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Abstract

The behavior of informed traders, or 'smart money,' in sports betting markets has long been of interest to researchers. In this paper, we focus specifically on the behavior of smart money in Major League Baseball (MLB) daily fantasy sports (DFS) contests to determine if they avoid cognitive behavioral biases to increase their expected earnings. Specifically, we investigate whether smart money avoids the hot hand bias, where individuals tend to overestimate the likelihood of success for players on a hot streak. Using a dataset of MLB DFS contests, we find that winning lineups have lower usage rates for players exhibiting the hot hand compared to losing lineups. This suggests that smart money identifies and fades the hot hand strategy to increase their expected earnings.

Keywords: behavioral bias, daily fantasy sports, hot hand, informed trader, smart money

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Introduction

In sports betting markets, informed traders, referred to as 'smart money', seek to generate profits by exploiting market prices that deviate from market efficiency. Such deviations may occur due to bookmaker error or failure to capture all available information. However, prices may also deviate from the efficient market price if bookmakers identify profitable deviations. According to the Levitt (2004) hypothesis, bookmakers set prices that maximize profits rather than balance books. When bettors exhibit behavioral biases, such as the favorite-longshot bias,[1] for example, books may adjust market prices slightly to extract additional rents from biased individuals. Smart money, in return, increases their expected earnings by betting against the bias.

This paper aims to investigate whether smart money avoids cognitive behavioral biases, specifically the hot hand, thus creating opportunities for additional profits. To achieve this, we analyze the behavior of smart money in daily fantasy sports (DFS) Major League Baseball (MLB) contests offered by DraftKings. Previous research by Losak et al. (2023) demonstrates that, despite there not existing profitable gains from selecting "hot" players to DFS lineups, and no market mispricing of player streakiness, DFS entrants were more likely to choose players on a hot streak for their lineups. While those results were focused on aggregate entrant behavior, this paper focuses on the behaviors of skilled DFS entrants.

We find that winning MLB DFS lineups use players exhibiting the hot hand less often compared to losing lineups. As only a small percentage of total entrants accumulate most profits in DFS contests (Miller & Singer, 2015), it is reasonable to assume, ceteris paribus, that winning entrants are more likely to be skilled than losing entrants. Although the skill levels of entrants in our data are not directly measurable, we interpret the lower usage rates of hot players in winning lineups as evidence that informed traders identify and fade the cognitive hot hand bias to enhance their expected earnings.

The paper is structured as follows. First, we provide an overview of smart money and informed traders, market efficiency, the chance versus skill debate in DFS contests, and the hot hand behavioral bias as it pertains to DFS markets. Second, we describe our data and empirical strategy, including a description of how DFS baseball contests work on DraftKings. Third, we present the results of our empirical model, highlighting characteristics of winning and losing lineups. Finally, we discuss the implications of our findings and conclude the paper.

Literature Review

Smart Money in Prediction Markets

Prior to the advent of DFS, academic researchers studied sports betting markets as a convenient way to test theories of financial markets. Betting markets offer a collection of data where prices are determined by market forces, individual participants are rewarded for being correct, and outcomes have a clear beginning and end point where profits and losses are realized (Sauer, 1998). Surowieki (2005) notes that markets function as effective aggregators of disparate information, producing consensus “prices” that reflect the collective wisdom of market participants. Even when many market participants lack expert knowledge, market forces tend to produce prices (odds or point spreads) that provide unbiased forecasts of outcomes.

In traditional financial markets, even though they are generally considered to be ‘efficient,’ there exists compelling evidence of informed traders who possess superior information and consistently outperform average investors. Finnerty (1976) shows that insiders are better informed and do earn above expected returns. Easley et al. (2002) find evidence of informed traders in option markets, with changes in options volume linked to news providing information about future stock prices. Ziobrowski et al. (2004) establish that United States Senators earn on their common stock transactions in excess of normal market returns, evidence that they benefit from their access to non-public insider/regulatory information. Ali et al. (2008) present evidence that institutional traders with medium-size stakes in companies have better information when trading around earnings announcements.

Research into specific betting markets demonstrates the presence of informed traders. For instance, Asch et al. (1982) identify the existence of a class of informed bettors in horse racing markets, who possess knowledge allowing them to participate in the market for financial gain and help correct market prices that may have strayed from efficient forecasts of outcomes. Gandar et al. (1998) find that movements in National Basketball Association (NBA) point spreads between open and close are generally in the correct direction, suggesting updated lines incorporate new information and/or correct any biases in opening lines. Comparable results are found in Gandar et al. (2000) in the NBA totals market.[2] Similarly, Krieger and Fodor (2013) find that line movements in college basketball are significantly more likely than not to be in the correct direction.

There is also evidence to suggest that informed traders behave differently in betting markets compared to uninformed traders. For example, Ottaviani and Sørensen (2009) show in parimutuel markets that smart money may delay betting as they utilize insider information and beliefs of the underlying probability distribution to identify profitable betting stakes, a result consistent with those from Gandar et al. (2001), Gramm and McKinney (2009), Gramm et al. (2016), and Suhonen et al. (2018).[3] Paul et al. (2013) finds evidence of informed traders betting on underdogs in early season NBA games. These are all examples in which smart money identifies profitable opportunities in sports betting markets. To our knowledge, this is the first paper to consider smart money behavior in DFS markets.

Market Efficiency and a Skill-Based Game

An ongoing legal question is whether DFS constitutes a game of chance or skill. Prior to the 2018 Supreme Court overturning of the Professional and Amateur Sports Protection of 1992 (PASPA), legalized sports betting was not permitted in the United States, with the exception of Nevada. Despite this, DFS experienced rapid growth during the early 2010s, as the 2006 Unlawful Internet Gambling Enforcement Act (UIEGA) created a carve-out for fantasy sports, provided that all winning outcomes reflect the participants' relative knowledge and skill.[4] While the ongoing legalization of sports wagering after PASPA has somewhat reduced the significance of the issue, the chance versus skill question remains prevalent in states where sports gambling remains illegal.

A game is considered a game of skill if it meets two requirements, in accordance with Cabot and Miller (2011) and Losak (2021): firstly, it must contain elements of skill, and secondly, there must be heterogeneity in player skill levels. The presence of smart money would satisfy the second criteria. Empirical research provides evidence of skill-based elements in DFS games for various leagues, including MLB (Easton & Newell, 2019; Losak et al., 2023), the National Football League (NFL) (Easton & Newell, 2019; Losak, 2021), and NBA (Paul et al., 2020). Meehan (2015) posits that DFS is a game of imperfect information, where applying game theory can result in sustained profits. Getty et al. (2018) conclude that DFS games on FanDuel display significant skill elements, comparable levels to the corresponding real-world sports. Additionally, Miller and Singer (2015) found that just the top 1.3% of players won 91% of profits in their sample of DFS games, further supporting the idea that DFS is a game of skill.

One critical source of skill-based elements in DFS arises from player pricing inefficiencies. DFS operators assign player salaries that remain fixed throughout the drafting period. Efficient salary setting should integrate all available information on expected player production, such that past performance and game-specific settings should not have any explanatory power in forecasting player performance. However, departure from efficient pricing creates opportunities for skilled players to demonstrate their knowledge and improve their performances in contests. Paul et al. (2020) show that incorporating factors such as home court advantage, rest, and opponent quality could aid in building lineups with higher expected point totals in NBA contests. Losak (2021) demonstrates that incorporating home field advantage and injury information leads to better performances in NFL contests. Alternatively, Losak et al. (2023) illustrate that for MLB, selecting visiting players, players with handed advantages, playing in high-scoring environments, and batting higher in the order result in greater scores. Skilled players can use these and other strategies to improve lineup performance.

The Hot Hand Cognitive Bias

To increase their expected returns, DFS players may adopt strategies based on market inefficiencies. However, players may also use strategies that they believe are market inefficiencies but are, in fact, efficiently priced. Such strategies often arise from cognitive biases, in our case the hot hand. Mathematically speaking, the hot hand is the belief in game-to-game or within game positive serial correlation of production, such that strong performance in recent games leads to an increased likelihood of positive performances in the short-run. The hot hand is a type of recency bias, which Dugan and Greyserman (2019) define as the over-emphasis of recent information. Recent events are more memorable and are likely overweighted when assessing the probability of events (Tversky & Kahneman, 1973). The hot hand fallacy is a result of the persistent misunderstanding of randomness, according to Camerer (1989), and a widespread cognitive illusion, according to Kahneman (2011).

Numerous studies considered the existence of the hot hand. For example, Gilovich et al. (1985) find no evidence that NBA shooting performance in recent games impacts shooting in subsequent games. However, Miller and Sanjurjo (2018) find that the study by Gilovich et al. (1985) contained an empirical bias against identifying a hot hand effect, and correcting for this bias produced evidence of a hot hand effect. In baseball, Green and Zwiebel (2018) discover evidence of a hot hand in batter performances and observe a response by pitchers to pitch more carefully to hot batters.

While measurement error in random sports outcomes (see Stone, 2012) has led to mixed empirical results in studies searching for the hot hand, there is considerable evidence in an overwhelming belief in its existence (Gilovich et al., 1985; Losak et al., 2023; Tversky & Gilovich, 1989), which is reflected in betting markets. Gandar et al. (1988) show that NFL teams were less likely to cover the spread if they beat the point spread by more than ten points the previous week.[5] This likely results from point spreads being artificially high, relative to an unbiased forecast, driven by enthusiastic fans overweighting recent performance. Camerer (1989) find in basketball data a slight propensity for bettors to bet more on teams with winning streaks. Paul et al. (2011) find that NBA teams on winning streaks received a greater percentage of bets, while Paul et al. (2014) find teams on losing streaks received a smaller percentage of bets.

To our knowledge, only two studies have investigated the hot hand phenomenon in daily fantasy sports. Paul et al. (2020) identify a pricing inefficiency related to the hot hand in NBA contests. Specifically, NBA players were more likely to exceed salary expectations if they had exceeded them in recent games. Implementing a hot hand strategy resulted in improved DFS lineup performance. Conversely, Losak et al. (2023) find no evidence of a hot hand effect in MLB contests. Players who outperformed expectations in recent games did not score more than expected in the next contest, indicating market efficiency. It is important to note that the hot hand may affect different sports in distinct ways, as they have fundamentally different gameplay (see, for example, Green & Zwiebel's, 2018 comments on pitcher response to the hot hand).

Losak et al. (2023) also demonstrate significant increases in DFS lineup usage for MLB players exhibiting the hot hand, suggesting a cognitive behavioral bias among DFS players. However, they do not distinguish between skilled (informed) and unskilled entrants in their analysis. In Lakonishok and Lee (2001), financial insiders are considered to be 'contrarian investors,' suggesting that the actions of the informed traders are different from the typical traders. Lee and Piqueira (2019), however, show that even among insider traders, evidence of certain cognitive behavioral biases (e.g., anchoring bias) persists. Jegadeesh and Titman (1993) identify profitable momentum strategies, while Jegadeesh and Titman (2001) find support for the proposition that the returns are driven by delayed overreactions to earnings by investors. This suggests opportunities to profit from the behavioral biases of other investors may be persistent. We add to this literature by examining if skilled DFS players are equally prone to the hot hand behavioral bias.

Data and Methodology

Our study analyzes data from a specific set of classic DraftKings DFS contests, the "MLB $10K Chin Music [Single Entry]," similar to data used in Losak et al. (2023). These contests had $5 entry fees and were offered on 80 unique days during the 2019 season, typically with 2,379 entrants per contest. Each contest awarded payouts to the top 544 entrants, with the largest payout of $1,000 going to the first place entrant, and decreasing payouts thereafter (544th place receives $10). As a “classic contest,” entrants built lineups subject to a $50,000 salary cap, selecting two pitchers (P), one catcher (C), one first baseman (1B), one second baseman (2B), one third baseman (3B), one shortstop (SS), and three outfielders (OF). Better players are assigned higher salaries such that a lineup cannot consist of the best players at each position. Players accumulate points based on their real-world statistical contributions, with lineup entries ranked based on the aggregate performance of lineup selections.[6]

Our DraftKings data, obtained from RotoGuru and RotoGrinders, includes player information such as salaries, performance, and aggregate contest usage rates.[7] Lineup submissions are also available for all contest winners (individuals that received a payout), but not for losers.[8] Usage rates for losing entries can be derived from usage rates for winning entries. For instance, if a player's usage rate is 33.3% overall and 25% among winners, the usage rate in non-winning entries is approximately 35.8%. To analyze hot-handed batter performance, we exclude pitchers, players with zero overall ownership, and those not listed in the starting lineup. The latter exclusion is rational as they are unlikely to earn any points. We also exclude early-season and late-season contests, as well as contests with missing data, leaving us with 56 contests and 9,111 player-contest observations.[9,10]

If the hot hand is efficiently priced, smart money entrants should counter the hot hand bias by using fewer hot players, ceteris paribus, to avoid ties in DFS contests. Tied teams split payoffs, such that a winning lineup without ties is more valuable than a winning lineup with ties.[11] Thus, we assess if smart money treats the hot hand behavioral bias differently with the following hypothesis:

Hypothesis I_0: Given there is no strategic benefits to incorporating a hot hand strategy, usage rates for hot players are similar for smart money entrants as they are for all other entrants. Smart money is similarly impacted by the hot hand cognitive behavioral bias.

Hypothesis I_a: Since there are no strategic benefits to incorporating a hot hand strategy, usage rates for hot players are different for smart money entrants from all other entrants. Smart money avoids the cognitive behavioral bias.

We use final contest ranking as a proxy for consumer skill-level and smart money, as they are unobservable in our sample. Smart money is expected to perform better than lower-skilled players in contests, on average. Given the noisiness of this proxy, we acknowledge that this methodology significantly increases the likelihood of failing to reject the null hypothesis. However, evidence supporting the rejection of the null hypothesis would indicate strong support for the alternative hypothesis.

We calculate usage rates for different lineup cuts: top 544, top 250, top 100, and top 50. We expect average skill level to be higher, and a higher percentage of smart money to be present, in the top 50 compared to the top 544. We also calculate usage rates for the non-top 544/250/100/50 lineups. We utilize these usage rates as dependent variables in fractional logistic regression models, proposed by Papke and Wooldridge (1996), using quasi maximum likelihood. We prefer this method over OLS because usage rates are fractional values bounded between zero and one, inclusive.[12]

In total, we estimate eight fractional logistic regressions, four "top" lineup regressions and four "not top" lineup regressions segmented into groups based on lineup ranking. The following equation illustrates the variables considered:

$$Usage_{i,t,SPLIT} = \beta_0 + \beta_1 Salary_{i,t} + \beta_2 Hot_{i,t} + \beta_3 NotQualified_{i,t} + \beta_4 Home_{i,t} + \beta_5 Offhand_{i,t} + \beta_6 SwitchHitter_{i,t} + \beta_7 ImpliedRuns_{i,t} + \beta_8 PositionalOptions_{i,t} + \sum_{spot} \beta_{9,pos} Lineup_{i,t} + \sum_{pos} \beta_{10,pos} Position_{i,t} + \varepsilon_{i,t}.$$

Variables $Home_{i,t}$, $Offhand_{i,t}$, and $SwitchHitter_{i,t}$ are binary indicators for a player's location (home/away), handedness advantage, and switch-hitting ability, respectively. Hitters tend to perform better against pitchers that are of opposite hand (right-handed batters prefer to face left-handed pitchers and vice versa), while switch hitters can hit from both the left side and right side of the plate, such that they always have a handed advantage. In both cases, players with the offhand advantage are expected to perform better, and should therefore have higher usage rates. We control for defensive position and lineup spot, as well as DraftKings salary, $Salary_{i,t}$, as a measure of player quality. Losak et al. (2023) show that it is advantageous to select visiting players, players with handed advantages (offhand or switch), and players batting in the top half of the lineup—thus usage rates for those players are higher. Additionally, $PositionalOptions_{i,t}$ captures the slate size, with higher values indicating more options at a given position, which has been found to reduce player usage in prior research (Losak et al., 2023). Full summary statistics are presented in Table 1.

A player's team's run scoring environment is captured with $ImpliedRuns_{i,t}$. Using historical betting data from Sportsbook Reviews, this variable assigns runs from the total run line to the two competing teams, based on their win probabilities derived from moneyline measures using the Sauer (2005) method. For example, consider Team A as a -130 favorite and Team B as a +110 underdog, with the totals line at 8.5 runs. Converting moneylines to win probabilities gives Team A and Team B a 54.3% and 45.7% chance of winning, respectively. Divvying up the 8.5 runs based on win probability allocates 4.6 runs to Team A and 3.9 runs to Team B. If markets are efficient, this method, despite requiring numerous run scoring distributional assumptions, provides a reasonable estimate of the team's potential run scoring output and controls for other game characteristics, such as the quality of the opponent team's starting pitcher and bullpen, weather conditions, and more. Losak et al. (2023) show a profitable strategy for taking players on teams with higher implied run totals.

Finally, the hot hand variable. When entrants select players on DraftKings and click on individual player names, they are immediately exposed to an "at a glance" screen that shows that player's stats in their last game, last ten games, and season-long stats. Entrants can click on "game log" to see that player's game-by-game production, with most recent games appearing first. We presume this collection of information to be the driving mechanism for fans determining the player's current level of streakiness. As such, we use Losak et al.'s (2023) definition for the hot hand, denoted as HH_1. It is calculated as the ratio of a player's fantasy point production over their previous six starts to their salary, and compared against a threshold value calculated using 2018 data.[13] If the ratio is greater than the threshold value (0.289 points per 100 units salary), we identify the player as "hot." If the player's last six starts did not come over the previous 30 days, we classify the player as "Less Active." Otherwise, the player is classified as "Not Hot." Consider the following example from our data. On July 12th, 2019, Mike Trout, an outfielder for the Los Angeles Angels, was available to be selected for 5,300 units. Over his previous six starts, Trout scored 114 fantasy points, or 19 points per game. Dividing 19 by 114 and multiplying 100 produces a value of 0.358 points per 100 units salary, above the qualifying threshold of 0.289, thus labeling Trout "hot." Different time horizons (production in last three starts and last ten starts) are considered for robustness.

By scaling a player's production to his DraftKings salary, we define streakiness relative to a player's baseline abilities. While this definition may not perfectly highlight the hot hand and streakiness, especially given measurement error discussed by Stone (2012), it should capture how most DFS entrants perceive the hot hand. High scoring totals in recent performances likely constitutes what entrants use to identify hot players. Of our 9,111 observations, 841 (9.23%) are labeled "Hot," 7,711 (84.63%) are labeled "Not Hot," and 559 (6.14%) are labeled "Less Active."[14] Losak et al. (2023) see increased lineup usage for hot players despite there being no evidence of a profitable hot hand strategy.

Hot hand classifications by position, spot in the lineup, and salary range are included in Table 1. Players on the lower part of the salary range and lower in the lineup have lower hot hand percentages and higher less active percentages, which makes sense as these players are more likely to be benchwarmers or short-term fill-ins. Otherwise, hot hand percentages are comparable across positions, salary ranges, and spots in the lineup.

Results

Our analysis examines how strategic elements and cognitive biases impact usage rates for top versus non-top lineups. Given we use noisy proxies to identify skill, we expected *a priori* for it to be difficult to identify and attribute differences in usage to smart money behaviors. That said, we expected to find insights through slight deviations across lineup performance thresholds. Results from our fractional logistic regressions for winning and losing lineups are presented in Table 2, grouped by the top and non-top 544/250/100/50 lineups.

Estimates largely align with the directional effects found in Losak et al. (2023). Home team and lower batting order positions are associated with lower player usage rates on winning and losing lineups, while handed advantage and higher run scoring environments are associated with higher usage rates on both types of lineups. We find no statistical difference in the behavior of the top 50 lineups compared to the top 544 with respect to these strategic elements.

The hot hand, on the other end, provides evidence of shifting behaviors. The hot hand was shown to affect player usage rates in Losak et al. (2023), despite no evidence of improved lineup performance by incorporating a hot hand strategy. Table 2 displays declining coefficients as we move from one threshold to the next. The average marginal effect of the hot hand on usage rates is 0.010 percentage points in top 544 lineups, but just 0.006 percentage points for top 50 lineups. Figure 1 illustrates the different hot hand coefficients across the eight models. The hot hand coefficient remains similar for losing models, while tighter segmentation of winning lineups produces smaller coefficients. This suggests that smart money is less susceptible to the cognitive behavioral bias of the hot hand, and the percentage of lineups coming from smart money may increase with tighter groups.

To compare more directly winning and losing lineups, we run four additional fractional logistic regressions that consider the differences in usage rates between groups. Table 3 presents these results. A positive difference indicates higher usage rates for a player in winning lineups. We expected, *a priori*, that winning lineups would better identify profitable strategic opportunities, and better avoid behavioral biases such as the hot hand. The results demonstrate that winning lineups are less likely to select players in lower batting orders and more likely to choose players in high scoring run environments. There is slight evidence that winning lineups select players with handed advantage more frequently, but this result is statistically significant only for the top 544 segmentation at the 10% level. Moreover, our analysis reveals that top 100 and top 50 lineups are less likely to select hot players, which we attribute to the behaviors of smart money.

We test the robustness of these results by considering the differences in usage rates between winning and losing lineups. Table 4 provides hot hand coefficient estimates using the same fractional logistic regression model implemented in Table 3, but for five additional hot hand definitions. HH1 is our original hot hand measure that considers a player's production in their previous six starts, as long as those starts took place in the past 30 days (with a hot hand threshold of 0.289 points per 100 units salary). HH2 is similar to HH1, except no binary threshold is applied; a larger HH2 indicates a "hotter" player. HH3 is similar to HH1, but lowers the qualifying threshold (0.192 points per 100 units salary). Alternatively, HH4 raises the hot threshold (0.385 points per 100 units salary). HH5 and HH6 consider different time horizons for the hot hand threshold: three starts in the past 15 days and ten starts in the past 30 days, respectively. While the level of statistical significance changes by specification, the coefficient estimate is always negative. Also, apart from HH6 (which is the second most conservative hot hand definition, applying to just 3.4% of the sample), the magnitude of the coefficient increases (negatively) with the segmentation cut point. Collectively, our findings suggest that smart money is aware of the hot hand behavioral bias and avoids selecting these players to improve their own performance.

Discussion and Conclusion

Profit opportunities for smart money in sports betting markets typically arise from deviations in the efficient market price. In MLB DraftKings DFS contests, player prices are efficiently priced in relation to the hot hand. However, skilled DFS players can potentially increase their expected winnings by avoiding heavily owned hot players, reducing the likelihood of finishing tied. Our study shows that winning lineup entries, particularly those in the top 50, tend to have lower usage of hot-handed players. As higher ranked entries are more likely to be made up of skilled players, we conclude that skilled DFS players are less influenced by the cognitive bias and more likely to employ a fade-the-hot-hand strategy.

Our results are heavily conditional on the assumption that higher finishing lineups, on average, come from skilled players. The availability of more extensive contest and lineup data would have allowed for tracking individuals and classifying them by skill level based on their past performance and activity. That said, it is notable that we find evidence that smart money reduces their usage of hot players compared to other entrants, despite the noisy proxy for skill level. However, the current methodology does not determine if smart money is completely immune to the hot hand cognitive bias. Moreover, our results do not suggest that the hot hand effect does not exist, but rather, DFS entrants' response to the hot hand goes beyond what would be expected, even if a small hot hand effect exists.

Our study adds to the field of behavioral finance, providing evidence that informed traders are more inclined to avoid cognitive behavioral biases. We also contribute to the chance versus skill debate in DFS contests by demonstrating that skilled players tend to incorporate a fading the hot hand strategy in MLB DFS contests. This finding suggests that there is heterogeneity in skill levels among entrants, which is a necessary characteristic of a game of skill. Future research should investigate the hot hand and smart money in other sports, as the presence and profitability of hot hand strategies may vary (see Paul et al., 2020 for a profitable hot hand strategy for NBA contests). If in other sports selecting hot players yields profitable outcomes, or if recent player performance is not priced efficiently into salaries, smart money would be expected to adjust their usage of hot players to optimize expected earnings.

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Notes

[1] The favorite-longshot bias is the tendency for sports bettors to overestimate the chances of longshot or underdog outcomes and underestimate the chances of favorite outcomes. See Sauer (1998) for a more thorough discussion. Alternatively, the reverse favorite-longshot bias is the tendency to overestimate favorites and underestimate underdogs.

[2] Totals markets refer to bets on the aggregate score of the two teams competing in a game. Bettors can wager on the "over" or the "under." In basketball, a totals line of 200.5 would mean wagering on whether the combined score of two teams exceeds (over) or fails to surpass (under) 200 points.

[3] A parimutuel market is one in which payouts are based on the percentage of action taken on various legs of a bet. Consider a simple example in which there are three horses competing. Suppose $1,000 is wagered on horse A, $500 is wagered on horse B, and $500 is wagered on horse C. Suppose horse B wins. The total pot ($2,000), minus the house's cut, is distributed between the bettors that picked horse B. Suppose one specific bettor wagered $100 on horse B; that bettor would receive 20% of the payout. Parimutuel markets are in contrast with fixed odds markets in which payouts, conditional on winning the wager, are known at the time the wager was placed.

[4] See Losak (2021) for a further discussion on the history of the chance versus skill question.

[5] The point spread is the predicted margin of victory. If a team is a 6.5-point favorite, they are said to cover the spread if they win by at least seven points.

[6] Points are scored for the following: single +3 points, double +5 points, triple +8 points, home run (HR) +10 points, run batted in (RBI) +2 points, run scored (R) +2 points, base on balls (BB) +2 points, hit by pitch (HBP) +2 points, and stolen base (SB) +5 points.

[7] We purchased archived data from RotoGuru. Data from RotoGrinders can be found at the RotoGrinders ResultsDB at: https://rotogrinders.com/resultsdb/site/draftkings/. Be advised that historical data may no longer be available. Contact the authors if interested in working with this data set.

[8] There can be more than 544 winners due to ties; our data includes the full lineups of each entrant that received a payout, even those past 544th place.

[9] Early season contests are excluded since players would not have had enough games played to be considered "hot." Late season contests coincide with the beginning of the football season, in which less-skilled players may substitute away from baseball towards football. This shifts contest skill-level dynamics. Also, with expanded MLB rosters in September, playing time, especially among lower quality teams, is significantly more unpredictable.

[10] Broken down by month, most contests in our sample were played in May (6), June (20), July (10), or August (13).

[11] Finishing first with a unique lineup earns $1,000, while tying with one person for first means splitting the first and second place prizes ($1,600), reducing the payoff to $800.

[12] We considered alternative estimation techniques. Beta regressions do not allow for zero usage rates, which we observe in our data within winning lineup subgroups. Zero inflated beta regressions allow for zero valued observations, which are treated as being generated by a unique data generating process different than that for the proportional values. As we had no reason to

believe zeros were part of a different data generating process, we opted for the simpler fractional logistic regression.

[13] We use 2018 to compute our threshold value despite our subsequent analysis being conducted with 2019 data. We did not want to use data from deeper in the 2019 season, games that would have not yet occurred, in the methodology for defining a "hot" player during the early parts of the season. Therefore, we compute the "hot" threshold using the preceding season's data for our entire 2019 sample. Ultimately, the result is a threshold value, which we show produces robust results even if we shift it towards being more or less conservative.

[14] Losak et al. (2023) show their results are robust to the specific hot hand specification. In fact, results are comparable for seven different hot hand definitions. Therefore, we use their preferred specification, HH_1, for our analysis. However, we check this robustness in subsequent analysis.

Tables

Table 1

Variable Summary Statistics (n = 9,111)

Variable	Mean	SD	Min	Max	Hot (%)	Not Hot (%)	Less Active (%)
Usage Rate	0.0484	0.0619	0.0004	0.5496			
Top 544	0.0489	0.0784	0	0.7482			
Top 250	0.0490	0.0857	0	0.8538			
Top 100	0.0490	0.0953	0	0.9100			
Top 50	0.0490	0.1034	0	0.9800			
Not Top 544	0.0483	0.0614	0	0.5128			
Not Top 250	0.0483	0.0618	0	0.5458			
Not Top 100	0.0484	0.0619	0	0.5529			
Not Top 50	0.0484	0.0619	0.0004	0.5487			
Home (Home = 1)	0.4998	0.5000	0	1			
Offhand (L/R or R/L)	0.5769	0.4941	0	1			
Switch Hitter (Yes = 1)	0.1253	0.3311	0	1			
Implied Runs	4.6712	1.2565	1.4700	9.2084			
Positional Options	1.1700	0.3294	0.2953	1.7407			
Salary (/100)	39.793	7.5269	20	60			
20-29.99					0.0518	0.7539	0.1943
30-39.99					0.0824	0.8324	0.0853
40-49.99					0.1082	0.8676	0.0242
50+					0.1038	0.8932	0.0030
Defensive Position							
Catcher (C = 1)	0.1249	0.3306	0	1	0.0852	0.8199	0.0949
First Base (1B = 1)	0.1702	0.3759	0	1	0.0819	0.8736	0.0445
Second Base (2B = 1)	0.1756	0.3805	0	1	0.0950	0.8294	0.0756
Third Base (3B = 1)	0.1690	0.3748	0	1	0.1033	0.8467	0.0500
Shortstop (SS = 1)	0.1448	0.3519	0	1	0.0864	0.8385	0.0751
Outfield (OF = 1)	0.4175	0.3519	0	1	0.0978	0.8444	0.0578
Lineup Spot							
First (1st = 1)	0.1179	0.3225	0	1	0.0950	0.8799	0.0251
Second (2nd = 1)	0.1179	0.3225	0	1	0.1109	0.8574	0.0317
Third (3rd = 1)	0.1180	0.3226	0	1	0.0986	0.8912	0.0102
Fourth (4th = 1)	0.1180	0.3226	0	1	0.1060	0.8726	0.0214
Fifth (5th = 1)	0.1180	0.3226	0	1	0.1088	0.8558	0.0353
Sixth (6th = 1)	0.1174	0.3219	0	1	0.1065	0.8056	0.0879
Seventh (7th = 1)	0.1166	0.3209	0	1	0.0791	0.8051	0.1158
Eighth (8th = 1)	0.1131	0.3209	0	1	0.0563	0.8175	0.1262
Ninth (9th = 1)	0.0632	0.2434	0	1	0.0469	0.8160	0.1372

Table 2

Usage Rates in Top and Bottom Performing Lineups, Fractional Logit

Dependent Variable:	Winning Lineups		Top 250 Lineups		Top 100 Lineups		Top 50 Lineups	
Usage Rate (n = 9,110)	Winning	Losing	Winning	Losing	Winning	Losing	Winning	Losing
Salary (/100)	-0.045***	-0.030***	-0.045***	-0.032***	-0.043***	-0.033***	-0.040***	-0.033***
	0.003	0.002	0.004	0.002	0.004	0.002	0.005	0.002
Hot Hand	0.217***	0.271***	0.202***	0.266***	0.161**	0.263***	0.127*	0.262***
	0.048	0.037	0.054	0.037	0.063	0.037	0.070	0.037
Less Active	0.015	0.023	0.023	0.022	0.029	0.022	0.047	0.021
	0.072	0.057	0.082	0.057	0.091	0.057	0.100	0.057
Home	-0.339***	-0.205***	-0.360***	-0.221***	-0.383***	-0.229***	-0.394***	-0.232***
	0.032	0.023	0.036	0.023	0.042	0.023	0.046	0.023
Offhand Advantage	0.391***	0.343***	0.381***	0.350***	0.364***	0.353***	0.374***	0.353***
	0.033	0.024	0.038	0.024	0.044	0.024	0.049	0.024
Switch Hitter	-0.297***	-0.248***	-0.280***	-0.257***	-0.269***	-0.259***	-0.247***	-0.259***
	0.047	0.035	0.055	0.034	0.064	0.034	0.072	0.034
Implied Runs	0.636***	0.532***	0.627***	0.547***	0.612***	0.553***	0.599***	0.555***
	0.013	0.010	0.015	0.010	0.017	0.010	0.019	0.010
Lineup Spot (2nd)	-0.012	0.050	-0.024	0.044	-0.040	0.040	-0.048	0.038
	0.058	0.044	0.066	0.044	0.076	0.044	0.084	0.044
Lineup Spot (3rd)	0.045	0.066	0.030	0.065	0.026	0.063	0.009	0.063
	0.061	0.044	0.070	0.044	0.081	0.044	0.088	0.044
Lineup Spot (4th)	-0.077	-0.008	-0.091	-0.016	-0.079	-0.021	-0.106	-0.022
	0.057	0.043	0.066	0.043	0.078	0.042	0.086	0.042
Lineup Spot (5th)	-0.515***	-0.416***	-0.514***	-0.429***	-0.496***	-0.436***	-0.476***	-0.437***
	0.060	0.045	0.068	0.045	0.079	0.045	0.088	0.044
Lineup Spot (6th)	-0.944***	-0.804***	-0.961***	-0.821***	-0.959***	-0.830***	-0.955***	-0.833***
	0.063	0.046	0.071	0.046	0.080	0.046	0.090	0.046
Lineup Spot (7th)	-1.354***	-1.143***	-1.360***	-1.171***	-1.369***	-1.183***	-1.400***	-1.186***
	0.069	0.051	0.078	0.050	0.089	0.050	0.102	0.050
Lineup Spot (8th)	-1.666***	-1.412***	-1.677***	-1.445***	-1.671***	-1.460***	-1.639***	-1.465***
	0.074	0.053	0.085	0.053	0.098	0.053	0.109	0.053
Lineup Spot (9th)	-1.837***	-1.518***	-1.871***	-1.557***	-1.861***	-1.578***	-1.839***	-1.584***
	0.085	0.067	0.096	0.067	0.112	0.066	0.126	0.066
Positional Options	-1.000***	-0.966***	-0.998***	-0.970***	-0.997***	-0.972***	-0.994***	-0.973***
	0.048	0.037	0.053	0.037	0.063	0.037	0.070	0.037
Constant	-3.000***	-3.366***	-2.903***	-3.327***	-2.866***	-3.300***	-2.895***	-3.290***
	0.145	0.111	0.164	0.110	0.191	0.110	0.213	0.109
Positional Variables	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R-Squared	0.096	0.077	0.095	0.080	0.092	0.081	0.090	0.081

Note: Statistical significance is defined at the * 10%, ** 5%, and *** 1% levels. Robust standard errors included. Each model is estimated in Stata (StataCorp, 2019) using the *fracreg* command. McFadden's Pseudo R-Squared values are included as model goodness-of-fit measures. Positional variables are excluded from the model output for brevity.

Table 3

Difference in Usage Rates in Top and Bottom Performing Lineups, Fractional Logit

Dependent Variable: Usage Rate Difference (Top – Not Top) (n = 9,110)	Top 544	Top 250	Top 100	Top 50
Salary (/100)	-0.001***	-0.001***	-0.001***	-0.001*
	0.000	0.000	0.000	0.000
Hot Hand	-0.005	-0.006	-0.010*	-0.013**
	0.004	0.005	0.006	0.006
Less Active	-0.002	-0.001	0.000	0.001
	0.004	0.005	0.006	0.006
Home	-0.013***	-0.013***	-0.015***	-0.015***
	0.002	0.003	0.003	0.004
Offhand Advantage	0.004*	0.003	0.001	0.002
	0.002	0.003	0.003	0.004
Switch Hitter	-0.004	-0.002	-0.001	0.001
	0.003	0.004	0.005	0.006
Implied Runs	0.010***	0.008***	0.006***	0.005**
	0.001	0.002	0.002	0.002
Lineup Spot (2nd)	-0.007	-0.007	-0.009	-0.009
	0.006	0.007	0.008	0.009
Lineup Spot (3rd)	-0.002	-0.004	-0.004	-0.006
	0.006	0.007	0.009	0.010
Lineup Spot (4th)	-0.008	-0.008	-0.007	-0.010
	0.006	0.007	0.008	0.009
Lineup Spot (5th)	-0.009*	-0.008	-0.006	-0.005
	0.005	0.006	0.008	0.009
Lineup Spot (6th)	-0.013***	-0.014**	-0.013*	-0.013
	0.005	0.006	0.007	0.008
Lineup Spot (7th)	-0.019***	-0.017***	-0.017**	-0.018**
	0.005	0.006	0.007	0.008
Lineup Spot (8th)	-0.022***	-0.021***	-0.019***	-0.017**
	0.005	0.006	0.007	0.008
Lineup Spot (9th)	-0.026***	-0.025***	-0.023***	-0.021**
	0.005	0.006	0.008	0.009
Positional Options	-0.002	-0.002	-0.002	-0.002
	0.004	0.004	0.005	0.006
Constant	0.035***	0.040***	0.041**	0.038**
	0.011	0.013	0.016	0.018
Positional Variables	YES	YES	YES	YES

Note: Statistical significance is defined at the * 10%, ** 5%, and *** 1% levels. Robust standard errors included. Each model is estimated in Stata (StataCorp, 2019) using the *fracreg* command. Goodness-of-fit estimates are essentially zero, and are thus excluded for brevity. Positional variables are excluded from the model output for brevity.

Table 4

Difference in Usage Rates Hot Hand Robustness, Fractional Logit

Dependent Variable: Usage Rate Difference (Top – Not Top)	HH Description	% Sample Hot Hand	Top 544	Top 250	Top 100	Top 50
HH1	6 Starts in Last 30 Days	9.23%	-0.005	-0.006	-0.010*	-0.013**
(n = 9,110)	Binary Measure		0.004	0.005	0.006	0.006
HH2	6 Starts in Last 30 Days	NA	-0.054***	-0.067***	-0.079***	-0.108***
(n = 8,551)	Continuous Measure		0.017	0.020	0.024	0.027
HH3	6 Starts in Last 30 Days	43.73%	-0.006**	-0.007**	-0.007**	-0.010***
(n = 9,110)	Binary Measure		0.002	0.003	0.003	0.004
	Lower Threshold					
HH4	6 Starts in Last 30 Days	0.79%	-0.006	-0.020	-0.026	-0.038**
(n = 9,110)	Binary Measure		0.014	0.014	0.016	0.018
	Higher Threshold					
HH5	3 Starts in Last 15 Days	16.71%	-0.004	-0.004	-0.005	-0.008
(n = 9,110)	Binary Measure		0.003	0.004	0.005	0.005
HH6	10 Starts in Last 30 Days	3.41%	-0.011	-0.009	-0.007	-0.008
(n = 9,110)	Binary Measure		0.007	0.008	0.010	0.012

Note: Statistical significance is defined at the * 10%, ** 5%, and *** 1% levels. Robust standard errors included. Each model is estimated in Stata (StataCorp, 2019) using the *fracreg* command. Each column uses a different lineup finishing cutoff point, and each row uses a different hot hand definition. The continuous measure, HH2, uses the player's raw recent points per 100 salary rather than identifying hot based on a threshold value, such that a larger value for HH2 indicates a "hotter" player. Less active players are dropped from this specification.

Figures

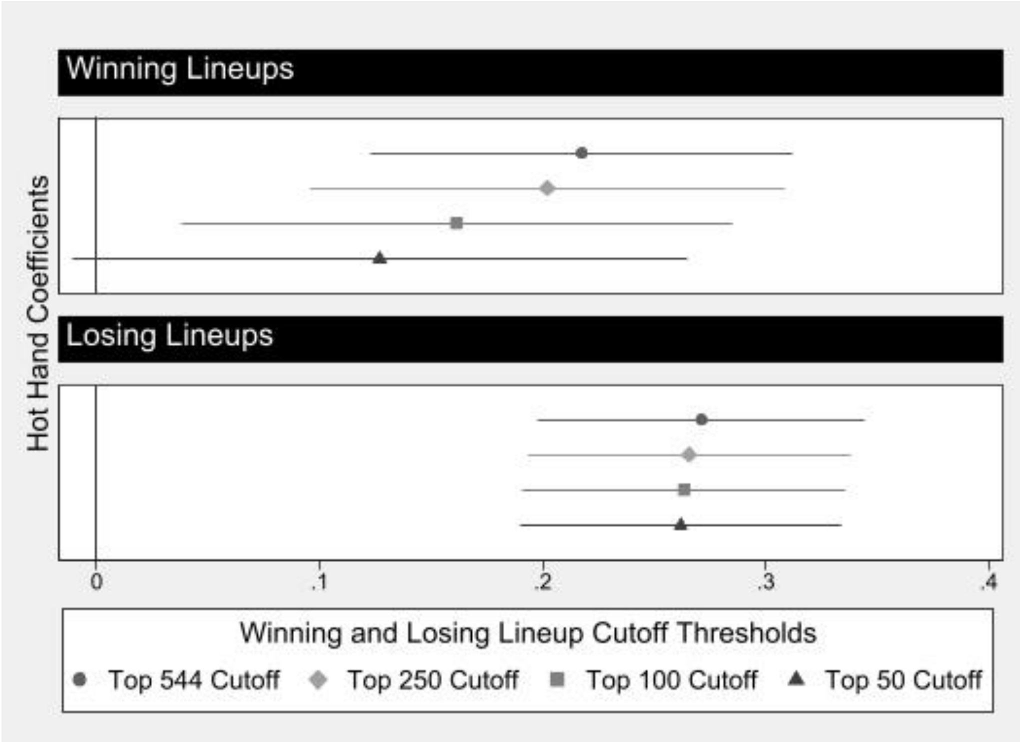

Figure 1: Hot Hand Fractional Logit Coefficients

Note: Coefficient estimates are extracted from the fractional logit regressions in Table 2 based on the various cut points for winning and losing lineups. The top plot includes hot hand coefficient estimates for lineups that finished within the top respective thresholds. The bottom plot includes hot hand coefficient estimates for lineups that did not finish within the top respective thresholds. 95% confidence intervals are presented for each estimate. A vertical line is drawn at zero to illustrate statistical significance of the coefficient. This plot was created using the coefplot command (Jann, 2013) in Stata (StataCorp, 2019).