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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 receiving gambling wins. We use novel bank transaction data from Japan, which contain information on both gambling bets and wins from public horse races with precise timelines. The estimation results reveal a positive marginal propensity to gamble (MPG) and consume (MPC) immediately following a win, although these effects dissipate within 12 weeks. Despite considerable heterogeneity in gambling intensity, the MPG and MPC remain stable. Light gamblers display no significant difference from non-gamblers in their MPC for government transfers in 2020. While liquidity constraints influence the MPC, they have no impact on the MPG. Moreover, we find little evidence supporting the loss-chasing effect, as gamblers increase bets when they are net winners.

JEL Classification Number: E21, D12, G51, L83, E64
Keywords: income shock; problem gambling; marginal propensity to consume; heterogeneity

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1 Introduction

Many individuals engage in gambling activities,[1] where gamble outcomes, particularly wins and losses, can significantly influence behavior. While some windfall income might be allocated to everyday expenses, large or no gambling wins may trigger addictive behaviors and disorders, commonly known as problem gambling. The social costs of problem gambling extend beyond treatment and correctional expenses, contributing to broader negative externalities such as increased crime and poverty. Further, 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. Despite its significance, 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." A key barrier to conducting rigorous empirical studies is the lack of data that capture both gambling bets and wins.

In this study, we investigate how gamblers respond to gross gambling wins, focusing on public horse races and using novel bank account transaction data from Japan.[2] The data, provided by Mizuho Bank, one of Japan's major banks, include actual transaction records related to gambling bets on a weekly basis. This unique dataset allows us to analyze changes in both gambling bets and consumption, referred to as the marginal propensity to gamble (MPG) and MPC, respectively, in response to the surprising component of gambling wins. We estimate the dynamic MPG and MPC over several weeks following the wins, offering new evidence that gambling wins can trigger repeated gambling behavior.

The bank account transaction data enable us to track individual inflows and outflows, including detailed gambling activities (the amount of wins and bets) at a weekly frequency. The benefits of our data and identification strategy cannot be overstated. By

[1]Gambling includes lotteries, public races, poker, slot machines, and various other games. In Japan, the gross revenue from gambling in 2019 amounts to 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), representing 2% of nominal GDP. In the U.S., the gross revenue from gambling, 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 define "wins" as gross earnings from bets, and "net wins" as profits from gambling, calculated as wins minus bets.

observing gambling bets, we can isolate the unexpected component of gambling wins, as bets and wins typically exhibit a proportional relationship. A distinct advantage lies in the system of online gambling for public horse races in Japan, which allows for precise identification of unexpected gambling wins. Specifically, during weekends when races occur, the bank temporarily restricts gamblers' accounts for non-gambling transactions, limiting use to online betting. By Monday morning, all gambling wins are automatically credited to their bank accounts. Thus, by setting the weekly time frequency where each week starts on Monday, the sequence of transactions is clear: 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 uncovers significant heterogeneity in gambling intensity, both in terms of the frequency and amount of gambling behavior. To accurately assess these heterogeneity, it is essential to track the individual gambling bets. We establish a balanced panel on a weekly basis over a four-year period (2019–2022), including 17,000 gamblers.

In this study, we address five key questions. The first question is how gamblers adjust their gambling bets in response to wins (MPG). We use a two-way fixed effect regression model where the dependent variable is the amount gambled (bets), and the main explanatory variable is the amount won (wins). Importantly, we control for previous weeks' bets to ensure that gambling wins are treated as an unexpected income shock. The estimation reveals that the on-impact MPG is 0.075, suggesting that gamble winners reinvest 7.5% of the unexpected component of their wins into further gambling within a week. If we exclude the control for previous bets, the on-impact MPG increases to 0.26, confirming the importance of accounting for prior betting behavior. Additionally, the effect of gambling wins on bets persists for up to three months, suggesting that the influence of wins on subsequent gambling behavior is both immediate and relatively long-lasting. Beyond the magnitude of bets, our analysis also investigates the extensive margin of gambling, showing that winning increases the likelihood of gamblers continuing to participate in future gambling activities. As their wins increase, gamblers are not only betting more but are also more likely to maintain their engagement in gambling.

Second, we estimate consumption responses, the MPC, where consumption is defined as transaction outflows excluding bets. A two-way fixed effect regression reveals that the on-impact MPC is 0.35, suggesting that gamble winners spend 35% of their wins on consumption within the first week. However, unlike the MPG, the MPC is less persistent, with the effect disappearing within a month. This short persistence contrasts sharply with the findings of Fagereng et al. (2021) and Auclert et al. (2018), who document a more sustained consumption response lasting around three years. The low persistence observed in our study suggests that simple two-agent heterogeneous models may adequately capture consumption dynamics, which echos Debortoli and Gali (2024) and Bilbiie (2024). We do not need to resort to computationally-intensive heterogeneous-agent models, although representative agent models remain insufficient to explain the significantly large MPC.

Third, we explore the heterogeneity among gamblers. Our study reveals substantial heterogeneity among gamblers in terms of their gambling intensity, which is defined by the frequency and proportion of gambling. While some individuals gamble every week and/or allocate nearly all their income to gambling, others engage in gambling only sporadically. Despite this substantial variation, the estimated MPG and MPC remain relatively stable across most gamblers, with notable exceptions for extremely heavy gamblers. The MPG and MPC are weakly negatively correlated, suggesting that gambling preferences may play a role in these behaviors according to simple economic models. Furthermore, we confirm that liquidity matters for the MPC, in line with many empirical studies such as Fagereng et al. (2021) and Ueda (2023). In contrast, we find that the MPG appears unrelated to liquidity, which contrasts with the findings of Brunk (1981) and Herskowitz (2021).

Fourth, we examine how gambling and consumption responses are influenced by past gambling outcomes. Our primary goal is to understand what factors contribute to problem gambling. We find that net positive wins (i.e., when wins exceed bets) lead to a discontinuous increase in gambling activity while decreasing consumption. This result is contrary to the so-called loss-chasing effect, where net negative wins typically drive increased gambling. Additionally, when gamblers experience no wins, there is a notable increase in consumption, suggesting a shift of spending to other leisure activities such as drinking and dining out. Furthermore, we observe a big win effect on consumption: the MPC increases with the size of the wins. In contrast, no similar effect is detected for gambling bets.

The final question we investigate is whether gamblers are special, and whether our findings on the MPC can be generalized beyond gamblers (external validity). To explore this, we expand our sample to include both gamblers and non-gamblers. Our comparison reveals that gamblers are generally older and predominantly male. When we compare the MPC for a special cash payment (SCP) issued during the COVID-19 pandemic between gamblers and non-gamblers, controlling for their observed characteristics, we find no significant difference in the MPC. This indicates that while gamblers may differ from non-gamblers in terms of demographic factors such as age and gender, these differences do not translate into a significantly different MPC once these characteristics are controlled for.

Literature Review Problem gambling, also referred to as 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). The increasing prevalence of gambling and problem gambling has been highlighted by various sources, including Science (1998), Science (2005), Abbott (2017) in World Health Organization, and Nature (2018). Despite the growing concern, studies on gambling remain relatively few and underfunded, as noted by Nature (2018).[3] Nature (2018) also highlights a concern regarding the distortion of funding within the gambling industry, which may result in biased research outcomes and policy recommendations.

One important area of research on gambling involves how gambling decisions are made, in which gambling is analyzed as one type of investment under risk and uncertainty.[4] See, for example, Friedman and Savage (1948), Kwang (1965), Rosett (1965), and Hartley and Farrell (2002). Prospect theory, developed by Kahneman and Tversky (1979), offers a framework for understanding asymmetric gambling decisions around a reference point (see also Kumar (2009), Snowberg and Wolfers (2010), and Chen et al. (2021)). Kumar (2009) examines how gambling decisions are correlated with investment decisions in the stock market.

In the context of how past gambling outcomes influence future gambling decisions, the literature identifies several key effects: break even, big win, and loss chasing effects. The break even effect, as discussed by Lien and Zheng (2015), shows that gamblers prefer to stop when they reach a break-even point, avoiding further losses. Edson et al.

[3]Nonetheless, there is a substantial body of work covering diverse topics from economic, social, and medical perspectives. Calado and Griffiths (2016) offer a meta analysis of problem gambling research from 69 empirical studies worldwide. They identify key issues in these studies, including the challenges of measuring problem gambling and the determinants influencing it, such as income, cultural factors, types of gambling, and demographics. The consequences of problem gambling are investigated, for example, by Muggleton et al. (2021) from an economic, social, and health perspective. Eadington (1999) examines economic characteristics of the casino industry.

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

(2023) identify the big win effect, where significant gambling wins lead to increased gambling, often followed by future losses. Chen et al. (2022) describe the loss chasing effect, where gamblers intensify their gambling after losses, while Kainulainen (2021) finds that gamblers might abstain from betting after losses. However, these studies typically cover short time frames, often within a day. In contrast, this study spans four years, examining gambling decisions on a weekly basis, which helps control for individual time-invariant characteristics and provides a more comprehensive view of gambling behavior over time.

Conversely, there is literature in the opposite direction, that is, how gambling wins influence economic decisions beyond gambling, such as consumption and labor supply. For example, Imbens et al. (2001) explore the effects of lottery wins on earnings, consumption, and savings using a lottery survey from Massachusetts. Kuhn et al. (2011) analyze interactions between lottery winners and their neighbors through a Danish postcode lottery survey. Fagereng et al. (2021) study the MPC from lottery wins using Norwegian tax records, finding that the effect on consumption persists for about five years. Cesarini et al. (2016) and Cesarini et al. (2017) use Swedish administrative data to examine the effects of lottery wins on health and labor supply. Golosov et al. (2021a) investigate the influence of lottery wins on labor earnings with U.S. administrative data. These studies contribute to economic models on static and dynamic optimization, including HANK models.

Previous empirical studies on gambles generally rely on three types of data: surveys, data from gambling agencies, and administrative data. First, surveys, such as telephone or face-to-face interviews, are the most common and provide direct measures of gambling behavior. However, these studies often face challenges like small sample sizes and reliability issues, as self-reported data can be inaccurate due to memory biases (Calado and Griffiths (2016), Imbens et al. (2001), Kuhn et al. (2011), Auer et al. (2023)). Second, data from gambling agencies are frequently used to study gambling decisions and behaviors (Snowberg and Wolfers (2010), Kumar (2009), Lien and Zheng (2015), Kainulainen (2021)). While these data are useful, they often suffer from distortions caused by the gambling industry and are challenging to link with other individual-level variables such as consumption and labor supply. Third, administrative data, which have become more prevalent in recent studies, offer detailed individual-level information and are valuable for analyzing the relationship between gambling wins and economic behaviors (Cesarini et al. (2016), Cesarini et al. (2017), Fagereng et al. (2021), Golosov et al. (2021a)). However, these data typically do not include information on gambling bets and are often collected annually, limiting the frequency of observations.

Our study is distinguished by its use of bank account transaction data (Baker (2018), Gelman (2021), Kubota et al. (2021), Ueda (2024)). Whereas previous research frequently relies on surveys, data from gambling agencies, or administrative records, our approach offers the advantage of actual transaction data encompassing both gambling bets and wins, as well as other outflows serving as proxies for consumption, on a weekly basis. Unlike self-reported surveys, our data facilitate continuous tracking of a substantial sample of gamblers over nearly four years, thereby providing a more precise and comprehensive perspective on gambling and consumption behaviors.

However, our study is not the first to utilize bank transaction data to examine gambling behavior. Muggleton et al. (2021) employ UK bank transaction data to investigate the association between gambling and higher levels of financial distress, as well as adverse social and health outcomes. There are two notable distinctions between our study and that of Muggleton et al. (2021). First, the time horizons differ: Muggleton et al. (2021) focus on the long-term consequences of gambling over a seven-year period, while our study examines short-term changes in gambling behavior following wins. The second distinction, related to the first, concerns the issues of correlation and causality. Gambling decisions are endogenous; gambling may lead to problem gambling, and problem gambling may, in turn, drive further gambling. Moreover, social and health status may both influence and be influenced by problem gambling. Thus, Muggleton et al. (2021) likely document a correlation between gambling and problem gambling rather than causality. In contrast, our study rigorously attempts to estimate the causal effects of gambling wins on gamblers' behaviors. In summary, while our work complements Muggleton et al. (2021) by providing causal inferences, it does not address the long-term consequences of problem gambling, whereas Muggleton et al. (2021) elucidate long-term associations between gambling and problem gambling.

Empirical literature on the MPC is voluminous. A prominent method for estimating the MPC involves episode identification, which utilizes specific events to detect income shocks and track subsequent consumption changes. Examples of such income shocks include 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 inheritances.[5] Gambling (lottery) wins

[5]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

represent a form of windfall income that provides an unexpected, salient, and transitory income shock, which can be utilized to estimate the MPC. Unlike other income shocks, such as stimulus payments or inheritances, gambling wins are often repeated, yet this repetition is seldom explored. Fagereng et al. (2021) analyze lottery wins using tax records but focus solely on one-time winners. Imbens et al. (2001) and Kuhn et al. (2011) conduct multiple-stage surveys with lottery winners but do not account for additional wins that may occur subsequently. One reason for not analyzing repeated wins is to exclude heavy gamblers, which is understandable given the lack of data on gambling bets. Our dataset, however, includes detailed information on gambling bets, allowing us to control for gambling intensity.

The theoretical prediction concerning the size effect of unanticipated shocks on consumption responses is negative, as suggested by the concavity of the consumption function (Carroll and Kimball (1996)). However, empirical evidence on this matter is mixed. While Fagereng et al. (2021) and Scholnick (2013) find evidence of a negative size effect, Fuster et al. (2020) and Gelman et al. (2022) report a positive effect. Gelman et al. (2022) attribute the positive correlation to cash management practices, and Baugh et al. (2021) interpret this positive correlation as evidence of mental accounting.

The remainder of this study is organized as follows. Section 2 provides the research background, with a focus on gambling in Japan and the bank account transaction data used in the analysis. Sections 3 through 7 present our estimation results, including an examination of gambling responses (Section 3), consumption responses (Section 4), heterogeneity in responses (Section 5), dependence on gambling wins (Section 6), and the representativeness of gamblers (Section 7). Section 8 concludes.

2 Backgrounds and Data

This section begins with a discussion of the research background on gambling. We then describe the bank account transaction data utilized in this study, detailing the collection of transactions related to gambling and consumption. Finally, we address the representativeness of the data.

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)).

2.1 Gambling in Japan

The gambling industry in Japan is substantial, wherein total sales in 2019 amounts to approximately 2% of nominal GDP.[6] 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. As of public races in 2019, the central horse race commands the largest share (28%), followed by the local horse race (7%), boat race (15%), bicycle race (7%), and motorcycle race (1%). Pachinko holds the largest sales share among all the gambling types (34%), while lotteries account for 9% of the total.[7]

While the gambling industry in Japan is substantial, data on the number of individuals who engage in gambling are less clear. Although no comprehensive census on gambling exists, the Problem Gambling Basic Countermeasure Act, enforced in 2018, mandates the government to conduct a survey every three years to assess the situation of problem gambling. Based on this act, the National Hospital Organization Kurihama Medical and Addiction Center conducted the first survey in 2020, with a report released in 2021.[8] One of the surveys targeted 17,955 Japanese nationals aged 18 to 74, with 8,223 valid responses (a response rate of 45.8%). The report indicates that 74.5% of respondents have engaged in gambling at some point (84.1% of males and 65.7% of females), and 33.6% of respondents participated in gambling in the past year. Among the types of gambling experienced, lotteries are the most common (63.7%), followed by pachinko (50.3%) and horse races (29.4%). The report also estimates that approximately 2.1% of the surveyed population, or 1.5% of around 8,000 individuals, are suspected of having a problem with gambling.[9]

[6] This total includes gross gambling revenues from public races, lotteries (including toto), and pachinko, which collectively totals 10.2 trillion JPY. These figures are sourced from public releases by gambling administrations, including the Japan Racing Association (JRA), Japan Sport Council, Pachinko Parchislot Industry Report, and the Ministry of Economy, Trade and Industry.

[7] The primary difference between investing in stocks and gambling lies in their risk profile. While stocks carry risk, they generally offer a positive expected return over the long term based on company growth and earnings. Public race betting is speculative and offers no inherent value or return unless one wins. The odds are often stacked against bettors, and over time, the expected return is negative, as gambling institutions take a cut.

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

[9] Among the limited literature on problem gambling in Japan, Ino et al. (2020) explore gambling participation and the risk of problem gambling using a survey of residents in Chiba Prefecture. Their findings reveal notable patterns in gambling participation and a significant correlation between age and

Public races are predominantly organized on weekends, with multiple races held each race day. Seasonality is evident due to high-grade races, such as Grade I events. The return rate, defined as the fraction of gambling wins relative to gambling bets, is approximately 75%, though it varies depending on the type of bet (e.g., bets on a single player (horse), a group of players, or the top two or three players).[10] Odds represent the return rate conditional on wins, and on average, the return rate equals the odds multiplied by the probability of winning. Consequently, bets with lower win probabilities have higher odds. Gamblers can choose their bets based on these odds, which means the probability of winning in public races may be more influenced by gamblers' skills compared to lotteries, where the probability of winning is largely independent of skill. Gambling wins are not taxed at the time of reimbursement; instead, winners are required to report their winnings on their tax returns. The amount of gambling bets ranges from a minimum of 100 JPY to a certain limit, which is set by gambling agencies to mitigate problem gambling.

Nowadays, gambles can also be conducted online.[11] This allows gamblers to place bets and collect wins without visiting physical gambling ticket booths. Over the past decade, internet and telephone gambling have become mainstream, accounting for over 80% of gambling activities in the 2020s. These online transactions are captured and observable through bank data.

In this study, we concentrate on online gambling related to central horse races organized by the JRA to identify the unexpected component of income shocks (see the next subsection).

2.2 Mizuho Bank Data

Through an academic agreement between Mizuho Bank and Waseda University, we have access to data provided by Mizuho Bank, one of Japan's three major banks. Mizuho Bank offers a comprehensive range of financial services to both individuals and corporations, both domestically and internationally, with branches in major urban areas and

the risk of problem gambling. Hayano et al. (2021) examine variations in problem gambling by gender and type of gambling, identifying significant problem gambling particularly in motorcycle, bicycle, and boat races.

[10]In contrast, the return rate for lotteries is significantly lower, around 45%, while the return rate for pachinko is estimated to be between 80% and 85%, although no official figure is available.

[11]Online casino and online pachinko are illegal. Only online public races and lotteries are permitted.

approximately 24 million individual customers out of a population of 120 million in Japan. The data are analyzed with strict measures in place to prevent the identification of individuals, including masking and other anonymization processes.

The data include both transaction-level and monthly individual-level information. The transaction data record all activities associated with Mizuho Bank, such as ATM withdrawals, payroll receipts, utility bill payments, and bank transfers. Each transaction entry includes details on date, monetary amount, an inflow or outflow indicator, an assigned identification code, and remarks in Japanese. The monthly individual-level data provide information on wealth, annualized income, borrowings from Mizuho Bank, and other personal details, including gender, residential area, and birth year.[12]

We outline the procedure for constructing variables related to gambling bets, wins, and consumption using Mizuho Bank data. The measurement of gambling bets and wins involves the following three steps. First, we search for specific keywords in the transaction remarks in Japanese to identify gambling-related transactions. The keywords used include "JRA Haraimodoshikin," "PAT Kounyuukin," "PAT Haraimodoshikin," and "JRA Direct Furikomi." Second, we verify the content of identified transactions to ensure they are related to gambling. Non-gambling transactions associated with public race agencies, such as transfers between horse owners and the agencies, are excluded. Third, using the inflow or outflow indicator in the transaction data, we classify transactions as either wins (inflows) or bets (outflows). This process allows us to focus on online gambling transactions while excluding those conducted at ticket booths. Consumption is defined as the sum of outflow transactions—such as cash withdrawals, interbank transfers, and credit card payments—excluding gambling bets.

The timing of bets and wins is crucial for accurate identification. It is important to note that in central horse racing, the transfer of gambling wins is automatic. Users are required to register new accounts (A-PAT) at Mizuho Bank specifically for central horse racing. During weekends when public races are held, Mizuho Bank temporarily suspends other transactions from these accounts, restricting usage to internet gambling on horse

[12] Wealth is defined as the balance of deposits at Mizuho Bank, encompassing demand deposits, time deposits, other banking accounts, public bonds, mutual funds, and life and non-life insurance balances, with demand deposits constituting the majority. Annualized income is calculated based on the sum of salaries received over the past 12 months for individuals with regular salary deposits at their Mizuho Bank accounts. For those without regular salary deposits, annualized income is derived from application forms, such as those used for opening a bank account or applying for loans.

races only. After placing bets over the weekend, all gambling wins are automatically credited to gamblers' bank accounts by Monday morning. Thus, by setting the time frequency to weekly, with each week beginning on Monday, the transaction timing is clearly delineated: bets are placed in week $t-1$, wins are recorded at the beginning of week t, and spending, including bets, occurs in week t and beyond.[13] During weekends when horse races are held, gamblers are unable to receive their gambling wins and place additional bets that are financed by wins. Consequently, the amount received at the beginning of week t represents their total gross wins accumulated from the previous week.

The automatic and immediate transfer of gambling wins is a significant advantage of using data on public races in Japan. For instance, in Japanese internet lotteries, wins are not automatically transferred to winners unless the accumulated amount exceeds 10,000 JPY. Manual transfers introduce an endogeneity problem, where an increase in money demand (e.g., a desire to gamble) can lead winners to collect past wins and subsequently increase their spending. Furthermore, even when wins exceed 10,000 JPY, transfers can take around a week to process, complicating the determination of whether wins lead to additional bets or vice versa. This issue also affects studies with low time frequency, such as those using annual administrative data.

After identifying gambling bets, wins, and consumption, we construct panel data at the weekly and individual levels. Each week starts on Monday, aligning the timing of gambling wins with the beginning of each week. The data cover the period from 2019 to 2022. It should be noted that the panel data are slightly unbalanced due to the removal of observations where gambling wins exceed 2 million JPY, in order to protect privacy. Additionally, the panel data include personal characteristics and financial information, such as wealth and annual income.

Furthermore, we construct two measures of gambling intensity at the individual level. The first measure is the proportion of gambling, defined as the ratio of the sum of gambling bets to the total sum of outflows, including bets, during the observation period. The second measure is the frequency of gambling, defined as the ratio of the number of weeks with positive bets to the total number of weeks. A frequency value of one indicates that the gambler participates in gambling every week.

The data have four main limitations. First, the data are exclusively from Mizuho

[13] In contrast, bicycle and motorcycle racing require a manual procedure to receive gambling wins.

Bank, and activities involving other banks or cash transactions are not captured. Second, due to anonymity constraints, individual-level data cannot be integrated into household-level data. Third, detailed information on bets and wins within a week is not available. While gamblers can place bets on multiple races (approximately 10 races per day) and purchase various types of tickets (e.g., single player wins, group wins, top two or three finishes) each weekend, our data only provide aggregated totals of bets and wins for each week. Fourth, our measure of consumption is relatively coarse. The data do not include detailed information on spending categories, preventing us from distinguishing true consumption. In this study, we use consumption and spending interchangeably, despite some purchased goods being durable or storable, meaning spending does not necessarily correspond to consumption in the same period.

We establish a weekly balanced panel for 17,411 gamblers, selected from approximately 250,000 gamblers with a history of online gambling on public races between 2019 and 2022 in the Mizuho Bank data. The sample size is reduced substantially due to the following selection criteria: (1) accounts must contain both bets and wins for central horse races; (2) accounts must have complete and consistent information on gender and birth year and exist before 2019; (3) weekly consumption (outflows minus bets) must not exceed 10 million JPY; (4) accounts must record positive consumption (excluding bets) for 20 weeks or more; and (5) the proportion of gambling must be less than 0.5. The last two conditions are applied to exclude accounts that are primarily used for gambling. Our analysis of the data reveals that many individuals use their bank accounts specifically for gambling purposes, which complicates tracking non-gambling expenditures. Consequently, we exclude these accounts from our analyses to ensure accurate measurement of non-gambling consumption.[14]

2.3 Descriptive Statistics

We present basic statistics for 17,411 gamblers in Table 1 at the account-week, account-month, or account level. The account-week level statistics cover key variables related to outflows and inflows, including consumption, gambling bets, and wins. The account-month level statistics provide data on variables available monthly. The account level statistics summarize personal characteristics, such as age and gender. To maintain anonymity, maximum and minimum values are not reported.

[14]Without criterion (5), the number of gamblers increases from 17,411 to 53,843.

Both outflows and inflows exhibit a large proportion of zero-valued observations on a weekly basis, resulting in medians of zero at the account-week level. The average weekly consumption is 63,000 JPY, while the mean gambling bets and wins are 7,100 JPY and 5,600 JPY, respectively. Gambling participation is indicated by a dummy variable, which takes the value of one if a gambler places bets in a given week. The average gambling participation rate is 0.52, indicating that 52% of individuals engage in gambling each week. As discussed below, the distribution of gamblers shows a bimodal pattern in terms of gambling intensity, with a substantial proportion participating nearly every week. The mean return rate, defined as the ratio of wins to bets, is 0.74, consistent with the official figure discussed in Section 2.1. However, the median return rate is substantially lower at 0.22, suggesting that returns from public horse races exhibit a fat right tail. The 100% loss dummy variable equals one when wins are zero (indicating a complete loss of bets) and the net win dummy equals one when net wins are positive (wins exceed bets). The mean of the net win dummy is 0.2, suggesting that 80% of gambles result in a loss. Additionally, the mean of the loss all dummy is 0.4, indicating that 40% of gambles result in a complete loss of the bets placed.

At the account level, it is notable that males dominate gambling activities, comprising 94% of the sample. The average age of gamblers is 60 years, indicating that the gamblers in our data are older than the national average age of 47, as reported by the National Institute of Population and Social Security Research in 2020. The mean proportion of gambling, which was selected to be less than 0.5, is 0.13, while the mean frequency of gambling is 0.52.

Figure 1 illustrates two key facts about gambling. The left-hand panel depicts the time-series changes in the aggregated amount of gambling bets and wins over a four-year period. This panel reveals a seasonality pattern, with increased activity during Grade I races, and shows that gambling did not decrease but rather increased during the COVID-19 pandemic starting in 2020. The right-hand panel presents the distribution of the return rate. At the weekly transaction level, there is a significant concentration at zero return, indicating that approximately 40% of bets result in a 100% loss. Additionally, there is a small peak at a return rate of one, which occurs when a horse a gambler bets on is declared a non-starter. When weekly transactions are aggregated over four years for each individual, the distribution of the return rate converges to 75%, as predicted by the central limit theorem.

The representativeness of the data (gamblers) is a crucial issue. To address this, we compare basic characteristics between gamblers and non-gamblers. We use residents of Chiba prefecture, a neighboring prefecture to Tokyo, for comparison because the original data set includes over 24 million individuals. We select Chiba residents who made at least one transaction at their Mizuho Bank accounts during the period from March 4, 2019, to March 25, 2019, reducing the number to approximately 3 million, which we consider sufficient for comparison. Figure 2 shows the distribution of age, wealth, annual income, and weekly outflows for gamblers in our data compared to all residents of Chiba prefecture.[15] The most notable difference is that gamblers in our data are generally older than Chiba residents. Gamblers also have slightly lower wealth compared to Chiba residents, but slightly higher income. The distribution of weekly outflows is similar between gamblers and Chiba residents.

In Online Appendix A, we present additional details on gambling activities, including transactions related to gambling and cumulative returns from these gambles.

3 Responses of Gambling Bets to Gambling Wins

In this section, we investigate how gamblers adjust their gambling behaviors following wins.

3.1 Baseline Regression

We use a two-way fixed effects regression model to estimate the causal effects of gambling wins on various outcomes. The baseline regression equation is specified 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 the outcome variable (e.g., gambling 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 a vector of control variables consisting of inflows minus wins, wealth, income, and borrowings in week $t-1$. The unit is 10,000 JPY unless otherwise noted.

[15] Observations of zero values for wealth and income are excluded from this comparison, as they are non-negligible. Specifically, for annual income, 36,744 out of 47,818 gamblers have zero income, compared to 422,440 out of 901,268 Chiba residents. For wealth, 3,668 out of 47,818 gamblers report zero wealth, while 37,992 out of 901,260 Chiba residents do.

The fixed effects are captured by α_i and α_t, which represent gambler and week-specific effects, respectively. Standard errors are clustered at the individual level throughout this study.

It should be noted that gambling wins win_{it} are endogenous and likely depend on gambling bets in the previous week bet_{it-1}. Given that the mean return rate is around 75%, large wins may not be entirely unexpected for gamblers who place large bets. This endogeneity issue is particularly pronounced among frequent gamblers. Therefore, it is crucial to include bet_{it-1} as a control variable.[16] Additionally, we control for bet_{it-2} and inflows minus wins in week $t-1$ to account for repeated gambling behavior and fluctuations in financial status. In Online Appendix B, we explore the predictability of gambling wins by estimating wins based on bets and various variables.

Coefficient β_τ is the key parameter of interest, indicating the marginal propensity out of an unanticipated component of gambling wins. To explore how the marginal propensities vary over time, we estimate the dynamic marginal propensities by running the regression for each τ ($\tau = -16, -15, \cdots, 16$ except for $\tau = -1$) using leading and lagging values of the outcome variable $Y_{it+\tau}$. This approach allows us to capture how the response to gambling wins evolves over time, providing insights into both immediate and delayed effects.

3.2 Estimation Results

In this subsection, we discuss the estimation results when the dependent variables are related to gambling bets. Table 2 provides detailed results from our baseline regression analysis, focusing on how gambling wins influence betting behavior.

Column (1) in Table 2 presents the main estimation result for $\tau = 0$, capturing the contemporaneous MPG. The estimated coefficient β_0 is positive and significant at 0.075. This finding suggests that gamblers allocate approximately 7.5% of the unexpected component of their gambling wins to additional bets within the same week.

Column (2) shows the results when we omit controls for previous bets (bet_{it-1}, bet_{it-2}) and inflows minus wins from week $t-1$. In this specification, the adjusted R^2 decreases from 0.58 to 0.49, and the coefficient β_0 rises significantly from 0.075 to 0.26. This

[16] Public races provide easily accessible information about racehorses and riders, allowing frequent gamblers to form expectations. Odds are also updated in real time before races, meaning that wins may not be completely unexpected for those placing significant bets.

increase suggests that neglecting to control for previous bets results in an overestimation of the MPG, as the positive correlation between $\delta_0^1 bet_{it-1}$ and win_{it} indicates that wins are partially expected based on previous bets.

The dynamic MPG is analyzed by estimating equation (1) for each τ. The left-hand panel of Figure 3 shows that β_τ decreases gradually from 0.075 to zero as τ progresses from 0 to 12 weeks. This indicates that the impact of gambling wins on gambling bets persists over approximately three months. In contrast, β_τ tends to be insignificant for negative values of τ. The figure also highlights that whether or not we control for previous bets significantly affects the MPG estimates. When bets are not controlled for, β_τ increases across a wide range of τ, including negative values. This finding suggests a potential overestimation of persistent gambling effects and underscores the importance of including controls for past betting behavior to obtain accurate MPG estimates.

We conduct additional regressions using different measures of gambling behavior as the dependent variable. First, we examine the impact on gambling participation, represented by a dummy variable that takes the value of one when a gambler places a positive bet in a given week (i.e., extensive margin, EM). As shown in column (3) of Table 2, the coefficient on win_{it} is significantly positive, indicating that an increase in gambling wins leads to a higher likelihood of participating in gambling. Next, we focus on gamble continuation, defined by a dummy variable that takes the value of one when a gambler places a positive bet in the current week, given that there was also a positive bet in the previous week. If no bet was placed in the previous week, the value is recorded as NA. This measure gives greater weight to repeated gamblers due to the unbalanced panel structure. The coefficient on win_{it} in column (4) is positive, suggesting that higher gambling wins make it more likely for gamblers to continue participating in gambling activities. Finally, we analyze the change in the amount of bets from the previous week, conditional on bets being positive in both periods (i.e., intensive margin, IM). Column (5) shows that the coefficient on win_{it} is positive at 0.07, which is consistent with the previously estimated size of the MPG. This result implies that larger gambling wins not only encourage gamblers to return to gambling sooner but also to increase their betting amounts. The dynamic responses for EM and IM are detailed further in Online Appendix C.

4 Responses of Consumption to Gambling Wins

In this section, we explore how gambling wins affect consumption. Table 3 and the right-hand panel of Figure 3 present the estimation results for equation (1) with consumption—defined as outflows minus gambling bets—as the dependent variable. Column (1) shows that the contemporaneous MPC, represented by the coefficient β_0, is significantly positive at 0.35. This indicates that gamblers spend 35% of their gambling wins on consumption during 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). This implies that failing to account for the endogeneity of gambling wins causes a slight underestimation of the MPC.

The dynamic MPC is estimated across various time horizons τ. The right-hand panel of Figure 3 illustrates that the effects of gambling wins on consumption are short-lived. Specifically, β_τ is significant only for two weeks ($\tau = 0$ and 1), indicating that the impact of gambling wins on consumption is transitory. This finding contrasts with the longer persistence documented in studies by Fagereng et al. (2021) and Auclert et al. (2018), which suggest MPC effects lasting around three years.

The shorter persistence in the MPC observed here has implications for macroeconomic modeling, as noted by Auclert et al. (2018). The difference in persistence is partly due to the inclusion of gambling bets as a control variable, which, when omitted, leads to more prolonged effects of gambling wins on consumption. The estimation results suggest that once bets are accounted for, the MPC is transitory, supporting the use of simpler two-agent heterogeneous models. This finding aligns with the arguments made by Debortoli and Gali (2024) and Bilbiie (2024), suggesting that computationally intensive heterogeneous-agent models may not be necessary, even though representative-agent models fail to explain the large MPC.

In columns (3) and (4) of Table 3, we provide the estimation results when alternative measures of consumption are used as the dependent variable. One of these measures is cash withdrawals, which include not only ATM withdrawals via cash and debit cards but also money transfers to cashless payment smartphone apps. The second measure is consumption excluding financial transactions associated with saving and investment, where these transactions are identified by filtering out those with remarks in Japanese that include keywords such as "repayments" or "securities." The results show that when either cash withdrawals or consumption excluding saving-related outflows is used, the on-impact MPC remains approximately 0.3, which is consistent with our previous findings.

5 Heterogeneity in Responses of Gambling Bets and Consumption

Substantial heterogeneity exists among gamblers, and their gambling and consumption behaviors likely vary significantly between heavy and light gamblers.

5.1 Gambling Intensity

In Section 2.2, we introduced two measures of gambling intensity at the individual level: the proportion and frequency of gambling. Figure 4 shows their distributions. For illustrative purposes, we include heavy gamblers whose proportion of gambling is 0.5 or larger in this section. The figure reveals that both the proportion and frequency of gambling exhibit bimodal distributions. On one side, a considerable fraction of heavy gamblers bet almost all of their income on gambling and participate nearly every week. On the other side, there exists a significant number of light gamblers with much lower gambling participation. Interestingly, when we exclude heavy gamblers with a proportion of gambling of 0.5 or higher, the distribution of the frequency of gambling shows little change. This suggests that the gambler population is distinctly divided into two groups: heavy and light gamblers.

5.2 Relations between MPG/MPC and Gambling Intensity

To investigate how the MPG and MPC vary with gambling intensity, we divide the sample of gamblers into several evenly sized groups based on their gambling intensity. For each group, we separately estimate the MPG and MPC by running the regression outlined in equation (1). This expanded analysis also includes heavy gamblers, defined as those whose proportion of gambling is 0.5 or larger. By segmenting gamblers in this manner, we aim to identify whether the responsiveness of both gambling and consumption to wins differs significantly between individuals with varying levels of gambling intensity.

Figure 5 illustrates the notable stability of the MPG and MPC estimates across different groups of gamblers, categorized by their gambling intensity. The MPG and MPC show minimal variation among gamblers with differing levels of gambling intensity. A key exception arises for heavy gamblers, particularly those whose proportion of gambling exceeds 0.75. For these individuals, the MPG tends to increase, while the MPC decreases as gambling intensity rises. However, this finding appears to be largely mechanical, as these heavy gamblers use their Mizuho Bank accounts predominantly for gambling purposes, thereby reducing the scope for non-gambling-related consumption.

The stable MPC result offers reassurance to researchers aiming to estimate the MPC for non-gamblers. Although we cannot directly observe gambling wins for non-gamblers, the stability of the MPC across groups suggests that if non-gamblers were to engage in gambling, their MPC in response to gambling wins would likely be around 0.35.

Additionally, when analyzing the extensive margin of gambling, we observe that the marginal propensity for gambling participation is significantly higher for very light gamblers, whose proportion of gambling is below 0.1. This could suggest that novice gamblers may be drawn into problem gambling, potentially influenced by experiencing early successes or "beginner's luck." For further details, refer to the Online Appendix C.

5.3 Simple Model

To explore the drivers of heterogeneity in the MPG and MPC, we construct a simple two-period model. In this model, gamblers live for two periods: when young and when old. When young, they receive endowment y, consume c_1, and save for the future. Gamblers can save by investing either in a risk-free asset s or a risky asset, which in this case is gambling denoted by g. Additionally, gamblers derive utility from gambling, denoted by $\kappa_i v(g)$. When old, they consume all remaining resources c_2. Gamblers, each denoted by i, are heterogeneous in terms of discount factor β_i and utility from gambling κ_i (and expectations of gambling returns 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 the risk-free rate of return, 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 $1/(1 + \beta_i + \kappa_i)$. The MPC decreases as either β_i or κ_i increases.

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

See Online Appendix D for details. 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 the relationship between the MPG and the MPC can vary based on the sources of heterogeneity among gamblers. There are three scenario. First, when heterogeneity in the discount factor (β_i) predominates, the MPC and MPG are positively correlated. In this scenario, gamblers with a high discount factor, who are less myopic and thus save more for the future, tend to exhibit both a lower MPC and a lower MPG. This occurs because saving in the risk-free asset is more attractive than gambling, leading to reduced consumption and gambling expenditures.

Second, if heterogeneity in the utility from gambling (κ_i) is the dominant factor, the MPC and MPG display a negative correlation. Gamblers with a high utility from gambling allocate less to consumption but more to gambling, resulting in a low MPC and a high MPG.

Third, if other forms of heterogeneity, such as optimism about gambling outcomes or perceived skill in gambling (π^H or θ^H), are the main factors, the MPC remains constant while the MPG varies. In this scenario, while variations in expectations or skills affect gambling behavior and thus the MPG, they do not impact the MPC directly.

Thus, the analysis provides a way to determine the source of heterogeneity (β_i, κ_i, π^H, or θ^H) by examining the correlation between the MPG and the MPC. In Online Appendix D, we present simulation results demonstrating that heterogeneity in β_i leads to a positive correlation between the MPC and the MPG, whereas heterogeneity in κ_i results in a negative correlation. Additionally, we discuss the robustness of these findings by extending the utility function from logarithmic to the constant elasticity of substitution (CES) forms and by considering heterogeneity in β_i, κ_i, θ^H, and CES parameters.

5.4 Relations between the MPG and the MPC

In order to calculate a correlation between the MPG and the MPC, we need a sufficient number of estimates for both measures across different groups of gamblers. Therefore, we divide gamblers into 100 groups based on various criteria, including bank account number (ID), the proportion of gambling, and the frequency of gambling, and run the regression specified in equation (1) for each group, where the ID is a 13-digit number randomly assigned to each Mizuho Bank user. We exclude heavy gamblers whose proportion of gambling is 0.5 or greater in this analysis. Only significant estimates are presented.

Figure 6 illustrates the relationship between the estimated MPG and MPC. When gamblers are grouped based on their ID, there is a significant negative correlation of -0.30 (p-value: 0.009) between the MPG and MPC. This implies that gamblers with a higher MPG tend to have a lower MPC. According to the simple model, this result suggests that heterogeneity in preferences for gambling (κ_i) plays a crucial role in explaining the differences among gamblers; in other words, gamblers differ due to their intrinsic preferences for gambling. However, this finding is not consistently robust across different groupings. When grouping based on the proportion or frequency of gambling, the correlations between MPG and MPC are not significant at -0.04 and 0.09, respectively.

5.5 Relations between MPG/MPC and Liquidity

In this subsection, we explore how liquidity constraints may contribute to heterogeneity in the MPG and MPC, beyond the effects of gambling intensity. Existing literature on gambling suggests that gambling can be a tool for financially constrained individuals (e.g., Herskowitz (2021)), while the literature on the MPC highlights the role of liquidity in explaining MPC variability, particularly noting that liquidity-constrained individuals often exhibit a high MPC (e.g., HANK models, Fagereng et al. (2021), Ueda (2023)).

To investigate this, we include an interaction term in our regression model:

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

where X_{it-1} represents variables that may lead to heterogeneous responses in the MPG and MPC, with the interaction effect captured by the coefficient ϕ. For X_{it-1}, we use wealth and a liquidity constraint dummy. The liquidity constraint dummy equals one if wealth is lower than monthly income (Kubota et al. (2021), Ueda (2023)).

Table 4 shows the estimation results. For the MPC, columns (4) and (5) display that the interaction term ϕ has significantly negative and positive coefficients when X_{it-1} is wealth and the liquidity constraint dummy, respectively. This indicates that liquidity-constrained individuals exhibit a higher MPC, consistent with the existing literature. When both variables are included in the model, as shown in column (6), ϕ remains significant only for wealth.

Regarding the MPG, columns (1) through (3) show that the coefficient ϕ is insignificant across all specifications, suggesting that liquidity constraints do not influence the magnitude of the MPG. However, Online Appendix C reveals significant results when the dependent variable is the extensive margin of gambling. This suggests that while liquidity constraints do not affect the amount of gambling bets, they do increase the likelihood of participation in gambling among liquidity-constrained gamblers as their wins rise.

6 Dependence of Bet and Consumption Responses on Past Gamble Outcomes

We have shown that the marginal propensities vary based on individual characteristics such as gambling intensity and liquidity constraints. Beyond these factors, past gambling performance, such as whether a gambler's net wins are positive, is also likely to impact both gambling and consumption behaviors. In Online Appendix E, we present graphical analyses that depict the associations between gambling bets, consumption, and past net wins, providing further insight into how previous outcomes influence future decisions.

6.1 Estimation with Past Gamble Outcomes

To analyze the influence of past gambling performance on gamblers' behavior, we extend equation (1) by incorporating several variables that capture the outcomes of previous gambling activities. Specifically, the regression model is expressed as

$$\begin{aligned} Y_{it} = {} & \beta win_{it} + BX_{it} \\ & + \delta_1 bet_{it-1} + \delta_2 bet_{it-2} + \gamma Z_{it-1} + \alpha_i + \alpha_t + \varepsilon_{it}, \end{aligned} \tag{6}$$

where X_{it} is a vector of variables representing past gambling outcomes. The vector consists of win_{it}^2, win_{it}^3, a dummy of net wins, a dummy of 100% loss, win_{it} times the dummy of net wins, and bet_{it-1} times the dummy of 100% loss.

The "big win" effect, frequently discussed in the problem gambling literature, can be interpreted in economics as an income effect, where larger gambling wins trigger stronger behavioral responses in terms of increased betting and consumption. To account for these non-linear effects, we include higher-order terms of gambling wins, specifically win_{it}^2 and win_{it}^3, in the model.

Additionally, we explore the "loss chasing" effect, where gamblers who experience losses may increase their gambling in an attempt to recover those losses. To assess whether overall profitability influences behavior, we include a net win dummy variable, which equals one if the gambler's wins exceed their losses. Examining the behavioral differences between positive and negative net wins helps in understanding the loss chasing effect.

Further, we define a 100% loss dummy, which takes the value of one if gambling bets are positive, but winnings are zero ($bet_{it-1} > 0$ and $win_t = 0$). Although we cannot calculate the MPG and MPC in this scenario, examining how a complete loss affects gambling and consumption decisions in the following week is of particular interest.[17]

Table 5 presents the results of our estimation, which are somewhat complex. To better understand these findings, we graph hypothetical responses of gambling bets and consumption in relation to changes in net wins. We calculate the changes in the dependent variable (plotted on the vertical axis) by assuming specific values for net wins (plotted on the horizontal axis) and betting amounts. The betting amounts are set to 0.01, 0.5, or 1 in units of 10,000 JPY. With these assumptions, we derive the value of gambling wins as net wins plus the corresponding betting amount. From this, we can also compute the net win dummy and the 100% loss dummy, which play a role in the model. An important note is that gambling wins cannot be negative, meaning that net wins must always be greater than or equal to negative betting amounts. We use this relationship to simulate changes in the dependent variable (either bets or consumption) for each combination of net wins and bets, applying the estimated coefficients from Table 5 to these scenarios. We apply all estimated coefficients, regardless of their statistical significance. However, this approach has little impact on the overall outcome of the simulations.

Figure 7 shows the simulation results, revealing a notable discontinuity at zero net

[17] Although topics like the "hot-hand" and "gambler's fallacy" are popular in gambling research, our data limitations prevent us from analyzing these phenomena..

wins. Focusing first on gambling bets, we observe that they tend to increase as net wins increase when net wins are positive. This aligns with the positive MPG previously identified. Interestingly, when net wins are negative, bets do not show an increase even as net wins rise (though there is a slight negative slope, it is statistically insignificant). However, when net wins transition from negative to marginally positive, we see a discontinuous jump in bets. This is driven by the positive coefficient on the interaction term $bet_{t-1}\times$net win dummy, indicating that bets increase sharply when a gambler shifts from net losses to net gains.

As a result, the overall response of bets forms a U-shape, with the lowest point at zero net wins. Importantly, no evidence of loss-chasing behavior is observed, as negative net wins result in decreased subsequent bets rather than attempts to recover losses through further gambling.

Second, for consumption, a discontinuity at zero net wins appears, but in the opposite direction compared to bets. As net wins rise, consumption increases, reflecting the positive MPC, regardless of whether net wins are positive or negative. However, when net wins transition from negative to marginally positive, consumption drops sharply due to a negative coefficient on the net win dummy. This suggests that gamblers prioritize gambling over consumption when they experience a small win, but favor consumption when facing a small loss.

An interesting pattern emerges with a 100% loss scenario: when gamblers bet 10,000 JPY and win nothing, consumption spikes, which is not seen with smaller bets. This is driven by a positive coefficient on the interaction term $bet_{t-1}\times$100% loss dummy and a negative coefficient on the 100% loss dummy. This indicates that gamblers might spend on leisure activities, such as drinking and eating out, to cope with the disappointment of a total loss when betting large amounts.

For gambling bets, we analyze both extensive and intensive margins. The extensive margin shows a clear discontinuity at zero net wins, with a noticeable increase in the likelihood of gambling when net wins shift from negative to positive. Notably, for the extensive margin, there is evidence of loss chasing: gamblers who experience a 100% loss show an increased likelihood of gambling, approaching the levels observed in gamblers with positive net wins.

The impact of large wins or income effects appears to be moderate. The simulations in Figure 7 reveal no distinct convexity or concavity in relation to net wins. According to Table 5, the coefficient on win_t^2 is significantly positive only for consumption, suggesting that gamblers tend to increase their MPC with larger wins.

6.2 Sub-group Estimation

To gain additional insights into gamblers' behavior, we conduct a sub-group estimation with the following regression:

$$\begin{aligned} Y_{it} = \beta win_{it} + \sum_j \beta^j win_{it} \times I_{jt} \\ + \delta_1 bet_{it-1} + \delta_2 bet_{it-2} + \gamma Z_{it-1} + \alpha_i + \alpha_t + \varepsilon_{it}, \end{aligned} \tag{7}$$

where I_{jt} is a dummy which takes one for each specific subsample j. Each subsample is based on the level of net wins, with approximately 50,000 observations per subsample. The highest net wins subsample serves as the base category, and a positive β^j indicates that the MPG or MPC for subsample j is higher than that for the base. This approach allows us to estimate variations in the MPG and MPC while controlling for the same fixed effects (α_i and α_t) across different subsamples. Unlike the previous analysis, which focused on the levels of bets and consumption, this estimation highlights variations in the marginal propensities to bet and consume.

Figure 8 shows the estimation results for the MPG and MPC. We observe that β^j for the MPG shows a discontinuous drop when net wins transition from positive to negative. This indicates that the MPG increases significantly with positive net wins, aligning with previous findings and contrasting with the loss chasing effect.

For consumption, β^j for the MPC does not exhibit a clear discontinuity around zero net wins. Instead, the MPC follows a V-shaped pattern, reaching its lowest point when net wins are around zero. As net wins increase, the MPC rises, reflecting a positive big win effect on the MPC. In Online Appendix E, we provide additional subgroup estimation results, dividing the sample based on return rate or wealth.

7 Are Gamblers Special?

Our study, inherently focused on gamblers, raises the question of how these findings might extend to non-gamblers.

Gamblers, as shown in Section 2.3, are not representative of the general population, often skewing towards older age and predominantly male. However, Section 5.2 suggests that non-gamblers, conceptualized as individuals with gambling intensity approaching zero, might resemble light gamblers in terms of their MPC. However, this remains speculative and does not rule out the possibility of a discontinuity between non-gamblers and light gamblers.

To explore this, we compare the MPC of gamblers with that of non-gamblers. This comparison aims to determine whether the behavior of light gamblers can be extrapolated to non-gamblers or if distinct differences exist.

Since non-gamblers do not receive gambling wins, it is necessary to identify an alternative source of income shock that is salient, transient, and unexpected. An appropriate income shock occurred in 2020 with the introduction of the SCP by the Japanese government during the COVID-19 pandemic, providing 100,000 JPY per person. As documented by Kubota et al. (2021) and Ueda (2023), the timing of the SCP varied across weeks and municipalities, facilitating the identification of the SCP income shock separate from aggregate shocks by incorporating week and individual fixed effects.

We focus on residents of Chiba Prefecture who received the SCP due to computational burdens. To compare the MPC between gamblers and Chiba residents (primarily non-gamblers), we estimate the following equation:

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

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, coefficient χ_{SCP} is significantly positive at 0.083, suggesting that the MPC among gamblers is 8.3% higher than that of non-gamblers.

It is important to acknowledge that MPC may exhibit considerable heterogeneity across various dimensions. Specifically, differences in age and wealth distributions between gamblers and non-gamblers could contribute to deviations in χ_{SCP} from zero. To address this, we perform 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 among gamblers is similar to that of non-gamblers. This finding implies that gamblers do not exhibit distinct MPC characteristics compared to non-gamblers. Furthermore, the table reveals that the MPC in response to the SCP, ψ_{SCP}, is 0.27, while the MPC in response to gambling wins, estimated solely for gamblers, is 0.28. This result suggests that the source of income shocks—whether the SCP or gambling wins—does not significantly influence the amplitude of the MPC.

It is worth noting that our sample primarily consists of light gamblers. The inclusion of heavy gamblers, whose proportion of gambling exceeds 0.5, could potentially alter these results. Nevertheless, the current estimation suggests that light gamblers are not markedly different from non-gamblers in terms of the MPC.

In the third column of the table, we present the estimation results with gambling bets as the dependent variable to examine the MPG. The coefficient on wins is significant at 0.075, while the SCP coefficient is insignificant at 0.001. This suggests that the source of income shocks may matter for gambling decisions: gambling incomes drive further gambling, whereas government transfers are less likely to do so.

8 Concluding Remarks

This study analyzed gamblers' responses to their wins, focusing on both betting and consumption behaviors. Our findings indicate that gamblers significantly increase both their bets and consumption following wins. Specifically, our analysis in Section 6 reveals that gamblers are more likely to increase their gambling activities as their wins rise, both in gross and net terms. This behavior aligns with patterns of easy gains and difficulty in quitting, potentially signaling a risk for problem gambling. However, this risk appears to be limited, as increased gambling activity primarily occurs when net wins are positive, and our results—except for the extensive margin—provide evidence against a strong loss-chasing behavior.

Future research should explore the long-term causes and consequences of problem gambling. Expanding the dataset to include a broader range of gamblers, particularly those with a higher proportion of gambling (0.5 or greater) and those participating in other types of gambling beyond public horse racing, would be valuable. Although establishing sharp causal inferences may be challenging, documenting patterns related to problem gambling remains a crucial area of study.

Additionally, examining other forms of gambling, such as lotteries and various public races, would provide insights into how these activities compare with JRA central horse racing. Understanding how gamblers substitute or complement these different types of gambling could further enrich our knowledge in this field.

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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 the 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

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 indicating gambling participation. EM (continue) is a dummy for repeat gambling participation. Intensive margin (IM) is the change in the amount of bets from the previous period, 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
	(1)	(2)	(3)	(4)
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)
$\text{Bet}_{t-1}\times$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		Bets
	Whole	Matched	
Wins	0.279***	0.276***	0.075***
	(0.031)	(0.030)	(0.005)
SCP	0.225***	0.265***	0.001
	(0.005)	(0.022)	(0.001)
SCP × Is Gambler	0.083***	0.042	
	(0.016)	(0.026)	
Observations	46,673,454	2,510,035	3,533,529
Adjusted R^2	0.055	0.113	0.586

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.

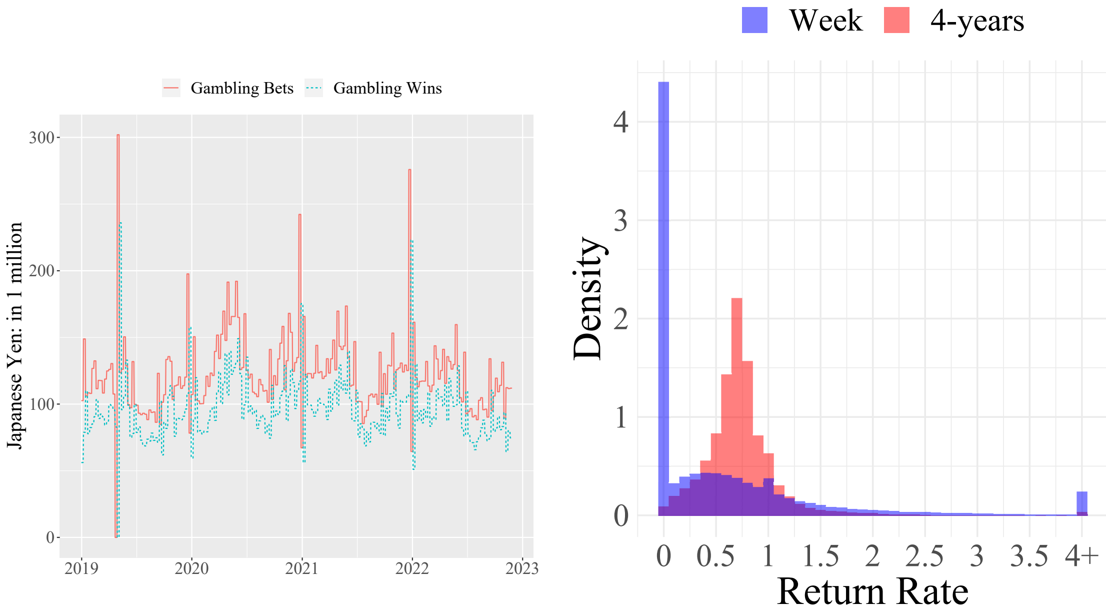

Figure 1: Facts on Central Horse Race Gamble

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

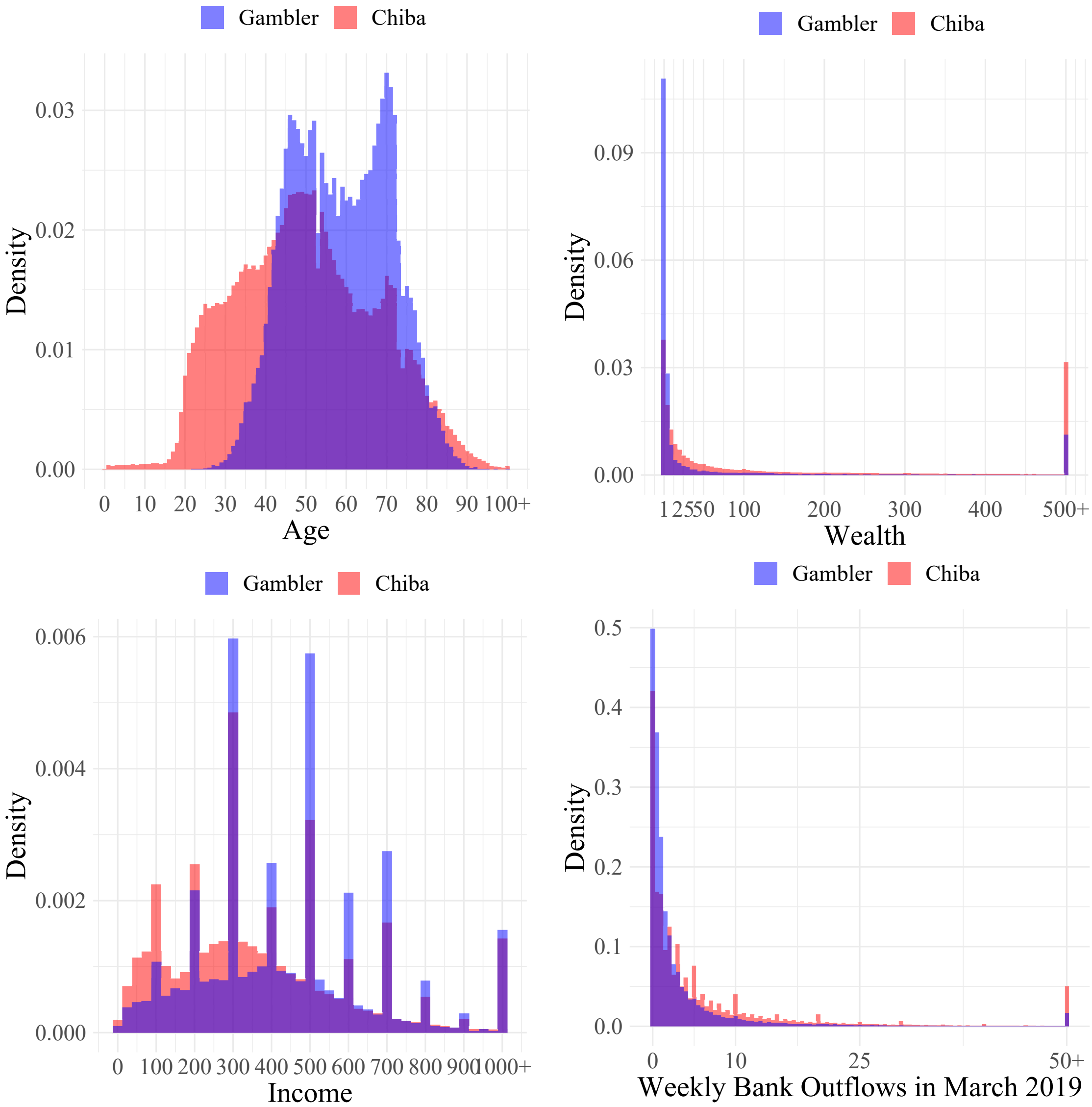

Figure 2: Comparisons of Gamblers and Non-Gamblers (Chiba Residents)

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

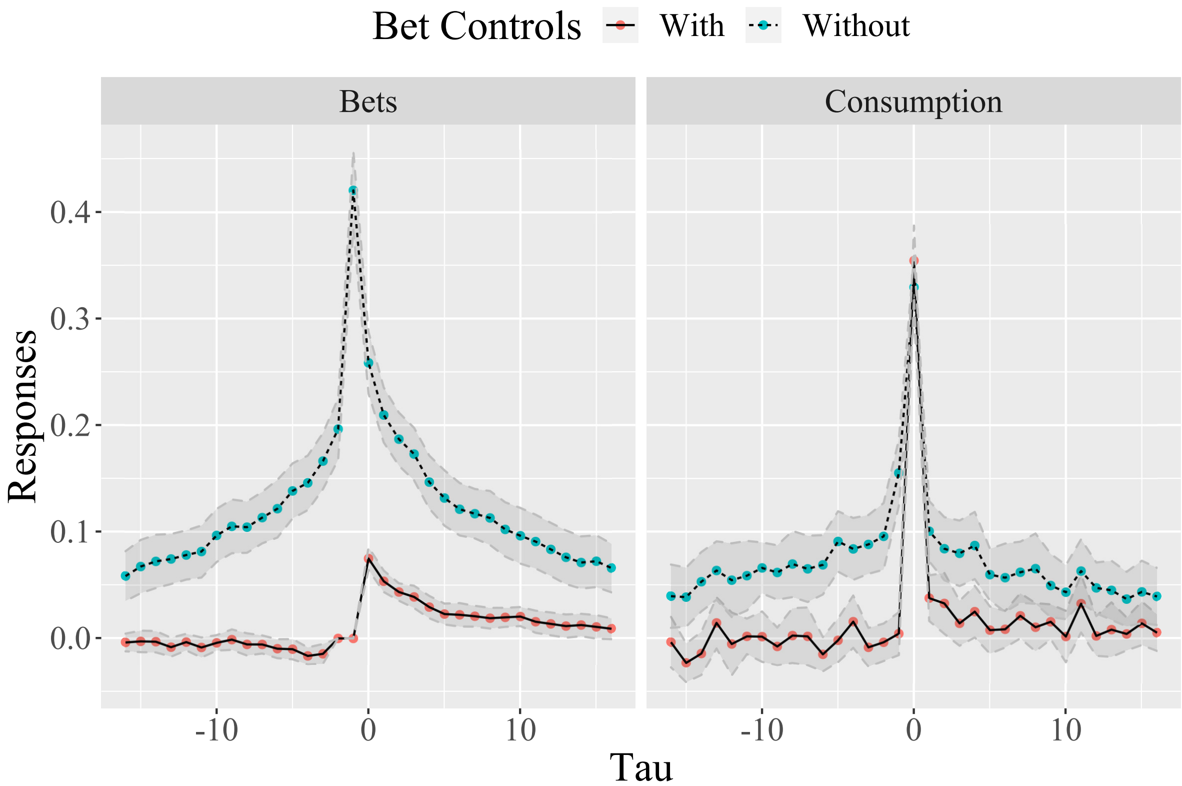

Figure 3: Dynamic Responses of Gambling Bets and Consumption

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

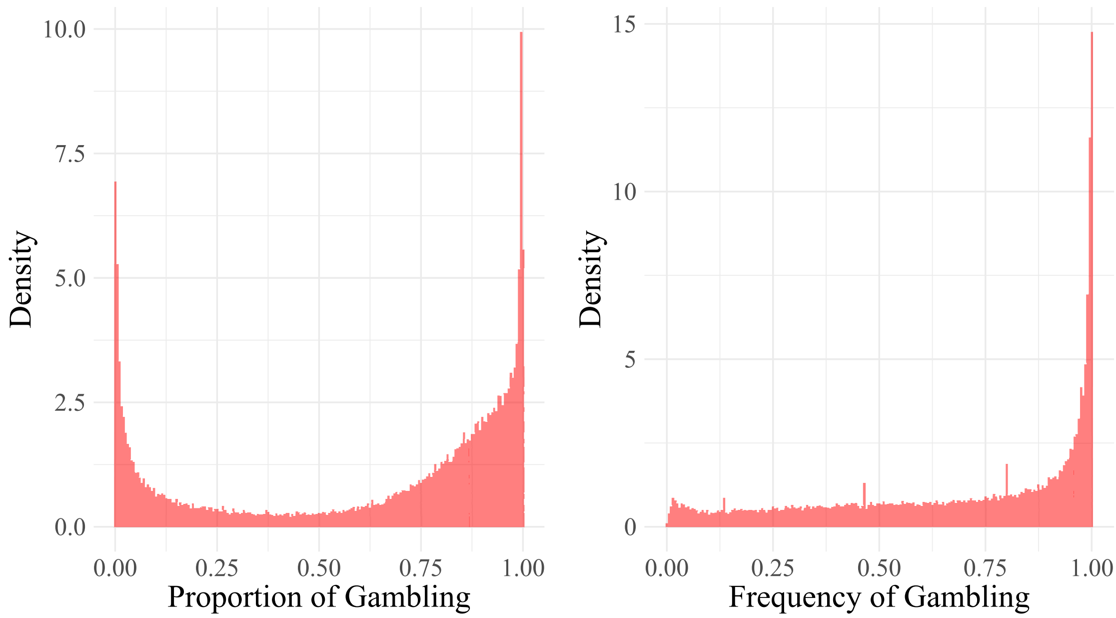

Figure 4: Distribution of Gambling Intensity

Note: The proportion of gambling is defined as the ratio of the total amount of gambling bets to the total outflows, including bets, during the observation period. The frequency of gambling is defined as the ratio of the number of weeks with positive bets to the total number of weeks. For illustrative purposes, we include heavy gamblers whose proportion of gambling is 0.5 or greater.

Figure 5: MPG and MPC by Gambling Intensity

Note: We estimate the MPG and MPC for each group divided based on the proportion of gambling (top) or the frequency of gambling (bottom). The horizontal axis represents gambling intensity (either the proportion or frequency of gambling), while the vertical axis shows the MPG or MPC. Heavy gamblers, defined as those with a proportion of gambling of 0.5 or higher, are included.

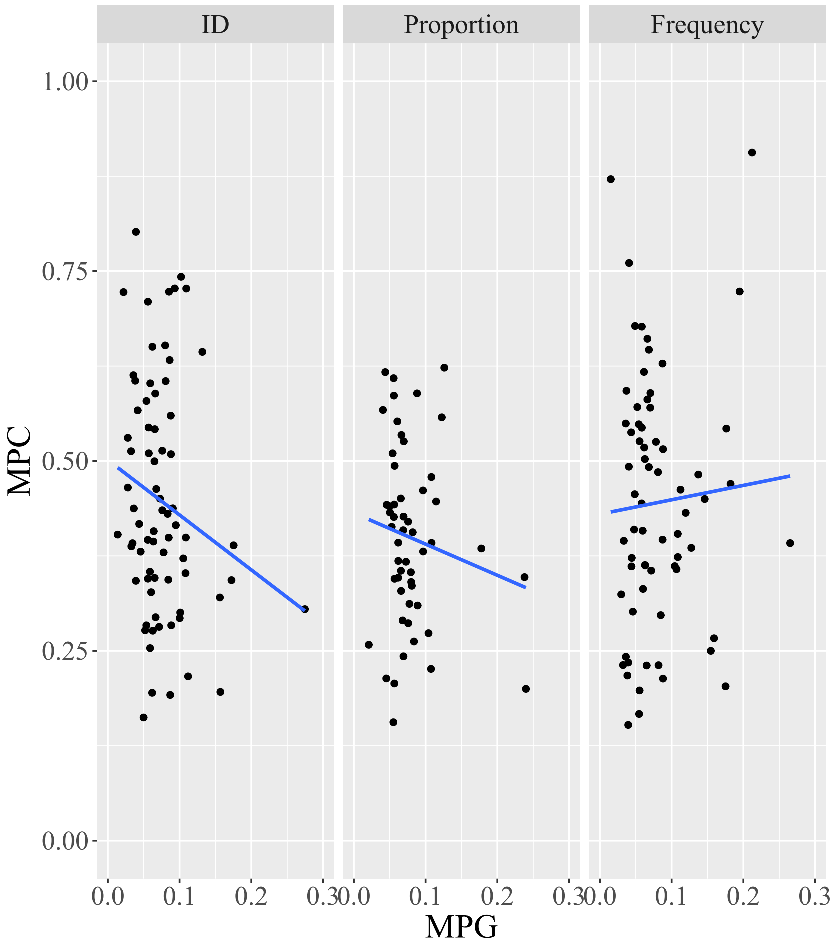

Figure 6: MPG and MPC Based on the Data

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

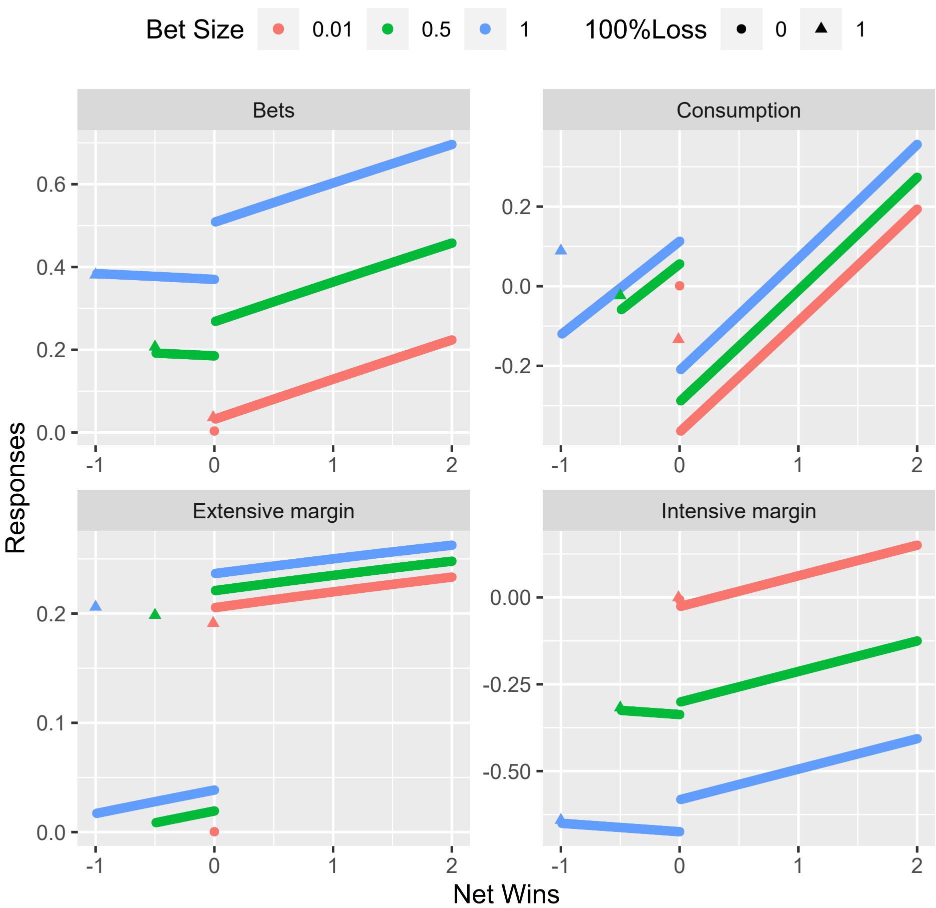

Figure 7: Simulated Bets and Consumption Based on Estimation Results

Note: We simulate the amounts of bets, consumption, the extensive margin, and the intensive margin based on the estimation results for each value of net wins and bets. All amounts are expressed in units of 10,000 JPY. The point representing 100% loss refers to the scenario where wins are zero and net wins equal minus bets.

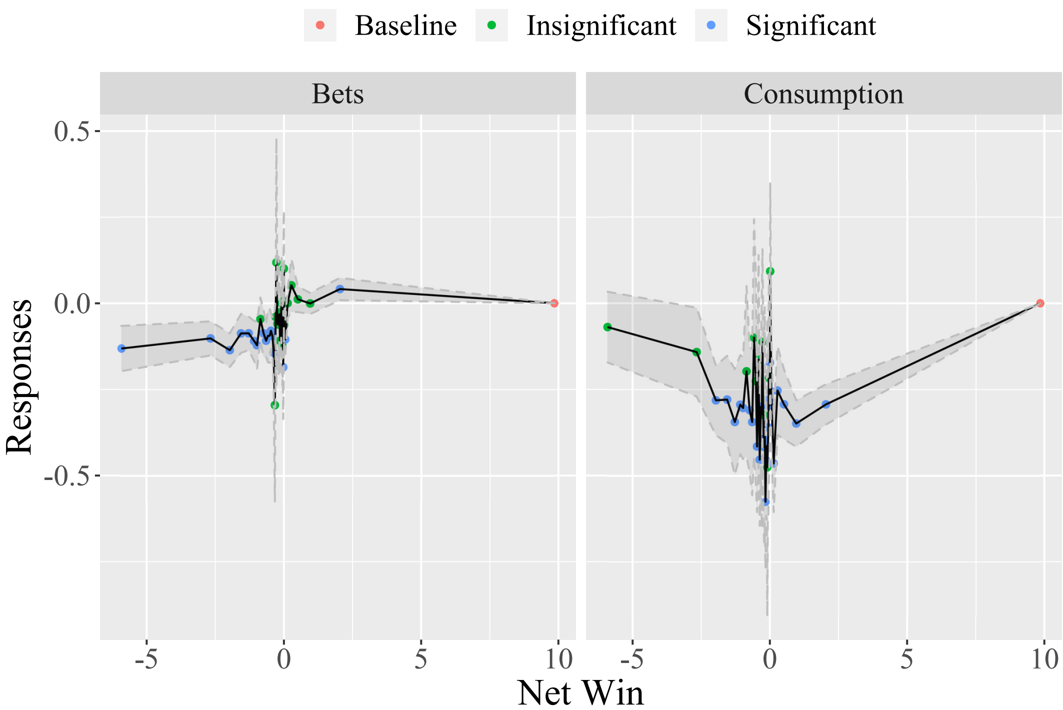

Figure 8: MPG and MPC Dependence on Net Wins

Note: The figure shows the difference of the MPG/MPC compared to the base value indicated by the red filled circle.

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

Fei Gao* Kozo Ueda†

September 20, 2024

A Gambling in Mizuho Data

This appendix offers a detailed analysis of gambling behavior observed in public race transactions from the Mizuho data. It highlights key patterns in gambling activity which our selection strategy has been built on. We present also supplementary observations on the gamblers' gambling outcomes.

A.1 Gambling Transactions

We summarize the features of gambling transactions to explain our selection criteria. We identified 248,630 (out of about 24 million) gamblers involved in public race gambling.

The 248,630 gamblers made over 82 million transactions recorded over four years. As shown in Table 1, gambling activities account for more than 50% of all transactions. With Table 2, we conclude that focusing on central horse racing is reasonable because horse racing is the most popular among the four types of public races, having the largest share in all transactions over 40%, and most gamblers focus on only one type of gambling.

The need for sufficient transactions of both gambling and consumption arises because we aim to analyze gamblers' responses. We investigate the number of transactions for each account. Table 3 reports the existence of inactive accounts (accounts that carry only a few transactions) and gambling-specialized accounts (accounts that have many

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Table 1: Transactions: Gambling and Non-gambling

Racing	Number	% (In transactions)	Players
Non-gambling	20,329,341	44.6%	206,852
Horse	19,660,532	43.1%	201,958
Boat	1,772,613	3.8%	9,765
Bicycle	3,271,886	7.1%	18,994
Motorcycle	514,709	1.1%	3,806

Table 2: Transactions: Multiple Gambling

Number of Public Races Gambled	1	2	3	4
Gamblers	230,414	1,899	89	11

gambling transactions but only a few consumption transactions). Only 193,316 accounts contain consumption transactions, and the median is low at 22, meaning that many bank accounts do not carry sufficient consumption transactions. By comparing percentiles between consumption and gambling bets, we learn that both gambling bets and consumption concentrate more on the left and right tails. However, consumption has a larger weight near zero and a longer right tail.

Table 3: The Number of Transactions for Each Gambler

Transactions	10%	25%	50%	75%	90%	Mean	SD	Gamblers
Transaction numbers								
Non-gambling inflows	2	7	30	92	164	66.100	242.800	222,067
Gambling wins (inflows)	2	7	33	103	182	69.590	100.200	232,888
Consumption (outflows)	1	4	22	121	418	130.900	283.900	193,316
Gambling bets (outflows)	5	21	91	187	212	120	136.600	221,911

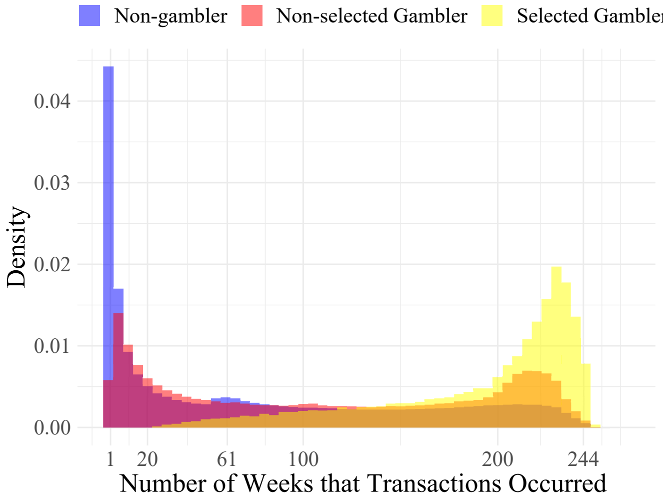

Figure 1: Number of Weeks that Transactions Occurred

Out of 248,630 gamblers, we selected 17,411 for our final database. The selection criteria are: (1) accounts must contain both bets and wins for central horse races; (2) accounts must have complete and consistent information on gender and birth year and exist before 2019; (3) weekly consumption (outflows minus bets) must not exceed 10 million JPY; (4) accounts must record positive consumption (excluding bets) for 20 weeks or more; and (5) the proportion of gambling must be less than 0.5.

As criterion (4), we select gamblers with positive consumption spending for at least 20 weeks. This selection criterion simultaneously removes gambling-specialized and inactive accounts. More importantly, it imposes no restrictions on gambling transactions or activity. We report the performance of this selection criterion in Figure 1, where the number of weeks that transactions occurred is presented. Gamblers, selected gamblers, and non-gamblers (the 24 million Mizuho users) are presented as different groups in the figure. The selection method eliminates inactive accounts (the left tail) and, more importantly, removes gambling-specialized accounts, which have limited consumption transactions.

A.2 Gambling Returns

Gambling return is an important subject as it represents windfall income (if won), financial harm (when the return is negative), and a possible trigger for gambling addiction. In our study, we examine 17,411 gamblers' responses to gambling outcomes (gambling wins, net wins, 100% losses, etc.); however, we omit the details of their gambling returns.

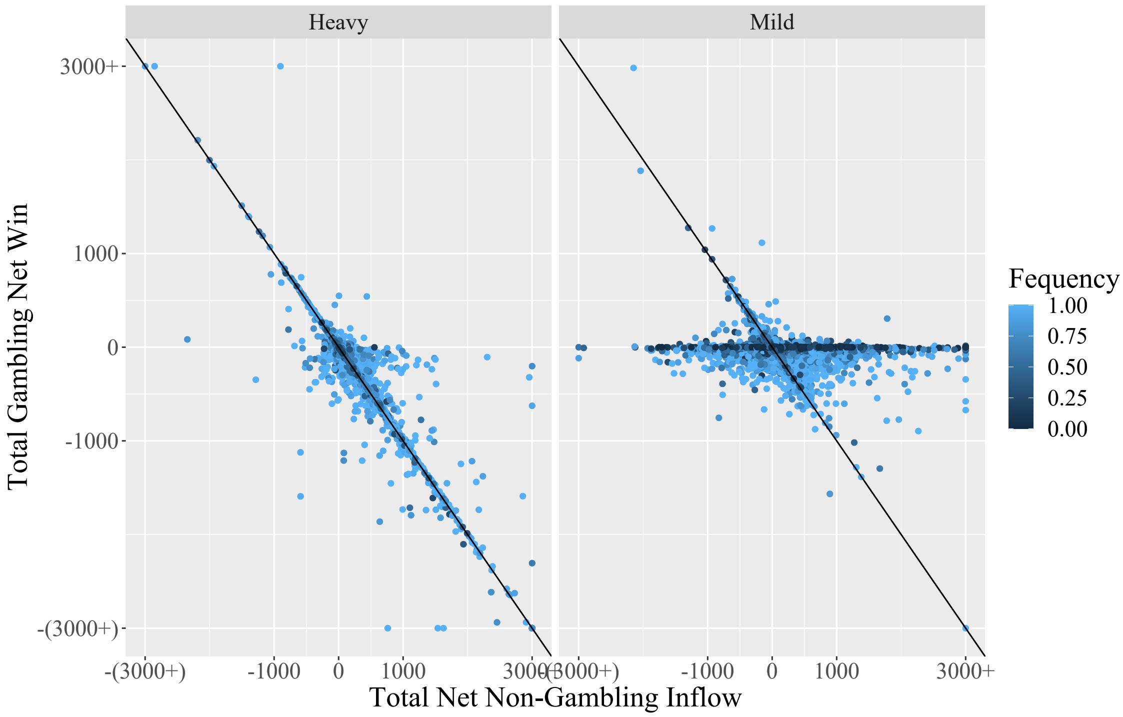

Figure 2: Total Returns from Gambling

In this section, we include heavy gamblers and discuss their gambling returns in Figure 2.

Negative gambling returns are common among gamblers. This is true not only at the weekly level but also over the entire four-year sample period. Most gamblers receive a negative total return from gambling, even those who have had large gambling wins. With heavy gamblers included, only 4,870 (i.e., 9%) out of 53,843 gamblers had a positive total gambling net win by the end of 2022.

The significant difference between mild and heavy gamblers in the figure cannot be overstated. We draw a solid line in the figure where the sum of the total gambling net win and total net non-gambling inflow equals 0. Heavy gamblers concentrate along this line, indicating that their account balances have not changed over the four years. In contrast, mild gamblers, whose gambling frequency is close to 0, and those who gamble moderately, concentrate along the line where the total gambling net win equals 0, indicating a different behavior from heavy gamblers.

Negative total gambling net wins do not necessarily mean that gamblers received no gambling wins. Returning to the full gambler sample, we find that only 17,416 out of 248,630 gamblers involved in public race gambling received no gambling wins.

To explore the connection between gambling wins and net wins, we accumulated the amount gambled and the amount won for each gambler to check how many gamblers had made a bet, received a gambling win, and had a positive gambling net win. In Table 4, we report the averages of the number of gamblers based on different time horizons.

The gap between the number of gamblers and the number of winners decreases as we shift from weekly to longer time intervals. This means that gamblers are more likely to receive a win if they gamble repeatedly. However, the number of positive net wins decreases over time, meaning gamblers are more likely to experience a negative gambling net win in the long term. This finding is consistent with the legally mandated 75% return rate.

Table 4: The Number of Gamblers

Who Gambled	Who Won	Who Made Positive Net Win	Measured By
36842	23828	6929	Week
43527	35735	7353	Month
47050	42271	6823	Quarter
51234	49263	6064	Year

B Predictability of Gambling Wins

In this section, we investigate to what extent gamblers can expect their gambling wins. We run the following regression:

$$win_{it} = \beta bet_{it-1} + \gamma Z_{it-1} + \alpha_i + \alpha_t + \varepsilon_{it}, \tag{1}$$

where Z_{it-1} is the vector of control variables consisting of wealth, borrowing, and income.

Table 5 shows the estimation results. The coefficient on bets is significant at around 0.9. This finding suggests that gambling win is approximately 0.9 of amount gambled in the previous week, which is larger than the designated market return rate 0.75 but smaller than one.

The adjusted R^2 of column (1), which only bet_{it-1} is included, is 0.289. It raises to 0.295 in column (3) once the individual fixed effect is included. The adjusted R^2 stays at 0.295 in column (5), which is the full-scale of the specification. The three control variables are not responsible to gambling wins.

More evidence suggests the three control variables are not explaining gambling wins. In column (2), the time fixed effect and three control variables are presented but they are not explainable for gambling wins: the adjusted R^2 is 0.002. The adjusted R^2 remains low even if the individual fixed effect is included in column (4), where the adjusted R^2 is 0.113.

These estimation results suggest that gambling wins are mostly unexpected, though accounting for the amount of bets significantly improves explanatory power.

Table 5: Predictability of Gambling Wins

	Dependent variable:				
	Win_t				
	(1)	(2)	(3)	(4)	(5)
Bet_{t-1}	0.900***		0.929***		0.929***
	(0.018)		(0.024)		(0.024)
Wealth		0.0001***		0.0003***	−0.0001***
		(0.00003)		(0.0001)	(0.00003)
Borrowing		0.00001		−0.001	−0.00005
		(0.00003)		(0.001)	(0.0001)
Income		0.00005*		−0.00000	−0.00000
		(0.00002)		(0.00000)	(0.00000)
Observations	3,553,068	3,551,891	3,553,068	3,551,891	3,551,891
R^2	0.289	0.002	0.295	0.113	0.295
Time Fixed effect	Yes	Yes	Yes	Yes	Yes
Individual Fixed effect	No	No	Yes	Yes	Yes

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

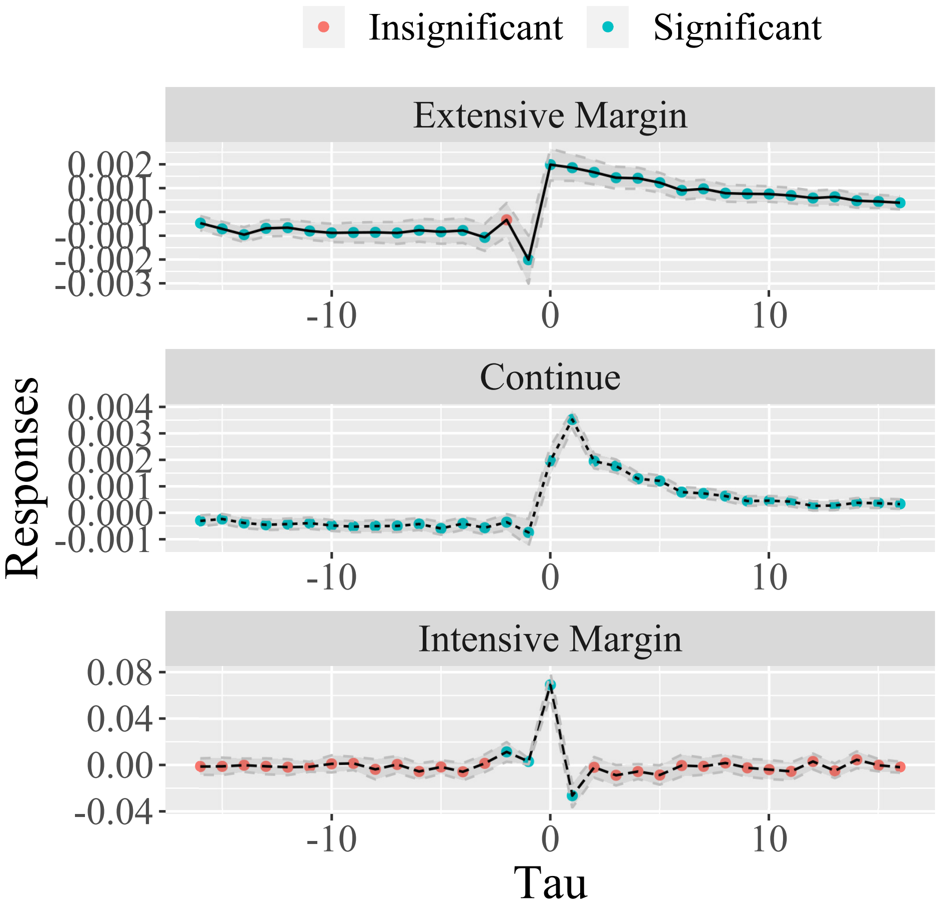

Figure 3: Dynamic Responses of Gambling Extensive and Intensive Margins

Note: Estimated coefficients on wins, β_τ, are displayed for $\tau = -16, -16, \cdots, 16$.

C Further Results of Responses

C.1 Dynamic Responses of Extensive and Intensive Margins

We extend our baseline specification to different dependent variables. Figure 3 shows dynamic responses of the marginal propensity of the extensive margin, the dummy of gamble continue, and the intensive margin to gambling wins. The two kinds of extensive margins are persistent, indicating the staggering effects on the participation in gambling. By contrast, the intensive margin increases only on impact.

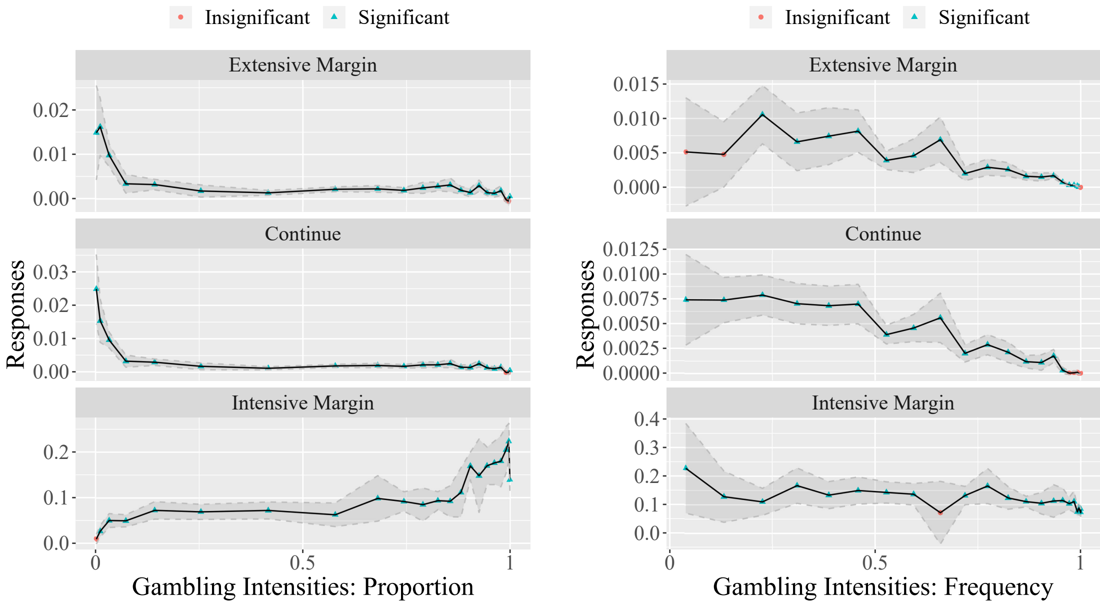

Figure 4: MPG (Extensive and Intensive Margins) by Gambling Intensity

Note: We estimate the marginal propensities for each group which is divided based on the proportion of gambling (left) or the frequency of gambling (right). 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.

C.2 Relations between Gambling Margins and Gambling Intensity

We investigate the relations between gambling (extensive and intensive) margins and gambling intensity. We expand the data to include heavy gamblers and evenly divide them into groups to estimate the marginal propensity of gambling margins by gambling intensity as we do for the MPG and MPC.

Figure 4 shows how gambling margins vary with the gambling intensity. The marginal propensity of the extensive margin is substantially higher for very light gamblers whose proportion of gambling is smaller than 0.1. This may indicate the process of novice gamblers falling into problem gambling after experiencing beginner's luck.

C.3 MPG and Liquidity Constraint

Table 6 shows the estimation results on the relationship between MPG and the liquidity constraint. The extensive margin entails a negative coefficient for the cross term with wealth (rows (1) and (3)) and a positive coefficient for the cross term with the liquidity constraint dummy (row (2)). This suggests that liquidity constrained gamblers are more likely to participate in gambles as their gambling wins increase.

Table 6: MPG/MPC and Liquidity Constraint

		Liquid const dummy	Its cross term	Wealth	Its cross term	Observations	R^2
Bets	(1)			0.0001***	-0.00000	3,533,125	0.584
				(0.00003)	(0.00001)		
	(2)	-0.084***	-0.007	0.0001***		3,533,125	0.584
		(0.016)	(0.012)	(0.00002)			
	(3)	-0.083***	-0.009	0.0001***	-0.00000	3,533,125	0.584
		(0.016)	(0.012)	(0.00003)	(0.00001)		
EM	(1)			0.00002***	-0.00000***	3,533,529	0.571
				(0.00001)	(0.00000)		
	(2)	-0.017***	0.002**	0.00002***		3,533,529	0.570
		(0.003)	(0.001)	(0.00001)			
	(3)	-0.016***	0.001	0.00002***	-0.00000***	3,533,529	0.571
		(0.003)	(0.001)	(0.00001)	(0.00000)		
EM (continue)	(1)			0.00002***	-0.00000***	3,533,529	0.571
				(0.00001)	(0.00000)		
	(2)	-0.018***	0.003*	0.00001**		3,533,529	0.570
		(0.003)	(0.002)	(0.00001)			
	(3)	-0.017***	0.001	0.00002***	-0.00000***	3,533,529	0.571
		(0.003)	(0.002)	(0.00001)	(0.00000)		

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

D Simple Model

D.1 Model

A gambler i maximizes the expected utility:

$$V = u(c_1) + \kappa v(x) + \beta \mathbb{E}\left[u(c_2)\right] \tag{2}$$

subject to

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

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

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 $\theta^H > \theta^L \geq 0$.

$$V = u(y - s - x) + \kappa v(x) + \beta \mathbb{E}\left[u(Rs + \theta x)\right]$$

FOCs wrt s and x:

$$-u'(c_1) + \beta R \mathbb{E}\left[u'(c_2)\right] = 0$$

$$-u'(c_1) + \kappa v'(x) + \beta \mathbb{E}\left[\theta u'(c_2)\right] = 0.$$

(i) Suppose $u(c) = \log(c)$ and $v(x) = \log(x)$. Then, we have

$$\begin{aligned}
0 &= -\frac{1}{c_1} + \beta R \mathbb{E}\left[\frac{1}{c_2}\right] \\
\Leftrightarrow \frac{1}{c_1} &= \beta R \left(\frac{\pi^H}{Rs + \theta^H x} + \frac{\pi^L}{Rs + \theta^L x}\right) \\
\Leftrightarrow \frac{1}{c_1} &= \beta \left(\frac{\pi^H}{(y - c_1) + (\theta^H/R - 1)x} + \frac{\pi^L}{(y - c_1) + (\theta^L/R - 1)x}\right),
\end{aligned} \tag{5}$$

and

$$-\frac{1}{c_1} + \kappa \frac{1}{x} + \beta \mathbb{E}\left[\frac{\theta}{c_2}\right] = 0$$

$$\begin{aligned}
\Leftrightarrow \frac{1}{c_1} - \frac{\kappa}{x} &= \beta \left(\frac{\pi^H \theta^H}{Rs + \theta^H x} + \frac{\pi^L \theta^L}{Rs + \theta^L x}\right) \\
\Leftrightarrow \frac{1}{c_1} - \frac{\kappa}{x} &= \beta \left(\frac{\pi^H \theta^H / R}{(y - c_1) + (\theta^H/R - 1)x} + \frac{\pi^L \theta^L / R}{(y - c_1) + (\theta^L/R - 1)x}\right).
\end{aligned} \tag{6}$$

These two equations enable us to obtain the solutions for c_1 and x.

Guess that the solution is given by $c_1 = y/(1+\beta+\kappa)$ and $x = \chi y$, and we verify this.

(Proof) Inserting this to equation (4) yields

$$1+\beta+\kappa = \beta\left(\frac{\pi^H}{\frac{\beta+\kappa}{1+\beta+\kappa}+(\theta^H/R-1)\chi}+\frac{\pi^L}{\frac{\beta+\kappa}{1+\beta+\kappa}+(\theta^L/R-1)\chi}\right)$$

$$\Leftrightarrow 1 = \beta\left(\frac{\pi^H}{\beta+\kappa+(\theta^H/R-1)\chi(1+\beta+\kappa)}+\frac{\pi^L}{\beta+\kappa+(\theta^L/R-1)\chi(1+\beta+\kappa)}\right)$$

$$\Leftrightarrow \frac{\pi^H}{\beta+\kappa+(\theta^H/R-1)\chi(1+\beta+\kappa)}+\frac{\pi^L}{\beta+\kappa+(\theta^L/R-1)\chi(1+\beta+\kappa)} = \frac{1}{\beta} \tag{7}$$

$$\Leftrightarrow \pi^H = \frac{\beta+\kappa+(\theta^H/R-1)\chi(1+\beta+\kappa)}{\beta} - \frac{\pi^L\left\{\beta+\kappa+(\theta^H/R-1)\chi(1+\beta+\kappa)\right\}}{\beta+\kappa+(\theta^L/R-1)\chi(1+\beta+\kappa)}$$

$$\Leftrightarrow (\theta^H/R-1)\chi(1+\beta+\kappa)\left\{\frac{1}{\beta}-\frac{\pi^L}{\beta+\kappa+(\theta^L/R-1)\chi(1+\beta+\kappa)}\right\} = \pi^H-1-\frac{\kappa}{\beta}+\frac{\pi^L(\beta+\kappa)}{\beta+\kappa+(\theta^L/R-1)\chi(1+\beta+\kappa)}$$

$$\begin{aligned}\Leftrightarrow (\theta^H/R-1)\chi(1+\beta+\kappa)\left\{\frac{1}{\beta}-\frac{\pi^L}{\beta+\kappa+(\theta^L/R-1)\chi(1+\beta+\kappa)}\right\} &= -\pi^L-\frac{\kappa}{\beta}+\frac{\pi^L(\beta+\kappa)}{\beta+\kappa+(\theta^L/R-1)\chi(1+\beta+\kappa)}\\ &= -\frac{\kappa}{\beta}-\frac{(\theta^L/R-1)\chi(1+\beta+\kappa)\pi^L}{\beta+\kappa+(\theta^L-1)\chi(1+\beta+\kappa)}\end{aligned}$$

$$\Leftrightarrow (\theta^H/R-1)\left\{\frac{1}{\beta}-\frac{\pi^L}{\beta+\kappa+(\theta^L/R-1)\chi(1+\beta+\kappa)}\right\} = -\frac{\kappa}{\beta\chi(1+\beta+\kappa)}-\frac{(\theta^L/R-1)\pi^L}{\beta+\kappa+(\theta^L/R-1)\chi(1+\beta+\kappa)}$$

$$\begin{aligned}&\Leftrightarrow \theta^H/R\left\{\frac{1}{\beta}-\frac{\pi^L}{\beta+\kappa+(\theta^L-1)\chi(1+\beta+\kappa)}\right\}\\ &= \frac{1}{\beta}-\frac{\pi^L}{\beta+\kappa+(\theta^L/R-1)\chi(1+\beta+\kappa)}-\frac{\kappa}{\beta\chi(1+\beta+\kappa)}-\frac{(\theta^L/R-1)\pi^L}{\beta+\kappa+(\theta^L/R-1)\chi(1+\beta+\kappa)}.\end{aligned} \tag{8}$$

By eliminating π^H, we can write equation (5) as

$$1+\beta+\kappa-\frac{\kappa}{\chi} = \beta\left(\frac{\pi^H\theta^H/R}{\frac{\beta+\kappa}{1+\beta+\kappa}+(\theta^H/R-1)x}+\frac{\pi^L\theta^L/R}{\frac{\beta+\kappa}{1+\beta+\kappa}+(\theta^L/R-1)\chi}\right)$$

$$\Leftrightarrow 1-\frac{\kappa}{\chi(1+\beta+\kappa)} = \beta\left(\frac{\pi^H\theta^H/R}{\beta+\kappa+(\theta^H/R-1)\chi(1+\beta+\kappa)}+\frac{\pi^L\theta^L/R}{\beta+\kappa+(\theta^L/R-1)\chi(1+\beta+\kappa)}\right)$$

$$\Leftrightarrow \frac{1}{\beta}-\frac{\kappa}{\beta\chi(1+\beta+\kappa)} = \theta^H/R\left\{\frac{1}{\beta}-\frac{\pi^L}{\beta+\kappa+(\theta^L/R-1)\chi(1+\beta+\kappa)}\right\}+\frac{\pi^L\theta^L/R}{\beta+\kappa+(\theta^L/R-1)\chi(1+\beta+\kappa)}$$

$$\begin{aligned}\Leftrightarrow \frac{1}{\beta}-\frac{\kappa}{\beta\chi(1+\beta+\kappa)} = &\frac{1}{\beta}-\frac{\pi^L}{\beta+\kappa+(\theta^L/R-1)\chi(1+\beta+\kappa)}-\frac{\kappa}{\beta\chi(1+\beta+\kappa)}-\frac{(\theta^L/R-1)\pi^L}{\beta+\kappa+(\theta^L/R-1)\chi(1+\beta+\kappa)}\\ &+\frac{\pi^L\theta^L}{\beta+\kappa+(\theta^L-1)\chi(1+\beta+\kappa)}\end{aligned}$$

$$\Leftrightarrow 0 = -\frac{\pi^L+(\theta^L/R-1)\pi^L-\pi^L\theta^L/R}{\beta+\kappa+(\theta^L/R-1)\chi(1+\beta+\kappa)} = 0$$

where we use equations (6) and (7) to derive the third and fourth lines, respectively. This shows that equation (5) is redundant given the solutions we guessed. Thus, $c_1 = y/(1+\beta+\kappa)$ and $x = \chi y$ serve as the solution. ■

Note that χ is given by the solution of equation (6). It is simplified as

$$\begin{aligned}0 = &-(\theta^L/R-1)(\theta^H/R-1)(1+\beta+\kappa)^2\chi^2 \\ &-\left\{\kappa(\theta^H/R+\theta^L/R-2)+\beta(\pi^H\theta^H/R+\pi^L\theta^L/R-1)\right\}(1+\beta+\kappa)\chi \\ &-(\beta+\kappa)\kappa. \end{aligned} \tag{9}$$

Assume that $\theta^L/R - 1 < 0$ and $\theta^H/R - 1 > 0$. Assume also $\kappa \geq 0$. Then, we have the following:

- MPC is $1/(1+\beta+\kappa)$, while MPG is χ.
- MPC is decreasing in β and κ.
- One of the solutions of χ is non-negative (specifically, $\chi > 0$ if $\kappa > 0$).
- Further, assume that $0 < \kappa, \chi \ll 1$. Then, MPG (non-negative χ) is increasing in κ and decreasing in β, because $\chi \sim \kappa/(1+\beta)$.

This result has the following implications:

- Heterogeneity in β : MPC and MPG are positively correlated.
- Heterogeneity in κ : MPC and MPG are negatively correlated.
- Heterogeneity in θ or π: MPC is homogeneous.
- Mizuho data suggest a negative correlation, if anything. This shows heterogeneity in κ. However, when MPC is low, there is not much correlation, which may also suggest coexistence of a heterogeneity in β. Further, β and κ may be negatively correlated.
- Heavy gamblers think wins as a permanent income, which may imply a large MPC. However, this argument is wrong. Suppose that heavy gamblers those with large κ. Their MPG χ is large, while MPC is small.

(ii) Suppose CES utility forms: $u(c) = c^{1-\sigma_c}/(1-\sigma_c)$ and $v(x) = x^{1-\sigma_x}/(1-\sigma_x)$. Then, we have

$$
\begin{aligned}
&0 = -c_1^{-\sigma_c} + \beta R \mathbb{E}\left[c_2^{-\sigma_c}\right] \\
\Leftrightarrow\ & c_1^{-\sigma_c} = \beta R \left\{ \pi^H (R(y-c_1) + (\theta^H - R)x)^{-\sigma_c} + \pi^L (R(y-c_1) + (\theta^L - R)x)^{-\sigma_c} \right\}
\end{aligned} \tag{10}
$$

and

$$
-c_1^{-\sigma_c} + \kappa x^{-\sigma_x} + \beta \mathbb{E}\left[\theta c_2^{-\sigma_c}\right] = 0
$$

$$
\begin{aligned}
\Leftrightarrow\ c_1^{-\sigma_c} = &\ \kappa x^{-\sigma_x} \\
&+ \beta \left\{ \pi^H \theta^H (R(y-c_1) + (\theta^H - R)x)^{-\sigma_c} + \pi^L \theta^L (R(y-c_1) + (\theta^L - R)x)^{-\sigma_c} \right\}
\end{aligned} \tag{11}
$$

- Varying $\beta \rightarrow$ positive correlation between MPC and MPG
- Varying κ or $\sigma_c \rightarrow$ negative correlation between MPC and MPG
- Varying $\pi^H \rightarrow$ Effects only on MPG

D.2 Simulation Results

Figure 5 shows correlations between the MPG and MPC based on the model. This confirms that heterogeneity in β_i generates a positive correlation, whereas heterogeneity in κ_i generates a negative correlation. Figure 6 shows further simulation results when we extend the utility function from the logarithm to the constant elasticity of substitution (CES). We consider heterogeneity in β_i, κ_i, θ^H, and CES parameters.

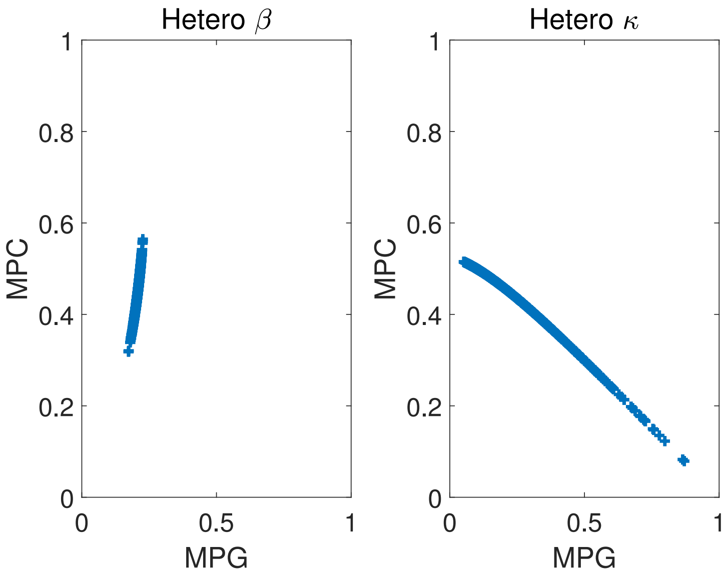

Figure 5: MPG and MPC Based on the Model

Note: The left- and right-hand panels represent cases in which heterogeneity exists in terms of discount factor β_i and utility from gambling κ_i, respectively. We set $\beta = 0.9$, $\kappa = 0.3$, $R = 1$, $\pi^H = 0.3$, $\theta^L = 0$, and $\theta^H = 2.33$ (so that the expected return of gambling is 0.7). Heterogeneity in β_i and κ_i is assumed to follow log normal distribution with standard deviation 0.2 and 1, respectively.

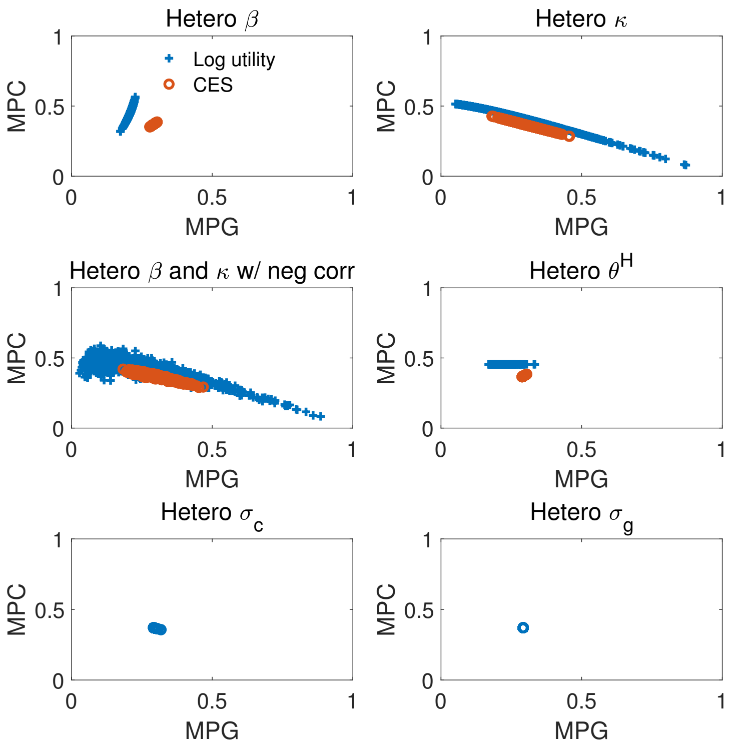

Figure 6: MPG and MPC Based on the Extended Model

Note: The left- and right-hand panels represent cases in which heterogeneity exists in terms of discount factor β_i and utility from gambling κ_i, respectively. We set $\beta = 0.9$, $\kappa = 0.3$, $R = 1$, $\pi^H = 0.3$, $\theta^L = 0$, and $\theta^H = 2.33$ (so that the expected return of gambling is 0.7). Heterogeneity in β_i and κ_i is assumed to follow log normal distribution with standard deviation 0.2 and 1, respectively.

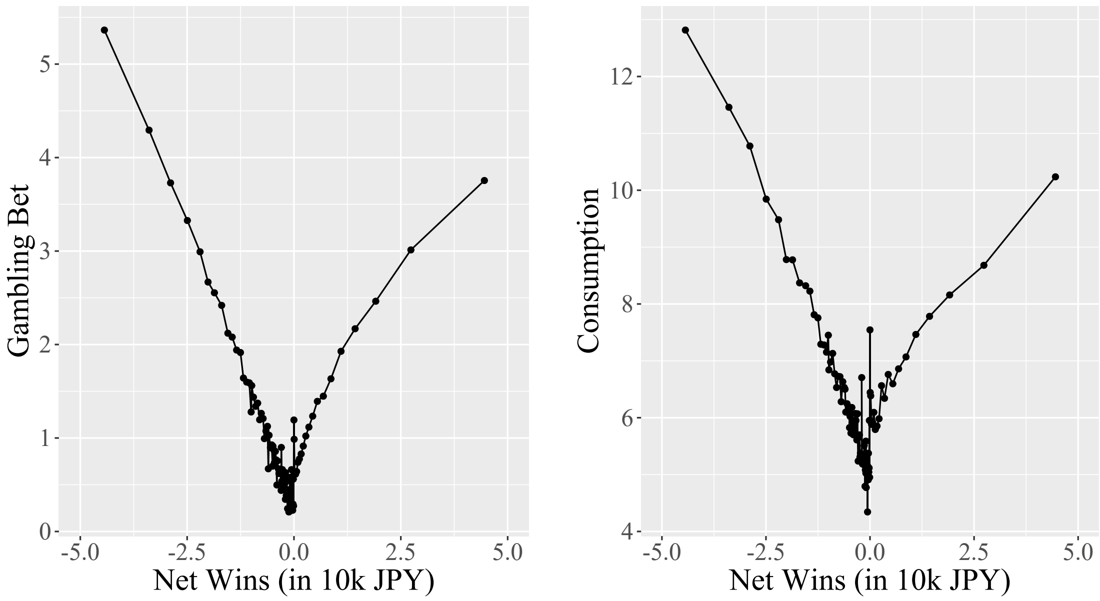

Figure 7: Relations between Bets, Consumption, and Net Wins

E Dependence of Bet and Consumption Responses on Net Wins

E.1 Graphical Associations between Bets/Consumption and Net Wins

Figure 7 shows a magnificent nonlinearity and asymmetry between net wins and net losses. Specifically, the left-hand panel illustrates that gambling bets tend to be large, as net wins are large. Similarly, gambling bets tend to be large, when net losses are large. This implies two possibilities. First, gamblers do gambles more either when they win or lose a considerable amount. On the one hand, when their wins are large, they may bet a lot (i.e., easy come, easy go). On the other hand, when they lose a lot, they may not finish gambles, but instead try to win back, which may result in problem gambling. However, there is a second possibility. This panel may simply reflect income/wealth effects: bets are larger, as gamblers are more wealthy or into gambles by nature (heavy gamblers). Thus, although the first possibility is intriguing, we need to discount this possibility because of the second possibility. Estimation using fixed effects would help eliminate the second possibility.

Furthermore, a close look at the left-hand panel indicates two things. First, there appears a discontinuity around zero net wins. Gambling bets jump when net wins turns from negative to positive. In other words, when gamblers suffer a net loss, they refrain from gambles. Second, the slope is greater when net wins are negative than that when they are positive. One possible interpretation of this result is that gamblers' propensity to win their losses back is stronger than their propensity to go easy after their wins, although gamblers may refrain from gambles if their losses are small.

The right-hand panel shows relations between net wins and consumption, which exhibits a similar pattern to those between net wins and gambling bets. Specifically, consumption tends to be large, as net wins or bets are large, which reflects income/wealth effects. A close look at the neighborhood of zero net wins indicates a discontinuity: consumption jumps when net wins are positive. Comparing between net wins and losses when the amount is large, we can observe asymmetry, that is, consumption is smaller when net wins are positive than they are negative.

E.2 Sub-group Estimation

We run the following regression:

$$\begin{aligned} Y_{it} = \beta_0 win_{it} + \sum_j \beta_0^j win_{it} \times I_{jt} \\ + \delta_{10} bet_{it-1} + \delta_{20} bet_{it-2} + \gamma_0 Z_{it-1} + \alpha_i + \alpha_t + \varepsilon_{it}, \end{aligned} \tag{12}$$

where I_{jt} is a dummy which takes one for a specific subsample j. We divide groups based on either the return rate or wealth.

Figure 8 shows the estimation results. The estimation results on the return rate are consistent with those on net wins (the return rate of one corresponds to zero net win). The MPG significantly increases when the return rate exceeds one by a slight margin, compared with that when the return rate is below one or greater than 10. By contrast, the MPC significantly decreases when the return rate is around one. The MPC tends to increase with the return rate, again suggesting a positive income effect.

The bottom panel of Figure 8 shows the dependence of the MPG and MPC on wealth (liquidity constraint). For the MPG, β_0^j is insignificant for all subsamples, illustrating the independence of the MPG on the liquidity constraint. By contrast, the MPC tends to decrease with wealth.

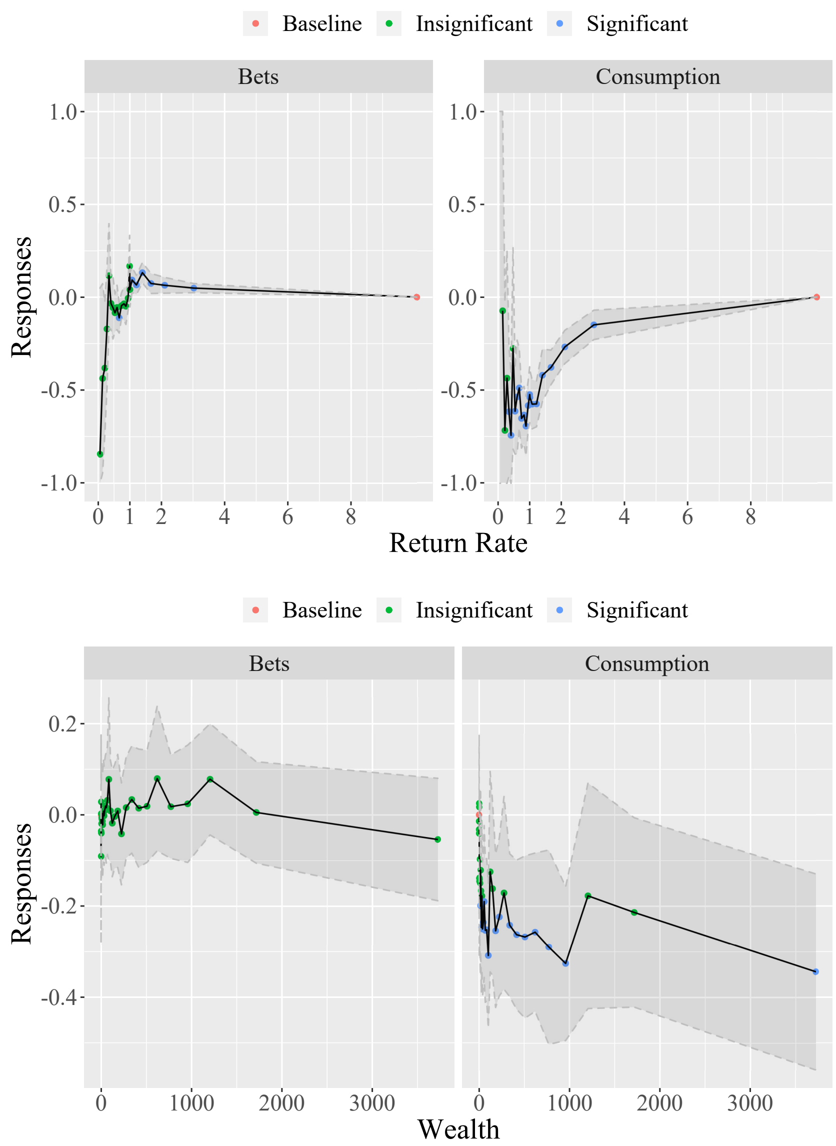

Figure 8: MPG and MPC Dependence on Return Rate and Wealth

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