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Early Outcomes and Future Risk-taking: Evidence from a Large Gambling Provider

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Abstract

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We examine how people's risk attitudes are affected by prior outcomes using an extensive dataset consisting of over 45 million sports bets placed by over 100,000 customers across seven years. We find that past successes increase future risk-taking, and we show that most (77-84%) of this effect is driven by the house money effect, while the rest (16-23%) is driven by risk-takers updating their beliefs about their ability. Finally, we provide evidence that risk-takers appear to have very short memories – only very recent successes are strong predictors of future risk-taking.

Keywords

Risk attitudes, house money effect, near-miss effect, sports betting.

JEL: G41, D90, C31, Z23

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1. Introduction

Understanding people's risk attitudes, particularly how they are affected by prior outcomes, is critical for understanding how people make decisions under uncertainty (Imas 2016). Financial economists have long known that past trading successes are associated with increased trading in the future. The typical explanation for this pattern is that investors update their beliefs about their ability upon observing performance. Past outcomes provide signals about a trader's ability, so a Bayesian should have a higher assessment of her ability following past successes.[1] While this explanation is reasonable, it is difficult to know whether this is actually the mechanism because past performance also affects the "balances" of people's "mental accounts" (Thaler and Johnson, 1990). Specifically, the "house money effect" posits that gains from a past success are stored in a specific mental account, and people are more likely to take on additional risks when they can mentally fund their risk-taking from prior gains (Thaler and Johnson, 1990). Thus, the house money effect also predicts that past successes should be followed by more risk-taking in the future. It is generally not possible to disentangle these mechanisms using data from the field because both explanations predict a positive correlation between past performance and future risk-taking.

In this study, we overcome the data limitations of prior studies by analyzing a unique, extensive panel dataset of sports betting at one of the largest betting companies in the Czech Republic. As Thaler and Ziemba (1988) note, sports betting markets have a very similar structure to conventional financial markets, making them suitable for analysis. Moreover, discount brokers and gambling sites use similar strategies to attract customers.[2] Our dataset comprises more than 45 million sports tickets covering over 90,000 customers over seven years. The size and richness of the data allow us to analyze the mechanism that drives the relationship between past success and future risk-taking activity.

Because our panel dataset is large among both dimensions – number of bettors and time – we can analyze risk-taking behavior at inception, i.e., a person's very first experience with the given type of risk. People's responses to risky outcomes at inception provide an ideal setting to examine the relative magnitudes of the house money effect and belief updating. Regarding the house money effect, financial economists have shown that people open, close, evaluate, and roll over their mental accounts in

[1] See, e.g., Gervais and Odean (2001), Nicolosi et al (2009), Glaser and Weber (2009), Seru et al (2010), Chiang et al (2011), Linnainmaa (2011), and Barber et al (2020)

[2] McCabe (2021) shows that Robinhood started targeting college campuses with promotions and views it as a target demographic. This approach is consistent with the phenomenon described in gambling literature, which shows that the target audience is single younger men (Barber and Odean, 2002; Andrikogiannopoulou and Papakonstantinou, 2020).

complex ways: Sometimes, people engage in relative evaluation within a portfolio (Hartzmark, 2015), and sometimes, they mentally frame across trades (Frydman, Hartzmark, and Solomon, 2018). Thus, the longer a risk-taker has been engaging in a risk-taking activity, the less clear it is whether the given mental account associated with that risk is at a gain or a loss. Similarly, the effects of prior outcomes on one's beliefs about her ability should be strongest at inception. For these reasons, we restrict attention to bettors whose first bet we can observe, namely, those who do not place any bets during the first three months of our sample period (January – March 2005).[3]

Another key feature of our data is that we are able to observe the outcomes of a unique type of bet known as an *accumulator*[4]. Whereas most bets are simple in that there is a positive payout if a single event occurs, in an accumulator bet, there are N>1 events that are specified, and the bet's payout is nonzero only if all N events occur. Thus, accumulators are far riskier than simple bets on average. For our study, the critical feature of accumulator bets is that they allow us to observe "near misses," namely, when exactly N-1 out of the N events occur.[5] In this scenario, the risk-taker receives a signal that she is skilled – similar to a winning bet – but in contrast to a winning bet, she does not receive a payout to generate any "house money." Thus, in a near miss, risk-takers should update their beliefs about their ability (similar to winning bets), but they do not receive any house money, so the house money effect cannot apply. By comparing the effects of a near miss and a winning bet on subsequent risk-taking activity, we can estimate the relative magnitudes of both channels, belief updating and the house money effect. Depending on the model specification, we find that roughly 77-84% of the relation between past wins and future risk-taking activity is driven by the house money effect with the remainder due to belief-revision about the risk-taker's ability.

After examining the relative magnitudes of the house money effect and belief-updating at inception, we next examine how risk-takers weigh the most recent outcome versus the previous two or three. For both winning bets and near misses, the effect of the most recent outcome is significantly stronger than the outcomes two or three events prior, suggesting that risk-takers have short memories and outweigh the most recent experience relative to those that happened just before. Alternatively, it is possible that

[3] Only 3% of the bettors in our sample ever have a "gap" between subsequent bets that are 3 months or longer. Thus, we are unlikely to misclassify many bettor's inception by applying this filter.

[4] Also known as a "parlay bet".

[5] A "near miss" (also known as a "near hit" or "near win") is said to occur when a gambler almost, but does not, achieve a winning outcome. A near miss is not characterized by the magnitude of a player's loss but rather, the realized state of the world being close (in some sense) to a state of the world in which a winning gamble would have been realized. For example, a "cherry–cherry–lemon" outcome on a slot machine can be considered a near miss because "cherry-cherry-cherry" would have resulted in a large winning payout for the gambler.

risk-takers frequently reset their mental account balances to 0, which is consistent with short-term memory but does not require it.

We contribute to the literature on past outcomes and future risk-taking by showing that even at inception, when past successes should be most informative about a risk-takers ability, the house money effect is the stronger force causing a risk-taker to continue taking risks. This is in contrast to the predominant explanation for the relation in the finance literature.[6] In addition, our finding that the most recent outcome has a significantly stronger effect than the ones that immediately precede it suggests that risk-takers have short memories and that the link between past outcomes and risk-taking are therefore likely small compared to innate characteristics of a person, e.g., her innate inclination to take or avoid risks.

Our paper also contributes to the gambling literature. Previous studies (e.g., Dixon and Schreiber, 2004, and Rocha Dores et al., 2020) document that the cognitive reaction to a near miss differs from other types of losses even though the payoffs are equal—both result in losing the amount wagered. Cote et al. (2003) analyze gambling on video lottery terminals and find that near misses cause an increase in subsequent gambling activity. Casinos and slot machine manufacturers appear to be aware of this fact, as near misses have been shown to occur at a higher frequency than expected for commercial slot machines (Reid,1986; Harrigan, 2009). Most prior research on the near-miss effect focuses on so-called "games of chance" like slot machines and scratchcards, whose outcomes do not depend on gamblers' skill. In contrast, traders in financial markets might be heterogeneous in their ability to identify mispriced securities, and some might be able to earn positive trading profits in expectation. In such settings, a near miss might provide useful feedback to the trader and not be associated with the negative emotion documented by Sharman and Clark (2016). Because prior literature on the near-miss effect is mostly concentrated in games of chance, little is known about the near-miss effect in settings where there might be skill, such as financial markets or sports betting.

Our findings also have implications for understanding retail investor trading in so-called "meme stocks." In recent years, gambling-like activity has significantly impacted the stock market. In the early 2020s, retail traders began actively trading meme stocks such as GameStop and AMC. These stocks' valuations rose far above what any realistic discounted cash flow analysis would justify, revealing significant limits

[6] See, e.g., Gervais and Odean (2001), Nicolosi et al (2009), Glaser and Weber (2009), Seru et al (2010), Chiang et al (2011), Linnainmaa (2011), and Barber et al (2020).

to arbitrageurs' ability to keep stock market prices in line with fundamentals.[7] Because there was basically no relation between these stocks' price movements and news about their cash flows or market-wide discount rates, trading these stocks was essentially a form of gambling. Moreover, many retail investors even exhibit signs of compulsive gambling (Cox et al., 2020). While it is widely accepted that the significant price run-ups due to meme trading had little relation to the firms' underlying cash flows, open questions remain regarding what causes retail traders to continue or quit their gambling activity and, thus, how long the meme stock mania is likely to persist.[8] To rigorously examine these questions, a researcher would need a large panel of risk-taking activity in the cross-section and long in the time series. This paper analyzes such a dataset and documents the importance of the near-miss effect on the risk-takers' propensity to continue taking risks. Regarding near misses and meme stock trading, a near miss could occur if a trader bought the stock too late, liquidated at just the wrong time (too early or too late), or was contemplating between two meme stocks and chose the wrong one. In terms of traditional fundamental value investing, many inputs determine a stock's future returns: the company's ability to innovate, the demand for its new products, the firm's ability to maintain its market share while its competitors are innovating, and regulatory risks. A near miss could occur if an investor were correct about all but one of these unknowns but incorrect about one of them, causing a loss for the investor. Although it is widely believed that near misses cause gamblers to increase their gambling activity, prior research has arrived at different conclusions, presumably because the studies generally rely on small laboratory samples.[9] Our findings suggest that as long as gamblers in the stock market can convince themselves that their losses are near misses, they will continue gambling even after suffering losses.

[7] In April 2020, GameStop was trading at under $3 per share. At the end of 2020, it was trading at just under $20 per share. On January 27, 2021, GameStop closed at $347.51 per share, more than a 1,600% increase from its closing price on January 11, 2021. This dramatic price run-up was accompanied by abnormally large trading volume: From January 13-29, roughly 100 million GameStop shares traded each day, an increase of more than 14 times its 2020 average. For an SEC report on this, see: https://www.sec.gov/files/staff-report-equity-options-market-struction-conditions-early-2021.pdf

[8] Recently, the mania started extending to other parts of the market, such as the option market (see, e.g., https://www.bloomberg.com/news/articles/2023-03-22/toys-or-tools-zero-day-options-start-changing-the-trading-game?leadSource=uverify%20wall)

[9] Barton et al (2017) summarize the research on the near-miss effect as follows: "near misses were found to be associated with increasing one's bet, decreasing one's bet, or having no effect, each in a different study, making it difficult to determine whether near misses are capable of influencing per-play betting behaviour."

2. Data

We analyze sports betting activity at one of the largest betting companies in the Czech Republic. Each bet takes one of two forms: *simple* or *accumulator*. A simple bet is a bet that a single event will occur, e.g., that a certain team will win a certain match. An accumulator bet[10] is a bet that multiple events will all occur: if any of the events in the accumulator bet does not occur, then the payout of the bet is 0. Thus, accumulators are inherently riskier (on average) than simple bets[11]. Moreover, accumulators provide an ideal setting to examine the near-miss effect because we can observe near misses, namely when exactly N-1 out of the N events on an accumulator occur.

Bets are placed on tickets. A ticket can contain multiple bets, in which case it is classified as a combinator ticket. Combinator tickets can contain either simple or accumulator bets. Most tickets, however, contain only one bet (simple or accumulator). We refer to such tickets as non-combinator tickets.

The following box summarizes the categorization of tickets and bets:

Bet and ticket classifications

Bet: either simple or accumulator
Simple bet: a bet that a single event will occur
Accumulator bet: a bet that all N events (N>1) listed on the bet will occur

Ticket: contains bets
Combinator ticket: a ticket that contains multiple bets
Non-combinator ticket: a ticket that contains just one bet

Most of the prior literature on the near-miss effect has examined the effects of a near miss in the context of a pure game of chance like slot machines. In contrast to such games of chance, some sports bettors might have superior information regarding the likely outcomes of sporting events, so in this respect, they are more similar to financial markets, where traders can also be heterogeneous in their ability to detect mispriced assets. This is further supported by Thaler and Ziemba (1988), who outline

[10] Also known as Parlay bet.

[11] To provide analogy to the stock market, accumulator, or parlay, is akin to a stock option. Investing into a single stock can be interpreted as a bet that the stock price will increase. Conversely, option is a bet that the stock price will meet or exceed the strike price, by a certain maturity date, assuming certain volatility.

the similarities between sports betting markets and conventional financial markets. Moreover, near miss in sports betting can be taken as an indication of ability. Thus, our setting provides an ideal setting to examine the effects of near misses in potentially skill-related risk-taking activities such as trading in financial markets.

We observe all betting activity—over 45 million sports tickets that were placed between January 2005 and February 2012 at the company. For each ticket, we can observe the following: the purchase date and time of the ticket; the date and time that the bets on the ticket were resolved; the stake and winnings of the ticket; a unique identifier for each customer so that we can track the bettor's activity across time; the bettor's gender, and age. Let us note that there are no incentives for customers to change providers. Loyalty programs exist, and, as a result, a customer is generally not able to receive better odds or lower fees at another company. Moreover, we are analyzing one of the largest gambling companies in the country with extensive geographical coverage, with no legislation barring companies to only specific area of the country. Consequently, customers should not need to switch companies after moving to a different location.

For the rest of our analysis, we aggregate bets to the person-date level and analyze betting activity across days because the evaluation of the ordering of intraday bets is problematic. Distinct tickets purchased by the same bettor on the same date often differ by just a few seconds or minutes, and later tickets are often purchased before the earlier ones' payoffs are determined. For example, if a bettor purchases multiple tickets at a branch, the branch might process the tickets in a different order from the order in which the bettor filled out the tickets. Thus, we do not lose much information or statistical power by aggregating to the daily level. Because we aggregate to the bettor-date level, the distinction between ticket and bet is no longer important. Henceforth, we will analyze a bettor's total betting activity on the given date regardless of how many tickets the bets were spread across on the given date.

We are particularly interested in the effects of the *very first* risky outcome that a risk-taker experience. Specifically, we are interested in examining how a risk-taker's propensity to continue is related to the first outcomes she experiences. Thanks to the richness of our data, we can restrict attention to individuals with a clearly defined inception. For each pair of consecutive bets placed by a bettor, consider the "gap" or "lag" between the dates these were placed. For example, if a bettor placed bet(s) on Monday, January 11, and then her next betting day was Friday, January 15 (of the same year), the gap between these betting days would be four days.[12] In our sample, over 90% of these gaps are seven days or less, and over 99% of them are 90 days or less. Additionally, we find that 97% of the sports bettors in our sample have a maximum gap of less than 90 days. Based on these statistics and the fact that our betting data began on January 1, 2005, we excluded from the sample all bettors whose first bet was placed before April 1, 2005. By doing so, we eliminate the potential influence of previous betting outcomes on the individual's decision-making, allowing us to examine the bettor's very first sports betting experience.

To the best of our knowledge, we are the first researchers who can adequately analyze this question using data from the field because most samples of gambling or investing activity are limited to short time periods or survey data, and researchers are therefore unable to examine the effects of initial outcomes on subsequent risk-taking activity.

We first consider the amount of risk that bettors take on the typical day that they place bets. We examine this by computing the average stake and odds across age groups and bet type (accumulator versus non-accumulator) in Table 1.

------------------ Insert Table 1 around here ------------------

In column 1, we see that, interestingly, the odds for the accumulator bets increase with age. Young risk-takers (under 20 years old) tend to place the least risky accumulators (mean odds = 218.4, median = 8.2), while accumulators tend to be riskiest among those in the 50-60 and greater than 60 categories (mean odds = 1,106.8 and 876.6; median = 20.8 and 21.6, respectively). Across the entire sample, the average odds equal 789.6, indicating that the average accumulator bet pays roughly 800 times the amount the risk-taker wagered if the accumulator is a winning bet, but the median (16.2) is significantly smaller.

In column 2, we consider non-accumulator bets. The odds for these bets are significantly lower than for accumulators, consistent with the idea that accumulators are the riskiest types of bets. Across the entire sample, the average (median) odds for accumulator bets is just 3.6 (1.8). As with accumulators, young risk-takers tend to place the least risky bets, with the average (median) odds being just 2.2 (1.5).

[12] In this example, the gap is 4, because if you take the difference between the dates of the two bets, the difference equals 4. Arguably, a better definition for the gap would be three days, because there are three days between the consecutive betting dates in this example. However, this trivial distinction is irrelevant for our purposes.

For non-accumulator bets, the riskiest bets are placed by risk-takers over 50 years old: the 50-60 age category has the highest mean (4.4), while the 60+ category has the highest median (2.1).

In columns 3-6, we consider the amount that risk-takers wager per day on the different types of tickets. As with columns 1-2, in columns 3-4, the betting activity for each person is aggregated to the daily level so that the sample consists of risk-taker*days such that the risk-taker places the given type of bet (accumulator or non-accumulator) on the given day. Across all age groups, risk-takers wager similar amounts on accumulators and non-accumulator bets, conditional on them making the given type of bet. For example, risk-takers under 20 wager 117.6 per day on average on accumulators and 124.3 per day on non-accumulators, conditional on them placing at least one bet of the given type on the given date. However, as we see from the number of observations, accumulator bets are far more common among risk-takers in this age group, with over twice as many observations (43,685) occurring for accumulators than non-accumulators (21,755). This indicates that young people are more than twice as likely to place accumulator bets than non-accumulator bets. Across the entire sample, we see that accumulator betting is more common than non-accumulator betting (N = 5.8 million versus N = 4.1 million), and conditional on placing a given type of bet, the stake is slightly larger for non-accumulator bets (304.1) than for accumulator bets (287.7).

In columns 5-6, we report unconditional analysis whereby the sample consists of all risk-taker*days where the risk-taker places either type of bet (accumulator or non-accumulator), but not necessarily the type of bet under consideration. The stake is set to 0 if a risk-taker did not place the given type of bet on the given date, and the number of observations is therefore the same for accumulators and non-accumulators. Here, we see that risk-takers tend to wager significantly more on accumulators (209.5) than non-accumulators (156.1), although this varies significantly by age. For example, risk-takers under 20 wager almost twice as much on accumulators (100.3) as non-accumulators (52.8), while risk-takers over the age of 60 wager slightly more on non-accumulators (104.7) than accumulators (91.3).

3. Results

3.1 Unconditional likelihood that a new risk-taker continues to take risks

Because our time period is both long and wide, we are able to analyze the long-term risk-taking activity of the people in our sample. That is, we restrict attention to risk-takers whose inception we can observe, namely, those who first participated after April 1, 2005. By making this restriction, we can examine the survival rate of new risk-takers. We report the distribution of these risk-takers' long-term total activity by age group in Table 2.[13]

------------------ Insert Table 2 around here ------------------

The 20-30 age group has the largest number of risk-takers (29,749), followed by the 30-40 age group (24,134). Many risk-takers take a very small number of risks before quitting: 9.6% of the people who enter our sample only take a risk on a single day, and over 21% (= 9.6% + 6.5% + 5.1%) take risks on three or fewer days before quitting. Table 2 highlights an important feature of our sample, namely, that we have a sufficiently long time series of risk-taking activities to analyze whether someone engages in persistent risk-taking activity or quits after her first experience. We can see that the most populated age category of longer-term risk-takers (taking risks on more than 100 dates) is the 30-40 age group. Overall, we have over 91,000 new risk-takers whose inception we can observe, with more than 38,000 of them taking risks on more than 30 distinct dates.

3.2 Past outcomes and future risk-taking activity

3.2.1. Short-run effects

Understanding people's risk attitudes, including how they are affected by prior outcomes, is critical for understanding how people make choices when faced with uncertainty. It has long been known that past successes lead to more risk-taking activity. When there is (potentially) a skill component to the payoffs that the risk-taker receives, the relation between past success and future risk-taking can operate through two distinct channels. First, the risk taker's positive feedback can cause her to update her assessment of her own ability, giving her more confidence to take on more risks in the future (Gervais and Odean, 2001). Second, suppose the risk-taker engages in mental accounting and separates her wealth into different accounts. In that case, she might be more willing to take on more risk because she is playing with house money and has little to lose (according to this method of mental accounting) because any future losses the risk taker incurs will simply be deducted from her past gains (Thaler 1980). Conversely, in a near miss, the risk-taker observes a positive signal about her ability, which should cause her to update her beliefs about her ability (the first channel), but since the payoff is 0, there can be no house money effect and the second channel cannot operate. Thus, by comparing the effects of a win and a near miss on subsequent risk-taking activity, we can estimate the magnitudes of both channels, which is something that prior researchers have been unable to do using data from the field (to the best of our knowledge) due to data limitations.

[13] For each risk-taker in our sample, we compute their age as of January, 2012.

For both channels – belief updating and the house money effect – the cleanest setting to analyze is the risk taker's first experience. Regarding beliefs, the incremental informativeness of a single outcome is likely small for a risk taker who has already observed hundreds of prior outcomes, whereas the incremental informativeness of an outcome should be relatively large when she has never observed any before. Regarding the house money effect, researchers do not know exactly when people "reset" their mental accounts to 0, and there is presumably heterogeneity across people in when and how they reset their accounts. Thus, following a long string of risk-taking outcomes, a recent win might reflect the mental account having a positive balance. Still, it might also reflect the mental account's balance moving from a very negative value to a slightly less one. In other words, following a long string of outcomes, there might not be any house money even after a positive payoff, and conversely, there might be residual house money (from prior positive payoffs) immediately following a negative payoff.

To examine the effect of a risk-taker's first outcome on her subsequent risk-taking activity, we consider the sample of all risk-takers whose inception we can observe. Another potential concern, especially for more frequent bettors, is risk-takers placing bets before their previous one has been resolved. To eliminate this concern, we further restrict the sample to risk-takers who observed the resolution of their bets before placing the next one.

The dependent variable is an indicator equaling one if the risk-taker continues on a subsequent day and 0 if she completely quits after experiencing her first outcome. Our independent variables of interest consist of an indicator that the cumulative payout of all the risks exceeds the total amount that was wagered, i.e., that the risk-taker profited from the first day of risks (*Net win*) and an indicator that the risk-taker experienced a near miss on the first day (*Near miss*). We also consider various control variables, including gender (*Male*), year fixed effects, age group fixed effects, measures of the person's use of accumulator bets on the first day of risk-taking, and indicators that the risk-taker experienced a sizeable net loss (*Large loss*) or net gain (*Large gain*) on the first day greater than 2,000 Czech koruny, or approximately 100 USD.[14]

------------------ Insert Table 3 around here ------------------

In column 1 of Table 3, we see that a risk-taker who profits from her first day of risk is 5.4 percentage points more likely to take risks again, i.e., 5.4 percentage points less likely to quit. Conditional on taking a risk at least once, the probability of quitting after the first outcome is just 9.6% (first column of Table

[14] The amount of net gain necessary to be classified as a *Large gain* is more than one tenth of the average Czech monthly salary.

2, bottom row). Thus, earning a profit on the first day of risk-taking reduces the likelihood that the person will quit on the first day by 56% (= 5.4% / 9.6%) relative to the baseline percentage. This result is consistent with risk-takers engaging in mental accounting. More specifically, it is consistent with the house money effect. However, it is also possible that the risk-takers are updating their beliefs about their ability and future expected returns: a winning outcome suggests the risk-taker might have the skill and should continue taking risks, while losing outcomes might suggest the opposite.

Examining the effects of both near misses and net wins allows us to disentangle the impact of belief updating and the house money effect. For near misses, the mental accounting explanation for why risk-takers continue to take risks no longer applies because there is no house money following a near miss, but the belief-updating explanation does apply. The coefficient of the near-miss indicator indicates that a near miss increases the likelihood that a risk-taker continues to take risks in the future by 0.9 percentage points. Conditional on betting at least once, the probability of quitting after the first bet is just 9.6% (first column of Table 2, bottom row). Thus, experiencing a near miss on the first day of sports betting reduces the likelihood that the better will quit on the first day by 9.4% (= 0.9% / 9.6%) relative to the baseline percentage. Comparing the magnitudes of this coefficient and the coefficient of the net winning indicator, we see that the effect of a near miss is roughly 16% (= 0.9% / 5.4%) as large as the effect of winning. Recalling that there are two reasons why one should expect a profitable bet to lead to subsequent risk-taking activity -- the house money effect and learning about one's ability -- the fact that near miss coefficient is 16% the magnitude of the coefficient of the winning indicator suggests that roughly 84% of the effect of winning on future risk-taking activity is due to the house money effect, and roughly 16% of it is due to risk-takers updating their beliefs about their ability.[15]

The coefficient of variable *Male* is highly economically and statistically significant, suggesting that men are far more likely than women to continue engaging in risky activity conditional on them starting. This is consistent with the large body of research suggesting that males are more prone to engage in risk-taking activities than females (e.g., Barber and Odean, 2002).

Of course, a risk taker can only experience a near miss in our setting if she places an accumulator bet. To ensure we are not simply capturing a correlation between risk takers' propensity to choose to place accumulator bets and their propensity to continue gambling, we also include an indicator for the risk taker placing an accumulator bet. The coefficient of this variable is positive and significant, suggesting

[15] Let s be the effect of a positive signal and let h be the effect of house money. Then our coefficient estimates suggest that s = 1.2% and s + h = 5.3%. Thus, s/(s+h) = 1.2%/5.3% = 22.6% and h/(s+h) = 4.1%/5.3% = 77.3%.

that gamblers who choose to place accumulator bets are more likely to continue gambling independent of the effect of a near miss.

One natural concern with the regression reported in the first column is that the *Accumulator* indicator might not sufficiently control for the correlation between risk-takers' propensity to place accumulator bets and their propensity to continue taking risks. For example, a risk-taker who places many accumulator bets is more likely to experience a near miss than one who only places one. Thus, the positive coefficient on the near miss indicator may capture a correlation between the number of accumulators the person bets and her propensity to continue gambling independent of whether the risk-taker experiences a near miss or not. To ensure that our results are not driven by such an omitted variable, in column 2, we include fixed effect brackets for the number of accumulators that the person purchased on their first day of taking risks. Even with these controls, the estimates of *Near miss* and *Net win* do not significantly change. With this alternative model of risk-taking activity, we find that roughly 19.2% (= 1.0% / 5.2%) of the effect of a positive outcome on subsequent risk-taking activity is due to belief-updating, while the house money effect drives the remaining 80.8% of the effect.

Disentangling the house money effect from potential wealth effects is often difficult. For example, if someone has house money, they experienced positive payoffs in the past, which increased their wealth; this increase in wealth may affect their future risk-taking activity. To ensure that wealth effects are not driving the sizeable positive coefficient of *Net win* in columns 1 and 2, in columns 3 and 4, we include indicators for the risk-taker experiencing a large (>2,000 Czech koruny, or approximately 100 USD) loss or gain. Not surprisingly, the coefficients of the extreme loss and extreme win indicator variables are negative and positive, respectively. However, neither is statistically significant, and the coefficient of *Net win* remains large and similar in magnitude to columns 1 and 2. This suggests that the positive relation between a net win and a risk-taker's propensity to continue taking risks is driven by the house money effect rather than wealth effects. Moreover, the coefficient of *Near miss* is identical to its value in columns 1 and 2, suggesting that when it comes to learning about one's ability, the sign of the profit variable is more important than the magnitude of the win or loss. Also, let us note that since we are analyzing the first bet an individual makes, there should not be any capital restriction concerns for gambling for one more day. Therefore, the results in Table 3 suggest that the positive coefficient on *Net win* is not driven by wealth effects but by the house money effect and belief-updating about one's ability.

We next conduct matching to more directly analyze causal effects in the potential outcome framework of the Rubin Causal Model (Holland, 1986). The model is based on two possible outcomes, one with and one without treatment:

$$y_{0i} = \mu_0 + \varepsilon_{0i} \text{ and } y_{1i} = \mu_1 + \varepsilon_{1i}.$$

Formally, it can be written as $y_{Ti} = \mu_T + \varepsilon_{Ti}$, where subscript T=1 denotes the treatment, and T=0 represents the control group. In reality, we observe only one outcome for each *i*, either y_{0i} or y_{1i} and the counterfactual outcomes must be estimated. We will use established RCT techniques to estimate the Average Treatment Effect on the Treated (ATET), where y_{0i} is estimated using the nearest-neighbor approach with an extensive set of controls.[16] In our context, the outcome variable of interest is an indicator for the risk-taker continuing to take risks in the future, and the terms μ_1 and μ_0 represents the probability of continuing to engage in risk-taking activity when the treatment does and does not occur, respectively, controlling for various characteristics.

We begin by estimating the treatment effect of a near miss on the first day of risk-taking. We perform exact matching on the risk-taker's gender and indicators for the risk-taker experiencing a net win, large win, and large loss. In particular, using our variable setting, we use exact matching for all indicator variables (*Male*, *Large loss*, *Large win*, and *Net win*) and approximate matching for bettors' *age*. We follow recommended procedures for constructing the control group and evaluating the average treatment effects on treated (ATET), e.g., Rosenbaum and Rubin (1985), Rubin (2008), and others. In particular, our control groups show excellent balancing of covariates used for matching, presented in mean differences and variance ratio for matched samples. Also, detailed density plots (available upon request for all cases) using the matched data appear to be nicely balanced.

----------------- Insert Table 4 around here ------------------

In column 1 of Table 4, Panel A, we report that the estimated average treatment effect of experiencing a near miss is a 1.08 percentage point increase in the likelihood of continuing to take risks in the future, which is highly statistically significant. As we discussed earlier in the context of the linear probability model, a natural concern is that a risk-taker can only experience a near miss if she places accumulator

[16] The treatment effect $E[y_{1i} - y_{0i}]$ is under random assignment equal to $\mu_1 - \mu_0$, motivating our choice of a randomized control trial (RCT).

bets, and it is possible that placing accumulator bets is associated with an increased propensity to continue to take risks in the future. We examine this possibility in column 2 by defining a treatment as choosing to place an accumulator bet. We find that ATET is very close to 0 (0.33 basis points) and is statistically insignificant (t-stat = 1), which suggests that the ATET of the near miss estimated in column 1 is not driven by a correlation between the propensity to place accumulator bets and the propensity to continue taking risks in the future. Nevertheless, we further explore this possibility in column 3, where the treatment event is the risk-taker placing an accumulator bet and not experiencing a near miss. Here, we see that the estimated ATET is negative and statistically significant, which again casts significant doubt on the notion that our results in column 1 are driven by a correlation between risk-takers' propensity to place accumulator bets and their propensity to continue taking risks after the first day.

In Panel B, we impose a more stringent filter on the sample and restrict attention to the 65,517 risk-takers who place accumulator bets on the first day of taking risks. In column 1 of Panel B, we report that the estimated average treatment effect of experiencing a near miss is a 1.14 percentage point increase in the likelihood of continuing to take risks in the future, which is highly statistically significant. In columns 2 and 3, we conduct exact matching on the number of accumulator bets that the risk-taker purchased on the first day of risk-taking, and in column 3, we include the mean odds as an additional matching variable. We find qualitatively similar results in each of these specifications: a near miss is associated with a 1.14 to 1.17 percentage increase in a risk-taker's propensity to continue taking risks, each of which is statistically significant.

Overall, the results in Panels A and B reveal that near misses increase the likelihood that a risk-taker will continue to take risks in the future. Because near misses do not generate any house money, we conclude that this effect is driven by the positive signal that the near miss reveals about the risk-taker's ability.

Finally, in Panel C, we estimate the ATET of a net win on the first day on the propensity to continue taking risks in the future. Note that when the risk-taker experiences a net win, she receives both house money and a positive signal about her ability. Thus, we expect the ATET of a net win to be significantly greater than the ATET's of the near miss estimated in Panels A and B. In column 1, we consider all risk-takers' first day of gambling. We find that a net win is associated with a 4.78 percentage point increase in the likelihood that a risk-taker continues taking risks in the future, which is significantly greater than the 1.08 percentage point increase associated with a near miss (Panel A, column 1). In terms of disentangling the effects of the house money effect and belief-updating, this suggests that 77% of the effect of a net win on subsequent risk-taking is due to the house money effect, while 23% is due to belief-updating.[17] In column 2, we exclude risk-takers who experience a winning bet but an overall net loss, and in column 3, we restrict attention to risk-takers who place accumulator bets on the first day. We find more sizeable estimates for the effect of a net win in these models. In the latter one, we find that a net win is associated with a 6.86 percentage point increase in the likelihood of continuing to take risks, which implies that the house money effect drives 84% of the association between a net win and subsequent risk-taking. In contrast, 16% is due to belief-revision.[18]

3.2.2 Longer-run effects

Until now, we have only examined very short-run effects, namely, the effects of betting outcomes on the very first day on the likelihood that the risk-taker will continue to take risks. This section analyzes whether near misses have longer-run effects on risk-taking behavior. We continue to restrict attention to risk-takers whose inception we can observe, namely, those whose first bet occurs after April 1, 2005. And, as before, we restrict the sample to individuals who observed the outcome of their bet before betting again.

Table 5 analyzes the determinants of continued risk-taking after two days of risk.

------------------ Insert Table 5 around here ------------------

The dependent variable is an indicator representing whether the individual continues taking risks in the sports betting market after the second day of risk-taking. In column 1, we find that net wins on both the first and second day are significant and positive predictors of future risk-taking activity, consistent with both the house money effect and belief-updating in response to positive feedback. Note that a net win on the second day has a much larger effect than winning on day one -- roughly 5x in column 1 (0.063 versus 0.013) and 2 (0.060 versus 0.011). To the extent that the signals on days 1 and 2 are equally informative about the person's ability, this result is consistent with the idea that the house money effect is the primary driver of the positive relation between past success and future risk-taking.[19] However, it is also consistent with risk-takers having short memory in that they primarily consider only the most recent outcomes when deciding whether or not to continue.

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[17] Note: 1.08% / 4.78% = 23%.

[18] Note: 1.08% / 6.86% = 16%.

[19] To see why, note that the risk-taker might have already closed the mental account from the day 1 gains by the time day 2 ends, and even if the account remained open, it is possible that the losses in day 2 exceeded the gains from day 1.

Examining near misses can help us understand why a net win on day 2 is so much more important than a net win on day 1. Suppose risk-takers have long memories, and the differential effect between a net win on day one and day two is simply due to risk-takers closing their mental accounts before day 3. According to this explanation, the effect of a near miss on day one should be roughly the same as a near miss on day two because both signals should be roughly equally informative about the person's ability, and people have long memories by assumption (according to this explanation). In contrast, if risk-takers have short memories and primarily rely only on their most recent outcomes when deciding whether or not to continue, we should see a much larger near-miss effect on day two compared to day one. Our evidence in rows 3 and 4 is consistent with this latter explanation: the coefficient of a near miss is far greater on day two than on day one. In column 1, the effect of a near miss on day two is more than six times as large as the effect of a near miss on day 1 (0.015 versus 0.002). Moreover, column 2 shows that the sign of a near miss on day 1 is actually negative (but insignificant), suggesting that risk-takers rely on only the most recent outcomes when deciding whether or not to continue. Thus, this evidence suggests that the effect of net wins on days one and two, reported in rows 1 and 2, is driven primarily by short-term memories rather than long-term memory plus mental accounts that are frequently reset.

To ensure that the coefficients of the *Near miss* variables are not simply capturing a relation between risk-takers' propensity to place accumulator bets and their propensity to continue taking risks, we again include the accumulator indicator variable in column 1 and group fixed effects on the number of accumulator bets in column 2. We find qualitatively similar results: there is a strong and significant relation between experiencing a net win on the second day of risk-taking and one's propensity to continue taking risks in the future. Regarding the economic significance, a net win on the second day is associated with a 6.0 percentage point increase in the propensity to continue taking risks, with the unconditional likelihood of quitting equal to 7.2%.[20] Thus, this 6.0 percentage point reduction is extremely significant relative to the baseline likelihood of quitting. Inspecting the first row (column 2), we see that conditional on taking risks on two days, a risk-taker who experienced a net win on the first day is 1.1 percentage points more likely to continue taking risks past the second day. This is also highly statistically significant, but the effect is much smaller than the 6.0 percentage point effect on the second day of risk-taking, implying that individuals might have very short memories.

Turning our attention to the near-miss effect, we see that a risk-taker who experiences a near miss on the second day of risk-taking is 90 basis points more likely to continue taking risks past the second day, which is statistically significant. In contrast, the coefficient of a near miss on the first day is actually

[20] This can be computed from Table 2 as 6.5/(100 – 9.6), or 6.5/(6.5 + 5.1 + … + 20.85).

negative, although insignificant. To the extent that the signals the risk-takers receive on days 1 and 2 are equally informative, we should expect to see similar effects of experiencing a near miss on these two days. The fact that there is such a significant difference reinforces the idea that risk-takers act as though they have concise memories.

In columns 3 and 4, we include indicators for the risk-taker experiencing a large loss or large win on days 1 or 2. These coefficients are generally close to 0 and are not statistically significant. Moreover, including them has very little impact on our coefficients for our variables of interest (the coefficients of *Net win* and *Near miss*). Thus, we conclude that our results are not driven by wealth effects, but rather, by the house money effect and belief-updating about one's ability.

----------------- Insert Table 6 around here ------------------

Table 6 extends the analysis to the decision to continue taking risks past the third day. As in Table 5, we find a strong effect for both a net win and a near miss on the third day, with the effect of a net win being significantly stronger (roughly 3.5 – 5 times stronger, depending on the specification), consistent with the idea that the house money effect plays a bigger role than belief-updating. In addition, we continue to find a much stronger effect for a net win on the most recent experience (day 3) compared to earlier experiences (days 1 and 2). While this pattern is consistent with the house money effect and accounts that close frequently, it is also consistent with risk-takers acting as though they have short-run memories.[21] We examine the impact of near misses on continued play to understand better why recent wins are much stronger predictors of continued risk-taking than more distant ones. To the extent that the signals the risk-taker observes about her ability on days 1-3 are equally informative if risk-takers have long-term memories, the effect of a near miss should be equally strong across all three days. However, this is not what we see in the data: there is a strong monotonic pattern, with near misses on day 3 being strong predictors of continued risk-taking, while near misses on day 1 are very weak predictors of continued risk-taking. Thus, risk-takers act as though they have concise memories: the most recent risk-taking experience has a much greater impact on the propensity to continue taking risks than even the second-to-most recent experience.

[21] Note that these explanations are not mutually exclusive. E.g., if a risk-taker has a short-run memory, it is likely that mental accounts will be frequently closed and reopened. Thus, short-run memory can be viewed as a channel by which mental accounts are reset.

3.2.3 Dynamic effects and channel analysis

In the previous sections, we focused on the start of an individual's betting activity and on their propensity to continue. While this approach allows us better identification, there are concerns that the effect of both belief updating and house money will be overstated. Both will arguably have a more significant impact on individuals betting for the first time than on seasoned risk-takers. Moreover, by analyzing the propensity to continue, we are unable to analyze the behavior and type of risk pursued after both near miss or win. In this section, we will analyze both the behavior during the entire period an individual gamble as well as the type of risk pursued in the gambling market.

We analyze the betting days starting from day four to avoid overlap with our previous analysis. Furthermore, to avoid the end-of-the-game problem, i.e., the possibility that a risk taker changes her betting strategy when she nears her exit from the game, we end the analysis four days before her last day as a gambler in our sample. To be consistent with the sample construction from previous sections, we focus only on individuals/days where individuals observed the outcome of their bets before betting again.

To capture risk takers' risk demand, we focus on the number of bets placed on the given day and the average stake for each bet. Since the results in our previous sections showed that risk takers in our sample appear to have concise memories[22], we analyze the effect of the previous day's outcome on the type of risk sought on the next day. Specifically, we study the impact of near miss or net win on the natural logarithm[23] of both the number of bets and the average stake she places on the following day. We report the effects of *Near miss* and *Net win* in Figure 1. The full regression model specifications and coefficients are available in the Appendix.

------------------ Insert Figure 1 around here ------------------

We first observe that both near miss and net win lead to an increase in the number of bets placed on the following day. This result is intuitive. Both outcomes should cause a risk taker to pursue more risk in the next period. Interestingly, we observe that near miss leads to more bets placed, with the difference being significant. This result indicates that while near miss leads to a risk taker to update her beliefs

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[22] This observation is supported by the fact that individuals in our sample exhibit short term memories for their first sport betting experiences, where the outcomes of their bets should be more informative about their abilities than later on in the sample.

[23] We use the logarithmic transformation of the dependent variable to directly observe the percentage change associated with the previous outcome.

about her ability positively, she might choose to diversify her future bets to recoup some of her losses. Importantly, this result shows that even a risk taker who has had a significant experience will update her beliefs about her ability following a near miss.

Secondly, we observe that while winning is associated with an increase in the average stake, the near miss effect does not have a significant impact. This result is consistent with our previous findings and reinforces our conclusion that the house money effect drives individuals' motivation for gambling. While suffering a near miss causes the risk taker to positively update her beliefs, she will not have the house money to increase her future stake. Therefore, these results suggest that a risk taker might increase the number of bets following belief updating but will not have the winnings to increase her stake.

This result further suggests that the house money effect, rather than belief updating, drives the propensity to gamble. Interestingly, despite the fact that incremental informativeness of a single outcome should be small for a risk taker with long experience, we find that risk takers will continue to update their beliefs following a near miss[24]. Moreover, this result further outlines the uniqueness of the near miss outcome. Despite being classified as a loss on paper, it does lead to belief updating and persistence in gambling, which could explain the persistence of gamblers or investors despite losing money. The effects of near miss on future behavior is an interesting area for future research.

4. Conclusion

We analyze the relation between people's risk attitudes and the initial outcomes they experience using an extensive dataset consisting of over 45 million sports bets placed by over 91,000 customers over seven years. Consistent with the prior literature, we find that past successes increase future risk-taking activity, a finding that financial economists generally attribute to risk-takers learning about their ability. However, such a relation is also consistent with the house money effect (Thaler and Johnson, 1990). Our sports-betting setting is ideally suited to test these two potential mechanisms for two reasons. First, our panel data are sufficiently rich in both the cross-section and time-series dimensions that we can analyze behavior at inception, i.e., when the risk-taker experiences her very first risk-taking outcomes. Inception is ideal for studying both the house money effects because we can safely assume the person's mental account balance is 0 when they begin taking risks. With regards to belief-revision,

[24] Especially when considering the concern that near miss could be weaker signal about her ability than a win. This result further supports our methodology, since the signal appears to be on par with net win, and further supports the idea that individuals appear to have very short memories.

the initial outcomes should have the most incremental information about one's own ability because there is no prior data for the person to consider: the only data consists of the day's outcome. Second, we can observe the outcomes of accumulator bets, which are bets that have positive payoffs only if all N events on the ticket occur; a "near miss" occurs when N-1 out of the N events occur. While both winning bets and near misses provide positive signals about the risk-taker's ability, only winning bets result in house money. Thus, we can estimate the relative impacts of belief revision and the house money effect by comparing the impacts of winning bets and near misses on subsequent risk-taking. Depending on the specification, we find that roughly 77-84% of the relation between past wins and future risk-taking activity is driven by the house money effect, with the remainder due to belief-revision about the risk-taker's ability. Thus, the house money effect appears to be an important but mostly neglected driver of the association between past trading performance and future trading activity.

We also provide evidence that risk-takers act as though they have very short memories. Specifically, the effects of net wins and near misses precipitately decline as one moves back in time, i.e., only the most very recent day's outcome is an economically significant predictor of future risk-taking activity. This suggests that the innate characteristics of a risk-taker are an important determinant of people's risk-taking behavior and that people's mental accounts are reset frequently, perhaps due to short-term memories. This is further supported when analyzing risk-takers' behavior throughout their career by observing that outcome remains a highly significant predictor of future risk-taking. Many gambling providers enact rules to stop individuals from further gambling following a sizeable win or a string of wins. Our results suggest that by enacting these rules, gambling providers are restricting individuals from higher future gambling, which might allow them to recoup some of the losses. However, these limits might offset the likelihood of developing an addiction.

Lastly, we provide evidence of near miss effect on the behavior of individuals. Despite being classified as a loss, it leads to a unique reaction more akin to winning. Risk takers take it as an indication of their ability, which then leads to a higher propensity to gamble. It is important to note that near miss as an outcome is virtually omitted from experimental research due to the clearly defined wins and losses in most experiments. While our empirical setup allows us to clearly define near miss by analyzing accumulator bets, let us note that an individual might suffer a near miss for a single bet in the event of a very narrow win or loss in the final minutes of a match. This can imply that as long as risk takers can convince themselves that their losses are near misses, they will continue to gamble despite suffering losses. This result could explain the persistence of meme stocks and the behavior of some retail investors.

References

Andrikogiannopoulou, A., & Papakonstantinou, F. (2020). History-dependent risk preferences: Evidence from individual choices and implications for the disposition effect. *The Review of Financial Studies*, *33*(8), 3674-3718.

Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics*, *116*(1), 261-292.

Barber, B., and T. Odean (2002). Online investors: Do the slow die first? *Review of Financial Studies* 15:455–87.

Barber, B., Lee, Y., Liu, Y., Odean, T., & Zhang, K. (2020). Learning, Fast or Slow. *The Review of Asset Pricing Studies*, 10(1), 61-93.

Barton, K. R., Yazdani, Y., Ayer, N., Kalvapalle, S., Brown, S., Stapleton, J., ... & Harrigan, K. A. (2017). The effect of losses disguised as wins and near misses in electronic gaming machines: A systematic review. *Journal of Gambling Studies*, *33*(4), 1241-1260.

Chiang, Y., Hirshleifer, D., Qian, Y., & Sherman, A. (2011). Do investors learn from experience? Evidence from frequent IPO investors. *The Review of Financial Studies*, 24(5), 1560-1589.

Côté, D., Caron, A., Aubert, J., Desrochers, V., & Ladouceur, R. (2003). Near wins prolong gambling on a video lottery terminal. *Journal of Gambling Studies*, 19(4), 433–438.

Cox, R., Kamolsareeratana, A., & Kouwenberg, R. (2020). Compulsive gambling in the financial markets: Evidence from two investor surveys. *Journal of Banking & Finance*, *111*, 105709.

Dixon, M. R., & Schreiber, J. E. (2004). Near-miss effects on response latencies and win estimations of slot machine players. *Psychological Record*, 54(3).

Frydman, C., Hartzmark, S. M., & Solomon, D. H. (2018). Rolling mental accounts. *The Review of Financial Studies*, 31(1), 362-397.

Gervais, S., & Odean, T. (2001). Learning to be overconfident. *Review of Financial Studies*, 14(1), 1-27.

Glaser, M., & Weber, M. (2009). Which past returns affect trading volume? *Journal of Financial Markets*, 12(1), 1-31.

Harrigan, K. A. (2009). Slot machines: Pursuing responsible gaming practices for virtual reels and near misses. *International Journal of Mental Health and Addiction*, 7(1), 68–83.

Hartzmark, S., 2015, The Worst, the Best, Ignoring All the Rest: The Rank Effect and Trading Behavior, *Review of Financial Studies* 28, 1024-1059.

Holland, P. W. (1986). Statistics and causal inference. *Journal of the American Statistical Association*, 81(396), 945-960.

Imas, A. (2016). The Realization Effect: Risk-Taking after Realized versus Paper Losses. *American Economic Review* 106, 2086-2109.

Linnainmaa, J. (2011). “Why do (some) households trade so much?” *The Review of Financial Studies*, 24(5), 1630-1666.

McCabe, C., 2021. It isn’t just AMC. Retail Traders Increase Pull on the Stock Market Retrieved from https://www.wsj.com/articles/it-isnt-just-amc-retail-traders-increase-pull-on-the-stock-market-11624008602.

Nicolosi, G., Peng, L., & Zhu, N. (2009). Do individual investors learn from their trading experience? *Journal of Financial Markets*, 12, 317-336.

Reid, R. L. (1986). The psychology of the near miss. Journal of Gambling Behavior, 2(1), 32–39.

Sharman, S., & Clark, L. (2016). Mixed emotions to near-miss outcomes: A psychophysiological study with facial electromyography. *Journal of Gambling Studies*, *32*(3), 823-834.

Rocha Dores, A., Rocha, A., Paiva, T., Carvalho, I., Geraldo, A., Griffiths, M., & Barbosa, F. (2020). Neurophysiological Correlates of the Near-Miss Effect in Gambling. *Journal of Gambling Studies*, 36, 653–668.

Rosenbaum, P. R., and D. B. Rubin. 1985. Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *American Statistician* 39: 33–38. https://doi.org/10.2307/2683903.

Rubin, D. B. 2008. For objective causal inference, design trumps analysis. *Annals of Applied Statistics* 2: 808–840. https://doi.org/10.1214/08-AOAS187.

Seru, A., Shumway, T., & Stoffman, N. (2010). Learning by trading. *The Review of Financial Studies*, 23(2), 705-739.

Sharman, S., & Clark, L. (2016). Mixed emotions to near-miss outcomes: A psychophysiological study with facial electromyography. *Journal of Gambling Studies*, 32, 823-834.

Thaler, R. (1980). Toward a positive theory of consumer choice. *Journal of economic behavior & organization*, *1*(1), 39-60.

Thaler, R. H., Ziemba, W. T., 1988. Anomalies: Parimutuel betting markets: Racetracks and lotteries. *The Journal of Economic Perspectives* 2 (2), 161–174.

Thaler, R. H., & Johnson, E. J. (1990). Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management Science*, *36*(6), 643-660.

Figure 1. Gambling outcomes effects on future risk

The figure presents 99 percent confidence intervals for the coefficients associated with *NetWin* and *NearMiss* observed in the previous bet. The full regression model includes similar controls as in the abovementioned analysis of days 1-3, e.g., indicators for sizeable win/loss and bettors characteristics. To avoid the end-of-the-game problem, i.e., the possibility that a risk taker changes her betting strategy when she nears her exit from the game, we end the analysis four days before her last day as a gambler in our sample. To be consistent with the sample construction from previous sections, we focus only on individuals/days where individuals observed the outcome of their bets before betting again. The dependent variables were *Ln(Number of Bets)* and *Ln(Mean stake)*. Therefore, the confidence intervals show the percentage impact on the particular variable.

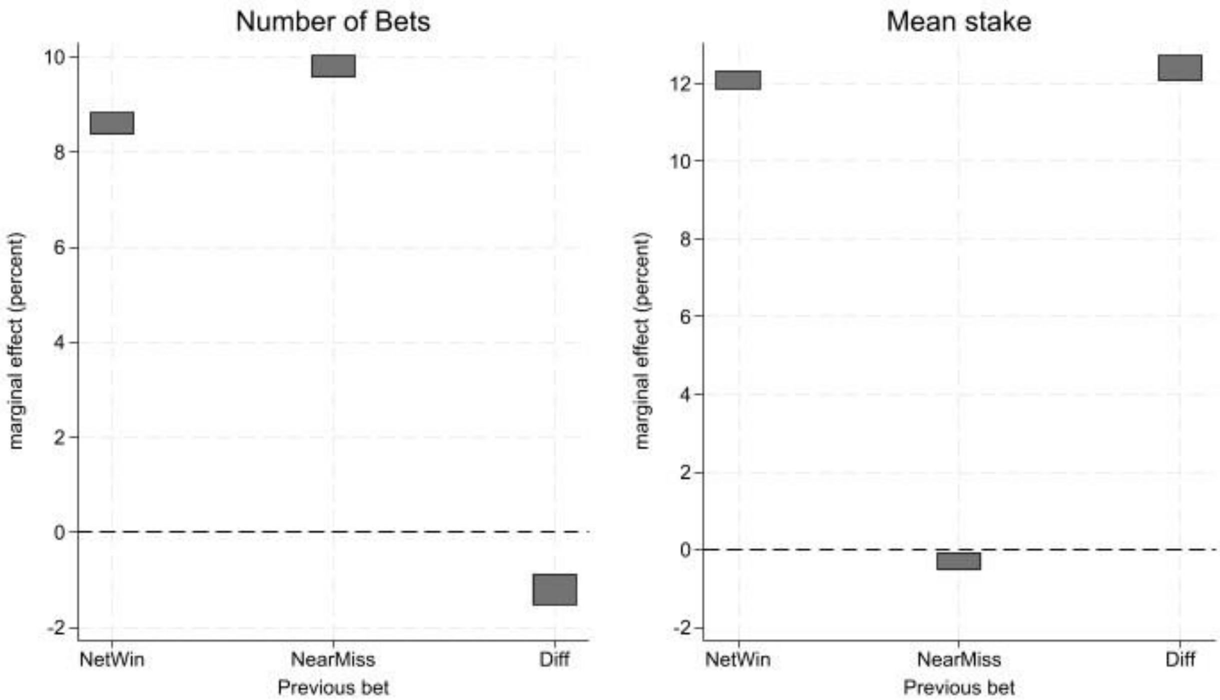

Table 1. Basic descriptive statistics: Mean and median distributions for betting characteristics across age groups

The sample consists of bettors whose first sports bet occurred after April 1, 2005. Columns correspond to daily characteristics of individuals actively betting for more than ten days. The first number on each cell represents the total number of observations (bettor*days). The first four columns describe the conditional distribution for betting on Accumulator and Non-Accumulator, respectively. Specifically, we only consider bettor*day observations where the bettor places the given type of bet (accumulator or simple bet) on the given date. The last two columns contain unconditional distribution for daily stakes. Specifically, in the last two columns, we consider all bettor*days where the bettor places either type of bet (accumulator or simple bet), and if the bettor does not place the given type of bet, the stake is set to 0 for the given bettor*day.

Age group	Statistic	Odds		Stake			
		Accumulators	Simple bets	Accumulators	Simple bets	Accumulators	Simple bets
<20	N	43,653	8,936	43,685	21,755	51,221	51,221
	Mean	218.38	2.20	117.56	124.32	100.26	52.80
	Median	8.18	1.47	50.00	40.00	40.00	0.00
20-30	N	1,159,331	174,446	1,161,679	607,987	1,414,492	1,414,492
	Mean	512.26	3.01	269.42	289.32	221.27	124.36
	Median	12.29	1.69	65.00	70.00	50.00	0.00
30-40	N	1,602,699	232,286	1,607,057	1,028,943	2,096,517	2,096,517
	Mean	738.77	3.33	393.86	411.09	301.90	201.76
	Median	15.17	1.80	95.00	100.00	50.00	0.00
40-50	N	1,347,372	171,820	1,353,793	1,012,587	1,900,578	1,900,578
	Mean	855.40	3.75	318.17	354.09	226.64	188.65
	Median	16.52	1.84	80.00	95.00	40.00	20.00
50-60	N	924,817	93,696	931,525	772,734	1,397,034	1,397,034
	Mean	1,106.80	4.43	187.12	213.93	124.77	118.33
	Median	20.84	1.94	60.00	84.00	30.00	30.00
>60	N	593,162	48,591	599,638	567,498	955,698	955,698
	Mean	876.56	4.38	145.43	176.23	91.25	104.65
	Median	21.59	2.10	50.00	66.00	20.00	30.00
missing	N	71,795	6,218	71,979	55,160	106,383	106,383
	Mean	708.73	3.31	231.33	201.18	156.52	104.31
	Median	27.78	2.10	70.00	80.00	30.00	20.00
Total	N	5,742,829	735,993	5,769,356	4,066,664	7,921,923	7,921,923
	Mean	789.57	3.55	287.72	304.07	209.54	156.09
	Median	16.16	1.80	70.00	86.00	40.00	10.00

Table 2. Distribution of long-term betting activity across age groups

The sample consists of bettors whose first sports bet occurred after April 1, 2005. Each row corresponds to an age group, specifically, the age of the bettor as of January 2012. Columns represent the number of distinct dates where the bettor placed a sports bet. The first number in each cell equals the total number of bettors in the given age group who placed sports bets on the given number of distinct dates; the second row equals the percentage of bettors in the given age group who placed sports bets on the given number of distinct dates over their lifetime.

Age group	Number of bettors: Distribution by number of days across age groups								
	1	2	3	4-10	11-20	21-30	31-100	>100	Total
<20	337	309	264	843	572	257	423	61	3,066
	10.99	10.08	8.61	27.5	18.66	8.38	13.8	1.99	100
20-30	2,977	2,275	1,913	5,948	4,417	2,434	6,133	3,652	29,749
	10.01	7.65	6.43	19.99	14.85	8.18	20.62	12.28	100
30-40	1,906	1,297	1,073	3,712	3,203	1,903	5,618	5,422	24,134
	7.9	5.37	4.45	15.38	13.27	7.89	23.28	22.47	100
40-50	1,377	904	686	2,436	2,044	1,252	3,814	4,658	17,171
	8.02	5.26	4	14.19	11.9	7.29	22.21	27.13	100
50-60	999	544	384	1,220	919	581	1,968	3,085	9,700
	10.3	5.61	3.96	12.58	9.47	5.99	20.29	31.8	100
>60	560	361	234	679	546	373	1,077	1,984	5,814
	9.63	6.21	4.02	11.68	9.39	6.42	18.52	34.12	100
missing	639	261	121	287	147	80	185	231	1,951
	32.75	13.38	6.2	14.71	7.53	4.1	9.48	11.84	100
Total	8,795	5,951	4,675	15,125	11,848	6,880	19,218	19,093	91,585
	9.6	6.5	5.1	16.51	12.94	7.51	20.98	20.85	100

Table 3. Continued betting after the first day (LP Model)

The sample consists of risk-takers whose inception we can observe, i.e., those whose first bet occurs after April 1, 2005. We also exclude those bettors who did not know the results of the previous bet when making the new one (6,543 bettors representing 7.1% of participants on the first day). We report coefficient estimates of a linear probability model. The dependent variable is a dummy variable equal to one if the individual continues betting after the first day. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Heteroskedasticity consistent standard errors are reported in parentheses. In columns 2 and 4, we use grouped fixed effects on the number of accumulator bets: the baseline is no accumulator (47.4 % of observations), then 1-2 (42.8% of observations), 3-9 (9.1%), and ≥10 (0.76%).

Variables	(1)	(2)	(3)	(4)
Net win	0.054***	0.052***	0.053***	0.051***
	(0.003)	(0.003)	(0.003)	(0.003)
Near miss	0.009***	0.010***	0.009***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)
Accumulator	0.010***		0.010***	
	(0.003)		(0.003)	
Large loss			-0.016*	-0.019**
			(0.009)	(0.009)
Large win			0.008	0.008
			(0.010)	(0.010)
Male	0.085***	0.085***	0.085***	0.085***
	(0.003)	(0.003)	(0.003)	(0.003)
Age group FE, year FE	yes	yes	yes	yes
Grouped Accumulator FE	no	yes	no	yes
R^2, adjusted	0.050	0.051	0.050	0.051
N (Observations)	85,042	85,042	85,042	85,042

Table 4: Near-miss effects, comparison with Accumulator bet using RCT approach.

Panel A. Near-miss effect versus Accumulator betting – Full sample.

This table reports the Average Treatment Effect on Treated (ATET), measuring the impact of near misses and net wins on the propensity to continue gambling after the first day. We use the same sample as in Table 3. In Panels A and B, exact matching was done using other coordinates from the regression model, i.e., a set of dummies: *Male*, *Large win*, *Large loss*, and *Net win*.

In Panel A, the treatment variables are (1) experiencing a near miss, (2) placing at least one accumulator bet, and (3) placing an accumulator bet and not experiencing a near miss. The dependent variable is staying in the game after the first day. Therefore, the ATET is a percentage point increase for continuing in the game after day one under (1)-(3) outcomes of using risky accumulator bets. Matching is conducted using nearest neighbor matching on the common support, using Mahalabish distance. The standard errors of the ATET (in parentheses) are computed with the robust option (at least two suitable matches for each treated).

Probability to continue betting after the first day	(1) Near Missed	(2) Accumulator	(3) Accumulator but not Near Missed
ATET	0.0108*** (.0031)	0.0033 (.0028)	-0.0030 (.0022)
p-value	<0.001	0.244	0.171
Number of treated	9,894	65,517	55,623
Number of observations	83,184	83,184	83,184

Panel B. Near-miss effect on sub-sample of Accumulator's bets.

In Panel B, we use the same matching coordinates as in Panel A; and we restrict the sample to only accumulator bets. The treatment effect is the near miss, and the control variables are as follows. In column (1), we use the same set of controls as in Panel A. In column (2), we add exact matching on the number of accumulator bets, and column (D) includes the additional matching variable, mean odds.

Matching is conducted using nearest neighbor matching on the common support, using Mahalabish distance. The standard errors of the ATET (in parentheses) are computed with the robust option (at least two suitable matches for each treated). **, and * denote statistical significance at 1%, 5%, and 10%, respectively. For the benefit of space, we present a balancing summary only for Panel B. In other cases, the quality of matching is similar, and detailed balancing tests, including graphs for control variables, are available in the Internet Appendix.

Probability to continue betting after the first day	(1) Standard matching set [Panel A]	(2) (1) + exact matching # of Accumulator's bet	(3) (2) + matching variable mean odds
ATET	0.0114*** (0.003)	0.0114*** (0.003)	0.0117*** (0.0045)
p-value	<0.001	<0.001	0.010
Number of treated	9,894	9,799	9,783
Number of observations	65,517	65,325	65,223
Balance: mean, *age*	-.0001	-.0003	0.0002
Balance: variance ratio, *age*	1.000	1.004	1.0003
Balance: mean, *mean odds*			0.0015
Balance: variance ratio, *mean odds*			1.0035

Panel C. Net win effect, Full sample

This Panel reports the Average Treatment Effect on Treated (ATET), where the treatment experiences a net win on the first day of betting, and the outcome is continued risk-taking after the first day. The setup and estimation were conducted similarly to previous panels, including the starting sample. Exact matching was done using other coordinates from the regression model, i.e., a set of dummies: *Male*, *Large win*, *Large loss.* The treatment variable is *Net win*, and the control set (sub-samples) are set as follows: (1) Standard (full) sample, (2) excluding those winning without a positive effect (excluding win with a net win<0), and (3) estimated on sub-sample of accumulators' bet, and (4) no Accumulator bets sub-sample.

The dependent variable is the indicator for continuing to place bets after the first day of risk-taking. Therefore, the ATET is a percentage point increase for continuing the game after day one under (1)-(4) outcomes of experiencing a net win.

Probability to continue betting after the first day	(1) Standard matching set	(2) (1) + excluding a win without the net win	(3) (1) - Only on a sample of A/R bets
ATET	0.0478*** (0.002)	0.0521*** (0.002)	0.0686*** (0.002)
p-value	<0.001	<0.001	<0.001
Number of treated	14,370	14,370	10,279
Number of observations	81,213	76,619	64,103
Balance: mean, *age*	0.00001	0.00001	0.00001
Balance: variance ratio, *age*	1.00001	1.00001	1.00001

Table 5. Continue betting after the second day. (LPM model)

The sample consists of risk-takers who bet on at least two dates and whose inception we can observe, i.e., those whose first bet occurs after April 1, 2005. In particular, we exclude those bettors who did not know the results of the previous bet when making the new one (5,123 bettors representing 6.2% of participants on the second day). We report coefficient estimates of a linear probability model. The dependent variable is a dummy variable equal to one if the individual continues betting after the second day. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Heteroskedasticity consistent standard errors are reported in parentheses. In columns 2 and 4, we use grouped fixed effects on the number of accumulator bets: the baseline is no accumulator (47.2 % of observations), then 1-2 (41.7% of observations), 3-9 (10.1%), and ≥10 (0.97%).

Variable	(1)	(2)	(3)	(4)
Net win (day 1)	0.013***	0.011***	0.012***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Net win (day 2)	0.063***	0.060***	0.064***	0.061***
	(0.003)	(0.003)	(0.003)	(0.003)
Near miss (day 1)	0.002	-0.000	0.002	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)
Near miss (day 2)	0.015***	0.009***	0.015***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)
Accumulator bet (day 1)	-0.005*		-0.005*	
	(0.003)		(0.003)	
Accumulator bet (day 2)	0.003		0.003	
	(0.003)		(0.003)	
Large loss (day 1)			0.002	0.003
			(0.009)	(0.009)
Large loss (day 2)			0.013	0.009
			(0.009)	(0.009)
Large win (day 1)			0.004	0.004
			(0.009)	(0.009)
Large win (day 2)			-0.011	-0.013
			(0.009)	(0.009)
Male	0.070***	0.070***	0.070***	0.070***
	(0.003)	(0.003)	(0.003)	(0.003)
Grouped Accumulator FE	no	yes	no	yes
R^2, adjusted	0.043	0.046	0.043	0.046
N (Observations)	77,667	77,667	77,667	77,667

Table 6. Continue betting after the third day. (LPM)

The sample consists of risk-takers who bet on at least three dates and whose inception we can observe, i.e., those whose first bet occurs after April 1, 2005. In particular, we exclude those bettors who did not know the results of the previous bet when making the new one (4,621 bettors representing 6.0% of participants on the third day). We report coefficient estimates of a linear probability model. The dependent variable is a dummy variable equal to one if the individual continues betting after the third day. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Heteroskedasticity consistent standard errors are reported in parentheses. In columns 2 and 4, we use grouped fixed effects on the number of accumulator bets: the baseline is no accumulator (47.5 % of observations), then 1-2 (42.1% of observations), 3-9 (9.4%), and ≥10 (1%).

Variable	(1)	(2)	(3)	(4)
Net win (day 1)	0.006***	0.005**	0.005**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Net win (day 2)	0.021***	0.018***	0.021***	0.018***
	(0.002)	(0.002)	(0.002)	(0.002)
Net win (day 3)	0.060***	0.057***	0.061***	0.058***
	(0.002)	(0.002)	(0.002)	(0.002)
Near miss (day 1)	0.004	0.002	0.004	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Near miss (day 2)	0.008***	0.006**	0.008***	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
Near miss (day 3)	0.017***	0.011***	0.016***	0.011***
	(0.003)	(0.003)	(0.003)	(0.003)
Accumulator (day 1)	-0.010***		-0.009***	
	(0.003)		(0.003)	
Accumulator (day 2)	0.006**		0.006**	
	(0.003)		(0.003)	
Accumulator (day 3)	0.000		0.000	
	(0.003)		(0.003)	
Large loss (day 1)			0.005	0.006
			(0.009)	(0.009)
Large loss (day 2)			0.033***	0.032***
			(0.009)	(0.009)
Large loss (day 3)			0.014*	0.009
			(0.008)	(0.008)
Large win (day 1)			0.003	0.003
			(0.009)	(0.009)
Large win (day 2)			0.002	0.003
			(0.009)	(0.009)
Large win (day 3)			-0.016*	-0.016*
			(0.009)	(0.009)
Male	0.055***	0.055***	0.055***	0.055***
	(0.003)	(0.003)	(0.003)	(0.003)
Grouped Accumulator FE	no	yes	no	yes
R^2, adjusted	0.043	0.045	0.043	0.046
N (Observations)	72,218	72,218	72,218	72,218

Appendix

Table 1.A – Dynamic effects on future risk-seeking

The sample consists of risk-takers whose inception we can observe, i.e., those whose first bet occurs after April 1, 2005. In particular, we exclude those observations where betters did not know the results of the previous bet, as well as the first and last three days of their activity in the sample. The full regression model includes similar controls as in the abovementioned analysis of days 1-3, e.g., indicators for sizeable win/loss and bettors characteristics. The dependent variables are Ln(Number of Bets) and Ln(Mean stake), both calculated at the daily level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Heteroskedasticity consistent standard errors are reported in parentheses.

Variables	Log(Mean Stake)	Log (Number of bets)
Net win$_{(t-1)}$	0.121***	0.086***
	(0.001)	(0.001)
Near miss$_{(t-1)}$	-0.003***	0.098***
	(0.001)	(0.001)
Large loss$_{(t-1)}$	0.683***	0.096***
	(0.002)	(0.003)
Large win$_{(t-1)}$	0.562***	0.069***
	(0.002)	(0.003)
Bettor FE	yes	yes
Year FE	yes	yes
R^2	0.669	0.447
R^2, adjusted	0.666	0.442
N (Observations)	6,621,000	6,621,000