Socioeconomic Status and Risk-Taking Anomalies: Evidence from Online Gambling*

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Abstract

We investigate how socioeconomic status (SES) shapes risk-taking anomalies in online gambling, focusing on the house money effect and loss chasing. Using betting data from over 4,000 players linked to census-based SES measures, we find that high- and mid-SES players are more likely to continue gambling after both gains and losses, whereas low-SES players reduce their stakes following losses. These findings challenge the common view that gambling anomalies are concentrated among disadvantaged individuals and reveal that responses to prior outcomes vary systematically with SES.

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1 Introduction

Lower socioeconomic status (SES) has been linked to a range of behavioral and cognitive tendencies that can perpetuate economic hardship. Individuals from lower SES backgrounds are more likely to exhibit diminished self-control, greater impatience, stronger present bias, and less consistency in their decisions (Spears, 2011; Carvalho et al., 2016; Haushofer and Fehr, 2014; Choi et al., 2014). A scarcity mindset has also been shown to impair decision-making by narrowing attention and increasing short-sightedness (de Bruijn and Antonides, 2022; Bertrand et al., 2004). Experimental research further demonstrates that financial scarcity reduces cognitive capacity, limiting individuals' ability to plan ahead or resist temptation (Mani et al., 2013; Mullainathan and Shafir, 2013). These behavioral patterns suggest that poverty may not only be a consequence of limited resources, but also a self-reinforcing condition shaped by the very decisions individuals make under economic stress.

While lower SES is associated with a range of behavioral tendencies, little is known about how these tendencies translate into actual financial decisions in repeated monetary choice environments. Gambling provides a particularly relevant context for examining this question. Unlike other financial domains such as the stock market, gambling requires minimal financial literacy, has low entry barriers, and is widely accessible across the socioeconomic spectrum. For example, stock market participation is highly unequal by income: only 11% of U.S. households in the bottom income quintile hold any stocks, compared to 82% in the top quintile (Kuhnen and Miu, 2015). By contrast, gambling tends to exhibit more balanced participation across SES groups. Moreover, online gambling environments are highly observable and transparent: information about risky bets is equally available to all players, as odds are clearly stated. These platforms are also less prone to external manipulation, allowing for cleaner measurement of behavioral responses. In addition, individuals face frequent, real monetary outcomes, making it possible to study how risk-taking evolves over time in response to previous gains or losses. As governments increasingly regulate gambling to minimize harm (Communications and Authority, 2022; Australian Gambling Research Centre, 2023), especially among vulnerable populations, understanding how behavioral responses to risk vary across SES is critical for designing effective policies.

In this paper, we are the first to reveal the correlation between SES and two anomalies in risk-taking behavior: the house money effect and loss chasing. The house money effect is the tendency to take more risks after experiencing gains. Previous studies have found ample evidence of the house money effect in various contexts, including lab experiments (Thaler and Johnson, 1990; Keasey and Moon, 1996; Weber and Zuchel, 2005; Ackert et al., 2006; Corgnet et al., 2015), financial markets (Frino et al., 2008; Liu et al., 2010; Hsu and Chow, 2013; Huang and Chan, 2014), and gambling (Ma et al., 2014; Suhonen and Saastamoinen, 2018; Andrikogiannopoulou and Papakonstantinou, 2020) (but see also Flepp and Rüdisser (2019)). This behavioral pattern suggests that prior outcomes can distort subsequent decisions, deviating from the standard expected utility model, which assumes that risk preferences are independent of past outcomes.

Loss chasing reflects a similar tendency to take more risks following prior losses. This behavior is considered a hallmark of problematic gambling and has been widely documented in various contexts, including lotteries in laboratory settings (Thaler and Johnson, 1990; Langer and Weber, 2008; Xu and Harvey, 2014; Imas, 2016; Zhang and Clark, 2020), financial trading by professional market-makers (Coval and Shumway, 2005; Liu et al., 2010), and investor behavior (Kaustia and Knüpfer, 2008; Andersen et al., 2019). However, some studies report that individuals become risk averse after losses (Imas, 2016; Suhonen and Saastamoinen, 2018), suggesting that this tendency is not universal. These conflicting findings suggest that loss chasing is context-dependent and may vary across individuals, domains, and the framing of prior outcomes.

House money effect and loss chasing are considered anomalies because they occur in contexts where the outcomes of previous decisions under uncertainty do not affect the probabilities or outcomes associated with current, independent decisions under uncertainty, particularly when these outcomes do not meaningfully affect individuals' wealth. Nevertheless, individuals have been observed to increase their risk-taking after both gains and losses. Importantly, whether there are differences across SES in the response to previous gains and losses has not been investigated yet.

We empirically examine whether individuals from different socioeconomic backgrounds respond differently to previous gains and losses, using a rich dataset of online gambling behavior. Online gambling provides an ideal setting for this analysis because platforms record complete, high-frequency data on real monetary decisions under uncertainty. Every wager, including its associated odds, stake, and outcome, is digitally logged, which allows us to observe behavioral responses to past outcomes in a natural yet precisely measurable environment. Our dataset consists of the full betting histories of 4,120 randomly selected users from a major Australian online sports betting platform, spanning a 12-month period. It includes detailed records of every bet, deposit, and withdrawal, as well as demographic information such as age, gender, and postcode. We merge these records with data from the 2016 Australian Census to assign each individual an Index of Relative Socioeconomic Disadvantage (Australian Bureau of Statistics, 2016), which serves as a proxy for SES. This rich combination of behavioral data and externally validated socioeconomic information allows us to examine whether risk-taking behavior following gains and losses systematically varies across SES groups.

We analyze behavioral responses to prior gambling outcomes at the weekly level, aggregating individual betting records to smooth out short-term fluctuations and capture meaningful patterns. We focus on two dimensions: the extensive margin, which captures the decision of whether to gamble at all in a given period, and the intensive margin, which reflects how much money is wagered conditional on gambling. This distinction allows us to separately examine how previous gains and losses influence both the likelihood of participation and the scale of engagement. Aggregating across all SES groups, we find clear evidence of the house money effect at both margins: players are more likely to gamble and bet more following gains. In contrast, while gambling participation also increases after losses, stakes tend to decrease—a pattern that only emerges once we control for previous betting intensity. This suggests that previous findings of loss chasing at the intensive margin may be confounded by persistent individual differences in gambling behavior.

When we break down the analysis by SES group, we find meaningful heterogeneity. At the extensive margin, high and mid SES players are more likely to continue gambling after both gains and losses, consistent with the house money effect and loss chasing. In contrast, low SES players show no significant change in participation following prior outcomes. At the intensive margin, the pattern shifts. Mid SES players increase their stakes most strongly after gains, followed by low SES players. High SES players also respond to gains, but the increase is relatively small. In response to previous losses, only low SES players significantly reduce their stakes, suggesting a more cautious approach after losing money.

These findings challenge the common perception that loss chasing is more prevalent among economically disadvantaged individuals. In our setting, it is higher SES players who are more likely to continue gambling after losses, whereas lower SES players appear more restrained. This may reflect tighter financial constraints or a heightened sensitivity to losses among the latter group. Interestingly, this pattern contrasts with prior studies on land-based gambling, which have documented higher participation among disadvantaged populations (Blaszczynski et al., 2015; Edgren et al., 2017; Fu et al., 2020). Our findings underscore the importance of context: unlike land-based venues, online gambling platforms offer equal access across SES groups, revealing different dynamics in gambling behavior. Overall, we find that responses to prior gains and losses differ systematically across SES groups and across margins of behavior. These differences highlight the importance of considering both the type of behavioral response and individuals' socioeconomic background when studying risk-taking under uncertainty.

Our paper contributes to multiple areas of the literature. First, it extends the behavioral economics of poverty by identifying a mechanism through which poverty may be reinforced by individuals' own responses to prior financial outcomes. While previous work has documented how poverty shapes preferences and cognitive function—through present bias, risk aversion, or reduced self-control (Haushofer and Fehr, 2014; Carvalho et al., 2016; Spears, 2011)—our study complements this literature by showing that risk-taking behavior following gains and losses differs systematically across SES groups. These findings offer new insight into how economic disadvantage shapes behavior under uncertainty and help us better understand decision-making in the face of socioeconomic hardship.

We also contribute to the literature on backward-looking reference points by providing empirical evidence that outcomes of past decisions influence subsequent choices.[1] While there is no consensus on the precise definition of a reference point, growing evidence supports the idea that

[1] Most economic models have focused on forward-looking reference points (see (O'Donoghue and Sprenger, 2018) for a review), in which reference points are drawn from the attributes of the current choice set. For empirical evidence, see (Baillon et al., 2019).

reference points are shaped, at least in part, by past outcomes. Recent work in neuroeconomics interprets this path-dependence as an efficient adaptation to cognitive constraints in value encoding (Glimcher and Tymula, 2023; Glimcher, 2022; Guo and Tymula, 2021; Frydman and Jin, 2022). Consistent with this perspective, prior research has shown that risk attitudes can be shaped by past macroeconomic shocks, such as financial crises (Malmendier and Nagel, 2011) or natural disasters (Cameron and Shah, 2013; Page et al., 2014). Our findings suggest that models incorporating backward-looking reference points should account for heterogeneity in how reference points adjust across socioeconomic groups.

Additionally, we contribute to the gambling literature by providing the first evidence on the socioeconomic gradient in gambling behavior that is not confounded by supply-side differences across neighborhoods. Previous research has shown that individuals from low SES backgrounds are at greater risk of problem gambling, with this risk amplified in disadvantaged areas where gambling venues are more concentrated (Welte et al., 2004; Barnes et al., 2013; Slutske et al., 2019; Rintoul et al., 2013). However, these studies primarily focus on land-based gambling and are limited by the uneven geographic distribution of gambling opportunities (Vasiliadis et al., 2013). In contrast, online gambling removes such geographic constraints and offers equal access to anyone with an internet connection. As online platforms become more widely used and concerns about gambling-related harm grow, it becomes increasingly important to understand how socioeconomic disadvantage shapes online gambling behavior. To date, no study has examined this relationship. Our study fills this gap by providing the first evidence that individuals from low SES neighborhoods exhibit distinct patterns of online gambling compared to those from more advantaged areas.

The paper is structured as follows: Section 2 describes the data, Section 3 presents the results, and Section 4 concludes.

2 Data

We use individual-level panel data from a prominent Australian online sports betting provider. Our sample consists of every wager and deposit made by 4,120 players over 12 months, from July 2018 to July 2019. These players were randomly selected by the operator, with the only inclusion criterion being that they had wagered more than five times during the 12 months. This minimal eligibility criterion is designed to prevent selection bias and ensure the resulting sample represents the population who gambled with the operator over one year. The data includes demographic characteristics (age, gender, and postcode), as well as details of wagers, deposits, and withdrawals. For each wager, we know the sports event, the odds for the bet, the amount staked, whether the wager won or lost, the payout, and the account balance before the wager.

To measure disadvantage, we match each gambler's postcode with the Australian Bureau of Statistics (ABS) census data on neighborhood disadvantage. We use the 2016 census measure of neighborhood disadvantage – the Index of Relative Socioeconomic Disadvantage (IRSD) – at the postal area level[2] (Australian Bureau of Statistics, 2016). IRSD categorizes all Australian postcodes into deciles based on the index of disadvantage. A low score in the IRSD indicates that an area has many people in low-skill occupations, with fewer qualifications and low household income. The IRSD data includes both the raw index of disadvantage and the corresponding decile, which indicates the disadvantage in a given area relative to the rest of Australia. For example, the lowest scoring 10% of postcodes have a decile of disadvantage equal to 1 - these are the most disadvantaged neighborhoods in Australia. An important caveat is that more disadvantaged postcodes are generally less populated so less than 10% of Australians will live in the decile with the most disadvantaged neighborhoods and more than 10% of Australians will live in the most advantaged decile of neighborhoods. Since we do not know each player's income, we use neighborhood disadvantage based on their postcode as a proxy for their SES. In the remainder of this paper, we refer to people living in different neighborhoods as low, mid, and high SES. Low SES captures players living in the bottom four deciles (1,084 players), mid SES those in deciles five to seven (1,247 players), and High SES live in the top three deciles (1,789 players). However, note that these people are not necessarily low, high, or mid SES, rather they live in neighborhoods that experience different rates of disadvantage. As such, our measure of neighborhood disadvantage is correlated with individual disadvantage, but we note that there may be some people living in low SES neighborhoods who are not personally of low SES.

Online gambling is a sequential decision-making process, in which each wager occurs in the

[2]Postal areas use the same 4-digit number as regular postcodes and can be matched accordingly.

context of previous gambles and their outcomes. Under standard expected utility theory, however, each wager should be treated as an independent decision. That is, past outcomes do not influence the objective probability of future events.

3 Results

3.1 Gambling Participation and Outcomes across SES

We first provide some general comparison of gambling participation, patterns, and outcomes across SES in our sample (see Table 1).

Table 1: Summary statistics

	SES			Difference[3]		
	High	Mid	Low	H-L	H-M	M-L
Participation Rate[1]	401.2	364.5	328.1	73.1***	36.6***	36.4***
Annual Bets (mean)	173.2	177.0	194.4	-21.1	-3.8	-17.3
Annual Bets (median)	44	45	47	-3	-1	-2
Annual Stake (mean)	$8,785.9	$9,358.0	$10,876.2	-$2,090.3	-$572.0***	-$1,518.2*
Annual Stake (median)	$648.4	$500.0	$651.1	-$2.7	$148.4***	-$151.1*
Top 10% High Volume Players[2]	9.8%	9.6%	12.4%	-2.5%**	0.2%	-2.8%**
Annual Results (mean)	-$373.4	-$537.1	-$543.7	$170.3***	$163.7	$6.6***
Annual Results (median)	-$32.2	-$30.3	-$43.1	$10.9***	-$1.9	$12.8***
Players in Profit	36.9%	36.6%	30.4%	6.5%***	0.3%	6.2%***
Number of Players	1,789	1,247	1,084			

[1] Number of players per 1,000,000 population of the postcode.
[2] Players in the top 10% of betting volume ($\geq$ 570 bets)
[3] Significance is measured by the Wilcoxon rank-sum test, except for "Players in Profit" where the Chi-square test is used. *** p<0.01, ** p<0.05, * p<0.1

To meaningfully measure the differences in participation rates in online gambling across SES, we need to account for the fact that fewer people live in low SES deciles according to the 2016 Australian census data (Australian Bureau of Statistics, 2016). To address this, we assign each player the online gambling participation rate for their postcode, measured as the number of players per 1,000,000 residents in that postcode. The first row in Table 1 shows the average participation rate across SES groups. We observe the lowest participation rate of 328 per million in the low SES group, the highest rate of 401 per million in the high SES group, and an intermediate rate of 365 per million in the mid SES group. The results of the Wilcoxon rank-sum test indicate that the differences in participation rates among SES groups are statistically significant. This participation pattern contrasts with land-based gambling trends, where studies have shown higher participation in disadvantaged areas (Blaszczynski et al., 2015; Edgren et al., 2017; Fu et al., 2020).

Although they are less likely to be in our sample, low SES participants are on average more active. On average, over a one-year period, a low SES player places 21 bets more than high SES player and 17 bets more than mid SES player. Additionally, on average, low SES players stake significantly more over the one year than mid SES players (by $1,518) and more, but not significantly, than high SES players (by $2,090). The distributions of both the number of bets and stakes are extremely wide: the lowest 1% of bets includes as few as 6, and stakes as little as $16.50, while the highest 1% reaches 1,839 bets and $115,010. To account for this variability, we use the Wilcoxon rank-sum test, which is robust to outliers and suitable for skewed distributions.[3]

When we define high-volume players as those who are in the top 10% based on the number of bets placed (these are players who placed at least 570 bets), consistent with the previous analysis, we find significantly more high-volume players among low SES (12.4%), than among high and mid SES (9.6-9.8%).

Result 1. *Residents of low SES neighborhoods are less likely to be in our sample but on average place more bets and spend more money on gambling.*

When it comes to outcomes, low SES players lose more. On average, over one year, low SES players lose $170 more than high SES and $7 more than mid SES, with both differences statistically significant. Again, these differences are smaller for the median players. This disparency in outcomes is further supported by the finding that 36.9% of high SES players and 36.6% of mid SES players achieve a positive profit, compared to 30.4% of low SES players, which is significantly fewer.

Result 2. *Low SES players lose more compared to high and mid SES players.*

[3]See Section **??** for the distributions of gambling outcomes.

3.2 House Money Effect and Loss Chasing

We formally investigate how previous bet outcomes affect risk taking, using a fixed-effects OLS regression model with the following specification:

$$\textit{Risk-Taking}_{i,t} = \beta_1 PrevGain_{i,t} + \beta_2 PrevLoss_{i,t} + \beta_3 PrevStake_{i,t} + \boldsymbol{\beta}^\top \mathbf{X}_{i,t} + \alpha_i + \varepsilon_{i,t}. \qquad (1)$$

We define t as a 7-day window to capture short-term behavioral responses while smoothing out daily noise. Risk-taking behavior in gambling can be influenced by recent outcomes, but using a single-day measure may introduce excessive volatility due to daily fluctuations. A weekly aggregation balances the need to detect meaningful shifts in behavior following gains or losses, while reducing the noise from day-to-day fluctuations and rare extreme bets.

Our key variables of interest are $PrevGain_{i,t}$ and $PrevLoss_{i,t}$, which represent the cumulative net result during week $t-1$ (i.e., the 7 days immediately preceding week t). If the cumulative result is positive, it is coded as $PrevGain_{i,t}$ (e.g., a net gain of +200 is coded as $PrevGain_{i,t} = 200$ and $PrevLoss_{i,t} = 0$). Conversely, if the cumulative result is negative, it is coded as $PrevLoss_{i,t}$ (e.g., a net loss of -200 is coded as $PrevGain_{i,t} = 0$ and $PrevLoss_{i,t} = 200$). If the house money effect and loss chasing are present, we expect the coefficients on $PrevGain_{i,t}$ and $PrevLoss_{i,t}$ to be positive, reflecting increased risk-taking following prior gains or losses, respectively.

In addition to $PrevGain_{i,t}$ and $PrevLoss_{i,t}$, we also include $PrevStake_{i,t}$, the total amount wagered during week $t-1$, as a control variable. This accounts for the possibility that players differ in their general tendency to gamble, regardless of recent gains or losses. For instance, a player who consistently places large bets may be more likely to continue gambling the following week, regardless of whether they previously won or lost. Including $PrevStake_{i,t}$ helps us isolate the effects of prior outcomes from persistent individual patterns in gambling intensity.

To measure risk-taking, we consider two outcome variables: *Gambling Participation* and *Stake*, which correspond to the extensive and intensive margins of gambling behavior, respectively. *Gambling Participation* is a binary indicator of whether the player placed at least one bet during the week. For readability in the regression tables, we scale this variable by a factor of

1,000. *Stake* captures the total amount of money wagered during the week, reflecting the intensity of risk-taking among those who participate. While *Gambling Participation* captures the decision to gamble at all, *Stake* provides a more granular view of risk-taking behavior. By examining both outcomes, we assess not only whether individuals are more likely to gamble following previous gains or losses, but also whether they place larger bets, capturing both the extensive and intensive margins of gambling behavior.

$\mathbf{X}i, t$ includes time-varying control variables that may affect gambling behavior, such as monthly dummies ($Augustt$, $September_t$, $October_t$, $November_t$) to account for weekly and seasonal patterns. These controls help isolate the effects of our key variables. α_i denotes individual fixed effects, capturing unobserved, time-invariant characteristics, and $\varepsilon_{i,t}$ is the error term. Table 2 presents the results.

Table 2: Effects of previous gains and losses on gambling participation and stake

	Gambling Participation			Stake		
	(1)	(2)	(3)	(4)	(5)	(6)
Previous Gain	0.030**		0.027*	5.045***		2.192***
	(0.014)		(0.015)	(0.663)		(0.839)
Previous Loss	0.021**		0.018**	1.403***		-0.993***
	(0.008)		(0.009)	(0.335)		(0.197)
Previous Stake		0.003***	0.001*		0.723***	0.696***
		(0.001)	(0.000)		(0.090)	(0.094)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	288496	288496	288496	288496	288496	288496
Num of Players	5548	5548	5548	5548	5548	5548
R-Squared	0.049	0.047	0.049	0.305	0.524	0.602

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors are clustered at the player level.

Columns (1)–(3) of Table 2 report the effects of previous outcomes on gambling participation. In Column (1), both previous gains and previous losses significantly increase the likelihood of participation in the following week. A gain of $1,000 in the previous week is associated with a 0.030 percentage point increase in the probability of participating this week, while a loss of $1,000 increases it by 0.021 percentage points. These effects remain significant even after controlling for the amount staked in the previous week in Column (3), though the magnitudes are slightly reduced. Taken together, these results suggest that both positive and negative recent experiences, along with the level of prior engagement, encourage continued gambling. The fact that prior gains and losses both raise participation supports the presence of both house money and loss-chasing tendencies in the extensive margin of gambling behavior.

Result 3. *House money effect is present on both the extensive and intensive margins.*

Columns (4)–(6) of Table 2 present the effects of outcomes from the previous week on the amount wagered in the current week, capturing the intensive margin of gambling behavior. A gain of \$1 in the previous week increases the total stake in the current week by approximately \$5.05 in Column (4), and this effect remains significant and positive even after controlling for prior stake in Column (6), though the magnitude decreases to \$2.19. This pattern is consistent with the house money effect, where players tend to bet more after experiencing gains.

Result 4. *Loss-chasing is observed only on the extensive margin. At the intensive margin, prior losses are associated with lower stakes after controlling for baseline gambling intensity.*

In contrast, the effect of previous losses on stake flips sign once $PrevStake_{i,t}$ is included. While Column (4) shows a positive and significant association between past losses and current stake, this effect becomes significantly negative in Column (6). This suggests that, after accounting for baseline gambling intensity, players bet less following losses. The reversal implies that previous findings on loss-chasing behavior may have been confounded by persistent individual betting patterns. By including $PrevStake_{i,t}$, we isolate the dynamic effect of losses more precisely, revealing that players may in fact become more cautious after losing, rather than chasing their losses.

3.3 House Money Effect and Loss Chasing Across SES Groups

In this section, we examine whether the effects of previous gains and losses on gambling behavior vary across SES groups. To investigate this, we estimate the model in equation 1 separately for each group. While Table 2 in the previous section presented results both with and without controlling for prior stake, this section focuses on the specification that includes prior stake to account for baseline gambling intensity. Table 3 summarizes the estimated effects of previous outcomes on gambling participation and stake across SES groups.

Table 3: Effects of previous gains and losses on gambling participation and stake, across SES groups

	Gambling Participation			Stake		
	High	Mid	Low	High	Mid	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Previous Gain	0.063**	0.040*	0.010	1.745**	4.987***	1.057***
	(0.025)	(0.021)	(0.008)	(0.777)	(1.112)	(0.078)
Previous Loss	0.032***	0.026**	0.009	-0.031	-0.234	-1.274***
	(0.012)	(0.011)	(0.006)	(0.667)	(0.607)	(0.091)
Previous Stake	0.002	0.000	0.001***	0.259***	0.599***	0.867***
	(0.002)	(0.000)	(0.000)	(0.041)	(0.075)	(0.026)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	125372	87152	75972	125372	87152	75972
Num of Players	2411	1676	1461	2411	1676	1461
R-Squared	0.055	0.053	0.039	0.133	0.645	0.799

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the player level.

3.3.1 House Money Effect Across SES Groups

First, we examine the house money effect and how it differs across SES groups. Table 3 shows that at the extensive margin, high SES players exhibit the strongest response to prior gains: a gain of $1,000 increases their likelihood of gambling participation by 0.063 percentage points, compared to 0.040 for mid SES players. In contrast, low SES players show no statistically significant response. This pattern suggests that individuals with greater financial resources may be more willing to re-engage in gambling after a win.

At the intensive margin, however, mid SES players show the largest increase in stake following gains, with a $1 gain associated with a $4.99 increase in betting amount, compared to $1.75 for high SES and $1.06 for low SES. One possible explanation is that mid SES players are both financially capable of increasing their stakes and more motivated to do so following a win. In contrast, high SES players may be less sensitive to marginal gains, showing a more muted adjustment despite having sufficient resources. Low SES players again show the weakest response, possibly due to tighter financial constraints that limit their ability to scale up betting after gains.

Result 5. *High SES players exhibit the house money effect only on the extensive margin, while mid SES players respond most strongly on the intensive margin.*

3.3.2 Loss Chasing Across SES Groups

Table 3 reveals heterogeneity in loss-chasing behavior across SES groups. At the extensive margin, both high and mid SES players are more likely to participate in gambling following a loss, with effects of 0.032 and 0.026 percentage points, respectively, per $1,000 lost. However, there is no statistically significant effect among low SES players. At the intensive margin, only low SES players respond significantly, reducing their stake by $1.27 for every dollar lost. This suggests that while higher SES players may continue gambling to recover losses, low SES individuals may become more cautious after a loss, possibly due to tighter financial constraints or increased risk aversion in the face of limited resources.

Result 6. *Loss-chasing behavior is observed on the extensive margin for high and mid SES players, while only low SES players reduce their stake following losses.*

This pattern stands in contrast to the common perception that loss-chasing, as a hallmark of gambling anomalies, is more prevalent among economically disadvantaged individuals. Instead, our results show that higher SES players are more likely to continue gambling after losses, while lower SES players reduce their betting intensity, possibly reflecting greater caution under tighter financial constraints.

4 Discussion

Our study provides new insights into the relationship between SES and anomalies in risk-taking behavior, specifically the house money effect and loss chasing. While these effects have been documented previously in various contexts, including gambling (Ma et al., 2014; Suhonen and Saastamoinen, 2018; Andrikogiannopoulou and Papakonstantinou, 2020), whether they manifest differently across socioeconomic groups has remained unclear. We find meaningful heterogeneity: High and mid SES players are more likely to continue gambling after both gains and losses, consistent with the house money effect and loss chasing at the extensive margin. In contrast, low SES players reduce their stakes after losses, indicating greater financial restraint at the intensive margin.

A key strength of our study lies in the scope and detail of our dataset. By capturing every bet placed by a large, diverse sample of individuals over the course of a year, we have the opportunity to analyze long-term gambling behaviors. The dataset combines sports betting data, including demographic information, with the 2016 Australian Census data, which features the Index of Relative Socioeconomic Disadvantage, allowing us to classify individual players according to their SES. Our dataset provides high-stakes decisions in a setting with minimal external manipulation. Unlike traditional land-based gambling or stock market participation, which can be limited by location or technical barriers such as the complexity of trading platforms, online gambling eliminates many of these obstacles. Therefore, our data enables us to examine gambling behaviors in a more inclusive and externally valid context, offering valuable insights into how these behaviors vary across different socioeconomic groups.

To better understand our findings, we consider possible explanations for the distinct behavioral responses observed across SES groups. Rather than a single pattern of anomalies, we find that responses to gains and losses differ across socioeconomic groups and behavioral margins. One key factor may be financial constraints. Low SES players often face tighter budgets, increasing the perceived cost of continuing to gamble after losses. In our context, lower SES individuals appear to respond to losses by reducing risk, while higher SES individuals continue gambling.

In addition to financial constraints, psychological costs may also play a role. A given monetary loss could pose a more serious threat to daily living for a low SES individual, compared to a high SES individual for whom the same amount may only reduce discretionary spending. This heightened sensitivity may lead to more cautious behavior, rather than increased risk-taking. Together, these mechanisms suggest that lower SES players may exhibit greater financial restraint in response to prior outcomes, while higher SES players continue gambling or even take more risks.

While our study provides valuable insights, it also has limitations. First, we do not have exact income data for each individual and instead use postcode-based socioeconomic indices as proxies for SES. Although postcode information may not capture precise income levels, it offers a reasonable approximation given common issues with income misreporting. For example, McMillan and Western (2000) demonstrates that postcode-based measures are a practical and cost-effective method for assessing socioeconomic status, particularly when individual-level income data is unavailable.

Additionally, because our dataset only captures gambling activity on this specific platform, leaving gambling on other platforms unobserved. This limitation could introduce noise but also suggests that the anomalies we observe likely represent a lower bound. Access to multi-platform usage data could offer deeper insights into the generalizability of our findings.

Despite its limitations, our study offers novel and policy-relevant insights into how socioeconomic disadvantage shapes behavioral responses to financial outcomes. By revealing that individuals from lower SES backgrounds react differently to prior gains and losses, we challenge prevailing assumptions in the literature on poverty and risk-taking. These findings reveal how economic context and structural constraints interact with behavioral tendencies, offering a more nuanced view of decision-making under disadvantage. Our results provide a foundation for designing better-targeted policies to reduce financial harm and promote economic resilience.

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A Distribution of Weekly Stakes

Figure 1 to Figure 3 show the weekly distribution of stakes for participants in the high, mid, and low SES groups, respectively. The distributions differ notably across groups in both shape and dispersion.

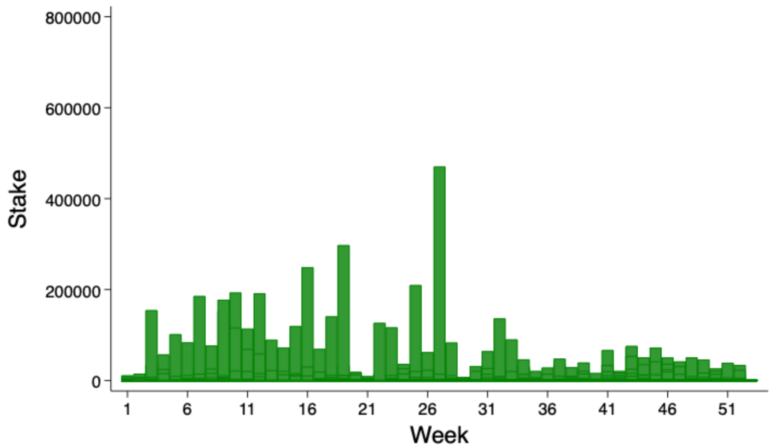

Figure 1: Weekly stake distribution (high SES)

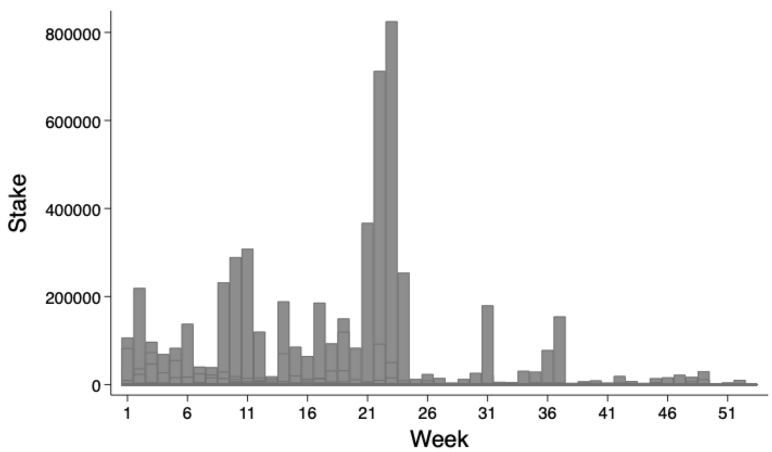

Figure 2: Weekly stake distribution (mid SES)

High SES players exhibit relatively stable betting behavior throughout the year, with moderate fluctuations and several spikes during the first half of the year (Figure 1). In contrast, mid SES players show more pronounced peaks in the middle of the year, especially around weeks 24–26, and greater variability in stake amounts (Figure 2). Low SES players' betting behavior is highly concentrated between weeks 26 and 36, with a sharp and narrow peak centered around week 30

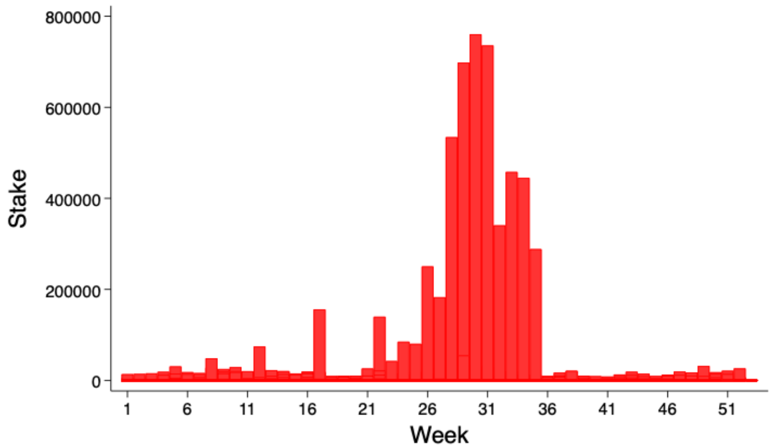

Figure 3: Weekly stake distribution (low SES)

(Figure 3), indicating more clustered and time-specific gambling behavior.

To statistically assess differences in these distributions, we perform pairwise Mann–Whitney U tests. We find significant differences in stake distributions between high and mid SES players ($z = 5.196$, $p < 0.0001$), high and low SES players ($z = 2.349$, $p = 0.0188$), and mid and low SES players ($z = -2.437$, $p = 0.0148$). These results suggest that gambling patterns vary meaningfully across socioeconomic groups, not only in magnitude but also in temporal distribution.