A large-scale prospective study of big wins and their relationship with future financial and time involvement in actual Daily Fantasy Sports contests

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Keywords: gaming, gambling, big win effect, early big win, daily fantasy sports, mahalanobis distance matching, prospective study

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Abstract

Objective: Early big wins might have a psychological impact upon gamblers that increases their likelihood of intemperate gambling; however, there has been a paucity of empirical research examining this effect using actual gambling data.

Method: We assessed the effects of daily fantasy sports (DFS) big wins on subsequent play by analyzing a prospective dataset from a major DFS provider (N = 34,596 DFS subscribers) representing over 18 million entries into DFS contests.

Results: We found that experiencing a big win in DFS is associated with subsequently increased DFS engagement (i.e., increased contest entry fees, contest entries) and losses (i.e., higher net loss). However, the effect of a big win on engagement and losses decays over time. Whereas theorists have highlighted the effects of early big wins, our analyses indicated that *later* big wins had a relatively stronger effect on DFS engagement. Sensitivity analyses confirmed the robustness of most results, with somewhat greater support for big wins' effects on engagement metrics than losses.

Conclusion: Our results collectively indicate the existence of a big win effect DFS. For some players, big wins might instill unrealistic expectations about future probabilities of winning and lead to increased, and potentially excessive, engagement. Explanations from cognitive psychology (e.g., illusion of control) and behavioral psychology (e.g., operant conditioning) might help to explain the big win effect.

Keywords: gaming, gambling, big win effect, early big win, daily fantasy sports, mahalanobis distance matching, prospective study

Public Health Significance Statement: Our study suggests that for some DFS players, big wins can promote ongoing and potentially risky DFS engagement behaviors, including future gambling losses. These findings have important implications for DFS operators and stakeholders, who should consider the promotion of healthy behaviors for players following large wins (e.g., setting some winnings aside for necessary expenses). The results also emphasize the need for more research into the relationship between big wins and DFS-related problems.

Other Data Statement: Some of the raw data used for this study (i.e., 2014 cohort data) have been used in other published manuscripts, including: 1) an epidemiological description of DFS player behaviors, 2) a study of longitudinal playing trends of DFS playing behaviors, 3) a study assessing relationship between social DFS behaviors and risky play, and 4) a study of natural groups of DFS players. The current study is unique from these other studies because 1) it examines novel research questions, 2) uses a matched-pairs approach, 3) tests different outcomes, and 4) analyses the data with survival analysis, count models, and panel regression.

Formative experiences in individuals' lives can have a lasting impression on future behaviors (Tversky & Kahneman, 1973; Muthukrishnan & Kardes, 2001; Do et al., 2018). Gambling studies have examined whether potentially formative experiences such as winning a large prize during one's first few gambling sessions (Weatherly, Sauter, & King, 2004) might predict future risky gambling behaviors. Early big wins are defined as subjectively large prizes won by gamblers during an initial and formative period of their gambling experience (Custer & Milt, 1985). The early big win effect on gambling behavior seems plausible and could be rooted in biases associated with both availability and representativeness heuristics (Tversky and Kahneman, 1971, 1973). The large size of the win, for example, could impact the availability heuristic, as the subjectively meaningful sum of money is likely to make the outcome of winning more salient, relative to other wagers. The 'early' aspect of the phenomenon could impact the representativeness heuristic, as the limited number of trials relative to the large event might falsely lead individuals to believe that the outcome is likely to reoccur often.

Although there is no consensus as to what constitutes "early" or "big" (Weatherly et al., 2004), the first writings about early big wins derive from Custer's (1984) clinical observations suggesting that early big wins are events occurring during an initial phase of gambling and on a scale that is nearly equal to or greater than one's annual salary. Custer identifies an "early big win effect", as a big win during one's first few gambling experiences that instills unreasonable optimism about continued winning, leading to an increase in gambling, gambling losses, and eventually, the development of gambling-related problems (1984, pp. 36-37). Custer & Milt (1985) later describe the definition of "big" in a way that it could be taken to mean any win that is comparable to some quotient of one's annual earnings (i.e., a month's salary or more; see also Weatherly et al., 2004). Researchers have observed reports of early big wins among as many as half of gamblers with problems in clinical settings, and suggested that they play a role in early persistence in gambling, due in part to distorting the gambler's perception of his or her ability to determine outcomes (Lesieur & Custer, 1984). Although there is very limited prospective empirical evidence about these clinical claims, many researchers suggest that early big wins play a role in the development of gambling-related problems, particularly among young people (Derevensky & Gilbeau, 2015; Griffiths, King & Delfabbro, 2016; Turner, Zangeneh & Littman-Sharp, 2006; Turner, Jain, Spence, & Zangeneh, 2008; Williams et al., 2015).

In the present study, we used pre-registered hypotheses and methods to examine the role of big wins in daily fantasy sports (DFS) engagement and losses, based on DFS player records from one of the largest DFS providers (DraftKings, Inc.). DFS is a partially skill-based online gaming activity which shares many attributes with popular gambling activities that are also partially skilled-based such as poker and sports betting. We study DFS because it overlaps and shares characteristics with traditional gambling games (see Nelson et al., 2019), is a relatively new gaming activity that many users are likely experiencing for the first time, and contains large tournaments with jackpot sized payouts each week, thus providing a reasonable sample of big winners to analyze. For this work, we introduce two competing definitions of the term "big win" — one that is an adaptation of Custer's (1984) original definition (i.e., *Custer* definition; wins greater than or equal to $1,000), and another that is based on the ratio of players' largest prize won to how much they spend on an entry fee (i.e., *Prize Ratio* definition).

Using these two operationalizations of big wins, our analysis of the DFS player records proceeds in four primary ways, following our pre-registered research plan. First, we provide a census of DFS big wins by examining three cohorts of DFS players who first deposited on the website DraftKings during 2013, 2014, and 2015, to assess how many experienced a big win.

Second, we examine the effects of big wins on DFS play by identifying whether players who experience a big win show subsequently increased DFS engagement compared to those who do not experience a big win. Third, we investigate the durability of observed big win effects by exploring whether they diminish over time. Fourth, we study the relevance of time in the effects of big wins on DFS play.

Method

Study design:

We used a longitudinal prospective cohort design with continuous time points comprising weekly aggregates of players' online DFS data from DraftKings (one of the largest DFS operators) between August 1, 2013 and December 26, 2016 (i.e., the analytic study period). Because American football (i.e., the NFL) is the most popular DFS offering (Gillies, 2016), we purposefully selected cohorts of players who made their first DFS deposits near the beginning of the 2013, 2014, and 2015 NFL seasons, respectively. As such, our initial pool of participants includes all players who made their first deposit on DraftKings between August 1, 2013 and September 30, 2013 (2013 cohort, N = 12,041), as well as commensurately sized samples of players who first deposited money on DraftKings between August 1, 2014 and September 30, 2014 (2014 cohort, N = 12,041) and between August 1, 2015 and September 30, 2015 (2015 cohort, N = 12,041). This equates to an initial sample of 36,123 players. Of these players, 1,527 did not enter any DraftKings contests during the study period. We excluded these players and therefore our final analytic sample comprised 34,596 players.

DraftKings provided us with each player's initial deposit date and entire contest history (measures include number of contest entries, amount spent on entry fees, and amount won in prizes) from that initial deposit date to December 31, 2016. In addition to contests that require an entry fee, DraftKings offers free contests that either pay a tiny fraction of the people who enter or do not involve any payouts (i.e., play-for-fun). While we initially specified in our pre-registration that we would exclude free contests, we ultimately decided to include free contests in all calculations given their potential for actual cash payouts, which could affect key metrics such as net loss.

Dataset creation procedures

For each player, we generated weekly aggregates of their playing behavior (i.e., total entry fees, net loss and number of contest entries for each week they played). Because we believed that many players would be participating in primarily NFL-based DFS contests, for the purpose of this paper, we defined a "week" as a seven-day period beginning on a Tuesday at midnight (e.g., 2013-08-07 00:00:00). Under this assumption, for each player, we calculated weekly aggregates for contest entry fees, winnings, and number of contest entries. For each week, we also calculated each player's net loss (i.e., that week's total winnings minus that week's total losses). We considered the players' "first week" as the week they made their first deposit on DraftKings. Players who signed up earlier on during the recruitment period had more available weeks than players who signed up later (see pre-registration for additional details of how we constructed weekly aggregates).

Measures

Identifying variables

Player ID: Identification numbers used to distinguish one player from another.

Week number t: Given a player/Player ID, a week number of 1 means the week that the player made his first deposit into his DraftKings account. A week number of 2 means the week after the week of first deposit. "Week *t*" refers to (*t*-1) weeks after the week of first deposit.

Dependent variables

Our main dependent variables consisted of:

Current week's entry fees: The total amount a player spent on entry fees in Week *t*.

Current week's net loss: The sum of all entry fees minus the sum of all cash winnings over the contests the player entered with contest start times in Week *t*.

Current week's number of entries: The total number of entries submitted into contests in Week *t*.

Persistence: Persistence is, among big winners, the number of consecutive months they play (i.e., in which they entered at least one paid DFS contest) during their active duration following the big win. We tracked persistence for a total of six 4-week (i.e., six prototypical month) periods.

Frequency: Frequency is, among big winners, 100 times the number of active days on DraftKings 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.

Independent variables

Our main independent variable was experiencing a big win. As discussed previously, we defined the term "big win" in two different ways:

Big Win Measure 1 (Adaptation of Custer & Milt's definition; hereafter, "Custer's" definition):

Custer's & Milt's (1985) extension of Custer's (1984) writings on big wins among individuals experiencing gambling problems informed our first measurement approach to empirically defining a "big win." This definition of "big win" is based on the average monthly discretionary income in the U.S., which we calculated as (*Income after taxes - Average annual expenditures* divided by 12) based on the U.S. Bureau of Labor Statistics data table "Table 1800. Region of residence: Average annual expenditures and characteristics, Consumer Expenditure Survey, 2013-2014". The resulting average annual discretionary income after taxes for all consumer units (average annual income after taxes minus food, housing, transport, clothing, and healthcare) is approximately $18,532; dividing this figure by 12 months comes to approximately $1,544. Taking the smallest possible value that is within the same order of magnitude as this figure (i.e., $1,000), we classified a big win as a single prize that equals or exceeds $1,000. These players were identified with an indicator variable, *BigWin1*, coded as "1" for players who experienced a big win during the prior week and "0" otherwise.

Big Win Measure 2 (Prize ratio-based measure):

Our second measure of "big win" begins with the idea of a prize ratio, the size of a prize divided by the largest entry fee the player had ever paid up to that week. For example, if the largest entry fee a player ever paid for was $5.00 at the time the player won a $48.00 prize in a contest, then the prize ratio would be $48.00/$5.00 = 9.6. Even if the $48.00 prize came from a $1.00 contest, because the player has a $5.00 entry in his past, the prize ratio for that win would still be 9.6 and not 48.0 (see pre-registration for additional details of the prize ratio calculation). We excluded prize ratios less than or equal to zero, as well as instances where the largest entry fee ever paid up to that week was $0.00. For each player cohort (i.e., 2013, 2014, and 2015) separately, we conducted a percentile ranking of prize ratios and classified the largest 1%[1] of prize ratios within the cohort as "big wins" (Five number summary of prize ratio for full sample of qualified Prize Ratio big wins (Min: 10.93; 25% 14.81; Median: 20.00; 75%: 37.04; Max: 20000.00)

Matching Covariates

Prior Week's Engagement (Total entry fees and Number of Entries).

Prior research has noted a close relationship between current activity and subsequent activity, particular in the domain of sports gambling (Ma et al., 2014). Therefore, we matched players based on prior DFS engagement in terms of total entry fees and total number of entries submitted into contests as of the end of the week prior to the week of the big win.

Cumulative Net Loss.

Because past financial engagement and success rates can inform future expectations and engagement patterns, we also matched players 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.

Analytic strategy

Significance Criteria

We regarded *p*-values less than 0.05 as criteria for statistically significant results. All reported *p*-values relied on two-tailed tests of significance.

Hypotheses and Analytic Plan

[1] Our approach to determining the percentage threshold for prize ratio is grounded in methods employed in research of actual DFS playing behavior (Nelson et al., 2019; Edson & LaPlante; 2020) for separating more involved players. Specifically, we took the percentile rankings of all prize ratios in the analytic data greater than 1.0 and the minimum value of prize ratio within each percentile. Graphing these minimums along a histogram, the top percentile evidenced the largest jump in terms of separation from other percentiles (see supplementary analyses for histogram figure).

Hypothesis 1: A small percentage (less than 0.1%) of DFS players will experience a big win, diversely defined.

To examine how each definition of big wins classifies DFS players (Hypothesis 1), we noted which players had a big win based on just the $1,000 threshold, which players had a big win based on just the Prize Ratio criterion, which players had a big win based on both criteria, and which players did not have a big win. Based on previous research with actual DFS player data (Wiley, Tom, Edson, & LaPlante, 2020), we anticipated that a small percentage (less than 0.1%) of DFS players would experience a big win, diversely defined.

Hypothesis 2: Players who experience a big win will exhibit more DFS engagement (i.e., higher weekly total entry fees, weekly net loss and weekly number of entries) in the following week when compared with players who do not experience a big win.

Our primary interest in Hypothesis 2 was to test how big wins influence engagement outcomes. However, we expected early big wins to be very infrequent, leaving us with potentially small sample sizes, issues with statistical power, limited variation in the big win measures, and model estimation problems when using conventional regression techniques (Hair, Black, Babin, & Anderson, 2010; Lu, Cai & Tong, 2018). Moreover, we sought to accurately compare how engagement outcomes differ for people who experience a big win with those who do not, but the use of observational data prevented random assignment (Shah et al., 2005) of the treatment variable (i.e., experiencing a big win). To remedy these issues, we followed a matched pair approach. More specifically, we used Mahalanobis distance matching (Chang et al., 2018; Jung & Yoon, 2018) to pair big winners with matching controls.

First, we identified all big winners for each week of the study period, starting at Week 1. We began at Week 1 because Turner et al. (2006) found that an early big win in the first few days of one's first real gambling experience was associated with future problem gambling. For Week 1 big winners (n_{CUST} = 25, n_{PR} = 280), we picked matched controls randomly because all matching covariates are equal to zero. Next, we used the *matchit*() function from the *MatchIt* package in R (Ho et al., 2011) to match each big winners from subsequent weeks with another player who played that same week but did not experience a big win on the aforementioned covariates (i.e., total entry fees, number of entries, and cumulative net loss) based on the Mahalanobis distance (King & Nielsen, 2019; Stuart, King, Imai, & Ho, 2011). We set the parameter *ratio* = 1 so that each treatment case is matched to only one control case. If there were multiple viable matching controls (i.e., multiple matches), we 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 utilized the nearest neighbor method, which yielded the lowest mean difference between the big winners and corresponding matching controls. We then checked the summary of balance table to ensure that for each of the covariates, the mean difference between the big winners and their matched controls were less than the corresponding mean difference between the big winners and the rest of the unmatched sample of players (see supplementary analyses). After applying exclusion criteria (see *Matching Filters*, below) and conducting the matching process, we arrived at a final Custer matched sample of 1,654 players (827 Custer big winners and 827 matched controls) and a final Prize Ratio matched sample of 4,262 players (2,131 Prize ratio big winners and 2,131 matched controls).

After conducting the matching procedure, we performed matched pairs *t*-tests (see Moore, McCabe, & Craig, 2009, p. 428) and assessed mean differences in the (1) entry fees, (2) net losses and (3) numbers of entries of the big winners and their matching controls during their week after the big wins (e.g., if the big win occurred in Week 1, then we compare the big winner and his matched control on Week 2 results; if the big win occurred in Week 43, then we compare the two players on their Week 44 results). We assessed the effect size of matched pair differences using Cohen's *d* (Cohen, 1988).

Hypothesis 3: For players who experience a big win, the big win's effect on DFS engagement tends to diminish over time.

To test Hypothesis 3, we tested for differences on the three DFS engagement measures in the weeks beyond the subsequent week following the early big win. Specifically, in addition to testing mean differences of DFS engagement between big winners and their matched pairs in the week following the big win, we also used matched pairs *t*-tests to assess mean differences between the DFS engagement measures of big winners and their matched pairs in the second week following the big win, third week following the big win, etc., up to the twenty-fourth week following the big win (i.e., at least six prototypical months, or rather six 4-week [prototypical month] periods). We graphed the Cohen's *d*'s derived from these analyses, where the *x*-axis reflected 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 reflected the Cohen's *d* value for that week number. We also indicated the weeks where the associated *t*-value for each Cohen's *d* is significantly greater than 0. We examined this graph to determine whether the big win effect diminishes or dissipates over time (in terms of decreasing values of Cohen's *d* or decreasing observations statistical significance over time, respectively).

Hypothesis 4: Among big winners, shorter time from first deposit to a big win will be associated with more persistence (i.e., more months played consecutively during active duration) and greater frequency (i.e., percentage of active playing days during their active duration) following the big win.

Persistence

To test how persistence may vary depending on how early in a player's DFS experience the big win occurred, we first constructed two new datasets. Dataset 1 included the subgroup of big winners from the Custer matched sample who experienced an initial Custer big win during their rookie NFL season (n = 371) and Dataset 2 included the subgroup of players from the Prize Ratio matched sample who experienced an initial Prize Ratio big win during their rookie NFL season (n = 1,439). We included only players from who experienced an initial big win during their rookie NFL season in these analyses, given the potential contaminating effects of NFL seasonality that exists for this DFS sample (Edson & LaPlante, 2020) on persistence trends. 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 that player's DFS experience in which the big win event occurred.

We then created six new variables, Month 1 through Month 6, for each player that correspond to each prototypical month (i.e., four-week period) following their personal big win event. These variables corresponded to the weeks 1 through 4, 5 through 8, 9 through 12, 13 through 16, 17 through 20, and 21 through 24 after the week of the big win, respectively. For example, if a player experienced a big win in his Week 6, then Month 1 would cover the player's Week 7 through Week 10, and Month 2 would cover the player's Week 11 through Week 14. We set each Month variable equal to "1" if the player had at least one entry into a contest during those weeks and "0" if they did not enter a contest during that four-week period.

We first 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. This plot shows the percentage of big winners who stopped playing at each month, beginning at the month following the big win and the subsequent five months.

To empirically assess how the week of the big win affects persistence, we created a survival curve with a Cox regression model and hazard rate (Cox, 1972) with the week of the big win as the predictor and the number of months of continued play as the outcome variable. This plot shows how the week number in which the big win occurred was associated with persistence in the six months following the big win event. Here we estimated two Cox regression models: 1) a model with just the independent variable (week of big win) predicting the hazard function, and 2) a model with added controls for frequency of play and entry fees per day (i.e., total entry fees divided by number of active days) in all available weeks leading up to, and including, the week of the big win event. This second model thus controlled for potentially confounding effects of time and financial engagement across the sample of big winners.

Frequency

For these same subsamples of big winners, to test how players' general engagement in DFS may vary depending on how early in their DFS experience the big win occurred, we employed ordinary least squares (OLS) linear regression to model the frequency of days players 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 and added control variables for frequency of play and entry fees per day (i.e., total entry fees divided by number of active days) in all available weeks leading up to, and including, the week of the big win. This model thus controlled for potentially confounding effects of time and financial engagement across the sample of big winners. We conducted the necessary tests (e.g., residual plots, quantile-quantile plots) to ensure that all major assumptions of OLS are satisfied (e.g., homoscedasticity, no autocorrelation, normality in the distribution of residuals).

Matching Filters

For Hypothesis 1, we considered all big wins that met the aforementioned Custer & Prize Ratio definitions. For subsequent hypotheses we needed to consider (1) having sufficient follow-up period; and (2) the potential, for individuals who experience multiple big wins, that a previous big win could bias the effect of a subsequent big win and/or one's eligibility as a matched control. As such, for Hypotheses 2 through 4, we considered players eligible as big winners if (1) they experienced their first big win by the respective definition for the given week and (2) they had at least 24 following weeks where they were eligible to play AND did not experience another big win by the respective definition during those weeks. We considered players eligible as matched controls if (1) they had not experienced a big win by the respective definition before and during the given week, (2) had at least 24 following weeks where they were eligible to play, and (3) did not experience a big win by the respective definition during those weeks.

Sensitivity Analyses

Supplementing our main analyses, and to test for the robustness of the findings from the main analyses, we complete sensitivity analyses that: (1) utilize an alternative methodological approach to test our hypotheses by using fixed effects time series regression models and derivations of survival analyses, (2) control for highly profitable players (i.e., professionals), and (3) test Hypothesis 4 with a count (i.e., Poisson regression) model. We also extend our planned confirmatory analyses by conducting an unplanned exploratory examination of the relationship between experiencing a big win and a proxy measure for potential DFS-related problems (i.e., voluntary self-exclusion [VSE] from the DFS website; Caillon et al., 2019; LaBrie & Shaffer, 2011).

The Cambridge Health Alliance IRB determined this study was exempt from IRB review.

Results

Planned confirmatory analyses

Providing a Census of DFS Big Wins. Our analytic sample includes 34,596 DFS players who collectively submitted 18,331,156 entries into DFS contests between August 1, 2013 and December 26, 2016 (i.e., the analytic study period). Out of the 34,596 DFS players in our analytic sample, 3,335 of them (9.6%) experienced at least one type of big win. Of these 3,335 players who experienced a big win, 1,862 (55.8%) experienced only a Prize Ratio big win, 464 (13.9%) experienced only a Custer big win, and 1,009 (30.3%) experienced both a Prize Ratio and Custer big win during the study period. In all, 1,473 players (4.3% of the analytic sample; 44.2% of big winners) experienced at least one Custer big win and 2,871 players (8.3% of the analytic sample; 86.1% of big winners) experienced at least one Prize Ratio big win during the study period. A descriptive analysis of big wins indicates that they are not necessarily mutually exclusive to either Custer's definition or the Prize Ratio definition. Out of all big wins in our study (N =10,600), 5,814 (54.9%) qualified under just the Custer definition, 3,077 (29.0%) qualified under just the Prize Ratio definition, and 1,709 (16.1%) qualified under both definitions.

Examining the Effects of Big Wins on Subsequent DFS Engagement. In the week immediately following their big win, compared to their matched controls, Custer big winners (N = 1,654) submitted more entries (Mean[SD]$_{BW}$ = 56.5[121.2]; Mean[SD]$_{MC}$ = 25.0[84.1]; t[826] = 6.2, $p < 0.05$, Cohen$_d$ = 0.50), paid more entry fees (Mean[SD]$_{BW}$ = 550.1[795.8]; Mean[SD]$_{MC}$ = 149.9[325.3]; t[826] = 13.9, $p < 0.05$, Cohen$_d$ = 0.64), and experienced a greater net loss (Mean[SD]$_{BW}$ = 253.1[526.3]; Mean[SD]$_{MC}$ = 48.0[182.4]; t[826] = 10.9, $p < 0.05$, Cohen$_d$ = 0.45). Prize ratio big winners (N = 4,262)[2] likewise submitted more entries (Mean[SD]$_{BW}$ = 34.7[92.9]; Mean[SD]$_{MC}$ = 14.8[44.7]; t[2130] = 8.9, $p < 0.05$, Cohen$_d$ = 0.43), paid more entry fees (Mean[SD]$_{BW}$ = 362.5[1543.7]; Mean[SD]$_{MC}$ = 112.3[651.4]; t[2130] = 6.9, $p < 0.05$, Cohen$_d$ = 0.27), and had a greater net loss (Mean[SD]$_{BW}$ = 145.0[672.0]; Mean[SD]$_{MC}$ = 28.9[258.7]; t[2130] = 7.4, $p < 0.05$, Cohen$_d$ = 0.22) compared to their matched controls in the week following the big win.

Investigating the Durability of Big Win Effects on Subsequent DFS Engagement. Figure 1 shows Cohen's *d* standardized effect sizes for the number of entries, entry fees, and net loss for the subsequent week (i.e., the week following the big win event; Week 1) and for the following 23 weeks, for both big win definitions. For all outcomes, the trends for both big win definitions indicate a mostly persistent and statistically significant difference between cases and controls, but also show a decreasing size of Cohen's *d* (i.e., diminishing effect) and/or increased likelihood of non-significant corresponding *t*-values (i.e., dissipation effect) as time progresses. Notably however, the effect of experiencing a big win by either definition on all outcomes (including net loss) does not begin to dissipate until after several weeks. The effect of Custer big wins on entries and entry fees does not dissipate *at all* during the 24-week follow-up period.

[2] The five number summary of the prize ratio measure for the full sample of Prize Ratio big winners in the matched sample is: (Min: 10.93; 25% 14.81; Median: 20.00; 75%: 36.43; Max: 20000.00).

*** Insert Figure 1 here ***

Assessing the Relevance of Time to Big Win Effects on Subsequent DFS Engagement. A Kaplan-Meier survival curve modeling persistence among big winners at each four-week period following the big win event is presented in Figure 2. The subsamples of Custer big winners (n = 371) and Prize Ratio big winners (n = 1,439) exhibited similar rates of persistence in the 24 weeks following their big win.

Cox Proportional Hazard models indicate that the week of a big win has an extremely small, albeit significant, negative effect on the hazard function for both Custer big winners (Hazard Ratio [HR] = 0.98, CI = [0.97,0.99]) and Prize Ratio big winners (HR = 0.98, CI = [0.98,0.99]). These effects remain small but still significant after controlling for players' frequency and entry fees per day in the weeks leading up to, and including the week of the big win, for both Custer big winners (HR = 0.99, CI = [0.98,0.9952]) and Prize Ratio big winners (HR= 0.98, CI = [0.98,0.99]).

Linear regression models likewise indicated a small but significant positive effect of big win week on subsequent frequency of play, among both Custer big winners (b = 0.56, β= 0.23, SE = 0.13, p = 0.000) and Prize Ratio big winners (b = 0.55, β= 0.22, SE = 0.07, p = 0.000). These significant effects also remain after controlling for play frequency and entry fees per day in the weeks leading up to, and including the week of the big win among Custer big winners (b = 0.61, β= 0.25, SE = 0.12, p = 0.000) and Prize Ratio big winners (b = 0.73, β= 0.28, SE = 0.07, p = 0.000). Linear regression models satisfied all basic regression diagnostics (see supplementary analyses for diagnostic test results) .

*** Insert Figure 2 here ***

Planned sensitivity analyses

We ran a series of planned sensitivity analyses to test for the robustness of the results from the main analyses with different model specifications. The full results of these sensitivity analyses are available in the supplementary analyses.

For the first sensitivity analyses, we conducted a series of fixed effects regression analyses with robust standard errors that test the overall robustness of the matched pairs analyses (i.e., Hypotheses 2 & 3), as well as derivations of our survival analyses (Hypothesis 4) that assess the effects of grouped time intervals (i.e., experiencing a big either within or after a four week period), with a sixteen week follow up period. Both the panel analyses and survival analyses control for players' cumulative net loss, cohort effects (i.e., week of first deposit), and contest week. 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 when there is an immeasurable unobserved effect in each individual (Wooldridge, 2006). 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. The drawback relative to matching is that it makes more restrictive assumptions about the nature of confounding. Finally, unlike the matched pairs analyses, which exclude big winners who experience subsequent big wins (i.e., big wins that occur during the 24 weeks following their initial big win), the fixed effect sensitivity analyses encompass all big wins/big winners.

The panel analyses confirmed most of the results of our main analyses. Specifically, the fixed effect panel analyses found that Custer & Prize Ratio big winners evidenced significantly elevated entries and entry fees both during the week after the big win event, with decreasing effect size during the subsequent weeks (Figure 3). However, these analyses did not find significantly elevated levels of net loss during the follow-up period among big winners, by either definition.

Notably, unlike the matched control analyses, these panel analyses did not initially filter out big winners who experienced subsequent big wins. As an unplanned exploratory sensitivity analysis, we applied this same filter (i.e., excluding big winners who experience subsequent big wins during the 24 weeks following the initial big win event) to the panel analyses. In these revised sensitivity analyses, both big win definitions had a strong and significant effect on increased net loss, signifying that the significant effect of big wins on losses is contingent upon application of that filter.

The sensitivity survival analyses fully confirmed the results of our main survival analyses. Kaplan Meier curves indicated that big wins extend duration, but that early big wins (i.e., within the first four weeks of depositing) have smaller impacts than later big wins (see Figure 4 for prize ratio results). Cox Proportional Hazard models likewise indicated that big wins are related to duration of active wagering and more active days, but the net effect size is larger for big wins coming after the first four weeks of activity.

*** Insert Figure 3 here ***

*** Insert Figure 4 here ***

In another set of planned sensitivity analyses, we re-ran the analyses used to test Hypotheses 2, 3 and 4 after excluding players who appear to be professional based on their net profits at the end of the study period. We started with the federal minimum wage of $7.25/hour (US DOL, 2019), scaled it up to its monthly equivalent of $1,160/month, and then multiplied that value by 28 months (for our study period) to get a threshold of $32,480. We consider that a player "appears to be professional" if their profit over the study period is equal to or exceeds $32,480. Excluding these players (N = 58; n_{BW} = 44; n_{MC} = 14) and their corresponding big winners/matched controls, the results for all hypotheses did not change. This finding suggests that by our operational definition, "professional players" did not have a substantial effect on the results of our main analyses.

Finally, we tested Hypothesis 4 with a Poisson count model to assess for the robustness of the results from the Cox PH analysis. The results of the Poisson count model were very similar to the results of the Cox PH models reported in the main analyses. A Poisson model for Custer big wins did not find a significant effect of week of big win on mean levels of persistence, while a Poisson model for prize ratio big wins found a significant but weak positive effect of week of big win on mean levels of persistence. These results partially confirm the robustness of the survival analyses in the main analytical approach.

Unplanned exploratory analyses

For both big win definitions, all outcomes variables evidenced substantial skewness. To test the appropriateness of parametric testing in our matched-pairs design, we ran two exploratory sensitivity analyses. First, we conducted Wilcox signed-rank tests between big winners and matched controls for all outcomes. Second, we reran the matched pairs *t*-tests on the natural log transformations for entries and entry fees. We could not reliably take the logarithm of net loss because the profiting players had negative — in some cases, large and negative — values of net loss. The results of these analyses confirmed the robustness of the initial matched pairs *t*-tests. All signed-rank tests indicated true location shifts that were significantly different from zero and all matched pairs t-tests with log transformations were significant with large corresponding Cohen's *d*'s. The details of both of these tests are available in the supplementary analyses.

Finally, given the importance of understanding whether big wins might be associated with future DFS-related problems, we tested whether big winners by either definition were more likely to voluntarily self-exclude at any future period following their big win event. We used exact conditional logistic regression (Mehta and Patel, 1995) to test this assertion. In these analyses, we controlled for the number of available weeks left in the study period following the week of the big win to account for the fact that earlier matching weeks allot players more time to potentially self-exclude.[3] These unplanned exploratory analyses showed that both Custer big winners (b = 0.12, CI = [-0.85,1.40], p = 1.0) and prize ratio big winners (b = 0.47, CI = [-1.63,2.56], p = 0.601) were no more likely to self-exclude than their respective matching control cases.

Discussion

Key Findings

In this study, we examined how "big wins," based on two operational definitions, were associated with future financial and time involvement in DFS based on a sample of 34,596 subscribers to DraftKings. We also tested how the timing of the big win might have influenced persistence and frequency of play following the big win event. Several key findings are important to highlight. First, we found that although a minority of players experienced a big win by either definition (1,473 for Custer and 2,871 for Prize Ratio), these figures are still considerably higher than what we had hypothesized (i.e., less than 0.1% of the time), suggesting

[3] In our Transparent Change document detailing this exploratory analysis (see Transparent Change 5 document on our OSF page), we also stated that we would control for self-excluding before the matching week. However, none of the players in our samples self-excluded before the matching week.

that big wins, while still indeed a rare occurrence in DFS, happen with greater frequency than we initially expected. Second, matched pairs analyses showed that big winners' total entries (i.e., the time involvement dimensions of DFS) as well as entry fees and net loss (i.e., the financial involvement dimension of DFS) were elevated in the initial weeks following a big win compared to matched controls. Third, an examination of the effect sizes of these comparisons during the 24 weeks following the big win event points to a diminishing effect of big wins over time in DFS. Fourth, while the originators of the big win effect (Custer, 1984; Custer & Milt, 1985) and initial research on the subject of big wins (Weatherly et al., 2004) point to *early* big wins in particular as having a more meaningful effect, the results of our analyses of persistence and frequency among DFS big winners suggest that later big wins have a *slightly* stronger effect on future engagement. These findings collectively suggest that big wins in DFS tend to promote continued engagement, which for some players could be at levels that are both excessive and unhealthy. More research is needed that assesses the relationship between big wins and unhealthy engagement behaviors. However it would not be premature at this point to suggest that DFS and gambling operators take steps to reduce potential harms among big winners. This could include promoting responsible decisions and behaviors for big winners to follow, such as withdrawing some of their win to use in other leisure activities or deposit into their personal savings.

Notably, both definitions of big win (Custer and Prize Ratio) had a strong effect on DFS subsequent engagement and losses. Although these definitions were not necessarily mutually exclusive, only a minority of big wins met the criteria for both, which suggests that they 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.

This study provides an indication that both types of big wins are meaningful, however, future research might be needed to determine which definition carries more meaning for which players.

We conducted sensitivity analyses to test the robustness of our main analyses. These analyses confirmed most of the results of our main analyses, with the exception of big wins having an effect on elevated net loss. Further examination of these sensitivity analyses indicated that one of the exclusions we applied in the matched pairs analyses (i.e., removing big winners/matching candidates who experience a second/initial big win during the 24 weeks following the matching week) might have inadvertently removed more skilled players, or at the very least removed players who are more likely to experience a net win, from the matched samples. We applied this filter to account for the potential contaminating effects of experiencing multiple big wins, in order to better understand the effects of a singular big win on future DFS engagement and losses. Therefore, we feel this exclusion was appropriate. We should also note that DFS is a partially skill-based activity (Meehan, 2015), and that we were less interested in the effects of big wins on the engagement behaviors of skilled or professional players, for whom big wins might be expected as part of their efforts to grow their bankroll. Reflecting this goal, we had pre-registered and conducted a separate sensitivity analysis to identify and filter out “professional players,” which confirmed our initial results. A potential reason for this could be that we had already effectively removed professional players in our main analyses by excluding repeat big winners. This unique finding has substantial implications for how our main analyses should be interpreted. Specifically, rather than be generalized to DFS players as a whole, our main results possibly generalize only to less-skilled DFS players, who would be expected to behave more like a typical gambler.

Theoretical/Conceptual implications

Given the frequent resurfacing of the concept of “big wins” in the gambling literature and popular media, our study’s empirical findings have important implications for the substantive and theoretical understanding of this concept. We demonstrate that big wins do indeed influence future DFS behaviors, and this effect is consistent across time (i.e., number of entries) and financial (i.e., entry fees and net loss) dimensions. Why, then, does this significant effect exist? There are two major explanations for our results. First, users who receive a “cash windfall” from a big win event also experience a rapid increase in the amount of money in their DFS account, and by extension a larger “bankroll” of reserve funds that increases availability/accessibility. It follows that this influx of cash might lead to increased spending on DFS, rather than a transfer of this money to other parts of a person’s budget (e.g., leisure pursuits, life necessities, savings). Indeed, research from behavioral economics (Kuhn, Kooreman, Soetevent, & Kapteyn, 2011) shows that a greater supply of money after a lottery win led to an increase in discretionary spending. Although these ideas might explain a portion of the big win’s effect on future DFS involvement, we should note that the fixed-effect regression sensitivity analyses found a significant effect of big wins on subsequent engagement and losses each week, even while accounting for the prior week’s cumulative loss. These results therefore suggest that big wins effects might provide motivation for continued engagement, beyond simply the means to do so.

Second, explanations from cognitive psychology might help to explain the big win effect (Goodie & Fortune, 2013; Michalczuk, Bowden-Jones, Verdejo-Garcia, & Clark, 2011). Within this perspective, big wins might impact future gambling involvement because big winners develop cognitive distortions that make them think that big wins occur frequently when they actually do not occur frequently. Said another way, a big winner might have an inflated perceived probability (i.e., personal probability; see Moore, 2009, example 4.32) of winning.

This can lead big winners to continue to apply their perceived superior skills, attempt to exploit their inflated personal probabilities of winning, and seek more big wins. As a result, big winners might develop an "illusion of control" over their winning (Stefan & David, 2013), making them feel as though they are more in control of their performance when in fact chance plays a large role in winning, and *especially* in winning big. In this way, the big win effect might fit well into the pathways model of gambling (Blaszczynski & Nower, 2002), which argues that (1) increased accessibility, potentially facilitated via a big win, will lead to (2) operant/classical conditioning effects (i.e., continued engagement in order to repeat the big win experience, facilitated by an illusion of control), which can in turn lead to (3) problematic gambling behaviors (e.g., chasing losses), and eventually the development of gambling problems. Although our study provides strong evidence for Steps 1 and 2, the results of our analyses of big wins predicting a proxy for problems (i.e. voluntary self exclusion) do not suggest this pathway necessarily continues to Step 3. However, those analyses were exploratory and should be qualified by the potential limitations of self-exclusion as a proxy for DFS problems. Specifically, some gambling researchers have expressed skepticism of self-exclusion as a proxy for gambling-related problems, given the diverse reasons individuals might choose to self-exclude, some of which might not be related to experiencing problems (Griffiths & Auer, 2016). These arguments also might apply to DFS. Further investigations are needed that employ a more concrete measure of harm in understanding the potential ramifications of big wins and health outcomes.

Third, it is possible that big wins represent an extreme form of operant conditioning (Skinner, 1938; Staddon & Cerutti, 2003). Whereas much of the research on intermittent reinforcement as it relates to operant conditioning principles concerns the timing of continued reinforcement on subsequent behavior (e.g., variable ratio schedule; see Zeeb et al., 2017), less has been said about how the size of the reinforcer affects response. The results of our study (in particular the lasting effects of big wins on continued engagement while controlling for prior net loss, in sensitivity analyses) suggest that the size of a single reinforcer might have a strong effect on continued behavior even after accounting for the duration and size of additional reinforcers in the domain of DFS play. Future research should further investigate how the timing, duration, and size of reinforcement independently affect continued behavior, both in context of DFS as well as other activities with similar reinforcement schedules.

The diminishing effect of big wins we observed over time appears to be consistent with exposure and adaptation models of gambling and gaming-related behaviors (LaPlante & Shaffer, 2007) previously observed in DFS and online gambling environments (LaPlante Schumann, LaBrie, & Shaffer, 2008; Edson & LaPlante, 2020). Here, novel activities or events such as a big win encourage an initial increase in the desire to gamble (i.e., exposure). However the novelty of the activity or event will eventually begin to wear over time, resulting in a decrease and plateauing effect (i.e., adaptation). Alternatively, adaptation could have resulted from big winners' desire, but failure to, repeat their big win experience, resulting in their departure from DFS. This particular mechanism could reflect rational behaviors in response to new information, consistent for example with typical behaviors observed on the Iowa Gambling Task (Bull, Tippett, & Addis, 2015). Even still, the diminishing effect we observed could simply be unique to DFS, or even our specific DFS sample, for whom engagement might have naturally diminished following each cohort's respective NFL season. Indeed, prior research using these data has observed strong NFL seasonality, an indication that the cohorts are very NFL-centric (Edson & LaPlante, 2020).

The results of our study also call into question the central idea of the big win hypothesis that big wins need to happen early on to have a significant effect on future engagement, at least in one product domain (DFS). However, despite later big wins having a stronger effect, we would stop short of suggesting there is a *late* big win effect in DFS, considering the extremely small effect sizes of later big wins on persistence and frequency of play. Rather, the results of our study suggest that big wins in DFS have a strong effect on future engagement regardless of when they happen.

Finally, although this study examined the big win effect in one activity (DFS), researchers should consider its wider application to other activities, including areas outside of gambling, especially given that many of the fundamentals potentially underlying the big win effect (e.g., illusion of control) have broader applications. Scholars should consider, for instance, whether conspicuously large successes, monetary or non-monetary, in any competitive activity (e.g., publishing in a high-ranking journal in academia; securing a major lucrative deal in business) are associated with bolstered levels of immediate subsequent, and potentially long term, engagement in these activities, as well as whether the timing of the large success matters at all.

Study limitations

We highlight six limitations. First, we only had access to activity records from one major DFS provider (DraftKings). DFS tends to skew heavily towards males (Nelson et al., 2019) and is at least a partially skill-based activity (Ehrman, 2015), therefore the findings of our study might not be representative of gamblers more generally, for whom the big win effect was originally conceived. Furthermore, although we considered "early" big wins in terms of players' DFS (and specifically their DraftKings DFS) experience, some players might have experienced a big win earlier on with other fantasy sports, DFS, internet gambling, and land-based gambling platforms, that informed their experiences and expectations with DraftKings. Second, we only examined big win effects over a limited period of time and did not control for all potential seasonality, so it is possible that there may be effects beyond the range of our data. For example, involvement might increase again following a certain period of time, especially if there are particular sporting events that occur and might stimulate increases in involvement (e.g., the NFL Playoffs or FIFA World Cup). Third, we did not have access to a measure of financial means for gaming or gambling (e.g., household income), so it is possible that our definitions of big win (especially Custer's definition) might be perceived differently by individuals with higher income or wealth compared to individuals with lower income or wealth. Fourth, there are other potential variables that we were unable to measure due to data limitations that might have influenced engagement and losses following a big win, including skill level at DFS and experiencing a big win in other modes of gambling (e.g., a lottery jackpot). Fifth, our findings potentially should be considered generalizable to less skilled DFS players who experience a big win, not DFS players as a whole. Sixth, we recognize the inherent arbitrariness of trying to define a threshold for what types of wins can be considered "big". We designed this study to test the theoretical assertion that there exists some arbitrary threshold by which a gambling win is sufficiently "big" enough to have a large effect on subsequent behavior, grounding those thresholds in prior theory and research. Although the results of this study support this assertion, they do not establish that wins need to be necessarily "big" in order to have a large effect. Put more plainly, this study's results do not preclude the possibility that *any* win might have an effect on subsequent behavior that is proportional or roughly proportional to its size. This remains a competing assertion to the big win effect that deserves consideration.

Conclusions

Our study empirically demonstrated the *big win effect* in DFS, with diminishing effects over time, but not uniformly dissipating effects over time (i.e., the effect was persistent in some observations). Big wins in DFS lead to increased engagement for most players; however, less skilled players who are unable to quickly repeat the big win experience tend to experience increased losses, an indication that, for these players, big wins might instill unrealistic expectations about future probabilities of winning. These results suggest that big wins could lead to excessive and even unhealthy levels of engagement. Notably, our observations of the big win effect in DFS do not suggest that the *timing* of the big win has a substantial effect on subsequent engagement. We were unable to fully ascertain whether experiencing a big win in DFS leads to the development or continuation of DFS problems, which remains an important area for future research to consider. Overall, we believe the findings from this study can help researchers develop a greater understanding of the big win effect, including its potential for wider application to other fields of science.

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Manuscript Body Figures

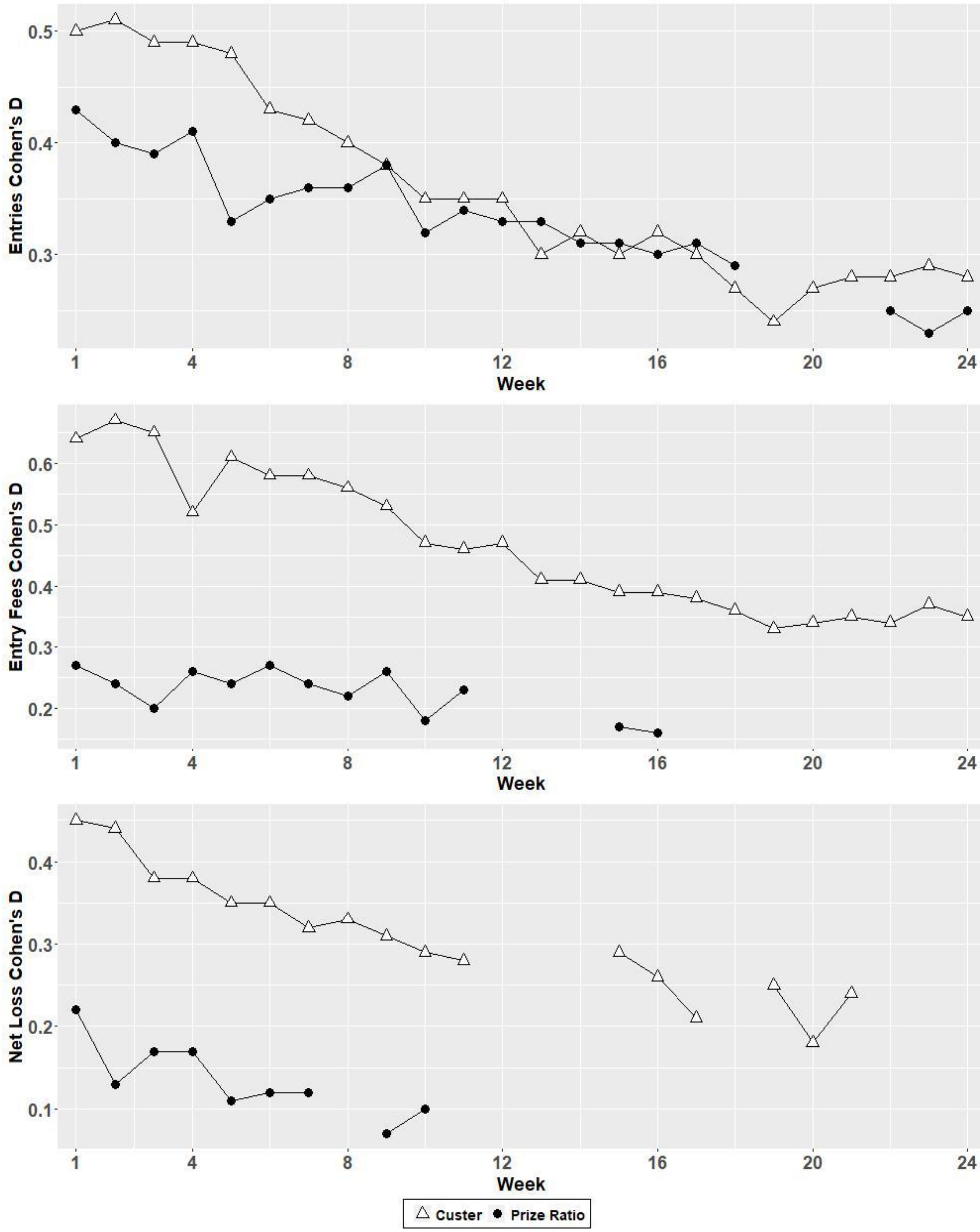

Figure 1. Cohen's d standardized effect sizes (entries, entry fees, and net loss) for the 24 weeks following a big win, for both big win definitions. Cohen's d's with corresponding t-values that are non-significant (i.e., p ≥ 0.05) are censored from these trendlines and thus are not displayed.

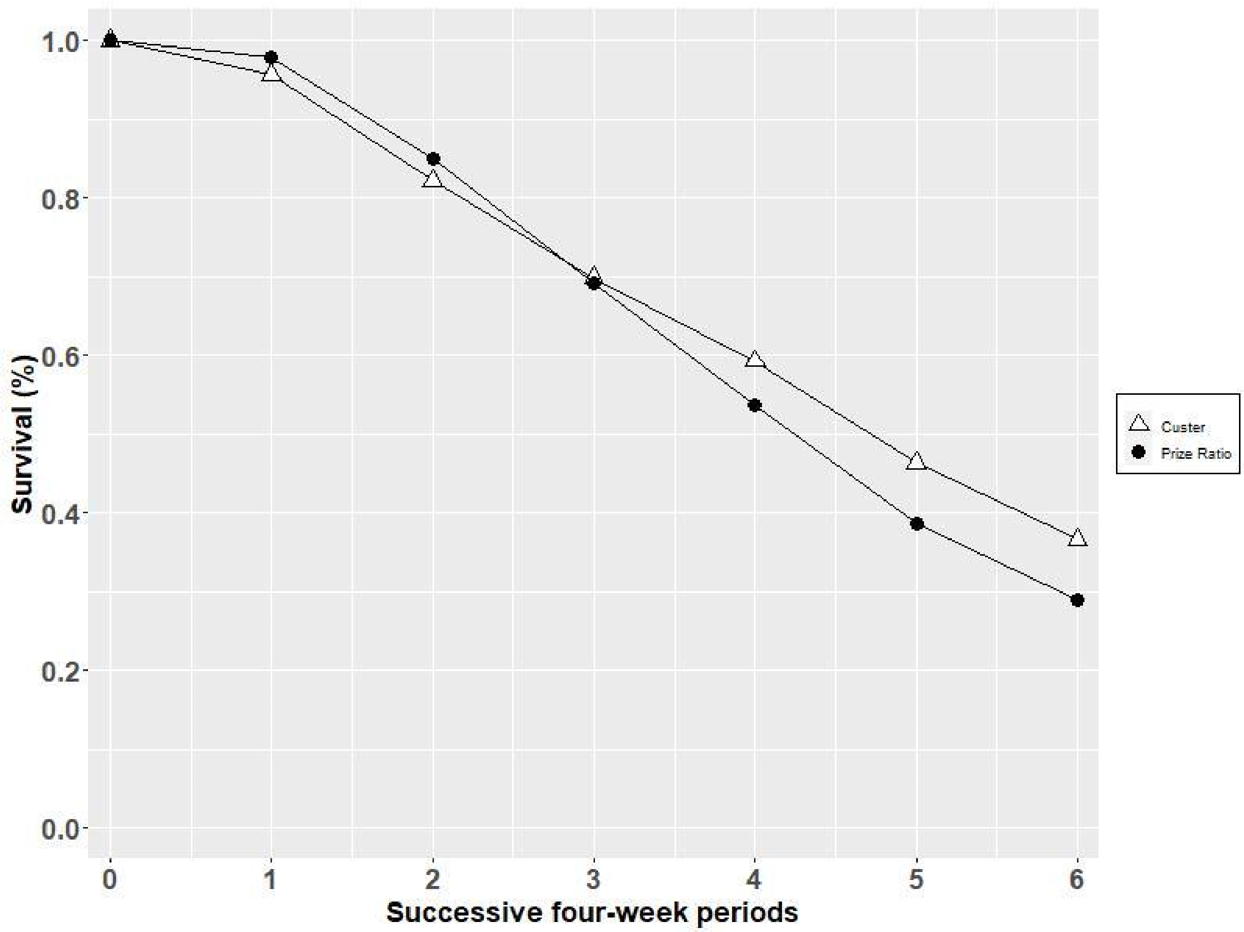

Figure 2. Kaplan-Meier survival curve of persistence among Custer big winners (n = 371) and Prize Ratio big winners (n = 1,439).

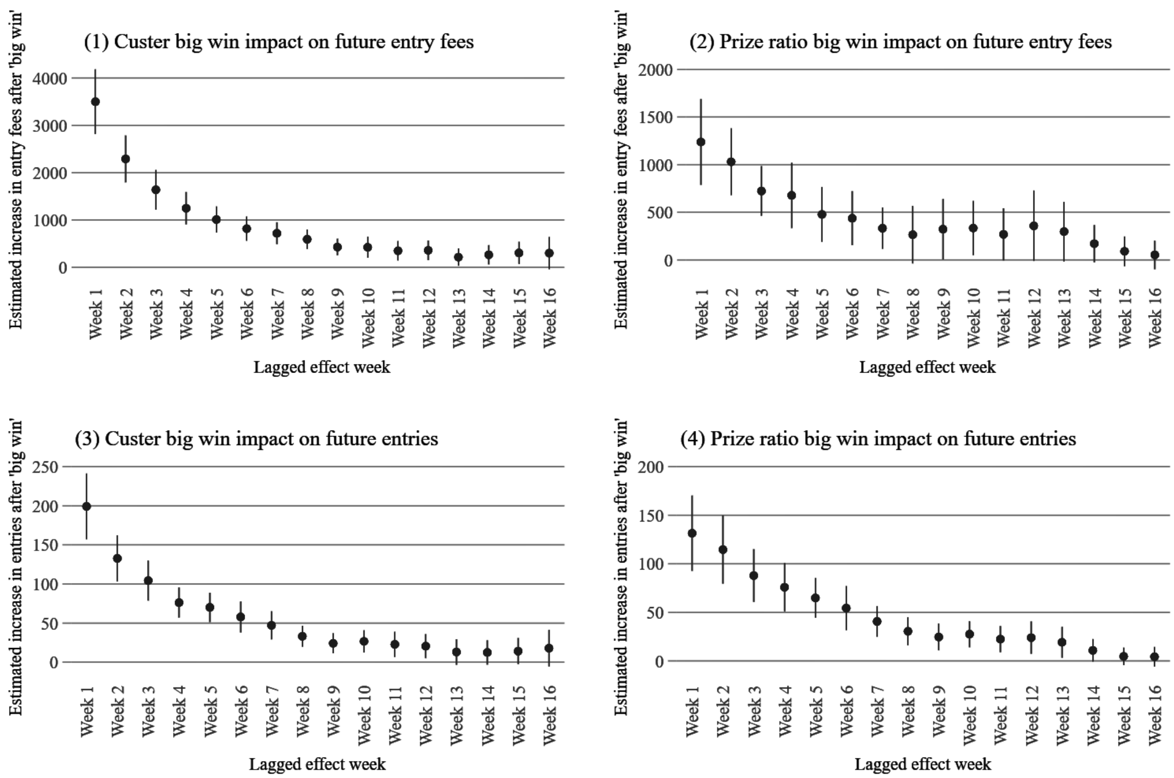

Figure 3. Estimates of lagged big win effects on entry fees (models 1 & 2) and entries (models 3 & 4). Regression coefficients are presented as dots and robust standard errors as vertical lines. Full results appear in the [supplementary analyses]

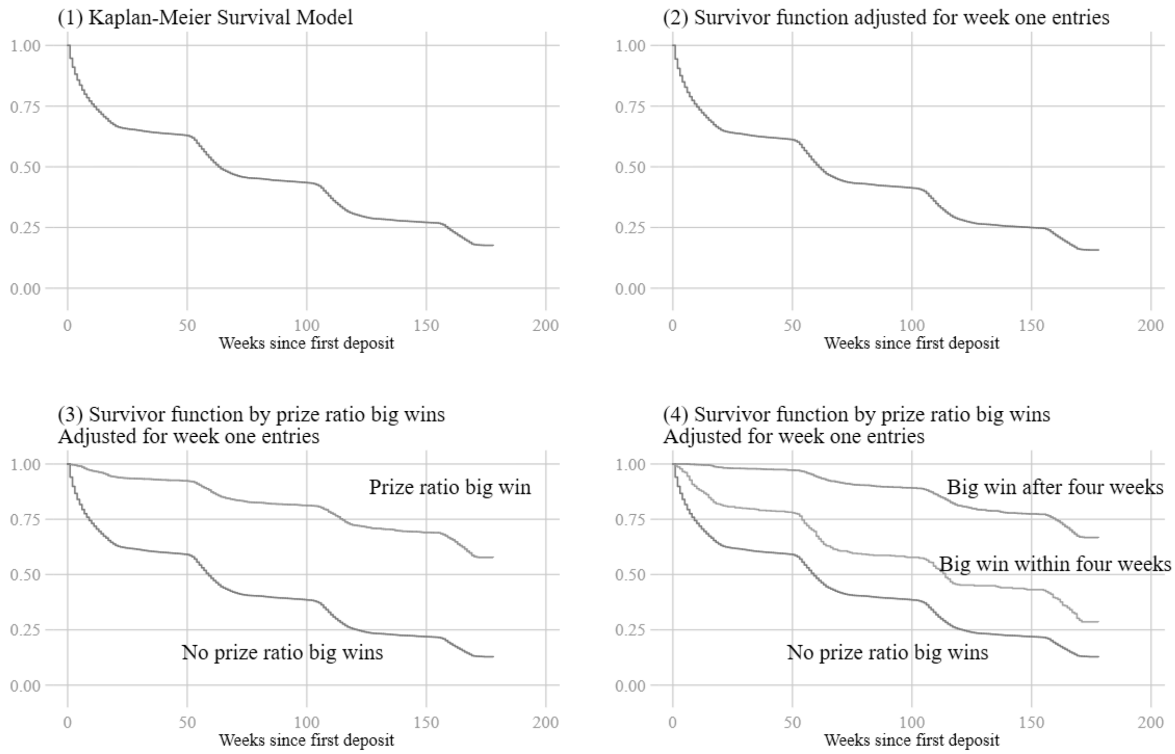

Figure 4. Kaplan-Meier survivor functions describing account activity length. (1) No controls; (2) Adjusting for number of entries in first week; (3) Adjusting for number of entries in first week and separate plots of prize ratio big winners and non-big winners; (4) Adjusting for number of entries in first week and separate plots of prize ratio big winners during first four weeks, after four weeks, and non-big winners.