Wins, Windfalls and Willpower: Liquidity and Self-Regulation in Online Sports Gambling

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Abstract

We study how gambling behavior responds to prior-day outcomes, liquidity shocks, and bettors' awareness of potential harm, using betting data for a random sample of 24,453 online sports bettors. Relative to days with no resolved bets, bettors are 7 to 8 percentage points more likely to place a bet following either a win or a loss. Bettors increase their stake size after wins and shift toward higher-odds bets after losses. Liquidity windfalls from annual tax refunds do not affect the gambling participation rate, but lead to stake escalation among bettors vulnerable to gambling harm. Safe-gambling tools curb betting only when they directly limit engagement with the platform. Reminder-based awareness nudges, which notify bettors when their gambling expenditure or time spent on the gambling platform exceeds self-set limits, reduce participation but shift bets toward higher-risk wagers.

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1 Introduction

Often advertised as entertainment, sports betting can lead to financial and psychological distress when betting behavior becomes compulsive. The existing literature emphasizes the importance of psychological drivers of gambling behavior (Mercier et al., 2018; Ioannidis et al., 2019), and the external environment may incrementally influence the frequency and intensity of gambling. Macroeconomic shocks can alter individuals' budget constraints and influence their risk-taking behavior. When gambling is easily accessible, such shocks can amplify the adverse health and financial consequences of gambling. Therefore, it is essential to understand how existing economic conditions influence betting behavior to inform public policy. Our study fills this gap by studying how gambling behavior varies with prior betting outcomes, macroeconomic conditions, and vulnerability to gambling-related harm, and by assessing the efficacy of self-control in curbing harmful gambling behavior.

To examine the association between economic conditions and risk-taking behavior, we study the Australian online sports betting market, which is legal and regulated under the Interactive Gambling Act of 2001, permitting bets only through licensed operators. There are no statutory limits on the number or amount of bets. Betting platforms are responsible for verifying the ages of bettors, as access is restricted to bettors aged 18 and older. Unlike lotteries, which are games of pure chance, sports betting involves leveraging one's knowledge of publicly available odds, teams, players, and events to form beliefs. Thus, involving real monetary decisions under uncertainty, online sports gambling provides an ideal empirical setting to examine how individuals' risk-taking behavior responds to shocks in their external environment.

We utilize administrative data from two major Australian sports betting platforms. These data cover the complete betting history of 24,824 randomly selected bettors between March 2023 and February 2024. The dataset provides information on each wager, such as timestamps, stake size, odds, outcome, and bet type. We structure the dataset as a bettor-day panel. This set-up allows us to control for bettor fixed effects as

economic controls for baseline risk preferences and other time-invariant heterogeneity among bettors, and date fixed effects to control for heterogeneity common among all bettors, such as outcomes of sporting events.

These two sports betting platforms offer a wide range of products with varying levels of complexity. Simple fixed-odds bets dominate market activity. Complex, multi-leg, and exotic bets, which have higher odds, remain a niche market. This skew toward relatively simple products is consistent with bounded rationality and choice overload, as bettors gravitate toward less cognitively demanding and more familiar options. Most bets are placed as single-leg wagers with modest stakes and relatively low expected payouts, suggesting that bettors weigh trade-offs between complexity, payout potential, and ease of understanding in ways that echo key behavioral models.

A functional betting account requires account creation and identity verification. Once completed, a bettor may transfer funds into their account, and winnings are credited to the same account and can be withdrawn to a linked bank account. Nearly all account funding transactions are digital, with card payments and real-time bank transfers enabling immediate account funding. A significant fraction of bettors are young males. Females tend to prefer wagers with higher odds, suggesting gender differences in bet selection. As women generally display lower risk tolerance than men, this pattern likely reflects 'for fun' betting by females. Based on our sample, a bettor loses, on average, AUD 2,561 per year, where loss is defined as the difference between the aggregate amount of bets and winnings. These features determine the incentives, constraints, and cognitive frames through which bettors undertake risks, offering insights into how behavioral biases interact with market design to sustain persistent engagement despite negative expected returns.

Our analysis reveals that bettors adjust their contemporaneous betting activity to the prior-day gambling outcomes. Bettors are 6.4 to 7.8 percentage points more likely to place a bet following both a loss and a win relative to days with no resolved bets, consistent with reinforcement-based updating. On days following a win, bettors also increase the size of their stakes by 41.1 percent, suggesting a house-money effect in

which recent gains are perceived as disposable. We also find evidence of risk-taking as bettors increase the average odds, rather than the size, of their bets after losses. On average, bettors stake 1.9 and 1.7 times their prior-day winnings and losses, respectively. Female bettors adjust more conservatively than males, reducing stakes more sharply after losses and increasing them less after wins. Older bettors, those aged 55+, also respond cautiously, reducing their stake size after wins but showing no adjustment after losses.

We exploit a natural experiment created by Australia's fiscal calendar to study how predictable liquidity shocks affect gambling behavior. Australia operates a Pay-As-You-Go (PAYG) income tax system, under which tax is withheld from wages throughout the financial year (that runs from July 1 to June 30) based on the assumption that each paycheck reflects a stable annual income. When income varies over the year, as it often does, it results in excess withholding, which typically leads to a tax refund. Most workers receive non-trivial tax refunds between July and October. In 2022-23, the tax refund averaged approximately AUD 3,000 (see Australian Tax Office and H&R Block). Several welfare benefits are indexed to inflation, with most changes implemented between July and September, providing an income boost to eligible individuals. Together, these mechanisms create an exogenous increase in disposable income during the July–October window, independent of bettors' prior gambling behavior. This structure enables us to investigate whether increases in liquidity influence bettors' responses to recent gambling outcomes.

Some of the bettors are classified as at risk of gambling harm by the vendor's proprietary algorithm. Due to behavioral vulnerabilities, such as present bias, limited self-control, and heightened sensitivity to recent outcomes, these individuals could respond more intensely to changes in liquidity. We test this conjecture by examining how behavioral responses to prior-day wins and losses change following a predictable liquidity shock, comparing at-risk and non-risk bettors before and after the event. We find that liquidity does not affect either gambling participation or odds selection. The increase in liquidity leads to larger stake sizes following both wins and losses. To-

gether, these findings suggest that while liquidity does not attract new betting activity, it intensifies feedback-driven monetary exposure of bettors.

Next, we focus on *self-regulation*, where a bettor voluntarily adopts safe gambling tools, designed to minimize gambling-related harm. These tools are categorized as deposit limit management, time management, market restrictions, self-exclusion, and awareness nudges. Unlike objective risk classifications, which rely on external algorithms or diagnostic criteria, the adoption of these tools captures self-perceived control and a decision to self-regulate. This construct is important because it reflects an individual's awareness of potential harm or risk exposures and willingness to engage with tools designed to reduce it, offering a lever for intervention.

The usage of safe gambling tools is relatively low. Only 13 percent of bettors use at least one of the safe gambling tools during the sample period. Deposit limit management is the most frequently used safe gambling tool that allows bettors to set caps on their deposits over a specified time period (e.g., day, week, month). We find that the activation and deactivation of safe-gambling tools are largely episodic, while continued usage is persistent. After a series of losses, bettors are more likely to activate (if inactive) and deactivate (if active) safe-gambling tools. In contrast, after consecutive wins, all forms of tool engagement decline. This pattern is consistent with heightened emotional reactivity and self-regulation following losses, and complacency and a tendency to maintain the status quo following wins. These findings suggest that losses seem to create a moment when people are more willing to reflect on their gambling and take steps to manage it.

We find that users of most of these tools do not exhibit more restrained betting behavior. Awareness nudges, where a bettor receives a notification when the amount bet or time spent on the platform exceeds a chosen threshold, reduce participation. However, among bettors who continue to bet, the average odds of their bets increase. This finding suggests that while reminders may discourage betting activity at the extensive margin, they may also shift bets toward higher-risk bets. A plausible explanation is that awareness nudges prompt bettors to be more selective in where they place riskier

but rewarding bets. Deposit limit management does not significantly affect the betting behavior of users who set such limits. These results suggest that subjective recognition of gambling harm translates into behavioral restraint only when safe gambling tools restrict bettors' engagement with the betting platform (as in self-exclusion), rather than when bettors merely cap their liquidity or receive reminders.

A large body of literature in behavioral economics and finance documents systematic deviations from rational choice. Prospect theory (Kahneman & Tversky, 1979), mental accounting (Thaler, 1985), and realization utility (Barberis & Xiong, 2012) predict that feedback from recent outcomes shapes subsequent decisions by altering reference points and utility from realized gains or losses. These ideas are supported by evidence from stock trading (Odean, 1998a), experimental tasks (Erev et al., 2008; Imas, 2016), and game show data (Post et al., 2008), where patterns like the disposition effect and house money behavior emerge consistently. A growing body of research uses sports betting markets to test these mechanisms. Andrikogiannopoulou & Papakonstantinou (2018) show that bettors predominantly follow momentum-based beliefs consistent with regime-shifting models, while Andrikogiannopoulou & Papakonstantinou (2020) demonstrate that reference-point updating generates history-dependent risk preferences, shedding light on the micro-foundations of the disposition effect. Extending this line of work, Andrikogiannopoulou & Papakonstantinou (2021) estimate heterogeneous utility functions using a hierarchical mixture model and find robust evidence of probability weighting and more limited loss aversion. Moskowitz (2021) finds that pricing anomalies in betting markets arise from momentum-driven misperceptions that reverse once outcomes are realized. We contribute to this literature by examining how feedback from prior outcomes affects contemporaneous betting behavior. We document that external shocks and self-recognized vulnerability jointly shape risk-taking.

A related body of work in finance examines investors' preference for positively skewed, lottery-like payoffs. This literature shows that such skewness-seeking behavior affects both portfolio choice and asset prices. de Roon & Karehnke (2017) formalize

how modest deviations from symmetry generate meaningful changes in optimal portfolios and risk premia. Bougherara et al. (2022) find that individuals often combine risk aversion with skewness seeking, implying that a desire for rare large gains can coexist with an overall dislike of variance. Some studies find that investors with preferences for skewness overpay for lottery-like securities (Lin & Liu, 2018), drive seasonal mispricing in options and equities (Doran et al., 2012), and shape aggregate return premia in markets with stronger gambling cultures (Kumar et al., 2011; Blau et al., 2019). Some studies focus on the association between gambling and gambling attitudes and financial decisions. Chen et al. (2014) find that firms in gambling-prone regions undertake riskier and more innovative projects. Recent household-level evidence shows that online sports betting and investment activity are influenced by gambling preferences and feedback from financial gains (Baker et al., 2024; An et al., 2025). Our study adds to this literature by providing direct, micro-level evidence of skewness-seeking under repeated feedback and real monetary stakes.

Complementing economic models of decision-making is a rich literature in psychology, psychiatry, and public health that examines gambling as a behavioral addiction with profound health implications. Problem gambling has been linked to impulsive behavior, distorted beliefs, and impaired self-regulation (Toneatto et al., 1997; Clark, 2010), and is often co-morbid with emotional distress and mental health disorders (Kessler et al., 2008; Dowling et al., 2015, 2019). The structural features of gambling markets, such as fast-paced betting and advertising, exacerbate these risks, particularly among vulnerable populations (Hing et al., 2015; Hastings & Shapiro, 2018). Harm minimization tools have been promoted as interventions. Still, their effectiveness remains uncertain, with studies showing that they are often used reactively after episodes of distress rather than proactively to prevent harm (Delfabbro & King, 2017; Gainsbury et al., 2014). Our study builds on this work by using voluntary engagement with safe gambling tools as a proxy for self-regulation. We find that users of harm minimization tools continue to exhibit feedback-driven escalation. This finding suggests that self-awareness does not necessarily translate into behavioral restraint. This

disconnect between intention and action highlights the challenges of addiction management and the need for more effective regulatory and clinical responses.

2 Data Description

We use administrative betting records from a sample of 24,824 bettors drawn from two major licensed Australian online gambling platforms. The sample includes all bettors who placed at least one bet in the prior six months *and* have been registered users for at least 30 days. The operator provided a random sample of bettors with oversampling of bettors flagged as 'at-risk' by the in-house harm detection algorithm. We apply inverse probability weights based on sampling frequencies provided by the platform operator, ensuring our estimates are representative of the full population of active bettors.

The dataset contains the complete betting history of bettors from March 1, 2023, to February 29, 2024. Each record is a transaction. A transaction may involve single or multiple bets across various markets. We observe bet placement and resolution times, cash and bonus stakes, total stake, odds at placement, bet type, and outcome. Transactions may involve single or multiple bets across various markets. Table A.1 presents a list of markets (sports) covered by these two betting platforms. Markets include horse and greyhound racing, soccer, rugby, basketball, cricket, motor sports, and others. We also observe each bettor's age, gender, postcode, and a binary indicator of at-risk status as determined by the operator's harm detection algorithm.

We observe the timestamps of both bet placement and result. We do not observe the underlying sporting event or match itself, which limits our ability to track betting dynamics tied to specific events. Instead, we focus on daily betting activity. For each calendar day in which a user placed or settled a bet, we compute the total cash staked, the total net result of settled bets, and the stake-weighted average odds. Multi-leg bets are split proportionally by the stake to ensure accurate measurement of total exposure. We restrict attention to bets with valid outcomes and complete information. We exclude bets that were void, canceled, or refunded because they do not entail any actual

monetary exposure and therefore lack realized outcomes. We use the cash stake variable as our definition of expenditure, reflecting a bettor's actual out-of-pocket spending. Our final sample comprises 24,453 bettors, of whom 4,819 are identified as at risk by the operator's harm-detection algorithm.

3 Market Setting

3.1 Product and Platform Landscape

3.1.1 Bet Types and Formats

Figure 1 depicts the structure of online sports betting activity disaggregated by product and bet type. Simple bets (fixed win or place, for instance) dominate the market. Complex bets (Trifectas, First Four, and Same Race Multi) are used far less frequently. Bet formats exhibit a similar pattern. Single-leg bets, where a bettor selects one outcome, are far more common than multi-leg bets that involve linked outcomes across events. These include the same game multis, such as betting on a football team to win and a specific player to score, multi-sport bets, and mixed combinations. The lower panels show that average odds rise sharply with complexity. Same-race multi and same-game multi, where the bettor must satisfy multiple simultaneous conditions, resulting in low win probabilities but high payouts, represent extreme cases.

[Insert Figure 1 Here]

These patterns are consistent with several behavioral mechanisms. Prevalent use of simple bet types aligns with theories of limited attention and bounded rationality. When faced with multiple betting options, bettors tend to favor choices that are less cognitively demanding or easier to understand (Iyengar & Kamenica, 2010). The sporadic use of high-odds bets supports models of non-linear probability weighting, in which agents overvalue small probabilities of large wins (Tversky & Kahneman, 1992), attracting bettors exhibiting long-short bias (Snowberg & Wolfers, 2010). Figure 1 provides a descriptive benchmark for the structure of wagering activity. Bettors appear to

trade off complexity, potential payout, and ease of decision-making in ways that are well-documented in behavioral economics.

3.2 How Bettors Fund Their Accounts

Figure 2 presents a pie chart showing the methods used by bettors to fund their betting accounts. The majority of transactions (66.5%) are made using credit and debit cards. The second most common way is real-time transfer services (19.1%), which enable near-instantaneous deposits directly from bank accounts. Mobile wallets, such as Apple Pay or Google Pay, account for 13.7% of deposits. Other non-digital methods (cash/in-person (at sports betting outlets) and traditional bank transfers, which represent 0.4% and 0.3% of transactions, respectively) are nearly absent.

[Insert Figure 2 Here]

This distribution reflects the digital-first nature of online gambling platforms, suggesting that bettors overwhelmingly prefer instantaneous and frictionless payment methods. This feature aligns with research showing that digital payment methods correlate positively with consumer spending (Soman, 1999; Prelec & Simester, 2001; Soman, 2001, 2003; Liu et al., 2021). Research indicates an increase in risk-taking associated with access to funds at relatively low transaction costs (Laibson, 1997; Agarwal et al., 2018). The digital infrastructure of gambling platforms not only facilitates participation but may also amplify behavioral biases associated with immediacy and reduced attention to costs.

3.3 Temporal Patterns in Sports Gambling

In Figure 3, we present betting activity over time. The top two rows show patterns in monetary activity, including cash (bettor's own funds) and free (platforms' promotional credits) stakes, while the bottom row displays participation rates, measured as the share of bettors who place at least one bet on a given day. Daily series (left) reveal a strong seasonality in both cash and free stake volumes. Activity rises steadily through

the week, peaking on Saturdays, and drops sharply on Sundays and Mondays. These cycles are highly persistent across the year and are also visible in average stake sizes, suggesting that bettors not only bet more often but also in larger amounts at the end of the week. Weekly aggregation (middle) reveals seasonal spikes in overall betting volumes and participation. The most notable increase in the number of active bettors and their stakes occurs in November, coinciding with the Melbourne Cup Carnival, a major racing event in Australia. This spike is accompanied by a broad increase in both the number of active bettors and the size of their stakes. The rightmost panel summarizes day-of-week averages. As many sports events are held on the weekend, Saturday records the highest total and average stakes among all days of the week. Midweek sports betting activity is relatively flat, with Wednesday and Thursday representing minor troughs.

[Insert Figure 3 Here]

These patterns occur at the intersection of leisure time, sporting event schedules, and promotional cycles. Major sporting events typically occur on weekends, and bettors are relatively less time- and attention-constrained on Saturdays and Sundays, which allows them to engage more with the betting platform. The descriptive evidence is consistent with findings of Della Vigna & Malmendier (2006), who show that time-use constraints and salience play key roles in shaping economic decisions. Bettors may derive utility not only from outcomes but also from participating in culturally significant events (Brunnermeier & Parker, 2005), which could explain the increase in betting activity in November.

3.4 Bettors' Demographic Profiles

Figure 4 summarizes betting behavior by age and gender. The left column describes the demographic distribution of bettors. Most users are male (87 percent), and the age distribution is heavily skewed toward younger adults, peaking in the late 20s and declining steadily through middle and older age. The center column plots aggregate

and average stake values by age. Aggregate betting activity increases as bettor ages rise towards the mid-30s and declines for bettors at older ages. The average stake size is relatively uniform, with a consistent age profile. Patterns in free stake mirror those in cash stake, but the economic magnitude is much smaller. The average bet odds also have a flat age profile, but older bettors tend to favor bets with lower odds, suggesting a shift in risk-taking in the life-cycle.

[Insert Figure 4 Here]

The bottom panel shows that approximately 15.3% of bettors are female who wager smaller amounts but tend to select bets with higher odds. Given that the literature suggests women are at least as risk-averse as men (Powell & Ansic, 1997; Charness & Gneezy, 2012; Filippin & Crosetto, 2016), these patterns are consistent with low-stakes 'fun' among casual bettors. Due to their numbers, males account for a large share of the aggregate cash stake. These gender differences in both participation and betting style align with prior work documenting gender gaps in gambling intensity and time allocation (Humphreys & Carcedo, 2012), and highlight the substantial gender segregation in sports wagering.

3.5 Gambling Losses

Figure 5 plots the daily dollar losses of bettors. The series shows that bettors consistently earn negative returns, with only a small number of days showing gains. In our sample, an average bettor on these platforms loses approximately AUD 2,561 per year. This amount is non-trivial relative to the median annual salary in Australia (AUD 74,240 in 2022–23 (see Australia Tax Office Statistics).

[Insert Figure 5 Here]

The platform takes a margin from the steady flow of bets by pooling wagers across bettors and events. Levitt (2004) shows that bookmakers can still earn profits in the

long run without perfectly balancing each side of a bet by exploiting bettors' biases. This figure reinforces a central tension in the economics of gambling: bettors face persistent losses by design, yet continue to engage. The real monetary stakes provide an empirical setting to study risk perception and behavioral persistence in the face of unfavorable odds.

4 Methods and Results

In this section, we explore how bettors respond to recent gambling outcomes. We test whether past gains or losses shape subsequent participation, stake size, and bet selection, and examine systematic heterogeneity by gender, age, and vulnerability to gambling harm.

4.1 Prior Day Outcomes

A central prediction of reinforcement learning and mental accounting models is that past outcomes influence future risk-taking (Thaler, 1985; Barberis & Xiong, 2012). Prior studies in experimental and financial settings suggest that recent outcomes affect both the likelihood of re-engaging and the level of risk taken (Odean, 1998b; Post et al., 2008; Imas, 2016). Using our betting data, we examine how prior-day outcomes influence subsequent betting activity, providing a direct test of feedback-driven behavior in a setting involving real monetary stakes.

To quantify these dynamics, we estimate the following regression model:

$$Y_{it} = \beta_1 \text{Loss}_{it-1} + \beta_2 \text{Win}_{it-1} + \gamma_i + \gamma_t + u_{it}, \tag{1}$$

where Y_{it} is the outcome of interest, whether a bet is placed, the size of the bet (conditional on betting), or the average odds of bets placed by bettor *i* on date *t*. Loss_{it-1} and Win_{it-1} are dichotomous variables that equal 1 (0 otherwise) if a bettor experiences a loss or win, respectively, on date *t-1*. The omitted category is the days on which no bets were resolved. Bettor fixed effects, denoted γ_i, to control for any time-invariant characteristics of bettors, such as baseline preferences for risk, attention, or financial

literacy. Date fixed effects, denoted γ_t, account for shocks that may influence betting behavior on a given day. We double-cluster standard errors by bettor to account for serial correlation in betting behavior and by date to capture common shocks, such as the outcomes of sporting events or platform-wide promotions, which affect all bettors simultaneously (Bertrand et al., 2004; Cameron & Miller, 2015; Abadie et al., 2023).

Table 2 shows that prior-day outcomes influence next-day betting behavior across extensive, intensive, and risk margins. In column (1), the dependent variable is *Bet Placed*, a dichotomous variable that equals 1 if a bettor places a bet on a given day, and equals 0 otherwise. We find that bettors are 6.9 and 8.2 percentage points more likely to place a bet after a loss and a win, respectively, consistent with reinforcement-based updating. In column (2), the results suggest that bet size increases sharply after a win but declines negligibly after a loss. Based on the average cash stake size of AUD 334.6, the estimated coefficients imply a decline of AUD 7.9 after a loss and an increase of AUD 134.6 after a win. These results align with the house-money effect and models of mental accounting. In these models, bettors exhibit higher risk tolerance when playing with perceived gains, overconfidence, and when utility is realized (Thaler & Johnson, 1990; Thaler, 1985; Odean, 1998a; Barberis & Xiong, 2012) or when they treat losses as separate from their current wealth (Shefrin & Statman, 1985).

[Insert Table 2 Here]

In column (3) of Table 2, the results suggest bettor shifting towards lower-probability but higher-payout outcomes after losses. In the absence of an increase in the cash stake, this finding implies that bettors selectively raise the riskiness of their bets, aligning with the findings of previous studies (Gneezy & Potters, 1997; Post et al., 2008; Snowberg & Wolfers, 2010).

Next, we examine heterogeneity in bettors' responses to prior-day outcomes in Table 3. In Panel A, the results suggest that female bettors are more responsive at the extensive margin, but adjust bet size more cautiously on the intensive margin. We detect

no gender differential in odds selection, suggesting similar decision rules around risk type, but differing spending intensity. This pattern of more conservative stake adjustments, particularly after losses, is consistent with experimental evidence that women exhibit greater sensitivity to adverse outcomes and are more likely to stop investing in loss domains (Eckel & Grossman, 2002, 2008).

[Insert Table 3 Here]

In Panel B of Table 3, we test whether baseline results vary across age groups. We find no evidence of heterogeneity in bet placement or odds choice by age. However, relative to bettors aged 18–40, those aged 41–55 and 56 and older decrease their stakes by 9.2 percent and 18.1 percent, respectively, after wins. These results indicate a more conservative adjustment among older bettors, plausibly reflecting greater financial discipline or experience-based caution. The lack of statistical significance for interaction terms between prior-day losses and age groups further suggests that stake reductions following losing days are broadly similar across age groups, consistent with evidence that losses carry strong emotional salience in recreational settings (Eckel & Grossman, 2002).

[Insert Figure 6 Here]

To complement the result in Table 2, we estimate two metrics that provide a direct and interpretable measure of how bettors adjust their bets in response to prior-day outcomes. The reinvestment (loss-chasing) rate is defined as the logarithm of the cash stake relative to the prior-day gain (loss). Figure 6 shows the estimated average rates. On average, bettors stake about 1.9 and 1.7 times their previous-day gains and losses. Both reinvestment and loss-chasing rates are positive and economically meaningful, reinforcing that bettors anchor new decisions on past outcomes.

4.2 Macroeconomic Shocks and Gambling Behavior

In this section, we examine whether external economic conditions systematically influence betting decisions. In particular, do macroeconomic shocks affect how bettors participate in gambling, the amount they stake, and the level of risk they take?

4.2.1 Tax Returns and Social Transfers in Australia

We focus on a salient and well-identified institutional feature of Australia's fiscal calendar: the predictable increase in disposable income that occurs each year between July and October due to the tax returns. Australia operates a Pay-As-You-Go (PAYG) taxation system, under which personal income tax is withheld throughout the year. The official financial year runs from July 1 to June 30. Each year, all taxpayers submit a tax return at the end of the financial year to reconcile their actual tax liabilities with the amounts withheld during the year. For most wage earners, this process results in a tax refund. The refund size depends on earnings, deductions, and eligibility for various offsets, but it is typically non-trivial. For instance, a worker who is employed for only one month and earns AUD 18,000 during that time would be taxed as if their annual income were AUD 216,000, leading to approximately AUD 5,568 withheld. Since their actual income is below the tax-free threshold, they would receive a full withheld amount as a tax refund upon filing a return. In 2022-23, the median wage and average tax refund for salaried employees aged 18 and older were approximately AUD 74,000 and AUD 3,180, respectively (see Australian Tax Office and H&R Block). These refunds are issued between July and October. The majority of claimants receive payment within 14 business days of lodging their return. These refunds are immediately available upon direct credit into a taxpayer's bank account by the Australian Tax Office. This timing introduces a concentrated liquidity shock to a broad base of bettors.

In addition to tax refunds, several major welfare programs are indexed to inflation at the start of the financial year and increased in September (and March) by the Department of Social Services. The indexation raises the fortnightly payment amounts for recipients and reflects cost-of-living increases, which are particularly significant

during periods of high inflation. The nominal increment in transfer payments complements the tax refunds and boosts individuals' disposable income. The aggregate effect is to ease short-term liquidity constraints for eligible bettors.

These two policy mechanisms, federally administered tax refunds and indexed benefit increases, generate a large, predictable, and exogenous income shock during the July–October window. The timing of these events is independent of bettors' gambling behavior, providing a natural experiment to examine how increased financial slack alters the gambling behavior of bettors. At-risk bettors may exhibit a higher marginal propensity to gamble with new income, reflecting vulnerabilities such as present bias, limited self-control, or mental accounting distortions (Laibson, 1997; Hastings & Shapiro, 2018). Understanding how vulnerable individuals respond to liquidity shocks is a key policy concern, given the links between gambling addiction, financial distress, and broader health outcomes.

4.2.2 Prior Outcomes, Liquidity Shocks, and Addiction Risk

Predictable cash inflows due to tax refunds and benefit payments' indexation alleviate short-term liquidity constraints. In this section, we investigate whether liquidity shocks exacerbate the baseline responses to recent wins and losses documented in the previous section. We estimate the following regression specification:

$$\begin{aligned} Y_{it} =& \beta_1 \text{Loss}_{t-1} + \beta_2 \text{Win}_{t-1} + \beta_3(\text{At Risk}_i \times \text{Post}_{t'}) + \\ & \beta_4(\text{Loss}_{t-1} \times \text{Post}_{t'}) + \beta_5(\text{At Risk}_i \times \text{Loss}_{t-1}) + \beta_6(\text{At Risk}_i \times \text{Loss}_{t-1} \times \text{Post}_{t'}) + \\ & \beta_7(\text{Win}_{t-1} \times \text{Post}_{t'}) + \beta_8(\text{At Risk}_i \times \text{Win}_{t-1}) + \beta_9(\text{At Risk}_i \times \text{Win}_{t-1} \times \text{Post}_{t'}) + \\ & \gamma_i + \gamma_t + u_{it}. \end{aligned} \tag{2}$$

In equation (2), subscripts i and t represent bettor and time, respectively. $At\ Risk_i$ is a dichotomous variable that equals 1 (0 otherwise) if a bettor is identified as at risk of gambling harm by the vendor's proprietary algorithm. We estimate equation (2) using a subset of the dataset spanning 8 months, from March 1, 2023, to October 31, 2023. $\text{Post}_{t'}$ is a dichotomous variable that equals 1 (0 otherwise) for the 4-month period

starting on July 1, 2023. γ_i and γ_t denote bettor and time fixed effects, respectively. The bettor fixed effects control for all time-invariant heterogeneity across bettors, and the time fixed effects absorb shocks common to all bettors on a given day. These fixed effects also absorb the direct effects of At Risk$_i$ and Post$_t$. Table 4 reports regression results based on equation (2).

[Insert Table 4 Here]

In column (1) of Table 4, the dependent variable equals 1 if a bet is placed on a given day. The direct effects of net wins and losses from bets settled on day $t-1$ align with our baseline estimates. The economic and statistical significance of the triple interaction terms indicates that the tax-induced variation in liquidity does not materially change the likelihood of betting for at-risk bettors. This pattern is consistent with the habitual nature of gambling, and with evidence that problem gamblers show weaker behavioral adjustment to recent outcomes (Kessler et al., 2008; Guryan & Kearney, 2008).

In column (2), the dependent variable captures the intensive margin: the log of stake size, conditional on placing a bet. The positive interaction betweenWin$_{t-1}$ and at-risk status indicates that, following a day in which the net outcome of settled bets was positive, at-risk bettors tend to increase their stake sizes more than non-risk bettors. The positive and statistically significant triple interaction terms, which reflect conditional differences, indicate that the baseline effect is amplified when liquidity is higher. Figure 7 illustrates this pattern: from July onward, average stake sizes for at-risk bettors rise relative to June, while those for not-at-risk bettors remain stable. Thus, while liquidity does not meaningfully affect the decision to participate, it does facilitate larger stake adjustments when betting occurs.

[Insert Figure 7 Here]

The triple interaction terms in column (3) of Table 5 are statistically non-significant.

This is plausible due to the structural features of sports betting markets. Bettors tend to return to familiar sports. As such, odds choices remain relatively stable and less sensitive to short-term liquidity fluctuations or prior-day net outcomes (Koehler et al., 2002).

Overall, the findings in this section indicate that increased liquidity does not induce additional betting on the extensive margin. Still, it does magnify outcome-contingent adjustments in stake size, particularly among at-risk bettors. These findings across extensive, intensive, and risk margins highlight the channels through which financial slack interacts with bettors' gambling behavior. Policies that target the escalation of stake size may therefore be effective in mitigating gambling related harm.

4.3 Voluntary Use of Safe Gambling Tools

Hitherto, we show that liquidity shocks intensify feedback-driven betting behavior, particularly among bettors identified as being at risk. This finding raises a question that we study in this section: Do bettors who self-regulate their betting by voluntarily adopting safe gambling tools behave differently? These tools, such as deposit limits, time-outs, and self-exclusion, are designed to promote self-regulation and reduce the risk of gambling-related harm.

The use of harm minimization tools may reflect elements of subjective pathology and self-regulation. Bettors may adopt these tools either because they recognize problems in their betting behavior or because they deliberately allocate a portion of their consumption budget to gambling and wish to manage exposure within perceived risk limits. Given the data constraints, we remain agnostic about the underlying motivation for activating one or more safe gambling tools. Prior work finds that users of these tools tend to exhibit stronger gambling urges, heightened emotional distress, and elevated impulsivity. (Gainsbury et al., 2014; Hing et al., 2015; Delfabbro & King, 2017; King & Delfabbro, 2017). These behavioral markers are consistent with the evidence on distorted outcome beliefs and impaired self-control among bettors experiencing gambling distress (Toneatto et al., 1997; Clark, 2010). In this section, we investigate who

uses these tools, how usage varies across bettors, and whether tool activation changes the baseline behavioral response.

4.3.1 Prevalence of Safe Gambling Tool Usage

In Table 5, we report the number of bettors who engage at least one of the safe gambling tools that we categorize into five main types. Overall, 3,192 bettors engaged with at least one form of safe gambling tools at least once. At-risk bettors form a minority of safe gambling tool users. They account for 36 percent of safe gambling tool users. Deposit limits are the most frequently used safe gambling tool, with about 87 percent of users adopting them. Weekly limits are the most common, followed by daily, while monthly or longer limits are rare. This pattern suggests that bettors who self-diagnose tend to manage their behavior through short- to medium-term liquidity constraints rather than long-term restrictions. Time-management tools, which let bettors restrict account access through scheduled block-outs, curfews, and short- to long-term self-exclusions, are the second most prevalent, used by 553 bettors. Within this group, medium and long take-a-break features dominate with 209 and 282 users, while curfews and block-outs are much less common. Bettors who perceive risk appear more inclined to pause gambling for sustained intervals rather than to schedule their activity daily.

[Insert Table 5 Here]

Other tools are much less prevalent. Only 127 bettors use market restrictions, and two-thirds of these are at risk, suggesting that some bettors who recognize their vulnerability attempt to remove entire market categories (racing or sports). Self-exclusion is the most extreme form of harm minimization, but its usage is rare, with only 11 users in the entire sample. Awareness nudges are also scarcely adopted, with only 31 users despite the minimal effort required to activate them. The low take-up indicates that most bettors either do not find reminders credible or prefer not to be interrupted while betting.

The numbers in Table 5 offer two main insights. First, usage is highly concentrated

in deposit limits, with other categories attracting only smaller subsets of bettors. Second, at-risk individuals are disproportionately represented among users of more restrictive safe gambling tools, such as time management and market exclusions. This point suggests that self-diagnosis of vulnerability is real, and its intensity varies. Safe gambling tool adoption functions as a behavioral marker that can reflect subjective recognition of gambling problems among at-risk bettors, and self-regulation among others who use such tools plausibly to manage exposure or maintain control.

[Insert Table 6 Here]

A key question is whether the use of safe-gambling tools reflects stable characteristics of bettors. Table 6 shows that activation and deactivation have low explanatory power from bettor fixed effects, as these are one-off decisions influenced by short-term factors like losses, mood changes, or daily events. In contrast, the continued daily use of these tools shows a high R^2 from bettor fixed effects, indicating persistent tool usage after adoption. Thus, most variation in safe gambling tool usage is likely due to cross-sectional differences rather than daily fluctuations. These results support the idea that activation and deactivation are situational, while continued usage is linked to persistent traits among bettors.

4.3.2 Timing of Safe Gambling Tool Usage

Next, we ask whether recent betting outcomes prompt bettors to engage the safe gambling tools. To test whether the activation, usage, and deactivation of safe-gambling tools depend on recent outcomes, we define streaks based on a bettor's consecutive wins or losses. A loss (win) streak equals one if the bettor lost (won) in each of the last n outcomes, where $n = 1, 2, 3, 4,$ or 7. Loss streaks are more common than win streaks. This gap increases with the length of the streak. Table 7 reports regression results.

[Insert Table 7 Here]

In Panel A, the coefficients imply that after 3 consecutive losses (gains), the likelihood of activating the safe gambling tool increases (decreases) by 16 (32) percentage points relative to its unconditional mean (0.124 percent). In panel B, the results imply increases of 26.6 and 53.2 percentage points following 3 consecutive losses and gains, respectively, in the likelihood of deactivating safe gambling tools relative to its average rate of 0.08 percent. These patterns are consistent with the idea that losses heighten attention to risk and prompt both protective and reactive responses, while wins foster complacency and stability. Consequently, loss streaks increase the volatility of safe-gambling behavior, as bettors become more likely to adjust their betting strategies. Overall, these patterns suggest that safe-gambling tools are used reactively in response to outcomes rather than as stable, forward-looking commitments.

4.3.3 Prior Betting Outcomes and Safe Gambling Tool Usage

Next, we ask whether safe gambling tools change the betting response to recent wins and losses. The use of safe gambling tools is endogenous to a bettor and provides a measure of self-regulation. If effective, these tools should attenuate feedback-driven betting. They may also reallocate behavior across three focal margins. A bettor might bet less often but with larger stakes when active, or maintain stake size but select more speculative bets. Understanding these trade-offs is crucial for evaluating whether voluntary harm minimization works as intended.

Table 8 reports regressions of betting activity on prior-day win and losses, interacted with indicators for safe gambling tool usage. In Panel A, we find that users of deposit limit management and market restriction type safe gambling tools are just as likely to return to the platform after wins and losses as non-users. Time management users show almost no increase in betting after wins or losses. Awareness nudges reduce the likelihood of betting by approximately 1.6 percentage points, respectively, compared to a 6.9 percentage point rise for non-users. Tools that reduce engagement with the betting platform, thus, curb betting at the extensive margin, whereas deposit limits and market restrictions do not. Dampening is stronger after losses than after wins, suggesting that self-regulation binds most when bettors confront negative feed-

back.

[Insert Table 8 Here]

Panel B of Table 8 shows that safe gambling tools affect betting behavior primarily after losses. Safe gambling tools lack efficacy as the incremental effect is statistically non-significant, suggesting that intensive margins do not differ statistically across users and non-users of safe gambling tools. Awareness nudges, as shown in Panel A, incrementally reduce the likelihood of placing a bet. However, the results in Panel C suggest that, conditional on betting, these users' average odds (relative to non-users) are about 42 percent higher. The negative incremental effect on participation and the positive effect on riskiness suggest that bettors who use awareness nudges substitute between the extensive and risk margins: betting less often but taking on greater risk when they do. Other categories show no systematic association with bet odds.

The results in this section highlight an important distinction. Tools that permit ongoing engagement, such as deposit limits, leave outcome-driven betting behavior unchanged. The findings for awareness nudges suggest that reminders without binding constraints may shift harmful behavior among margins. The results in this section show that the effectiveness of safe gambling tools depends on whether the mechanism directly reduces engagement with the gambling platform.

5 Discussion

The findings of this study are relevant to the United States, where online sports betting has expanded rapidly following the 2018 repeal of the Professional and Amateur Sports Protection Act (PASPA). Since legalization, US sports betting markets have grown, generating over 66 billion dollars in wagers in 2023 (see American Gaming Association). As in Australia, betting in the US is predominantly digital and integrated into household expenditure and liquidity, creating conditions conducive to impulsive betting. Using transaction-level data and staggered state-level legalization, Baker et al. (2024) show that access to online sports betting crowds out household saving and

investment, increases reliance on consumer credit, and exacerbates financial fragility among constrained households. These balance-sheet responses indicate that betting activity in the US is closely tied to household liquidity and financial constraints, rather than being purely a form of entertainment. Consistent with this interpretation, betting activity in the US has been increasing over time (see Commercial Gaming Revenue Tracker, 2023).

Australia provides a useful mature-market benchmark for understanding how these dynamics may evolve in the US as markets move from rapid adoption to steady-state participation. In our setting, betting intensity is state-dependent. Temporary increases in available funds amplify betting among already vulnerable bettors in a low-friction environment where stakes and frequency can be adjusted immediately. Bettors with greater capacity to place larger or more frequent wagers can create windows of heightened risk because liquidity relaxes constraints when reinforcement dynamics are active. The US institutional environment, characterized by continuous mobile access and rapid feedback, closely matches these features, pointing to the relevance of the same reinforcement–liquidity interaction documented in this study.

Our findings also have implications for consumer-protection policies. While light-touch 'responsible gambling' tools can reduce participation on the extensive margin, our results show that remaining bettors may increase risk exposure. This indicates that such tools do not necessarily mitigate escalation among active users. More broadly, vulnerability in online betting markets arises from the interaction of reinforcement, liquidity, and low frictions rather than solely from entry into betting.

Nevertheless, there are institutional differences between Australia and the US, including advertising restrictions, consumer protection regimes, and broader social safety nets. Still, the similarity in betting platforms, available sports, and observed behavioral responses across settings suggests that the mechanisms linking reinforcement-driven escalation and liquidity likely generalize. Overall, the US experience of a booming regulated sports betting industry following the repeal of PASPA reinforces the central message of our analysis: online sports betting is not merely a form of entertainment

expenditure but a financial activity in which risk evolves dynamically through reinforcement and liquidity interactions.

6 Conclusion

This paper documents that gambling behavior is shaped by prior outcomes, liquidity shocks, and bettors' own recognition of harm. Reinforcement from wins and selective risk-taking after losses drives systematic escalation in exposure. Liquidity does not attract new participation but amplifies monetary risk-taking, especially among vulnerable bettors. Safe gambling tools are likely effective when they directly limit bettors' ability to engage with the platform, suggesting that policy interventions should target mechanisms that constrain engagement rather than merely inform behavior.

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Table 1: **Descriptive Statistics**

This table presents the summary statistics of key variables used in the analysis. The *Reinvestment Rate* is defined as the logarithm of the ratio between the bet size on day t and the value of the bettor's net gain on day $t-1$. The *Loss Chasing Rate* is defined analogously as the logarithm of the ratio between the bet size on day t and the prior day's net loss. The data are observed at the individual-day level and cover the period from March 1, 2023, to February 29, 2024.

Variable	N	Mean	SD	p25	p50	p75
Bet placed	1,340,474	0.97	0.18	1.00	1.00	1.00
Stake (in AUD)	1,304,246	334.63	4,431.64	17.00	50.00	164.00
Stake-weighted odds	1,304,246	10.14	86.99	2.22	4.00	7.67
Reinvestment rate	228,721	0.60	1.94	-0.54	0.54	1.61
Loss chasing rate	546,609	0.55	1.58	-0.39	0.45	1.39
Used safe gambling tools	1,340,474	0.20	0.40	0.00	0.00	0.00
Prior day loss	1,340,474	0.84	0.37	1.00	1.00	1.00
Prior day win	1,340,474	0.15	0.35	0.00	0.00	0.00

Table 2: **Prior-day outcomes and betting behavior**

This table reports the relationship between prior-day betting outcomes and current-day betting behavior. *Bet placed* equals one if the bettor places any bet on a given day. *Bet size* equals the natural logarithm of bet size. *Bet odds* equal the natural logarithm of bet size-weighted odds, representing the average odds of bets placed by a bettor on a given day. The independent variables, Loss_{t-1} and Win_{t-1}, are indicators equal to one if the bettor experienced a net loss or net win, respectively, on the previous day. A net loss (gain) is based on bets settled on day *t-1*. The omitted category includes days with no bets settled on the previous day. The data are at the individual-day level, covering the period from March 1, 2023, to February 29, 2024. All regressions include individual and postcode-by-date fixed effects. Standard errors are clustered at the individual and date level, with t-statistics reported in parentheses. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)
	Dependent variable:		
	Bet placed	Ln(Cash stake) | Bet placed = 1	Ln(Cash weighted odds) | Bet placed = 1
Loss_{t-1}	0.069***	-0.024*	0.028***
	(16.231)	(-1.959)	(3.652)
Win_{t-1}	0.082***	0.338***	0.008
	(19.471)	(25.094)	(1.029)
R^2	0.114	0.621	0.538
N	1,340,474	1,304,246	1,304,246
Bettor FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
SE Clustered by	Bettor, Time	Bettor, Time	Bettor, Time

Table 3: **Prior-day outcomes and betting behavior: Heterogeneity**

This table reports the relationship between prior-day betting outcomes and current-day betting behavior. *Bet placed* equals one if the bettor places any bet on a given day. *Bet size* equals the natural logarithm of bet size. *Bet odds* equal the natural logarithm of bet size-weighted odds, representing the average odds of bets placed by a bettor on a given day. The independent variables, Loss_{t-1} and Win_{t-1}, are indicators equal to one if the bettor experienced a net loss or net win, respectively, on the previous day. A net loss (gain) is based on bets settled on day *t-1*. The omitted category includes days with no bets settled on the previous day. In Panels A and B, we report results by gender and age groups, respectively. The data are at the individual-day level, covering the period from March 1, 2023, to February 29, 2024. All regressions include individual and postcode-by-date fixed effects. Standard errors are clustered at the individual and date level, with t-statistics reported in parentheses. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

Panel A

	(1)	(2)	(3)
	Dependent variable:		
	Bet placed	Ln(Cash stake) | Bet placed = 1	Ln(Cash weighted odds) | Bet placed = 1
Panel A			
Loss_{t-1}	0.066***	-0.021	0.027***
	(14.914)	(-1.639)	(3.437)
Win_{t-1}	0.080***	0.344***	0.007
	(18.057)	(24.462)	(0.829)
$\text{Loss}_{t-1} \times \mathbb{1}_{\text{Female}}$	0.029*	-0.039	0.004
	(1.951)	(-0.923)	(0.176)
$\text{Win}_{t-1} \times \mathbb{1}_{\text{Female}}$	0.026*	-0.076*	0.014
	(1.743)	(-1.674)	(0.545)
R^2	0.115	0.621	0.538
Panel B			
Loss_{t-1}	0.068***	-0.026	0.033***
	(12.012)	(-1.605)	(3.135)
Win_{t-1}	0.083***	0.393***	0.001
	(14.668)	(21.879)	(0.109)
$\text{Loss}_{t-1} \times \mathbb{1}_{41 \leq \text{Age} \leq 55}$	0.007	0.010	-0.008
	(0.708)	(0.346)	(-0.449)
$\text{Loss}_{t-1} \times \mathbb{1}_{\text{Age} \geq 56}$	-0.006	-0.009	-0.017
	(-0.610)	(-0.277)	(-0.901)
$\text{Win}_{t-1} \times \mathbb{1}_{41 \leq \text{Age} \leq 55}$	0.005	-0.063*	0.018
	(0.547)	(-1.951)	(0.978)
$\text{Win}_{t-1} \times \mathbb{1}_{\text{Age} \geq 56}$	-0.011	-0.151***	0.004
	(-1.152)	(-4.333)	(0.195)
R^2	0.114	0.622	0.538
N	1,340,474	1,304,246	1,304,246
Bettor FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
SE Clustered by	Bettor, Time	Bettor, Time	Bettor, Time

Table 4: **Prior-day outcomes and betting behavior**

This table reports the relationship between prior-day betting outcomes and current-day betting behavior. *Bet placed* equals one if the bettor places any bet on a given day. *Bet size* equals the natural logarithm of bet size. *Bet odds* equal the natural logarithm of bet size-weighted odds, representing the average odds of bets placed by a bettor on a given day. The independent variables, Loss_{t-1} and Win_{t-1}, are indicators equal to one if the bettor experienced a net loss or net win, respectively, on the previous day. A net loss (gain) is based on bets settled on day *t-1*. The omitted category includes days with no bets settled on the previous day. The data are at the individual-day level, covering the period from March 1, 2023, to October 31, 2023. All regressions include individual and postcode-by-date fixed effects. Standard errors are clustered at the individual and date level, with t-statistics reported in parentheses. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)
	Dependent variable:		
	Bet placed	Ln(Cash stake) | Bet placed = 1	Ln(Cash weighted odds) | Bet placed = 1
Loss_{t-1}	0.067***	-0.037**	0.038***
	(9.143)	(-1.971)	(3.143)
Win_{t-1}	0.082***	0.297***	0.020
	(10.828)	(14.513)	(1.580)
At $\text{Risk}_t \times \text{Post}_{t'}$	-0.007	0.089	-0.010
	(-0.507)	(1.572)	(-0.417)
$\text{Loss}_{t-1} \times \text{Post}_{t'}$	-0.006	-0.003	-0.022
	(-0.600)	(-0.119)	(-1.301)
$\text{Win}_{t-1} \times \text{Post}_{t'}$	-0.008	-0.005	-0.030
	(-0.773)	(-0.155)	(-1.647)
$\text{Loss}_{t-1} \times \text{At Risk}_t$	-0.042***	0.040	-0.010
	(-4.482)	(1.065)	(-0.569)
$\text{Win}_{t-1} \times \text{At Risk}_t$	-0.043***	0.201***	-0.008
	(-4.631)	(4.817)	(-0.411)
$\text{Loss}_{t-1} \times \text{At Risk}_t \times \text{Post}_{t'}$	0.003	0.119**	-0.005
	(0.258)	(2.160)	(-0.208)
$\text{Win}_{t-1} \times \text{At Risk}_t \times \text{Post}_{t'}$	0.005	0.123**	0.013
	(0.342)	(2.108)	(0.541)
R^2	0.127	0.637	0.548
N	1,340,474	1,304,246	1,304,246
Bettor FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
SE Clustered by	Bettor, Time	Bettor, Time	Bettor, Time

Table 5: **Usage of Safe Gambling Tools**

This table reports the number of unique bettors who activated at least one safe gambling tool during the sample period. These numbers are not weighted. Panel entries correspond to the broad tool categories (Deposit Management, Time Management, Market Restrictions, Self-Exclusion, and Awareness Nudges) as well as their subcategories. *Any* tool indicates whether a bettor used at least one tool of any type. Categories and subcategories are not mutually exclusive: a bettor may use multiple tools simultaneously, and counts therefore overlap across rows. Figures are conditional on using at least one safe gambling tool, and are reported separately for all bettors, for bettors not identified as at addiction risk, and for bettors identified as at addiction risk.

Safe Gambling Tool Category	Number of bettors | Used Safe Gambling Tool		
	All	Not At Risk of Gambling-related Harm	At Risk of Gambling-related Harm
0. Any safe gambling tool	3,192	2,030	1,162
1. Deposit limit management	2,782	1,879	913
1.1. Daily limit	421	295	126
1.2. Weekly limit	2,278	1,494	784
1.3. Monthly limit	219	139	80
1.4. Longer than monthly limit	238	160	78
2. Time management	553	235	318
2.1. Weekday block-out	71	22	49
2.2. Weekend block-out	48	16	32
2.3. Weekday curfew	49	16	33
2.4. Weekend curfew	47	15	32
2.5. Short take-a-break	79	25	54
2.6. Medium take-a-break	209	85	124
2.7. Long take-a-break	282	137	145
3. Market restrictions	127	38	89
3.1. Racing	96	28	68
3.2. Sports	68	23	45
4. Self exclusion	11	7	4
4.1. Self exclusion	11	7	4
5. Awareness nudges	31	14	17
5.1. Amount nudges	30	13	17
5.2. Time nudges	8	3	5

Table 6: **Variance Decomposition of Safe Gambling Tool Usage**

This table reports the average daily probability of a safe gambling tool usage and the explanatory power of unobserved bettor and time heterogeneity. The dependent variable Activation equals 1 for the first instance in which a bettor activates any safe gambling tool (0 otherwise). The dependent variable Usage equals 1 if at least one tool in the relevant category is active on a given day (0 otherwise). The dependent variable Deactivation equals 1 for the first instance in which a bettor has no active safe gambling tools after previously having at least one active (0 otherwise). Reported R^2 values are from regressions with (i) bettor fixed effects only and (ii) bettor and date fixed effects jointly. The sample covers March 1, 2023, to February 29, 2024.

	R^2	
	Bettor Fixed Effects	Bettor and Date Fixed Effects
Any safe gambling tool – Activation	0.038	0.039
Any safe gambling tool – Usage	0.853	0.855
Any safe gambling tool – Deactivation	0.044	0.045

Table 7: **Determinants of Safe Gambling Tool Usage**

This table examines whether bettors are more likely to use safe gambling tools following recent betting streaks. In Panel A, the dependent variable Activation equals 1 for the first instance in which a bettor activates any safe gambling tool (0 otherwise). In Panel B, the dependent variable Deactivation equals 1 for the first instance in which a bettor has no active safe gambling tools after previously having at least one active (0 otherwise). Streaks are defined based on the bettor's most recent outcomes, irrespective of calendar time. For example, a loss streak of length three equals one if the bettor lost in each of their last three consecutive betting outcomes. The table reports separate coefficients for loss and win streaks of varying lengths. Standard errors are double clustered at the bettor and date level, and t-statistics are presented in parentheses. The sample period is March 1, 2023, to February 29, 2024.

	(1)	(2)	(3)	(4)	(5)
	Streak length in last (·) outcomes				
	1	2	3	4	7
Panel A: Dependent variable – Safe Gambling Tool – Activation					
Loss streak	0.0004*	0.0003***	0.0002**	0.0003***	0.0001
	(1.8772)	(4.0970)	(2.3171)	(2.6668)	(1.0360)
Win streak	0.0000	-0.0002*	-0.0004**	-0.0003	0.0009
	(0.2307)	(-1.8992)	(-2.5820)	(-0.9712)	(0.4863)
R^2	0.0386	0.0386	0.0386	0.0386	0.0386
Panel B: Dependent variable – Safe Gambling Tool – Deactivation					
Loss streak	-0.0002	0.0002***	0.0002***	0.0002***	0.0003***
	(-1.2195)	(3.0869)	(3.3906)	(2.8055)	(3.0921)
Win streak	-0.0005**	-0.0002**	-0.0004***	-0.0004**	-0.0010**
	(-2.5277)	(-2.1577)	(-4.2232)	(-2.1963)	(-2.3238)
R^2	0.0446	0.0446	0.0446	0.0446	0.0446
N	1,340,474	1,340,474	1,340,474	1,340,474	1,340,474
Bettor FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
SE Clustered by	Bettor, Time	Bettor, Time	Bettor, Time	Bettor, Time	Bettor, Time

Table 8: **Prior-day outcomes and betting behavior: Role of safe gambling tools**
This table reports the relationship between prior-day betting outcomes and current-day betting behavior. *Bet placed* equals one if the bettor places any bet on a given day. *Bet size* equals the natural logarithm of bet size. *Bet odds* equal the natural logarithm of bet size-weighted odds, representing the average odds of bets placed by a bettor on a given day. In Panel A, the independent variables, Loss_{t-1} and Win_{t-1}, are indicators equal to one if the bettor experienced a net loss or net win, respectively, on the previous day. A net loss (gain) is based on bets settled on day *t-1*. The omitted category includes days with no bets settled on the previous day. $\mathbb{1}_{\text{Used Safe Gambling Tools}}$ is a dichotomous variable that equals 1 (0 otherwise) if a bettor used any of the safe gambling tools accessible on two betting websites. The data are at the individual-day level, covering the period from March 1, 2023, to February 29, 2024. All regressions include individual and postcode-by-date fixed effects. Standard errors are clustered at the individual and date level, with t-statistics reported in parentheses. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)	(5)
	Safe Gambling Tool:				
	All Tools	Deposit Management	Time Management	Market Restriction	Awareness Nudges
Panel A: Dependent Variable: Bet placed					
Loss_{t-1}	0.069***	0.069***	0.069***	0.069***	0.069***
	(15.890)	(15.926)	(16.227)	(16.198)	(16.252)
Win_{t-1}	0.082***	0.082***	0.082***	0.082***	0.082***
	(19.001)	(19.058)	(19.464)	(19.420)	(19.492)
$\mathbb{1}_{\text{Used Safe Gambling Tools}}$	-0.001	-0.001	0.071***	-0.026	0.104***
	(-0.059)	(-0.039)	(3.290)	(-0.657)	(6.449)
$\text{Loss}_{t-1} \times \mathbb{1}_{\text{Used Safe Gambling Tools}}$	-0.002	-0.002	-0.069***	-0.001	-0.085***
	(-0.121)	(-0.104)	(-3.172)	(-0.028)	(-18.731)
$\text{Win}_{t-1} \times \mathbb{1}_{\text{Used Safe Gambling Tools}}$	-0.001	-0.002	-0.075***	0.012	-0.085***
	(-0.091)	(-0.113)	(-3.449)	(0.296)	(-10.708)
R^2	0.114	0.114	0.114	0.114	0.114
N	1,340,474	1,340,475	1,340,476	1,340,477	1,340,479
Panel B: Ln(Cash stake) | Bet placed = 1					
Loss_{t-1}	-0.024*	-0.024*	-0.025**	-0.024*	-0.024*
	(-1.891)	(-1.883)	(-2.007)	(-1.933)	(-1.963)
Win_{t-1}	0.333***	0.334***	0.337***	0.337***	0.338***
	(23.588)	(23.761)	(25.067)	(25.006)	(25.011)
$\mathbb{1}_{\text{Used Safe Gambling Tools}}$	-0.388***	-0.439***	-0.263	0.056	0.336
	(-6.749)	(-7.172)	(-0.917)	(0.371)	(0.949)
$\text{Loss}_{t-1} \times \mathbb{1}_{\text{Used Safe Gambling Tools}}$	-0.001	0.001	0.352	-0.053	0.111
	(-0.017)	(0.027)	(1.183)	(-0.411)	(0.425)
$\text{Win}_{t-1} \times \mathbb{1}_{\text{Used Safe Gambling Tools}}$	0.045	0.035	0.336	0.077	0.111
	(0.844)	(0.635)	(1.169)	(0.569)	(0.304)
R^2	0.622	0.622	0.621	0.621	0.621
N	1,304,246	1,304,246	1,304,246	1,304,246	1,304,246
Panel C: Dependent Variable: Ln(Cash weighted odds) | Bet place = 1					
Loss_{t-1}	0.026***	0.027***	0.027***	0.028***	0.027***
	(3.343)	(3.427)	(3.614)	(3.619)	(3.610)
Win_{t-1}	0.007	0.007	0.008	0.008	0.008
	(0.802)	(0.880)	(1.002)	(1.025)	(0.980)
$\mathbb{1}_{\text{Used Safe Gambling Tools}}$	-0.024	-0.019	-0.135	0.055	-0.313***
	(-0.794)	(-0.583)	(-0.863)	(0.529)	(-5.206)
$\text{Loss}_{t-1} \times \mathbb{1}_{\text{Used Safe Gambling Tools}}$	0.017	0.009	0.197	0.006	0.360***
	(0.617)	(0.326)	(1.266)	(0.094)	(12.001)
$\text{Win}_{t-1} \times \mathbb{1}_{\text{Used Safe Gambling Tools}}$	0.019	0.012	0.167	-0.002	0.349***
	(0.681)	(0.400)	(1.058)	(-0.028)	(4.043)
R^2	0.538	0.538	0.538	0.538	0.538
N	1,304,246	1,304,246	1,304,246	1,304,246	1,304,246
Bettor FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
SE Clustered by	Bettor, Time	Bettor, Time	Bettor, Time	Bettor, Time	Bettor, Time

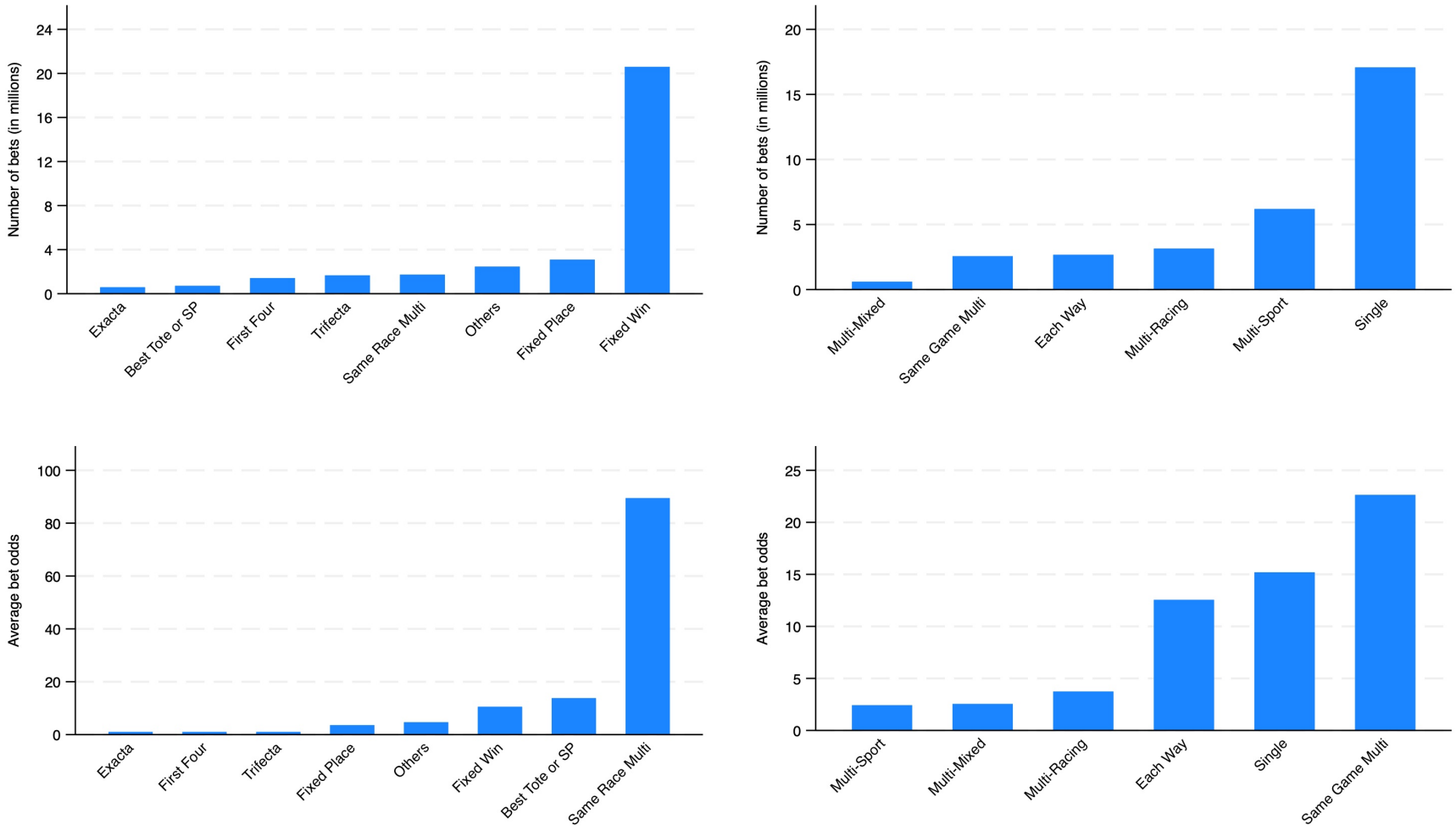


Figure 1: The figure presents four bar charts summarizing the distribution and characteristics of betting activity. The top-left panel shows the total number of bets placed across different product types, with infrequent products grouped under *Others*. The top-right panel displays the number of bets by bet type. The bottom-left panel shows the average odds associated with each product type, while the bottom-right panel reports the average odds by bet type. The sample period spans one year, from March 1, 2023, to February 29, 2024.

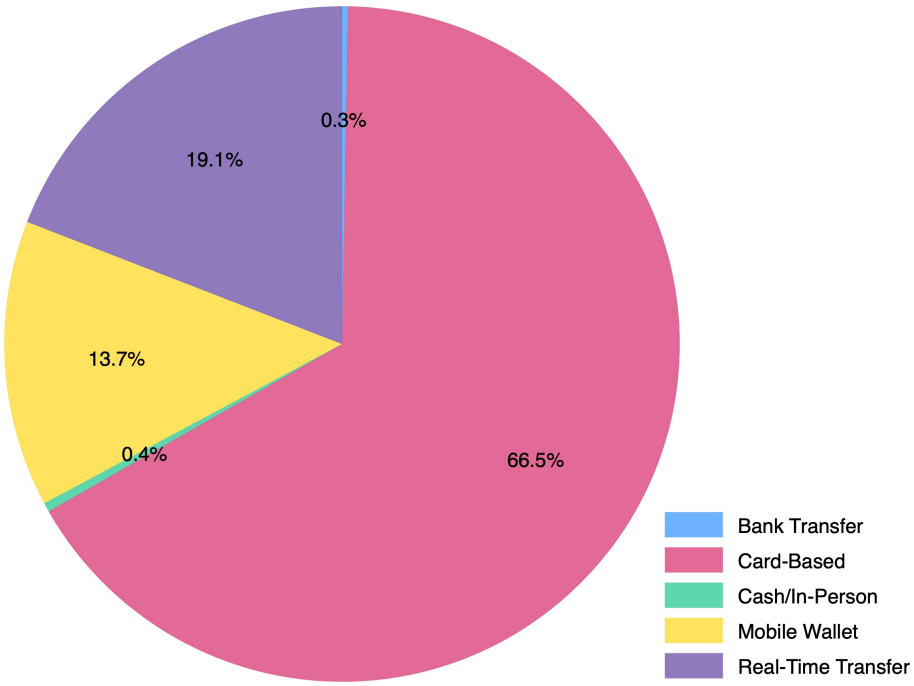


Figure 2: The figure displays a pie chart showing the distribution of financial transactions across payment method groups. The chart segments transactions into five categories: Card-Based, Mobile Wallet, Real-Time Transfer, Bank Transfer, and Cash/In-Person. Real-Time Transfer includes services such as POLi and Split Payments that enable immediate fund transfers. Each slice represents the share of total transactions attributed to each payment group, with proportions labeled in percentages.

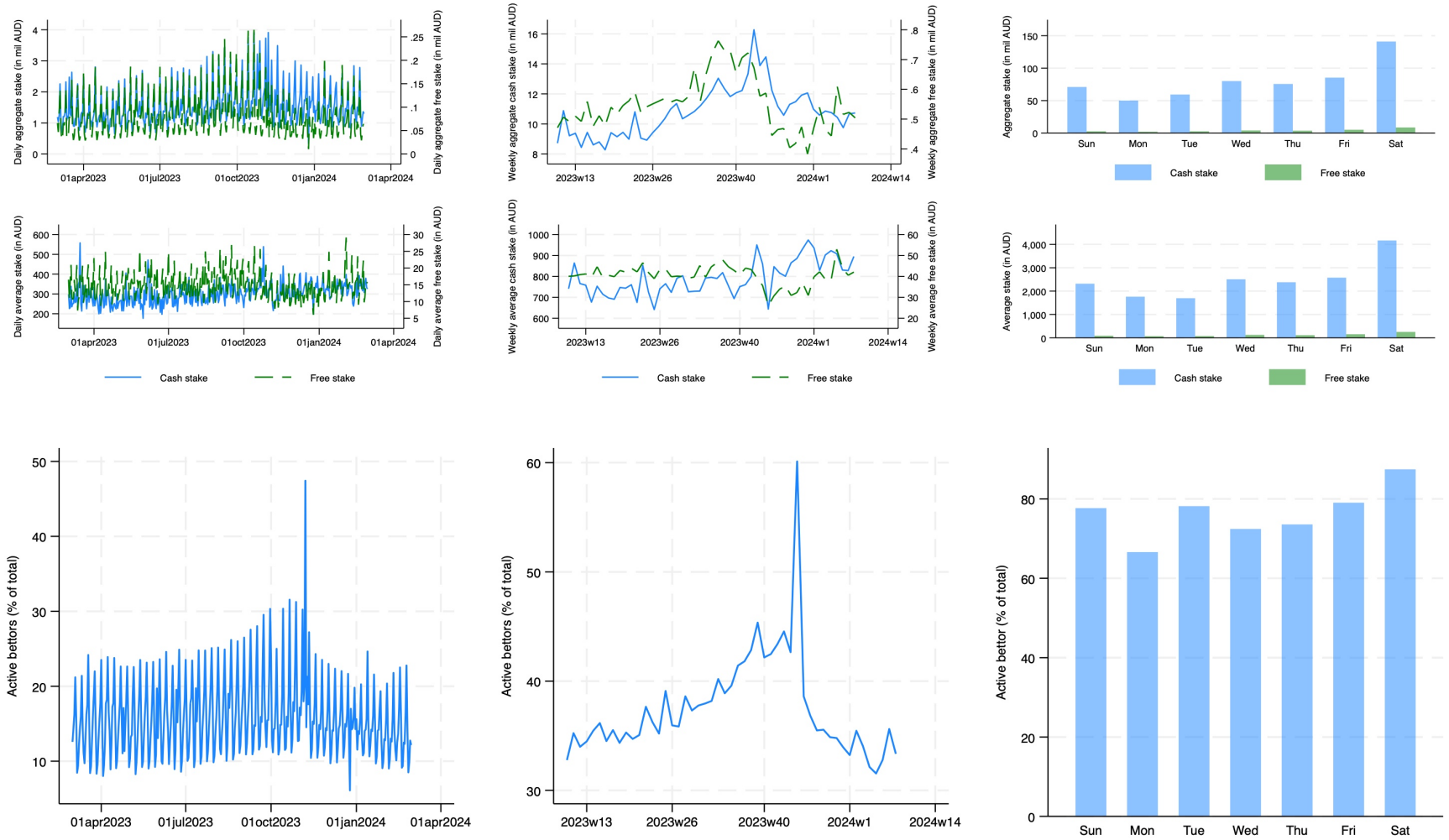


Figure 3: The figure illustrates aggregate betting behavior over time. The top panel shows aggregate and average cash and free stake by day, week, and day of the week. The bottom panels show active bettors (as a percentage of the total) by day, week, and day of the week. The fraction of active bettors is calculated as the share of unique bettors placing at least one bet, divided by the total number of unique bettors.

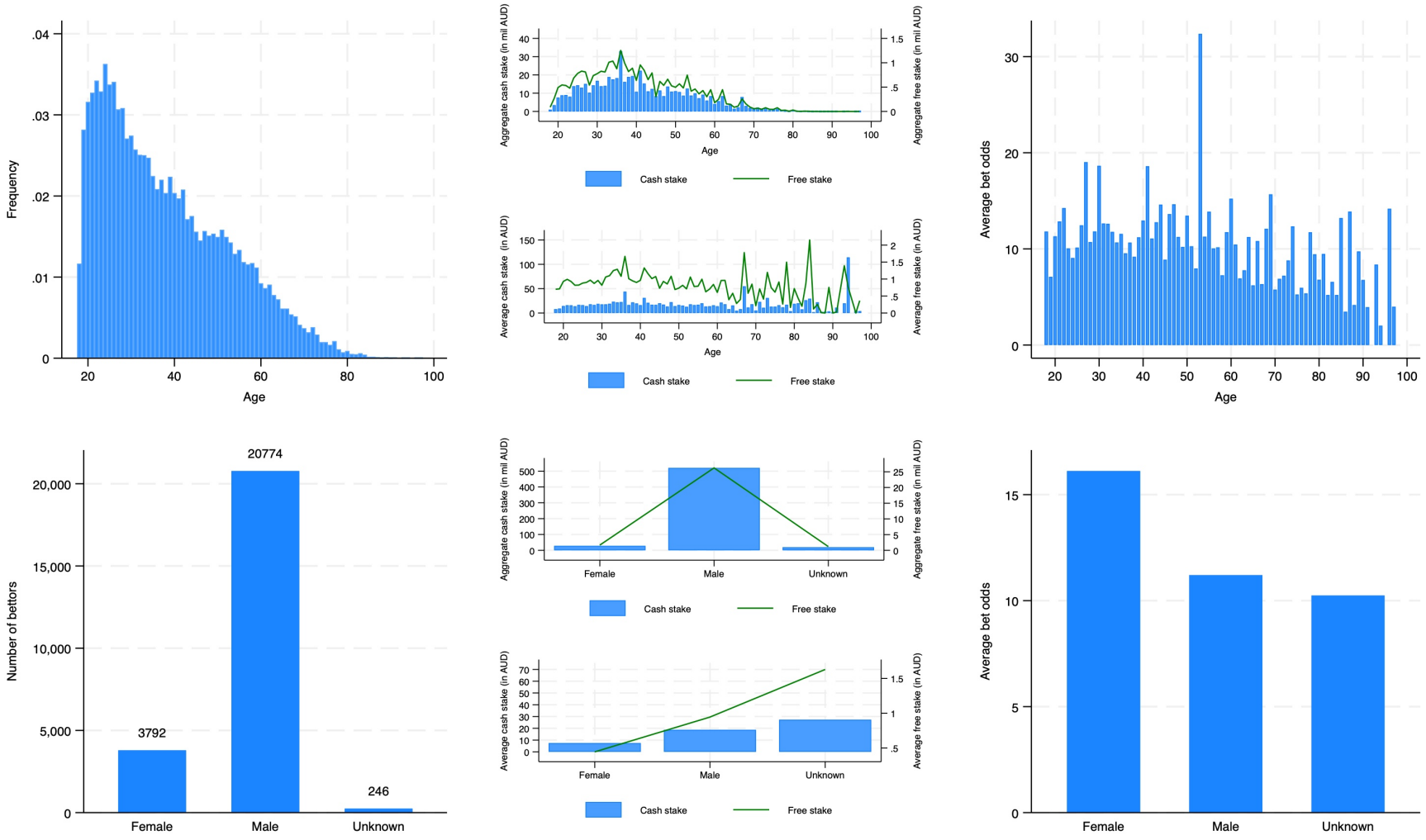


Figure 4: This figure summarizes the betting behavior by age and gender. The top panel presents the age distribution of bettors, as well as aggregate and average cash and free stake by age, and average bet odds by age. The bottom panels are analogously presented for the gender of bettors. The sample period is from March 1, 2023, to February 29, 2024.

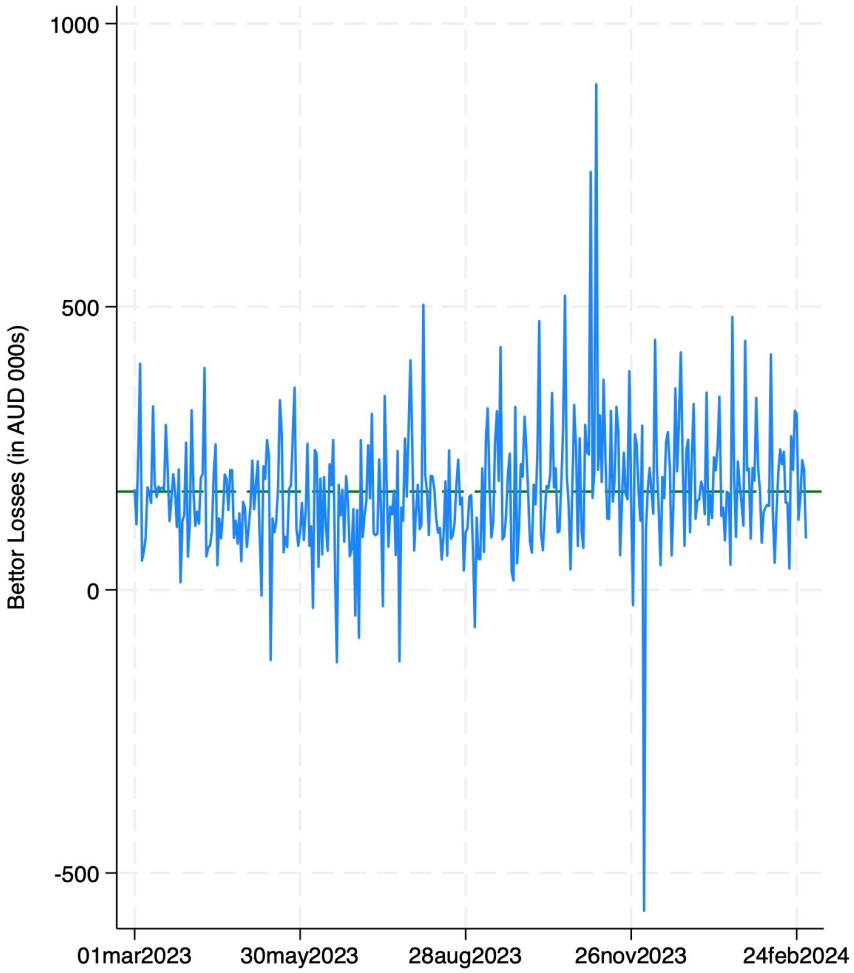


Figure 5: This figure presents the daily time series of bettor losses over the period from March 1, 2023, to February 29, 2024. Bettor losses is defined as the total amount wagered by bettors minus their total winnings.

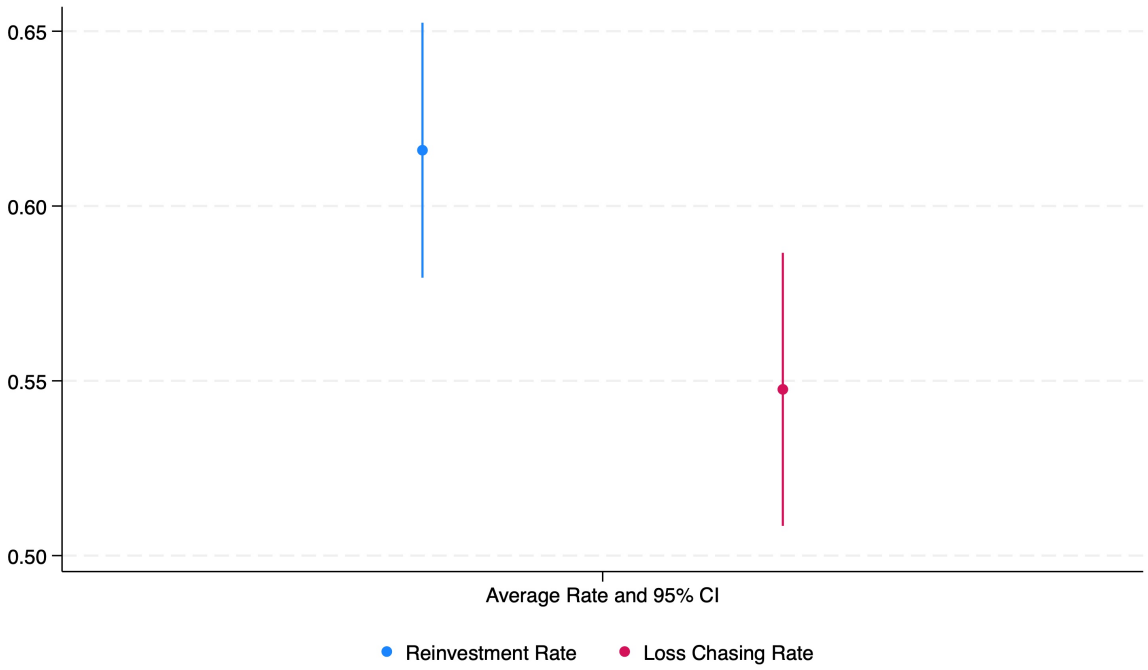


Figure 6: This figure illustrates that, after winning, bettors tend to reinvest their gains rather than scale back, while after losing, they escalate their stakes in an attempt to recover. The *Reinvestment Rate* is defined as the logarithm of the ratio between the bet size on day t and the value of the bettor's net gain on day $t-1$. The *Loss Chasing Rate* is defined analogously as the logarithm of the ratio between the bet size on day t and the prior day's net loss. The data are observed at the individual-day level and cover the period from March 1, 2023, to February 29, 2024. All regressions include postcode-by-date fixed effects. Standard errors are clustered at the individual and date level.

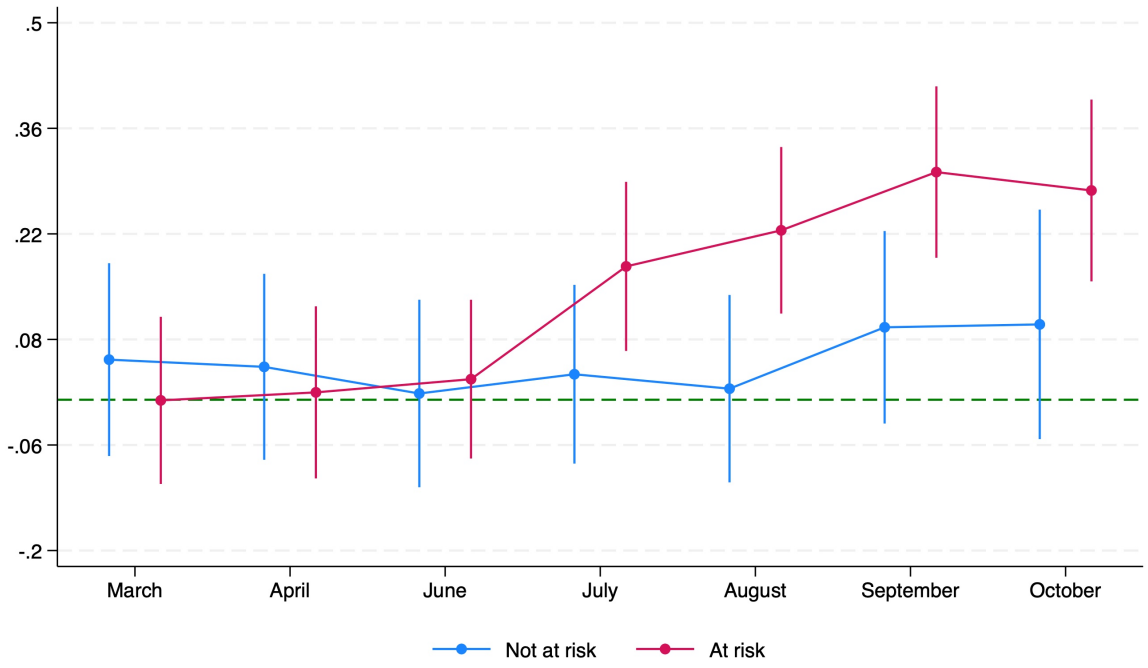


Figure 7: The figure shows monthly coefficient estimates of log cash stake from March to October 2023, separately for at-risk and not at-risk bettors. The vertical axis shows the deviation in log cash stake relative to May (the omitted month), while the horizontal axis marks the calendar months of 2023. A dashed green horizontal line at zero indicates the reference point (May). The figure captures how betting intensity varies around the end of the Australian financial year and how these patterns differ by risk classification. The data are observed at the individual-day level, covering the period from March 1, 2023, to October 31, 2023. Standard errors are clustered at the bettor and date level.

Online Appendix

Wins, Windfalls and Willpower: Liquidity and Self-Regulation in Online Sports Gambling

Table A.1: **Sports Types**
This table presents a list of sports covered in the two focal betting platforms.

Sports
Horse Racing
Greyhound Racing
Soccer
Harness Racing
Basketball
Rugby League
Australian Rules
Tennis
Table Tennis
Mixed Martial Arts
Esports
American Football
Baseball
Cricket
Rugby Union
Ice Hockey
Golf
Darts
Boxing
Volleyball
Motor Sport
Badminton
Snooker
Handball
Surfing
Netball
Gaelic Sports
Cycling
Athletics
Bowls
Novelty
Pool
Hockey
Politics
Yachting
Swimming
Specials
Water Polo
Sailing