The Impact of Investment Gains on Gambling Consumption*

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Abstract

Using unique Australian investment app data, we document gamblers' propensity and sensitivity to spend money on online sports betting upon experiencing mutual fund investment gains. Employing past asset weights within portfolios as instruments for current positions, we find that investment gains lead to more gambling for individuals who previously gambled, suggesting a complementary relationship. We propose that changes in risk attitude resulting from mutual fund investment experiences drive this increased gambling consumption. This tendency, however, hinders the growth of investment wealth, particularly among financially vulnerable individuals. Our study highlights the intricate connection between investment and gambling consumption.

Keywords: Gambling, Sensation Seeking, Risk Tolerance

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1 Introduction

The study of the relationship between gambling and investing in the stock market has sparked considerable academic interest, albeit it has led to mixed findings. On the one hand, studies show that gambling and investing are substitutes, where individuals reduce investing as a response to greater availability or attractiveness of gambling (e.g., Dorn et al. 2015; Gao and Lin 2015; Cookson 2018; Cox et al. 2020). In contrast, others show a complementary relationship, where those inclined to gamble also exhibit a propensity to invest in stocks (e.g., Kumar 2009; Dorn and Sengmueller 2009; Grinblatt and Keloharju 2009; Kumar et al. 2011), and winning a lottery increases stock market participation (Briggs et al. 2021; Cheng et al. 2022).

Notably, most studies examining the relationship between gambling and investing have focused on investing as the primary outcome variable. However, it remains unclear whether investment gains affect gambling consumption, which was used as a critical measure of risk preference in the previous research (Andrikogiannopoulou and Papakonstantinou 2020). The global online gambling market, valued at 100 billion U.S. dollars,[1] is rapidly expanding alongside the recent surge in stock market participation by retail investors (Barber et al. 2022). Given that a significant portion of individual investors worldwide are highly susceptible to compulsive gambling (Cox et al. 2020; Calado and Griffiths 2016; Dorn and Sengmueller 2009), and the ambiguity in the relationship between financial wealth and risk preferences,[2] an empirical examination of how investment gains influence one's propensity toward risk tolerance in relation to gambling con-

[1] https://www.statista.com/outlook/amo/online-gambling/worldwide

[2] The relationship between financial wealth and risk preference has been extensively studied, but findings are mixed. Some studies, such as those by Brunnermeier and Nagel (2008) and Chiappori and Paiella (2011), show an insignificant effect of financial wealth on risk-taking. Conversely, Calvet et al. (2009), Calvet and Sodini (2014), and Paravisini et al. (2017) demonstrate a positive relationship between financial wealth and risk tolerance.

sumption, is deemed important.

A common limitation of previous studies investigating the relationship between gambling and investing is their reliance on aggregate data, often overlooking individual-level behaviors and the nuanced dynamics at play. Heterogeneity across individuals may play a critical role in understanding the relationship between gambling and investing. By analyzing individual-level, single-source panel data that combines investment gains and gambling consumption, we explore intricate patterns and variations in risk tolerance, offering insights into whether investment gains serve as substitutes or complements to gambling consumption for different individuals. This refined approach promises a more comprehensive understanding of the complex interplay between these two financial behaviors.

Specifically, we utilize data from *Raiz Invest*, a prominent Fintech investment app in Australia, which allows users to invest in mutual funds tailored to their preferred risk profiles. Our dataset encompasses users' mutual fund selections, monthly capital contributions from February 2016 through August 2021, and consumption data sourced from their linked bank accounts. The consumption data contains expenditures related to online sports betting, including both the amount and frequency, based on the textual description of bank account transactions. These comprehensive and granular data enable us to explore how investment gains from mutual funds influence risk tolerance, as measured by gambling consumption in online sports betting.

Australia offers an optimal context for exploring this research question, boasting the highest gambling participation rate globally, with over 80% of the adult population engaged.[3] Given the pervasive nature of gambling in the country, we benefit from a significant statistical power derived

[3] http://news.bbc.co.uk/2/hi/asia-pacific/6313083.stm

from a vast number of observations, enabling a thorough examination of individual investment gains and gambling consumption. Moreover, with the rising popularity of sports betting around the world, our insights into the interplay between investment and gambling consumption hold relevance for numerous countries undergoing financial market development.

However, due to potential endogeneity concerns, drawing a causal inference of the impact of investment on risk tolerance in terms of gambling consumption is challenging. For instance, individuals' unobservable gambling preference might influence both their likelihood to engage in sports betting and their participation in the mutual fund market. To address this issue, we employ an instrumental variable (IV) approach, exploiting the exogenous asset price fluctuations: we use the wealth proportion in each underlying asset of a portfolio from two periods before to predict its current share of total investment as the Bartik-Instrument (e.g., Bartik 1991; Jean and Katz 1992; Adao et al. 2019; Goldsmith-Pinkham et al. 2020; Di Maggio et al. 2020; Borusyak et al. 2022). This serves as a relevant instrument because a previously high asset allocation would likely persist in the current period unless there is extensive or frequent portfolio rebalancing. This instrument should also meet the exclusion restriction since past asset allocations are exogenous to market-driven asset price changes.

Using this approach, we document that changes in (unrealized) investment gains have a positive causal relationship with both the amount spent on gambling and the likelihood of gambling within a given month. An additional Australian dollar (AUD) gain from investment results in an increase of 0.00455 AUD in gambling spending or a 0.002 percentage point increase in the likelihood of gambling. This indicates that individuals tend to increase their gambling consumption as their investment gains rise, suggesting that investment behaviors complement gambling consumption. Additionally, we observe heightened sensitivity among those with a strong inclination towards gambling[4]; although they may not gamble every month, an increase in investment gains often leads to increased gambling spending.

Next, we explore a potential explanation for why investment gains positively affect gambling consumption, possibly through an individual's shifting attitude toward risk tolerance, as measured by their choices of riskier investment portfolios. Our findings indicate that higher returns from mutual fund investments encourage individuals to opt for riskier portfolios. The link between investment gains and gambling consumption is indeed more conspicuous among those with higher risk tolerance; we demonstrate that the impact of investment gains on risk preferences is reflected in both increased gambling consumption and the choice of riskier portfolios. This explanation holds even when considering alternative explanations, such as wealth effects, temporary increases in cash inflows, other potential behavioral forces (e.g., addiction, hedonic consumption), and the portfolio rebalancing to riskier investments, all of which can be ruled out.

In addition to the finding that investment gains increase gambling consumption, we identify negative implications on personal finance beyond gambling, especially for financially vulnerable individuals. First, we find that investment wealth grows at the slowest rate for gamblers in the top quintile of gambling tendency. In particular, the gambling consumption is positively associated with lower net deposits to investment accounts, attributing to the slow growth of investment wealth. Second, we find that this slow growth in investment wealth due to spending on gambling

[4] In this paper, gambling tendency is measured by the average monthly spending on gambling, as detailed in Section 4.

is even more conspicuous among the lowest-income group. These findings demonstrate that experiencing investing returns can lead to unintended, negative consequences for individuals with low income, making them more vulnerable to the complementary effect of investment gains on gambling consumption.

Related Literature: While previous studies have recognized a connection between gambling and investing behaviors using aggregated data, they have not pinpointed the specific dynamics at play, particularly the effect of investment gains on gambling consumption. The motivations for gambling consumption are diverse, ranging from a propensity to seek high-yield, lottery-like investment securities (Kumar 2009; Mitton and Vorkink 2007; Bali et al. 2011; Conrad et al. 2014; Doran et al. 2012; An et al. 2020), and sensation seeking (Grinblatt and Keloharju 2009; Dorn and Sengmueller 2009; Chava et al. 2023), to religious doctrines of leniency toward gambling (Kumar et al. 2011; Han and Kumar 2013). In particular, the causal substitution effect of gambling on speculative investment has been demonstrated in cases where large lottery prizes serve as a quasi-natural experiment (Gao and Lin 2015; Dorn et al. 2015). Additionally, windfall gains from the lottery have been shown to lead to increased stock market participation (Briggs et al. 2021; Cheng et al. 2022). However, due to the lack of data availability on gambling at the individual level, the causal inference regarding the impact of investment gains on gambling has been under-explored. In this regard, our data granularity allows us to gain a deeper understanding of the interplay between gambling and mutual fund investment, and our paper is one of the first to examine this relationship and to demonstrate that it varies across individual profiles.[5]

[5] Cookson (2018) studies the effect of investment on gambling consumption by using the introduction of prize-linked savings accounts in Nebraska as a quasi-experiment. While it also studies the same directional effect, since we exploit the exogenous change in asset prices of a portfolio at the market level, as opposed to a newly introduced financial

In a broader context, this paper contributes to the expanding body of literature exploring the connection between equity investment and consumption. Several studies have identified a positive effect of stock investment gains and dividend income on spending (Di Maggio et al. 2020) as well as a negative impact of social investing on charitable giving (An et al. 2023). There is also evidence of an immediate and enduring spending response following positive wealth shocks in the stock market (Andersen et al. 2022). In terms of sensation seeking, Imas et al. (2022) observed that individuals increase their entertainment spending in response to significant stock investment gains, whether positive (due to the wealth effect) or negative (as a form of retail therapy). Medina et al. (2021) and Keloharju et al. (2012) further explored this phenomenon, showing that shareholders tend to purchase more products from the companies they hold shares in, driven by loyalty. Similarly, our paper contributes to this literature by providing a holistic view of how mutual fund investment gains affect individuals' gambling spending, as a form of risk-related consumption, and further enhances the understanding of the nuanced dynamics with respect to how the increased gambling spending in turn slows down the growth in investment wealth.

The paper is organized as follows: Section 2 offers a comprehensive description of the data used in our analyses. Section 3 details our identification strategies, aimed at establishing a causal relationship between investing and gambling. In Section 4, we articulate the impacts of investment on gambling. Finally, we draw our conclusion in Section 5.

product confined to one particular state, for causal inference, our settings allow a more generalizable interpretation.

2 Data and Summary Statistics

2.1 Data Description and Variables Construction

This section provides details about our data from *Raiz Invest*, a prominent investment app in Australia.[6] Upon registration, individuals provide demographic details such as age, gender, income, and wealth. They then establish financial objectives, such as purchasing a car, and align these with specific investment horizons. Raiz Invest offers a menu of 5 different mutual fund portfolios consisting of the following domestic and international ETFs with varying degrees of asset allocation: Australian High Interest Cash (AAA), SPDR S&P/ASX 200 Fund (STW), iShares Asia 50 AUD (IAA), iSharesEurope (IEU), iShares Core Composite Bond (IAF), Russell Australian Select Corporate Bond (RCB), and iShares S&P 500 ETF (IVV): the offering ranges from Portfolio 1 (indicating the lowest risk) to Portfolio 5 (indicating the highest risk).[7] Individuals select a portfolio that suits their risk preference in order to accomplish their financial goals. Once this portfolio choice is made, the app will automatically make investments on behalf of individuals, reinvest any dividends, and rebalance every quarter to maintain the stipulated asset allocation.[8]

On the investment side, we can observe this portfolio choice along with the month-end investment account balance. Based on both price changes and dividend income of underlying ETFs of a

[6] For a more general description of the app, refer to An et al. (2023) and An et al. (2021). Similar data have also been used in Gargano and Rossi (2018).

[7] Appendix Figure A1 confirms that portfolios with a higher risk level have greater volatility and higher average return in a monotonic manner. While the annualized Sharpe ratio is not strictly monotonically increasing in the portfolio riskiness label, due to the composition of Portfolio 1, which heavily concentrates on money market investments, Sharpe ratio is also generally increasing in the riskiness of the portfolio.

[8] Portfolio 1 maintains asset allocation of 24.5% AAA, 13.5% STW, 3% IAA, 3% IEU, 30% IAF, 23% RCB, 3% IVV. Portfolio 2 maintains asset allocation of 9.6% AAA, 21.2% STW, 3% IAA, 3% IEU, 30% IAF, 25% RCB, 8.2% IVV. Portfolio 3 maintains asset allocation of 3% AAA, 31.7% STW, 8% IAA, 4.1% IEU, 19.2% IAF, 25% RCB, 9% IVV. Portfolio 4 maintains asset allocation of 3% AAA, 43.6% STW, 13.8% IAA, 6.4% IEU, 3% IAF, 21.3% RCB, 8.9% IVV. Portfolio 5 maintains asset allocation of 3% AAA, 54% STW, 23.5% IAA, 7.1% IEU, 3% IAF, 4% RCB, 5.4% IVV.

portfolio at the monthly frequency, we can construct *Return* for each ETF, and as a result, we can also compute the valuation of each ETF in dollar terms, which will be crucial in identification as shift-share. Consequently, we can define *Balance* as the sum of the balance from one month ago that has earned an investment return over a month and *New-Net-Deposit*, which is the difference between a new deposit into the investment account and the withdrawal from the account in the following manner:

$$\text{Balance}_{i,t} = \sum_{n=1}^{N} \text{Balance}_{n,i,t\text{-}1} \times (1 + \text{Return}_{n,t}) + \text{New-Net-Deposit}_{i,t},$$

for user i and year-month t.

We also observe spending transactions from individuals' linked bank accounts, which include date, amount, merchant, and simple description of transaction. Based on the textual description of merchants, we confined to spending related to online sports gambling by filtering transactions whose textual description of the merchant includes one of the top 5 players in the online sports betting industry in terms of market share during our sample period (Sportsbet, UBet, Ladbrokes, BetEasy, and Bet365).[9] We aggregate the spending amount on these websites to the individual-month level, and we use this gambling expenditure as well as the gambling occurrence as our main measures of gambling consumption in the paper.

2.2 Summary Statistics

Our dataset comprises monthly records of 99,552 unique gamblers spanning from February 2016 to August 2021. Table 1 presents statistics of individuals who engaged in online sports gambling

[9] We manually checked and removed falsely identified merchants. For instance, a merchant named "Rubette" includes "ubet" in the textual description, but as this merchant is not related to gambling, we removed it.

with a positive expenditure during the sample period. The data indicates consistent gambling consumption among these individuals, with instances of substantial betting. These individuals participated in online sports gambling 21% of the time, with an average expenditure of 49.55 AUD on a monthly basis.

Concerns might arise regarding the external validity of our data, considering the potential self-selection bias of the sample population choosing to use the investment app. If a significant portion of the gamblers in our dataset are those who gravitate toward heavy gambling but opted for the app as a means to curtail their habits and pivot toward mutual fund market investment, then our dataset may not accurately reflect the profile of an average Australian gambler. However, it is essential to note that, despite these potential selection biases, our data show strong correlations with the Australian Gambling Statistics. This comprehensive report, produced by the Queensland Government Statistician's Office, provides information of the annual per capita gambling amounts of all types at both the national and the provincial level, lending credibility to our dataset's representativeness.

Figure 1 presents a time-series comparison between the per capita amount spent on online sports betting in our dataset and the overall gambling consumption in Australia. As shown, both the magnitude and the trajectory of these trends align closely. To further understand this observed synchronicity, we conducted a regression analysis at the province-year level, considering the latest available data from the Australian Gambling Statistics, which extends up to 2019.[10] The results, presented in Table 2, confirm a statistically significant correlation between these two vari-

[10] At the time of drafting the manuscript, Australian Gambling Statistics is available only up to 2019, and thus, we examine the correlation between our data and the national statistics for the overlapping eight provinces over three years.

ables. This strong alignment lends further weight to our dataset's representativeness and external validity.

In preparation for our primary empirical analysis, we first reaffirm established findings indicating that specific demographic traits correlate with a propensity to gamble. Columns 1 and 2 of Appendix Table A1 clearly demonstrate that younger and male users exhibit a higher likelihood of gambling within our sample, potentially because these groups are more risk-tolerant (Brooks et al. 2019). Furthermore, individuals with a more substantial income and a shorter investment horizon also tend to engage in more gambling. Thus, the tendency to gamble correlates with both risk appetite and financial status.

3 Identification and Empirical Strategy

Next, we outline the identification strategies for estimating the causal impact of changes in investment gains on gambling consumption and explore potential factors that could explain this relationship.

3.1 Relationship Between Changes in Investment Gains and Gambling Consumption

Addressing the intrinsic relationship between investment gains and gambling consumption is challenging, primarily due to potential endogeneity issues. For instance, an inherent risk-taking propensity might influence gambling and investment behaviors. To robustly establish causality between these two domains, we take inspiration from Di Maggio et al. (2020) and employ a Bartik-instrument-styled IV approach (e.g., Bartik 1991; Jean and Katz 1992; Adao et al. 2019; Goldsmith-Pinkham et al. 2020; Borusyak et al. 2022). The returns from a portfolio arise from the endogenously chosen asset allocation and the exogenous asset price fluctuations. Our approach aims to leverage the latter to establish causality.

Specifically, we use the asset allocation from two months prior (instead of the more recent month) for each asset within a mutual fund portfolio and then interact this with the asset's current return (return between the previous and current months). This variation plays as an instrument for the prior month's asset allocation, once again interacting with the asset's contemporary return. Given that portfolio rebalancing happens quarterly based on pre-set asset allocation criteria, our chosen IV should hold relevance. The idea is that the asset allocation percentage from two months prior would closely mirror that from the preceding month, satisfying the relevance criterion. Furthermore, in this setup, monthly investment return variation is solely due to asset price changes, which are dictated exogenously by the asset market. They do not result from a individual's deliberate portfolio choices, thereby fulfilling the exclusion criterion.

We next run the first-stage and second-stage regressions with the following specification:

$$\text{First stage:} \quad \text{OLS}\Delta\text{Gain}_{i,t} = \rho \cdot \text{IV}\Delta\text{Gain}_{i,t} + \kappa_t + \varepsilon_{i,t} \tag{1}$$

$$\text{Second stage:} \quad \text{Y}_{i,t} = \beta \cdot \widehat{\text{OLS}\Delta\text{Gain}}_{i,t} + \phi_t + \epsilon_{i,t} \tag{2}$$

where $\text{OLS}\Delta\text{Gain}_{i,t}$ and $\text{IV}\Delta\text{Gain}_{i,t}$ are defined as,

$$\text{OLS}\Delta\text{Gain}_{i,t} = \sum_{n=1}^{N} \text{Balance}_{n,i,t\text{-}1} \times \text{Return}_{n,t} - \sum_{n=1}^{N} \text{Balance}_{n,i,t\text{-}2} \times \text{Return}_{n,t\text{-}1} \tag{3}$$

$$\text{IV}\Delta\text{Gain}_{i,t} = \sum_{n=1}^{N} \text{Balance}_{n,i,t\text{-}2} \times \text{Return}_{n,t} - \sum_{n=1}^{N} \text{Balance}_{n,i,t\text{-}2} \times \text{Return}_{n,t\text{-}1} \tag{4}$$

For each individual i, year-month t and asset type n. κ_t and ϕ_t are year $\times$ month fixed effects (controlling for any unobserved time shock that is common across individuals). Similar to Di Maggio et al. (2020), to control for unobservable time-invariant individual characteristics that might affect both the outcome variables and investment gains, we include individual fixed effects, but this term is canceled out in the first difference estimation.

The main outcome variable $Y_{i,t}$ is gambling consumption, including (1) monthly changes in the amount of gambling (in dollars), i.e., Δ Gambling-amount and (2) monthly changes in the indicator variable of whether individuals spend money on gambling, i.e., $\Delta \mathbb{1}$(Gambling). Given the panel nature of the data, these two variables capture individual i's variations in gambling consumption (both frequency and amount) over time.

OLSΔGain$_{i,t}$ in Equation 3 indicates changes in investment return between the current month and the previous month, which reflects both endogenous asset allocation choice and exogenous asset price changes while IVΔGain$_{i,t}$ in Equation 4 should only reflect exogenous asset price changes as we fix the asset portfolio over two-time periods.[11] In other words, the proportion of individual asset investment within a portfolio does not serve as a predictor for future asset prices. Using this instrument enables us to gauge the causal relationship between investment gains and gambling tendencies (i.e., β in Equation 2). Furthermore, we conduct additional analyses: (1) exploring asymmetrical reactions to both upward and downward shifts in portfolio returns and (2) documenting heterogeneous effects based on gambling tendency[12] to assess the extent to which individual heterogeneity affects the impact of changes in investment gains on gambling.

[11] Dividends are automatically re-invested in the assets on a pro-rata basis. Hence, these gains should be interpreted as both returns from price fluctuations and dividend income.

[12] To measure gambling tendency, we first calculate the total amount of spending on gambling during the data sample period and then divide it by the total number of months. This approach gives us a monthly gambling amount per individual. Using this metric, we divide the individuals by five quintiles, i.e., top 20%, 20% $\sim$ 40%, 40% $\sim$ 60%, 60% $\sim$ 80%, and bottom 20%, and explore data variations based on these quintiles.

3.2 Potential Explanation

To further understand the connection between investment gains and gambling consumption, we explore a potential driving force behind this relationship. We suggest a plausible explanation that an individual's change in attitude toward risk tolerance could influence how investment gains affect their gambling consumption. A potential hypothesis is that higher investment gains could heighten individuals' risk tolerance, which, in turn, encourages them to engage more in gambling.

3.2.1 Impact of Changes in Investment Gains on Risk Tolerance

We first demonstrate how changes in investment gains influence variations in portfolio selections. Specifically, as investment gains change, individuals are inclined to opt for riskier investment portfolios. To test this idea, we run the following regression equation for our analysis:

$$\text{First stage:} \quad \text{OLS}\Delta\text{Gain}_{i,t} = \rho \cdot \text{IV}\Delta\text{Gain}_{i,t} + \kappa_t + \varepsilon_{i,t} \tag{5}$$

$$\text{Second stage:} \quad \Delta\text{Portfolio}_{i,t} = \beta \cdot \widehat{\text{OLS}\Delta\text{Gain}}_{i,t} + \phi_t + \epsilon_{i,t} \tag{6}$$

where all the notations are the same as Section 3.1. The dependent variable is $\Delta\text{Portfolio}_{i,t}$, which indicates the difference between the current month's and past month's portfolio choices. This analysis mainly investigates how the change in investment gains shifts an individual's risk tolerance (i.e., β in Equation 6). As explained in Section 2, a choice of portfolios represents an individual's risk tolerance, so we can build a link to how the change in investment gains shapes a change in risk tolerance.

3.2.2 Impact of the Change in Risk Tolerances on Gambling

We next examine how a shift in portfolio choice affects gambling consumption by estimating the following equation:

$$Y_{i,t} = \beta \cdot \Delta\text{Portfolio}_{i,t} + \phi_t + \epsilon_{i,t} \tag{7}$$

where all the notations are the same as Section 3.1. The dependent variables, $Y_{i,t}$, are also the same as in Equation 2, which are (1) Δ Gambling-amount, indicating the difference between the current month's and past month's gambling amounts, and (2) $\Delta\,\mathbb{1}$(Gambling), indicating the difference between whether a user gambled in the current month and whether the individual gambled in the past month. The independent variables include $\Delta\text{Portfolio}_{i,t}$, which indicates the difference between the current month's portfolio choice and the past month's portfolio choice, and year-month fixed effects to control for any unobserved time shock that is common across individuals. Similar to the approach in Section 3.1, we take the first difference to control for time-invariant individual characteristics that might affect both the outcome variables and the change in portfolio choices. Combined with the analysis described in Section 3.2.1, this framework enables us to examine how the change in risk tolerance ultimately affects gambling consumption.

3.2.3 Alternative Explanations

Despite the suggested possible explanation related to risk tolerance, the relationship between investment gains and gambling could be attributed to other factors such as wealth effects, temporary increases or decreases in cash inflows, other behavioral forces (e.g., addiction, hedonic consumption), or portfolio rebalancing (i.e., the reallocation of resources to riskier investments). To support the idea that individual changes in risk tolerance are at play, we conduct falsification tests to rule out these other potential alternative explanations. While we cannot definitively establish that risk tolerance is the sole driving force, we provide compelling evidence that these other factors are unlikely to be relevant in our context.

4 Main Results

4.1 Baseline Analysis

We begin by presenting the results on how monthly changes in mutual fund investment gains influence corresponding monthly variations in gambling consumption by estimating Equations 1 and 2. In Table 3, Columns 1 and 2 reveal a general positive association between investment gains and both the amount/frequency of gambling and the probability of gambling, but it can stem from the endogeneity of the change in mutual fund investment gains.

In order to make causal inferences, we instrument asset allocations within a portfolio in the past month with asset allocations two previous months ago by exploiting exogenous variation in asset price changes as explained in Section 3.1. Column 3 reports the first stage result of Equation 1. Given our instruments (i.e., the asset allocations from two months prior) are inherently akin to the allocations from the previous month, the magnitudes of our estimates align closely. Also, based on the large F-statistic (431.48), which is larger than the rule-of-thumb threshold of 10 as in Stock and Yogo (2005), instruments are strong predictors of monthly changes in investment gains, and the relevance assumption of the instrument variable approach is met.

Columns 4 and 5 present the results from the second stage of Equation 2. After accounting for the endogeneity of investment gains, we continue to observe a positive relationship between unrealized investment gains and gambling consumption: one additional AUD gain from investment leads to a 0.00455 AUD increase in gambling consumption and a 0.002 percentage point increase in the likelihood of gambling within the same month.

A potential limitation of our initial results, however, could be the omission of another factor that simultaneously affects gambling consumption alongside variations in investment gains. As noted by Di Maggio et al. (2020), a specific concern is that changes in an individual's labor income might significantly impact their gambling consumption, even if these changes are unrelated to investment gains. It is possible that fluctuations in cash inflows, whether temporarily increased or decreased, could affect gambling consumption independently of changes in investment gains.

To address this concern, we included monthly income variations as an additional covariate in our regression equation. Although our statistical power is reduced by limiting the sample to users who self-report as full-time employees and for whom we can observe consistent monthly income data based on textual descriptions (i.e., 3,105 gamblers out of 99,552 in the baseline), Table 4 confirms that even when controlling for changes in labor income, investment gains continue to affect the general population's inclination to gamble positively. This finding supports the conclusion that the positive relationship between investment gains and gambling consumption is indeed causal.

Overall, this finding aligns with previous research documenting a positive relationship between gambling and investment behaviors (e.g., Cheng et al. 2022; Briggs et al. 2021; Dorn and Sengmueller 2009) and entertainment-related spending (Imas et al. 2022). Specifically, Imas et al. (2022) observed that individuals increased their entertainment spending following significant wealth shocks, suggesting that people derive direct utility from hedonic consumption, which drives increased spending after experiencing both positive and negative financial gains. While our findings are similar - since one might argue that gambling consumption is a form of entertainment-related spending - we propose that "hedonic" purchases may not be the driving force. Instead, we suggest that a behavioral factor, *risk tolerance*, may be influencing the positive relationship between investment gains and gambling spending. We will elaborate on this in Section 4.4.

4.2 Responses upon Different Investment Experiences

Although our earlier analyses considered overall changes in investment gains, we did not distinguish between positive changes and negative changes in monthly investment gains. Do individuals gamble more when they experience greater gains or losses from their investments? This raises an empirical question about how individuals react to gains versus losses in adjusting their gambling consumption. Similar to Imas et al. (2022), to provide a clearer understanding, we focus on the specific reactions to changes in investment gains and examine how individuals' gambling consumption differs in response to relatively positive or negative investment gains on a month-to-month basis.

Columns 1 and 2 of Table 5 report the results when the current month's investment return surpasses that of the previous month for the two dependent variables, whereas Columns 3 and 4 depict scenarios where the current month's investment return lags behind the prior month's performance. The results highlight the following salient pattern: individuals tend to increase their gambling spending and frequency following a positive deviation in their monthly investment return. Such behavior suggests that individuals who either possess or accrue wealth via investment returns may view gambling as complementary. Similarly, they indicate a positive sensitivity by reducing their gambling consumption amount and frequency when faced with an unfavorable monthly investment return shift. Moreover, the magnitude of the coefficient of OLSΔGain is greater when OLSΔGain is positive, implying that the complementary relationship between the investment and gambling consumption is more pronounced when the gain from the investment, compared to the previous month's gain, is relatively more positive.

Unlike the positive skewness typically seen in the return distribution of lottery-like assets, such as risky individual stocks, gambling, and cryptocurrency, the mutual funds in our app exhibit negative skewness. We report the first four moments of daily returns by portfolio type in Appendix Table A2, and even Portfolio 5, the app's most risky mutual fund, shows negative skewness. This characteristic helps explain why mutual fund investments and online sports betting are not perfect substitutes. Instead, individuals likely perceive positive investment returns as extra income and negative returns as a loss of income. Consequently, they tend to increase gambling spending when they gain from investments and reduce gambling spending when they incur losses.

4.3 Heterogeneous Effects

4.3.1 Income Level

We next explore how the impact of investment gains on gambling consumption varies among individuals with different income levels. To do this, we divide our sample into five income brackets based on the income levels users reported when they signed up for the app: above 250K AUD, between 100K AUD and 200K AUD, between 50K AUD and 100K AUD, between 10K AUD and 50K AUD, and below 10K AUD. We then estimate Equation 1 and 2 from Section 3.1 again for each of these income groups. The findings, presented in Table 6, reveal that the positive link between changes in investment gains and gambling consumption is statistically significant only for the group with the lowest income. In contrast, this relationship does not hold for the other higher-income groups. This observation aligns with the idea that individuals with lower incomes are more likely to increase their discretionary spending, including gambling, when they have extra income - which is different from the higher income groups. This result could also be more supportive evidence of the complementary relationship between the change in investment gains and gambling consumption that is robust to income effects, which is already documented in Section 4.1.

4.3.2 Gambling Tendency

We further investigate whether there are heterogeneous effects among a specific subset of gamblers who consider gambling more seriously than others. We focus mainly on individuals' gambling tendencies - the extent to which they gamble seriously, measured by the monthly average gambling amount. Depending on this tendency, the complementary relationship between investment and gambling may manifest differently. For example, do heavy gamblers increase (or decrease) their gambling if they earn more (or less) from investments? Understanding how heterogeneity in gambling tendencies influences the complementary relationship between investment and gambling consumption is not straightforward. By using granular individual-level single-source data and accounting for differences in gambling tendencies, we examine the varying effects of investment gains on gambling consumption across individuals with different levels of gambling seriousness.

We first calculate the average monthly gambling amount for 99,552 users and categorize them into quintiles, and then, we estimate Equation 3 and 4 for each group separately. Table 7 presents the results. Column 1 contains the result from the top 20% (of their gambling tendency, i.e., heavy gamblers) group, and Column 5 contains the result from the bottom 20% (of their gambling tendency, i.e., light gamblers). Columns 2, 3, and 4 include the results from 20% $\sim$ 40%, 40% $\sim$ 60%, and 60% $\sim$ 80% quantiles, respectively. The upper table shows the results using the dependent variable, Δ Gambling-amount, and the lower table shows the results using the dependent variable, $\Delta\, \mathbb{1}$(Gambling).

Two interesting observations should be highlighted: (1) In all the quintiles, the complementary relationship between investment and gambling consumption holds, implying that gambling tendency does not mainly drive this positive relationship. (2) However, the magnitude of the coefficient on OLSΔGain is the greatest for the heaviest gambling group and gradually decreases as the gambling tendency becomes lighter - the sensitivity is even monotonic in the gambling tendency when we focus on monthly changes in gambling amount. These results suggest that when individuals have extra income from investment activities, gambling is the avenue they spend money on. This pattern is observed from all the gambling quintiles yet is more salient among the group of individuals who gamble most seriously. At the same time, confirming the finding in Section 4.1, gambling is not an addiction good for the average gambler because we do not observe a non-statistical relationship or even a negative relationship for the group with the highest gambling tendency.[13]

[13]We additionally analyze how the relationship between investment gains and gambling consumption differs among groups with varying gambling habits, especially in response to positive and negative changes in monthly returns from mutual fund investments. This analysis, based on the approach used in Table 5, is conducted separately for each gambling tendency group. Please see the details in Appendix A.1

4.4 Potential Explanations

4.4.1 A Plausible Explanation

So far, we have shown the link between changes in investment gains and gambling consumption appears to be positive (indicating a complementary relationship) and stronger for individuals with a high gambling tendency than for those with a low tendency. Then, a key follow-up question is why this relationship holds. Although isolating a single driving force for this pattern is complex, our analysis suggests a possible explanation rooted in risk tolerance: we propose that gains from mutual fund investments may lead individuals to become more comfortable with taking risks, thereby increasing their likelihood of gambling. This hypothesis is supported by our assessment of individual risk tolerance through their choice of mutual fund portfolios.

To illustrate this point, we first demonstrate that individuals tend to favor riskier investments as their experience with mutual funds grows. This trend is visually supported by the time trend of average portfolio choices in Figure 2, which shows that users generally shift towards riskier mutual funds over time as they have more experience in investments. Additionally, Figure 3 breaks down portfolio choices by gambling tendency, revealing that individuals with higher gambling tendencies generally exhibit a stronger preference for riskier portfolios. Regression analyses, detailed in Equations 5 and 6 in Section 3.2.1, further confirm this behavior. As shown in Table 8, the positive and statistically significant coefficient on OLSΔGain indicates that higher investment gains are associated with a preference for riskier mutual funds, highlighting a clear pattern of evolving risk preferences. Thus, combining all of these findings, greater changes in investment gains lead individuals to take more risks, as reflected in their selection of riskier mutual fund options.

Continuing with Equation 7 in Section 3.2.2, we also examine the relationship between shifting risk tolerance and gambling habits to determine if a tendency toward risk leads to increased gambling. The results in Table 9 confirm this connection, with a positive and statistically significant coefficient for ΔPortfolio across both columns, indicating that riskier mutual fund choices are linked to heightened gambling consumption. By combining the findings from Table 8 and Table 9, we can conclude that changes in investment gains influence risk perception, pushing individuals toward riskier options. This shift in risk perception ultimately leads to increased gambling consumption.

Last, to further confirm the conclusion that individual risk preferences influence the relationship between investment gains and gambling consumption, we conduct an additional empirical investigation. Following the approach outlined in Equations 1 and 2 in Section 3.1, we run regressions across different portfolio categories separately, with the results presented in Table 10. The findings highlight that the complementary dynamics between investment gains and gambling are most pronounced among the riskiest investment choices, with little evidence for more conservative options. This pattern further suggests that risk tolerance plays a crucial role in shaping the observed complementary relationship.

Previous studies that examined the relationship between investment and gambling consumption mainly leverage time-invariant risk preferences represented by gambling preferences and exploit how this gambling-driven risk preference plays a role in investment decisions (e.g., Kumar 2009; Dorn and Sengmueller 2009; Grinblatt and Keloharju 2009; Kumar et al. 2011; Dorn et al. 2015; Gao and Lin 2015; Cookson 2018; Cox et al. 2020). Different from these studies, within-individual time variation allows us to measure the change in risk tolerance represented by the mutual fund portfolio choices. This variation, i.e., dynamics in risk tolerance, helps us demonstrate that changes in investment gains can shift an individual's gambling consumption via changes in risk tolerance. Thus, the suggested explanations contribute to the stream of literature studying the relationship between investment and gambling consumption, and propose one plausible underlying force that drives this relationship.

4.4.2 Discussions About Alternative Explanations

Although heightenend risk tolerance from investment experiences is a possible explanation, the relationship between investment gains and gambling might also be affected by other factors such as wealth effects, short-term fluctuations in cash inflows, behavioral factors (e.g., addiction, hedonic consumption), or the reallocation of resources toward riskier investments. To strengthen the argument that changes in individual risk tolerance are responsible, we perform falsification tests to rule out these other potential influences. While we cannot definitively determine that risk tolerance is the only factor at play, we present strong evidence suggesting that these alternative factors are less salient in our context.

Wealth Effect: Individuals might increase their gambling consumption in response to higher investment gains, as they may perceive an increase in their overall wealth. If this rationale were the primary and sole factor, we would expect an increase in gambling consumption across the entire sample regardless of income levels. However, our analysis reveals that this effect is not uniform; it varies based on income level. As discussed in Section 4.3.1, the positive impact of investment gains on gambling consumption is only observed in the low-income group, with no significant effect seen in higher-income individuals. Therefore, the heterogeneity in the impact of investment gains on gambling consumption suggests that factors beyond wealth effects are at play. Specifically, our finding that investment gains lead to an increased risk tolerance and, subsequently, greater gambling consumption offers a more nuanced understanding of the connection between investing and gambling.

Temporal Increases in Cash Inflows: Another possible explanation could be that a temporary shift in individuals' cash inflows drives overall gambling spending. However, as demonstrated in Section 4.1, even after controlling for monthly changes in temporal cash inflows for a given individual, we still observe the same pattern: an increase in investment gains leads to greater gambling consumption. Therefore, any temporary change in cash inflows is unlikely to be the driving force behind the positive relationship between investment gains and gambling.

Other Behavioral Forces: Given that investment and gambling behaviors are similar - both involve putting capital at risk in hopes of making a profit - another behavioral force, such as addiction to gambling, might drive the results. The idea is that as individuals gamble more, they are likely to become addicted, leading to increased gambling regardless of changes in investment gains. However, this explanation can be ruled out based on our analysis of the asymmetric responses in Section 4.2. Our findings show that individuals tend to increase (decrease) their gambling consumption as they gain (lose) more. If addiction were the driving force, we would expect individuals to increase gambling even when they incur losses from investments. However, given that individuals reduce their gambling consumption when monthly changes in gains from their investments go down, we conclude that addiction is not a likely explanation.

Similarly, the hedonic consumption proposed by Imas et al. (2022) may not be the driving force behind our findings, as we observed that individuals reduce gambling spending when they incur investment losses. If the positive relationship between investment gains and gambling consumption were driven by hedonic consumption, we would expect individuals to increase gambling spending even in the event of an investment loss. However, as discussed in Section 4.2, individuals tend to decrease their gambling consumption when they experience investment losses, suggesting that hedonic consumption is not the primary factor driving this behavior.

Portfolio Rebalancing Motives: Typically, investors reallocate resources to more or less risky assets based on their expectations of returns and risk uncertainty when investing in mutual funds. One might argue that our empirical results are purely driven by portfolio rebalancing motives in the sense that gambling is a part of their overall investing portfolio on top of the mutual fund investments on the app: individuals' risk tolerance might not change, but they rather allocate more resources to riskier assets as they gain more returns. If that is the case, users would rebalance between investment in mutual funds and online sports gambling, which should be reflected in the form of a significant sensitivity of gambling amount and frequency to mutual fund returns regardless of the mutual fund they currently hold. However, Table 10 indicates that this sensitivity is only pronounced for users who hold a relatively riskier mutual fund. Therefore, a more plausible explanation is that once risk appetite is shifted to a higher level, users go beyond the limited menu of 5 different portfolios by spending more on gambling.

4.5 Consequences on Personal Finance beyond Gambling

Finally, we extend our previous analyses by exploring the broader impact of gambling on gamblers' finances. Specifically, we examine how gambling consumption influences financial health, with a focus on the growth of investment wealth. We analyze the evolution of investment account balances over time since app registration, comparing individuals with different levels of gambling tendencies. By taking into account each group's portfolio choices, which reflect their risk tolerance, we assess whether gambling consumption hinder asset accumulation.

We first show the progression of gamblers' investment wealth over time in Figure 4, in which the balance of investment accounts in this app is normalized by the initial balance at the time of registration. Panel A shows results for the entire sample, while Panel B breaks them down by income group.[14] We highlight two key findings: First, we find that investment wealth grew at the slowest rate for gamblers with the highest gambling tendency, as depicted in Panel A. The growth of account balances is influenced not only by exogenous growth in mutual fund asset values but also by the choice of new deposits into their investment accounts. Recall from Figure 3 that gamblers with a higher gambling tendency tend to choose riskier portfolios, and recall from Appendix Table A1 that riskier portfolios earned higher investment returns in the sample period. Thus, we can rule out the argument that slower growth in heavy gamblers' investment accounts is driven by their overall portfolio choices. Rather, we find that the gambling tendency is positively associated with lower net deposits, which is the primary driver of slower investment

[14]In both figures, the light blue line represents the top 20% quintile (i.e., heavy gamblers), and the dark blue line represents the bottom 20% quintile (i.e., light gamblers). The quintiles are defined in Section 4.3.2. The high-income group includes individuals with an annual income above 250K AUD, while the low-income group includes those with an annual income below 10K AUD.

wealth growth.

Second, it is particularly interesting that this pattern is more pronounced in the low-income group, while it is not evident in the high-income group, as shown in Panel B of Figure 4. This suggests that low-income individuals are more susceptible to the effects of investment gains on gambling consumption, making them more vulnerable to potential financial setbacks. The fact that high-income individuals do not exhibit the same tendency highlights the uneven impact of investment gains across different income levels. For low-income individuals, the complementary effect between investment gains and gambling consumption could lead to a cycle where the benefits of investment gains are offset by increased gambling consumption, hindering their overall financial growth. This finding again emphasizes the importance of understanding the specific financial behaviors and vulnerabilities of different income groups when assessing the broader implications of investment activities.

In summary, experiencing investment gains can lead to unintended negative real outcomes for low-income individuals, increasing their susceptibility to the complementary relationship between investment gains and gambling consumption.

5 Conclusion

In conclusion, our study provides significant insights into the relationship between investment gains and gambling consumption, reflecting how financial gains can influence individuals' tendencies to engage in gambling activities. By adopting a Bartik instrumental variable approach, we demonstrate that investment gains have a causal effect on increasing both the amount spent on gambling and the likelihood of engaging in gambling. This relationship is especially pronounced among individuals with a higher tendency toward gambling, suggesting that investment behaviors and gambling consumption may complement each other, driven by a shift in risk tolerance as individuals experience financial gains.

Moreover, our findings reveal important implications for financially vulnerable individuals. We observe that the sensitivity of gambling consumption to investment gains is more acute among low-income groups, leading to slower growth in their investment wealth. This is particularly evident in heavy gamblers, where increased gambling consumption is linked to reduced net deposits into investment accounts. These results underscore the potential for unintended negative consequences, as positive investment gains may exacerbate financial vulnerabilities, making gambling-prone individuals more susceptible to the compounding effects of gambling and investing.

Overall, our research contributes to the broader understanding of how financial market participation intersects with gambling consumption. It highlights the need for policymakers to consider these dynamics, particularly in the context of regulating gambling and protecting financially at-risk populations. By addressing these issues, we can better support individuals in managing their financial health amidst the intertwined influences of investing and gambling.

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Figure 1: External Validity of Data

Notes: This figure shows the time trends of the per capita amount of online sports betting in our data and that of all types of gambling in Australian Gambling Statistics at the yearly frequency. The Y-axis indicates the per capita amount of online sports betting, and the X-axis indicates a time unit measured by year. The red colored line indicates the per capita amount of online sports betting from all types of gambling based on the national statistics from Australian Gambling Statistics, and the blue colored line indicates the per capita amount of online sports betting from our dataset.

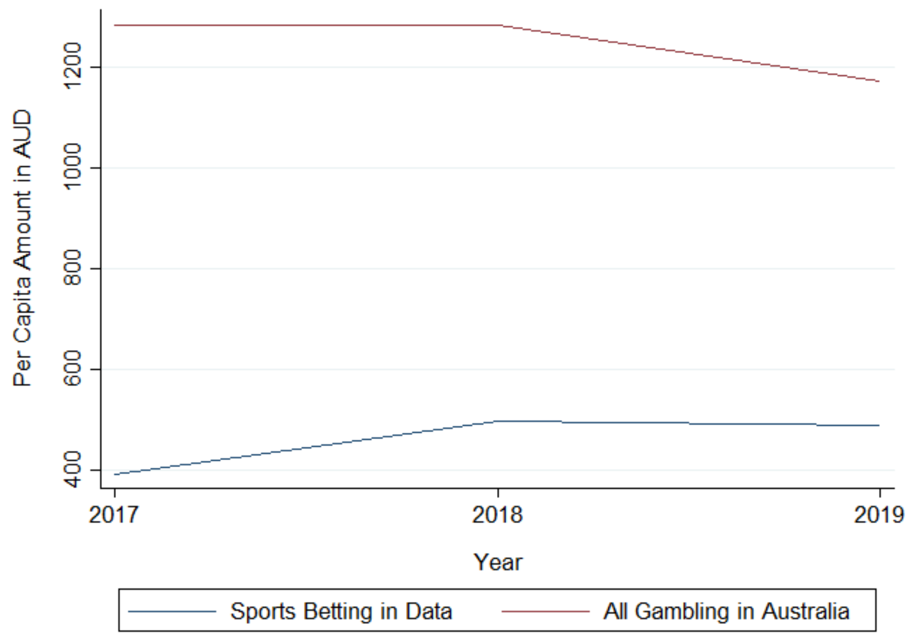


Figure 2: Portfolio Choice over Time

Notes: This figure presents the time-series of the average choice of the portfolio across individuals during our data sample period. The average choice of the portfolio (per individual) is calculated as follows:

$$\text{Average Portfolio}_{\tau} = \frac{1}{N}\sum_{i}\text{Portfolio}_{i,\tau}$$

where i indicates individual and τ indicates the number of months since app registration. $\text{Portfolio}_{i,\tau}$ indicates individual i's portfolio choice at time τ. The X- axis indicates the number of months since app registration, and the Y-axis indicates $\text{Average Portfolio}_{i,\tau}$. The stand error bars are calculated at the 95% level.

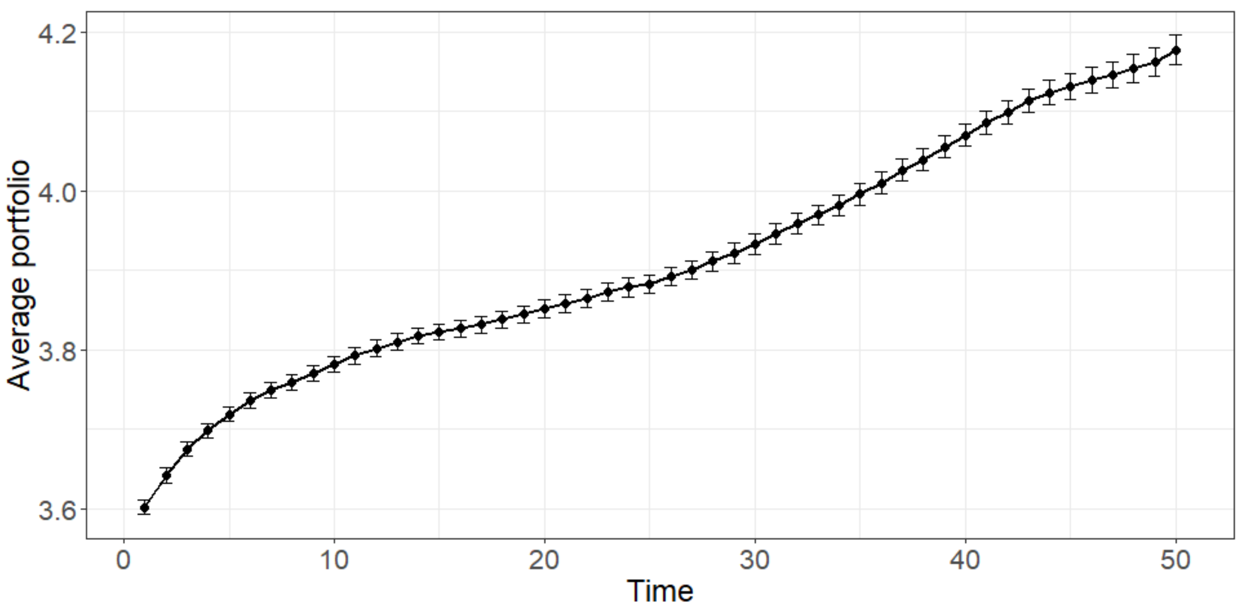


Figure 3: Portfolio Choice by Gambling Tendency

Notes: This figure presents the average choice of the portfolio per individual by groups (i.e., measured by gambling tendency) during our data sample period. The average choice of the portfolio (per individual) is calculated as follows:

$$\text{Average Portfolio}^G = \frac{1}{N}\frac{1}{T}\sum_{i\in G}\sum_{\tau}\text{Portfolio}_{i,\tau}^G$$

where i indicates individual, τ indicates the number of months since app registration, and G indicates gambling tendency quintile,
$G \in \{$Top20%, Top 20-40%, Top 40-60%, Top 60-80%, Bottom 20% $\}$, as defined in Section 4. N is the number of individuals in each quintile. T is the total number of months in the sample. $\text{Portfolio}_{i,\tau}^G indicates the portfolio choice of individual i at time \tau$ in gambling tendency group G . The stand error bars are calculated at the 95% level.

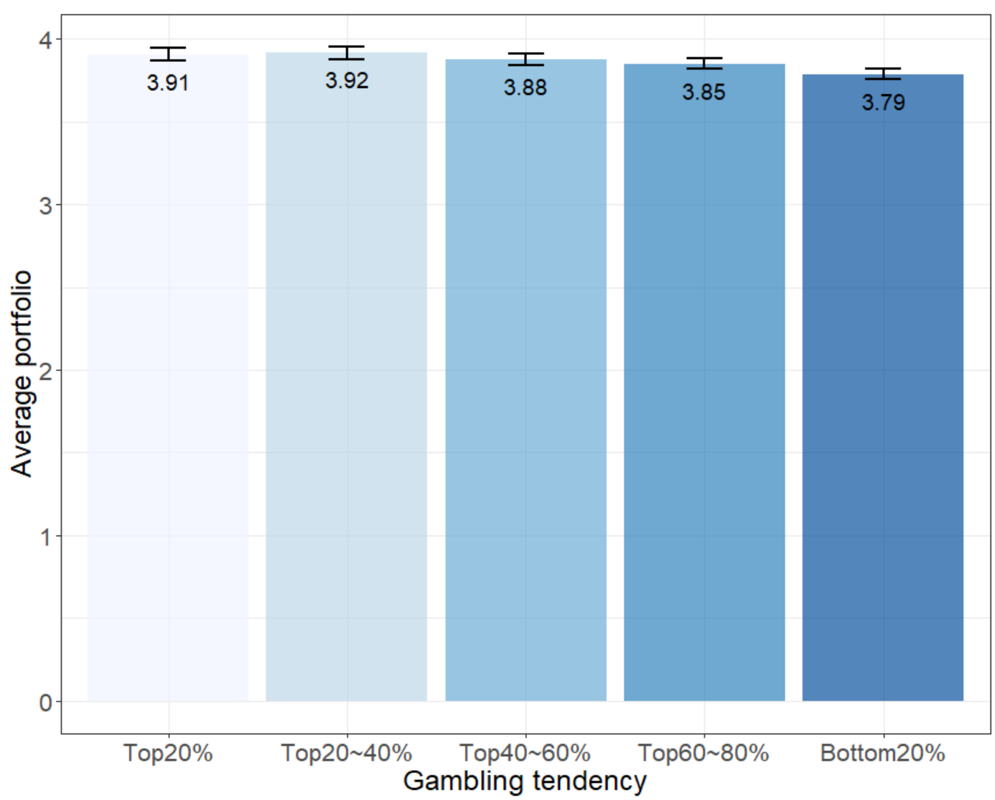
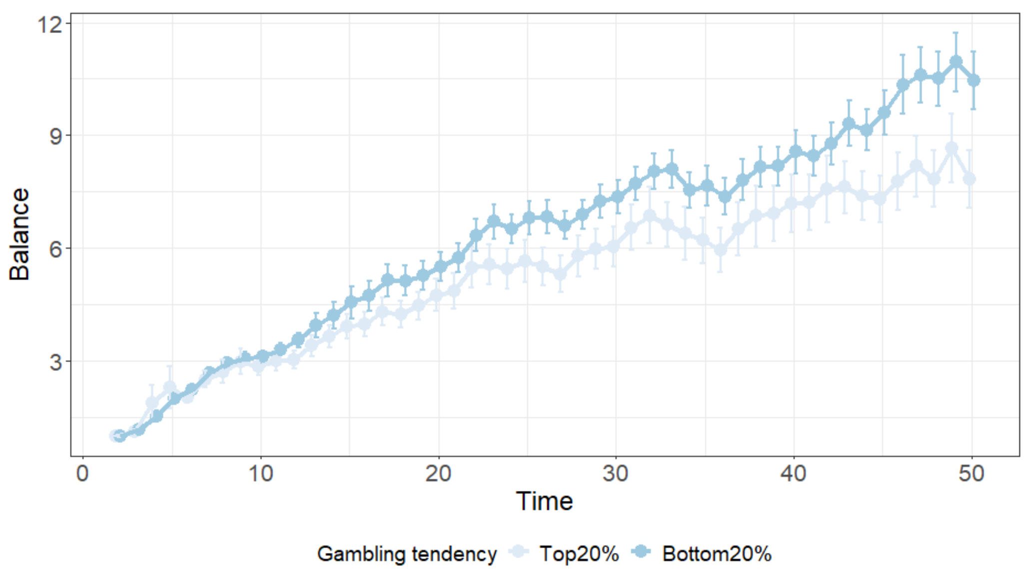


Figure 4: Evolution of Gamblers' Investment Wealth

Notes: This figure shows the evolution of gamblers' investment wealth by groups, i.e., measured by gambling tendency, Top20%, Top 20-40%, Top 40-60%, Top 60-80%, and Bottom 20%, as described in Section 4. The Y-axis indicates the gambler's balance that is normalized by the 1st period's investment wealth. In other words, each gambler's balance is divided by their 1st period's balance to show the change in their investment wealth over time. The X-axis indicates the number of months since the registration of the app. The light blue line indicates the top 20% quintile (i.e., heavy gamblers), and the dark blue line indicates the bottom 20% quintile (i.e., light gamblers). The standard error bars are calculated at the 95% level. Panel A shows the results from the entire sample, and Panel B shows the sub-sample results from the high-income group (i.e., annual income above 250K AUD) on the left panel and from the low-income group (i.e., annual income below 10K AUD) groups on the right panel.



(A) Evolution of Gamblers' Investment Wealth

(B) By Income Group

Table 1: Summary Statistics

Notes: This table reports summary statistics for data variables used in this paper. Gambling-amount refers to the amount of monthly expenditure on online sports gambling for each individual. Δ (Gambling-amount) refers to monthly changes in the amount of expenditure on online sports gambling for each individual. $\mathbb{1}$(Gambling) is an indicator variable equal to one if a user has spent on online sports gambling in a given month. Δ $\mathbb{1}$(Gambling) refers to monthly changes in $\mathbb{1}$(Gambling) for each individual. Portfolio Choice refers to holding a mutual fund in the app, which ranges from 1 (least risky portfolio) to 5 (most risky portfolio). Balance refers to the amount of investment in mutual funds in the app. OLSΔGain refers to monthly changes in investment gains in dollar terms, i.e., the difference between gain from the mutual fund investment in the current month and that in the past month.

	N	Mean	Std	p25	p50	p75
Gambling-amount	2,810,013	49.55	193.10	0	0	0
Δ Gambling-amount	2,810,013	-0.77	116.68	0	0	0
$\mathbb{1}$(Gambling)	2,810,013	0.21	0.41	0	0	0
Δ $\mathbb{1}$(Gambling)	2,810,013	-0.002	0.39	0	0	0
Portfolio Choice	2,810,013	3.86	1.38	3	4	5
Balance	2,810,013	1205.05	2672.39	38.30	264.54	1030.69
OLSΔGain	2,810,013	-0.07	74.57	-3.88	0.0001	4.54

Table 2: External Validity of Data

Notes: This table shows that our dataset is representative of the national statistics on gambling. In particular, we estimate the following equation:

$$\text{National Gambling}_{p,t} = \beta \cdot \text{Sports Betting in Data}_{p,t} + \phi_t + \mu_p + \epsilon_{p,t}$$

For the notations, p denotes province, and t denotes year. For the dependent variable, we use the per capita amount of all types of gambling reported in Australian Gambling Statistics at the province-year level. For the main independent variable, we use the per capita amount of online sports betting in our data at the province-year level. ϕ_t is year fixed effects, and μ_p is province fixed effects. Standard errors are clustered at the province level and written in parentheses. Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	All Gambling in Australia (1)
Sports Betting in Data	2.913**
	(1.165)
Fixed Effects	
Year	Yes
Province	Yes
Observations	24
R-squared	0.951

Table 3: Baseline Result

Notes: This table shows the relationship between monthly changes in mutual fund investment gains and gambling consumption. Using Two Stage Least Squares (2SLS), we estimate the following equations, Equations 1 and 2 in Section 3:

$$\begin{aligned} &\text{First stage:} \quad \text{OLS}\Delta\text{Gain}_{i,t} = \rho \cdot \text{IV}\Delta\text{Gain}_{i,t} + \kappa_t + \varepsilon_{i,t} \\ &\text{Second stage:} \quad \text{Y}_{i,t} = \beta \cdot \widehat{\text{OLS}\Delta\text{Gain}}_{i,t} + \phi_t + \epsilon_{i,t} \end{aligned}$$

For the notations, i denotes individual, and t denotes year $\times$ month. The dependent variables, $Y_{i,t}$, are as follows: (1) Δ Gambling-amount indicates the difference between the current month's and past month's gambling amounts, and (2) $\Delta\,\mathbb{1}$(Gambling) indicates the difference between whether a user gambled in the current month and whether the user gambled in the past month. The main independent variables is OLSΔGain, which indicates the difference between the current month's investment return and the past month's investment return in dollar terms. κ_t and ϕ_t are year $\times$ month fixed effects. Similar to Di Maggio et al. (2020), using the first difference approach, we control for time-invariant individual characteristics that might affect both the outcome variables and capital gains. Columns (1) and (2) report the results from OLS. Column (3) reports the results of the first stage regression for the 2SLS analysis, and Columns (4) and (5) report the results from the second stage analysis. Standard errors are clustered at the user level and written in parentheses. Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	OLS		IV		
	Δ Gambling-amount	$\Delta\,\mathbb{1}$(Gambling)	OLSΔGain	Δ Gambling-amount	$\Delta\,\mathbb{1}$(Gambling)
	(1)	(2)	(3)	(4)	(5)
OLSΔGain	0.00493***	0.00002***		0.00455***	0.00002***
	(0.00131)	(0.000004)		(0.00136)	(0.000004)
IVΔGain			0.97194***		
			(0.00060)		
Fixed Effects					
Year $\times$ Month	Yes	Yes	Yes	Yes	Yes
Observations	2,810,013	2,810,013	2,810,013	2,810,013	2,810,013
R-squared	0.010	0.036	0.940	.	.
F-statistics	.	.	431.478	.	.

Table 4: Robustness Check to Control for Income

Notes: This table shows that the baseline results are robust to controlling for monthly changes in inflows into bank accounts, which is a proxy for income. In comparison to the baseline results, we additionally control for this proxy for income in the following equations, Equations 1 and 2 in Section 3:

$$\text{First stage:} \quad \text{OLS}\Delta\text{Gain}_{i,t} = \rho \cdot \text{IV}\Delta\text{Gain}_{i,t} + v \cdot \Delta\text{Income}_{i,t} + \kappa_t + \varepsilon_{i,t}$$
$$\text{Second stage:} \quad Y_{i,t} = \beta \cdot \widehat{\text{OLS}\Delta\text{Gain}}_{i,t} + \omega \cdot \Delta\text{Income}_{i,t} + \phi_t + \epsilon_{i,t}$$

For the notations, i denotes individual, and t denotes year $\times$ month. The dependent variables, $Y_{i,t}$, are as follows: (1) Δ Gambling-amount indicates the difference between the current month's and past month's gambling amounts, and (2) $\Delta\,\mathbb{1}$(Gambling) indicates the difference between whether a user gambled in the current month and whether the user gambled in the past month in dollar terms. The main independent variables is OLSΔGain, which indicates the difference between the current month's investment return and the past month's investment return in dollar terms. κ_t and ϕ_t are year $\times$ month fixed effects.
In particular, we additionally include $\Delta\text{Income}_{i,t}$, which indicates the difference between the current month's income and the past month's income. Note that monthly income during the full data observation periods and self-reported full-time employment status are observed only from a limited group of sample population, i.e., 3,105 gamblers, so the total number of observations for this analysis is smaller than 99,552 gamblers in the baseline analysis in Table 3. Column (1) reports the result from the dependent variable, Δ Gambling-amount, and Column (2) reports the result from the dependent variable, $\Delta\,\mathbb{1}$(Gambling). Standard errors are clustered at the user level and written in parentheses. Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Dependent Variable (DV):	
	ΔGambling-amount	$\Delta\mathbb{1}$(Gambling)
	(1)	(2)
OLSΔGain	0.0116*	0.00000610
	(0.00697)	(0.00000438)
ΔIncome	0.00280**	0.000000442
	(0.00130)	(0.000000640)
Fixed effects		
Year $\times$ Month	Yes	Yes
Observations	103,050	103,050

Table 5: Responses upon Different Investment Experiences

Notes: This table shows gambling consumption responses upon different realizations of mutual fund investment gains. We run the baseline regressions, Equations 1 and 2 in Section 3, separately when OLSΔGain$_{i,t} > 0$ and OLSΔGain$_{i,t} < 0$, where i denotes individual, and t denotes year $\times$ month. Columns (1) and (2) show the impact of investment gains on gambling consumption when monthly changes in investment gains are positive, while Columns (3) and (4) show the results when monthly changes in investment gains are negative. Standard errors are clustered at the user level and written in parentheses. Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Positive Changes (OLS Δ Gain > 0)		Negative Changes (OLS Δ Gain < 0)	
	Δ Gambling-amount	Δ $\mathbb{1}$(Gambling)	Δ Gambling-amount	Δ $\mathbb{1}$(Gambling)
	(1)	(2)	(3)	(4)
OLSΔGain	0.00582***	0.00002***	0.00361**	0.00002***
	(0.00164)	(0.000005)	(0.00151)	(0.000004)
Fixed Effects				
Year × Month	Yes	Yes	Yes	Yes
Observations	1,489,394	1,489,394	1,361,372	1,361,372

Table 6: Heterogeneous Responses by Income Group

Notes: This table shows the impact of mutual fund investment gains on gambling consumption across different income levels. We run the baseline regressions, Equations 1 and 2 in Section 3, separately based on the individuals' yearly income level (Above 250K AUD, between 100K and 200K AUD, between 50K and 100K AUD, between 10K and 50K AUD, and Below 10K AUD). Column (1) reports the result for the highest income group and Column (5) reports the result for the lowest income group. Panel A uses monthly changes in the amount of gambling as the dependent variable, and Panel B uses monthly changes in the likelihood of gambling as the dependent variable. Standard errors are clustered at the user level and written in parentheses. Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Panel A. Dependent Variable (DV): Δ Gambling-amount				
	Income level				
	(1)	(2)	(3)	(4)	(5)
	Above 250K	100K $\sim$ 200K	50K $\sim$ 100K	10K $\sim$ 50K	Below 10K
OLSΔGain	0.00186	0.00161	0.00167	0.00517	0.00373**
	(0.01492)	(0.00498)	(0.00450)	(0.00795)	(0.00155)
Fixed Effects					
Year $\times$ Month	Yes	Yes	Yes	Yes	Yes
Observations	10,343	96,990	199,222	81,006	2,463,205

	Panel B. Dependent Variable (DV): $\Delta\,\mathbb{1}$(Gambling)				
	Income level				
	(1)	(2)	(3)	(4)	(5)
	Above 250K	100K $\sim$ 200K	50K $\sim$ 100K	10K $\sim$ 50K	Below 10K
OLSΔGain	-0.00003	0.00001	-0.000005	0.00002	0.00002***
	(0.00004)	(0.00002)	(0.00001)	(0.00003)	(0.000005)
Fixed Effects					
Year $\times$ Month	Yes	Yes	Yes	Yes	Yes
Observations	10,343	96,990	199,222	81,006	2,463,205

Table 7: Heterogeneous Responses by Gambling Tendency

Notes: This table shows the impact of mutual fund investment gains on gambling consumption across different gambling tendencies. Gambling tendency is measured by the average monthly gambling amount, and we discretize the users into five groups by 20 percent quintile from top 20% to bottom 20%. Then we run the baseline regressions, Equations 1 and 2 in Section 3, separately for each group. Column (1) reports the result for the group with the highest gambling tendency and Column (5) reports the result for the group with the lowest gambling tendency. Panel A uses monthly changes in the amount of gambling as the dependent variable, and Panel B uses monthly changes in the likelihood of gambling as the dependent variable. Standard errors are clustered at the user level and written in parentheses. Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Panel A. Dependent Variable (DV): Δ Gambling-amount				
	Gambling tendency				
	(1)	(2)	(3)	(4)	(5)
	Top 20%	$20 \sim 40\%$	$40 \sim 60\%$	$60 \sim 80\%$	Bottom 20%
OLSΔGain	0.01925***	0.00667**	0.00380***	0.00147**	0.00100***
	(0.00743)	(0.00300)	(0.00138)	(0.00060)	(0.00019)
Fixed Effects					
Year × Month	Yes	Yes	Yes	Yes	Yes
Observations	459,630	504,620	537,270	609,024	740,222

	Panel B. Dependent Variable (DV): $\Delta\, \mathbb{1}$(Gambling)				
	Gambling tendency				
	(1)	(2)	(3)	(4)	(5)
	Top 20%	$20 \sim 40\%$	$40 \sim 60\%$	$60 \sim 80\%$	Bottom 20%
OLSΔGain	0.00003***	0.00002*	0.00003***	0.00001	0.00001***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.000005)
Fixed Effects					
Year × Month	Yes	Yes	Yes	Yes	Yes
Observations	459,630	504,620	537,270	609,024	740,222

Table 8: The Impact of Changes in Investment Gains on Risk Tolerance

Notes: This table shows the impact of mutual fund investment gains on the portfolio choice, which we use as a proxy for risk tolerance. Using Two Stage Least Squares (2SLS), we estimate the following equations, Equations 5 and 6 in Section 3:

$$\begin{aligned} \text{First stage:} \quad & \text{OLS}\Delta\text{Gain}_{i,t} = \rho \cdot \text{IV}\Delta\text{Gain}_{i,t} + \kappa_t + \varepsilon_{i,t} \\ \text{Second stage:} \quad & \Delta\text{Portfolio}_{i,t} = \beta \cdot \widehat{\text{OLS}\Delta\text{Gain}}_{i,t} + \phi_t + \epsilon_{i,t} \end{aligned}$$

For the notations, i denotes individual, and t denotes year $\times$ month. The dependent variable is $\Delta\text{Portfolio}_{i,t}$, which indicates the difference between the current month's and past month's portfolio choices. A higher change in the portfolio indicates that a user has opted for investing in a more risky portfolio. κ_t and ϕ_t are year $\times$ month fixed effects. Standard errors are clustered at the user level and written in parentheses. Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Dependent Variable (DV):
	$\Delta\text{Portfolio}_{i,t}$
	(1)
OLSΔGain	0.00005***
	(0.000003)
Fixed effects	
Year × Month	Yes
Observations	2,810,013

Table 9: The Impact of Changes in Risk Tolerance on Gambling

Notes: This table shows the relationship between changes in risk tolerance, which is measured by the portfolio choice, and gambling consumption. We estimate the following equation, Equation 7 in Section 3:

$$\mathrm{Y}_{i,t} = \beta \cdot \Delta \mathrm{Portfolio}_{i,t} + \phi_t + \epsilon_{i,t}$$

For the notations, i denotes individual, t denotes year x month. The dependent variables, $Y_{i,t}$, are as follows: as follows: (1) ΔGambling-amount indicates the difference between the current month's and past month's gambling amounts, and (2) $\Delta\,\mathbb{1}$(Gambling) indicates the difference between whether a user gambled in the current month and whether the user gambled in the past month. The main independent is $\Delta\mathrm{Portfolio}_{i,t}$, which indicates the difference between the current month's portfolio choice and the past month's portfolio choice. ϕ_t are year $\times$ month fixed effects. Standard errors are clustered at the user level and written in parentheses. Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Dependent Variable (DV):	
	ΔGambling-amount	$\Delta\mathbb{1}$(Gambling)
	(1)	(2)
$\Delta\mathrm{Portfolio}_{i,t}$	1.08377***	0.00731***
	(0.30624)	(0.00103)
Fixed effects		
Year $\times$ Month	Yes	Yes
Observations	2,810,013	2,810,013
R^2	0.010	0.036

Table 10: Heterogeneous Effects by Risk Tolerance

Notes: This table shows the impact of mutual fund investment gains on gambling consumption across different degrees of revealed risk preference measured by mutual fund selection. We run the baseline regressions, Equations 1 and 2 in Section 3, separately for each of the different portfolio choices. Column (1) reports the result for the group that chose the most risky portfolio, i.e. Portfolio 5 and Column (5) reports the result for the group that chose the least risky portfolio, i.e. Portfolio 1. Panel A uses monthly changes in the amount of gambling as the dependent variable, and Panel B uses monthly changes in the likelihood of gambling as the dependent variable. Standard errors are clustered at the user level and written in parentheses. Standard errors are clustered at the user level and written in parentheses. Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Panel A. Dependent Variable (DV): Δ Gambling-amount				
	Risk Tolerance				
	(1)	(2)	(3)	(4)	(5)
	Portfolio=5 (most risky)	Portfolio=4	Portfolio=3	Portfolio=2	Portfolio=1 (least risky)
OLSΔGain	0.00390**	0.00433	0.00973	−0.00584	−0.00584
	(0.00169)	(0.00289)	(0.00627)	(0.01660)	(0.01660)
Fixed Effects					
Year × Month	Yes	Yes	Yes	Yes	Yes
Observations	1,437,142	665,226	321,011	169,327	169,327

	Panel B. Dependent Variable (DV): $\Delta\ \mathbb{1}$(Gambling)				
	Risk Tolerance				
	(1)	(2)	(3)	(4)	(5)
	Portfolio=5 (most risky)	Portfolio=4	Portfolio=3	Portfolio=2	Portfolio=1 (least risky)
OLSΔGain	0.00002***	0.00002**	0.00003*	−0.000002	−0.000002
	(0.00001)	(0.00001)	(0.00002)	(0.00004)	(0.00004)
Fixed Effects					
Year × Month	Yes	Yes	Yes	Yes	Yes
Observations	1,437,142	665,226	321,011	169,327	169,327

A Internet Appendix

A.1 Asymmetric Responses by Gambling Tendency

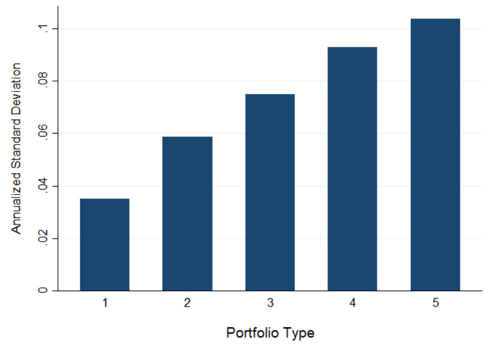
We additionally analyze how the relationship between investment gains and gambling consumption differs among groups with varying gambling habits, especially in response to gains and losses from mutual fund investments. This analysis, based on the approach used in Table 5, is conducted separately for each group with a different gambling tendency.

The findings are detailed in Tables A3 and A4. Table A3 focuses on changes in gambling amounts, while Table A4 examines changes in the likelihood of gambling. Each table categorizes individuals by their gambling intensity, from the heaviest gamblers in Column 1 to the lightest in Column 5. The analysis distinguishes between positive gains and negative losses, with the top panel addressing gains and the bottom panel addressing losses.

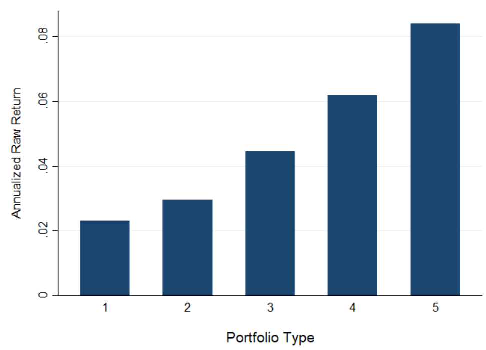
Several insights emerge from this analysis. First, a positive relationship between investment gains and gambling consumption is observed across all groups, reinforcing the complementary nature of these activities. Second, the impact of changes in investment gains is most pronounced among heavy gamblers, indicating that they react more strongly to investment performance than lighter gamblers. Last, while the overall analysis suggests that individuals adjust their gambling consumption more, following positive changes in investment gains, the detailed breakdown reveals that heavy gamblers are more responsive to negative changes, whereas lighter gamblers react more to positive changes. This nuanced response suggests that the general trend observed in the full sample may predominantly reflect the behaviors of non-heavy gamblers, highlighting a distinct difference in how heavy versus light gamblers respond to shifts in investment gains.

Figure A1: Portfolio Performance

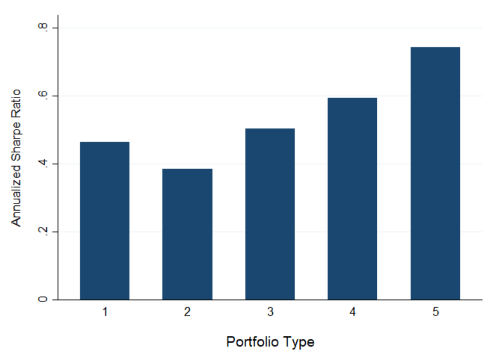
Notes: This figure shows the annualized performance of each portfolio the app provides, using monthly returns. Portfolio Type 1 is the least risky one, while Portfolio Type 5 is the most risky one. Panel A shows the annualized standard deviation by portfolio type. Panel B shows the annualized average return by portfolio type. Panel C shows the annualized Sharpe ratio by portfolio type.



(A) Standard Deviation



(B) Mean Return



(C) Sharpe Ratio

Table A1: Characteristics of Gamblers

Notes: This table shows characteristics associated with a gambler and risk tolerance of gamblers in terms of portfolio choice. Standard errors are clustered at the user level and written in parentheses. Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	1(Gambler) (1)	1(Gambler) (2)
Age	-0.00501***	-0.00374***
	(0.000266)	(0.0000636)
Male	0.180***	0.146***
	(0.00493)	(0.00134)
Net Wealth		
Net wealth above 10,000 below 50,000	0.0169***	0.0256***
	(0.00645)	(0.00615)
Net wealth above 50,000 below 100,000	0.0191**	0.0209***
	(0.00820)	(0.00797)
Net wealth above 100,000 below 250,000	0.0164	0.0104
	(0.0101)	(0.00966)
Net wealth above 250,000	0.0149	0.000128
	(0.00959)	(0.00871)
Income		
Income above 10,000 below 50,000	0.0428***	0.0814***
	(0.00900)	(0.00638)
Income above 50,000 below 100,000	0.0549***	0.104***
	(0.00954)	(0.00583)
Income above 100,000 below 250,000	0.0669***	0.119***
	(0.0114)	(0.00820)
Income above 250,000	0.103***	0.149***
	(0.0229)	(0.0218)
Investment horizon		
Investment horizon between 5 and 10 years	-0.0218***	-0.0254***
	(0.00597)	(0.00559)
Investment horizon between 10 and 15 years	-0.0457***	-0.0592***
	(0.00914)	(0.00865)
Investment horizon between 15 and 25 years	-0.0262**	-0.0439***
	(0.0122)	(0.0117)
Investment horizon above 25 years	-0.0400***	-0.0532***
	(0.00921)	(0.00854)
Employment		
Employment= part-time	-0.0134	
	(0.0104)	
Employment= full-time	0.0106	
	(0.0101)	
Employment= self-employed	-0.00518	
	(0.0116)	
Employment= retired	-0.0186	
	(0.0197)	
Investment reason		
Investment reason= general	0.00530	
	(0.0111)	
Investment reason= long-term	-0.0398***	
	(0.0108)	
Investment reason=purchase	0.00534	
	(0.0145)	
Investment reason=short-term	-0.00407	
	(0.0119)	
Year x Month FE	Y	Y
User FE	N	N
Observations	1,505,295	16,303,509
R-squared	0.063	0.054

Table A2: Portfolio Profile

Notes: This table shows the first four moments of daily return by portfolio type.

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5
Mean	0.001930	0.002456	0.003718	0.005158	0.006997
Standard Deviation	0.010156	0.016952	0.021602	0.026807	0.029920
Skewness	-1.38	-2.15	-1.76	-1.50	-1.43
Kurtosis	7.15	10.69	8.40	7.60	8.20

Table A3: Heterogeneous Asymmetric Responses by Gambling Tendency (DV: ΔGambling-amount)

Notes: This table shows the asymmetric response in gambling consumption upon different realizations of mutual fund investment gains and its heterogeneous effects by a different gambling tendency. We run a regression by using 2SLS, where the dependent variable is ΔGambling-amount indicates the difference between the current month's and past month's gambling amounts. The independent variables include OLSΔGain, which indicates the difference between the current month's investment gains and the past month's investment gains, and year $\times$ month fixed effects to control for any unobserved time shock that is common across individuals. Similar to Di Maggio et al. (2020), using the first difference approach, we control for time-invariant individual characteristics that might affect both the outcome variables and capital gains. Based on a gambling tendency that is measured by the average monthly gambling amount, we discretize the users into five groups by 20 percent quintile from top 20% to bottom 20%. In addition, we divide the observations into two cases where the OLSΔGain is greater than 0, and the OLSΔGain is smaller than 0. After that, we estimate the equations separately for each group based on a combination of gambling tendency and OLSΔGain. The upper table shows the results of the earning case and the lower table shows the results of the loss case. Column (1) contains the results from the highest monthly gambling amount group, and Column (5) contains the results from the lowest monthly gambling amount group. OLSΔGain indicates the predicted value of the difference between the current month's investment gains and the past month's investment gains. Standard errors are clustered at the user level and written in parentheses. Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Panel A. Dependent Variable (DV): ΔGambling-amount when OLSΔGain > 0				
	Gambling tendency				
	(1)	(2)	(3)	(4)	(5)
	Top 20%	20 $\sim$ 40%	40 $\sim$ 60%	60 $\sim$ 80%	Bottom 20%
OLSΔGain	0.01895**	0.00935***	0.00668***	0.00285***	0.00162***
	(0.00907)	(0.00342)	(0.00162)	(0.00070)	(0.00023)
Fixed Effects					
Year $\times$ Month	Yes	Yes	Yes	Yes	Yes
Observations	241,305	264,286	280,860	317,784	385,159
R^2	0.01995	0.01613	0.02210	0.02593	0.01601

	Panel B. Dependent Variable (DV): ΔGambling-amount when OLSΔGain < 0				
	Gambling tendency				
	(1)	(2)	(3)	(4)	(5)
	Top 20%	20 $\sim$ 40%	40 $\sim$ 60%	60 $\sim$ 80%	Bottom 20%
OLSΔGain	0.02068**	0.00489	0.00185	0.00039	0.00055***
	(0.00824)	(0.00322)	(0.00146)	(0.00064)	(0.00020)
Fixed Effects					
Year $\times$ Month	Yes	Yes	Yes	Yes	Yes
Observations	218,325	240,334	256,410	291,240	355,063
R^2	0.03185	0.03369	0.04054	0.04249	0.02618

Table A4: Heterogeneous Asymmetric Responses by Gambling Tendency (DV: $\Delta\,\mathbb{1}$(Gambling))

Notes: This table shows the asymmetric response in gambling consumption upon different realizations of mutual fund investment gains and its heterogeneous effects by a different gambling tendency. We run a regression by using 2SLS, where the dependent variable is $\Delta\,\mathbb{1}$(Gambling) indicates the difference between whether a user gambled in the current month and whether the user gambled in the past month. The independent variables include OLSΔGain, which indicates the difference between the current month's investment gains and the past month's investment gains, and year $\times$ month fixed effects to control for any unobserved time shock that is common across individuals. Similar to Di Maggio et al. (2020), using the first difference approach, we control for time-invariant individual characteristics that might affect both the outcome variables and capital gains. Based on a gambling tendency that is measured by the average monthly gambling amount, we discretize the users into five groups by 20 percent quintile from top 20% to bottom 20%. In addition, we divide the observations into two cases where the OLSΔGain is greater than 0, and the OLSΔGain is smaller than 0. After that, we estimate the equations separately for each group based on a combination of gambling tendency and OLSΔGain. The upper table shows the results of the earning case and the lower table shows the results of the loss case. Column (1) contains the results from the highest monthly gambling amount group, and Column (5) contains the results from the lowest monthly gambling amount group. OLSΔGain indicates the predicted value of the difference between the current month's investment gains and the past month's investment gains. Standard errors are clustered at the user level and written in parentheses. Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Panel A. Dependent Variable (DV): $\Delta\,\mathbb{1}$(Gambling) when OLSΔGain > 0				
	Gambling tendency				
	(1)	(2)	(3)	(4)	(5)
	Top 20%	$20 \sim 40\%$	$40 \sim 60\%$	$60 \sim 80\%$	Bottom 20%
OLSΔGain	0.00001	0.00001	0.00003***	0.00002**	0.00002***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Fixed Effects					
Year $\times$ Month	Yes	Yes	Yes	Yes	Yes
Observations	241,305	264,286	280,860	317,784	385,159
R^2	0.04799	0.02735	0.02870	0.03195	0.02650

	Panel B. Dependent Variable (DV): $\Delta\,\mathbb{1}$(Gambling) when OLSΔGain < 0				
	Gambling tendency				
	(1)	(2)	(3)	(4)	(5)
	Top 20%	$20 \sim 40\%$	$40 \sim 60\%$	$60 \sim 80\%$	Bottom 20%
OLSΔGain < 0	0.00005***	0.00003**	0.00003**	-0.000003	0.00001**
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Fixed Effects					
Year $\times$ Month	Yes	Yes	Yes	Yes	Yes
Observations	218,325	240,334	256,410	291,240	355,063
R^2	0.05685	0.05345	0.06079	0.05991	0.04017