5-1-2024

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Abstract

Despite mixed evidence, sport participants and fans heavily believe in the existence of the hot hand. Prior literature examining NBA and NFL betting markets found betters were biased towards hot teams. Using a unique market and data set, this study identifies if the hot hand is prevalent in daily fantasy baseball contests, if there is a profitable hot hand selection strategy, and if consumers believe in its existence. Results show that while there is no evidence of a hot hand effect, and no evidence of a profitable hot hand strategy, consumers believe in and incorporate it in their lineup decisions.

Keywords: behavioral bias, daily fantasy sports, baseball, hot hand

Behavioral Biases in Daily Fantasy Baseball: The Case of the Hot Hand

The existence of the hot hand is a controversial debate in sport. Sport participants and spectators overwhelmingly believe in the hot hand in basketball (Gilovich et al., 1985; Tversky and Gilovich, 1989). Raab, Gula and Gigerenzer (2012), similarly find a majority of players and coaches believe in hot hand effects in volleyball. It is often believed that recent successful performances indicate the likelihood of subsequent successes. In professional darts tournaments, Stins et al. (2018) find evidence that performance in the second throw of a three-throw leg was not independent of the first throw.

Economists and statisticians have typically been more skeptical of the hot hand. Gilovich et al. (1985) studied the shooting performances of NBA players and Cornell men's and women's basketball players, and found that recent success had no impact on subsequent performances. They also attribute the term hot hand to basketball fans and commentators. "In describing an outstanding performance by a basketball player, reporters and spectators commonly use expressions such as 'Larry Bird has the hot hand,' or 'Andrew Toney is a streak shooter'" (Gilovich et al., 1985).

The early takeaway from this line of research was that, while recent hot performance did not seem to impact subsequent performance, people believed in its existence anyway (Tversky and Gilovich, 1989). Gilovich et al. (1985) showed that recent success affected players' predictions of success, despite not impacting their performances. They conclude that belief in the hot hand can be attributed to a misconception of chance in random sequences. Even Nobel Laureate Daniel Kahneman called the hot hand a "massive and widespread cognitive illusion" (Kahneman, 2011).

However, other findings have been less committal to dismissing the hot hand. Hooke (1989) cites the complexity of modeling the effects of pitchers and defense in batting when examining the hot hand in baseball. He concludes that there probably is a hot hand effect in baseball, though it is likely not large and is difficult to tease out. Based on the 2012–2013 NBA season, Bocskocsky, Ezekowitz and Stein (2014) find that players who are exceeding expectations in recent shooting (“hot”) are more likely to take the team’s next shot—and take more difficult shots—facing tighter defenses.

More recently, Miller and Sanjurjo (2018) revisited Gilvich et al. (1985) and concluded that a substantial bias to reject the identification of a hot streak was embedded in the analysis. Upon revisiting the original data, Miller and Sanjurjo (2018) do identify a hot hand. Green and Zwiebel (2018) find evidence of a hot hand in batting performances in MLB. But they also identify that pitchers appear to respond to a hot hand. When pitchers face batters with particularly high percentages of home runs or extra base hits in recent past, the batters are more likely to be walked. Ötting et al. (2020) find serial correlation within turns of dart throwing, but admit that while there may be a weak hot hand effect, the evidence was inconclusive.

From the literature, two critical elements tend to impact the ability to estimate a hot hand effect. First, sport outcomes are impacted by many external factors, many of which could complicate a hot hand analysis. In baseball, the quality of the opposing pitcher, individual pitcher-batter matchups, defense quality, and many other factors could impact game results. Second, sport outcomes tend to be incredibly noisy, reducing the statistical power of most serial correlation-based tests (see Stone, 2012 for more information). Thus, a large amount of data is needed to reject the null hypothesis of a “no hot hand” effect. Miller and Sanjurjo (2018) argued that the approach from Gilvich et al. (1985) systematically reduced the sample size, thus increasing the likelihood of not identifying a hot hand. Stone (2012) illustrates that measurement error derived from random sport outcomes can be problematic in empirical tests of the hot hand, especially when the variance of true ability in the population is smaller than randomness of the data generating process. For example, consider a hypothetical baseball player labeled as “hot” entering play. Despite hitting the ball incredibly hard all four times he came up to bat, due to bad luck, a defender happened to be positioned in the perfect location to record the out each time. Based on an outcome-driven approach to the hot hand, that player would certainly not be described as hot, given the player failed to get a single hit. However, that player clearly is still “hot,” despite the outcomes not supporting that conclusion. We do not observe hot hand in game data; rather, we observe hot hand plus measurement error.[1]

This study adds to the hot hand literature in two critical ways. First, it considers hot hand with a unique baseball data set. Second, it borrows from prior literature focusing on the hot hand in sport betting to examine a new marketplace: daily fantasy sports. Betting markets have been used countless times to examine how consumers systematically overvalue the hot hand effect. Gander et al. (1988) identified that NFL teams that beat the point spread by more than 10 points in the previous week were less likely to cover the spread this week because public perception of their current hot handedness exaggerated the point spread. Alternatively, Woodland and Woodland (2000) found no excess returns to a contrarian strategy betting against streaks, concluding that any improvement or decline in team performance appeared to be embedded in the final point spread already. Levitt (2004) suggested that bookmakers may not be strictly pricing to balance betting action, as had been previously widely assumed. If this is the case, bettor preferences for betting on teams on relative hot streaks may not always show up in final point spreads. Paul and Weinbach (2005) find that for the NBA, betting against teams on two or more game winning streaks was a profitable strategy for the period 1995–1996 to 2001–2002.

Betting volume may also provide an indicator of consumer behavioral bias regarding the hot hand. Camerer (1989) analyzed basketball betting data and concluded that there was a small tendency for bettors to bet too much/often on teams on winning streaks. Paul et al. (2011) examine NBA betting data, and while they do not report any profitable betting strategies against streaks, teams on winning streaks received a greater percentage of bets. With NFL data, Paul et al. (2014) found that teams on losing streaks attracted a smaller percentage of bets, indicating some belief in a sort of hot hand or streakiness, or at least a preference for betting on teams that have performed well recently.

This study extends this line of thinking into the daily fantasy sports (DFS) space. Similar to betting markets, DFS includes prices that may or may not appropriately factor in the hot hand. DFS consumers compete by selecting individual players as part of lineups, in which betting volume in this space constitutes how frequently individual players are selected. A more thorough discussion of DFS is provided in the next section.

The key questions in this paper can be summarized as follows. First, is evidence of a hot hand effect present in DFS scoring? Second, do DFS prices accurately capture any hot hand effect? Third, how do consumers respond to players on a hot streak? In addressing these questions, we utilize DraftKings data for batters from the 2019 MLB season. We illustrate that, while there is no evidence of a hot hand strategy, and while the hot hand appears to be accurately captured in DFS prices, consumers are heavily biased towards selecting hot players. This is clear evidence of a hot hand behavioral bias from consumers.

The following section describes the empirical strategy of the paper, including discussing the setup of a DFS contest, defining the hot hand, and providing a theoretical discussion of the methodology. Sections three, four, and five answer the key questions introduced in the previous paragraph. The sixth section provides summarizing and concluding remarks.

Empirical Strategy

DraftKings and Daily Fantasy Sports

The two largest DFS providers are DraftKings and FanDuel. With 60% DFS market share as of 2019, DraftKings is the more prominent of the two, hence we use DraftKings data in our analysis.[2] We focus exclusively on batters in this study, as attempts to measure hot handedness (and how it is defined) would be different for pitchers and hitters.

After paying a contest entry fee, DraftKings consumers create lineups from a pool of available players and compete against each other in contests to win cash prizes. For the purposes of this study, "consumers" is used to describe an individual who enters a lineup into a DraftKings contest, while "players" describe the actual MLB players that are selected by consumers as part of lineups. In a contest, consumers are given virtual currency that they use to buy/select players for their lineups. Selecting a player comes at a price, which is assigned by DraftKings based on the player's expected point contributions. The better the player is expected to perform, the higher his salary will be. Players score points based on their real-life performances, and those points accumulate for the consumers. A breakdown of standard DraftKings baseball scoring settings is available in Table 1. Consumers win real prizes based on how their lineups perform relative to the other lineups submitted to the contest.

In a "classic" contest, consumers select 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).[3] Consumers are given 50,000 units of virtual currency to create their lineup, with better players costing more to select. Salaries are assigned to players in increments of 100, and many players are assigned the same salary. For hitters in our sample, player salaries range from 2,000 to 6,000 units of virtual currency as detailed in Table 2.[4] In this study we exclude any player not listed in their team's starting lineup that day since it is clearly an optimal strategy to avoid starting players that are not playing.[5] Starting lineup data come from Retrosheets.[6]

Our key DraftKings-related data come from RotoGuru and RotoGrinders.[7] RotoGuru provides data on player salaries and points scored for most of the players in our sample. We supplement that data with information from RotoGrinders and various internet sources when data were missing.

RotoGrinders also contains our contest-specific and usage data. DraftKings provides a name to every contest it offers, and contests with the same name have the same contest settings. Contests can vary by entry fee, number of entries in the contest, whether consumers can submit multiple entries, the size of the prize pool, and the payout structure. There may be nuanced strategic differences in optimal lineup construction depending on the contest settings.[8] To keep the strategic elements constant, we focus on just one contest type in our analysis. Being the contest with the largest number of offerings in our sample, we focus on the "MLB $10K Chin Music [Single Entry]" contest offered on 80 unique days throughout the 2019 MLB regular season. This is a $5 entry fee contest with 2,379 entries where each consumer can only submit a single lineup. The prize structure is progressive, such that the first-place winner gets the largest payoff of $1,000. The prize declines for second ($600), third ($400), fourth ($300), all the way down to the marginal winners at 544th ($10).[9] From our RotoGrinders data, we calculate each player's contest's usage rate, or *field* percentage, by identifying how frequently a player appears in submitted lineups for that contest. Overall, our data consist of 11,675 player-contest observations (approximately 146 players per contest).

Defining the Hot Hand

Tversky and Gilovich (1989) introduce the concept of the “hot hand” with a statement about the perception of observers. “Many observers of basketball believe that the probability of hitting a shot is higher following a hit than following a miss, and this conviction is at the heart of the belief in the ‘hot hand’ or ‘streak shooting.’” Tversky and Gilovich (1989) find no evidence of positive serial correlation, with the frequency of streaks of various lengths being not statistically different from what would be expected by chance. Camerer (1989) interprets the belief in the hot hand as “a mistake generated by persistent misunderstanding of randomness.” In an analysis of the number of bets placed on either side of NBA games, Paul et al. (2011) claim that a general belief in the hot hand by betting market participants can be inferred by the tendency for bettors to place more bets on teams on winning streaks, and fewer bets on teams on losing streaks. For this paper, this logic would translate to contest consumers having a tendency to draft players on recent “hot streaks.”

We reinforce our conclusions regarding the hot hand (HH) by incorporating various definitions. HH_1 and HH_2, defined in the follow paragraphs, are our preferred definitions, but results are robust to various configurations. Each definition is outcome-driven, which could introduce a measurement error problem (see Stone, 2012). Ideally, ex-ante probabilistic measures of player production would be used instead to capture how a player’s expected production is impacted by recent hot performance rather than the player’s actual production. That said, this ex-ante measure would be a difficult-to-measure latent variable. Also, given a major component of this study is to examine how consumers respond to the hot hand, it seems more likely that most consumers would make their decisions based on actual past production rather than predicted past production.

Our first hot hand definition, HH_1, is constructed using a similar line of thinking as Green and Zwiebel (2018), who focus on the performance of a batter in his most recent 25 at bats. It is a categorical variable that takes on a value of "hot", "not hot", or "not qualified". To qualify, a player must have started at least six games over the previous 30 days, thus excluding players such as Minor League call-ups, players returning from injury, players who are often bench contributors, and many players in the early part of the season. Without recent playing time, it could be misleading classifying these players as either "hot" or "not hot". For those players that do qualify, a player is classified as "hot" if they exceed a certain threshold score based on their recent past-six-start performances.

Data from the 2018 MLB season was used to calculate the HH_1 threshold. For each player-game observation for all starting batters for the 2018 MLB season, player *i*'s performance on that day *t* is measured by their DraftKings points per 100 units salary, or

$$\mathrm{PtsPer100Sal_{i,t}} = \frac{\mathrm{DKPoints_{i,t}}}{\mathrm{DKSalary_{i,t}}/_{100}}. \tag{1}$$

The mean and standard deviation of the distribution is calculated, and the threshold value is the point such that any value greater than half a standard deviation greater than the mean is considered "hot". Production is scaled by the player's expected production, given by DraftKings salary. This allows our threshold value to consider the player's baseline abilities when determining if the player is "hot" relative to their expected contributions. Since $PtsPer100Sal_{i,t}$ can only take on non-negative values (batters cannot score negative points), and there is a mass-point at zero since any player that scores zero points that day will take on that zero value,

$PtsPer100Sal_{i,t}$ is a heavily right-skewed distribution as can be seen in Figure 1. The defined threshold value calculates to approximately 0.289 points per 100 units salary.

To then classify the observations in our 2019 sample as HH_1 hot, we implement the following procedure. For player *i* on day *t*, we extract his DraftKings point totals over his previous six starts.[10] Next, we take an average of those performances and divide by his per 100 DraftKings salary for day *t*. Conditional on the player qualifying, if that calculated number is greater than or equal to the defined threshold, the player is defined as "hot". Otherwise, the player is defined as "not hot". Formally,

$$\mathrm{RecentPtsPer100Sal_{i,t}} = \frac{100}{G_w \times \mathrm{DKSalary_{i,t}}} \sum_{g=-G_w}^{-1} \mathrm{DKPoints_{i,g}} \tag{2}$$

and

$$HH_{1,i,t} = \begin{cases} Hot & g_{i,t,w} \geq G_w \; \& \; threshold \; \leq \mathrm{RecentPtsPer100Sal_{i,t}} \\ Not\ Hot & g_{i,t,w} \geq G_w \; \& \; threshold \; > \mathrm{RecentPtsPer100Sal_{i,t}} \\ Not\ Qualified & g_{i,t,w} < G_w \end{cases}, \tag{3}$$

where $g_{i,t,w}$ is the number of games started by player *i* over the previous *w* (30 in HH_1) days, G_w is the games-started requirement to qualify (6 for HH_1), and threshold is the $\mathrm{PtsPer100Sal_{i,t}}$ hot threshold. From Equation 3, according to HH_1, 1,077 player observations (9.2%) are defined as "hot", 9,763 player observations (83.6%) are defined as "not hot", and 835 player observations (7.2%) do not qualify.

The relatively low percentage of defined "hot" players, despite a half standard deviation above the mean threshold, comes from two key points. First, the threshold was defined by examining single game outcomes which will inherently be noisier and have a greater spread than the six-game average measure that should smooth out at least some game-to-game randomness. Second, because of the skewed nature of the distribution, a half standard deviation above the mean is at a higher percentile (75.4 percentile) of the 2018 distribution than what one would expect from a half standard deviation above the mean for, let us say, the normal distribution (69.2 percentile). Since our goal is to identify hot recent performance relative to expected contributions, it seems reasonable to have a relatively high threshold to qualify.

Our second hot hand definition, HH_2, considers a continuous measure rather than a binary classification. Rather than implement the results of Equation 2 in Equation 3, HH_2 uses the results from Equation 2 for qualified players. This value takes on a minimum of zero, first quartile of 0.140, mean of 0.189, third quartile of 0.233, and maximum of 0.536.

Our next few definitions consider various hot hand thresholds using the same methodology as HH_1. HH_3 sets the 2018 calculated threshold at the mean rather than half a standard deviation above the mean (0.192 threshold, 61.7 percentile in 2018). HH_4 sets the calculated threshold at one full standard deviation above the mean (0.385 threshold, 84.7 percentile in 2018). HH_3 classifies 5,039 player observations (43.2%) as "hot", while HH_4 classifies just 96 player observations (0.8%) as "hot".

HH_5 and HH_6 utilize the half standard deviation threshold calculated using Equation 1 (0.289 threshold, 75.4 percentile in 2018) but change the number of game windows to be classified as qualifying and to be part of a player's recent performance. HH_5 considers the player's previous three starts instead of six, and those starts must have occurred in the previous 15 days to qualify ($w = 15;\ G_w = 3$). HH_6 considers the player's previous 10 starts, which must have occurred in the previous 30 days to qualify ($w = 30;\ G_w = 10$).[11] HH_5 classifies 1,917 player observations (16.4%) as "hot", 9,211 (78.9%) as "not hot", and 547 (4.7%) do not qualify. HH_6 classifies 393 player observations (3.4%) as "hot", 9,506 (81.4%) as "not hot", and 1,776 (15.2%) do not qualify.

Finally, we consider a more sequential definition of hot hand. HH_7 is a set of indicator variables specifying if the player is hot based on production in the previous game ($HH_{7,1}$), in each of the past two games ($HH_{7,2}$), in each of the past three games ($HH_{7,3}$), and if the player has been hot in at least each of the past four games ($HH_{7,4}$). "Hot" is defined based on a simple regression of DraftKings salary on DraftKings fantasy points and is equal to one if a player's actual points on that day exceed the predicted points value based solely on salary. Of the 11,675 player observations in the sample, 2,847 (24.4%) are $HH_{7,1}$, 1,348 (11.5%) are $HH_{7,2}$, 612 (5.2%) are $HH_{7,3}$, and 306 (2.6%) are $HH_{7,4}$. By definition, players that are $HH_{7,4}$ hot are also $HH_{7,1}$, $HH_{7,2}$, and $HH_{7,3}$. Well less than 50% of observations are $HH_{7,1}$ given the right skewed nature of the dependent variable.

Efficient DFS Markets and Theoretical Approach

Sport betting markets are often used to test the efficient market hypothesis (EMH), going back as early as Zuber et al. (1985) and Sauer (1988). According to the EMH, a market is efficient if all available information is incorporated into the current price of an asset, such that it is impossible to systematically outperform the market (Fama, 1970). Since DraftKings only incorporates publicly available data and does not have access to insider information (insiders cannot participate in contests, so operators cannot learn from them), this paper tests for semi-strong form market efficiency in DraftKings' baseball pricing mechanism.

This study utilizes a three-pronged approach to analyzing the hot hand in baseball DFS. First, we look for the existence of hot hand in DFS scoring. Recent overperformance may be predictive of subsequent outperformance (hot hand). We test the following hypothesis:

Hypothesis $\mathbf{I_0}$: Invoking a hot hand strategy will not produce DFS lineups that score higher than expectations.

Hypothesis $\mathbf{I_a}$: Players that are defined as “hot” are likely to score more compared to similar players that are “not hot”; invoking a hot hand strategy will produce DFS lineups that score higher than expectations.

Second, we use tests of the efficient market hypothesis to identify if the hot hand is efficiently priced into DFS salaries. A few recent papers have examined pricing inefficiencies in DFS pricing mechanisms. Losak (2021) identified multiple inefficiencies in DraftKings’ NFL salaries between 2016 and 2018. Paul et al. (2020) did the same for the NBA and identified an inefficiency pertaining to the hot hand. Real-world players that exceed scoring expectations in previous games were found to outperform salary expectations in the next contest. Our study utilizes a similar empirical approach as those other studies but is the first paper to analyze these effects for MLB in the context of DFS.

If there is a hot hand effect in DFS, but DFS operators do not efficiently price it into player salaries, there is an opportunity for skilled consumers to make lineup selection strategies against the inefficiency and increase their expected point output and expected earnings. If there is not a hot hand effect but DraftKings includes it in their salary formulations anyway, there also exists an opportunity to select against the mispricing and increase expected earnings. In situations where there is a hot hand and it is efficiently priced, and where there is not a hot hand and it is efficiently not priced in, we have markets behaving efficiently. In those cases, selecting a player based on their ability to outperform recent performances will have no impact on expected lineup performance since it either does not matter or is already priced into player salaries. Formally, we test the following hypothesis:

Hypothesis II_0: The hot hand (or the lack of a hot hand) is efficiently priced into DraftKings salaries such that there does not exist a profitable hot hand DFS lineup selection strategy.

Hypothesis II_a: The hot hand is not efficiently priced into DraftKings salaries, such that consumers who identify and select against the inefficiency will see higher expected lineup performance.

Third, we examine consumer response to the hot hand. Are consumers more inclined to select a player as part of their lineup if the player is currently "hot"? Formally, we test the following hypothesis:

Hypothesis III_0: Player lineup usage is not a function of a player's hot status.

Hypothesis III_a: Player lineup usage is impacted by a player's hot status.

When examining hot hand, Brown and Sauer (1993) suggest that team performance may indeed be related to streaks, though it may be difficult to identify them, as betting lines might be adjusted already to incorporate streaks. Bettors performing poorly could indicate that they have simply raised expectations beyond what a real hot hand would justify. Alternatively, bettors may believe in a hot hand effect that is not actually there.

This test acknowledges the importance of considering more than just market prices or betting volume when drawing a conclusion about behavioral biases and the hot hand. Hence, we analyze all hypotheses collectively and consider the various conclusions that can be drawn from the combinations of results from the three tests. For example, consider a scenario in which we fail to reject the null hypotheses for each of the three tests. In that case, a possible conclusion would be that there is no evidence that invoking a hot hand strategy will result in better performance, and thus DraftKings does not factor the hot hand into prices, and consumers do not factor hot hand into their lineup selection strategy. Alternatively, consider a scenario in which the null hypothesis is rejected in each of the three tests. This would be evidence that there exists a hot hand strategy in DFS that is not efficiently priced in player salaries and consumers respond by adjusting their usage of those mispriced players.

The previous examples provide just two of the eight possible conclusions from this empirical strategy. The following sections apply formal empirical tests to Hypotheses I, II, and III.

Is Hot Hand Apparent in MLB DFS Scoring?

The first empirical question determines if players that are "hot" score more than players that are "not hot". This essentially tests for the existence of the hot hand in baseball DFS, which would likely also indicate a general hot hand in MLB batters. It is important to emphasize that failure to prove the existence of hot hand does not rule out its existence. As mentioned earlier, it takes a "large" amount of data to fight through measurement error and all the noise in baseball data to identify a hot hand effect. This test will, instead, identify if there is an obvious and noteworthy hot hand effect that then subsequently bleeds into DFS consumer selection strategy.

To test for the hot hand, we estimate the following model using ordinary least squares

$$\begin{gathered}\mathrm{PtsPer100Sal}_{i,t} = \beta_0 + \beta_1 \mathrm{Hot}_{i,t} + \beta_2 \mathrm{NotQualified}_{i,t} + \beta_3 \mathrm{Handed}_{i,t} + \\ \beta_4 \mathrm{SwitchHitter}_{i,t} + \beta_5 \mathrm{ImpliedRuns}_{i,t} + \beta_6 \mathrm{Home}_{i,t} + \textstyle\sum_{pos} \beta_{7,pos} \mathrm{Position}_{i,t} + \\ \textstyle\sum_{spot} \beta_{8,spot} \mathrm{Lineup}_{i,t} + \varepsilon_{i,t},\end{gathered} \tag{4}$$

where our variable of interest, $PtsPer100Sal_{i,t}$, is as previously defined and measures each player's performance relative to expectations. $Handed_{i,t}$ is an indicator equal to one if the batter and starting pitcher are opposite handed (left versus right or right versus left), and $SwitchHitter_{i,t}$ is an indicator if the batter is a switch hitter. In both cases, the batter has an advantage over the pitcher, and by definition, $Handed_{i,t}$ always equals one for switch hitters, so the true effect of being a switch hitter is $\beta_3 + \beta_4$. $\mathrm{Home}_{i,t}$ is an indicator whether the player is on the home team. Spot in the order (lineup) and positional dummy variables are included as well.

$ImpiledRuns_{i,t}$ uses historical money lines and total run lines from Sportbook Reviews to calculate individual team expected scoring totals.[12] First, money lines are converted to team win probabilities using the method in Sauer (2005).[13] Second, we distribute the implied run totals to the two teams based on their win probabilities. If the total run line is 9 runs and the home team has exactly a 50% win probability, each team is credited with an expected 4.5 implied runs. While this is a somewhat simple approach that requires a few run-scoring distributional assumptions, it should do a sufficient job capturing the general run-scoring environment for each team. This variable should also capture the following team-specific information that would be relevant to fantasy scoring: park factors, opposing pitcher effects (starting pitcher and bullpen), weather effects, and fatigue/travel factors, among others. While this variable may also capture home team effects, we include $\mathrm{Home}_{i,t}$ as a separate variable to address any potential betting market price inefficiencies related to home team bias (see Gandar et al., 2004; Paul et al., 2008; Losak and Sabel, 2021 as examples where home bias is considered in baseball betting markets).

Summary statistics for our non-hot hand variables are listed in Table 3, with a correlation matrix provided in the Appendix. The sample is nearly split in half in terms of home and away players. Batters have the handed advantage over the starting pitcher more frequently than not, and switch hitters represent about 13% of the sample. Since players may be eligible under multiple defensive positions, frequencies by defensive position add up to more than 100%. Observations are mostly distributed evenly across the batting order, except for the ninth spot in the lineup. Since the ninth spot is typically reserved for pitchers to hit in the National League and pitchers are not included in the sample, it makes sense that the ninth spot in the lineup is underrepresented relative to the other spots in the order. The usage variable is discussed in depth later.

Results are provided in Table 4. Coefficient estimates for the non-hot hand variables appear stable regardless of the HH definition used. Players on the home team score slightly less compared to visiting players. While one might expect the opposite result due to a home field advantage, home batters may also get fewer at bats on average. If the home team is ahead at the end of the top of the ninth inning, the game is final and the team does not bat during the bottom of the inning. Offhand is positive and statistically significant while switch is negative and statistically significant. As previously mentioned, all switch hitters are also labeled as offhand as well. Overall, the effect is positive—batters with a handed advantage score more on average—although it is slightly less for switch hitters who may not necessarily be batting from their dominant side. As expected, implied runs is positive and statistically significant, indicating a higher expected scoring environment leads to higher point totals. Although most of the lineup coefficients are not statistically significant, their ordering is as expected: players batting later in the lineup are expected to score less, as they may have fewer batting opportunities in a game, while players towards the top of the lineup are expected to score more. The coefficients of determination for each model are especially low (0.005), indicating that there is likely both a strong degree of randomness in scoring as well as additional batter/matchup specific variables not accounted for in the model.

Our main variables of interest are the HH terms. Of the seven HH definitions, each of the coefficients were negative, although only HH_2, HH_3, and HH_6 returned statistically significant. This result provides some evidence of a **negative** hot hand effect, which is less intuitive than the alternative of a positive hot hand effect. This coefficient may be capturing regression to the mean: if a player is hot in recent games, his salary may be positively impacted even if the player's baseline abilities are the same. Increasing salary would increase the denominator of the dependent variable which would reduce the magnitude of the fraction. It could also be the case that pitchers approach players that are hot more carefully, as illustrated in Green and Zwiebel (2018), which may also suppress their scoring.

Ultimately, there is no evidence that playing the hot hand improves expected scoring (**Hypothesis $\mathbf{I_0}$**). However, this does not eliminate the possibility of the hot hand existing. As previously stated, there may be a significant amount of noise and randomness in the outcome variable and measurement error in the model such that we would need more data to identify the true effect.

Is Hot Hand Efficiently Priced?

The second empirical question determines if the hot hand is efficiently priced in DraftKings player salaries. We estimate the following model using ordinary least squares

$$\begin{gathered}\mathrm{Pts}_{\mathrm{i,t}} = \gamma_0 + \gamma_1 \mathrm{Salary}_{\mathrm{i,t}} + \gamma_2 \mathrm{Hot}_{\mathrm{i,t}} + \gamma_3 \mathrm{NotQualified}_{\mathrm{i,t}} + \gamma_4 \mathrm{Handed}_{\mathrm{i,t}} + \\ \gamma_5 \mathrm{SwitchHitter}_{\mathrm{i,t}} + \gamma_6 \mathrm{ImpliedRuns}_{\mathrm{i,t}} + \gamma_7 \mathrm{Home}_{\mathrm{i,t}} + \sum_{\mathrm{pos}} \gamma_{8,\mathrm{pos}} \mathrm{Position}_{\mathrm{i,t}} + \\ \sum_{\mathrm{spot}} \gamma_{9,\mathrm{spot}} \mathrm{Lineup}_{\mathrm{i,t}} + \epsilon_{\mathrm{i,t}}.\end{gathered} \tag{5}$$

Since $\mathrm{Salary}_{\mathrm{i,t}}$ is now included as a right-hand-side variable, our dependent variable is not adjusted for salary. If markets are efficient, all relevant information should be included in salary, such that all our non-salary γ coefficients should not return statistically significant. Statistical significance in any of the coefficients, including the hot hand coefficient, γ_2, is evidence of mispricing in the MLB pricing mechanism.

Results are provided in Table 5. As with the previous set of results, coefficient estimates for non-hot hand variables are relatively stable, regardless of the HH definition. Salary is positive and statistically significant as expected; players costing higher salaries are expected to score more points. Home players score fewer points than what their salary would predict, indicating that DraftKings likely does not properly account for the negative scoring expectations from playing at home. The same applies for offhand, implied runs, and lineup controls. Once player salaries are published for a contest, they do not change. For a typical contest during the season, salaries are made available at some point the evening before (generally while games that evening are being played). This could make it difficult to incorporate into salaries game-specific factors, such as the starting pitcher, spot in the lineup, weather conditions, or anything else that may impact that day's game outcome. If DraftKings relies more heavily on season performance and only makes conservative adjustments based on the opponent and the player's recent performance, it would make sense that incorporating knowledge of certain strategic game elements would result in greater expected performance from consumers.

Hot hand coefficients are all non-statistically significant and change directional effects depending on the specification, failing to reject $\textbf{Hypothesis II}_{\mathbf{0}}$. Combining results from the first and second tests, it seems that since being "hot" does not increase expected point production, DraftKings does not include that information in its pricing. We are agnostic regarding whether DraftKings pricing decisions are intentional.

How Do Consumers Respond to Hot Hand?

The third empirical question determines how consumers respond to hot hand. We estimate the following model using ordinary least squares

$$\begin{gathered} ln(\mathrm{Field}_{i,t}) = \delta_0 + \delta_1\mathrm{Salary}_{i,t} + \delta_2\mathrm{Hot}_{i,t} + \delta_3\mathrm{NotQualified}_{i,t} + \\ \delta_4\mathrm{Handed}_{i,t} + \delta_5\mathrm{SwitchHitter}_{i,t} + \delta_6\mathrm{ImpliedRuns}_{i,t} + \delta_7\mathrm{Home}_{i,t} + \\ \delta_8\mathrm{PositionalOptions}_{i,t} + \sum_{pos}\delta_{9,pos}\mathrm{Position}_{i,t} + \sum_{spot}\delta_{10,spot}\mathrm{Lineup}_{i,t} + \varphi_{i,t}. \end{gathered} \tag{6}$$

$\mathrm{Field}_{i,t}$ is the percentage of consumer lineups (times 100) player *i* appears on day *t*. As listed in Table 3, the median usage rate is 2.78%, the average is 5.01%, the third quartile is 6.14%, and the maximum is 54.96%. Since $\mathrm{Field}_{i,t}$ is a positive right-skewed measure (every player in the sample is selected in at least one lineup), we take the natural log of the dependent variable.[14] We also include an additional variable, $\mathrm{PositionalOptions}_{i,t}$. Some contests will fall on days with fewer real-life games happening than others. On those days, certain players may see higher usage because there are fewer substitutable players to select on DraftKings. The variable is calculated by taking the number of starting players available to be selected on DraftKings at a player's position that day and dividing it by the average of the number of players that are typically available to select for that position over the sample. A number greater than one indicates there are more options available than is typical, and a number less than one indicates there are fewer options available than is usual. If a player is listed under multiple positions, the numerator is the sum of total options at both that player's position, and the denominator is the sum of the averages of number of players available at each position. The remainder of the variables are the same as in previous models.

Results are provided in Table 6. Again, results are robust to the HH specification. Consumers seem to identify advantages in selecting visiting players, selecting batters with the handed advantage, selecting batters playing in higher scoring environments, and selecting players batting higher in the lineup. As expected, positional options is negative and statistically significant: as there are more options for consumers to pick from at a player's particular position, that player's ownership declines. Despite not being statistically significant in either of our previous sets of models, the less active variable is negative and statistically significant; a player who is identified as less active is utilized in fewer lineups. This may be because of the risk associated with taking such a player. By definition, consumers have fewer recent games of performance in which to analyze a player, so taking somebody in that situation may be perceived as riskier. Also, if they are typically bench players, their inclusion in the starting lineup may be less anticipated, and ownership may be down for consumers who build their lineups prior to team lineups being set in the real world. Finally, less active players may be coming back from recent injury, which may create uncertainty regarding if they are at full playing ability. Given the only benefit to playing a less active player would be to have a contrarian lineup, it is a rational conclusion that the risks of taking a less active player outweigh the benefits.

The key results come from the HH coefficients. Despite there being no evidence of a perceived value to taking hot hand players, nor there being evidence of mispricing of the hot hand by DraftKings, consumers are heavily biased towards taking "hot" players ($\mathbf{Hypothesis\ III_a}$). Taking the exponential of the hot hand coefficient and subtracting one provides relative marginal effects. According to HH_1, a player's usage rate goes up 41.4% if the player is "hot" (95% confidence interval between 33.8% and 49.4%). That marginal effect is 23.5% for HH_3, 89.7% for HH_4, 38.6% for HH_5, and 40.6% for HH_6. For HH_2, a 0.1 increase in our continuous variable leads to an 18.1% increase in usage. Finally, usage rates go up by 16.5%, 41.4%, 83.2%, and 135.7% if the player is hot the previous game, the previous two games, the previous three games, and the previous four or more games, respectively. Note that all of these are percentage changes, not percentage-point changes. A 41.4% usage increase for a player at 20% usage would result in an increase in usage rate to 28.3%.

Even if the hot hand did exist and we did not have enough data to identify it, the response from consumers is much greater than what would be expected under the existence of a small hot hand effect, especially after considering consumer responses to other identified inefficiencies. There is clearly a consumer behavioral bias towards the hot hand.

One potential drawback to our approach thus far is the lack of consideration of the opponent quality in the classification of a player's hot streak. If a good team plays against a subpar opponent, a player's good performance can be mistaken for the hot hand rather than a consequence of the opponent quality.[15] To address this, we introduce a new variable to each of our models: $RecentImpliedRuns_{i,t}$. To construct this variable, we take the average of player i's team's implied run total over his previous $g_{i,t,w}$ starts and divide that number by that player's team's average over the 2019 season. A ratio greater than one indicates that the run scoring environment over the player's previous starts was easier than was typically the case during the season; said differently, the player faced a relatively easier schedule. A ratio less than one indicates the opposite: a relatively more difficult schedule. We interact this measure with our hot hand variable.

Table 7 provides results applying our new variable to each of the first three models. We only provide results for HH_1 and HH_2, although results are robust for each of the HH specifications. Because the Less Active players would not have enough data for recent game implied run totals, they are dropped from these models, leaving 10,840 observations for $G_w = 6$. Non-hot hand-related results are comparable to previous conclusions. The hot hand variables are not statistically significant in the points per salary regression, nor significant in the points today regression, yet positive and statistically significant in the usage regression. These are all consistent with previous conclusions. There is some evidence that recent implied runs is negatively related to today's points per salary, providing evidence for expected team-level regression to the mean. This is reflected in the usage regression, with a decrease in usage rate by 9.1% for a one standard deviation (0.290) increase in recent implied runs.

The interaction of recent implied runs with hot hand shows some evidence of statistical significance. Players with an easier relative schedule will see less of a hot hand usage increase compared to players with tougher recent schedules, providing evidence that consumers are cognizant of the nature of the hot streak, even though there is no evidence that this impacts actual scoring. According to Figure 2, there is evidence that the behavioral bias is more prevalent for players generating their hot streaks against a tougher and neutral schedule. While the effect of the hot hand is positive for all levels of recent implied runs, it is only statistically significant (at the 10% level or better) for players with a recent implied runs value under 1.03.

Final Remarks

The purpose of this paper was to continue the recent analysis of the hot hand effect in professional sports while applying the discussion to a unique setting. Much recent work has challenged the prevailing belief in the literature that the hot hand is a "widespread cognitive illusion", and this paper adds to that discussion. Ultimately, we fail to identify a viable hot hand strategy in DraftKings DFS baseball, but acknowledge that our sample may not be sizeable enough to identify an effect, given the immense amount of noisiness in game and player outcomes.

This paper's key finding illustrates how consumers perceive the hot hand. Despite there being no evidence of a hot hand effect, or evidence of a strategy where taking hot players results in higher scoring, DFS consumers significantly increase their usage of players that are classified as hot, a result that is robust to various definitions of the hot hand. These results are similar to findings in Paul et al. (2011) and Paul et al. (2014). These studies use betting percentages for NBA and NFL games, respectively, to identify that even though sportsbooks do not move betting lines in response to the hot hand, betting volume shifts rather significantly towards the “hot” teams.

The behavioral bias is likely magnified by DraftKings highlighting recent player performance on the lineup selection page. Also, while there does not appear to be any scoring advantages to playing the hot hand, this sizeable behavioral bias could introduce a profitable strategy to bet against the hot hand. In tournament structured contests, where the top lineup earns a sizeable payout with diminishing prizes the lower the lineup finishes, there is value to submitting a contrarian lineup. If two lineups are tied for first place, the entrants split the combined prize for first and second place. Playing against the hot hand increases the probability of playing a unique lineup, and having a unique lineup reduces the likelihood of a tie.

Future research should further delve into the makeup of specific lineups. Do consumers impacted by the behavioral bias perform worse on average? Results should also be replicated for other contest price levels as financial motivators may impact the prevalence of the behavioral bias. Finally, results should be replicated for various sports, as the role of the hot hand likely varies, and thus consumer behaviors may vary as well.

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Notes

[1] We thank an anonymous reviewer for pointing us to this area in the literature. This concept provides a stronger theoretical and mathematical framework as to why the early literature was initially more inclined to fail to identify a hot hand effect.

[2] https://www.vox.com/2020/1/29/21112491/daily-fantasy-sports-betting-dfs-merch-analysis-weatherman

[3] DraftKings offers many different contest styles. While the "classic" contest is the primary contest of interest in this study, there are also single-game "showdown" contests that center around single, typically nationally televised prime-time games, "tiered" contests that remove salaries and have consumers build lineups by selecting players from different tiers, head-to-head contests in which consumers face single opponents winner-take-all, and more.

[4] On first glance, salaries do not appear large enough to force much budgetary concerns around the 50,000 cap. However, pitcher salaries are typically double if not triple the salary of hitters. After selecting two pitchers for a lineup, it becomes necessary to select batters at various points of the salary distribution.

[5] If the player is ruled out for the game with sufficient time before the start, most consumers will be able to use this information in their lineup selection. DraftKings also automatically filters out players who are not in the starting lineup. While some players are scratched from the starting lineup at the last second, these represent a relatively small portion of players.

[6] The information used here was obtained free of charge from and is copyrighted by Retrosheet. Interested parties may contact Retrosheet at "www.retrosheet.org".

[7] Archived data from RotoGuru was purchased. Data from RotoGrinders can be found at the RotoGrinders ResultsDB at: https://rotogrinders.com/resultsdb/site/draftkings/.

[8] For example, consider contests where only first place wins versus contests where half the field wins. In the former case, optimal lineup construction strategy would be to maximize lineup scoring variance, increasing the lineup's possible point ceiling. In the latter case, optimal lineup construction strategy would be to maximize expected point totals. Also, there are incentives to avoid ties (split the prize winnings), so in larger contests, savvy consumers may take lesser owned players to reduce the likelihood of finishing in a tie.

[9] It is important to emphasize that this is only one set of parameters for a classic style contest. Contests vary significantly in terms of entry fee (anywhere from pennies to hundreds of dollars), participants (as few as two to as many as tens or hundreds of thousands), maximum allowed entries per user (single-entry and multi-entry contests exist), and payout structures (anywhere between half the pool wins to winner-take-all).

[10] When considering recent performance for the hot hand, suspended games were removed from the data set. These are games that started on one day but finished on a different day, in some cases weeks later, often because of weather. There were four such games during the 2019 season: OAK @ DET on 5/19, KCR @ CWS on 5/27, STL @ NYM on 6/13, and KCR @ BOS on 8/7.

[11] The median series length is three games, hence motivating the last three game performance. When DFS consumers click on a player name and the "Game Log" tab while selecting their lineups, they see that player's performances over their last ten games (if they have played ten games).

[12] https://sportsbookreviewsonline.com/scoresoddsarchives/mlb/mlboddsarchives.htm

[13] A general discussion of money line to implied win probability conversion techniques is available in Berkowitz et al. (2018).

[14] We also test a beta regression given the proportional nature of the Field variable. While not presented here, results are robust to ordinary least squares. We present the coefficients of the log-linear OLS model as relative marginal effects are easier to calculate, which is especially important given the skewed nature of the variable.

[15] A special thanks to an anonymous reviewer for drawing this potential concern with our definitions of the hot hand to our attention.

Tables

Table 1

DraftKings Scoring Categories

Scoring Categories			
Single (1B)	+3 Pts	Run Batted In (RBI)	+2 Pts
Double (2B)	+5 Pts	Run (R)	+2 Pts
Triple (3B)	+8 Pts	Base on Balls (BB)	+2 Pts
Home Run (HR)	+10 Pts	Hit By Pitch (HBP)	+2 Pts
		Stolen Base (SB)	+5 Pts

Table 2

DraftKings Positional Player Summary Statistics

Position	N	Mean	Min	First Quartile	Median	Third Quartile	Maximum
Catcher	1,484	3,485	2,000	3,000	3,400	3,900	5,800
First Base	2,026	4,112	2,000	3,700	4,100	4,500	5,800
Second Base	1,997	3,836	2,000	3,300	3,800	4,300	5,600
Third Base	1,958	4,055	2,000	3,500	4,000	4,600	5,800
Shortstop	1,705	3,987	2,000	3,400	4,000	4,500	5,900
Outfield	4,839	4,096	2,000	3,600	4,100	4,500	6,000

Table 3

Covariate Frequencies and Summary Statistics

Categorical Variables					
Home		Offhand Matchup		Switch Hitter	
Home	Away	L/R or R/L	L/L or R/R	Yes	No
5,830 (50.1%)	5,845 (49.9%)	6,759 (57.9%)	4,916 (42.1%)	1,537 (13.2%)	10,138 (86.8%)
Quantitative Variables					
		Mean	SD	Min	Max
Implied Runs		4.675	1.244	1.470	9.208
Recent Implied Runs		1.025	0.124	0.555	1.563
Positional Options		1.202	0.343	0.308	1.849
Defensive Position					
Catcher	First Base	Second Base	Third Base	Shortstop	Outfield
1,484 (12.7%)	2,026 (17.4%)	1,997 (17.1%)	1,958 (16.8%)	1,705 (14.6%)	4,839 (41.4%)
Lineup Spot					
Lineup – 1st	Lineup – 2nd	Lineup – 3rd	Lineup – 4th	Lineup – 5th	
1,332 (11.4%)	1,381 (11.8%)	1,393 (11.9%)	1,394 (11.9%)	1,393 (11.9%)	
Lineup – 6th	Lineup – 7th	Lineup – 8th	Lineup – 9th		
1,369 (11.7%)	1,360 (11.6%)	1,328 (11.4%)	725 (6.2%)		
Usage Data (Field% X 100)					
Min	1st Quartile	Median	Mean	3rd Quartile	Max
0.04	1.18	2.78	5.01	6.14	54.96

Table 4

Results: Does the Hot Hand Exist in DFS Scoring?

	Dependent Variable: Fantasy Points Today / 100 Salary (n = 11,675)						
	HH1	**HH2**	**HH3**	**HH4**	**HH5**	**HH6**	**HH7**
Hot Hand	-0.009 (0.006)	-0.058** (0.026)	-0.006* (0.004)	-0.008 (0.018)	0.003 (0.005)	-0.018* (0.010)	
Less Active	-0.001 (0.008)	-0.003 (0.008)	-0.003 (0.008)	-0.0002 (0.008)	0.002 (0.010)	0.005 (0.005)	
Hot Hand (Previous Day)							0.006 (0.004)
Hot Hand (Last 2 Games)							0.003 (0.006)
Hot Hand (Last 3 Games)							0.008 (0.008)
Hot Hand (Last 4 Games)							-0.005 (0.011)
Home	-0.007* (0.004)	-0.007* (0.004)	-0.007* (0.004)	-0.007* (0.004)	-0.007* (0.004)	-0.007* (0.004)	-0.006* (0.004)
Offhand	0.017*** (0.004)	0.017*** (0.004)	0.017*** (0.004)	0.017*** (0.004)	0.017*** (0.004)	0.017*** (0.004)	0.017*** (0.004)
Switch	-0.010* (0.006)	-0.010* (0.006)	-0.010* (0.006)	-0.010* (0.006)	-0.010* (0.006)	-0.009 (0.006)	-0.010* (0.006)
Implied Runs	0.007*** (0.002)	0.007*** (0.002)	0.008*** (0.002)	0.008*** (0.002)	0.008*** (0.002)	0.008*** (0.002)	0.008*** (0.002)
First Base	-0.006 (0.005)	-0.006 (0.005)	-0.006 (0.005)	-0.005 (0.005)	-0.005 (0.005)	-0.006 (0.005)	-0.005 (0.005)
Second Base	0.001 (0.005)	0.001 (0.005)	0.001 (0.005)	0.001 (0.005)	0.001 (0.005)	0.001 (0.005)	0.001 (0.005)
Third Base	0.001 (0.005)	0.001 (0.005)	0.001 (0.005)	0.001 (0.005)	0.001 (0.005)	0.001 (0.005)	0.001 (0.005)
Shortstop	0.007 (0.006)	0.007 (0.006)	0.008 (0.006)	0.007 (0.006)	0.007 (0.006)	0.007 (0.006)	0.007 (0.006)
Outfield	-0.002 (0.005)	-0.001 (0.005)	-0.001 (0.005)	-0.002 (0.005)	-0.002 (0.005)	-0.002 (0.005)	-0.002 (0.005)
Lineup 2nd	0.004 (0.007)	0.004 (0.007)	0.004 (0.007)	0.004 (0.007)	0.004 (0.007)	0.004 (0.007)	0.004 (0.007)
Lineup 3rd	0.004 (0.007)	0.004 (0.007)	0.004 (0.007)	0.004 (0.007)	0.004 (0.007)	0.004 (0.007)	0.004 (0.007)
Lineup 4th	0.002 (0.007)	0.002 (0.007)	0.002 (0.007)	0.002 (0.007)	0.002 (0.007)	0.002 (0.007)	0.002 (0.007)
Lineup 5th	-0.002 (0.008)	-0.002 (0.008)	-0.002 (0.008)	-0.002 (0.008)	-0.002 (0.008)	-0.002 (0.008)	-0.002 (0.008)
Lineup 6th	-0.004 (0.007)	-0.004 (0.007)	-0.004 (0.007)	-0.004 (0.007)	-0.004 (0.007)	-0.004 (0.007)	-0.004 (0.007)
Lineup 7th	-0.010 (0.008)	-0.011 (0.008)	-0.010 (0.008)	-0.010 (0.008)	-0.010 (0.008)	-0.011 (0.008)	-0.009 (0.008)
Lineup 8th	-0.0003 (0.008)	-0.001 (0.008)	-0.001 (0.008)	-0.0001 (0.008)	-0.0002 (0.008)	-0.002 (0.008)	0.00005 (0.008)
Lineup 9th	-0.015 (0.009)	-0.016* (0.009)	-0.015* (0.009)	-0.015 (0.009)	-0.015 (0.009)	-0.016* (0.009)	-0.015 (0.009)
Constant	0.159*** (0.010)	0.170*** (0.012)	0.161*** (0.011)	0.158*** (0.010)	0.157*** (0.010)	0.158*** (0.010)	0.156*** (0.010)
R^2	0.005	0.005	0.005	0.005	0.005	0.005	0.005
F Statistic	3.2173***	3.3151***	3.1838***	3.0782***	3.0667***	3.4087***	2.8826***

Note: Statistical significance is defined at the * 10%, ** 5%, and *** 1% levels. Robust standard errors included (HC3).

Table 5

Results: Is Hot Hand Efficiently Priced?

	Dependent Variable: Fantasy Points Today (n = 11,675)						
	HH1	**HH2**	**HH3**	**HH4**	**HH5**	**HH6**	**HH7**
Salary (/100)	0.079***	0.080***	0.079***	0.078***	0.079***	0.080***	0.080***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.014)	(0.013)
Hot Hand	-0.222	-1.099	-0.110	0.052	0.095	-0.556	
	(0.248)	(1.040)	(0.149)	(0.804)	(0.194)	(0.411)	
Less Active	-0.327	-0.356	-0.354	-0.308	-0.328	-0.106	
	(0.258)	(0.261)	(0.264)	(0.258)	(0.322)	(0.195)	
Hot Hand (Previous Day)							0.174
							(0.172)
Hot Hand (Last 2 Games)							-0.003
							(0.227)
Hot Hand (Last 3 Games)							0.405
							(0.340)
Hot Hand (Last 4 Games)							-0.221
							(0.411)
Home	-0.431***	-0.431***	-0.429***	-0.431***	-0.431***	-0.426***	-0.425***
	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)
Offhand	0.492***	0.490***	0.493***	0.492***	0.494***	0.491***	0.489***
	(0.154)	(0.154)	(0.154)	(0.154)	(0.154)	(0.154)	(0.154)
Switch	-0.230	-0.229	-0.229	-0.229	-0.230	-0.231	-0.227
	(0.228)	(0.228)	(0.228)	(0.228)	(0.228)	(0.228)	(0.228)
Implied Runs	0.572***	0.570***	0.572***	0.575***	0.575***	0.569***	0.571***
	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)
First Base	-0.110	-0.114	-0.109	-0.106	-0.106	-0.115	-0.107
	(0.215)	(0.215)	(0.215)	(0.215)	(0.215)	(0.215)	(0.215)
Second Base	0.047	0.048	0.048	0.045	0.044	0.046	0.043
	(0.200)	(0.200)	(0.200)	(0.200)	(0.200)	(0.200)	(0.200)
Third Base	0.106	0.104	0.105	0.104	0.108	0.108	0.107
	(0.203)	(0.203)	(0.203)	(0.203)	(0.203)	(0.203)	(0.203)
Shortstop	0.446**	0.445**	0.449**	0.448**	0.447**	0.441*	0.444*
	(0.227)	(0.227)	(0.227)	(0.227)	(0.227)	(0.227)	(0.227)
Outfield	0.142	0.141	0.143	0.142	0.142	0.139	0.138
	(0.182)	(0.182)	(0.182)	(0.182)	(0.182)	(0.182)	(0.182)
Lineup 2nd	0.171	0.171	0.171	0.168	0.164	0.165	0.169
	(0.301)	(0.301)	(0.301)	(0.301)	(0.301)	(0.301)	(0.301)
Lineup 3rd	0.418	0.414	0.416	0.417	0.417	0.420	0.423
	(0.324)	(0.324)	(0.324)	(0.324)	(0.324)	(0.324)	(0.325)
Lineup 4th	0.062	0.056	0.057	0.058	0.057	0.062	0.065
	(0.312)	(0.312)	(0.312)	(0.312)	(0.312)	(0.312)	(0.312)
Lineup 5th	-0.379	-0.382	-0.385	-0.386	-0.389	-0.378	-0.381
	(0.310)	(0.310)	(0.310)	(0.310)	(0.310)	(0.309)	(0.310)
Lineup 6th	-0.723**	-0.729**	-0.730**	-0.729**	-0.735**	-0.729**	-0.732**
	(0.302)	(0.302)	(0.302)	(0.302)	(0.302)	(0.302)	(0.302)
Lineup 7th	-1.167***	-1.175***	-1.172***	-1.170***	-1.176***	-1.176***	-1.180***
	(0.307)	(0.307)	(0.307)	(0.307)	(0.307)	(0.306)	(0.306)
Lineup 8th	-1.117***	-1.121***	-1.117***	-1.116***	-1.118***	-1.123***	-1.126***
	(0.325)	(0.325)	(0.325)	(0.325)	(0.325)	(0.326)	(0.325)
Lineup 9th	-1.765***	-1.769***	-1.764***	-1.762***	-1.767***	-1.765***	-1.779***
	(0.358)	(0.358)	(0.358)	(0.358)	(0.358)	(0.358)	(0.358)
Constant	2.260***	2.421***	2.271***	2.246***	2.213***	2.212***	2.109***
	(0.592)	(0.614)	(0.592)	(0.592)	(0.591)	(0.594)	(0.594)
R^2	0.035	0.035	0.035	0.035	0.035	0.035	0.035
F Statistic	21.384***	21.323***	21.271***	21.304***	21.214***	21.469***	19.327***

Note: Statistical significance is defined at the * 10%, ** 5%, and *** 1% levels. Robust standard errors included (HC3).

Table 6

Results: How do Consumers Respond to the Hot Hand

	Dependent Variable: ln(Field) (n = 11,675)						
	HH1	**HH2**	**HH3**	**HH4**	**HH5**	**HH6**	**HH7**
Salary (x100)	-0.035***	-0.037***	-0.036***	-0.034***	-0.035***	-0.035***	-0.033***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Hot Hand	0.346***	1.677***	0.212***	0.640***	0.329***	0.344***	
	(0.027)	(0.115)	(0.017)	(0.083)	(0.022)	(0.040)	
Less Active	-0.138***	-0.094**	-0.080**	-0.162***	-0.222***	-0.101***	
	(0.037)	(0.037)	(0.037)	(0.037)	(0.046)	(0.026)	
Hot Hand (Previous Day)							0.153***
							(0.020)
Hot Hand (Last 2 Games)							0.194***
							(0.025)
Hot Hand (Last 3 Games)							0.259***
							(0.036)
Hot Hand (Last 4 Games)							0.252***
							(0.052)
Home	-0.181***	-0.182***	-0.184***	-0.180***	-0.180***	-0.181***	-0.177***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Offhand	0.353***	0.355***	0.351***	0.351***	0.359***	0.351***	0.351***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Switch	-0.232***	-0.234***	-0.234***	-0.232***	-0.236***	-0.234***	-0.236***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Implied Runs	0.570***	0.573***	0.571***	0.565***	0.566***	0.568***	0.560***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Positional Options	-0.935***	-0.937***	-0.935***	-0.933***	-0.929***	-0.938***	-0.928***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
First Base	-0.153***	-0.146***	-0.153***	-0.156***	-0.154***	-0.155***	-0.159***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Second Base	0.013	0.013	0.011	0.020	0.011	0.015	0.012
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Third Base	-0.071***	-0.068***	-0.070***	-0.069***	-0.063***	-0.069***	-0.069***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Shortstop	0.065***	0.066***	0.060**	0.066***	0.067***	0.066***	0.058**
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Outfield	-0.238***	-0.236***	-0.240***	-0.237***	-0.236***	-0.236***	-0.244***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Lineup 2nd	0.028	0.029	0.027	0.033	0.029	0.033	0.035
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.033)
Lineup 3rd	0.115***	0.121***	0.120***	0.115***	0.118***	0.115***	0.125***
	(0.033)	(0.033)	(0.034)	(0.034)	(0.033)	(0.034)	(0.033)
Lineup 4th	0.055*	0.065**	0.063*	0.061*	0.059*	0.060*	0.066**
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
Lineup 5th	-0.381***	-0.377***	-0.372***	-0.376***	-0.381***	-0.374***	-0.369***
	(0.033)	(0.033)	(0.033)	(0.034)	(0.033)	(0.034)	(0.033)
Lineup 6th	-0.727***	-0.717***	-0.715***	-0.717***	-0.722***	-0.720***	-0.716***
	(0.035)	(0.035)	(0.035)	(0.036)	(0.035)	(0.036)	(0.036)
Lineup 7th	-1.083***	-1.072***	-1.076***	-1.080***	-1.077***	-1.081***	-1.077***
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Lineup 8th	-1.306***	-1.300***	-1.306***	-1.305***	-1.300***	-1.306***	-1.310***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Lineup 9th	-1.484***	-1.477***	-1.486***	-1.487***	-1.485***	-1.488***	-1.490***
	(0.048)	(0.047)	(0.047)	(0.048)	(0.047)	(0.047)	(0.048)
Constant	1.312***	1.069***	1.286***	1.322***	1.281***	1.349***	1.211***
	(0.077)	(0.079)	(0.077)	(0.078)	(0.077)	(0.078)	(0.077)
R^2	0.490	0.492	0.490	0.486	0.494	0.486	0.488
F Statistic	514.11***	519.45***	516.76***	507.73***	530.06***	507.86***	471.11***

Note: Statistical significance is defined at the * 10%, ** 5%, and *** 1% levels. Robust standard errors included (HC3).

Table 7

Robustness: Addressing Quality of Recent Opponents in Hot Hand Definition

Dependent Variable (n = 10,840)	**Fantasy Points Today / 100 Salary**		**Fantasy Points Today**		**ln(Field)**	
HH Definition	**HH1**	**HH2**	**HH1**	**HH2**	**HH1**	**HH2**
Salary (x100)			0.080***	0.081***	-0.032***	-0.034***
			(0.014)	(0.014)	(0.002)	(0.002)
Hot Hand	0.017	-0.152	0.560	-5.013	0.799***	2.907***
	(0.053)	(0.221)	(2.120)	(8.625)	(0.236)	(0.991)
Recent Implied Runs	-0.028*	-0.048	-0.853	-1.660	-0.329***	-0.192
	(0.015)	(0.044)	(0.615)	(1.716)	(0.072)	(0.202)
Hot Hand X	-0.025	0.097	-0.732	3.943	-0.428*	-1.148
Recent Implied Runs	(0.051)	(0.212)	(2.023)	(8.321)	(0.225)	(0.955)
Home	-0.007*	-0.007*	-0.458***	-0.458***	-0.183***	-0.184***
	(0.004)	(0.004)	(0.154)	(0.154)	(0.017)	(0.017)
Offhand	0.016***	0.016***	0.460***	0.458***	0.368***	0.370***
	(0.004)	(0.004)	(0.161)	(0.161)	(0.018)	(0.018)
Switch	-0.012**	-0.012**	-0.298	-0.292	-0.247***	-0.250***
	(0.006)	(0.006)	(0.236)	(0.236)	(0.025)	(0.025)
Implied Runs	0.008***	0.008***	0.599***	0.597***	0.569***	0.574***
	(0.002)	(0.002)	(0.071)	(0.071)	(0.008)	(0.008)
Positional Options					-0.899***	-0.899***
					(0.024)	(0.024)
First Base	-0.005	-0.005	-0.095	-0.098	-0.127***	-0.120***
	(0.006)	(0.006)	(0.224)	(0.224)	(0.025)	(0.025)
Second Base	0.001	0.002	0.084	0.087	0.025	0.025
	(0.006)	(0.006)	(0.212)	(0.212)	(0.024)	(0.024)
Third Base	0.001	0.001	0.137	0.134	-0.076***	-0.073***
	(0.005)	(0.005)	(0.212)	(0.212)	(0.023)	(0.023)
Shortstop	0.010	0.010	0.514**	0.513**	0.081***	0.081***
	(0.006)	(0.006)	(0.239)	(0.239)	(0.026)	(0.026)
Outfield	-0.002	-0.002	0.123	0.125	-0.233***	-0.232***
	(0.005)	(0.005)	(0.191)	(0.191)	(0.022)	(0.022)
Lineup 2nd	0.005	0.005	0.199	0.193	0.027	0.028
	(0.007)	(0.007)	(0.308)	(0.308)	(0.034)	(0.034)
Lineup 3rd	0.005	0.005	0.423	0.418	0.119***	0.125***
	(0.008)	(0.008)	(0.330)	(0.330)	(0.033)	(0.033)
Lineup 4th	-0.001	-0.001	-0.044	-0.051	0.059*	0.070**
	(0.008)	(0.008)	(0.319)	(0.318)	(0.033)	(0.033)
Lineup 5th	-0.003	-0.003	-0.427	-0.430	-0.372***	-0.369***
	(0.008)	(0.008)	(0.316)	(0.316)	(0.034)	(0.033)
Lineup 6th	-0.007	-0.007	-0.821***	-0.830***	-0.716***	-0.705***
	(0.008)	(0.008)	(0.313)	(0.313)	(0.036)	(0.036)
Lineup 7th	-0.009	-0.010	-1.165***	-1.176***	-1.050***	-1.038***
	(0.008)	(0.008)	(0.322)	(0.323)	(0.037)	(0.037)
Lineup 8th	0.002	0.001	-1.090***	-1.101***	-1.238***	-1.232***
	(0.009)	(0.009)	(0.342)	(0.342)	(0.041)	(0.041)
Lineup 9th	-0.016	-0.017*	-1.824***	-1.834***	-1.408***	-1.401***
	(0.010)	(0.010)	(0.376)	(0.377)	(0.050)	(0.050)
Constant	0.186***	0.216***	3.002***	3.981**	1.453***	1.061***
	(0.019)	(0.047)	(0.851)	(1.847)	(0.105)	(0.220)
R^2	0.006	0.006	0.035	0.035	0.493	0.495
F Statistic	3.3553	3.3831	18.924	18.832	457.73	463.58

Note: Statistical significance is defined at the * 10%, ** 5%, and *** 1% levels. Robust standard errors included (HC3).

Figures

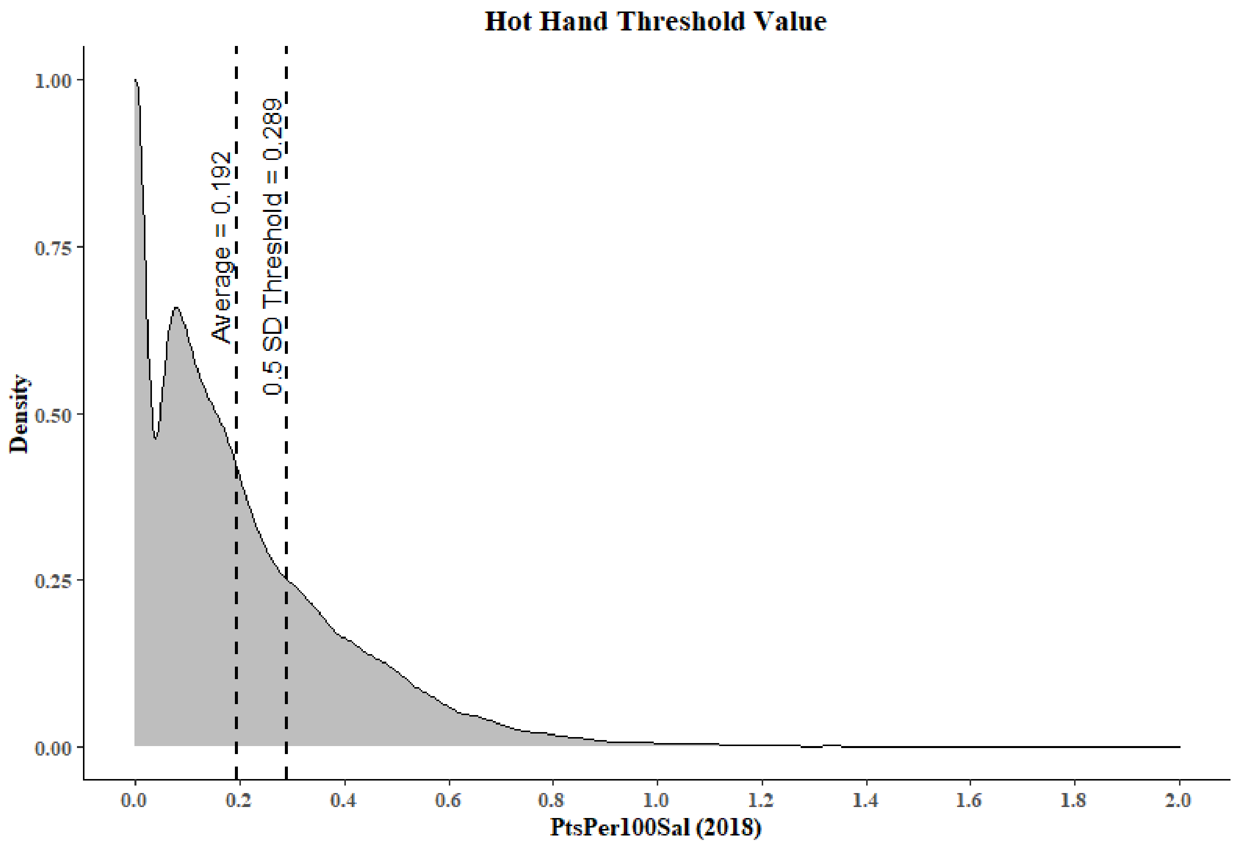

Figure 1: 2018 Points Per 100 Salary Density with Thresholds

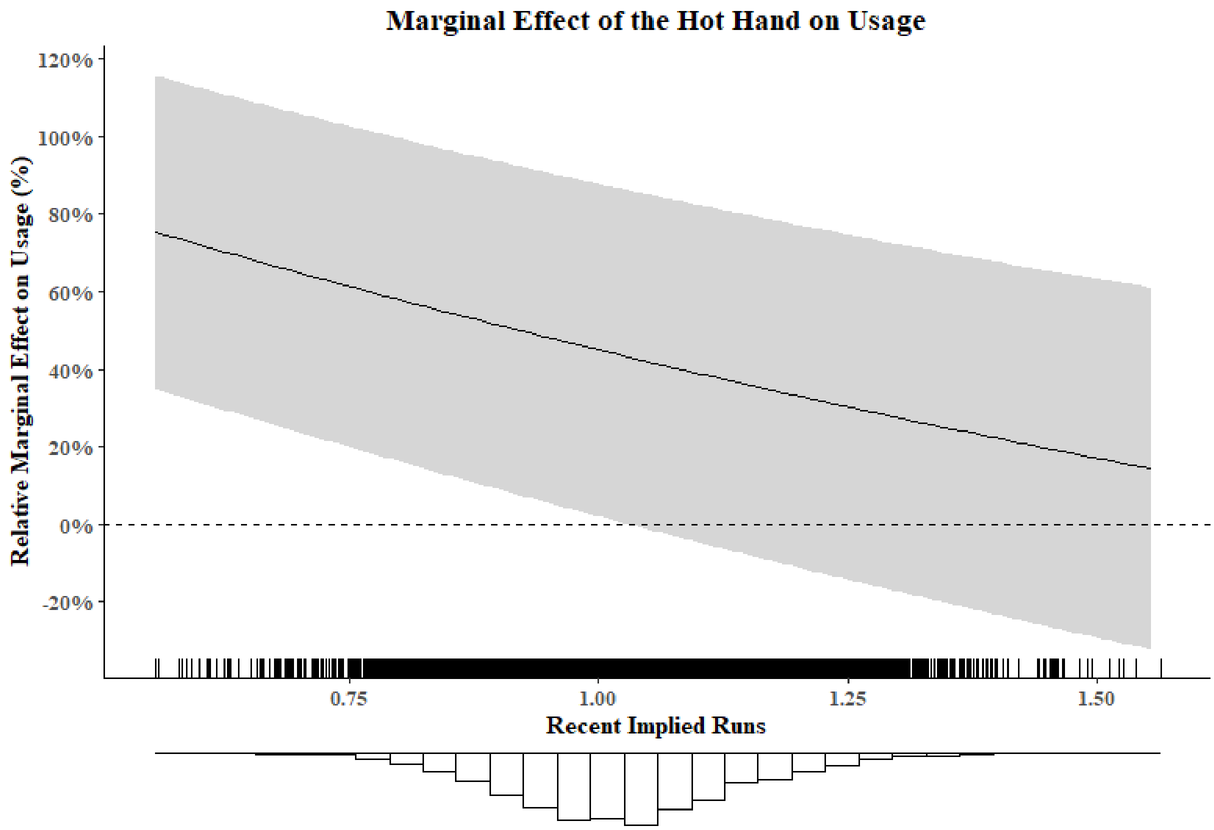

Figure 2: Hot Hand Marginal Effect by Recent Implied Runs

Note: Marginal effects are derived from the interaction between the hot hand variable and recent implied runs in HH_1 *for the usage model. Confidence intervals are provided at the 90% level. A histogram for recent implied runs is provided. This plot was created using the ggplot (Wickham, 2016) and patchwork (Pederson, 2020) packages in R (R Core Team, 2021).*

Appendix

Table A1

Covariate Correlation Matrix

	Salary	Hot Hand (HH_1)	Recent Implied Runs	Home	Offhand	Switch	Implied Runs	Positional Options
Salary	1.000	0.061	0.221	-0.021	-0.037	0.031	0.344	-0.007
Hot Hand ($\mathbf{HH_1}$)	0.061	1.000	0.098	-0.013	-0.012	-0.001	-0.038	0.005
Recent Implied Runs	0.221	0.098	1.000	-0.003	-0.029	0.011	0.057	0.076
Home	-0.021	-0.013	-0.003	1.000	-0.003	0.010	0.235	-0.0002
Offhand	-0.037	-0.012	-0.029	-0.003	1.000	0.332	0.003	0.009
Switch	0.031	-0.001	0.011	0.010	0.332	1.000	-0.024	-0.010
Implied Runs	0.344	-0.038	0.057	0.235	0.003	-0.024	1.000	0.010
Positional Options	-0.007	0.005	0.076	-0.0002	0.009	-0.010	0.010	1.000