



A large-scale prospective study of big wins and their relationship with future involvement and risk among actual online sports bettors^{*}

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ABSTRACT

Clinicians have proposed that big wins early in a gambler's betting experience can lead to increased involvement, and eventually problematic gambling. Understanding how this effect manifests in online sports betting is important, as this form of gambling has grown increasingly popular worldwide and continues to expand.

Methods: Using matched pair analysis and other methods (e.g., survival analysis, fixed effects regression), we examined big wins' ability to predict future gambling involvement and behavior using bet level data from 36,328 sports gamblers who subscribed to a large, European online gambling operator. Big wins were defined two ways. **Results:** Big wins in sports betting were associated with increased engagement, losses, and risk in the following weeks, with the impact declining over time. The exact timing of when a big win occurs after subscribing does not appear to have a major effect on subsequent behaviors. These findings held for both definitions of big wins.

Implications: This study supports the existence of a big win effect in online sports betting, but more research is needed to determine whether there is an "early" big win effect, and whether big wins are indeed associated with problematic gambling.

1. Introduction

1.1. The early big win effect and general big win effect

Although our understanding of disordered gambling and gambling behavior in general has evolved and become more nuanced, there are still important and influential theories with limited support. One of these is the notion that a large win early in one's gambling career will lead to future problem gambling: the big win effect (Custer, 1984; Custer & Milt, 1985; Davies, 2022). Specifically, in widely-cited clinical reports, Custer described the early winning phase, where the individual who will later experience problem gambling begins gambling with a significant stroke of luck. Eventually, winning comes to an end and shifts to a losing phase where the individual begins to lose control over their gambling. After the gambler depletes all of their winnings, and then their bankroll (i.e., money available for gambling), debts begin to mount and the individual begins to display behavior emblematic of what was

referred to as compulsive gambling at the time. Custer argued, drawing from his clinical experience, that the notable shift was due to a big win that occurred early in the gamblers' gambling careers (Custer, 1984). Thus, early big wins are defined as subjectively large prizes (typically worth around a month's salary) won by gamblers during an initial and formative period of their gambling experience (Custer & Milt, 1985), that have the potential to promote excessive and even problematic gambling.

While these clinical observations clearly highlight the importance of early gambling big wins, it remains unclear whether early big wins are only important in the context of an individual's entire gambling experience (regardless of gambling product or service), or whether early big win effects can also be unique for specific gambling products or operator experiences (e.g., individual early big win effects for: brick-and-mortar gambling, online gambling, sports gambling at a specific operator, etc.). It is also unclear whether there is simply a *general* big win effect – does any substantially large win influence future gambling behavior,

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regardless of when it occurs? Outside of retrospective self-report studies, researchers are better equipped to test a general big win effect, or product/operator-specific early big effects, than they are an early big win effect that occurs early on in an individual's gambling experience.

The potential psychological mechanisms behind the big win effect are numerous. Illusion of Control (Stefan & David, 2013), or the idea that someone's big win is the direct result of their keen skill and mastery of the craft (and therefore future big wins will inevitably follow) represents one potentially important mechanism. Operant conditioning (Skinner, 1963), or reinforcement of behavior through reward schedule, is another. Still other explanations come from behavioral economics, such as the availability heuristic (Tversky & Kahneman, 1973), whereby meaningful amounts of winnings are more likely to stick in one's head than more modest winnings. The representative heuristic (Tversky & Kahneman, 1971), could also explain the effects of early big wins that happen after only limited amounts of play, which can lead one to believe that these are common occurrences. Relatedly, the "hot hand" effect (Gilovich, Vallone, & Tversky, 1985) suggests that big wins might occur in streaks, and that subsequent big wins are likely to follow an initial big win. Finally, there is the house money effect (Thaler & Johnson, 1990), where a gambler might more freely gamble away a big win believing it to be the house's money they are risking, rather than their own. It should also be noted that while some of these psychological mechanisms could underlie both early and general big win effects, a few might be particular to just one type. For example, illusion of control, hot hand, and house money effects could apply to any big win, with less relevance for formative big wins early in the career, whereas the representative heuristic is clearly more likely to speak to early big wins specifically. Furthermore, while all of these mechanisms are quite different from one another, there is one potential common thread throughout all of them: as time goes on following the big win without a repeat big win, the effect of the big win on behavior would presumably be expected to diminish or even deteriorate over time.

1.2. Assessing the big win effect: laboratory and self-report studies

Although foundational research by Custer (1984) first advanced the notion of the early big win effect, more recent clinical evidence is also supportive of it. For example, the majority of individuals receiving treatment from the National Gambling Treatment Service in the United Kingdom (i.e., England, Scotland, Wales, and Northern Ireland) reported having an early big win (National Gambling Treatment Service, 2021). These types of clinical reports have helped to emphasize the idea of early big wins as a major catalyst to the development of problem gambling.

Moreover, while at least some discussions of the big win effect more generally have focused on specific products, such as jackpots in electronic gambling machines (EGMs; e.g., Donaldson, Langham, Rockloff, & Browne, 2016; Rockloff & Hing, 2013), the potential for big wins and big win effects does not appear to be confined any one product. Multi-game parlays in sports betting, for instance, have the potential to turn small stake sizes into enormously large prizes. Even games where players can at most double their stake (e.g., Blackjack) have the potential for large payoffs at higher stakes.

Consistent with Custer's initial observations, most previous literature has focused on the effects of early big wins rather than big wins more generally. Researchers empirically testing the early big win effect have either confined their tests to laboratory settings (Kassinove & Schare, 2001; Weatherly, Sauter, & King, 2004) or relied on self-report data (Edgerton, 2015; Turner, 2006). Among these studies, evidence of an early big win effect has been fairly mixed, with potentially greater evidence for a lifetime early big win effect and less evidence for a product-specific early big win effect. For example, participants in a simulated slot experiment who experienced a big win on their 5th spin played longer than those who experienced a big win on their first spin as well as those who never experienced a big win (Weatherly et al., 2004). In a self-report study, individuals with disordered gambling on average

reported significantly larger first wins than those who were non-problem gamblers (Turner, 2006). One study suggested that the early big win effect is not only present but has a larger effect compared to other variables commonly associated with problem gambling such as impulsivity and erroneous beliefs (Turner, 2008). However, at least two studies assessing early big wins have reported null results (Edgerton, 2015; Kassinove & Schare, 2001), one of which was a longitudinal study that assessed the role of early big wins in later development of Gambling Disorder (Edgerton, 2015).

As previously noted, the vast majority of research assessing the big win effect has been laboratory-based or relied on self-report. Though these designs certainly have merit, they also present some methodological issues when trying to accurately measure certain constructs such as gambling behavior. Turner (2006), for instance, asked respondents to retrospectively self-report an event that might have happened 30 years previously, which presents significant risk for recall bias. Self-report of gambling expenditure, more generally, has been shown to be unreliable (Braverman, Tom, & Shaffer, 2014; Heirene, Wang, & Gainsbury, 2021). For example, Braverman and colleagues noted that 34%–40% of participants self-reported favorable distortions of their gambling gains/losses relative to their actual performance. Even more importantly, they report that the size of the discrepancy between reported performance and actual performance was correlated with self-reported problem gambling symptoms.

Many lab and self-report study designs also rely on samples of small groups of university students, who might have limited generalizability to the broader population of gamblers (Gainsbury & Blaszczynski, 2011). Other studies rely on online convenience samples. However, these samples too face similar issues in terms of data integrity and validity (Pickering & Blaszczynski, 2021). Experimental studies' limited time horizons are also not ideal for assessing longer-term changes in gambling behavior or the later development of disordered gambling in the real world. In addition, laboratory studies do not (and to stay in compliance with contemporary research ethics commissions, probably cannot) have participants wager their own money, nor truly receive large sums of actual money in the form of big wins. In some cases, participants wager "lab points" whose utility might not be 100% (i.e., not $r = 1$) correlated with the size of participants' rewards for joining the study. The inability to gamble with one's own money in these scenarios can lead to strategies and behaviors different from what occurs in real-life gambling environments (Weatherly & Phelps, 2006). These complications with lab research are in addition to the typical biases in lab studies such as the Hawthorne effect, or behavioral changes in response to being observed in an experimental setting (Landsberger, 1958; Merrett, 2006; Roethlisberger & Dickson, 1939). Thus, while the big win effect has been evaluated empirically, there are still substantial questions that remain unanswered, including whether it manifests in actual gambling behavior.

1.3. Assessing the big win effect: actual user record data

A more contemporary research approach has used actual gambling record data to assess traditional theories. We are aware of only two studies that assessed the big win effect using actual user record data (Edson, Tom, Philander, Louderback, & LaPlante, 2021; Smith, Levere, & Kurtzman, 2009). Both of these studies used \$1000 as their threshold for "big win". Edson & colleagues also used a separate definition that defined big wins as multiplications of wager size (see discussion of Prize Ratio, below). Smith and colleagues examined big wins (and losses) among 356 poker players, finding that players tended to play less aggressively following a big win. Edson and colleagues conducted a more focused analysis on big wins specifically, analyzing a prospective dataset of 34,596 Daily Fantasy Sports (DFS) subscribers from a major DFS provider, DraftKings, which was based on over 18 million entries into DFS contests. Their findings showed that experiencing a big win in DFS significantly predicted future increased DFS engagement (i.e.,

increased contest entry fees and more contest entries) and losses (i.e., higher net loss), yet also showed that the relationship between a big win and engagement and losses decays over time. They also observed that later big wins had a slightly stronger, albeit very small, effect compared to earlier big wins on future DFS engagement, which led them to conclude that timing of big wins in DFS is likely of little importance.

However, both poker and DFS are considered to be more “skilled” forms of gambling with unique player pools, and the findings from these studies regarding the effects of big wins on player behavior might not be generalizable to other products. DFS also is not legally recognized as a form of gambling by some jurisdictions (Weston, 2021). Importantly, we are not aware of any research on the big win effect using actual gambling records for online sports gambling, which remains one of the most popular forms of online gambling in Europe (European Gaming & Betting, 2019), and whose popularity in the ripe U.S. gambling market is likely to increase following a 2018 U.S. Supreme Court ruling that ended Federal restrictions on sports wagering (Legal Sports Report, 2020). Hence, examining big wins in gambling formats such as sports betting remains important.

2. The present study

The current study expands our knowledge of the big win effect by examining big wins evident in actual gambling records for sports bettors. Guided by prior research assessing the big win effect among DFS players (Edson et al., 2021), this study used matched pair analysis, survival models, and several robustness tests to empirically assess the big win effect among all individuals who subscribed to a major European online sports gambling website during February 2015. Lacking self-report data (and thus a viable clinical measure of problem gambling), we use actual gambling records to assess the big effect in terms of its association with excessive engagement. Specifically, we focus on the extent to which big wins promote increased betting engagement (i.e., total stake, number of bets), risk (i.e., increased odds and stake size), and losses (i.e., net loss) (Research Question 1). Given that many of the psychological mechanisms for the big win effect (e.g., illusion of control, availability heuristic) are predicated on its weakening over time, we also assessed this possibility: whether the big win effect weakens, or disappears entirely, over time (Research Question 2). Finally, in addition to testing the big win effect more generally, we also sought to conduct a limited test of the *early* big win effect hypothesis – specifically, are earlier wins within a single gambling operator and product more meaningful, in terms of increased risk and engagement, than later ones (Research Question 3). We call this test “limited” because Custer considered early big wins in the context of a gambler’s entire life. Here, our examination of temporality is limited to the gambler’s experience with a single product and operator.

More specifically, the present study assessed:

- (1) How big wins in actual online sports betting are associated with future sports betting engagement/risk/loss metrics among all online sports bettors who subscribed to a sports betting website during February 2015;
- (2) Whether the empirical relationship between a big win and sports betting engagement metrics changes depending on how many weeks have elapsed since the big win; and,
- (3) Whether the effects of having a big win vary depending on the amount of time between someone’s entrance onto a sports betting website and their big win (i.e., is there an *early* big win effect, at least within a single product domain)?

3. Method

3.1. Data and participants

Participants included all individuals who subscribed to bwin, a large

online sports betting and online gambling operator based in Europe, during February 2015. Bet-by-bet sports gambling data were delivered to us by bwin, with all datetimes for each bet in GMT (Greenwich Mean Time). The datetimes for all other data (i.e., bettor data, deposit and withdrawal data) were in CET (Central European Time) and did NOT switch to CEST during daylight savings. We converted the date-times in all files to each bettor’s local date and time based on their country of record (i.e., the country in which they subscribed to bwin). We only had access to the bettors’ country of record and no smaller geographic unit. The vast majority of these bettors were from member countries of the European Union (McAuliffe, Louderback, Edson, LaPlante, & Nelson, 2022; Nelson et al., 2021). For bettors who reside in countries with multiple time zones, we utilized the time zone of the most populous city in that country.

Measures included number of selections/propositions, amount spent on stake, and amount won in prizes for each bet placed from each bettor’s initial February 2015 subscription date through July 16, 2020 (i.e., the latest date a bet was placed in the data). In all, the data comprised bet-level information for a total of $n = 36,328$ individual bettors. For each bettor, we generated weekly aggregates of their engagement behaviors and losses (i.e., total stake, number of bets, and net loss for each week they played) and calculated the median values of wager size and betting odds for each week they played, to assess riskiness of betting. Here, we define a “week” as a seven-day period beginning on a Sunday at midnight (e.g., 2021-02-21 00:00:00). We considered the bettors’ “first week” as the week they subscribed to bwin. Bettors who signed up earlier during the recruitment period had more available weeks than bettors who signed up later.

3.2. Study design

We employed a longitudinal prospective cohort design with repeated time points and preregistered our study on the Open Science Framework prior to conducting any analyses. Each time point comprises weekly aggregates of bettor-level sports gambling engagement and performance on the bwin website . Time points are repeated for each bettor for each week since they subscribed, starting with the week of subscription (week 1) and the last available full week the bettor was eligible to play when the data the were delivered to us in July 2020 (i.e., between week 281 and week 284, depending on the week the bettor subscribed during February 2015). We used matched pair analysis to match each big winner with a sports bettor exhibiting similar engagement and risk profiles during the week of the big win, but who did not experience a big win that week, and compared both individuals on subsequent week engagement, risk, and loss metrics.

3.3. Measures

3.3.1. Identifying and demographic variables

Identifying and demographic variables in the data included bettor ID, gender, age, and week number (see Table 1 for descriptions).

Table 1
Identifying and demographic variables.

Bettor ID:	Identification numbers used to distinguish one bettor from another.
Gender	Each bettor’s self-reported gender at registration (only male or female was available)
Age	Each bettor’s self-reported age, in whole years, at registration
Week number t	Given a Bettor ID, a week number of 1 means the week that the bettor subscribed to bwin. A week number of 2 means the week after the week of subscription. For example, if an individual subscribed on Wednesday, 2019-11-06, then the start and end times for that person’s week 1 would be Sunday 2019-11-03 00:00:00 and Saturday 2019-11-09 23:59:59, respectively, and the corresponding week 4 would start at Sunday 2019-11-24 00:00:00. The exact number of days represented in week 1 vary from bettor to bettor, depending on the date of subscription.

3.3.2. Dependent variables

Edson et al. (2021) examined the effects of big wins on engagement outcomes (i.e., total entry fees, number of entries), and losses (i.e., net loss). We used analogous outcome measures for sports betting (Table 2). In addition, we extended the original analyses by also examining the effects of big wins on the “riskiness of betting” outcomes (i.e., stake size and betting odds).

3.3.3. Independent variables

Our main independent variable of interest was experiencing a big win. We defined the term “big win” in two different ways (Table 3).

3.3.4. Covariates and transformations

We matched big winners and matched (i.e., non-big winner) controls on five variables. These included measures tapping prior engagement, prior riskiness of betting, and previous losses (Table 4).

3.4. Inference criteria

We used a statistical significance level of $\alpha = 0.05$. All reported p -values rely on two-tailed tests of significance.

3.4.1. Hypotheses and analytic plan

Prior to testing our hypotheses, we first conducted a brief census of big win events among our sample of sports bettors during the study period, specifically noting how many bettors experienced at least one big win based on just Custer’s definition, how many bettors experienced at least one big win based on just the Prize Ratio definition, how many bettors experienced at least one big win based on both definitions, and how many bettors did not have a big win.

We also calculated a similar census of big wins themselves during the study period, noting how many big wins that met just Custer’s definition occurred, how many big wins that met just the Prize Ratio definition occurred, and how many big wins that met both definitions occurred.

Hypothesis 1. Online sports bettors who experience a big win will exhibit more sportsbook engagement (i.e., higher total stake and a greater number of bets placed), greater losses, and more risky engagement (i.e., higher median stake size and higher median betting odds) in the following week when compared with bettors who do not experience

Table 2
Dependent variables.

<i>Current week’s total stake</i>	The total amount a bettor spent on sports betting wagers in week t
<i>Current week’s net loss</i>	The sum of all stakes minus the sum of all winnings across the sports bets the bettor made in week t . Sports bets made during week t but resolved after week t still count towards this measure’s calculation
<i>Current week’s number of bets</i>	The total number of sports bets submitted in week t
<i>Current week’s median stake size</i>	The median of stake for sports bets submitted during week t . We used the median instead of mean to partially mitigate the outsized effects of outliers.
<i>Current week’s median odds</i>	The median of calculated odds (e.g., calculated odds for an even money bet is 2.0 [i.e., the bet returns double the amount of the stake]) for sports bets submitted during week t . We used the median instead of mean to partially mitigate the outsized effects of outliers.
<i>Persistence</i>	Among big winners, the number of consecutive prototypical “months” (i.e., 4-week periods) they play (i.e., in which they made at least one sports bet on bwin) following the week of the big win. We tracked persistence for a total of six 4-week periods.
<i>Frequency of play</i>	Among big winners, the number of active days on bwin sportsbook during the 24 weeks (i.e., six prototypical months) following their big win divided by their total active duration (i.e., number of days, inclusive, between first active day and last active day) during this same 24-week period, and multiplied by 100.

Table 3
Independent variables.

<i>Big win measure 1 (Custer’s definition)</i>	Our first measure of “big win” is derived from the clinical observations of Custer (1984), later Custer and Milt (1985), and finally an adaptation of those conceptualizations proposed by Edson et al. (2021), which is any single prize that is greater than or equal to €1000. For a given bettor/week, this variable takes a value of 1 if the bettor experienced at least one Custer Big Win that week, otherwise 0.
<i>Big win measure 2 (Prize Ratio definition)</i>	Our second measure of “big win” is Prize Ratio (Edson et al., 2021), which is the size of a prize divided by the largest wager on a single bet the bettor had ever made up to and including that bet. Among all winning bets, we considered those that fell in the top 1% of prize ratios to meet the criteria for Prize Ratio big win (i.e., we ordered all winning bets by prize ratio and took the top 1%, which might have included some instances of multiple big wins from the same bettor). For a given bettor/week, this variable takes a value of 1 if the bettor experienced at least one Prize Ratio Big Win that week, otherwise 0.

Table 4
Matching covariates.

<i>Prior week’s engagement (total stake and number of bets)</i>	We matched bettors based on prior sports betting engagement in terms of total stake and total number of bets during the week prior to the week of the big win.
<i>Prior week’s riskiness of betting (stake size and odds)</i>	We matched bettors based on prior sports betting riskiness in terms of median stake size and median betting odds during the week prior to the week of the big win.
<i>Cumulative net loss</i>	Because past success rates might inform future betting behaviors, we matched bettors based on their cumulative net loss (i.e., running net loss since they first deposited) as of the end of the week prior to the week of the big win. Sports bets made during this period that did not resolve until the week of the big win, or later, did not count towards this calculation.

a big win.

Our primary interest in Hypothesis 1 is to test how big wins immediately influence subsequent engagement, risk, and loss outcomes. We specifically seek to assess how these outcomes differ for people who experience a big win with those who do not, yet the use of observational data prevents random assignment (Shah, Laupacis, Hux, & Austin, 2005) of the treatment variable (i.e., experiencing a big win). To remedy these issues, we followed a matched pair approach. Matched pair analysis is an appropriate way to simulate experimental designs with observational data, and has gained a significant amount of traction in addiction research specifically and public health research more generally (Chan et al., 2022). Examples in the gambling literature include: Auer, Hopfgartner, & Griffiths, 2018; Braverman, LaPlante, Nelson, & Shaffer, 2013; Edson et al., 2021; Gray, LaPlante & Shaffer, 2012; Madden, Petry, & Johnson, 2009). We used Mahalanobis distance matching (King & Nielsen, 2019; Stuart, King, Imai, & Ho, 2011) to pair big winners with matching controls. In their study of big wins in DFS, Edson et al. (2021) found that Mahalanobis distance substantially outperformed similar distance methods such as propensity score, in terms of accurately matching big winners and matched controls.

Our matching procedure involved first identifying all big winners for each week of the study period, starting at Week 1. For Week 1 big winners, we picked matched controls randomly because all matching covariates are equal to zero. For the remaining weeks, we used the *matchit()* function from the *MatchIt* package in R v. 4.1.1 (Ho, Imai, King, & Stuart., 2011; R Core Team, 2022) to match each big winner with another bettor who played that same week but did not experience a big win, using the five aforementioned covariates (i.e., number of bets,

total stake, median stake size, median odds, and cumulative net loss) based on Mahalanobis distance. We set the parameter ratio equal to 1 so that each treatment case is matched to only one control case. If there were multiple viable matching candidates (i.e., multiple matches), *matchit()* chose one randomly. The MatchIt package includes several methods for matching that are applicable for the present dataset: exact, subclassification, nearest neighbor, optimal, and coarsened exact. We compared each of these methods and used the optimal matching method, which resulted in the lowest mean difference between the big winners and corresponding matching controls. A summary of the balance table (see supplementary materials), shows that, for each matching covariate, the mean difference between the big winners and their matched controls was less than the corresponding mean difference between the big winners and the rest of the unmatched sample of bettors.

After conducting the matching procedure, we tested [Hypothesis 1](#) using a matched pair *t*-test (see [Moore, McCabe, & Craig, 2009](#), p. 428) with Welch's approximation for degrees of freedom to assess mean differences between the big winners and their matching controls on (1) total stake, (2) number of bets, (3) net loss, (4) median stake size, and (5) median odds during their week after the big win (e.g., if the big win occurred in Week 1, then we compared the big winner and his matched control on Week 2 results; if the big win occurred in Week 48, then we compare the two bettors on their Week 49 results).

Hypothesis 2. For bettors who experience a big win, its effect on sports betting engagement/risk/losses will tend to diminish and/or dissipate over time.

To test [Hypothesis 2](#), we assessed trend differences on the five outcome variables in the weeks beyond the subsequent weeks following the early big win. Specifically, in addition to testing mean differences of outcomes between big winners and their matched pairs in the week following the big win, we used a matched pair *t*-test to assess mean differences of outcomes between big winners and their matched pairs in the second week following the big win, and repeating this up to the 24th week (i.e., approximately 6 prototypical months) following the big win. We graphed the Cohen's *d* effect sizes ([Cohen, 1988](#)) derived from these analyses, where the x-axis reflects the week number (starting with week 1 after the week of the big win and ending with week 24 after the week of the big win) and the y-axis shows the Cohen's *d* value for that week number. We also indicated the weeks where the associated *t*-value for each Cohen's *d* was significantly greater than 0. We then examined this graph to determine whether, for each outcome, the big win effect diminishes (i.e., decreased size of Cohen's *d* over time) and/or dissipates (i.e., increased likelihood of non-significant corresponding *t*-values over time).

Hypothesis 3. Among big winners, shorter time to a big win (within a single product domain) will be associated with more persistence (i.e., more months gambling consecutively during active duration) and greater frequency (i.e., percentage of active days during active duration) following the big win.

3.5. Persistence

To test how persistence may vary depending on how early in a bettor's experience on bwin's sports betting platform the big win occurred, we first constructed two new datasets. Dataset 1 comprised the subgroup of bettors who won over €1000 in a single contest (i.e., Custer's definition) and Dataset 2 comprised the subgroup of bettors who experienced a big win based on prize ratio (i.e., Prize Ratio definition). To measure when the big win occurred, we created a new variable in each of the two datasets that is assigned a numeric value based on the week number in which the big win event occurred for each respective bettor.

We then created six new variables for each bettor that correspond to each prototypical month (i.e., four-week period) following their personal big win event. These variables were: month 1 (i.e., weeks 1–4 after the week of the big win), month 2 (i.e., weeks 5–8 after the week of the

big win), month 3 (i.e., weeks 9–12 after the week of the big win), month 4 (i.e., weeks 13–16 after the week of the big win), month 5 (i.e., weeks 17–20 after the week of the big win) and month 6 (i.e., weeks 21–24 after the week of the big win). Each month variable was set to 1 if the bettor placed one or more bets during that month and 0 if the bettor did not place a bet.

The resultant variable, Persistence, is a time-based dropout variable, which is well suited for survival analysis. We created a survival curve based on the non-parametric Kaplan-Meier estimator ([Efron, 1988](#)) with months on the x-axis and the probability of persistence on the y-axis. Then, to empirically assess how the week of the big win affects persistence, we estimated two Cox Proportional Hazards models: (1) a model with just the independent variable (week of big win) predicting the hazard function, and (2) a second model with added controls for a bettor's age, gender, frequency of play and stake per day (i.e., total stake divided by number of active days) in all available weeks leading up to, and including, and the week of the big win event. This second model controls for potentially confounding effects of time and financial engagement across the sample of big winners and any potential effects of gender and age as covariates.

3.6. Frequency of play

For both sub-samples of big winners, to test how bettors' general engagement in sports betting may vary depending on how early in their sports betting experience the big win occurred, we employed ordinary least squares (OLS) linear regression to model the frequency of days bettors are active during the 24-week period following the big win, with week of big win as the sole independent variable. Next, we estimated the same regression model with added controls for age, gender, frequency of play, and stake per day (i.e., total stake divided by number of active days) in all available weeks leading up to, and including, the week of the big win. We chose OLS regression for this analysis as the outcome of interest, Frequency, was amenable to this type of analysis, and most researchers have familiarity with it. We conducted the necessary tests (e.g., residual plots, *qq* plots) to ensure that all major assumptions of OLS were satisfied (e.g., homoscedasticity, no autocorrelation, normality in the distribution of residuals), which are available in the online supplement. These tests indicated no major violations of regression assumptions.

3.7. Matching filters

For conducting a census of big wins and big winners, we considered all big wins that met the aforementioned Custer & Prize Ratio definitions. For the subsequent analyses that test hypotheses, we considered: (a) the presence of a sufficient follow-up period; and (b) the potential for previously experienced big wins to affect one's eligibility as a matching control. As such, for the purpose of hypothesis testing, we considered bettors eligible as big winners if: (a) they experienced their first big win by the respective definition for the given week (i.e., for repeat big winners, we only counted their first big win) and (b) they have at least 24 following weeks where they are eligible to play. We considered bettors eligible as matched controls if: (a) they had not experienced an initial big win by the respective definition before and during the given week, and (b) have at least 24 following weeks where they are eligible to play.

3.8. Sensitivity analyses

Testing for Confounding Bias. Although matched pair analysis is intended to reduce confounding by effectively simulating a randomized control trial, there is still potential for confounding bias because the variables on which we match big winners to controls might not represent all the factors that confound the relationship between experiencing a big win and our outcome variables. Therefore, as an initial sensitivity

analysis, we computed e-values (Haneuse, VanderWeele, & Arterburn, 2019) for each of the Cohen's d 's we calculated for testing Hypotheses 1 and 2 in matched pair analysis. E-values help to address the concern that observational studies cannot foreseeably control for all unmeasured confounders. Using the effect size of interest, e-values provide a theoretical estimate of the amount of unmeasured residual confounding that would be necessary to nullify said effect size of interest (Basham & Karim, 2002). We used the R package 'EValue' to compute e-values, specifically using the function `evalues.MDO()`.

In addition to e-values, we also re-ran the matched pair analysis testing Hypothesis 2 (i.e., graphing Cohen's d of outcome variables for the 24 weeks following the big win), after dropping specific matched pairs from each re-run. First, we dropped any matched pairs that contained either a repeat big winner (i.e., the big winner experienced one or more big wins of the respective definition during the 24 weeks following the big win) OR a matched control big winner (i.e., the matched control experienced an initial or several big wins of the respective definition during the 24-week follow up period). Then we dropped ONLY matched pairs that involved a repeat big winner of the respective definition. Finally, we dropped ONLY matched pairs that involved a matched control big winner of the respective definition. We visually compared the revised figures from these sensitivity analyses with the main figure to determine whether repeat big winners or matched control big winners individually or collectively confounded the main results.

Assessing the Percentage of Matched Pairs That Support Hypotheses 1 and 2. For each of the paired t -tests we calculated for the 24 weeks following a big win, we calculated: (1) the percentage of matched pairs that support the hypothesis (i.e., the big winner has a higher value on the metric than the matched control), (2) the percentage of matched pairs that tie (i.e., the big winner has the same value on the metric as the matched control, including zero values for weeks that neither made a bet), and (3) the percentage of matched pairs that do not support the hypothesis (i.e., the matched control has a higher value on the metric than the big winner).

Fixed Effects Panel Models. Consistent with sensitivity analyses employed by Edson et al. (2021), we estimated a set of complementary fixed effects regression models that test the overall robustness of the matched pair analyses (i.e., Hypotheses 1 & 2), as well as derivations of survival analyses (Hypothesis 3) that assess the effects of grouped time intervals (i.e., experiencing a big win either within or after a 4-week period), with a 16-week follow up period. We estimated two derivations of the fixed effects models. As Edson et al. (2021) describe: "the fixed effect model design allows for the removal of potential individual-level endogenous error that is constant over time. Fixed-effect models are commonly used in panel data sets [e.g., bet-by-bet gambling record data] when there is an immeasurable unobserved effect in each individual ... unlike matching, then, the fixed effects model is still valid even if we did not measure all person-level variables that predict having a big win" (pg. 7). First, we estimated the fixed effects models including big winners who experienced subsequent big wins during the 24 weeks following the initial big win event. Next, to assess the potential effects that multiple big winners might have had on the overall results, we re-estimated the fixed effects models excluding big winners who experience subsequent big wins (i.e., big wins that occur during the 24 weeks following their initial big win). All fixed effect models were estimated using Stata 15.

Incorporating All Gambling Activity. In addition to bet-by-bet level sports data, for this sample of bettors we also have data for their activity on other gambling products on bwin (i.e., casino games, poker, and bingo) at the daily aggregate level. For our final sensitivity analysis, we substituted pertinent outcome variables (i.e., total stake, net loss with regards to sports betting engagement) with corresponding metrics that account for all gambling activity available in the matched pair analyses. Additionally, in the fixed effects analyses and survival analysis derivations, we substituted pertinent outcome and control variables (i.e., total stake, net loss) with the weekly aggregates of these same metrics for all

gambling activity available for each bettor. We limited these analyses to total stake and net loss outcomes because these outcomes are not specific to sports betting (e.g., as opposed to median odds) and their values are not dependent on product mechanics (e.g., casino betting is faster paced than sports betting, thus bettors can rack up more bets in less time). These revised analyses helped us to determine whether any big win effects we identified in the main analysis were attenuated or enhanced by activity on other products outside of sports betting.

3.9. Planned exploratory analyses

Assessing the Prevalence and Effects of No Immediate Withdrawal Following the Big Win. One of the major concerns surrounding big wins is the tendency for bettors to continue gambling with those winnings in order to repeat the big win experience, rather than partially re-allocating at least some of the winnings to other activities or to one's personal savings (Edson et al., 2021). It follows that gamblers who intend to continue gambling with all of their winnings would choose not to withdraw any money immediately following the big win. Therefore, as an added exploratory analysis, we examined the prevalence and effects of big wins that are followed by a withdrawal soon after (i.e., within 24 hours following the win) AND in which the withdrawal is not reversed (see Parke & Parke [2019] for more information on reverse withdrawals) AND where the withdrawal is not accompanied by a deposit or deposits greater than or equal to the withdrawal, within that same 24-hour period. We first calculated the count and percentage of all big wins that occur during the study period that are followed by a withdrawal soon after. Then, among the subsets of big winners we used for examining Hypothesis 3, we assessed the count and prevalence of big winners who withdrew soon after their big win. Using this same sample, we coded "withdrew soon after" as a dummy variable and substituted this predictor for "week of big win" into the analyses we specified for predicting persistence and frequency outcomes for testing Hypothesis 3.

Assessing Gender and Age Effects. We ran an alternative specification of the matched pair analyses testing Hypothesis 1 to account for the potential interaction effects of gender and age on the big win effect. For these analyses, we estimated a log-transformed linear regression model with robust standard errors on the following main outcomes: total stake, number of bets, median stake size, and median odds during the subsequent week. The main independent variable was big winner status (versus matched control), and we controlled for bettor age (as of initial registration with bwin) and gender (male vs. female). We then added two interaction terms to each of these models: age with big winner status and gender with big winner status.

4. Human subjects

The Cambridge Health Alliance Institutional Review Board determined that this study was exempt from IRB review because it uses secondary data.

5. Results

5.1. Descriptive analyses

A total of 27,926 big wins occurred during the approximately five-year study period. There were 22,688 (81.2% of all big wins) that met only the Prize Ratio criterion, 514 (1.8%) that met both criteria, and 4724 (16.9%) that met only Custer's criterion. Out of the 36,328 bettors in our analytic sample, 9393 (25.9%) experienced at least one big win by either definition. The vast majority of the big winners (9105 bettors, 97.0% of big winners, 25.1% of all players) experienced at least one Prize Ratio big win. Bettors who experienced at least one Custer big win were rare (709 bettors, 7.5% of big winners, 2.0% of all players).

In all, 5238 big wins met the Custer definition (prize of 1000 euros or more). Of these, 1663 (31.7%) were associated with combo bets (bets

associated with multiple propositions, where all propositions need to win in order to win the bet, also known as parlays) or system bets (i.e., bets associated with multiple propositions, where only some propositions, or specific combinations, need to win in order to win the bet). The remainder were associated with single bets. The majority of Custer big wins (3,619, 69.1%) were associated with an in-game (a.k.a., live-action) bet, where a proposition can only be selected once a contest begins and whose odds can change throughout the contest. The remainder were associated with pre-match (aka, fixed-odds) bets. The

median odds of bets associated with Custer big wins was 2.0 (i.e., pays even money, that is, winnings include both the stake size and the refunded stake itself), and the median stake size was 800 euros.

In all, 23,202 big wins met the Prize Ratio definition (top 1% of Prize Ratio among all bets placed). Of these, the vast majority (16,322, 70.3%) were associated with combo bets or system bets, and a minority (5,581, 24.1%) were associated with an in-game bet. The median odds of bets associated with Prize Ratio big wins was 10.88 (i.e., pays approximately 11:1), and the median stake size was 5 euros.

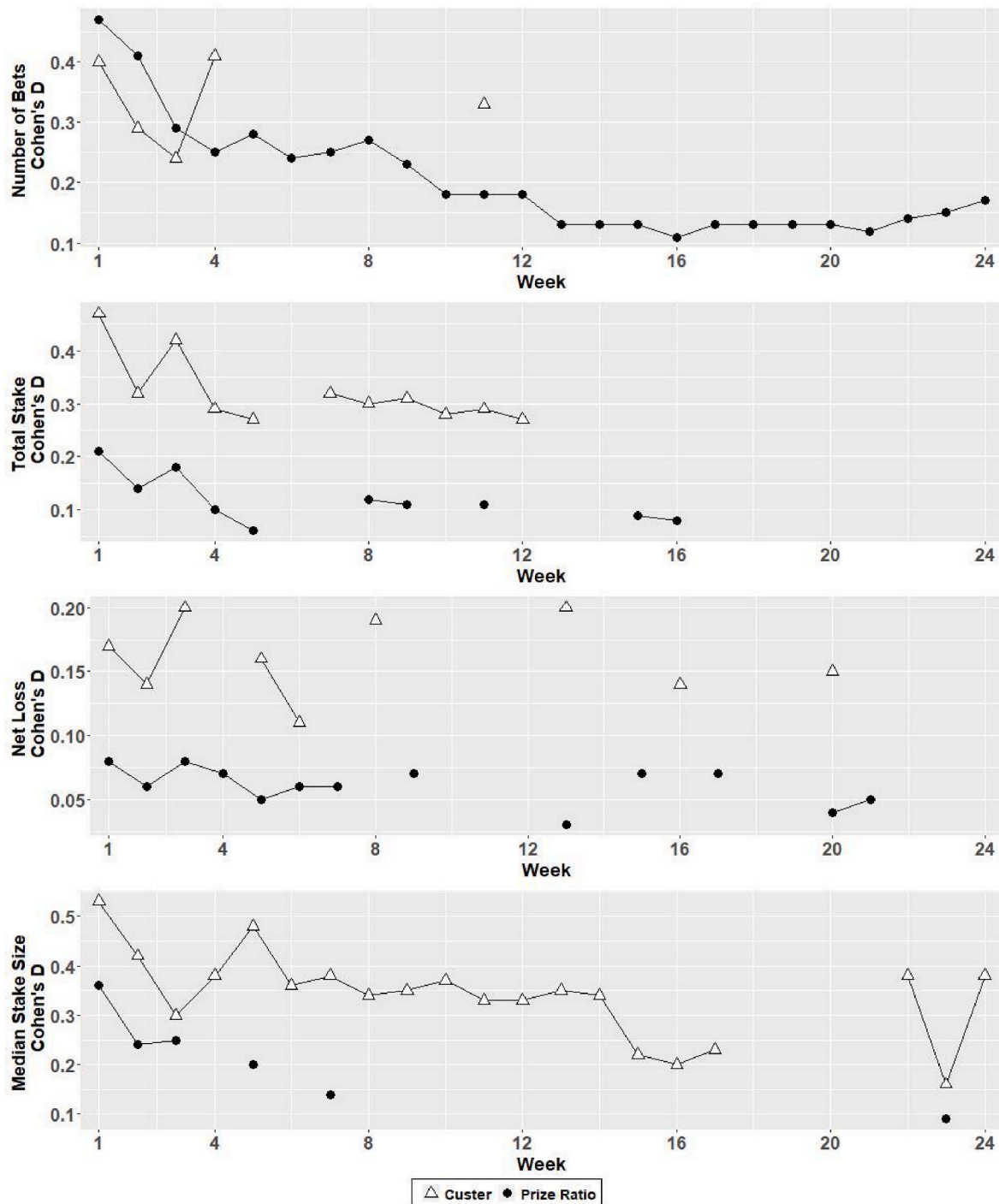


Fig. 1. Cohen's *d* standardized effect sizes (bets, total stake, net loss, median stake size) for the 24 weeks following a big win for both big win definitions (notes: Cohen's *d*'s with corresponding *t*-values that are non-significant (i.e., *p* greater than or equal to 0.05) are censored from these trendlines and thus are not displayed; graphing lines denote adjacent time points that are both significant, to further illustrate any instances of robustness to deterioration effects; median odds was excluded because subsequent week analyses [Hypothesis 1] were not supported for this outcome).

The minimum qualifying Prize Ratio threshold (as a reminder, unlike betting odds, this is based on the largest wager placed up to that bet, not the wager of the bet) was 3.7 X the wager (25%: 4.3X, Median: 5.5X, 75%: 8.2X, Max: 2912.9X). Considering only Prize Ratio big wins experienced by Prize Ratio big winners in the matched sample, the five-number summary of Prize Ratio for these wins is as follows: (Min: 3.7X, 25%: 4.3X, Median: 5.5X, 75%: 8.2X, Max: 635.9X). To put these numbers in perspective, the five number summary of Prize Ratio for all winning bets that occurred during the two-year study period is as follows: (Min: 0.00001X, 25%: .1X, Median: .2X, 75%: .6X, Max: 2912.9X).

5.2. Confirmatory analyses

5.2.1. Examining the effects of big wins on immediate subsequent sports betting engagement and risky behavior

During the week following the big win, compared to matched controls, Custer big winners in the matched sample ($N = 693$) placed more bets (Mean [SD]_{BW} = 33.8 [115.6]; Mean [SD]_{MC} = 18.5 [54.8]; $t [692] = 3.3$, $p < .05$; $\text{Cohen}_d = 0.40$), staked more money (Mean [SD]_{BW} = 2211.8 [5444.7]; Mean [SD]_{MC} = 451.5 [1434.3]; $t [692] = 8.6$, $p < .05$; $\text{Cohen}_d = 0.47$), experienced greater net loss (Mean [SD]_{BW} = 159.0 [1064.5]; Mean [SD]_{MC} = 35.4 [211.1]; $t [692] = 3.0$, $p < .05$; $\text{Cohen}_d = 0.17$) and had a higher median stake size (Mean [SD]_{BW} = 71.4 [156.2]; Mean [SD]_{MC} = 18.0 [37.0]; $t [692] = 8.9$, $p < .05$; $\text{Cohen}_d = 0.53$). Custer big winners did not significantly differ from matched controls on median betting odds (Mean [SD]_{BW} = 100.2 [779.0]; Mean [SD]_{MC} = 121.6 [1633.1]; $t [692] = 0.3$, $p = .75$) during the week following the big win event.

Compared to matched controls during the week following the big win, Prize Ratio big winners in the matched sample ($N = 9024$) placed more bets (Mean [SD]_{BW} = 20.1 [51.7]; Mean [SD]_{MC} = 8.5 [25.4]; $t [692] = 19.9$, $p < .05$; $\text{Cohen}_d = 0.47$), staked more money (Mean [SD]_{BW} = 166.0 [976.0]; Mean [SD]_{MC} = 85.7 [699.6]; $t [692] = 6.7$, $p < .05$; $\text{Cohen}_d = 0.21$), experienced greater net loss (Mean [SD]_{BW} = 22.1 [333.7]; Mean [SD]_{MC} = 7.7 [103.6]; $t [692] = 4.0$, $p < .05$; $\text{Cohen}_d = 0.08$) and had a higher median stake size (Mean [SD]_{BW} = 6.5 [21.8]; Mean [SD]_{MC} = 5.3 [21.4]; $t [692] = 3.7$, $p < .05$; $\text{Cohen}_d =$

0.36). As with Custer big winners, Prize ratio big winners did not significantly differ from matched controls on median odds (Mean [SD]_{BW} = 70.72297.5; Mean [SD]_{MC} = 102.1 [2652.4]; $t [692] = 1.3$, $p = .20$) during the week following the big win event.

5.2.2. Assessing the diminishing/deterioration effect of big wins in sports betting over time

Fig. 1 contains plots of Cohen's d 's derived from each of the matched pairs t -tests between big winners and matched controls for the four outcomes that were significant in subsequent week analysis (i.e., we excluded the median odds outcome due to the absence of an initial Big Win effect), across the 24 weeks following the big win event. For number of bets across Prize Ratio matched pairs, we observed just a diminishing effect (i.e., long-term decreasing value of Cohen's d over time). For number of bets and net loss across Custer matched pairs, we observed just a deterioration effect (i.e., increased likelihood/frequency of non-significant underlying t -tests over time). For the remaining outcomes for both matched pair groups (Custer and Prize Ratio), we observed both a diminishing and deterioration effect. Notably, Custer big wins elicited the strongest overall effect size (for median stake size during week 1) whereas Prize Ratio big wins had the most consistent significant effect (i.e., longest tail; for number of bets).

5.2.3. Assessing the relevance of the timing of big wins on subsequent sports betting engagement

Custer big winners ($n = 693$) and Prize Ratio big winners ($n = 9074$) had similar rates of persistence during the 6 months following the big win event (Fig. 2). Compared to their matched controls, Custer big winners had elevated persistence during only month two, while Prize Ratio big winners had elevated persistence compared to matched controls for all six months. In a Cox Proportional Hazard analysis modeling persistence, the week of a big win had an extremely small, albeit significant, negative effect on the hazard function for both Custer big winners (Hazard Ratio [HR] = 0.996, 95% CI = [0.995, 0.997]) and Prize Ratio big winners (HR = 0.9988, 95% CI = [0.9983, 0.9992]). These significant effects remain after controlling for players' frequency of play and stake per day in the weeks leading up to, and including the

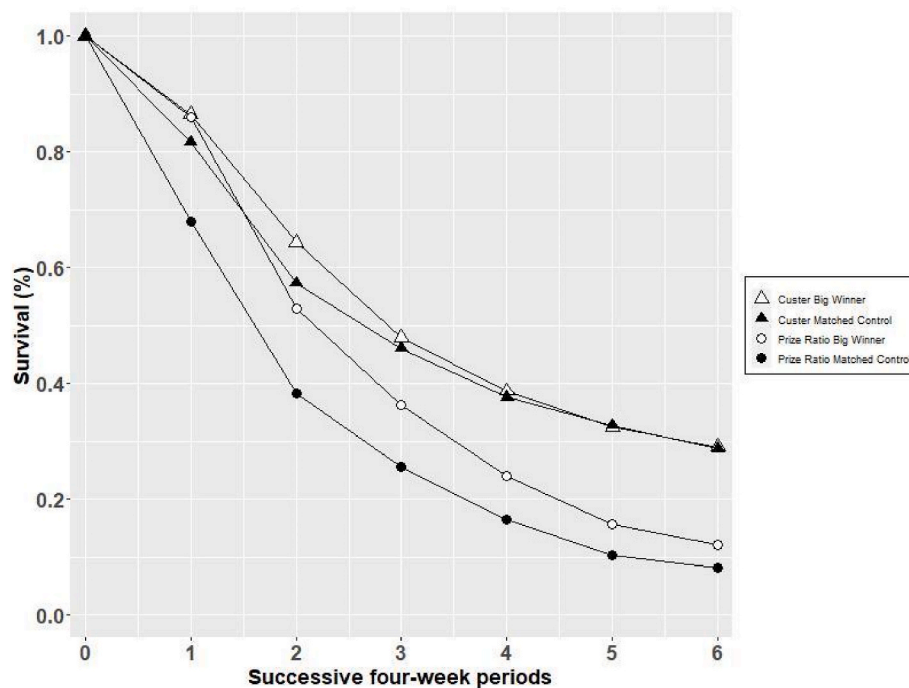


Fig. 2. Kaplan-Meier survival curve of persistence among Custer big winners ($n = 693$), Custer matched controls ($n = 693$), Prize Ratio big winners ($n = 9074$), and Prize Ratio matched controls ($n = 9074$).

week of the big win, as well as bettor gender and age, for both Custer big winners (HR = 0.997, 95% CI = [0.995, 0.998]) and Prize Ratio big winners (HR = 0.9993, 95% CI = [0.9988, 0.9998]).

Similarly, linear regression models indicated that week of the big win had a small negative effect on frequency of play for Prize Ratio big winners ($b = -0.06$, $\beta = -0.10$, $SE = 0.007$, $p < .05$). The effect of week on the big win on frequency of play for Custer big winners was not significant ($b = -0.00$, $\beta = -0.10$, $SE = 0.015$, $p = .932$). Moreover, the effect of week of the big win on frequency of play for Prize Ratio big winners became non-significant after accounting for frequency of play and stake per day in the weeks leading up to and including the week of the big win, as well as bettor gender and age ($b = -0.01$, $\beta = -0.01$, $SE = 0.008$, $p = .27$).

5.2.4. Planned sensitivity analyses

The full results of the sensitivity analyses, including all graphs and tables, are available in the online supplement. Here we provide a summary of each:

The median e-values for Custer big matched pairs during the 24-week follow-up period were 1.7 for Custer matched pairs and 1.3 for Prize Ratio matched pairs. The maximum e-values (2.6 and 2.4 for Custer and Prize Ratio big winners respectively) both fell on Week 1. The consistently high e-values we observed suggest that our matched pairs test results were robust.

Upon examination of the revised Cohen's d graphs, after removing matching cases where either big winner or matched control experienced an additional/initial big win, we observed that the big win effect (Week 1) gets stronger for the net loss outcome, for both Prize Ratio and Custer matched pairs. In contrast, for total stake, the big win effect during Week 1 disappears for Prize Ratio matched pairs and becomes weaker for Custer matched pairs. After removing matching cases where just big winners experience another big win, the big win effect disappears for the number of bets outcome for Custer matched pairs, while the big win effect becomes slightly stronger for the net loss outcome for both Custer and Prize Ratio matched pairs, and for all outcomes the dissipation effect happens more quickly. Finally, after removing matching cases where just matched pairs experienced an initial big win during the 24-week follow-up period, there appears to be little change in the results, with a single exception: the dissipation effect of prize ratio big wins on median stake size does not happen as quickly among Prize Ratio matched pairs.

An examination of the percentage of matched pairs that support Hypotheses 1 and 2 revealed some unique insights on the potential timings for how long the big win effect tends to last (see Supplementary Materials). For all outcomes, the point of convergence (i.e., the point where the percentage of cases in which big winners and matched controls are equal (i.e., tie) on the raw metric begins to exceed the percentage of cases in which big winners are greater than matched controls on the raw metric) is at approximately Week 4 for Prize Ratio matched pairs and somewhere between Week 6 or 7 for Custer matched pairs.

Finally, after re-running confirmatory hypothesis tests for the total stake and net loss outcomes, and taking into account the effects of big wins on all gambling activity (casino games, poker, and bingo, in addition to sportsbook) related to these outcomes, we observed that the big win effect on total stake disappears during Week 1 for Prize Ratio matched pairs, and becomes noticeably weaker for Custer matched pairs (in terms of size of Cohen's d). However, for net loss, the big win effect on Week 1 remains and becomes noticeably stronger for both big win definitions on the net loss outcome, although its effect appears to dissipate and/or deteriorate more quickly afterward.

We estimated a set of fixed-effect and random-effect models that assess the impact of the Custer and Prize Ratio big wins on our outcome variables. As in our matched pair analysis, we use weeks since the first bet as our unit of time and account IDs as our panel variable. In all our models, we find statistically significant and economically meaningful effect sizes from big wins on weekly stakes, net loss, and bets. Our

models also control for cumulative net loss. A Custer big win is associated with a \$4866 increase in the next week's stakes, a \$387 increase in net loss, and a 31 unit increase in the number of bets. A Prize Ratio big win is associated with a \$176 increase in stakes, a \$27 increase in net loss, and a 22 unit increase in bets. We find similar effects on median stake size and weak effects of big wins on median odds levels. The Custer big win is statistically significant at the $\alpha = 0.05$ level, but the model shows poor goodness-of-fit. The Prize Ratio big win has no statistically significant effect on median odds.

To validate our findings related to [Hypothesis 2](#), we fit fixed-effect regression models similar to those above but added lagged big win variables of up to 16 weeks. We find that effects generally are statistically significant throughout the period, but the size of the coefficients and the standard errors generally appear to decay over time. The only persistent effect is the impact of Prize Ratio big wins on number of bets, which shows a statistically significant effect in all 16-week lag effects.

To test the robustness of our findings related to [Hypothesis 3](#), we estimated a set of Kaplan-Meier survivor functions and a set of Cox Proportional Hazard Models that differ from our main analyses specifically in terms of how the timing of early/late big wins is measured. Instead of a numeric "week number" predictor, these analyses collapse it into two categories of "early" (within four weeks) and "later" (after four weeks). The Kaplan-Meier survivor functions estimate the likelihood that an individual account would become dormant. In these analyses, we find that big wins extend the survival function, but that early big wins (within the first four weeks of account opening) have smaller impacts than later big wins, which contrasts with our main survival analyses. Unlike the matched pair analysis, the fixed-effect analysis cannot correct for survivorship bias in comparing early big wins to later big wins.

Similar to our Kaplan-Meier modeling, we regress our big win variables on the length of account activity in weeks. We find evidence supporting the impact of big wins on activity length. For example, in one model a big win at some point in the player's experience on the site is related to a 60% reduction in the probability of observing a final week of activity in any given period. Again, we observe that the net effect size is larger for big wins occurring after the first four weeks of play, rather than during that period.

5.2.5. Planned exploratory analyses

Out of the 5238 Custer big wins that occurred during the study period, 1004 of them (19.2%) involved the big winner net withdrawing (i.e., withdrawal[s] exceeds deposit[s]) within 24 hours. Out of the 23,202 Prize Ratio big wins that occurred during the study period, 447 of them (1.9%) involved the big winner net withdrawing within 24 hours. Among the matched pair sample of Custer big winners ($n = 693$), 200 of them (28.8%) net withdrew within 24 hours of the big win. Among the matched pair sample of Prize Ratio big winners ($n = 9074$), 88 of them (0.97%) net withdrew within 24 hours of the big win. Accounting for frequency of play and stake per day in the weeks leading up to, and including the week of the big win, as well as bettor gender and age, net withdrawing after the big win had a substantial negative effect on persistence for Prize Ratio big wins (HR = 0.57, 95% CI = [0.46, 0.70]) but no significant effect on persistence for Custer big wins (HR = 1.00, 95% CI = [0.85, 1.18]). Accounting for frequency of play and stake per day in the weeks leading up to, and including the week of the big win, as well as bettor gender and age, net withdrawing did not have a statistically significant effect on frequency of play for either Custer big winners ($b = -0.95$, $\beta = -0.01$, $SE = 2.48$, $p = .703$) or Prize Ratio big winners ($b = 3.6$, $\beta = 0.10$, $SE = 3.34$, $p = .279$).

Finally, upon estimating log transformed linear regression models with robust standard errors on each of the main outcomes (excluding net loss) during Week 1, we did not detect any interaction effects between big winner status and age or between big winner status and gender that were significant at $p < .05$.

6. Discussion

Using actual digital betting record data from a large sample of online sports bettors ($N = 36,328$) from a large European gambling operator, we assessed the effects of big wins on future sports betting engagement, losses, and risk. In addition to replicating Edson and colleagues' (2021) original analyses of big wins in DFS, we also expanded upon their work by examining additional outcomes (i.e., risk metrics — median betting odds and median stake size) as well as conducting additional novel exploratory analyses (e.g., assessing the prevalence/effects of big wins followed by a withdrawal soon after) and sensitivity analyses (e.g., calculating e -values). The present study represents an important extension of this original work and is one of the first to assess the big win effect among actual online sports gamblers with prospective gambling record data.

6.1. Key findings

We found that experiencing a big win was associated with increased engagement initially, with little impact beyond an approximately four-week period. These results were robust in both the main matched pair analyses and fixed effects sensitivity analyses, suggesting that our results are not contingent on the modeling approach. Additional sensitivity analyses that excluded matched pairs involving multiple big winners and incorporated betting activity from other products (i.e., casino, poker, and bingo) also revealed very similar findings, again strengthening the evidence for the presence of a big win effect in the domain of sports betting based on actual behavioral data. Moreover, we saw significant effects for both definitions of big win (Custer and Prize Ratio). Here we reiterate Edson et al.'s (2021) conclusion that the two definitions "are likely tapping different dimensions of 'big.' Specifically, whereas the Custer definition might represent an absolute or objective measure of 'big,' the Prize Ratio definition could represent a measure of 'big' that is more subjective and relative to an individual's traditional wager size" (p. 10). In sports betting, we find that different betting behaviors might lead a bettor to one definition. Specifically, large stake bettors who play short odds are more likely to experience a Custer big win, while low-stakes long-odds bettors are more likely to experience a Prize Ratio big win.

However, although the pathways to these definitions of big win might differ, their effects on future engagement and losses remain similar. There were some notable differences. Custer big wins exhibited greater magnitude of effects on absolute stake and net loss (see Fig. 1), which is likely the result of individuals who experience Custer big wins already betting at greater magnitudes of play. Prize ratio big wins, on the other hand, appear to have a longer lasting effect on general engagement behaviors, namely number of bets (see Fig. 1) and persistence (see Fig. 2). On the whole, we believe both of these definitions hold unique value, and deserve consideration from stakeholders and in future investigations of big wins.

These findings on big wins and subsequent increased engagement generally replicate those found for big wins in DFS by Edson et al. (2021), which suggests the big win effect is not particular to any one form of wagering. Overall, we interpret these similarities as resulting from product features inherent in DFS and online sports betting, as well as potential cognitive states and traits of the players themselves (e.g., perceived knowledge about sporting outcomes) that are similar in these gaming formats. DFS and online sports betting both have a wide variety of sporting contests to bet on each day at a variety of levels of stakes, so big winners have a wide variety of betting opportunities to wager on following their big win. Both products also use a built-in withdrawal and deposit account that displays individuals' overall funds available for gambling, so a large influx of money from the big win would be clearly visible to them, making them aware of their larger bankroll, and the bets that they could place with it.

That big win effects appear to decline over time gives credence to a

handful of potential cognitive mechanisms and social/behavioral effects. One of these is that, following a big win, bettors now have more money with which to gamble, and consumption generally increases with gains in wealth, consistent with the *wealth effect* (Mehra, 2001). Several explanations from cognitive and behavioral psychology might also explain increased engagement following a big win. Specifically, big win effects could result from several cognitive biases or distortions (Granero et al., 2020; Ledgerwood et al., 2020) experienced by players such as the availability heuristic (Fortune & Goodie, 2012), representative heuristic (Tversky & Kahneman, 1971), house money effect (Thaler & Johnson, 1990), "hot hand" effect (Gilovich, Vallone, & Tversky, 1985), and insensitivity to small sample sizes (Leonard & Williams, 2016), which make the odds of experiencing a big win seem far better than they actually are and also could lead to big winners to attribute their big win to skill over luck. Sports betting contains some degree of skill (Trippiedi, 2014); however, the scant probability of consistently winning and an even lower probability of winning big suggests that luck plays a more dominant role. Yet, studies have shown that gambling winners often attribute their success to their own skill or ability (i.e., the illusion of control), instead of chance (Myrseth, Brunborg, & Eidem, 2010; Zhou et al., 2012).

A second explanation, drawn from behavioral psychology, is focused on the operant conditioning (Skinner, 1963) process that occurs when a gambler experiences winning, leading to reinforcement of betting behavior, and thus more sustained or persistent gambling to seek another win. Although much of the literature on operant conditioning has focused on within-session behavior with well-documented effects of wins on future reinforcement of gambling behavior in experimental studies (see Barton et al., 2017; Leino et al., 2016), discussion of between-session or longer-term reinforcement processes in the literature, like we see here, is comparably rare (e.g., Redish, Jensen, Johnson, & Kurth-Nelson, 2007).

Given that we do not have access to psychometric measures on participant cognitive distortions or biases, or the extent of operant conditioning, we cannot directly test these potential explanations for big wins effects empirically, other than to suggest that they could be playing a role in explaining the effects of big wins on future online sports betting engagement.

6.2. Differences between online sports betting and DFS

We observed three important differences between our findings and the DFS findings reported in Edson et al. (2021). First, while we found weak evidence for an early big win effect in the matched pair analyses of this study, Edson and colleagues (in their matched pair analyses) observed weak evidence for a late big win effect. That is, big wins that happen later on in DFS, within a single product domain, tended to have a stronger effect on increased engagement compared to earlier wins, although like this study the effect size they observed was very small. The fixed effect sensitivity analyses we conducted in this study also suggest that earlier big wins (i.e., within the first 4 weeks) elicit a weaker effect than later big wins (i.e., after 4 weeks) on continued engagement. We have no clear explanation for these differences between the matched pair and fixed effect sensitivity analyses in this area, although slight differences in methodology (e.g., *week number* was treated as a numeric predictor in matched pair analysis, while the fixed effect analyses treated "early" and "later" big wins as categorical predictors separated by a slightly arbitrary four-week threshold) could explain the conflicting results. Overall, we interpret this inconsistency as a potential sign that the effect of the timing of big wins (at least within a single product domain) is probably of lesser importance. Future research should focus on the timing of big wins over an individual's entire life course, in addition to within-product timing.

Second, Custer big wins were rarer in this study (i.e., 7.5% of big winners experienced at least one Custer big win) than Edson and colleague's DFS study (i.e., 44.2% of DFS big winners experienced a Custer

big win). On a similar note, prize ratios in Edson et al.'s DFS study tended to be much higher (median of 20X) than the ratios of Prize Ratio big wins in this study (median of 5.5X). We attribute both of these differences to the differential play mechanics of DFS and sports betting. In DFS, the headliner contests that tend to yield extremely large prizes are always guaranteed to have a (big) winner. In sports betting, big wins result only from short-odds/large stake bets or long odds bets (e.g., multi-prop parlays and large system bets such as "goliaths"), with none of these bets guaranteed to win. On one hand, we expect most individuals to either be hesitant or flat out not have the ability to risk 800 euros (the median stake size of a Custer big win) on a single bet. On the other hand, bets with long odds (e.g., multi-prop parlays, large system bets such as "goliaths") are extremely unlikely to pay off. Between the two sides, compared to DFS, we can expect a lower prevalence of Custer big wins and a lower threshold for what constitutes a Prize Ratio big win in online sports betting.

Third and finally, the effects of big wins on net loss slightly differed between the two products. In Edson et al.'s DFS study, while big wins had a positive effect on net loss among all matched pairs (main analyses) and all big winners (fixed-effects analyses), this effect disappeared when repeat big winners (presumed to be more professional players) and their matched pairs were removed from those analyses. This suggests that a big win's effect on subsequent losses in DFS was only confined to players for whom the big win was not a sign of greater skill. In this study, the positive effect of big wins on net losses in sports betting remained even though we initially included matched pairs and big winners who experienced several big wins. The effect of big wins on net loss became stronger when we removed matched pairs where the big winner had subsequent big wins during the 24-week follow-up period, suggesting that the inclusion of skilled players had some effect on the main results. Even still, their inclusion did not remove the significant effect of big wins on net loss. This difference suggests that, compared with DFS, for which big wins in many cases might be a sign of actual skill, big wins in sports betting could be more so related to luck. If this is the case, it could potentially lead sports bettors, in particular, to misattribute their winnings to perceived skill and bet more money in order to replicate their past results, which could in more cases than not lead to mounting demoralizing losses. It should be noted in this study we did not fully test the latter assertion – whether big winners, more often than not, experience net losses that deplete their initial big win and lead them deeper into a state of net loss – future research can and should test this assertion.

6.3. Theoretical and practical implications

Early evidence from clinicians such as Custer (1984) and contemporary clinical reports (Davies, 2022) suggest that big wins, particularly those that occur early on in the gambling experience, serve as precursors to increased gambling and the development of gambling problems. This study was supportive of the first part of this assertion, namely that big wins have an effect on future engagement, losses, and risk in online sports betting. This study—like a previous study of big wins in DFS by Edson et al. (2021)—did not find strong evidence for an *early* big win effect, insofar as early big wins kept bettors active, but for no more weeks than it would have at any other point in time. A potential reason we, along with the previous DFS study, observed these null findings could be due to design limitations inherent to both – specifically, only being able to examine the timing of big wins within the confines of single product and operator domains. The combined findings of that study, and our own, suggests that any early big win effects within single product and operator domains are either weak or non-existent. It remains possible that early big wins (i.e., true early and formative gambling experiences) are more meaningful than later ones, however without access to an individual's entire gambling history, this will be difficult to tease out and assess.

Our findings can help to inform evidence-based recommendations and have practical implications for gambling operators and people who

bet on sports alike. First, operators should consider tools to promote responsible gambling (RG) and player safety that are deployed after a player experiences a big win by either definition. This proactive RG approach might include emails, push notifications and/or site pop ups that inform the player of their big win with links to RG resources, a recommendation to withdraw at least some of their winnings to their bank account, and/or personalized normative messaging (e.g., "Most people who win big save some of it for later, have you considered saving or investing your winnings?"), which has been shown to be effective in curbing excessive gambling (Celio & Lisman, 2014; see a review on normative messaging in Saxton, Rodda, Booth, Merkouris, & Dowling, 2021). Recommendations to withdraw at least some of the big win could be particularly effective for promoting responsible gambling, given evidence from the present study, which shows that: (1) most big winners, left to their own devices, choose not to immediately withdraw their big win, (2) continued engagement following a big win tends to result in net losses, and (3) immediate withdrawals following a prize ratio big win tends to lead to less persistent play. Future research should consider testing the efficacy of this type of messaging, and its effects on withdrawal behavior and engagement following a big win.

Second, additional steps that operators could take after a player gets a big win might include advising players of the actual odds of winning (e.g., see Gainsbury, Abarbanel, Philander, & Butler, 2018) and making it clear that luck plays a large role in determining winning (even in skill-based products), and especially in winning big. Such an approach would help to clarify the role that chance plays in big wins, thus potentially reducing false confidence or cognitive distortions regarding the outsized role of skill in determining sports betting outcomes.

6.4. Study limitations

Our study is not without limitations. First, to be consistent with long-standing clinical observations about the magnitude of big wins (Custer, 1984; Custer & Milt, 1985; Kassino & Schare, 2001) and recent empirical research on big wins (e.g., Edson et al., 2021), we selected the 1000 euro threshold for the Custer definition and the top 1% of prize ratios for the prize ratio definition. Other researchers might identify or select different big win thresholds, and therefore might reach different conclusions than those we arrived at in this study.

Second, the intent of this study was to test the popular assertion that there exists an arbitrary threshold by which a sports gambling win is large enough to have a large effect on subsequent behavior. However, there exists the possibility that wins, more generally, have a linear effect on subsequent behavior that is roughly proportional to their size. More research is needed to test this assertion, which would call into question whether there truly is a "big win" effect, rather than just a "win effect".

Third, our basic description of the median stakes and median odds of both Custer and Prize Ratio big wins (see beginning of the Results section) indicates that big wins of both definitions derive from only certain types of bets (i.e., high stakes bets for Custer big wins and long odds bets for Prize Ratio big wins). Unlike gambling products where single actions have multiple possible payout-to-stake ratios (e.g., lotteries and scratch tickets, EGMs, poker tournaments), sports bets typically have only two: zero and the one where the gambler wins. In order for a typical sports bettor to have a chance of a big win, they either have to bet a large amount or pick a bet with long odds. In this study, although we matched big winners with controls with similar median stake sizes and betting odds, and controlled for these variables in fixed-effects analysis, in at least some cases it is possible that we could have been comparing people with big wins to people who never gave themselves a chance to have a big win. At the very least, our matched pairs analyses in particular might have systematically excluded individuals who play at low stakes and betting odds — meaning the results of this study could potentially represent the big win effect on future engagement among sports bettors trying for big wins, rather than sports bettors more generally.

Fourth, our betting account data are from only one online sports

betting provider, so it is possible that the players in our sample also had accounts and/or played with other operators. This might have limited our ability to potentially capture “early” big wins for individuals who had been gambling extensively before engaging in online sports betting on bwin, or who might have experienced a big win on another operator’s website during the study period. Bettors also could have changed their level of engagement with other Internet and land-based gambling operators. However, we were only able to monitor changes in playing behavior with the single operator described here. Although it would be very difficult to coordinate with multiple gambling operators to obtain betting account data for the same individuals, future studies should seek to obtain account data from more than one operator to assess big wins and engagement on more than one gambling platform.

Finally, this study did not include a measure of problem gambling to assess the relationship between experiencing a big win and problem gambling, which represents an important direction for future research on big wins in sports betting, as well as big wins in gambling more generally. Because bettors generally cannot easily recall gambling expenditures (Braverman et al., 2014; Heirene et al., 2021), we strongly recommend the continued use of actual gambling data based on betting records to examine big wins — however, we also recommend that this future research consider linking gambling data to self-report outcomes that include a problem gambling measure.

6.5. Conclusion and future directions

We found that big wins in online sports betting predict increased engagement and losses, and risk in subsequent weeks, with diminishing effects that ultimately dissipate after approximately four weeks. These findings were true for two unique definitions of “big win”: Custer and Prize Ratio. This work shows that the nuances of gambling are evident through exhaustive examination of player records for research purposes. The findings diverge from popular conceptions of big wins and their influence on players. While fields of science might rely heavily on such conventional wisdom in their infancy, doing so perpetually might imperil the development of appropriate prevention and intervention efforts. Yet, to fully understand the big win effect, it appears that multiple lines of evidence, from lived experience, tightly controlled scientific experiments, and ecologically valid data sources are needed to come together for comprehensive understanding of this phenomenon.

Author credit

Timothy C. Edson played a lead role in formal analysis (matched pair and most exploratory and sensitivity analyses), supervision, writing, conceptualization, methodology and project administration. Kahlil S. Philander played a supporting role in formal analysis (fixed effects sensitivity analysis), methodology, conceptualization, and writing. Matthew A. Tom, Eric R. Louderback, Taylor G. Lee, John M. Slabczynski, and Debi A. LaPlante played a supporting role in conceptualization, methodology, and writing.

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Data availability

The data that support the findings of this study are available from the

corresponding author, upon reasonable request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.chb.2023.107657>.

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