Account Observations Sample size: 17,411				
Age	43	48	58	69	75	58.480	12
Proportion of gambling	0.003	0.015	0.071	0.217	0.374	0.131	0.140
Frequency og gambling	0.054	0.177	0.502	0.887	0.985	0.521	0.350
Gender		Male:	16,335	94%	Female:	1,076	6%

Notes: The unit is 10,000 JPY. Consumption exc FT represents consumption excluding financial transactions associated with saving and investment. 100% loss and net win dummies take the value of one when a win is zero and net wins are positive (wins > bets), respectively.

Table 2: Estimation of the MPG

	Dependent variable:				
	Bets		EM	EM (Continue)	IM
	(1)	(2)	(3)	(4)	(5)
Win_t	0.075***	0.258***	0.002***	0.002***	0.068***
	(0.005)	(0.014)	(0.0003)	(0.0003)	(0.005)
Bet_{t-1}	0.333***		0.019***	0.018***	−0.651***
	(0.013)		(0.001)	(0.001)	(0.014)
Observations	3,545,303	3,562,773	3,545,303	2,098,627	2,070,597
Adjusted R^2	0.584	0.488	0.531	0.359	0.276
Time fixed effect	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes
Bet Controls	Yes	No	Yes	Yes	Yes
Yes					

Notes: Bet control variables are bet_{t-1}, bet_{t-2}, and $inflow_{t-1}$. Other control variables are wealth, borrowings, and annual income. The dependent variable for the extensive margin (EM) is a dummy of gambling participation. That for the EM (continue) is a dummy of gambler repeat gambling participation. That for the intensive margin (IM) is the change in the amount of bets from the latest one, conditional on bets being positive in both periods. *p<0.1; **p<0.05; ***p<0.01

Table 3: Estimation of the MPC

	Dependent variable:			
	Consumption		Cash withdrawals	Consumption exc fin transfers
Win_t	0.354***	0.329***	0.300***	0.349***
	(0.016)	(0.015)	(0.014)	(0.017)
Bet_{t-1}	−0.120***		−0.162***	−0.126***
	(0.029)		(0.019)	(0.029)
Observations	3,533,125	3,550,535	3,533,125	3,533,125
Adjusted R^2	0.155	0.146	0.196	0.137
Bet Controls	Yes	No	Yes	Yes

Notes: Bet control variables are bet_{t-1}, bet_{t-2}, and $inflow_{t-1}$. Other control variables are wealth, borrowings, and annual income. Consumption is defined as the sum of outflow transactions with gambling bets excluded. "Consumption exc fin transfers" is consumption excluding financial transfers related to saving (repayments) and investment. *p<0.1; **p<0.05; ***p<0.01

Table 4: MPG/MPC and Liquidity Constraint

	Dependent variable:					
	Bets			Consumption		
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity constraint dummy		-0.084^{***}	-0.083^{***}		-1.633^{***}	-1.612^{***}
		(0.016)	(0.016)		(0.110)	(0.112)
Its cross term		-0.007	-0.009		0.067^{**}	0.042
		(0.012)	(0.012)		(0.027)	(0.028)
Wealth	0.0001^{***}	0.0001^{***}	0.0001^{***}	0.007^{***}	0.007^{***}	0.007^{***}
	(0.00003)	(0.00002)	(0.00003)	(0.001)	(0.001)	(0.001)
Its cross term	-0.00000		-0.00000	-0.0001^{***}		-0.0001^{**}
	(0.00001)		(0.00001)	(0.00002)		(0.00002)
Observations	3,533,125					
Adjusted R^2	0.584	0.584	0.584	0.155	0.155	0.155

Notes: Bet control variables are bet_{t-1}, bet_{t-2}, and $inflow_{t-1}$. Other control variables are borrowings, and annual income. The liquidity constraint dummy is defined as a dummy that takes the value of one when wealth is lower than monthly income. *p<0.1; **p<0.05; ***p<0.01

Table 5: MPG and MPC Dependence on Past Gamble Outcomes

	Dependent variable:				
	Bets	EM	EM (Continue)	IM	C
	(1)	(2)	(3)	(4)	(5)
Win	−0.013	0.022***	0.020***	−0.024	0.233***
	(0.027)	(0.001)	(0.001)	(0.029)	(0.047)
Bet_{t-1}	0.384***	0.017***	0.019***	−0.650***	−0.122***
	(0.017)	(0.001)	(0.001)	(0.018)	(0.038)
Bet_{t-2}	0.222***	0.010***	0.003***	0.192***	0.082***
	(0.010)	(0.001)	(0.001)	(0.013)	(0.023)
Win^2	−0.001	−0.0005***	−0.0004***	−0.0003	0.002***
	(0.001)	(0.00002)	(0.00002)	(0.001)	(0.001)
Win^3	0.00000	0.00000***	0.00000***	−0.00000	−0.00001
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Dum:100%Loss	0.033*	0.191***	0.206***	0.006	−0.136***
	(0.017)	(0.002)	(0.002)	(0.028)	(0.045)
Dum:NetWin	0.027	0.205***	0.208***	−0.021	−0.368***
	(0.027)	(0.003)	(0.003)	(0.034)	(0.056)
Win×Dum:NetWin	0.111***	−0.007***	−0.008***	0.113***	0.043
	(0.019)	(0.001)	(0.001)	(0.020)	(0.033)
Bet_{t-1}×Dum:100%Loss	−0.036	−0.002	−0.003**	0.003	0.347***
	(0.034)	(0.002)	(0.001)	(0.038)	(0.062)
Observations	3,533,529	3,533,529	2,098,627	1,813,815	3,533,529
Adjusted R^2	0.586	0.556	0.407	0.306	0.155

Notes: *p<0.1; **p<0.05; ***p<0.01

Table 6: MPC Comparison between Gamblers and Non-Gamblers

	Dependent variable:	
	Consumption	
	Whole	Matched
Wins	0.279***	0.276***
	(0.031)	(0.030)
SCP	0.225***	0.265***
	(0.005)	(0.022)
SCP × Is Gambler	0.083***	0.042
	(0.016)	(0.026)
Observations	46,673,454	2,510,035
Adjusted R^2	0.055	0.113

Notes: SCP represents the special cash program that paid 100,000 JPY per person during the COVID-19 pandemic. "Matched" is selected Chiba residents who have similar personal profile. "Is Gambler" is a dummy that takes the value of one for gamblers. *p<0.1; **p<0.05; ***p<0.01.

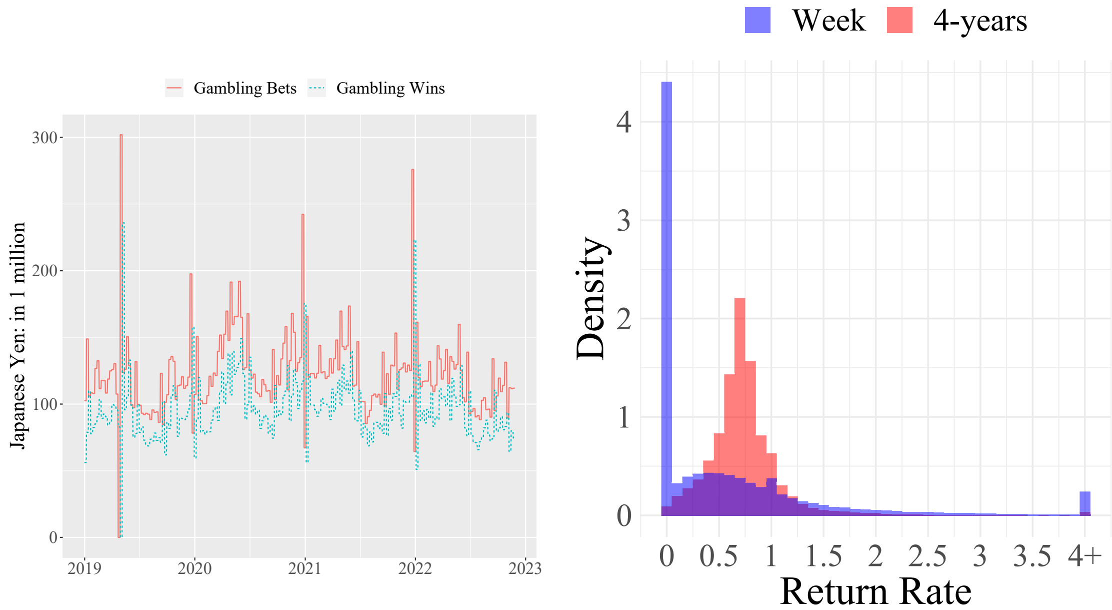

Figure 1: Facts on Central Horse Race Gamble

Note: The return rate is defined as the ratio of (ex post) wins to bets, when bets are positive.

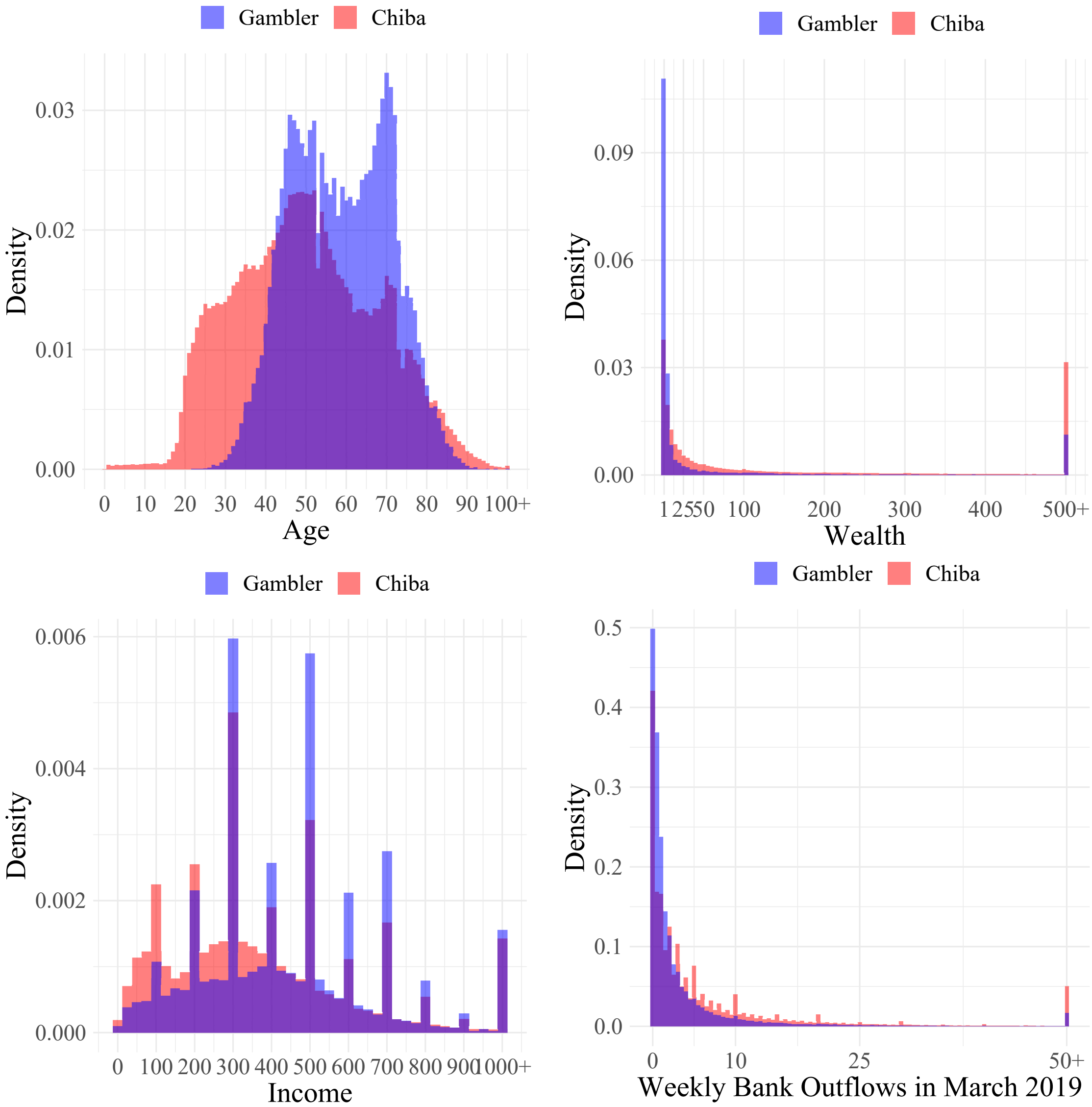

Figure 2: Comparisons of Gamblers and Non-Gamblers (Chiba Residents)

Note: Wealth, income, and weekly outflows are in 10,000 JPY. Zero observations are excluded for wealth and income.

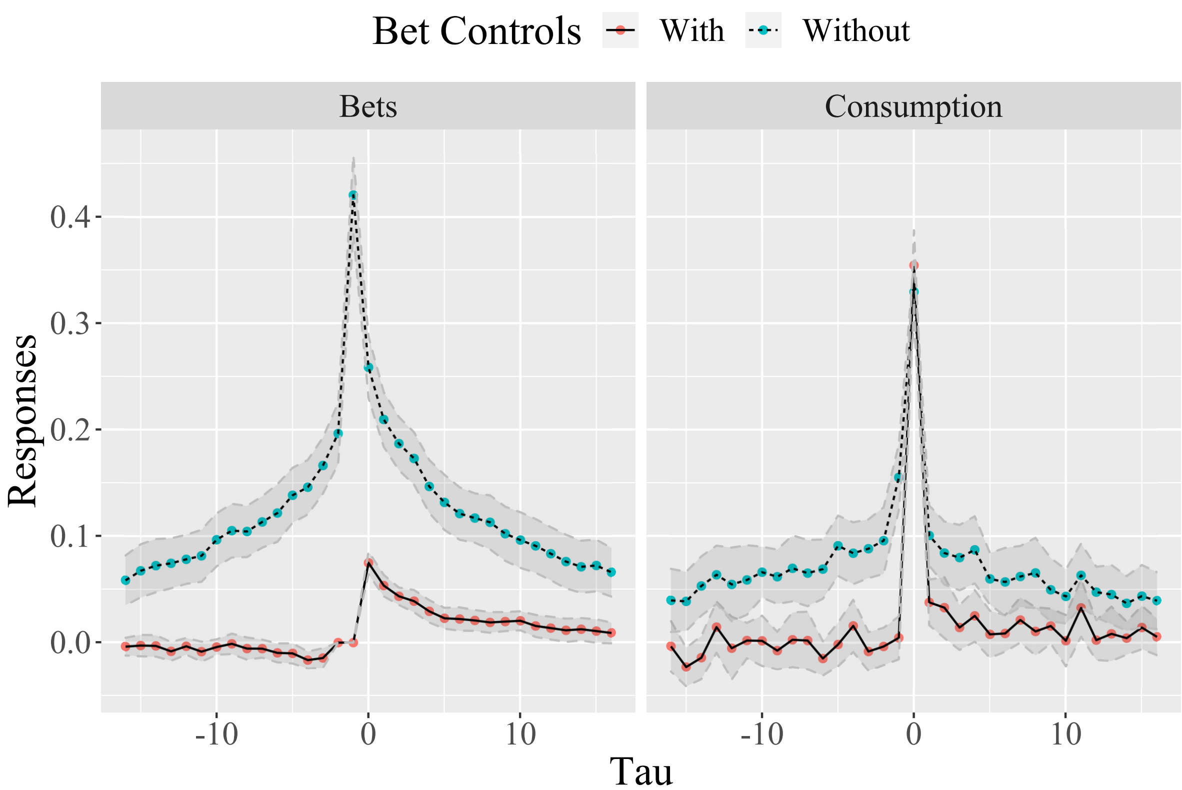

Figure 3: Dynamic Responses of Gambling Bets and Consumption

Note: Estimated coefficients on wins, β_τ, are displayed for $\tau = -12, -11, \cdots, 12$.

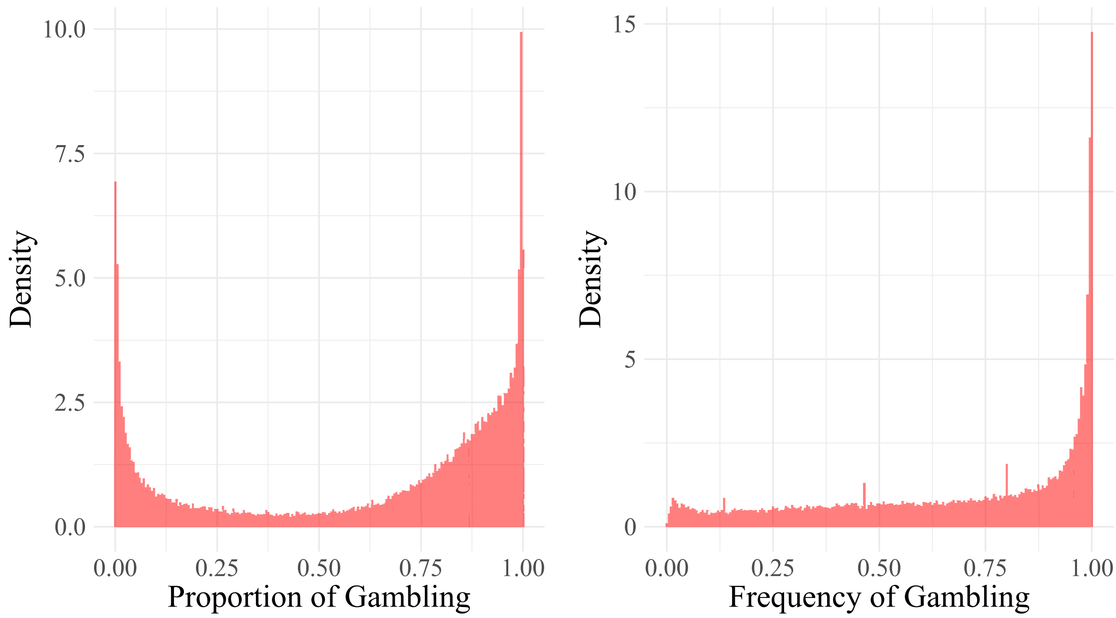

Figure 4: Distribution of Gambling Intensity

Note: The proportion of gambling is defined as the fraction of the sum of gambling bets to the sum of outflows including bets in our observation periods. The frequency of gambling is defined as the fraction of the number of weeks with positive bets to the total number of weeks. For an illustrative purpose, we include heavy gamblers whose proportion of gambling is 0.5 or larger.

Figure 5: MPG and MPC by Gambling Intensity

Note: We estimate the MPG and MPC for each group which is divided based on the proportion of gambling (top) or the frequency of gambling (bottom). The horizontal axis is the gambling intensity (the proportion or frequency of gambling), while the vertical axis is the MPG or MPC. We include heavy gamblers whose proportion of gambling is 0.5 or larger.

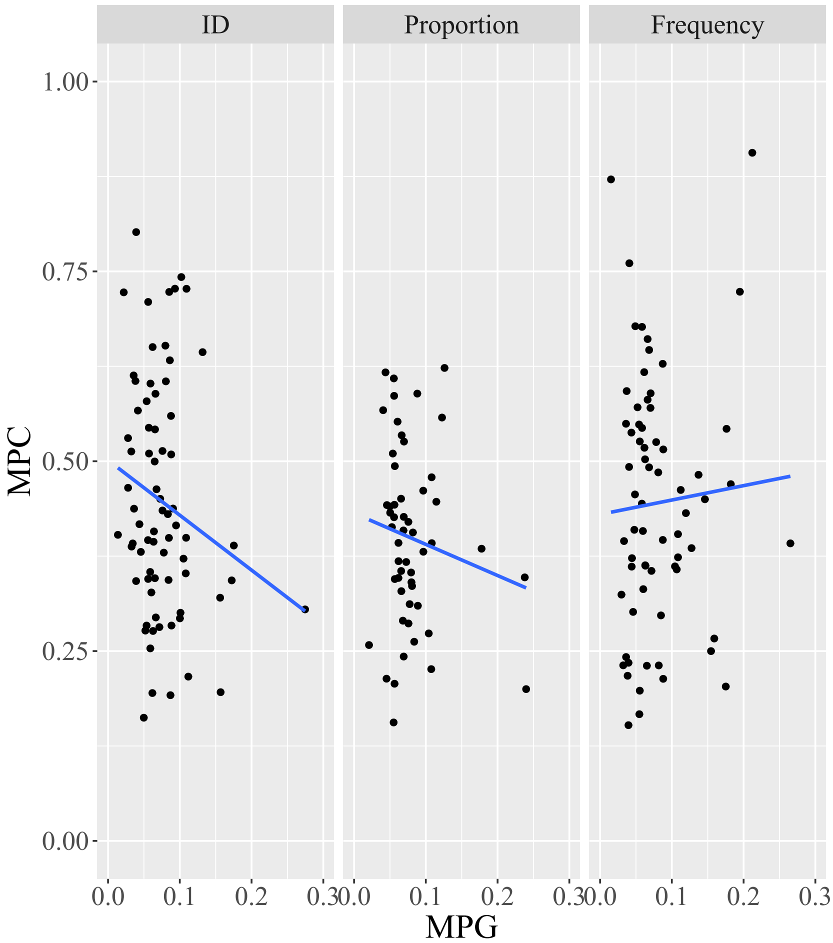

Figure 6: MPG and MPC Based on the Data

Note: The MPG and MPC are estimated by groups, which are divided based on the account number (ID, left), the proportion of gambling (middle), and the frequency of gambling (right). Only significant estimates are plotted.

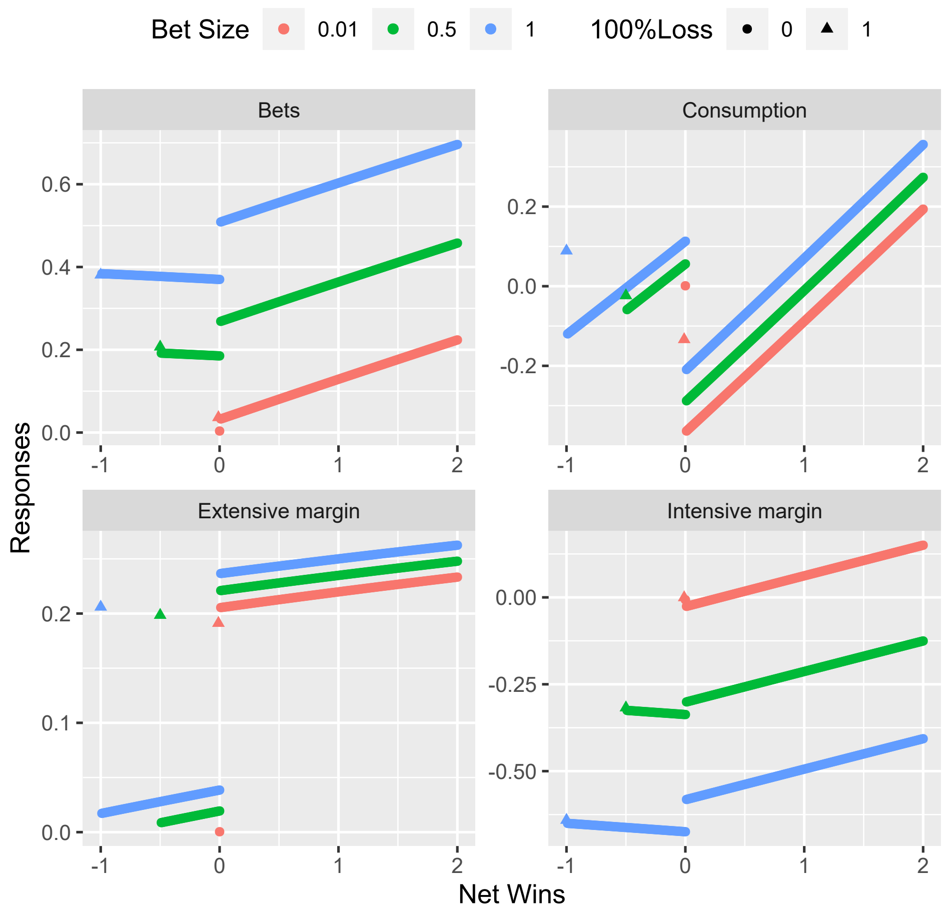

Figure 7: Simulated Bets and Consumption Based on Estimation Results

Note: We simulate the amount of bets, that of consumption, the extensive margin, and the intensive margin from the estimation results for each value of net wins and bets. The unit is 10,000 JPY for bets, consumption, bets, and net wins. The point of 100% loss indicates the case in which wins are zero and net wins equal minus bets.

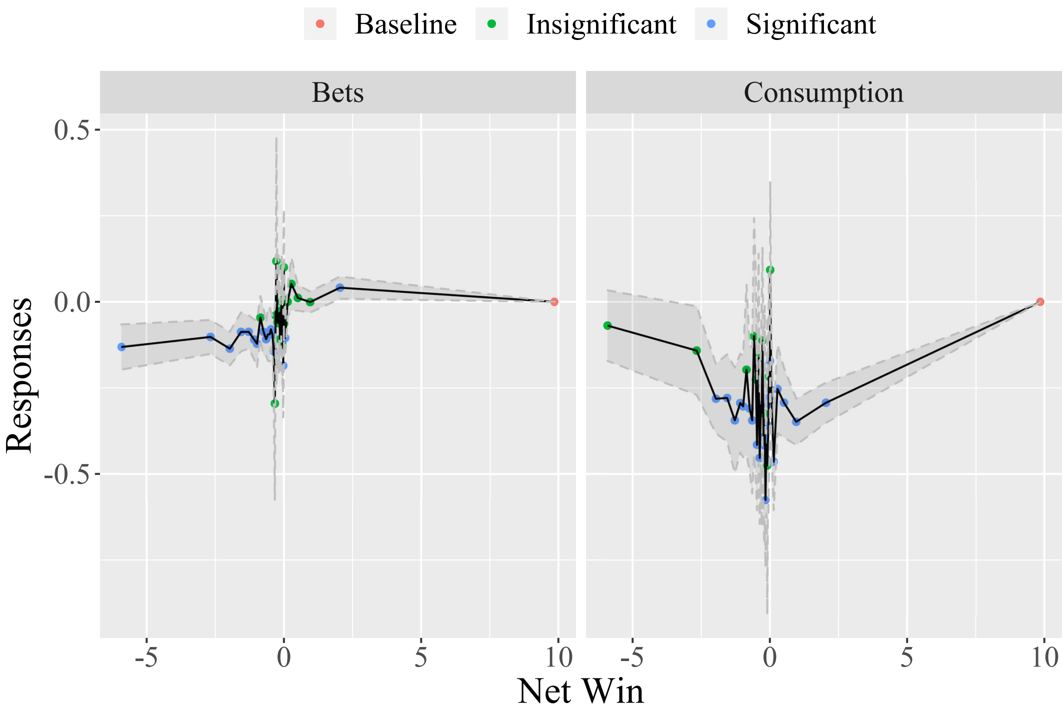

Figure 8: MPG and MPC Dependence on Net Wins

Note: The figure shows the difference of the MPG/MPC compared with its base shown in the red circle.