Behavioral Biases in the NFL Gambling Market: Overreaction to News and the Recency Bias

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ABSTRACT

This paper examines the recency bias and overreaction in the NFL betting market from 2003 to 2017. Consistent with the recency bias, bettors are more likely to bet on teams who have won previous outcomes. We add to the literature and find that the magnitude of prior wins and losses in the previous weeks' plays a greater importance than the sole outcome of wins and losses in betting behavior. Additionally, our results show that bettors wager 2.1% less on the home team when their first-string quarterback does not play, and 3.1% more on the home team when the visitor's first-string quarterback does not play, which is consistent with overreaction. Finally, our results show that bookmakers earn "over the odds" thanks to bettors' quasi-rational behavior as they commit the recency bias.

JEL Classification: G1, G4, L83

Keywords: Overreaction, Recency Bias, Behavioral Bias, NFL, Gambling

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ABSTRACT

This paper examines the recency bias and overreaction in the NFL betting market from 2003 to 2017. Consistent with the recency bias, bettors are more likely to bet on teams who have won previous outcomes. We add to the literature and find that the magnitude of prior wins and losses in the previous weeks' plays a greater importance than the sole outcome of wins and losses in betting behavior. Additionally, our results show that bettors wager 2.1% less on the home team when their first-string quarterback does not play, and 3.1% more on the home team when the visitor's first-string quarterback does not play, which is consistent with overreaction. Finally, our results show that bookmakers earn "over the odds" thanks to bettors' quasi-rational behavior as they commit the recency bias.

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1. Introduction

The field of behavioral finance has identified a plethora of behavioral and cognitive patterns affecting rationality during financial decision-making. These predictable patterns of quasi-rationality or 'biases' are rooted in our psychobiological makeup. The related literature has traditionally focused on monetary decisions made within the framework of traditional financial markets. In this paper, we step outside of the conventional focus on 'financial investors' and concentrate on gamblers betting on National Football League (NFL) games. We find that NFL gamblers are afflicted by biases identified in the behavioral finance literature, specifically, the recency bias and overreaction to news.

The recency bias refers to the cognitive pattern of over-emphasizing recent data or events while overlooking less recent ones. The recency bias is also related to the availability heuristic examined by Tversky and Kahneman (1973), as individuals consider the probability of events based on the relevant information that comes to mind, and thus overweight more current information over less current information. Overreaction, like the recency bias, is related to Tversky and Kahneman's availability heuristic. The overreaction bias refers to the overt exaggerated response to new and recent information, which results in securities being overbought or oversold in financial markets. Therefore, intuitively, said biases are often studied together.

In this paper, we explore how previous games' outcomes influence bettors' wagers during the thirteen NFL seasons that took place between 2003 and 2017. The bookmaker sets the spread and total (discussed below) with knowledge of the previous game's outcomes. As such, the bookmaker has already incorporated the recent success (or lack thereof) prior to the gamblers placing their wagers. In fact, research shows that betting on teams with recent success has a negative and significant impact on game outcomes (Camerer, 1989; Paul & Weinbach, 2005;

Shank, 2018). Thus, betting on teams with recent performance can be described as a bias given that it results in a further negative expected return.

Consistent with the recency bias, we find that bettors are more likely to wager on the home team if the home team covered the spread more often in the previous three weeks, and the visitor team covered the spread less often consistent with prior literature. We add to the literature by demonstrating that the magnitude of how many points each team covers, or fails to cover, the previous weeks' spread plays a greater role in gambling behavior than simply if the team has won or lost its previous game. Moreover, NFL bettors also overreact to news about the availability of the first-string quarterback. We find that gamblers wager 2.1% less on the home team when their first-string quarterback does not play, and 3.1% more on the home team when the visitor's first-string quarterback does not play. Additionally, these results are corroborated when examining the totals market. Finally, we show that bookmakers enjoying profits, after transaction costs, in excess of what might be expected in a fair game due to bettors' quasi-rationality wagers from committing the recency bias.

The sports betting market provides several benefits over traditional financial markets in considering behavioral biases. First, the potential payouts of gains and losses are known – that is – the expected returns – can be observed. This stands in contrast to financial markets where investors' expectations may only be inferred by complex models of expectations. Second, the games on which the bettor places a wager have a short duration with a known end date, whereas, for equities, investors' time horizons cannot be observed.. Third, sports betting markets share similar essential features with the stock market, such as liquidity and wide information availability (Thaler and Ziemba, 1988; Avery & Chevalier, 1999; Durham et al., 2005). A further argument proposed in favor of using sports markets to study market efficiency is that they are idiosyncratic.

“That assets’ risk is idiosyncratic implies that an asset pricing model is unnecessary. Therefore, tests of market efficiency and/or superior individual performance do not suffer from the joint hypothesis problem (Fama, 1970)” (Andrikogiannopoulou & Papakonstantinou, 2018, p. 1957).

The two major forms of betting in the NFL are the spread and total, which are both set by the bookmaker. The spread specifies the least margin by which the favorite team must win. As such, bettors can wager on the favorite to win by this margin (i.e., the spread) or the underdog to lose by less than the margin or win outright. The total refers to the number of points both teams will combine to score. The bettor can then bet the game outcome will be “over” or “under” this total. For example, in a game between the Pittsburg Steelers (the favorite) and the Cleveland Browns (the underdog), if the spread is -10 (i.e., the Steelers must win by more than 10 points) and the total is 50, a bettor who bets on the Steelers to win by more than 10 points (also known as covering the spread) and on the “over” will win if the actual score is Steelers 31 – Browns 20.

The bookmaker does not payout at a 1:1 relationship and is not a pari-mutuel betting system. The vast majority of NFL games against the spread and in the totals market have a payout of -110, which means that the bettor must wager $110 in order to win $100. The $10 (4.55%) commission the bookmaker charges to make a bet is called the *vigorish*.[1] Due to the vigorish, a gambler would have to consistently win 52.38% of their bets to earn a profit.[2] If the bookmaker has no private information about the market and is uninterested in taking a side, it should set the spread and total in each game, so the percentage of bets on each side (i.e., the favorite “covering”/ “failing to cover” in the spread market and “over”/ “under” in the total market) is between 47.62% and 52.38% to ensure a profit. However, most people are unaware that bookmakers do not function

[1] $10/$220 = 4.55%
[2] $110/$210 = 52.38%

this way, as they do not aim to have equal amounts wagered on each side of the bet. Levitt (2004) examines the behavior of bookmakers and finds that the bookmaker rarely has an equal amount bet on each side of a gamble, which is confirmed by Paul and Weinbach (2007), Paul and Weinbach (2011), and Shank (2019a). Levitt (2004) argues that bookmakers use their expertise to set the betting lines in order to maximize their profits as they can set the lines to get more than 52.38% on the losing side on average and earn more than a 5.45% profit on average.

Our results have considerable implications due to the size of the sports gambling industry. As it relates to the NFL, the American Gambling Association estimated that nearly $100 billion was wagered in 2016, with almost $5 billion occurring on the Super Bowl alone. However, in 2016 only Nevada and Delaware had fully legalized sports betting. Conversely, as of the end of 2019, 17 additional states had legalized sports betting, with more currently working on new legislation. As such, the $90 billion gambled in 2016 has likely already increased significantly due to being more available and will likely continue as more states make it legal. Furthermore, as it relates to all sports, H2 Gambling Capital (2013) estimates that the total amount of global wagers on sports was near $1 trillion in 2012. As such, the ramifications of our results could have large monetary impacts.

2. Literature Review

Lee et al. (2008) examine the recency bias among financial analysts and find that analyst's overweight recent information, and that an analyst's forecast of long-term corporate growth is optimistic during expanding economic times and pessimistic during economic contractions. Additionally, Ashton and Kennedy (2002) find that auditors overweight recent information when issuing ‘going concern’ reports. Kliger and Kudryavtsev (2010) find that the price reaction is stronger to analyst recommendation upgrades (downgrades) when accompanied by positive (negative) stock market returns, as investors overweight recent market behavior in their purchasing and selling decisions. While examining investor behavior, Nofsinger and Varma (2013) find that the recency bias contributes to an investor's probability of repurchasing previously owned stocks. Furthermore, Ma et al. (2014) argue that investors succumbing to the recency bias causes the timing of the 52-week high post earnings announcement drift puzzle. Given that even sophisticated investors and analysts are susceptible to the recency bias, we expect that NFL gamblers will also overweight recent outcomes when making betting decisions. That is, we expect bettors to wager on teams that played well and won in the most recent weeks, and wager against teams who performed poorly in the recent past.

Overreaction to news in traditional financial markets has been well established in seminal papers, including De Bondt and Thaler (1985), Howe (1986), and Daniel et al. (1998). Furthermore, the literature finds evidence of overreaction in the options market (Stein, 1989), the futures market (Huang, 2011), bankruptcy filings (Reyes & Waissbluth, 2016) and, of particular relevance to the analysis in this paper, the ‘in-play’ betting market in international one-day cricket (Norton, Gray and Faff, 2015).[3] However, there is financial literature showing an underreaction to news such as post-even return drift (e.g., Chan et al., 2001; Gompers et al., 2003; Hong & Kacperczyk, 2009; Michaely et al., 1995). As such, we examine how news about the availability of the team's first-string quarterback plays in wagering patterns. If bettors overreact to the news,

[3] Norton et al. provide a summary of literature on the efficiency of sports betting markets (pp. S165 to S166 noting a range of anomalous findings, Similarly, Miller Jr. & Rapach (2013) report mixed evidence in the literature relating to NFL efficiency (p. 10) while their study rejects the efficiency. We refer readers to these summaries as we have chosen to highlight the behavioral literature on the psychological phenomena we study and which, in turn, under the inefficiencies we uncover.

they will place more money against the team without its starting quarterback. Conversely, if they underreact to the news, their betting behavior won't change.

Our paper has commonalities with three papers showing that bettors exhibit behavioral biases consistent with the recency bias in the NFL gambling market (Durham et al.,2005; Moskowitz,2015; and Andrikogiannopoulou & Papakonstantinou2018). Our paper differs from these papers in key ways. In particular, the dependent variable in our analysis is the aggregate flow of funds on each game. Durham et al. (2005) and Moskowitz (2015) study the change between the opening and closing lines and find that these changes reflect past patterns. The quoted odds studied in these papers are employed as the authors argue that the change is due to too many wagers being on one side of the bet. However, the odds may also change for other reasons, such as new information. Andrikogiannopoulou and Papakonstantinou (2018) analyze a panel of individual bettors and also find that gamblers prefer to wager on teams with recent success. Andrikogiannopoulou and Papakonstantinou (2018) examine the likelihood of making a bet and do not consider the amount of money wagered on the game. In contrast, we argue that the magnitude of previous outcomes is more important than the dummy variable (win or loss) used in the aforementioned research. That is, we maintain that a team covering the spread by 30 in the previous game will have a greater impact on betting behavior than covering the spread by 1.

3. Data

We purchase NFL data for regular season games from 2003 through 2017 from sportsinsight.com following established precedent (e.g., Paul and Weinbach, 2011; Paul et al., 2011; Paul et al., 2014; Shank, 2019b). The dataset provides the opening and closing lines for the spread and total from the bookmaker and the score outcome for all games. Furthermore, data on betting percentages for the spread and over are hand collected from sportsinsight.com, and data on the starting quarterback of each game is hand collected from game logs.

One important issue regards the timing of the bookmaker's spread and total and when gamblers place their bets. The majority of NFL games are on Sundays, with one game played on Thursdays and Mondays. The bookmaker normally posts the spread and the totals for all games for the week on either Monday or Tuesday. However, bookmakers can adjust their spread or total up until the day of the game. This adjustment between the open and close for the spread has an average of 0, with 90% of all changes being less than 3 points in either direction. Gamblers can bet any time after the initial spread or total is posted and can cancel their bet at any time prior to the start of the game if they change their mind for any reason. Regardless of when the gambler places the bet, their gamble and the future payout for the game will be compared to the final spread or total value similar to a pari-mutuel market. For example, if the opening total line is 50 when a bettor places a bet on the over and the closing total line is 52. The bettor will lose if the game outcome totals 51, as their bet is compared to the closing line and not what the line was when they placed their bet. Therefore, we use the closing (final) spread and total in our analysis.

We examine two ways to measure the recency bias. First, we consider both teams' momentum, which is the number of games the team has covered either the spread or the over in their previous three games in keeping with previous research (Durham et al., 2005; Moskowitz, 2015; Andrikogiannopoulou & Papakonstantinou, 2018). If bettors are overweighting recent performance, they will bet more on teams that have covered the spread or over more often than not in recent games. Second, we examine the extent to which the team covered (or failed to cover) the spread or the over to create a continuous variable. For instance, if a team covered the spread in the previous week by 30 points, bettors susceptible to the recency bias would wager more on said team than on a team that only covered the spread by 1 point in the previous week. Additionally, we examine said continuous variables in each of the previous three weeks. If bettors exhibit the recency bias, the last week's outcomes will hold more weight than weeks further into the past. The literature provides no guidance on an appropriate time frame over which bettors' recency bias might be examined. Therefore, in addition to the three week window on which we initially focus, we consider, and confirm, our analysis using a five week window in robustness tests presented later in the paper. Table 1 displays the definitions of the variables used in the paper.

[Table 1 about here]

Figure 1 is a picture taken from a popular sports wagering information site called Covers.com on January 18th, 2020 (the day before the game). The screenshot provides the last eight games the Green Bay Packers played (the information for their opponent, the San Francisco 49ers, is also listed on the same webpage), whether they won or lost against the spread (ATS), the margin of victory or loss against the spread (ATS Mar), whether they covered the over or under (O/U), and the number of points by which they covered the over (OU Mar). As such, the variables that we employ to measure the recency bias are variables that gamblers have access to.

[Figure 1 about here]

To examine overreaction to news, we use hand collected data on every game to determine who the starting quarterback is. Suppose the team's first-string quarterback at the beginning of the season is either injured or benched. In that case, bettors might overreact to this news by wagering on the opposing team, even though this information should have already been incorporated into the spread or over by the bookmaker. In the NFL, the quarterback is the most important player and the key driver of a team's success or failure. Therefore, news events about the first-string quarterback not being able to play would constitute the most significant news event for NFL bettors. In fact, we find that the home team wins 57% of games (i.e., 1281 wins out of a sample of 2229 games) when both teams have their first-string quarterbacks starting the game. Alternatively, when the visiting team's first-string quarterback is unable to play, the home team has a winning percentage of 72% (i.e., 375 wins out of a sample of 521 games). Lastly, in games where the home team's first-string quarterback does not play, but the visitor's team's quarterback can play, the home team only wins 41% winning percentage (i.e., 208 wins out of a sample of 512 games). That is, the home team wins 15% more of its games when the visitor team's quarterback does not play, and loses 16% more of its games when their quarterback does not play. Therefore, we posit that as a result of an overreaction by bettors, if the home team's first-string quarterback is not playing, the visiting team will receive more wagers. Furthermore, we expect that this overreaction will be stronger if it is the first game after the first-string quarterback does not play, as there will be less information about the backup quarterback who now has to start for their team. Figure 2 displays the injury report for both teams, the Green Bay Packers and the San Francisco 49ers. Therefore, gamblers will know if either team's first-string quarterback is not playing.

[Figure 2 about here]

4. Results

Table 2 presents the summary statistics of the sample. From 2003 to 2017, the home team only covers the spread in 48.6 percent of the games. Furthermore, the two teams combine to cover the over 50.3 percent of the time. Thus, *prima facie* evidence suggests that the NFL betting market is efficient as both game outcomes are between 47.62% and 52.38%. Panel B shows that both the home team and the visitor team play a game without their first-string quarterback nearly 20 percent of the time. Additionally, about 5 percent of the games have a backup quarterback making their first start of the season. Panel C shows that gamblers place wagers on the home team 47.8 percent of the time. This is inconsistent with the previous literature showing that bettors prefer betting on the home team (Paul & Weinbach, 2011; Shank, 2019a). However, our data from 2003 to 2017 is a significantly larger dataset than the previously mentioned papers, each of which only used two separate two-year samples. We also find that bettors place a wager on the over more than 64 percent of the time, consistent with previous literature (Paul & Weinbach, 2011; Shank, 2019a). This suggests that the bookmaker does not adjust the opening and closing lines in order to get between 47.62% and 52.38% on each side of the bet to ensure a profit consistent with Levitt (2004). Panel D illustrates that both the home and visitor teams have covered the spread or the over in about half (i.e., 1.5) of their previous three games. Panel E shows that the home team typically covers the spread by 0.1 points and the over by 0.47 points, demonstrating the bookmaker's forecast accuracy.

[Table 2 about here]

Table 3 presents the results on the drivers of gamblers' betting behavior, where the dependent variable is the percentage bet on the home team (that is, the aggregate flow of funds on each game) using OLS regressions with robust standard errors. Column 1 examines the momentum of the home and away team without considering how much they covered or lost to the spread in the previous three weeks. We omit games from the first three weeks of the season as variables looking back three weeks would include games played the previous season and would be inconsistent with the recency bias. Furthermore, in addition to our variables on interest, we include the spread of the game and a dummy variable that equals 1 if the home team is the underdog to control for team characteristics, game characteristics, and previous findings that gamblers prefer to bet on the favorite (Paul & Weinbach, 2011; Shank, 2019a).[4]

[Table 3 about here]

The results in column 1 of Table 3 show that gamblers are significantly more likely to place a wager on the home team if the home team has covered the spread more often than not in the past three weeks, with a coefficient of 1.51, and the away team has failed to cover the spread more times in the recent weeks, with a coefficient of -1.76. Therefore, for every one game that the home team covered in the previous three weeks, gamblers wager 1.51% more on the home team. This is consistent with the recency bias as the bettors are overweighting recent game outcomes and irrationally wager on the team with the recent success. Additionally, our results show that bettors are significantly more likely to bet on the home team, the more the home team is favored (i.e., -10 is more of a favorite than -3). Finally, they are less likely to bet on the home team if they are the underdog.

Column 2 of Table 3 examines how gamblers behave when considering how well the home and visitor team performed against the spread in the previous three games. That is, do investors behave differently if the home team covered the spread by only 1 point versus 30 points? The results show that gamblers do react to the magnitude of wins or losses against the spread in the previous weeks as all three variables are significant at the 1% level. Additionally, both the coefficients and t-statistics show that gamblers place greater emphasis on the most recent game (t-1) versus the game two or three weeks prior, consistent with the recency bias. This is illustrated

[4] The literature examining potential drivers of gambler wagering preferences does not typically include fixed effects in the model (for example, see Durham et al., 2005 or Moskowitz, 2015). However, our results are unchanged when including time fixed effects in the model. Additionally, team fixed effects appear inappropriate in this literature. Teams vary considerably over the sample period as players and coaches change teams, from season to season and even within a season. Peterson (2008) makes a similar point about firm fixed effects in corporate finance.

by the coefficients of the lagged variable *home points spread covered* in column 2 where the first lag is 0.07 and the second and third lag 0.03 and 0.04, respectively. The first lag has more importance than the second and third lags suggesting that bettors' memory of the most recent game is stronger than their memory of the previous two games. The coefficients of the lagged variables for *visitor points spread covered* show that the most recent game has a greater effect (in absolute terms),-0.11, than the result a fortnight ago, -0.06, which, in turn, has a greater effect than the result three weeks ago, -0.04. Column 3 reports regression results where we subtract the visitor points spread covered from the home points spread covered. The results show that gamblers prefer to bet on the home team when the home team covered the spread by more points, and the more points the away team failed to cover the spread in the previous weeks. Overall, we find that bettors significantly overweight recent game outcomes when placing their wagers even though the bookmaker has already factored this into the spread.

Column 4 of Table 3 presents the results for our variables, looking at overreaction to news about the first-string quarterback. We find that gamblers bet on the home team 2.17% less when the home team's first-string quarterback is not playing and 2.92% more when the visitor's first-string quarterback is not playing. Furthermore, the coefficient is about the same regardless of whether it is the second-string quarterback's first game or not. These results demonstrate that NFL bettors significantly overreact to news about a team's first-string quarterback even though this news is available to everyone and should already be incorporated into the spread.

The results in Table 3 for the spread are corroborated by the results shown in Table 4 for totals for the previous week's game outcomes. Unlike the spread market where one team wins and one team loses against the spread, both teams either cover the over or cover the under. For example, the results in the first three columns show that the more success each team has had in covering the over in the past three weeks, the more gamblers will wager on the over. In column 6, the home and visitor team momentum variables are insignificant, with the magnitude of past performance is significant for the home (visitor) team in the past two (three) weeks. As such, our results show that the magnitude of previous outcomes is more important than just the game outcome.

[Table 4 about here]

Tables 3 and 4 show that aggregate flows into the spread and overs market are consistent with bettors' exhibiting the recency bias and overreacting. The analyses reveal biases but they do not, in themselves, reveal evidence that the biases lead to market inefficiency. Investors behaving quasi-rationally is perhaps only a "smoking gun" for *prima facie* market inefficiency. In equity markets, efficiency would be considered using a generally accepted asset pricing model and then examining the alpha to consider if there were statistically significant abnormal returns. The NFL betting market does not, however, have an equivalent to a generally accepted model that generates estimates of expected returns. However, it does have a model of expectations against which we might consider *prima facie* efficiency or inefficiency, although no consideration of efficiency can avoid the joint hypothesis conundrum: a *prima facie* rejection of efficiency might simply be a function of a bad model. Our model of expectations is simply that the returns for a bettor in the NFL gambling market should follow a *martingale*.

In introducing the concept of a *martingale*, Campbell, Lo, and MacKinlay (1997) write that "[t]he prominent Italian mathematician Girolamo Cardano proposed an elementary theory of gambling in his 1565 manuscript *Liber de Ludo Aleae* (*The Book of Games of Chance*) in which he wrote: The more fundamental principle of all in gambling is simply equal conditions, e.g., of opponents, of bystanders, of money, of situation, of the dice box, and of the die itself. To the extent to which you depart from that equality, if it is in your opponent's favour, you are a fool, and if in your own, you are unjust" (pp. 29 – 30). In a fair game, a player's expected new wealth in the next period should equal her wealth in this period. In other words, a bettor should walk away from the table with no more money, or less money, than she started with. We use this notion to test whether the biases we have documented matter. In doing so, we take account of Jensen's (1978) insight that we need to take transaction costs into account, and therefore our consideration of whether bettors' biases make the market inefficient account for the 4.55% vigorish.

In Table 5, we compare how a few of our recency bias and overconfidence measures relate to betting outcomes. We do not have data on individual bettors, so we must put ourselves in the shoes of a representative bettor exhibiting the biases we uncover to consider the effect of biases on outcomes. Each analysis shows how gamblers would fare if they had exhibited a particular bias in their bets on each game in our sample. The first column details the criteria that we used to compute the number of wins (column 2), losses (column 3), and win percentage (column 3). Furthermore, columns 4 and 5 display how profitable betting solely on this strategy would be if the gambler bet $110 on every game. However, due to the typical $10 vigorish, they would only earn $100 if they win the bet (and lose the $110 if they lost). As such, Table 5 documents the wealth transfers from the sports bettor to the bookmakers.

[Table 5 about here]

Panel A of Table 5 examines the wealth transfer in the overall NFL gambling market based on the percentage of gamblers on each side of the bet. Panel A1 shows that when more than 50% of the gamblers wager on the home team, the home team covers the spread 48.6% of the time. Conversely, when more gamblers bet on the away team (i.e., less than 50% bet on the home team), the gamblers win 51.4% of the time (i.e., 100% - 48.6%). However, even though gamblers are more accurate when they bet on the away team, they still do not earn a profit due to the 4.55%

vigorish. Similarly, Panel A2 examines the wealth transfer based on betting with or against the public in the totals market. The results show that gamblers in the totals market pick the correct bet roughly 50.6% of the time when the majority bet on either the over or under. However, once again, this strategy is not successful as the bookmaker still receives a profit.

Panel B of Table 5 examines the transfer of wealth based on the recency bias. Here we use the number of points the home team covered the spread (over) in the previous week minus (plus) the number of points the visiting team covered the spread (over) in the previous week as our measure of recency bias as it considers both the home and visiting team in one variable. For both the spread (Panel B1) and the totals market (Panel B2), we split the variable into four quantiles and compare how each of the quantiles performs on their wagers. However, to examine the extremes of the bias, we only report the findings of quartile one and four.

Quantile 1 (Q1) in Panel B1 of Table 5 shows the results for when our home points spread covered variable minus the visitor points spread covered variable in the previous one week results in a value between negative 68 and negative 12.5 (i.e., the lowest quartile). Given that the visitor team performed much better than the home team against the spread, Table 3 suggests that more bettors would wager against the home team. In this situation, the results show that betting on the visiting team would produce a winning bet 48.4% of the time. Quantile 4 shows the results for games where the home team outperformed the visiting team in the previous week, after adjusting for the spread. In this situation, gamblers succumbing to the recency bias would wager on the home team. However, the home team only wins 46.2%, which is lower than the 47.6% required to keep the market efficient. This result has two implications. This result supports Levitt (2004) and demonstrates that the bookmaker uses the gamblers biases against them and sets the spread to maximize profit, even if it violates the market efficiency of keeping outcomes between 47.62% and 52.38%.

Panel B2 of Table 5 uses the same methodology in the totals market. In quantile 1, which goes against the recency bias where gamblers are less likely to bet on the over due to their recency bias, we find that betting on the over produces a win rate of 52.4%. When we examine the fourth quantile, where gamblers are more likely to bet on the over, we find that the games result in an over only 49% of the time. Overall, Panel B demonstrates that the bookmaker earns higher returns as gamblers who succumb to the recency bias lose more money than those who do not.

Panel C of Table 5 examines gambler's overreaction to the news of a starting quarterback, either playing or not playing in the game. Here, we test all four possible outcomes: both teams play their starting quarterback, only the home team plays their starting quarterback; only the visiting team plays their starting quarterback; and neither team plays their starting quarterback. Panel C1 shows that when the home quarterback does not play, and the visiting quarterback does, the home team only wins 45.5% of the games. In this situation, Table 3 shows that gamblers are more likely to wager on the visiting team. Since this is far below the efficiency threshold of 47.6%, the results show that the bookmaker is not accurately adjusting the spread to account for the home team missing their quarterback. When examining games where only the home team has their starting quarterback, the home team covers the spread nearly 51% of the time. Once again, it appears that the sportsbook is not using the gamblers overreaction to their benefit while setting the spread. However, this result does not violate market efficiency.

Finally, Panel C2 of Table 5 examines the role of having a starting quarterback not play has in the totals market. While none of the scenarios can produce a profitable strategy, we find interesting results that games are more likely to result in an over when only the home team is missing their starting quarterback. At the same time, betting the under is a better strategy when only the visiting quarterback does not play. Given that gamblers are more likely to bet on the under when one of the teams is missing their starting quarterback, it appears that the sportsbook is more accurate in setting the total when the home team is missing their starting quarterback.

5. Robustness

Our model of the recency bias involves making assumptions about bettors' memories. In particular, limiting the analysis to the preceding three weeks precludes us from considering any possibility of people remembering games that happened four weeks ago. For robustness, we rerun our analyses from Table 3 and Table 4 using data from the previous five games rather than the previous three.

Table 6 examines the momentum variables for both the spread and totals market, and shows that gamblers still wager more on the home team when they have covered the spread more often, and the visitor team has covered less frequently in their previous five games. Additionally, the magnitude of how much the home team covers the spread in the previous game, and the visitor team fails to cover the spread in the last three games are significant contributors to wagering decisions. This is consistent with the results in Table 3. Similarly, in the totals market, we find that the more points the home team covered the total in the previous two weeks, and the more points the visitor team covered in the previous four weeks is positively related to the percentage bet on the over. Additionally, consistent with previous results, we find that the magnitude of the coefficients decreased the less recent the last game occurred in both the spread and the totals market. Finally, gamblers continue to bet against the team starting a backup quarterback. Overall, the inferences we made using only the previous three weeks' games remain unchanged when considering additional games. Moreover, since the game's outcome five weeks prior is not significant for the home or visitor team, in either the spread or totals market, we do not further extend our window.

[Table 6 about here]

Finally, in Table 7, we split our sample between the 2003-2008 season and the 2009-2016 seasons to ensure that our results are not driven by only a few years' worth of data (we omit 2017 to ensure the sub-samples cover the same timespans). We find that the home (visitor) team's momentum is positively (negatively) related to the percent bet on the home team. Furthermore, we find that the previous game's outcome for the home team is positively related to the amount bet on the home team from 2009 and 2016, whereas the last two games outcomes for the visiting team are negatively correlated in both subsamples. In the totals market, we find that the number of points covered by the home (visitor) team in the previous two (one) games contributes to the percentage bet on the over. Finally, gamblers are more likely to bet on the home team in the spread market if the home team's quarterback is playing while the visiting team's quarterback is not playing, with the coefficients having a stronger impact on the more recent sample. Similarly, we find that the quarterback not playing for either the home or visiting team is related to gamblers wagering less on the over in the most recent sample. These results show that gamblers are more aware of news related to the quarterback in the 2009-2016 sample compared to the 2003-2008 sample. These results may be related to a transition in the NFL game to being more pass heavy, making the quarterback even more important. For example, from 2003 to 2016, the average passing yards per game increased 28% from 203 to 256 while the average rushing yards per game decreased by 8%

from 118 in 2003 to 109 in 2016. Overall, we find results consistent with those we reported earlier for both the spread and the totals in both subsamples.

[Table 7 about here]

6. Conclusion

In this paper, we examine gamblers' behavior in the National Football League (NFL) betting market. Specifically, we posit that NFL gamblers, like investors in traditional financial markets, are afflicted by the recency bias and overreaction to news related to the starting quarterback. Our results strongly support the existence of recency bias in the NFL betting market as bettors significantly overweight recent game outcomes when placing their wagers. Similarly, we find that gamblers stray away from placing bets on teams with backup quarterbacks as they overreact to news. Additionally, we show that bookmakers enjoy abnormal returns related to the recency bias and overreaction. That is, the bookmaker sets the spread and total to generate profits over and above those that the bookmakers should earn simply by making the vigorish, due to the bettor's preference for betting on teams with better previous performance. Finally, these results are robust to sensitivity tests of changing the number of game lags and examining our results in subsamples.

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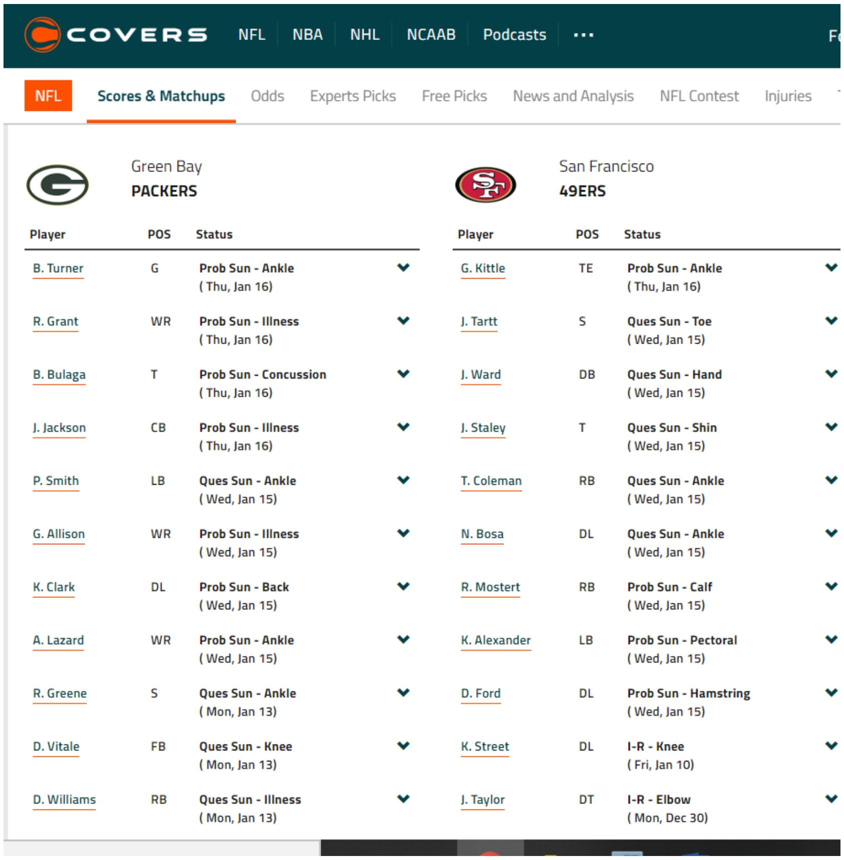
Date	VS	Score	BG	ATS	ATS Mar	O/U	OU Mar
Jan 12, 2020	SEA	W 28 - 23		W -4.5	+0.5	O 46.0	+5.0
Dec 29, 2019	@ DET	W 23 - 20		L -13.5	-10.5	U 44.0	-1.0
Dec 23, 2019	@ MIN	W 23 - 10		W 4	+17.0	U 47.0	-14.0
Dec 15, 2019	CHI	W 21 - 13		W -4	+4.0	U 40.0	-6.0
Dec 8, 2019	WAS	W 20 - 15		L -13	-8.0	U 42.5	-7.5
Dec 1, 2019	@ NYG	W 31 - 13		W -6.5	+11.5	O 43.5	+0.5
Nov 24, 2019	@ SF	L 8 - 37		L 3	-26.0	U 48.0	-3.0
Nov 10, 2019	CAR	W 24 - 16		W -5	+3.0	U 49.0	-9.0

Figure 1. Covers.com Screenshot on Previous Game Outcomes

This table provides a snapshot of the previous games for the Green Bay Packers. Columns 1, 2, and 3 present the date the game was played, the team it was against and the final score of the game respectively. The column ATS provides a W or L based on if the Packers won or lost against the spread while the corresponding coefficient provides the spread of the game (i.e. -4.5). ATS Mar depicts how much the Packers were beaten or lost after accounting for the spread. O/U presents an O (U) if the Packers and the corresponding team beat (failed to cover) the over and the corresponding number presents what the over / under total was. The final column depicts the outcome of the over / under after adjusting for the posted total.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NFL Scores & Matchups Odds Experts Picks Free Picks News and Analysis NFL Contest Injuries

Green Bay PACKERS

Player	POS	Status
B. Turner	G	Prob Sun - Ankle (Thu, Jan 16)
R. Grant	WR	Prob Sun - Illness (Thu, Jan 16)
B. Bulaga	T	Prob Sun - Concussion (Thu, Jan 16)
J. Jackson	CB	Prob Sun - Illness (Thu, Jan 16)
P. Smith	LB	Ques Sun - Ankle (Wed, Jan 15)
G. Allison	WR	Prob Sun - Illness (Wed, Jan 15)
K. Clark	DL	Prob Sun - Back (Wed, Jan 15)
A. Lazard	WR	Prob Sun - Ankle (Wed, Jan 15)
R. Greene	S	Ques Sun - Ankle (Mon, Jan 13)
D. Vitale	FB	Ques Sun - Knee (Mon, Jan 13)
D. Williams	RB	Ques Sun - Illness (Mon, Jan 13)

San Francisco 49ERS

Player	POS	Status
G. Kittle	TE	Prob Sun - Ankle (Thu, Jan 16)
J. Tartt	S	Ques Sun - Toe (Wed, Jan 15)
J. Ward	DB	Ques Sun - Hand (Wed, Jan 15)
J. Staley	T	Ques Sun - Shin (Wed, Jan 15)
T. Coleman	RB	Ques Sun - Ankle (Wed, Jan 15)
N. Bosa	DL	Ques Sun - Ankle (Wed, Jan 15)
R. Mostert	RB	Prob Sun - Calf (Wed, Jan 15)
K. Alexander	LB	Prob Sun - Pectoral (Wed, Jan 15)
D. Ford	DL	Prob Sun - Hamstring (Wed, Jan 15)
K. Street	DL	I-R - Knee (Fri, Jan 10)
J. Taylor	DT	I-R - Elbow (Mon, Dec 30)

Figure 2. Covers.com Screenshot of Injury Report

This figure reports a snapshot of the injury report for the Green Bay Packers and the San Francisco 49ers. For each team, it lists the player's name and position they play. The status provides the report on how injured they are, which is either probable (Prob) to play, questionable (Ques) to play, out / not going to play (not pictured), or on the injury reserve (I-R) representing they are out several games.

Table 1: Variable Definitions

Variable	Definitions
Home Bet Percentage	The percentage of dollars wagered that are placed on the home team
Over Bet Percentage	The percentage of dollars wagered that are placed on the over
Spread	The number of points the favorite team must win by in order to win the bet
Total	The total points both teams must combine to score in order for the over to win the bet
Home Underdog	A dummy variable that equals 1 if the home team is the not the favorite (i.e. predicted to lose) or 0 otherwise
Points Over Covered	The number of points by which the team covered the over in the given week
Points Spread Covered	The number of points by which the team covered the spread in the given week
QB Out	A dummy variable that equals to 1 if the team's starting quarterback does not play in the game and 0 otherwise
QB Out First Game	A dummy variable that equals to 1 if the teams backup quarterback gets their first start of the season and 0 otherwise
Team Over Momentum	The number of games in the past 3 games in which the team covered the over
Team Spread Momentum	The number of games in the past 3 games in which the team covered the spread

Notes: This table displays the definitions of variables used in the analysis

Table 2: Summary Statistics

Variable	Mean	Standard Deviation	Min	Max
Panel A: Game Outcomes				
Home Cover Percentage	48.6	50	0	100
Over Percentage	50.3	50	0	100
Panel B: Injury Data				
Home QB Out	19.5	39.6	0	100
Visitor QB Out	19.6	39.7	0	100
Home QB Out First Game	5.00	21.8	0	100
Visitor QB Out First Game	4.95	21.7	0	100
Panel C: Betting Percentages				
Home Team Bet Percentage	47.8	17.3	8	84
Over Bet Percentage	64.3	11.9	11	98
Panel D: Momentum				
Home Team Spread Momentum	1.453	0.863	0	3
Visitor Team Spread Momentum	1.431	0.854	0	3
Home Team Over Momentum	1.475	0.862	0	3
Visitor Team Over Momentum	1.487	0.871	0	3
Panel E: Points Covered				
Home Points Spread Covered	0.132	13.45	-49.50	52
Visitor Points Spread Covered	-0.111	13.43	-42.50	46
Home Points Over Covered	0.474	13.34	-35	68.50
Visitor Points Over Covered	1.143	13.39	-35.50	68.50

Notes: This table presents the summary statistics for the variables of interest for the full sample (n= 3371). Panel A displays the games' outcomes, Panel B details the percentage of games in which the starting quarterback does not start, Panel C presents the betting percentages on the games, and Panel D displays the summary statistics for the momentum variables. Table 1 displays the definitions for all the variables

Table 3: Percentage Bet on the Home Team

VARIABLES	1	2	3	4	5	6
Spread	-1.34***	-1.30***	-1.30***	-1.32***	-1.40***	-1.19***
	(-20.640)	(-19.605)	(-19.652)	(-20.106)	(-21.534)	(-17.721)
Home Underdog	-12.90***	-13.00***	-12.98***	-12.99***	-12.80***	-13.24***
	(-16.839)	(-16.939)	(-16.898)	(-16.923)	(-16.577)	(-17.452)
Home Team Spread Momentum	1.51***					1.35***
	(7.009)					(4.404)
Visitor Team Spread Momentum	-1.76***					-0.90***
	(-7.817)					(-2.899)
Home Points Spread Covered T-1		0.07***				0.03*
		(4.963)				(1.738)
Home Points Spread Covered T-2		0.03**				-0.00
		(2.231)				(-0.256)
Home Points Spread Covered T-3		0.04**				0.00
		(2.482)				(0.156)
Visitor Points Spread Covered T-1		-0.11***				-0.08***
		(-7.670)				(-4.828)
Visitor Points Spread Covered T-2		-0.06***				-0.04**
		(-4.376)				(-2.148)
Visitor Points Spread Covered T-3		-0.04***				-0.02
		(-2.934)				(-1.326)
Home Points Spread Covered -			0.09***			
Visitor Points Spread Covered T-1			(8.601)			
Home Points Spread Covered -			0.05***			
Visitor Points Spread Covered T-2			(4.601)			
Home Points Spread Covered -			0.04***			
Visitor Points Spread Covered T-3			(3.869)			
Home QB Out				-2.17***		-2.11***
				(-4.359)		(-3.830)
Visitor QB Out				2.92***		2.75***
				(5.712)		(4.959)
Home QB Out First Game					-2.10**	-0.42
					(-2.513)	(-0.457)
Visitor QB Out First Game					3.09***	0.46
					(3.290)	(0.444)
Observations	3,303	3,297	3,297	3,310	3,310	3,297
R-squared	0.629	0.630	0.629	0.623	0.619	0.638

Notes: This table present the OLS regression results with the dependent variable being the percentage of wagers placed on the home team. See Table 1 for variable definitions. T-statistics are presented under the coefficients with significance displayed at the 10% (*), 5% (**), and 1% (***) levels.

Table 4: Percentage Bet on the Over

VARIABLES	1	2	3	4	5	6
Total	1.09***	1.05***	1.05***	1.14***	1.15***	1.02***
	(26.901)	(25.708)	(25.688)	(27.855)	(28.570)	(23.963)
Home Team Over Momentum	1.16***					0.37
	(5.386)					(1.215)
Visitor Team Over Momentum	1.06***					-0.26
	(4.991)					(-0.808)
Home Points Over Covered T-1		0.07***				0.06***
		(5.250)				(3.791)
Home Points Over Covered T-2		0.06***				0.05***
		(4.100)				(2.847)
Home Points Over Covered T-3		0.02				0.01
		(1.422)				(0.694)
Visitor Points Over Covered T-1		0.08***				0.08***
		(5.477)				(4.883)
Visitor Points Over Covered T-2		0.06***				0.07***
		(4.544)				(4.273)
Visitor Points Over Covered T-3		0.04***				0.05***
		(2.896)				(2.926)
Home Points Over Covered + Visitor Points Over Covered T-1			0.08***			
			(7.506)			
Home Points Over Covered + Visitor Points Over Covered T-2			0.06***			
			(6.062)			
Home Points Over Covered + Visitor Points Over Covered T-3			0.03***			
			(3.115)			
Home QB Out				-0.67		-0.85
				(-1.323)		(-1.515)
Visitor QB Out				-0.67		-0.52
				(-1.360)		(-0.951)
Home QB Out First Game					-0.88	-0.43
					(-0.975)	(-0.435)
Visitor QB Out First Game					-1.90**	-1.25
					(-2.205)	(-1.263)
Observations	3,325	3,319	3,319	3,332	3,332	3,319
R-squared	0.217	0.229	0.229	0.206	0.207	0.232

Notes: This table present the OLS regression results with the dependent variable being the percentage of wagers placed on the over. See Table 1 for variable definitions. T-statistics are presented under the coefficients with significance displayed at the 10% (*), 5% (**), and 1% (***) levels.

Table 5: Profitability and Gambler Preferences

Panel A: Betting with the crowd	**Home Wins**	**Home Losses**	**Home Win %**	**Earnings betting on Home Team**	**Earnings betting on Visiting Team**
Panel A1: Percent Bet in Point Spread Market					
Greater than 50%	788	834	48.6%	-$12,940	-$3,280
Less than 50%	811	858	48.6%	-$13,280	-$3,410
	Over Wins	**Over Losses**	**Over Win %**	**Earnings betting on Over**	**Earnings betting on Under**
Panel A2: Percent Bet in Totals Market					
Greater than 50%	1477	1444	50.6%	-$11,140	-$18,070
Less than 50%	199	204	49.4%	-$2,540	-$1,490

Panel B: Betting and the Recency Bias	**Home Wins**	**Home Losses**	**Home Win %**	**Earnings betting on Home Team**	**Earnings betting on Visiting Team**
Panel B1: Home Points Spread Covered - Visitor Points Spread Covered T-1					
Q1: -68 to -12.5	435	408	51.6%	-$1,380	-$7,050
Q4: 13.5 to 63.5	381	443	46.2%	-$10,630	$2,390
	Over Wins	**Over Losses**	**Over Win %**	**Earnings betting on Over**	**Earnings betting on Under**
Panel B2: Home Points Over Covered + Visitor Points Over Covered T-1					
Q1: -55 to -11.5	442	402	52.4%	-$20	-$8,420
Q4: 14 to 70	412	425	49.2%	-$5,550	-$2,820

Panel C: Betting and Overconfidence	**Home Wins**	**Home Losses**	**Home Win %**	**Earnings betting on Home Team**	**Earnings betting on Visiting Team**
Panel C1: Home and Visiting Team Quarterback Status in Point Spread Market					
Home QB Playing & Visiting QB Playing	1065	1108	49.0%	-$15,380	-$6,350
Home QB Not Playing & Visiting QB Playing	230	276	45.5%	-$7,360	$2,300
Home QB Playing & Visiting QB Not Playing	260	251	50.9%	-$1,610	-$3,500
Home & Visiting QB Not Playing	68	78	46.6%	-$1,780	$320
	Over Wins	**Over Losses**	**Over Win %**	**Earnings betting on Over**	**Earnings betting on Under**
Panel C2: Home and Visiting Team Quarterback Status in Totals Market					
Home QB Playing & Visiting QB Playing	1119	1089	50.7%	-$7,890	-$14,190
Home QB Not Playing & Visiting QB Playing	265	245	52.0%	-$450	-$4,650
Home QB Playing & Visiting QB Not Playing	244	268	47.7%	-$5,080	-$40
Home & Visiting QB Not Playing	72	74	49.3%	-$940	-$520

Notes: In this table we compare how recency bias and overconfidence measures relate to betting outcome. The first column details the criteria that we used to compute the number of wins (column 2), losses (column 3) and win percentage (column 4) for the home team or over. Columns 4 and 5 displays how profitable betting solely on the strategy of with or against the recency bias or overconfidence measure would be if the gambler bet $110 on every game. However, due to the typical 10% vigorish the gambler would only profit $100 if they win the bet (and lose the $110 if they lose).

Table 6 Percentage Bet on Home Team or Over

VARIABLES	Home Team	VARIABLES	Over
Spread	-0.98***	Total	0.89***
	(-13.025)		(18.039)
Home Underdog	-13.40***	Home Team Over Momentum	0.49*
	(-15.419)		(1.765)
Home Team Spread Momentum	1.43***	Visitor Team Over Momentum	-0.47*
	(5.106)		(-1.714)
Visitor Team Spread Momentum	-0.75**	Home Points Over Covered T-1	0.08***
	(-2.555)		(4.325)
Home Points Spread Covered T-1	0.04**	Home Points Over Covered T-2	0.05***
	(1.985)		(2.991)
Home Points Spread Covered T-2	0.01	Home Points Over Covered T-3	0.01
	(0.283)		(0.527)
Home Points Spread Covered T-3	0.01	Home Points Over Covered T-4	0.06***
	(0.695)		(3.315)
Home Points Spread Covered T-4	-0.02	Home Points Over Covered T-5	-0.01
	(-1.075)		(-0.707)
Home Points Spread Covered T-5	-0.01	Visitor Points Over Covered T-1	0.09***
	(-0.485)		(5.100)
Visitor Points Spread Covered T-1	-0.09***	Visitor Points Over Covered T-2	0.10***
	(-4.757)		(5.634)
Visitor Points Spread Covered T-2	-0.06***	Visitor Points Over Covered T-3	0.07***
	(-3.548)		(3.718)
Visitor Points Spread Covered T-3	-0.05***	Visitor Points Over Covered T-4	0.05**
	(-2.740)		(2.541)
Visitor Points Spread Covered T-4	-0.02	Visitor Points Over Covered T-5	0.02
	(-1.293)		(1.208)
Visitor Points Spread Covered T-5	-0.03	Home QB Out	-1.53***
	(-1.637)		(-2.638)
Home QB Out	-2.70***	Visitor QB Out	-1.20**
	(-4.642)		(-2.120)
Visitor QB Out	3.08***	Home QB Out First Game	-1.26
	(5.301)		(-1.131)
Home QB Out First Game	0.18	Visitor QB Out First Game	-0.48
	(0.176)		(-0.440)
Visitor QB Out First Game	0.45		
	(0.393)		
Observations	2,457	Observations	2,474
R-squared	0.640	R-squared	0.245

Notes: This table present the OLS regression results with the dependent variable being the percentage of wagers placed on the home team or the over. See Table 1 for variable definitions. T-statistics are presented under the coefficients with significance displayed at the 10% (*), 5% (**), and 1% (***) levels.

Table 7 Percentage Bet on Home Team or Over in Split Sample

VARIABLES	Home Team	Home Team	VARIABLES	Over	Over
	2003-2008	**2009-2016**		**2003-2008**	**2009-2016**
Spread	-0.86***	-1.21***	Total	1.03***	1.05***
	(-7.537)	(-13.976)		(13.360)	(18.136)
Home Underdog	-16.71***	-11.05***	Home Team Over Momentum	0.06	0.43
	(-12.843)	(-10.769)		(0.101)	(1.028)
Home Team Spread Momentum	1.87***	1.31***	Visitor Team Over Momentum	-0.35	-0.05
	(3.435)	(3.042)		(-0.627)	(-0.124)
Visitor Team Spread Momentum	-0.99*	-0.82*	Home Points Over Covered T-1	0.03	0.10***
	(-1.745)	(-1.860)		(1.000)	(4.511)
Home Points Spread Covered T-1	0.01	0.05**	Home Points Over Covered T-2	0.01	0.07***
	(0.286)	(2.364)		(0.215)	(3.563)
Home Points Spread Covered T-2	-0.00	0.01	Home Points Over Covered T-3	-0.01	0.02
	(-0.123)	(0.465)		(-0.409)	(0.814)
Home Points Spread Covered T-3	0.02	-0.01	Visitor Points Over Covered T-1	0.06*	0.10***
	(0.821)	(-0.442)		(1.770)	(4.570)
Visitor Points Spread Covered T-1	-0.10***	-0.07***	Visitor Points Over Covered T-2	0.03	0.11***
	(-3.500)	(-3.135)		(0.951)	(5.320)
Visitor Points Spread Covered T-2	-0.05*	-0.06***	Visitor Points Over Covered T-3	0.05*	0.03
	(-1.714)	(-2.592)		(1.875)	(1.563)
Visitor Points Spread Covered T-3	-0.02	-0.04*	Home QB Out	-0.69	-1.88***
	(-0.736)	(-1.837)		(-0.793)	(-2.652)
Home QB Out	-1.91**	-2.84***	Visitor QB Out	0.51	-2.32***
	(-2.258)	(-3.934)		(0.554)	(-3.644)
Visitor QB Out	2.96***	3.48***	Home QB Out First Game	1.02	-0.94
	(3.549)	(4.655)		(0.583)	(-0.769)
Home QB Out First Game	1.25	-0.49	Visitor QB Out First Game	-1.21	-0.31
	(0.909)	(-0.403)		(-0.735)	(-0.251)
Visitor QB Out First Game	0.85	0.01			
	(0.498)	(0.011)			
Observations	1,177	1,668	Observations	1,178	1,689
R-squared	0.630	0.654	R-squared	0.179	0.315

Notes: This table present the OLS regression results with the dependent variable being the percentage of wagers placed on the home team or the over. See Table 1 for variable definitions. T-statistics are presented under the coefficients with significance displayed at the 10% (*), 5% (**), and 1% (***) levels.