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When do reference points update? A field analysis of the effect of prior gains and losses on risk-taking over time

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When do reference points update?

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Abstract

We study how temporal separations affect recurring decision-making under risk and thus ask when reference points update. Using both experimental and panel data from a casino, we analyze how individual risk-taking behavior during a casino visit depends on the outcomes of temporally separated prior visits. Our results show that small prior gains lead to more risk-averse behavior in the next visit, but small prior losses have no effect on subsequent risk-taking. These results suggest an asymmetric temporal effect of small prior gains and losses, whereby gains affect subsequent choices for longer than losses. Thus, the reference point—which determines subsequent risk-taking behavior—updates much faster after small losses than after small gains. Further, we find that risk-taking greatly depends on the size of prior outcomes. Whereas large prior losses also impact subsequent choices and strongly reduce risk-taking, large prior gains only have a marginal effect, if any.

Keywords: Decision-making · Risk-taking · Field experiment · Longitudinal data · Casino gambling
JEL Classification: C23 · C93 · D81 · D90

1. Introduction

Do you remember approximately how much you won or lost during your last casino visit? If so, how would this alter your risk-taking behavior in a future visit?

For recurring decision-making such as in this example, the reference point determines how prior outcomes affect subsequent risk-taking behavior (Weber and Zuchel 2005). Thereby, the reference point serves as a zero point against which changes in wealth, i.e., gains or losses, are coded (Kahneman and Tversky 1979). If the reference point updates after a prior outcome, subsequent risk choices are segregated and thus unaffected by prior gains and losses. However, if the reference point does not fully update after a prior outcome, prior outcomes are integrated into subsequent choices and thus alter future risk-taking (Thaler and Johnson 1990).

Previous studies that have investigated the effect of prior outcomes on subsequent risk-taking behavior show contradictory results. Some studies find that decision makers react to a gain with more risk-averse behavior (e.g., Harrison 2007; Rüdisser et al. 2017), whereas others find that decision makers react to a gain with risk-seeking behavior (e.g., Thaler and Johnson 1990; Keasey and Moon 1996; Ackert et al. 2006; Suhonen and Saastamoinen 2017). Analyses of behavior following a loss show the same ambiguity: While some studies find that decision makers react to a prior loss with risk-seeking behavior (e.g., Andrade and Iyer 2009, Smith et al. 2009; Huang and Chan 2014), others find that decision makers react to a loss with more risk-averse behavior (e.g., Shiv et al. 2005; Liu et al. 2010).

While most of the earlier studies find that prior outcomes do affect subsequent choices and thus imply that the reference point does not fully update, these studies primarily focused on choices that follow immediately after the prior outcomes are observed. In the experiment developed by Thaler and Johnson (1990), for example, participants observe a prior gain or loss and then immediately afterward choose between a gamble and a sure outcome. In several other studies (e.g., Shiv et al. 2005; Andrade and Iyer 2009; Imas 2016), participants invest money in a lottery or in a risky asset over several rounds. After each round, the participants observe the outcome and immediately decide how much to invest in the next round. The same also holds true for field studies. Suhonen and Saastamoinen (2017), for example, analyze horse race bettors' behavior during a single race day. The race day consists of 10 races that occur within three hours, which does not leave much time for thought between races.

Many real-life decisions, however, are not immediately made one after the other but rather temporally separated. For example, decision makers may bet on their favorite football team once per week or invest money in a financial asset once per month. To date, the consequences regarding updating the reference point remain unclear if a decision maker has more time to reflect on his or her decision outcomes, to complete other tasks between the decisions, or even to discuss the experience with someone else. Longer passages of time between a decision outcome and subsequent decision-making might reset the decision makers' behavior and make the effect of the prior outcome negligible, thereby leading to an update of the reference point. Alternatively, the effect of the prior outcome might outlast the temporal separation in decision-making, implying that the reference point has not fully updated. In this paper, we thus ask how a temporal separation between observing a decision outcome and subsequent decision-making influences reference-point updating. Furthermore, we investigate whether the effect of a temporal separation in the presence of a prior gain is different from the effect of a temporal separation in the presence of a prior loss.

We address these open questions by using data from a Swiss casino, which offers several major advantages.[1] First, casino customers act in a natural environment and typically make recurring decisions under risk. Thereby, the customers decide themselves how many gambles they want to play and when they want to leave the casino. Second, casino customers face real gains and losses, which act as strong incentives to reveal their true behavior. Third, the risk-taking behavior of customers is readily observable through the casino's reporting system. In addition, fourth and most importantly, returning customers can be observed over multiple visits that form naturally occurring temporal separations between prior outcomes and subsequent decisions.

To test how a temporal separation between decisions influences reference-point updating, we conduct two different empirical studies. First, we run a randomized field experiment in the casino; second, we analyze a large panel data set that contains the gambling records of casino customers over

[1] Casinos are a well-recognized area for studying decision-making under risk. Indeed, scholars study individual risk-taking behavior in casinos (e.g., Croson and Sundali 2005; Narayanan and Manchanda 2012; Islam et al. 2014; Rüdisser et al. 2017) and reconstruct casino-like tasks for laboratory experiments (e.g. Chau and Phillips 1995; Weber and Zuchel 2005; Cárdenas et al. 2014).

time. For the experiment, we randomly selected customers to receive 5 Swiss francs (CHF)[2] upon entering the casino in March 2016, which they were asked to bet on either red or black on a modified roulette wheel, with a winning probability of 50%. This procedure exogenously determined the outcome of the first gamble and resulted in 152 participants who started their casino visit with a gain and 154 participants who started their casino visit with a loss. The control group consists of 218 casino customers who entered the casino normally. We then analyzed the gambling behavior of the winners, the losers and the control group during their initial visit and during any subsequent visit within the following four months.

We find that the initial gain of the winners triggers significantly lower levels of risk-taking behavior, not only during the first visit but also during the second visit. Thus, despite a temporal separation, a decision maker's reference point does not fully update in the presence of prior gains. In contrast, the initial loss of the losers does not alter their risk-taking during the initial visit or during any subsequent visit. This result implies that after experiencing a loss, the reference point updates immediately, and subsequent choices remain unaffected by the prior loss.

In our second analysis, we study a large panel data set that was recorded in the same casino between August and November 2016. The data contain the gambling records of 4,348 slot machine players who reported a total of 24,784 visits. Because these players were unaffected by the experiment, we study their gambling behavior in isolation from any exogenous shocks. As the customers accumulate potentially large prior outcomes over time, we can additionally differentiate between the effects of different-sized prior outcomes on subsequent temporally separated risk-taking decisions.

Using player-level fixed-effects regression models, we find that small gains from prior visits trigger significantly lower levels of risk-taking behavior in subsequent visits. This effect persists for the second visit but diminishes afterward. By contrast, small losses from prior visits do not alter risk-taking in any subsequent visit. Thus, in line with our experimental results, we find that decision makers do not update their reference point immediately in the presence of small prior gains but do so in the presence of small prior losses. Regarding large prior losses, we find that gamblers reduce their risk-taking

[2] During the period of data collection, the exchange rate between CHF and U.S. dollars (USD) was approximately at par. Thus, all values can be read as USD as well.

behavior when accumulated losses have strong impacts on decision makers' absolute level of wealth. Large prior gains, however, only marginally reduce risk-taking, if there is any effect at all.

Our paper makes several major contributions to the literature on recurring decision-making under risk. First, we advance the literature by investigating temporal separations between recurring decisions—an element that has not yet been explored in prior studies. Second, we find that a temporal separation between observing a decision outcome and a subsequent risk choice facilitates an update of the reference point in the presence of small prior losses, but it does not lead to an immediate update of the reference point in the presence of small prior gains. Therefore, our results suggest that decision makers mentally cling to small gains, while they edit out losses much faster. Third, large prior outcomes have different effects on risk-taking behavior compared to small prior outcomes due to their potential impact on decision makers' absolute wealth level.

The remainder of this paper is structured as follows: In Section 2, we present the theoretical framework and discuss the related empirical literature. In Section 3, we describe our experimental field study. In Section 4, we present our panel data study, and in Section 5 we conclude.

2. Theoretical framework and related empirical literature

2.1. Theoretical framework

The prospect theory introduced by Kahneman and Tversky (1979) provides a descriptive model for one-shot decision-making under risk. Within this framework, decision makers behave as if they are maximizing the weighted expected utility of a value function (Weber and Zuchel 2005). This value function is defined over gains and losses relative to a reference point and is concave for gains and convex for losses. The loss function is steeper than the gain function, thereby indicating loss aversion (Kahneman and Tversky 1979). Given this value function, prospect theory predicts risk-averse behavior in the domain of gains and risk-seeking behavior in the domain of losses. If a prospect is defined as a one-shot gamble that yields a positive amount x with probability p and a negative amount y with probability $(1 - p)$, the value V of this prospect is defined as

(1) $V = \pi(p)v(x) + \pi(1 - p)v(y)$

where $v(\cdot)$ represents the value function and $\pi(\cdot)$ is the decision-weighting function (Kahneman and Tversky 1979).[3] For example, a coin toss to win or lose \$5 would be valued as

(2) $V = \pi(0.5)v(5) + \pi(0.5)v(-5) < v(0)$

which, due to loss aversion (i.e., $v(5) < |v(-5)|$), is typically less attractive than not gambling at all and thus leads to risk-averse behavior.

In practice, however, many decisions are inherently sequential, such that prior outcomes are present. For example, how would a prior gain or loss of \$10 alter an individual's decision to enter the previously presented coin-toss gamble? Tversky and Kahneman (1981) acknowledge that the effect of prior outcomes on risk-taking behavior is ambiguous because such outcomes could be either considered or neglected in a decision maker's evaluation of potential subsequent outcomes. Thaler and Johnson (1990) extend Kahneman and Tversky's (1979) work by proposing several editing rules, according to which prior outcomes might be coded in a two-stage gamble. They suggest that prior outcomes could be integrated and thus coded jointly with the potential subsequent outcomes; segregated and thus coded separately from the potential subsequent outcomes; or a combination of both.

Integration of prior outcomes

If prior outcomes are consequently integrated with potential subsequent outcomes, which Thaler and Johnson (1990) label the "prospect theory with memory" editing rule, subsequent choices are affected. In the presence of a prior gain of \$10, for example, the decision to enter a coin-toss gamble of winning or losing \$5 is edited and valued as

(3) $\pi(0.5)v(15) + \pi(0.5)v(5) < v(10)$

which is typically less attractive than simply keeping the \$10, given the concave gain function, and leads to risk-averse behavior.[4] In this case, the reference point does not update and thus remains at \$0, which corresponds to the solid value function depicted in Figure 1.

[3] The decision-weighting function depicts one's subjective assessment of the probabilities, where small probabilities are typically overweighted and large probabilities underweighted (Kahneman and Tversky 1979).
[4] If $\pi(0.5)=0.5$, then this situation is equivalent to Equation (3) in Thaler and Johnson (1990).

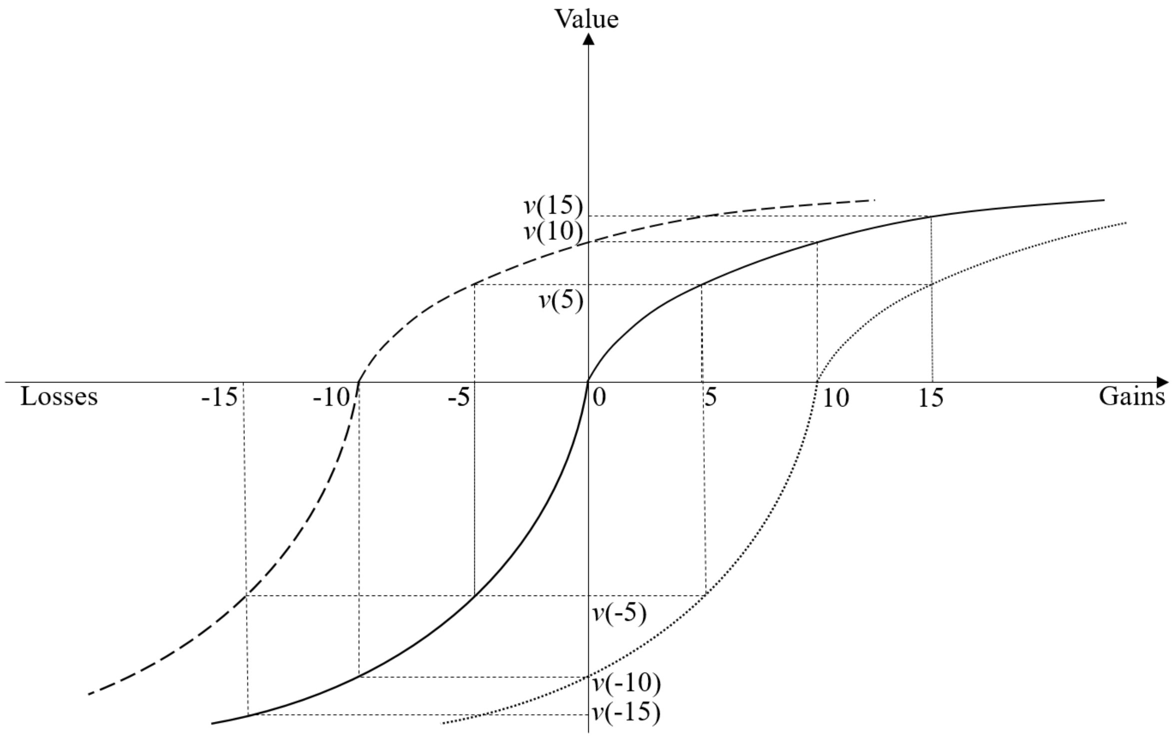

Figure 1: Value functions and reference points for prior gains and losses

In the presence of a prior loss of \$-10, the decision to enter a coin-toss gamble of winning or losing \$5 is edited and valued as

(4) $\pi(0.5)v(-15) + \pi(0.5)v(-5) > v(-10)$

which is typically more attractive than having a guaranteed loss of \$-10, given the convex loss function, and leads to risk-seeking behavior. Again, the reference point does not update and remains at \$0. According to Weber and Zuchel (2005), the integration of prior losses is a major explanation for the escalation of commitment, where the decision maker intensifies risk-taking actions following losses.

Segregation of prior outcomes

Thaler and Johnson (1990) label a consequent segregation of prior outcomes the "prospect theory without memory" editing rule, implying that prior outcomes do not affect the coding of subsequent gambles.[5] After a prior gain of \$10, the reference point updates to \$10, and the subsequent gambling opportunity is evaluated against this new reference point. Thus, the coin-toss gamble of +/-\$5 with a prior gain of \$10 is edited as in Equation (2). The dotted curve depicted in Figure 1 represents the

[5] Because we consider two-stage gambles here, the "prospect theory without memory" editing rule is equal to what Thaler and Johnson (1990) label the "concreteness" editing rule.

updated value function for the second-stage decision. Analogously, in the case of a prior loss of \$-10, the reference point updates to \$-10, and the second-stage gamble is also evaluated as in Equation (2). The dashed curve in Figure 1 represents the updated value function.

Combination of integration and segregation of outcomes

Instead of integrating or segregating prior outcomes into or from subsequent potential outcomes, decision makers could also employ a combination of the two, which Thaler and Johnson (1990) label the "quasi-hedonic" editing rule. According to this rule, a decision maker segregates prior gains from subsequent potential gains but integrates prior gains with subsequent potential losses. Thus, in the presence of a prior gain of \$10, the decision to enter a coin-toss gamble of +/-\$5 is edited and valued as

(5) $\pi(0.5)[v(10) + v(5)] + \pi(0.5)v(5) > v(10)$

which limits the influence of risk aversion and facilitates risk-seeking behavior. This risk-seeking tendency is known as the "house-money effect" (Thaler and Johnson 1990). When the integration and segregation of prior gains are combined, the reference point is regarded as dynamic (Peng et al. 2013). If the second-stage gamble results in a win, the reference point updates to \$10 (dotted curve in Figure 1), but if it results in a loss, the reference point remains at \$0 (solid curve in Figure 1). In contrast, in the presence of a prior loss, editing depends on whether an opportunity to break even exists (Thaler and Johnson 1990). Given no opportunity to break even, the quasi-hedonic editing rule suggests that subsequent outcomes will be segregated. Thus, the coin-toss gamble of +/-\$5 with a prior loss of \$-10 is edited and valued as

(6) $\pi(0.5)[v(-10) + v(-5)] + \pi(0.5)[v(-10) + v(5)] < v(-10)$

which tends to produce risk-averse behavior because the reference point updates to \$-10 (dashed curve in Figure 1). If $2\pi(0.5) = 1$, this evaluation simplifies to the strict segregation of prior losses, as in Equation (2). In contrast, if the decision maker has an opportunity to break even, subsequent outcomes are integrated, and the reference point remains at \$0. Thus, the coin-toss gamble of +/-\$5 with a prior loss of \$-10 is edited and valued as in Equation (4), which facilitates risk-seeking behavior and is generally referred to as the "break-even effect" (Thaler and Johnson 1990).

Overview of editing rules for recurring decisions

Table 1 provides an overview of the coding and the risk behavior predicted by the editing rules in the presence of a prior gain and a prior loss. Moreover, the table shows that risk-taking behavior is inherently linked to the question of whether the reference point has updated.

Table 1: Overview of editing rules

	Prior gains		**Prior losses**		
Editing rule	**Coding**	**Risk behavior**	**Coding**	**Risk behavior**	**Reference point**
Prospect theory with memory	integration	risk-averse	integration	risk-seeking	no update
Prospect theory without memory	segregation	risk-averse	segregation	risk-averse	update
Quasi-hedonic editing rule	integration with subsequent loss segregation with subsequent gain	risk-seeking	segregation without break-even opportunity integration with break-even opportunity	risk-averse without break-even opportunity risk-seeking with break-even opportunity	dynamic

2.2. Related empirical literature

Many studies have empirically tested the effect of prior outcomes on risk-taking behavior and thus their effect on the movement of the reference point. For example, Thaler and Johnson (1990) asked participants in their laboratory study to choose between a gamble and a safe amount of money immediately after observing a prior gain or loss. They find that decision makers become more risk-seeking in the presence of prior gains, which supports the house-money effect. More recently, Suhonen and Saastamoinen (2017) investigated individual-level betting data from 10 horse races that occurred within three hours. Because the bettors made riskier wagers in the domain of gains, their findings are also consistent with the house-money effect. Additionally, several studies have provided further evidence for the house-money effect (e.g., Ackert et al. 2006; Battalio et al. 1990; Frino et al. 2008; Houser and Xiao 2015; Hsu and Chow 2013).

By contrast, Harrison (2007) reexamines Clark's (2002) experimental data and finds that decision makers who were endowed with house money showed higher levels of free-riding when asked to contribute to a public good immediately afterward. The data from Clark's (2002) public-good experiment can thus be interpreted as more risk-averse behavior following an initial provision of money, i.e., a prior gain. Similarly, the field experiment conducted by Rüdisser et al. (2017) shows that a prior gain leads to more risk-averse behavior. In their study, ordinary casino customers received free play vouchers at the entrance and thus started gambling with a prior gain. Thereafter, these customers showed more risk-averse behavior during their casino visit compared to customers who entered the casino without receiving free playing vouchers.[6]

Turning to the effect of prior losses, Andrade and Iyer (2009) ran three laboratory experiments to analyze the effect of anticipated and experienced losses on subsequent behavior. In the first step, Andrade and Iyer (2009) asked their participants to set up a plan for how they would place bets in two subsequent gambles. Thereafter, the participants played the first round and observed the outcome, but prior to the second gamble, they were given a chance to deviate from their planned behavior. The authors find that decision makers plan to avoid risk in round two when anticipating a loss in round one, but they in fact showed significant risk-seeking behavior in the second gamble when they experienced a loss as the outcome of their first gamble. In their field study, Huang and Chan (2014) find the same result when analyzing investor data. They compare investors' morning and afternoon risk-taking and find that investors seek to break even if they experience morning losses, implying that risk-seeking behavior increases following a loss. Several other studies also find evidence for this break-even effect (e.g., McGlothlin 1956; Smith et al. 2009; Zhang and Semmler 2009; Suhonen and Saastamoinen 2017).

By contrast, the experimental study of Shiv et al. (2005) shows that participants invested less in a risky asset after they experienced a loss in the previous investment round. Thus, they became more risk-averse after a loss. Similarly, when studying investors' market behavior on the Taiwan Stock Exchange, Liu et al. (2010) find that investors are more conservative in the afternoon when experiencing morning losses.

Finally, in the laboratory experiments conducted by Imas (2016), the participants were asked to make investment decisions across four rounds. Imas (2016) finds that decision makers become more risk-seeking in the fourth round if the prior losses are perceived as paper losses, while decision makers become more risk-averse in the fourth round if the prior losses are realized, i.e., transferred to another

[6] Furthermore, a few studies, such as Gertner (1993) and Etchart-Vincent and l'Haridon (2011), show that a prior gain does not change subsequent risk-taking behavior.

account, after three rounds. Thus, Imas (2016) concludes that the realization of losses updates the reference point.

The literature review shows that most studies find that a prior outcome leads to a significant change in subsequent behavior and thus that the reference point does not fully update. Independently of the direction of the reported effects, earlier research exclusively focused on setups or settings in which decision makers have relatively little time between observing an outcome and making the next decision. One notable exception is Hsu and Chow's (2013) field study, in which they investigate investor behavior following gains over purchasing periods of three, four, five, and ten trading days. The authors find that investors who realized a gain made riskier investment decisions in short subsequent purchasing periods, but not in long subsequent purchasing periods. The authors thus conclude that the house-money effect weakens, suggesting that an investor's reference point adapts over time. However, in their analysis, Hsu and Chow (2013) do not address the self-selection issues that potentially drive their results. More precisely, their control group, which consists of investors without morning gains, might be systematically different from their comparison group, which consists of investors with morning gains.

With regard to the editing rules, Thaler and Johnson (1990) do not comment on the aspect of time between multiple decisions. However, the literature has mostly neglected the impact of temporal separations between observing an outcome and making the next decision on the updating of the reference point. Thus, it remains unclear whether and how prior outcomes affect decisions over longer time periods. We address this important issue by using data from a real-life casino, where temporal separations naturally occur between the casino visits of the customers.

3. Field experiment

Our field experiment was conducted in a Swiss casino. In this casino, customers receive a personalized playing card upon entering. The customers use this card to play at slot machines but also to play a table game such as "black jack" or "roulette". When playing at a slot machines, customers insert the card directly into the slot machine and when playing at table games, customers hand the card to the croupier and play with traditional casino chips. While the personalized playing card has several advantages for gamblers, such as a bonus point program and increased convenience while gambling, it has also one major advantage for the casino operator: it allows the operator to track the gambling behavior of its customers. For slot machines, key gambling data such as the total wager, the number of games, and the wins and losses of each customer are automatically stored in the casino's reporting system. For table games, the croupiers manually enter the same data into the reporting system as soon as a customer decides to leave the table. Thus, the casino can construct a rich data set of each customer's gambling experience over time.

The purpose of the experiment was to randomly determine the outcome of the first wager, which we refer to as the treatment wager, and thus assign individuals to a group with a prior loss or a prior gain. Thereafter, we observed the customers' subsequent decision-making behavior during their entire visit as well as during subsequent visits using the casino's data from the playing cards.

3.1. Procedure and design

In late February 2016, six thousand email addresses from the casino's mailing list were randomly chosen.[7] These six thousand people were informed by email that they would receive 5 CHF worth of free play the next time they enter the casino. They were also informed that the 5 CHF must be wagered on a modified roulette wheel, with a 50% probability of doubling it and a 50% probability of losing it.

Upon entering the casino, the 5 CHF were automatically loaded onto the personalized playing cards of the eligible customers. These 5 CHF were only valid on the modified roulette wheel located next to the entrance and could be wagered on either red or black.[8] In total, 306 customers received 5 CHF worth of free play upon entering and played the modified roulette wheel as their first gamble.[9] These 306 customers form our treatment group. Through the modified roulette wheel, the treatment group was randomly split into 152 winners (who doubled their 5 CHF) and 154 losers of the treatment gamble (who lost their 5 CHF). Thus, those who lost the treatment wager started gambling in the presence of a prior loss, and those who won the treatment wager started gambling in the presence of a prior gain.

[7] The entire list includes roughly 10,000 addresses and consists of casino customers who have visited this particular casino before, thereby having agreed to receive information on events, promotions, etc.
[8] Each eligible customer could play on the modified roulette wheel only once. Because the modified roulette wheel had no house edge, other customers were not allowed to play or to buy in with their own money.
[9] We excluded 16 customers (5%) who received the free play but did not play the modified roulette wheel as their first gamble.

Our control group consists of all customers who were also on the mailing list but did not receive an email. These customers entered the casino without playing the modified roulette wheel but were also tracked through their individual playing cards. Thus, all individuals come from the same population, and any differences between the treatment and the control group should not be driven by different individual characteristics.[10] Following this procedure, we constructed a control group of 218 participants.

The data collection occurred from March through June 2016. During this period, we tracked the treatment gamble and the subsequent gambling behavior of both our treatment and control groups. This setup generated a unique and rich data set of 524 customers, several of whom made more than one visit to the casino within the reported period. Figure 2 shows our experimental design. Comparing the behavior of subjects from the treatment group to the control group in visit 1, visit 2, and visit 3 allowed us to examine how the initial exogenous win or loss affected reference-point updating in the presence of temporally separated decisions.

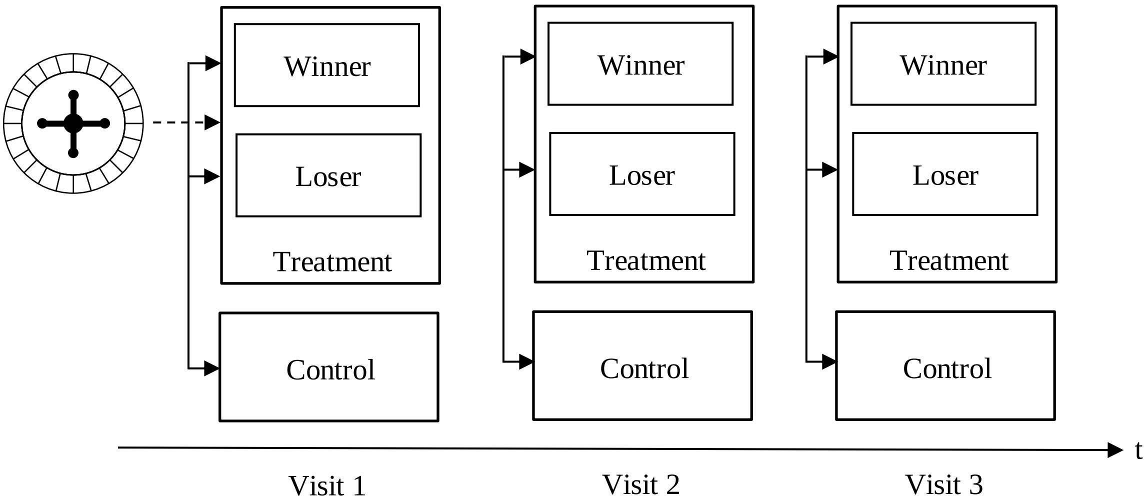

Figure 2: Experimental design

[10] In subsection 3.4, we address the experimental validity in more detail by comparing the treatment group to the control group before the experiment took place.

3.2. Variables and data structure

Apart from the treatment wager, which is exactly one gamble, the data collected from the players' individual playing cards are at the session level. A session is defined as all games played at a specific slot machine or table game.[11] A visit consists of all sessions a participant plays during one trip to the casino, with the first visit being an individual's gambling on the day he or she spun the modified roulette wheel or entered our control group. All following visits are then enumerated.

In our analysis, we employ three main variables that measure an individual's attitude toward risk. The first measure is the *average wager*, which we define as the average wager per game within a session. The average wager has been used in several other studies that analyze risk-taking behavior in different settings such as horse races (McGlothlin, 1956), game shows (Gertner, 1993), laboratory experiments (e.g., Haigh and List 2005), or casinos (Rüdisser et al. 2017). For the same type of game, e.g., blackjack or a particular slot machine, higher wagers are associated with higher levels of risk-taking because higher wagers yield higher potential returns but simultaneously risk higher potential losses. The second measure is the *total wager*, which is adapted from Suhonen and Saastamoinen (2017) and refers to the total amount a gambler has wagered within a session. Thereby, a higher amount wagered in total implies higher risk-seeking behavior, and vice versa. The third measure is labelled *casino risk measure* and is calculated as a game's specific risk factor multiplied by the *total wager*. A game's specific risk factor is determined by the casino and depicts both the percentage a gambler would lose if he or she played the same game an infinite number of times and the volatility of the payoffs. Thereby, slot machines with low risk factors have a higher payout rate but also lower volatility of payoffs, and vice versa. For example, slot machine A might have a risk factor of 2%, whereas slot machine B has a risk of factor of 8%. Thus, slot machine A returns more money to gamblers in absolute terms; however, slot machine B has higher volatility of payoffs. Slot machine B is thus considered riskier. A higher *casino risk measure* is therefore associated with higher levels of risk-taking, and vice versa.

Our data set also includes various control variables. For example, we observe the *number of games* played during a session and a visit, which allows us to control for the length of a player's

[11] If a subject played at a slot machine or a table and then moved around the premises of the casino to go to the toilet or have a drink before finally returning to the same slot machine or table, two sessions were reported.

gambling experience. We also measure the number of days between two visits, which we label *days until return*. For the multivariate analysis, we also construct various dummy variables, such as *session dummies* and *visit dummies*, to control for general differences or trends across sessions and visits. Finally, we create a *game source dummy* for each table game and slot machine to control for the individual characteristics of the different games, such as minimum bets, maximum bets, or the payoff structure.

3.3. Descriptive statistics

Table 2 shows the descriptive statistics of our experimental study for visit 1, visit 2 and visit 3. The mean values are higher than the median values, implying that there are a few gamblers who play extensively within a visit. However, in Switzerland, social welfare regulations require casino operators to ensure that no individual gambles to the point of risking personal bankruptcy (Meyer 2009).

For all three visits, the *average wager* fluctuates around 12 CHF, and the *total wager* falls between 4,986 CHF and 5,993 CHF.[12] Finally, the *casino risk measure* is 240 for the first visit, 276 for the second visit, and 228 for the third visit. The data reveal that for all three risk measures, the average risk-taking behavior was highest in visit 2.

Studying the attrition rate of our participants, we find that 469 (371) participants returned to the casino at least once (twice) within four months. Analyzing the return rates per group in detail, we observe that 139 (91.4%) winners of the treatment wager, 138 (89.6%) losers of the treatment wager, and 192 (88.1%) control group participants returned to the casino for a second visit. Analyzing the return rates for the third visit, we again find that the relative reduction in group size is very similar among the three groups: compared to the second visit, 111 (79.9%) winners, 106 (76.8%) losers and 154 (80.2%) control group participants remained in our sample. In total, these return rates appear similar for all three groups, and no group exhibits a systematically higher or lower attrition rate compared to the other two groups.

[12] A *total wager* of 5,000 CHF seems very high but should not be confused with actual wins or losses. For example, if a gambler plays 50 hands of blackjack and wagers 20 CHF per game, his *total wager* is 1,000 CHF. However, her loss is only 200 CHF if we assume that she wins only 40% of the games.

Table 2: Descriptive statistics for visit 1, visit 2 and visit 3

	N	Mean	Std. dev.	Median
Visit 1 attributes				
number of games	524	1,582	1,979	912
number of sessions	524	5.1	5.5	3
average wager	524	11.9	28.2	2.4
total wager	524	5,227	9,416	2,241
casino risk measure	524	240	392	115
Visit 2 attributes				
number of games	469	1,570	1,863	914
number of sessions	469	5.1	5.6	3
average wager	469	12.6	36.3	2.3
total wager	469	5,966	14,322	2,520
casino risk measure	469	276	795	118
days until return	469	17.5	24	7
Visit 3 attributes				
number of games	371	1,531	1,823	915
number of sessions	371	5.2	6.0	3
average wager	371	11.9	29.6	2.2
total wager	371	4,986	9,654	2,318
casino risk measure	371	228	399	114
days until return	371	10.2	13.2	6

Notes: Descriptive statistics of gambling behavior for visit 1, visit 2 and visit 3 collected during the experimental field study between March and June 2016.

3.4. Experimental validity

Before proceeding with our main analysis, we check the validity of our experiment. One concern might be that the email attracted a specific group of gamblers who would not have come to the casino without the promised 5 CHF. To rule out this concern, we also collected data on the gambling behavior of the participants during their visit prior to the experiment, i.e., visit 0. Thus, we can analyze whether the later-treated participants were initially different from the participants in the control group and thus somehow self-selected into the treatment group.

Of the 306 later-treated participants, i.e., winners and losers combined, 303 (99.0%) had visited the casino at least once in two months before the experiment. In comparison, of our control group of 218 participants, 200 (91.7%) reported a visit within two months prior to the start of our experiment. These figures provide evidence that refutes the concern about self-selection, as more and not fewer participants from the treatment group compared to the control group reported a visit 0 prior to our intervention. Moreover, the results of the t-tests displayed in Table 3 show that the *average wager*, the *total wager* and the *casino risk measure* are not significantly different between the treatment and the control groups during the visit before the experiment. This preliminary analysis therefore supports the validity of our experimental design.

Table 3: T-tests that compare treatment and control groups before the experiment (visit 0)

	treatment: winner and loser			control			|t|
	N	Mean	SE	N	Mean	SE	
Visit 0 attributes							
average wager	303	12.16	1.57	200	12.45	1.89	0.12
total wager	303	6,110.90	573.3	200	5,959.39	771.33	0.16
casino risk measure	303	299.44	27.00	200	298.53	38.49	0.04

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

3.5. Results

In this section, we first present the impact of the treatment wager on risk-taking behavior within the entire first visit. This first part of the results section is comparable to all existing laboratory and field studies because we analyze the effect of a prior outcome on subsequent risk-taking in situations where decision makers have little time for thought. Thereafter, in the second part of our results section, we focus on the effect within the second and third visits, which are temporally separated from the first visit. Finally, we discuss the limitations of our experimental study.

Before turning to the results, we follow Suhonen and Saastamoinen (2017) and logarithmize our three measures of risk because their distributions are heavily left-skewed.[13] The three main measures of risk that we use in our subsequent analysis are therefore *ln(average wager)*, *ln(total wager)*, and *ln(casino risk measure)*.

[13] Nevertheless, if we use the absolute values, the results remain qualitatively the same.

3.5.1. Impact of the treatment wager on visit 1

Figure 3 shows the impact of the treatment wager on the mean *ln(average wager)* for the entire visit 1, including whiskers that illustrate the standard deviation. Within visit 1, the winners of the treatment wager show lower levels of risk-taking behavior compared to the control group. By contrast, the losers of the treatment wager do not seem to exhibit different risk-taking compared to the control group. This first result indicates that a prior gain leads to lower subsequent risk-taking, while a prior loss has no effect.

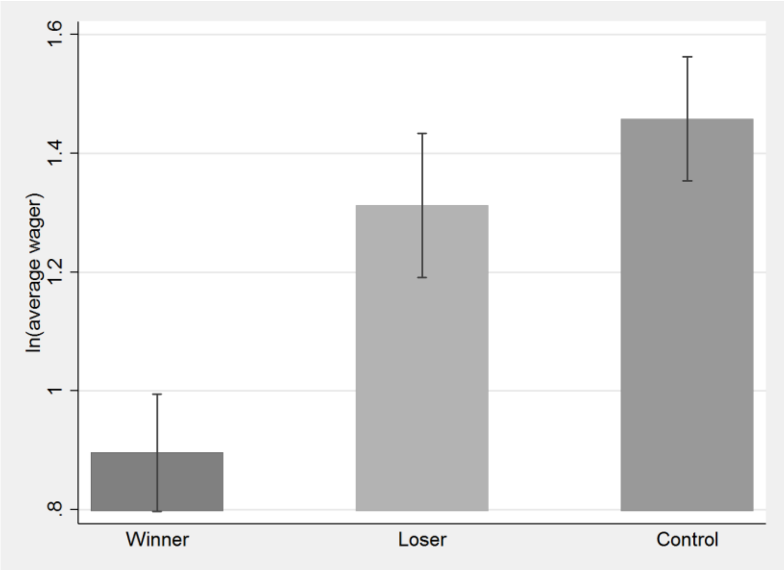

Figure 3: *ln(average wager)* for entire visit 1

Proceeding to the multivariate analysis, we analyze our data from visit 1 at the session level. We code both treatment groups as dummies (*winner* and *loser)* and include them in a linear regression as our main variables of interest. For visit 1, we observe 524 participants playing a total of 2,676 sessions. Table 4 shows the results of the three regressions run on *ln(average wager)*, *ln(total wager)*, and *ln(casino risk measure)*. In Column (1) and Column (2*)*, we include *session dummies* to control for the number of sessions played as well as *game source dummies*. In Column (3), we exclude the *game source dummies* because the *casino risk measure* already incorporates the characteristics of the different games. Finally, we include the variable *cumulative number of games played* in all of the estimated models.

The estimates in Table 4 show that winners significantly reduce their risk-taking behavior while losers do not significantly change their risk-taking compared to the control group. This finding is consistent for all three risk measures. Specifically, Table 4 shows that in comparison with the control group, the winners reduce their average wagers by 22% given the same table game or slot machine. Similarly, the winners reduce their total amount bet by 27%, and the casino risk measure decreases by 36%. Finally, when we test for differences in the coefficients of *winner* and *loser*, we find in all three columns that winners also show significantly lower levels of risk-seeking behavior compared to the losers.[14]

Table 4: Results of OLS estimation for entire visit 1

	ln(average wager)	*ln(total wager)*	*ln(casino risk measure)*
	(1)	(2)	(3)
winner	-0.22***	-0.27***	-0.36***
	(0.08)	(0.10)	(0.11)
loser	-0.10	-0.11	-0.15
	(0.09)	(0.12)	(0.12)
cumulative number of games played	-0.00	0.0004***	0.0004***
	(0.00)	(0.00004)	(0.00004)
session dummies	Yes	Yes	Yes
game source dummies	Yes	Yes	No
N	2,676	2,676	2,676
R^2	0.69	0.40	0.20

Notes: The table reports the OLS estimates for *ln(average wager), ln(total wager)*, and *ln(casino risk measure)* for the visit when the treatment gamble occurred. The data are analyzed at the session level. Heteroscedasticity-robust and clustered standard errors at the player level are reported in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

The analysis shows that initial winners keep their prior gains in mind throughout the entire visit 1, thereby altering their behavior toward lower levels of risk-taking. Because we control for the number of games played and the number of sessions played, more risk-averse behavior is robust toward the duration of gambling. Thus, the reference point of winners does not update after the treatment wager within visit 1. However, in the presence of prior losses, participants do not significantly alter their behavior, implying that the reference point quickly updates.

3.5.2. Impact of the treatment wager on subsequent visits 2 and 3

Any subsequent visit includes a temporal separation that is by far larger than a break between single sessions because participants leave the casino, go home to sleep, go to work, and so forth, before they return to the casino. Therefore, we now turn our attention to the persistence of the effect of the treatment wager in subsequent visits.

[14] The results of Wald tests for the equality of coefficients for Column (1) are as follows: F(1, 523) = 2.73; Probability > F = 0.10; for Column (2): F(1, 523) = 3.35; Probability > F = 0.07; and for Column (3): F(1, 523) = 2.83; Probability > F = 0.09.

Figure 4 shows the mean *ln(average wager)* and the corresponding standard deviation of all three groups for visit 2 and visit 3. The figure illustrates that during visit 2, the winners of the treatment wager again have lower *ln(average wager)* values compared to both the losers and the control group. For visit 3, however, the differences decrease.

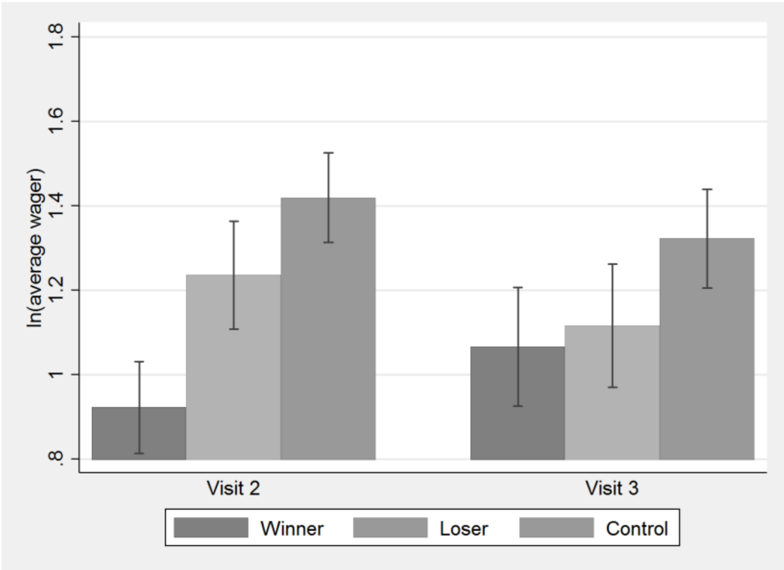

Figure 4*: ln(average wager)* for entire visits 2 and 3

Our multivariate analysis for visit 2 and visit 3 includes 469 participants who played a total of 4,315 sessions. We create interaction terms between the group dummies (*winner* and *loser*) and *visit dummies* to analyze the effect's persistence over time. In comparison to the models shown in Table 4, we now not only include *session* and *game source dummies* but also *visit dummies* as well as dummies for the number of days between the visits and dummies for the number of days that have passed since visit 1, in which the treatment wager occurred. The *visit dummies*, the *days since visit 1 dummies* and the *days since last visit dummies* control for potential selection effects because certain participants decide to return to the casino sooner than others.

Table 5: Results of OLS estimation for entire visits 2 and 3

	ln(average wager)	*ln(total wager)*	*ln(casino risk measure)*
	(1)	(2)	(3)
winner × visit 2	-0.16*	-0.19*	-0.21*
	(0.08)	(0.11)	(0.11)
winner × visit 3	-0.13	-0.32**	-0.20
	(0.09)	(0.13)	(0.14)
loser × visit 2	-0.11	-0.11	-0.12
	(0.10)	(0.14)	(0.14)
loser × visit 3	-0.15	-0.23	-0.05
	(0.09)	(0.14)	(0.16)
cumulative number of	-0.00	0.0001***	0.0001***
games played	(0.00)	(0.00002)	(0.00002)
session dummies	Yes	Yes	Yes
game source dummies	Yes	Yes	No
visit dummies	Yes	Yes	Yes
days since visit 1 dummies	Yes	Yes	Yes
days since last visit dummies	Yes	Yes	Yes
N	4,315	4,315	4,315
R^2	0.72	0.39	0.42

Notes: The table reports the OLS estimates for *ln(average wager)*, *ln(total wager)*, and *ln(casino risk measure)* for the second and third visits after the treatment wager occurred. The data are analyzed at the session level. Heteroscedasticity-robust and clustered standard errors at the player level are reported in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

The results in Table 5 show that an initial gain also leads to risk-averse behavior in visit 2. Winners of the treatment gamble are estimated to reduce their risk-taking behavior in visit 2 by 16% to 21%. For visit 3, the estimated coefficients are still negative but are only significant for *ln(total wager)*. Thus, the data imply that even when controlling for visits and days, prior gains also affect risk choices that are temporally separated. Thus, the reference point has not updated after visit 1.

Our results suggest that the effect of winning the treatment wager dilutes over time. After visit 1, 28.3% of the treatment winners leave the casino with a net win, while only 21.5% of the control group participants leave the casino with a net win. This difference is a direct consequence of the decreased risk taken on by the treatment winners. Therefore, a higher share of the treatment winners start their visit 2 with a win, but not all of them. At the end of visit 2, of those leaving with a net win, the difference between the control group (21.3%) and the winners (26.2%) becomes even smaller. Finally, the difference vanishes completely at the end of visit 3, as 24.6% of the control group and 23.6% of the winners leave the casino with a gain.[15]

In contrast, we find no effect of an initial loss on the *ln(average wager)*, the *ln(total wager)*, and the *ln(casino risk measure)*. The data thus draw a general picture that prior losses do not significantly influence subsequent decision-making for longer time intervals. Given our previous result that losses do not have an effect within visit 1, it is not surprising that they also have no effect in any subsequent visit. The reference point after losses seems to immediately update; thus, subsequent decisions are unaffected, independent of temporal separations.

3.5.3. Limitations

One limitation of our field experiment is that the decision makers who participated in our study were informed by email that they were eligible to participate in the treatment wager. Thus, receiving the email could have resulted in some customers going to the casino who would have not gone without an incentive. These customers might generally be more risk-averse and thus drive our results. Even though our experimental validity tests indicate that this is unlikely to be the case, some concerns might remain. However, the outcome of the treatment wager at the roulette wheel is genuinely random. Thus, because our results show that the winners exhibit significantly lower levels of risk-taking behavior compared to the losers, we can rule out that the email alone explains our results.

Further, in the experimental study we conducted, we classified those who lost the 5 CHF on the modified roulette wheel as losers and thus as decision makers who started their gambling in the presence of a prior loss. Because the customers received the email before their actual visit, we argue that they perceive the 5 CHF as their own money; thus, a feeling of a loss was indeed triggered when they were unsuccessful on the modified roulette wheel.[16] However, one could state that the 5 CHF were never perceived as the participants' own money, and no real loss occurred. With the panel data study presented next, we can address this issue because we only study decision makers' gains and losses with their own

[15] We also have information on the gambling behavior of the participants during their fourth, fifth, and sixth visits following the treatment wager. However, we find that the effect of the treatment wager vanishes during the third visit and, in combination, that the group sizes become much smaller with each additional visit we study. We thus limit our analysis to three visits.

[16] In their laboratory experiment, Càrdenas et al. (2014) also distributed money to their treatment group in advance of their experiment, and the authors argue that the participants incorporated the money as their own during the time until their experiment started.

money. Thus, the panel data study also allows us to check the validity of our previously presented results.

4. Panel data study

4.1. Data and variables

We construct the panel data set in cooperation with the same casino as in our experiment. From the beginning of August 2016 until the end of November 2016, the casino tracked the gambling behavior of all gamblers who only played slot machines.[17] The data are aggregated at the visit level and consist of 4,348 individual gamblers with a total of 24,748 visits. For each visit of a gambler, the data set contains the *average wager*, the *total wager* and the *casino risk measure*, which we again employ as our risk measures. However, we focus on the *casino risk measure* because it is the only measure that incorporates each slot machine's inherent riskiness, and it therefore accounts for the choice of slot machine.[18] Further, the net gambling outcome (*result*), i.e., how much a gambler won or lost within a visit, the number of games played, the amount of time spent playing, and the date of the visit are recorded in the data set.

4.2. Descriptive statistics

Table 6 presents the descriptive statistics at the player level, where the average values for each player are calculated before the descriptive statistics thereof are generated.[19] In the four months contained in our data set, a gambler visited the casino 5.7 times on average. The standard deviation for the number of visits is 9.2, implying that there are some gamblers that visit the casino very frequently. Indeed, one individual visited the casino 111 times. An average gambler played 1,074 games within approximately 90 minutes. With regard to our risk measures, an average player wagered 6.7 CHF per game, wagered a total of 2,736 CHF per visit and is expected to lose 134 CHF based on the casino risk

[17] Because the casino was only willing to provide these data, our data set excludes gamblers who only play table games and gamblers who play both table games and slot machines.
[18] Because the data are aggregated at the visit level, we cannot control for *game source dummies*, as in our experiment. Thus, we believe that the c*asino risk measure* is the most adequate measure for these types of data. Nevertheless, our results remain qualitatively identical when we use *total wager* as an alternative measure for risk. The results for *average wager* show the same effect signs. However, the standard deviations when using *average wager* are considerably higher, and the effects are therefore not statistically significant.
[19] An alternative method is to calculate the descriptive statistics over all 24,748 player-visit observations. These statistics are shown in Table A.1 in the Appendix.

measure.[20] The median values are considerably smaller than the mean values which implies that the distributions of *average wager*, *total wager*, and *casino risk measure* are highly skewed to the right.

Table 6: Descriptive statistics (n=4,348)

Measure	Mean	Std. dev.	Median
visits	5.7	9.2	2
days until return	7.9	10.0	4
number of games	1,074	1,483	464
time	89.6	98.1	55.5
average wager	6.7	25.9	1.8
total wager	2,736	7,014	898
casino risk measure	134	308	41
result	-199	719	-73

Notes: The table shows the descriptive statistics at the player level. We first calculate the average for each gambler and then calculate the descriptive statistics based on all 4,348 gamblers. The variable *time* is measured in minutes.

Furthermore, Table 6 reveals that on average, a player loses 199 CHF when going to the casino. However, the median average loss is only 73 CHF; thus, the distribution of *result* is also right-skewed. The standard deviation of *result* is 719, which is more than three times larger than the mean value, implying a large variation in *result*.

4.3. Empirical methods

We use fixed-effects regression models (FE models) to conduct the analysis of our panel data. The main advantages of FE models are that they allow the researcher to control for unobservable but time-constant factors, such as an individual's inherent attitude toward risk, and for factors that change over time but are constant for all individuals, such as new slot machines at the casino or a free drink after five visits (Baltagi 2008). Thus, FE models allow a within-subject analysis to investigate how an individual's attitude toward risk changes depending on different prior outcomes.[21]

In all of the models, we use the natural logarithm of *casino risk measure* as the dependent variable. To estimate the effect of prior gains and losses on risk-taking behavior, we first need to define

[20] These averages are smaller than the averages reported for the experiment. This result is likely due to the nature of slot machines, which typically demand smaller minimum bets and exhibit less inherent risk than table games.
[21] We analyze slot machine players and thus only a subgroup of casino gamblers, which might be different from the entire population of casino gamblers. However, recent developments show that slot machines and electronic gaming machines represent more than 60% of all games played at casinos in the United States (American Gaming Association 2013). Additionally, the classic table games, such as blackjack, roulette, and poker, are also offered on slot machines. Moreover, we use individual fixed-effects models that only use the variation within individuals and not the variation between groups to estimate our effects.

the baseline risk, i.e., the level of risk-taking without any prior outcome.[22] In the following, we present two different approaches to address this issue and introduce the corresponding regression models.

Defining visit 1 as baseline risk without prior outcomes

Following Suhonen and Saastamoinen (2017), we manually set the prior outcome of visit 1 to zero. Thus, visit 1 serves as the baseline risk level without prior outcomes against which our model evaluates the effects of prior gains and losses. In all subsequent visits, the cumulative results from earlier visits constitute the prior outcome for an individual. We therefore split up the cumulative results into gains and losses and construct the indicator variable *prior.gain* (*prior.loss*), which equals one if the cumulative results from earlier visits are positive (negative) and zero otherwise. For example, if an individual leaves the casino with 100 CHF after visit 1 and with -200 CHF after visit 2, the cumulative result prior to visit 3 is -100 CHF; thus, *prior.loss* equals one while *prior.gain* equals zero at the beginning of visit 3. Formally, for every individual *i* and visit *t*, the first FE model takes the following form:

$$(7) \qquad ln(casino\ risk\ measure)_{\mathrm{it}} = \beta_1 * prior.\,loss_{\mathrm{it}} + \beta_2 * prior.\,gain_{\mathrm{it}} + X'\beta + \gamma_{\mathrm{i}} + \varepsilon_{\mathrm{it}}$$

where X is a matrix of control variables including visit dummies, dummies for the number of days since visit 1 and the number of days since the last visit, γ_i is the intercept for individual *i* and thus captures the individual-specific effect, and ε_{it} is the error term.

In a second model, we allow differently sized prior outcomes to have different effects on subsequent risk-taking behavior. Thus, we split up the cumulative results from earlier visits into multiple indicator categories. We construct one indicator variable for cumulative gains from prior visits of less than 50 CHF (*prior.gain<50*), one for cumulative gains between 50 and 100 CHF (*prior.gain.50-100*), and nine more for values between 100 and 200 CHF (*prior.gain.100-200*), 200 and 300 CHF (*prior.gain.200-300*), and so forth up to 1,000 CHF. Additionally, we create an indicator variable for cumulative prior gains larger than 1,000 CHF (*prior.gain>1,000*). In the same manner, we construct 12 indicator variables for differently sized prior losses. In total, the estimation model therefore includes 24 independent variables of interest and can be written as

[22] In comparison, the baseline risk-taking behavior in our experiment is defined by the control group. As a result, the analysis in the experiment is between subjects.

$$
\begin{aligned}
(8)\quad & ln(casino\ risk\ measure)_{\mathrm{it}} = \beta_1 * prior.loss < 50_{\mathrm{it}} + \beta_2 * prior.loss\ 50 - 100_{\mathrm{it}} \\
& + \cdots + \beta_{12} * prior.loss > 1{,}000_{\mathrm{it}} + \beta_{13} * prior.gain < 50_{\mathrm{it}} + \beta_{14} * prior.gain\ 50 - 100_{\mathrm{it}} \\
& + \cdots + \beta_{24} * prior.gain > 1{,}000_{\mathrm{it}} + X'\beta + \gamma_{\mathrm{i}} + \varepsilon_{\mathrm{it}}.
\end{aligned}
$$

Finally, to test how long prior outcomes influence subsequent risk-taking behavior, we interact our independent variables of interest with the visit number. We create interactions with the dummy variables for *visit 2* and *visit 3* and a dummy variable that covers visit 4 and all subsequent visits, which is labeled *visit* 4^{+}. The model with interaction terms can then be written as

$$
\begin{aligned}
(9)\quad & ln(casino\ risk\ measure)_{\mathrm{it}} = \beta_1 * prior.loss < 50_{\mathrm{it}} \times visit\ 2 \\
& + \cdots + \beta_{24} * prior.gain > 1{,}000_{\mathrm{it}} \times visit\ 2 + \cdots + \beta_{25} * prior.loss < 50_{\mathrm{it}} \times visit\ 3 \\
& + \cdots + \beta_{48} * prior.gain > 1{,}000_{\mathrm{it}} \times visit\ 3 + \cdots + \beta_{49} * prior.loss < 50_{\mathrm{it}} \times visit\ 4^{+} \\
& + \cdots + \beta_{72} * prior.gain > 1{,}000_{\mathrm{it}} \times visit\ 4^{+} + X'\beta + \gamma_{\mathrm{i}} + \varepsilon_{\mathrm{it}}.
\end{aligned}
$$

Defining prior outcomes of visit 1 as missing

Instead of assuming that there is no prior outcome for visit 1, we can set the outcome of visit 1 to missing and use the result after visit 1 as the prior outcome for a subsequent visit. Thus, our sample size is reduced to 20,436 visits made by 2,696 gamblers. The baseline risk is then defined as the level of risk an individual takes on if her cumulative result from all prior visits is equal to zero. However, it is very rarely the case that an individual has an accumulated result of exactly zero. Therefore, we create decile dummy variables from the distribution of the cumulative prior results (*prior.result.d1* to *prior.result.d10*) and define the decile that includes the cumulated prior result of zero as the baseline risk category. Thus, all other deciles are interpreted in relation to the baseline risk category that includes the prior outcome of zero. Formally, this FE model can be written as

$$
\begin{aligned}
(10)\quad & ln(casino\ risk\ measure)_{\mathrm{it}} = \beta_1 * prior.result.d1_{\mathrm{it}} + \beta_2 * prior.result.d2_{\mathrm{it}} \\
& + \cdots + \beta_{10} * prior.result.d10_{\mathrm{it}} + X'\beta + \gamma_{\mathrm{i}} + \varepsilon_{\mathrm{it}}.
\end{aligned}
$$

Finally, we again interact the decile dummy variables with the visit dummy variables *visit 2, visit 3,* and *visit*4^{+} to investigate the persistence of prior outcomes over time. The FE model with indicator deciles interacted with the visit number is shown in Equation A.2 in the Appendix.

4.5. Results

Table 7 presents the estimated coefficients for Equation (7) and Equation (8) in Column (1) and Column (2), respectively. The results in Column (1) show that both *prior.gain* and *prior.loss* have a significant and negative impact on risk-taking behavior measured by *ln(casino risk measure)*. In the presence of a prior gain, risk-taking is reduced by 34%, and in the presence of a prior loss, risk-taking is reduced by 41%. However, the results in Column (2) show that the higher magnitude of the effect of accumulated prior losses is mostly driven by large prior losses. In the presence of large prior losses of more than 1,000 CHF, risk-taking is estimated to decrease significantly by 56%, whereas small prior losses of less than 50 CHF do not significantly affect risk-taking. By contrast, small prior gains of less than 50 CHF do significantly reduce risk-taking by 33%, whereas large prior gains of more than 1,000 CHF have no significant effect.

Table 8 presents the results for Equation (9). To save space, we only show the coefficients of the smallest and largest gains and losses.[23] Analyzing the effect of a prior outcome's persistence over time strengthens our previous findings. Small prior losses do not have a significant impact on decision-making in visit 2 (*prior.loss<50 × visit 2)*, while small prior gains (*prior.gain<50 × visit 2*) do. Thereby, small prior gains of less than 50 CHF reduce risk-taking behavior by 57%. However, the effect of a small prior gain fades away after visit 2. Although the estimated coefficient for small gains is still negative for visit 3, it is not statistically significant due to the high standard errors. Further, large prior losses between 900 and 1,000 CHF as well as large losses of more than 1,000 CHF greatly reduce risk-taking by approximately 70% in visit 2 but do not have a statistically significant effect in any subsequent visit. The effect of large prior gains is less clear, but it seems that the magnitude slightly decreases compared to small prior gains. Analogously, the effect disappears after visit 2.

Overall, Table 8 shows no effect for subsequent visits 3 and 4^+ but significant effects for visit 2, whereby the results for visit 2 show a very similar pattern to those presented in Column (2) of Table 7. Thus, the effects found in Column (2) of Table 7 are mainly driven by the following visit 2 and then fade away.

[23] The detailed results are available from the authors upon request.

To summarize, following the approach of Suhonen and Saastamoinen (2017) and using visit 1 as the baseline risk behavior with no prior outcome, we find that small prior gains reduce risk-taking behavior in the following visit, whereas small prior losses have no effect on subsequent risk-taking. Thus, in the presence of small prior losses, decision makers update their reference point faster than in the presence of prior gains. Furthermore, large losses that are potentially wealth-influencing lead to the strongest reduction in the level of risk-taking.

Table 7: Results of FE estimation when defining visit 1 as the baseline risk without prior outcomes

	ln(casino risk measure)			
	(1)		(2)	
	Coefficient	Robust SE	Coefficient	Robust SE
prior.loss	-0.41**	0.17		
prior.gain	-0.34**	0.17		
prior.loss > 1,000			-0.56***	0.18
prior.loss 900 - 1,000			-0.51***	0.19
prior.loss 800 - 900			-0.56***	0.19
prior.loss 700 - 800			-0.53***	0.18
prior.loss 600 - 700			-0.43**	0.18
prior.loss 500 - 600			-0.44**	0.18
prior.loss 400 - 500			-0.41**	0.18
prior.loss 300 - 400			-0.41**	0.18
prior.loss 200 - 300			-0.41**	0.18
prior.loss 100 - 200			-0.44**	0.18
prior.loss 50 - 100			-0.32*	0.18
prior.loss < 50			-0.27	0.18
prior.gain < 50			-0.33*	0.18
prior.gain 50 - 100			-0.41**	0.19
prior.gain 100 - 200			-0.38**	0.18
prior.gain 200 - 300			-0.49***	0.19
prior.gain 300 - 400			-0.42**	0.19
prior.gain 400 - 500			-0.52***	0.19
prior.gain 500 - 600			-0.42**	0.19
prior.gain 600 - 700			-0.47**	0.20
prior.gain 700 - 800			-0.36*	0.19
prior.gain 800 - 900			-0.34*	0.20
prior.gain 900 - 1,000			-0.39*	0.21
prior.gain > 1,000			-0.29	0.18
visit dummies	Yes		Yes	
days since visit 1 dummies	Yes		Yes	
days since last visit dummies	Yes		Yes	
N	24,784		24,784	
n	4,348		4,348	
within R^2	0.02		0.02	

Notes: Displayed are fixed-effects estimates for the regression of attitude toward risk, i.e., *ln(casino risk measure)*, on several indicators of prior outcomes and different dummy variables as controls. The results in Column (1) are based on the estimations presented in Equation (7), and the results in Column (2) are based on Equation (8). We thereby follow the approach of Suhonen and Saastamoinen (2017), in which the prior outcome for the first visit is manually set to zero. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Results of FE estimation over time when defining visit 1 as the baseline risk without prior outcomes

	ln(casino risk measure)	
	Coefficient	Robust SE
prior.loss > 1,000 × visit 2	-0.73***	0.25
prior.loss 900 - 1,000 × visit 2	-0.71**	0.32
…		
prior.loss 50 - 100 × visit 2	-0.56**	0.25
prior.loss < 50 × visit 2	-0.37	0.26
prior.gain < 50 × visit 2	-0.57**	0.26
prior.gain 50 - 100 × visit 2	-0.79***	0.27
…		
prior.gain 900 - 1,000 × visit 2	-0.42	0.31
prior.gain > 1,000 × visit 2	-0.49*	0.26
prior.loss > 1,000 × visit 3	-0.67	0.54
prior.loss 900 - 1,000 × visit 3	-0.51	0.56
…		
prior.loss 50 - 100 × visit 3	-0.29	0.54
prior.loss < 50 × visit 3	-0.20	0.54
prior.gain < 50 × visit 3	-0.30	0.55
prior.gain 50 - 100 × visit 3	-0.56	0.55
…		
prior.gain 900 - 1,000 × visit 3	-0.83	0.71
prior.gain > 1,000 × visit 3	-0.25	0.54
prior.loss > 1,000 × visit 4^+	-0.13	0.20
prior.loss 900 - 1,000 × visit 4^+	-0.09	0.21
…		
prior.loss 50 - 100 × visit 4^+	0.12	0.21
prior.loss < 50 × visit 4^+	0.01	0.21
prior.gain < 50 × visit 4^+	0.12	0.21
prior.gain 50 - 100 × visit 4^+	0.13	0.22
…		
prior.loss > 1,000 × visit 4^+	0.07	0.23
prior.loss 900 - 1,000 × visit 4^+	0.13	0.21
visit dummies	Yes	
days since visit 1 dummies	Yes	
days since last visit dummies	Yes	
N	24,784	
n	4,348	
within R^2	0.03	

Notes: Displayed are fixed-effects estimates for the regression of attitude toward risk, i.e., *ln(casino risk measure)*, on several indicators of prior outcomes interacted with the visit number. Further, different dummy variables are included as controls. The results are based on the estimations presented in Equation (9) and follow the approach of Suhonen and Saastamoinen (2017), in which the prior outcome for the first visit is manually set to zero. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Turning to our second approach, Column (1) of Table 9 shows the results for Equation (10). The baseline risk is represented by the 8th decile, which includes accumulated prior outcomes between -110 and +45 CHF and thus includes the value zero. In relation to the 8th decile, the 1st decile through the 7th decile include accumulated prior losses, while the 9th and 10th deciles include accumulated prior gains. We are most interested in the coefficients of the 7th and the 9th deciles because they are the closest to the baseline decile and thus cover the effect of small prior losses and small prior gains. The 9th decile includes accumulated prior gains between 46 and 591 CHF, and its estimated coefficient is -0.08 (p-value < 0.07). Thus, small prior gains reduce subsequent risk-taking by 8% compared to the baseline decile. By contrast, the coefficient of the 7th decile, which includes accumulated prior losses between 354 and 111 CHF, is not statistically significant. Furthermore, we find that the largest prior losses, i.e., the 1st decile, which includes losses larger than 6,461 CHF, lead to the greatest reduction in risk-taking (-42%).

Analyzing the persistence over time in Column (2) of Table 9, we find that the effect of a small prior gain is negative and not significant for visit 2 but negative and significant for visit 3 (*prior.result.d8* × *visit 3*). By contrast, a small prior loss never leads to a significant change in risk-taking behavior. Furthermore, the effect of a large prior loss persists and leads to significantly lower levels of risk-seeking behavior even after four and more visits (*prior.result.d1* × *visit* 4^{+}). Thus, we again find that small gains and large losses have a significant effect on risk-taking that occurs after long temporal separations, while small prior losses do not lead to a significant change in subsequent behavior.

Overall, the results from the panel data analysis presented in Tables 7 through 9 are very similar and thus do not depend on our definition of the baseline risk. We find that reference points are not immediately updated in the presence of small gains; thus, risk-seeking behavior is also reduced for decisions that are temporally separated. This effect, however, fades away over time. In contrast, small prior losses do not affect subsequent decisions, implying that reference points are updated immediately. Furthermore, the size of the prior outcome seems to matter for subsequent decisions. Most importantly, large prior losses also significantly reduce risk-taking behavior, which might be due to wealth effects.

Table 9: Results of FE estimation when defining the prior outcomes of visit 1 as missing

	ln(casino risk measure)			
	(1)		(2)	
	Coefficient	Robust SE	Coefficient	Robust SE
prior.result.d1 (less than -6,461)	-0.42***	0.09		
prior.result.d2 (-6,460 to -3.471)	-0.24***	0.06		
prior.result.d3 (-3,470 to -2,126)	-0.20***	0.06		
prior.result.d4 (-2,125 to -1,276)	-0.16***	0.05		
prior.result.d5 (-1,275 to -734)	-0.13***	0.05		
prior.result.d6 (-733 to -355)	-0.05	0.05		
prior.result.d7 (-354 to -111)	-0.04	0.04		
prior.result.d8 (-110 to +45)	omitted			
prior.result.d9 (+46 to +591)	-0.08*	0.04		
prior.result.d10 (more than +592)	0.03	0.06		
prior.result.d1 × visit 2			-0.56*	0.29
prior.result.d2 × visit 2			-0.06	0.50
…				
prior.result.d7 × visit 2			0.07	0.08
prior.result.d8 × visit 2			omitted	
prior.result.d9 × visit 2			-0.10	0.08
prior.result.d10 × visit 2			0.10	0.11
prior.result.d1 × visit 3			-0.11	0.27
prior.result.d2 × visit 3			-0.53***	0.31
…				
prior.result.d7 × visit 3			-0.03	0.09
prior.result.d8 × visit 3			omitted	
prior.result.d9 × visit 3			-0.26***	0.09
prior.result.d10 × visit 3			-0.12	0.11
prior.result.d1 × visit 4^{+}			-0.41***	0.09
prior.result.d2 × visit 4^{+}			-0.22***	0.07
…				
prior.result.d7 × visit 4^{+}			-0.08	0.06
prior.result.d8 × visit 4^{+}			omitted	
prior.result.d9 × visit 4^{+}			-0.04	0.05
prior.result.d10 × visit 4^{+}			0.05	0.06
visit dummies	Yes		Yes	
days since visit 1 dummies	Yes		Yes	
days since last visit dummies	Yes		Yes	
N	20,436		20,436	
n	2,696		2,696	
Within R^2	0.03		0.03	

Notes: Displayed are fixed-effects estimates for the regression of attitude toward risk (*ln(casino risk measure)*) on indicator deciles of the variable *prior.result*. In both models, we define the 8th decile as the baseline category because it includes the prior outcome of zero. Further, different dummy variables are included as controls. The results in Column (1) are based on the model presented in Equation (10) and follow the approach in which we define the prior outcomes of visit 1 as missing. The results in Column (2) are based on the model presented in Equation (A.2) in the Appendix and follow the approach of defining visit 1 as missing. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Although we provide two different approaches to how to address the baseline risk, one might worry that unobserved gambling outcomes of the casino customers before August 2016 could bias our results. Indeed, our data collection starts at an arbitrary point in time, and it is likely that some gamblers in our sample had previously visited the casino. However, because we use individual fixed-effects when analyzing our data, we argue that these costumers likely add noise to our model but do not systematically bias our findings. Moreover, our panel data results are also in line with our experimental study, in which we make use of an exogenous shock. Overall, we therefore conclude that our results are valid.

5. Conclusion

In this study, we analyze the effect of temporal separations between observing a decision outcome and subsequent risk-taking behavior using data from a casino. Thereby, we shed more light on reference-point updating in the presence of prior gains and losses that have been experienced not only immediately before the next risky decision but also days before. Three novel findings originate from our experimental study and our panel data analysis.

First, in the presence of small prior gains, casino customers exhibit significantly more risk-averse behavior. Our regression results on the *ln(casino risk measure)* show that the magnitude of the risk reduction within the visit with the experimental treatment is 36%. In addition, the magnitude of the risk reduction in the second visit varies between 21% (experimental study) and 57% (panel data study). Thus, more risk-averse behavior after small gains is triggered for decision-making that directly follows and for decision-making that follows after a number of days. We therefore conclude that small prior gains are integrated with subsequent outcomes and do not lead to an immediate update of the reference point, even after temporal separations. However, the effect of small prior gains dilutes over time. This result makes intuitive sense because with more time passing, it becomes increasingly likely that other events, such as paydays or gains and losses from decisions made in other settings, will also influence risk-taking behavior.

Second, our analysis reveals that casino customers do not change their risk-taking behavior within or across visits after experiencing small losses. Therefore, decision makers segregate small prior losses and quickly update their reference point. In combination with the results for small prior gains, our results imply that decision makers mentally cling to small gains, while small losses are edited out much faster.

Third, the size of prior outcomes matters. Whereas small prior losses do not impact subsequent decision-making, large prior losses do. This effect is most pronounced for large accumulated losses of more than 1,000 CHF, which reduce risk-taking by 72% in the second visit. Such large losses are likely to be wealth-influencing and thus influence subsequent risk-taking behavior. In addition to potential wealth effects, other explanations for this finding include factors that produce a greater distaste for losses. Referring to two earlier theoretical studies, Imas (2016, p. 2094) notes the "increased salience of the potential downside of risk (Bordalo, Gennaioli and Shleifer 2012)" and "a diminished capacity for dealing with bad 'news' (Kőszegi and Rabin 2009 […])" as examples of such factors. By contrast, large prior gains only seem to marginally reduce risk-taking, if there is any effect at all.

These findings help with the understanding of recurring, but temporally separated, real-life decision-making under risk. Overall, our results reveal an asymmetric temporal effect of small prior gains and losses, whereby gains affect subsequent choices for a longer period of time. Regarding prior losses, Imas (2016) finds that the realization of a transfer is a sufficient condition to update the reference point. In our setting, leaving the casino should therefore make all gains and losses realized because money is cashed out and potential losses become final. Indeed, our results suggest that reference points are updated after small losses.[24] However, although neither stated or tested by Imas (2016), our results suggest that when a decision maker realizes a small gain, he or she does not immediately update the reference point. More research is clearly needed to shed light on the reasons why small prior gains seem to be remembered longer than small prior losses.

Our results have direct managerial implications for casino operators. For example, active management of the levels of gains and losses through promotions or offering games with distinct return-rate characteristics would allow casino operators to optimize their revenues. More precisely, casino operators could prevent their customers from experiencing very large losses within a particular visit

[24] Imas (2016) predicts that prior realized losses are not integrated, and the reference point therefore updates. However, he also predicts that under the assumption of sensitization in the myopic case, subsequent risk-taking behavior will be lower even if the reference point has updated.

because such losses trigger the most distinct risk-averse behavior.[25] For more general managerial implications, we must keep in mind the caveat of our casino sample, which consists of individuals who might have different risk preferences than the general public. However, because we only analyze differences either between casino customers or within customers, we are confident that our results also apply in other settings and therefore offer new business opportunities. For example, when risk-averse behavior is desirable, such as in the insurance industry, a small initial gain could trigger such behavior. A car insurer could increase the value of an insured car by installing higher-quality headlights for free after the contract has been signed. In turn, the insured person might experience a small gain through this increase in the car's value and thus engage in more risk-averse driving behavior in the near future. This and other similar examples provide interesting opportunities for future field studies.

[25] Preventing casino customers from realizing very large losses is also desirable from a social welfare perspective.

Appendix

Table A.1: Descriptive statistics (N=24,784; n=4,348)

Measure	N	Mean	Std. Dev.
days until return	24,784	7.2	12.2
games	24,784	1,669	2,042
time	24,784	129.7	134.2
average wager	24,784	9.13	49.36
total wager	24,784	4,204	12,020
casino risk measure	24,784	195	446
result	24,784	-245	1,656

Notes: The table shows the descriptive statistics at the visit level. We calculate the descriptive statistics directly from all 24,748 visits. The variable *time* is measured in minutes.

$$\begin{aligned} \text{(A.2)} \quad & ln(casino\ risk\ measure)_{\mathrm{it}} = \beta_1 * prior.result.d1_{\mathrm{it}} \times \mathrm{visit2} \\ & + \cdots + \beta_{10} * prior.result.d10_{\mathrm{it}} \times \mathrm{visit2} + \cdots + \beta_{11} * prior.result.d1_{\mathrm{it}} \times \mathrm{visit3} \\ & + \cdots + \beta_{20} * prior.result.d10_{\mathrm{it}} \times \mathrm{visit3} + \cdots + \beta_{21} * prior.result.d1_{\mathrm{it}} \times \mathrm{visit4}^{+} \\ & + \cdots + \beta_{30} * prior.result.d10_{\mathrm{it}} \times \mathrm{visit4}^{+} + X'\beta + \gamma_{\mathrm{i}} + \varepsilon_{\mathrm{it}} \end{aligned}$$

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