Journal of Economics and Finance (2021) 45:735–750
https://doi.org/10.1007/s12197-021-09557-5

# Patience is a virtue: exploiting behavior bias in gambling markets

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Accepted: 19 May 2021 / Published online: 17 June 2021


**Abstract**
We examine the influence of bettor behavior in sports gambling markets and the resulting creation of exploitable betting opportunities for patient bettors. Specifically, we build on past research on behavioral bias as a predictor of bettor behavior and explore how this behavior can result in market inefficiencies. Using data from National Football League games taking place between 2007-2019, we find that bettor decision-making is erroneously influenced by recent performance of teams. This bias creates profitable betting opportunities for those less subject to recency bias, and are surprisingly greater for the more prudent, patient bettor. Our findings confirm the need for additional research examining the influence of psychology and behavioral biases on individual decision making and how these factors can influence market efficiency.

**Keywords** Market Efficiency · Behavioral Bias · Sports Gambling · Decision Making

**JEL classification** G40 · G41

## 1 Introduction

Market efficiency is an integral underlying assumption in sports gambling markets. It is generally accepted that these markets operate similar to traditional financial markets in that information asymmetry will be reflected in prices as informed

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and uninformed actors ultimately create equilibrium (Sauer 1998). Similar to traditional financial markets, there is a constant search by investors (bettors) to gain informational advantages and exploit existing inefficiencies. One of the main streams of literature in the area of sports gambling markets focuses on this identification of market asymmetry or other informational advantages. Findings in this stream of literature have been mixed, at best, with most studies identifying short-term inefficiencies or historical inefficiencies that cannot be practically applied.

A common practice in examining sports betting markets is studying whether contextual factors can lead to a profitable betting strategy. Studies have explored ideas such as the impact of home-field advantage (Dare and Dennis 2011), travel distance for teams (Nichols 2014), and even the weather (Borghesi 2007), to name a few. Shank (2019) found that the home-field advantage is weaker in intradivision games and point-spreads are set such that informed bettors can profit accordingly. Continuing research in this area seeks to identify new or unexplored situations that might provide profitable betting opportunities.

A second stream of research in this area has focused more on betting strategies that are independent of contextual factors but, instead, identify market trends and inefficiencies in price/line setting or how other individual behavioral variables influence bettor decision-making. For example, Paul and Weinbach (2012) found profitable betting opportunities by using broad betting approaches such as simply betting against big favorites. Their study identified a trend in point-spread line setting that was inefficient. Davis et al. (2015) looked at how bettor knowledge of teams from the previous season in the NFL can lead to early season betting market inefficiencies. Paul and Weinbach (2005) found that, in general, bettors have a clear preference to bet the over in totals markets across all sports examined in their study.

Studies such as these are representative of a growing body of research embracing the factors of psychology and cognition and how these can influence bettor decision-making and, ultimately, betting market efficiency. Typically, such strategies involve acting quickly to exploit available inefficiencies. In contrast, we seek to identify how these psychological and cognitive biases can result in exploitable market asymmetries for the patient and informed bettor.

The current study extends research in this stream by examining how certain heuristics and biases an influence betting behavior, resulting in a novel exploitable market inefficiency. Specifically, we consider how recent performance in NFL regular season games influences many bettors. We consider that recent impressive (unimpressive) performance by a team might cause some bettors to overreact due to recency bias. We find support for this conjecture and, surprisingly, we find bettor perception often helps *create greater* inefficiency in the days leading up to a game.

## 2 Literature review

A number of studies have explored the role of recency bias in bettor decision-making behavior (e.g., Fodor et al. 2013). Simply put, recency bias is the notion that individuals are more apt to remember events that have occurred in the recent past as opposed to something that occurred in the more distant past. This perspectives works to create an overreliance on past information. This theoretical foundation is a particularly relevant concept in conditions of high uncertainty or lack of information, such as in sports betting markets. Naive bettors may simply rely on a recent team's success in a contest as a predictor for the subsequent contest.

The tendency for having a recency bias is directly tied to representative heuristics. Heuristics are cognitive shortcuts that individuals subconsciously take to reduce time and effort needed for decision-making (Tversky and Kahneman 1974). While these heuristics can be helpful in many situations, they can also be negative when they lead to inefficient or sub-optimal decision-making. This is due to a lack of pursuit of essential information and overreliance on the recent past. Compounding the potential issues related to heuristic-based decision-making is the presence of conservatism bias which suggests individuals are slow to update their current perspective based on their embeddedness due to past knowledge (Edwards 1968). Such conservatism allows the recency bias inefficiency to persist.

There are a multitude of other studies on bettor beliefs and wagering. Vergin and Scriabin (1978) introduced the point-spread theory, where bookmakers hold deliberate biases, such as an affinity for the team in their location, in developing a point spread. In a study on NBA seasons, Woodland and Woodland (2015) tested favorite-longshot bias, a theory where bettors favor the underdog over the favorite as a simple heuristic-based decision. Their results indicated that the larger the point-spread, the more likely the bettor will choose the underdog. Thus, cognitive biases can work collectively to subconsciously influence individual behavior. These biases skew the integrity of an efficient market and can provide insight into how to detect these inefficiencies.

Another example of bettor misperception regards the "hot hand" theory. The hot hand theory is based on the notion that individuals are more likely to favor teams with recent success when developing future performance expectations. Psychology research has studied this phenomenon and concluded that the perceptions by individuals related to a team's recent performance directly, and incorrectly, influenced their expectations of future success (Murtha 2013). In one of the more interesting and seminal gambling behavior studies, Gilovich et al. (1985) studied fans' and players' perceptions of the hot hand theory and their expectations of performance outcomes. Observers often believed recent success would manifest in momentum, but Gilovich et al. (1985) found no evidence of this commonly held belief of streak shooting or the hot hand.

Particularly relevant to our study, additional evidence has tied this bias directly to betting markets, with one study finding that teams with recent success were slightly more favored than they should have been (Camerer 1989). Interestingly, this inefficiency in the point-spread market was even more pronounced for teams with recent poor performance. Paul et al. (2011) found that when bettors believed in their hot hand, "teams on streaks attract(ed) significantly higher number of bets" (p. 42). This perspective directly ties back to bettor decision-making behavior and is a driver for our study's consideration of market inefficiencies. Building on these two theories of recency bias and hot hand, it is possible that bettor behavior will be influenced by perception of teams' recent success. We test this idea by examining how point-spread markets are update over time as bettors place their bets.

## 3 Data and methods

The outcome of an NFL game is rarely viewed, ex ante, as a 50/50 proposition. When approaching whether a bettor wager on the outcome of an NFL game, the starting consideration is the "spread" or the "line" of the game which is designed as a type of correction to the expectation of the game to be played. Basic theory suggests that the spread is developed by oddsmakers to balance the funds wagered on a game to create an exact, 50/50 split between the money wagered on Team A and on Team B. Oddsmakers are motivated to do so because the commission they charge (typically 10% on winning bets) will then create a riskless profit.[1] Oddsmakers use various tools and considerations in developing the spread, including home field advantage, health of the players, historic trends, and even the weather. When a bettor then chooses a team to support and makes a wager in this situation, it is thus called an "against the spread" (ATS) bet.

For example, suppose that in mid-December the Miami Dolphins, a team headquartered in a warm climate and that has recently been perceived as a below average squad, is slated to play the Green Bay Packers, a historically strong performing team that often plays its home contests in rough, wintery conditions. Bettors can expect that if they were to bet on the Green Bay Packers, it would not be for them to simply win, but to "cover" the spread—simply put, to not only win, but to win by more than a given amount...this amount being the point spread. Based on the simple pretext provided above as an example, it is easy to surmise that the Packers would be the favorite and the Dolphins the underdog. If the spread in this hypothetical game is -5.5 (spreads for favorites are listed with a negative number, while the identical amount is listed as a positive correction for underdogs), then the Packers must win by 6 or more points for their bettors to capitalize on their wagers. Alternatively, as the Dolphins are underdogs, if a bettor chooses to wager on them, the bettor would win the wager if the Dolphins lost by 5 points or less, or if the Dolphins unexpectedly won the game.

Our primary data source is thefootballlines.com which sells historical NFL opening and closing spread, moneyline, totals data, and final scores of games starting in the 2007-08 NFL season. We utilize data for the 2007-08 through 2018-19 NFL seasons. We clean the data for minor, season-to-season discrepancies in reporting. We then create the metric *PriorGameATS* defined as:

*PriorGameATS* = (Performance of Team A, relative to the spread, in Team A's last regular season game) – (Performance of Team B, relative to the spread, in Team B's last regular season game)

[1] Some researchers (e.g., Levitt 2004; Kain and Logan 2014; Paul and Weinbach 2012) note that bookmakers may choose, in some instances, to offer lines that seek to maximize profit (by tempting bettors to take the bookmaker's perceived, poor side of a wager) rather than seek a riskless, commission-only model. Regardless of bookmaker intention, our results herein seek to describe a contrarian-type wagering opportunity holistically made possible by market participants.

Coinciding with this definition, Team A (Team B) is the team which, in its last regular season game, performed relatively better (worse) against the spread. Thus, *PriorGameATS* is non-negative. We provide the following examples for clarification:

- In Week 7, Buffalo was favored by 5 points when it played Miami. Buffalo won this game 20-10. Also, in week 7, Atlanta was favored by 4 points when it played Philadelphia. Atlanta won this game 35-25. We consider a Week 8 game in which Buffalo plays Atlanta. Atlanta performed better than Buffalo, relative to the spread, when considering each team's prior game. (i.e., Buffalo covered its 5-point spread by 5 points. Atlanta covered its 4-point spread by 6 points. Thus, Atlanta is Team A in the Week 8 contest, and Buffalo is Team B.) The value of *PriorGameATS* is thus 6 – 5, or 1.
- In Week 8, Denver was a 3-point underdog against Chicago. Denver won this game 30-23. Denver did not play a game in Week 9. In Week 9, Seattle was a 3-point underdog against Washington. Seattle lost this game 17-13. We consider a Week 10 game in which Denver plays Seattle. Denver performed better than Seattle, relative to the spread, when considering each team's prior game. (i.e., Denver covered its 3-point spread by 10 points. Seattle failed to cover its 3-point spread by 1 point. Thus, Denver is Team A in the Week 10 contest, and Seattle is Team B.) The value of *PriorGameATS* is thus 10 – (-1), or 11.

We exclude Week 1 (opening week) games of each unique season from our sample, as teams have not yet had opportunities to impart meaningful impressions on the public in Week 1.[2] We study the remaining games, from Weeks 2-17 of each NFL season, from 2007-2018 (12 seasons). With 32 NFL teams competing in each year of our sample, this provides an initial sample of 240 regular season (Weeks 2-17) games to consider each year, totaling 2,880 regular season games.

Our focus is a "reversal" strategy that wagers on teams which performed relatively poorly in their prior games, compared to their current opponents. Specifically, we propose wagering an equal amount on every Team B in the *PriorGameATS* construction. We do so in anticipation that the betting public is influenced by their recency bias and tendency to go with the "hot hand", thus sensing too much weakness (strength) from Team B (Team A) based on its prior appearance. This may lead bettors to undervalue (overvalue) Team B's (Team A's) prospect in the game at hand. Akin to a troubled, or beaten down stock, might there be value to be had in investing in Team B? Akin to a shiny, or over-promoted stock, might there be value to be had in investing against Team A? Games in which both teams fared equally against the spread in their most recent contests (i.e., where *PriorGameATS* would be 0, thereby making impossible classifications of Team A/B) are excluded from consideration.

We consider the impact of *PriorGameATS* levels (0.5-9.5 points, 10-19.5 points, etc.) on the success of our reversal strategy. Smaller levels of *PriorGameATS*

[2] We also considered omitting Week 17 data as incentives to team performance in the final week of the season vary widely. This omission did not substantively change our findings.

indicate games that match opponents who performed somewhat similarly in their last appearances. In these situations, we anticipate relatively little overvaluation/undervaluation potential. With increasing levels of *PriorGameATS*, we hypothesize greater potential for valuation mistakes, resulting in market inefficiencies by which contrarian bettors might profit.

For comparison and robustness, we tabulate our results using both the closing line of the game (available in the marketplace immediately before kickoff) and the opening line of the game (the first prices on new games to be offered by bookmakers seeking bets). Opening lines are typically available on the Monday of a new NFL week, and then lines may change based on supply and demand or other factors until our games of interest start, with the final line noted as the closing line (mostly on Sunday mornings, six days after the opening lines were issued).[3] In order to consider whether any isolated season drives our results, we provide similar breakdowns for each of the 12 individual NFL seasons that make up our full sample.[4]

Next, we consider whether the level of *PriorGameATS* provides any information regarding the movement of the point spread for games, starting with the opening line and ending with the closing line. We hypothesize that the betting public is likely to drive the spread more toward (away from) Team A (Team B) in the interim between the opening and closing lines due to the behavioral biases presented. We suspect that this movement is more likely to be substantial at higher levels of *PriorGameATS*. As we study line movement during the week of an upcoming NFL game, we also consider whether or not there is any discrepancy when both teams contribute to the total *PriorGameATS* value.[5] We then consider, in greater detail, how often opening spreads of NFL games have moved in recent years, and to what degree, and what interplay this dynamic has with our wagering strategy.

[3] There are exceptions to this structure. Most commonly, for example, our opening line data in week X for teams participating in a week X-1 *Monday Night Football* game are not available until Tuesday of week X. There are never intervening games played between the opening and closing lines by either team in our sample observation games. While injuries are common in sport, particularly in a high contact sport such as professional football, the NFL attempts to disseminate information publicly, regarding injuries through the Physically Unable to Perform, or PUP list, and the Injured Reserve, or IR. Deadlines are established for teams to release their PUP and IR lists to reduce the uncertainty associated with key players' participation. It is rather rare for the bettors or oddsmakers to be unaware of a key injury, and, at least until some clarity emerges on player participation, there is usually a delay in the issuance of the opening line of a game.

[4] For robustness, we also consider whether the time since a team last played is material to our results. For example, each NFL team has one 'open' week on its schedule each year so that its prior performance in, e.g., Week 8 might have actually occurred in Week 6 rather than Week 7. Games also occur on Thursdays and Mondays each NFL week, as well as occasionally on Saturdays toward the end of each season. As we find no material differences in our results when considering the different times elapsed since teams' prior games we omit the formal results herein.

[5] For example, if Denver covered its prior game spread by 10, and Seattle failed to cover its prior game spread by 1, we say both Denver and Seattle contribute to the *PriorGameATS* value of 11. Games where Team B failed to cover its prior spread and Team A covered its prior spread, thus, exclusively make up the "both sides contributing" subsample. Alternatively, as an example, when Atlanta covered its prior game spread by 6, and Buffalo covered its prior game spread by 5, only one team (Atlanta) contributed to the *PriorGameATS* value of 1.

Finally, we consider whether the distinction between both teams contributing or only one team contributing to the *PriorGameATS* level plays a significant role when evaluating our reversal strategy. In all evaluations of our reversal strategy, we eliminate any contests in which the game resulted in a push bet (i.e., the ending score of the game was equal to the closing line). For example, if Denver is a 6-point favorite against Seattle in a matchup, and our reversal strategy dictates a wager on Seattle, as Team B, we eliminate the observation from consideration if Denver wins by exactly 6 points.[6]

In evaluations of our reversal strategy, we consider t-tests for one-sample difference of proportions tests of our strategy vs. the null hypothesis of less than or equal to a 50% success rate (i.e., *PriorGameATS* is completely immaterial). We also note that, given the standard 10% commission levied against winning wagers by bookmakers (i.e., vigorish), a strategy must actually succeed more than 52.38% of the time in order to prove profitable, net of fees.

## 4 Results and discussion

In Table 1, we consider the performance of our reversal strategy, which wagers on teams that underperformed, and/or whose opponents overperformed, relative to the closing spreads in the teams' prior games. Our primary finding is the success of this reversal strategy. In particular, if bettors utilize a reversal strategy when the cumulative *PriorGameATS* measure is 10 points or higher, the strategy proves profitable.

Negligible or low levels (0.5-to-9.5 points) of *PriorGameATS* do not provide profitable wagering opportunities. Such wagers actually prove profitable only 49.17% of the time when graded relative to each game's closing line (in Panel A).

Much more encouragingly, success rates for reversal strategies at *PriorGameATS* levels of 10-19.5 points, 20-29.5 points, 30-39.5 points, and 40+ points, are 54.39%, 53.48%, 52.65%, and 52.43%, respectively. These rates all demonstrate profitability, net of commission paid to oddsmakers on winning wagers, and we see the absolute best results, somewhat surprisingly, based on the medium-to-large levels of the *PriorGameATS* measure (10-19.5 points and 20-29.5 points). We note these higher success rates (of the 10-19.5 point and 20-29.5 point levels) are based on larger sample sizes than more extreme levels of *PriorGameATS*. Furthermore, the success rate of 54.39%, for the 10-19.5-point category, is statistically better than 50% (at the 5% significance level), and the 20-29.5-point category also demonstrates 10% statistical significance if we consider a one-tailed hypothesis test of the reversal strategy.

Panel B of Table 1 reconsiders the initial findings but grades reversal-based wagers relative to the opening lines of games, rather than their closing lines. While the basic findings of Panel B initially appear routine, they also identify

[6] The Team B's on which we wager, in order to implement our reversal strategy, need not be underdogs in their games. In fact, nearly half of Team B's are actually favorites when we wager on them. We consider, in omitted results, whether the favorite/underdog status of Team B affects our results and find the distinction to be immaterial.

**Table 1** This table presents results for wagering on National Football League (NFL) regular season games in Weeks 2-17 based on a reversal strategy which seeks to bet on (against) teams which relatively underperformed (overperformed) in their prior game of the current regular season. Data are from the 2007-2018 NFL seasons. Wins (W) and Losses (L) from utilizing such a strategy are recorded, as well as the winning percentage of the reversal strategy. Results are presented in aggregate, as well as for various levels of the variable of study, *PriorGameATS*. *PriorGameATS* is defined as: *PriorGameATS* = (Performance of Team A, relative to the spread, in Team A's last regular season game) – (Performance of Team B, relative to the spread, in Team B's last regular season game). Coinciding with this definition, Team A (Team B) is the team which, in its last game, performed relatively better (worse) against the spread. Thus, *PriorGameATS* is non-negative and our reversal strategy dictates wagering on Team B. Panel A (Panel B) presents results based on the closing line (opening line) made available for wagering by sportsbooks. Games that end in a push (tie) are omitted from the sample, as are games with *PriorGameATS* = 0. t-statistics are provided for the null hypothesis of a 50% success rate of the reversal strategy

| Panel A: Closing Line | | | | | | |
|---|---|---|---|---|---|---|
| | PriorGameATS | | | | | |
| | 0.5-9.5 | 10-19.5 | 20-29.5 | 30-39.5 | 40+ | Total |
| Reversal W | 534 | 458 | 269 | 119 | 54 | 1434 |
| Reversal L | 552 | 384 | 234 | 107 | 49 | 1326 |
| Pct. | 49.17% | 54.39% | 53.48% | 52.65% | 52.43% | 51.96% |
| t vs. 50% | -0.55 | 2.56 | 1.56 | 0.80 | 0.49 | 2.06 |
| Panel B: Opening Line | | | | | | |
| | *PriorGameATS* | | | | | |
| | 0.5-9.5 | 10-19.5 | 20-29.5 | 30-39.5 | 40+ | Total |
| Reversal W | 544 | 440 | 256 | 114 | 53 | 1407 |
| Reversal L | 542 | 402 | 247 | 112 | 50 | 1353 |
| Pct. | 50.09% | 52.26% | 50.89% | 50.44% | 51.46% | 50.98% |
| t vs. 50% | 0.06 | 1.31 | 0.40 | 0.13 | 0.30 | 1.03 |

some surprising results. Specifically, using *PriorGameATS* to launch a reversal strategy is less successful when operating based on opening line data. Success rates are lower than those seen in Panel A, falling to an unprofitable level.

Standard market efficiency theory posits an almost completely opposite dynamic than these findings. Efficiency generally holds that time and exposure to scrutiny will eliminate any mispricing of a particular asset. A wager on an NFL game, while atypical, is a type of financial asset (one with a set time for final valuation and two, easy-to-determine, possible final values). Efficiency leads to the expectation that closing lines should be more accurate than opening lines. In the case of wagers on NFL games, this hypothesizes reversal-based results that are *nearer* to 50% when using closing lines rather than opening lines. In the specific case of sports wagering, this efficiency would likely come about as the most efficient market participants (professional sports handicappers, frequently known as "wiseguys") detect mistakes in opening lines, and move spreads accordingly via sizable bets.

However, we detect something quite different in our study findings. Closing lines were found to be *less* efficient than opening lines when we consider a reversal strategy based on *PriorGameATS*. Information and opportunity do not actually make betting lines more efficient as NFL game times approach. On the contrary, a superior strategy for reversal-type bettors seems to be to wait until the last possible moment to make wagers. This is the case even though the NFL is the largest betting and media market in American sports.

This a surprising finding which flies in the face of market efficiency theory and further validates the presence and impact of behavioral biases in bettor decisions. We suspect the finding is likely driven by the contrast between naïve bettors and wiseguy sports handicappers. Typically, wiseguys have access to larger cash holdings with which to bet, thereby eliminating "soft" early/opening lines by betting accordingly and, thus, efficiently moving game lines closer to optimal levels (see Krieger and Fodor 2013). In fact, many wiseguys make every effort to stay abreast of newly issued lines so that they might quickly find opportunities to profit from inefficiencies.

However, when an enormous (though uninformed) public consensus forms and wishes to wager against (for) NFL teams which looked relatively horrible (stellar) in their prior outing, the typical dynamic seems to flip. The public-driven, near-uniform consensus of which team is good or bad in an upcoming contest can build a huge volume of public pressure that swamps the decisiveness, expertise, and cash reserves of the wiseguys who would otherwise mechanize efficiency. Waiting until near game time to use a *PriorGameATS*-based reversal strategy proves superior to betting based on *PriorGameATS* at the opening line. Public opinion, rooted in recency bias, will provide an increasingly useful opportunity to the contrarian, savvy bettor as the new game nears. This suggests there should be no rush to use superior information before the betting market becomes efficient. To the contrary, the fervor of the public's biases sometimes only increases this inefficiency as kickoff approaches.[7] We note some similarity, in this NFL wagering market, to the debate, in more traditional financial equity markets surrounding momentum and contrarian investment strategies. Specifically, the literature has long noted instances of successful momentum and contrarian investment frameworks (Schiereck et al. 1999; Lee et al. 2003; Goetzmann and Massa 2002). In our wagering market framework the best strategy appears to be a contrarian-type one, and its success appears amplified by patience in allowing momentum-type investors to first move the line to a 'price' more advantageous for the contrarian.

We also liken this dynamic to that seen in Brunnermeier and Nagel (2004), in which some of the world's best hedge-fund managers chose not to trade against the inflating tech bubble from 1998-2000. These managers suspected that widespread, artificial pressure from the unsophisticated public would limit any ability to profit

[7] One estimate is that less than 0.5% of bettors are 'professional,' so that they might be considered 'informed investors' in a more traditional financial sense (Bluth 1997). Their wiseguy/professional budget for wagering is, on average, considerably larger than a typical bettor; however, the overall public interest in the NFL games appears so large as to limit the correcting influence of wiseguys on inefficiency in many games. Other games have very limited interest from the public so that wiseguys indeed move the price to a more efficient point, sometimes quickly after the opening line is issued.

by selling overpriced tech stocks. As a result, managers did not attempt to sell these stocks.[8]

Given our initial findings in Table 1, we also further investigate the surprising dynamic in which lines seem to move toward *less* efficient levels when medium-to-high degrees of *PriorGameATS* are present. In Table 2, we document how frequently lines move, between opening and closing, toward the overperforming or underperforming team in the game at hand. To demonstrate, consider an example when Miami is playing Buffalo in a Week 7 game. In Week 6, Miami covered its spread by 6.5 points. In Week 6, Buffalo failed to cover its spread by 4 points. This results in a *PriorGameATS* level of 10.5 points and suggests a reversal wagering strategy of betting on Buffalo in Week 7. To further illustrate, consider a case where the Week 7 opening line is Buffalo, favored by 2.5 points. This line shifts during the week and closes at Buffalo favored by only 1.5 points. The line has thus shifted toward the overperforming team from the previous week (Miami), and in this example we see an effect similar to the overall trend of Table 1, where *waiting* to bet on the reversal play of Buffalo is actually better than rushing to wager at the opening line when employing a reversal strategy.

In Table 2, Panel A, we find that at low levels of *PriorGameATS* lines do not tend to move toward either overperformers or underperformers based on their prior games. However, starting at the 10-19.5-point level of *PriorGameATS,* lines move more frequently toward prior-game overperformers. 53.08% of games where the line moves during the week, it moves toward overperformers. The rate increases further to 54.63%, 57.63%, and 59.09% for *PriorGameATS* levels of 20-29.5 points, 30-39.5 points, and 40+ points, respectively. This disparity provides further evidence of our counterintuitive finding that inefficiency develops, rather than dissipates, while betting markets are open.

In Panels B and C, respectively, we separate our sample into games in which only one team contributes to the level of *PriorGameATS* and games in which both teams contribute. Our primary finding from considering these subsamples is that lines are more likely to move toward the overperforming team when *PriorGameATS* is driven by only one participant. The results of Panel C are stronger than those of Panel B, particularly at the 10-19.5-point and 20-29.5-point levels of *PriorGameATS*. Therefore, we actually see more consistent line movement toward overperformers when Team A (Team B) overperformed (underperformed) substantially in its prior game while Team B (Team A) overperformed (underperformed) to a lesser degree.

Given the surprising results of Table 1, in which we see an inefficiency that becomes *more* pronounced over time (i.e., waiting to wager on the *PriorGameATS* strategy sees better results as lines tend to move away from the underperforming teams upon which are strategy dictates wagering), and given the findings of Table 2 regarding line movement, we consider more detail on the degree of line movement and the success of our wagering approach in Table 3.

[8] In fact, some such hedge fund managers sought to ride the tech stock bubble, i.e., take the opposite approach to trading against inefficiencies. In the equity environment (where there is no analog to the end of an NFL game, which sets the value of a wager as final) the demand of the naïve public for tech stocks was even able to keep the price of some never-profitable stocks inflated for years. In extreme cases, hedge fund managers that traded correctly *against* the tech bubble even went insolvent due to client withdrawals before their assertions could be proven correct.

**Table 2** This table presents line movement counts, from the opening of games for wagering, until the closing of betting immediately prior to National Football League (NFL) regular season games in Weeks 2-17. Data are from the 2007-2018 NFL seasons. Results are presented in aggregate, as well as for various levels of the variable of study, *PriorGameATS*. *PriorGameATS* is defined as: *PriorGameATS* = (Performance of Team A, relative to the spread, in Team A's last regular season game) – (Performance of Team B, relative to the spread, in Team B's last regular season game). Coinciding with this definition, Team A (Team B) is the team which, in its last game, performed relatively better (worse) against the spread. Thus, *PriorGameATS* is non-negative and our reversal strategy dictates wagering on Team B. Panel A presents results for all games. Panel B presents results based on the subsample of games where Team A's relative performance is a positive value and Team B's relative performance is a negative value. Panel C presents results based on the subsample of games with either a negative value for Team A's relative performance or a positive value for Team B's relative performance. Games with *PriorGameATS* = 0 are omitted from the sample

Panel A: Full Sample

| | PriorGameATS | | | | | |
|---|---|---|---|---|---|---|
| | 0.5-9.5 | 10-19.5 | 20-29.5 | 30-39.5 | 40+ | Total |
| Move toward overperformer | 445 | 370 | 224 | 102 | 52 | 1193 |
| Move toward underperformer | 451 | 327 | 186 | 75 | 36 | 1075 |
| No Move | 227 | 166 | 109 | 53 | 17 | 572 |
| Over Pct (v Under) | 49.67% | 53.08% | 54.63% | 57.63% | 59.09% | 52.60% |
| Avg Move | -0.02 | 0.21 | 0.33 | 0.38 | 0.39 | |

Panel B: Both teams contributing to PriorGameATS

| | PriorGameATS | | | | | |
|---|---|---|---|---|---|---|
| | 0.5-9.5 | 10-19.5 | 20-29.5 | 30-39.5 | 40+ | Total |
| Move toward overperformer | 75 | 180 | 158 | 87 | 48 | 548 |
| Move toward underperformer | 72 | 181 | 143 | 70 | 33 | 499 |
| No Move | 40 | 82 | 84 | 46 | 16 | 268 |
| Over Pct (v Under) | 51.02% | 49.86% | 52.49% | 55.41% | 59.26% | 52.34% |
| Avg Move | 0.01 | 0.02 | 0.24 | 0.32 | 0.40 | |

Panel C: Only one team contributing to PriorGameATS

| | PriorGameATS | | | | | |
|---|---|---|---|---|---|---|
| | 0.5-9.5 | 10-19.5 | 20-29.5 | 30-39.5 | 40+ | Total |
| Move toward overperformer | 370 | 190 | 66 | 15 | 4 | 645 |
| Move toward underperformer | 379 | 146 | 43 | 5 | 3 | 576 |
| No Move | 187 | 84 | 25 | 7 | 1 | 304 |
| Over Pct (v Under) | 49.40% | 56.55% | 60.55% | 75.00% | 57.14% | 52.83% |
| Avg Move | -0.11 | 0.45 | 0.58 | 0.71 | 0.31 | |

In Panel A of Table 3 we present basic results showing the levels of closing and opening lines that are common in our sample. Then, in Panel B, we provide detail on how typical various levels of line movement between opening and closing lines are in our sample, and we provide detail on how successful our 'wager on underperformers' strategy, via *PriorGameATS* proves to be relative to the line movements in question. Via this analysis, we see increased detail regarding the superiority of waiting to wager via our strategy. For example, it is considerably more common for losing wagers at the opening line to become winning wagers (35 instances, total)

**Table 3** This table presents descriptive statistics regarding the frequencies of line magnitudes, line movements, and the role of recent performance in considering such movements. Line movements are measured from the opening of games for wagering, until the closing of betting immediately prior to National Football League (NFL) regular season games in Weeks 2-17. Data are from the 2007-2018 NFL seasons. *PriorGameATS* is defined as: *PriorGameATS* = (Performance of Team A, relative to the spread, in Team A's last regular season game) – (Performance of Team B, relative to the spread, in Team B's last regular season game). Coinciding with this definition, Team A (Team B) is the team which, in its last game, performed relatively better (worse) against the spread. Thus, *PriorGameATS* is non-negative and our reversal strategy dictates wagering on Team B. Panel A shows the counts and relative frequencies of different magnitudes of opening and closing spreads in games. Panel B shows the counts and relative frequencies of different levels of line movement between the opening and closing lines of games and describes results of our betting strategy at both the opening and closing betting line. 'W', 'L', and 'P' denote a win, loss, or tie (push) wagering result from our wagering strategy. For example, counts in the 'W to P' column represent the number of games where our strategy would win a wager at the opening spread of the game but only push (tie) at the closing spread. Games with *PriorGameATS* = 0 are included when totaling frequencies (counts) of games with various lines and line movements but are omitted from 'win/loss/push' results as there is no defined betting strategy when *PriorGameATS* = 0

| Panel A: Line magnitudes | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| At Closing Line | | | | | | At Opening Line | | | | | |
| Magnitude | Count | % of Total | Magnitude | Count | % of Total | Magnitude | Count | % of Total | Magnitude | Count | % of Total |
| 0 | 24 | 0.8% | 6-6.5 | 252 | 8.8% | 0 | 136 | 4.7% | 6-6.5 | 196 | 6.8% |
| 1-1.5 | 245 | 8.5% | 7-7.5 | 347 | 12.0% | 1-1.5 | 262 | 9.1% | 7-7.5 | 288 | 10.0% |
| 2-2.5 | 259 | 9.0% | 8-8.5 | 100 | 3.5% | 2-2.5 | 254 | 8.8% | 8-8.5 | 99 | 3.4% |
| 3-3.5 | 741 | 25.7% | 9-9.5 | 100 | 3.5% | 3-3.5 | 651 | 22.6% | 9-9.5 | 140 | 4.9% |
| 4-4.5 | 244 | 8.5% | 10-10.5 | 165 | 5.7% | 4-4.5 | 248 | 8.6% | 10-10.5 | 154 | 5.3% |
| 5-5.5 | 154 | 5.3% | 11+ | 249 | 8.6% | 5-5.5 | 165 | 5.7% | 11+ | 287 | 10.0% |
| | | | Total | 2880 | 100% | | | | Total | 2880 | 100% |
| Panel B: Line movement magnitudes and impact on PriorGameATS strategy | | | | | | | | | | | |
| Magnitude | Count | % of Total | W to W | P to W | L to W | L to L | P to L | W to L | P | W to P | L to P |
| 0 | 572 | 19.9% | 253 | 0 | 0 | 290 | 0 | 0 | 19 | 0 | 0 |
| 0.5 | 686 | 23.8% | 325 | 11 | 0 | 305 | 5 | 0 | 0 | 7 | 15 |
| 1 | 533 | 18.5% | 273 | 10 | 2 | 222 | 5 | 2 | 0 | 4 | 6 |
| 1.5 | 279 | 9.7% | 143 | 2 | 6 | 118 | 3 | 1 | 0 | 2 | 1 |
| 2 | 351 | 12.2% | 168 | 4 | 7 | 154 | 5 | 3 | 0 | 2 | 4 |
| 2.5 | 172 | 6.0% | 81 | 0 | 8 | 75 | 0 | 4 | 0 | 0 | 2 |

**Table 3** (continued)

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 3 | 133 | 4.6% | 60 | 2 | 4 | 57 | 1 | 4 | 0 | 2 | 2 |
| 3.5 | 44 | 1.5% | 19 | 0 | 2 | 20 | 0 | 1 | 0 | 0 | 1 |
| 4 | 43 | 1.5% | 22 | 1 | 1 | 14 | 1 | 1 | 0 | 1 | 1 |
| 4.5 | 18 | 0.6% | 6 | 0 | 0 | 11 | 0 | 1 | 0 | 0 | 0 |
| 5 | 17 | 0.6% | 8 | 0 | 0 | 9 | 0 | 0 | 0 | 0 | 0 |
| >5 | 32 | 1.1% | 10 | 1 | 5 | 10 | 0 | 4 | 0 | 0 | 1 |
| Total | 2880 | 100% | 1368 | 31 | 35 | 1285 | 20 | 21 | 19 | 18 | 33 |

**Table 4** This table presents results for wagering on National Football League (NFL) regular season games in Weeks 2-17 based on a reversal strategy which seeks to bet on (against) teams which relatively underperformed (overperformed) in their prior game of the current regular season. Data are from the 2007-2018 NFL seasons. Wins (W) and Losses (L) from utilizing such a strategy are recorded, as well as the winning percentage of the reversal strategy. Results are presented in aggregate, as well as for various levels of the variable of study, *PriorGameATS*. *PriorGameATS* is defined as: *PriorGameATS* = (Performance of Team A, relative to the spread, in Team A's last regular season game) – (Performance of Team B, relative to the spread, in Team B's last regular season game). Coinciding with this definition, Team A (Team B) is the team which, in its last game, performed relatively better (worse) against the spread. Thus, *PriorGameATS* is non-negative and our reversal strategy dictates wagering on Team B. Panel A presents results based on the subsample of games where Team A's relative performance is a positive value and Team B's relative performance is a negative value. Panel B presents results based on the subsample of games with either a negative value for Team A's relative performance or a positive value for Team B's relative performance. Games that end in a push (tie) are omitted from the sample, as are games with *PriorGameATS* = 0. t-statistics are provided for the null hypothesis of a 50% success rate of the reversal strategy

Panel A: Both teams contributing to PriorGameATS

| | PriorGameATS | | | | | |
|---|---|---|---|---|---|---|
| | 0.5-9.5 | 10-19.5 | 20-29.5 | 30-39.5 | 40+ | Total |
| Reversal W | 84 | 226 | 194 | 104 | 49 | 657 |
| Reversal L | 86 | 205 | 179 | 98 | 46 | 614 |
| Pct. | 49.41% | 52.44% | 52.01% | 51.49% | 51.58% | 51.69% |
| t vs. 50% | -0.15 | 1.01 | 0.78 | 0.42 | 0.31 | |

Panel B: Only one team contributing to PriorGameATS

| | PriorGameATS | | | | | |
|---|---|---|---|---|---|---|
| | 0.5-9.5 | 10-19.5 | 20-29.5 | 30-39.5 | 40+ | Total |
| Reversal W | 450 | 232 | 75 | 15 | 5 | 777 |
| Reversal L | 466 | 179 | 55 | 9 | 3 | 712 |
| Pct. | 49.13% | 56.45% | 57.69% | 62.50% | 62.50% | 52.18% |
| t vs. 50% | -0.53 | 2.64 | 1.78 | 1.26 | 0.73 | |

than for the reverse to occur (only 21 instances, total). Line movement's general, helpful impact on our strategy also develops because of games that either become ties ('pushes') or are no longer pushes at close and these results are also disproportionately favorable to our approach. For example, we record 31 (20) total instances where games that would push at the opening line become wins (losses) at the closing spread, and we record 33 (18) total instances where losses (wins) at the opening spread become pushes at the closing spread. It appears that waiting to wager indeed makes our initial, mild inefficiency for mid-to-high levels of *PriorGameATS* more inefficient.[9]

[9] To further consider the impact of specific levels of *PriorGameATS* on line movement, as well as our strategy performance, in unpublished results we reconstruct the findings of Table 3, Panel B for the various levels of *PriorGameATS* (and consider alternative segmenting of the sample, e.g., 5-point windows, 7-point windows, etc.). Results follow the general pattern of profitability, with greater profitability at closing lines, as would be expected given the results of Table 1 and Table 2.

We conclude our analysis by considering whether the more frequent shift of lines toward overperformers in games with only one team contributing toward *PriorGameATS,* as seen in Table 2, suggests a tweak to our reversal-based strategy. Specifically, in Table 4, we provide, in Panel A (Panel B), the win-loss results for the reversal strategy when both teams (only one team) contribute to the level of *PriorGameATS*.

In conjunction with Table 2, we find statistically significant, results for reversal-based wagering in Panel B. In particular, at a 10-19.5-point (20-29.5-point) level of *PriorGameATS*, we detect a profitable, successful wagering rate, even net of bookmaker commissions, of 56.45% (57.69%). Meanwhile, the success of reversal-based wagering when both teams contribute to *PriorGameATS*, as seen in Panel A, is less pronounced. As first noted in Table 2, NFL betting markets appear to be particularly likely to move inefficiently when one team, in its prior performance, was either very impressive (and thus lines move toward it) or very disappointing (and thus lines move against it).[10, 11]

## 5 Conclusion

Our findings highlight the impact of psychological and behavioral factors on common betting behavior. This study continues the evolution of sports betting market efficiency research in the direction of behavior and cognitive analyses as key factors used for identifying market asymmetries. Future research in this stream of literature should continue to explore how other psychological variables and cognitive processes can influence bettor decision-making, as well as the implications of these factors on the market. The areas of behavioral finance, organizational marketing, neuroscience, and the broader field of psychology each provide key concepts and variables that could be applied in the sports betting market setting.

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[10] In unreported results, inspired by Dare and Dennis (2011), we consider whether our baseline reversal strategy results differ when the strategy dictates wagering on a home team or away team in an NFL game. The results do not materially differ.

[11] In unreported results, inspired by Shank (2019), we consider whether our baseline reversal strategy results differ when the strategy dictates wagering in an intradivision NFL game or interdivision NFL game. The results do not materially differ.

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