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HOT SHOTS: AN ANALYSIS OF THE 'HOT HAND' IN NBA FIELD GOAL AND FREE THROW SHOOTING

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ABSTRACT

We investigate the hot hand hypothesis using detailed data on free throws and field goal attempts for the entire 2013-2014 and 2014-2015 NBA regular seasons. Free throws represent a more controlled setting, allowing a closer examination of the potential physiological mechanisms behind success in repeated motions, while field goal attempts represent the setting most observers have in mind when commenting on a player's repeated shooting success. We examine these two settings together, within the same players in the same games, permitting a more comprehensive analysis of the hot hand. We find a small hot hand effect for free throws, concentrated in second and third shots in a free throw sequence, in players shooting at least 100 free throws in a season, and in games where players shoot four to five free throws. We find the opposite results for field goal attempts. If a player makes a field goal, he is less likely to make his next field goal attempt. These results are robust to controlling for the characteristics of the previous shot. Interestingly, both offenses and defenses respond to made field goals as if the hot hand effect exists.

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1 Introduction

The question at the center of research into the hot hand is whether the common belief that previous shot success predicts future shot success is correct. This research began with Gilovich et al. (1985), who state their research question in the opening sentences of their paper as follows, "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.' These phrases express a belief that the performance of a player during a particular period is significantly better than expected on the basis of the player's overall record." Gilovich et al. (1985) find no existence of the hot hand in professional free throw and field goal shooting, or in collegiate field goal shooting in a controlled experiment. Thus, the authors conclude that the widespread belief in the hot hand is the result of a cognitive bias.

Gilovich et al. (1985) spawned a large interest in the hot hand. Recent research into the hot hand has often focused on controlled settings such as shooting experiments, the NBA 3-point contest, and free-throw shooting in games (Arkes, 2010; Aharoni and Sarig, 2012; Miller and Sanjurjo, 2014, 2015, 2018; Yaari and Eisenmann, 2011). In a series of papers, Joshua Miller and Adam Sanjurjo find evidence of shooting streaks in controlled and semi-controlled settings, including controlled shooting experiments and the NBA 3-Point Contest (Miller and Sanjurjo, 2014, 2015, 2018). Importantly, Miller and Sanjurjo (2018) demonstrate that the type of conditional probability analysis commonly used in controlled studies of the hot hand is biased against finding a hot hand effect. Correcting this bias produces strong evidence of a hot hand in controlled shooting experiments, including in the data originally used by Gilovich et al. (1985). Results from other movement patterns, such as pitching horseshoes, tennis, and bowling, also suggest that success in repeated movement patterns can increase the probability of success in future movements (Smith, 2003; Klaassen and Magnus, 2001; Dorsey-Palmateer and Smith, 2004).

However, the original question posed by Gilovich et al. (1985) is not whether a physiological mechanism exists for success in repeated movement patterns, but rather whether the widespread belief in the hot hand is correct. As referenced in the quote above from Gilovich et al. (1985), the most relevant setting for testing these beliefs is the run of play. Gilovich et al. (1985) conduct surveys suggesting that players and coaches believe the hand exists in the run of play, and general basketball fans also exhibit gambling habits that reflect beliefs in the hot hand (Brown and Sauer, 1993). In the run of play, players' shots can be many minutes apart, may be from very different locations, and possibly in very different game situations. Thus, it is unclear whether the results from controlled shooting situations will translate to game situations and the run of play.

Empirically testing for the hot hand in game situations poses a number of difficulties, the most important being accounting for player, opponent, shot and game characteristics. Papers have consistently found that both offenses and defenses react to made shots (Aharoni and Sarig, 2012; Rao, 2009; Csapo and Raab, 2014; Csapo et al., 2015; Attali, 2013; Bocskocsky et al., 2014). However, papers have been mixed in their findings of a hot hand. For example, Bocskocsky et al. (2014) find evidence for a hot hand after controlling for current and previous shot difficulty, while Rao (2009) finds no evidence of a hot hand. Csapo and Raab (2014) highlight the effects that defensive player adjustments can have on the success of the shooter, so if defensive players adjust to the prior success of the offensive player we would expect decreased success in the subsequent shots; however, their analysis is subject to the bias described by Miller and Sanjurjo (2018).

In this paper we analyze the hot hand in the NBA for both free throws, a more controlled shooting environment, and field goals in the run-of-play, which while not a controlled environment, are more relevant to evaluating spectators' beliefs in the hot hand. We compile detailed data regarding the universe of free throws and field goal attempts for the 2013-2014 and 2014-2015 NBA regular seasons and combine them with a large set of player and game characteristics. In free throws, we find a small hot hand effect, similar to Yaari and Eisenmann (2011) and Arkes (2010). If a player makes his previous free throw, he is about 1.6 percentage points more likely to make his next free throw, and the effect is larger for the second and third free throws in a set and larger still for players who take at least 100 free throws in a season. Furthermore, these effects are most pronounced when examining players who have taken at least five free throws in a game, where the coefficients approach results from some controlled shooting experiments (e.g., Miller and Sanjurjo, 2018), and we find that both the previous free throw and streaks of free throw success positively affect the probability of making the next free throw. Finally, we find that controlling for the characteristics of the previous free throw or free throws does not change our findings of a hot hand effect.

In the run of play, we find that both offenses and defenses respond to field goals as if the hot hand effect exists, but we do not find any evidence of a hot hand effect. In fact, our results suggest that making a field goal statistically significantly reduces the probability that a player makes his next field goal attempt by about 0.4 percentage points, even when controlling for current and previous shot characteristics. Additionally, we find that offensive and defensive responses, as well as the negative impact of making a field goal on the probability of making the next field goal attempt, are especially large when the previous field goal is a 3-point shot, compared to 2-point shots just inside the 3-point line. Finally, we do not find statistically significant coefficients when examining streaks of field goals, although when we do not include lagged shot controls we find that streaks of success in field goals make it even less likely the player makes his next field goal attempt.

Our paper makes a number of contributions to the literature on the hot hand. First, we examine roughly 84,000 free throw attempts and 350,000 field goal attempts taken by the same players within the same games. This allows a more direct comparison of the existence and magnitude of the hot hand effect in more controlled and less controlled settings. We also bring a larger set of controls than used in previous literature, and we demonstrate the importance of controls, even in fairly controlled settings such as free throw shooting. Along these lines, we advance the literature by including controls for both current and previous shot characteristics.

Second, we also introduce a new methodology to control for differences in players' shooting ability and account for Simpson's Paradox, adapted from Chen et al. (2016). Previous work has included player fixed effects to account for shooting ability and other time-invariant player characteristics (e.g. Arkes, 2010; Bocskocsky et al., 2014), although including fixed effects in a lagged-dependent variable model will lead to biased coefficients (Nickell, 1981; Nerlove, 1967, 1971). Instead, we include two measures of player's shooting percentage which do not include the current game, following a strategy employed by Chen et al. (2016) in testing the gambler's fallacy in three settings, refugee asylum court decisions, reviews of loan applications, and calls made by Major League Baseball umpires. We additionally show that our results are robust to including player-level fixed effects.

Third, we introduce new methods of testing for streaks of shots using a regression framework which also permits controlling for other factors. We first test for the hot hand using a straightforward regression framework similar to the approach of Chen et al. (2016) in examining the gambler's fallacy and also similar to Arkes (2010) who examines free throws. We also introduce a new test for success in streaks of previous shots. Here we examine the interactions of indicator variables for success in each of the previous four shots to estimate the effect of different lengths of streaks of success. Our strategy again builds upon Chen et al. (2016), and we are, to our knowledge, the first to apply it to the analysis of the hot hand. Although other papers have analyzed shooting success over more than just the previous shot in a regression framework (e.g. Bocskocsky et al., 2014), our strategy allows us to examine different streak lengths separately as opposed to analyzing the average or adjusted shooting percentage over a period of shots.

Fourth, we examine situations which may be more salient to players and coaches and thus elicit larger responses to made field goals. We first separate previous shots by whether they were 2-point or 3-point shots, hypothesizing that 3-point shots are more salient to both offenses and defenses than 2-point shots. To address concerns regarding the relative difficulty of making 2-point and 3-point shots and the signals these different difficulty levels may send, we additionally restrict our sample to shots just inside and just outside the 3-point line. We show that, although these shots are of similar difficulty, shots just outside the 3-point line elicit much larger responses and lead to a large negative effect on the probability of making the next shot.

Our empirical approach is similar to other previous studies who have used a multivariate framework to approach the hot hand. Rao (2009) finds no evidence a hot hand exists when employing a random effects probit model for a set of players on the Los Angeles Lakers. Bühren and Krabel (2015) use OLS and tobit models to estimate the impact of making a shot which forced overtime on the field goal shooting of that player in overtime, but caution that their findings may be a result of not being able to control for potential changes in the offensive and defensive players' responses to the success of that crucial shot. Green and Zwiebel (2017) find a hot hand in baseball and argue that the allocation of offensive and defensive resources is less fluid in baseball than in basketball. However, understanding these allocations is an interesting part of the hot hand story and provides an environment to understand the costs of economic agents reacting to this fallacy in a more general setting.

Finally Bocskocsky et al. (2014) control for other factors which may affect shot success, and they find mixed evidence of whether the hot hand exists, depending on which of their measures of previous success is used. Bocskocsky et al. (2014) develop two measures of previous shot success, "simple heat" and "complex heat." Simple heat is the player's shooting percentage over the previous four shots within each game. Complex heat adjusts for previous shot difficulty. Bocskocsky et al.

(2014) first predict the difficulty of each shot. They then adjust actual shooting percentage over the previous four shots with the predicted shooting percentage to construct complex heat. In a similar manner, Bocskocsky et al. (2014) include a predicted shot difficulty measure to control for current shot difficulty. However, including a predicted value in a regression in the manner of Bocskocsky et al. (2014), instead of directly controlling for the characteristics of shots, likely generates biased coefficients. We reproduced many of the results in Bocskocsky et al. (2014) using our data, including their finding of a hot hand. Our reproduction suggests that their finding of a hot hand is driven by the inclusion of predicted shot difficulty instead of directly controlling for shot characteristics. When predicted shot difficulty is replaced with controls for shot difficulty, we find that previous shot success is negatively correlated with current shooting success.[1]

The rest of this paper is organized as follows. Section 2 overviews our play-by-play shot data and statistical methods, Section 3 discusses our results, and Section 4 concludes.

2 Data and Methods

2.1 Data

We use three data sources for our analysis. Our main data source is play by play data for the 2013-2014 and 2014-2015 NBA regular seasons from `http://www.bigdataball.com`.[2] This data set provides the date and teams for every game and detailed information for every event in each game, including field goal attempts, free throws, rebounds, fouls, timeouts, etc., as well as the players who were on the court at the time of each event. For field goal attempts, this data contains the time of the field goal attempt, whether the field goal attempt went in, the shot type, and the shot location in x-y coordinates, which we use to calculate the shot distance from the basket. We merge this with publicly available data on additional detailed in game field goal attempt characteristics from `http://www.nbasavant.com`.[3] Representing the universe of field goal attempts taken during these seasons, this data contains the number of dribbles taken before shooting and number of seconds on the ball before shooting. Importantly, the data also contain information on the defense, including

[1] Details regarding our reproduction are available upon request.

[2] See `https://www.bigdataball.com/nba-playbyplay-stats-multipleseasons/` for more information on this data set.

[3] See `http://www.nbasavant.com/shot_search.php` for more information about the data from NBA Savant.

the name of the nearest defender and distance from the nearest defender to the shooting player. We limit our sample to the 2013-2014 and 2014-2015 regular seasons because these two seasons have data on the defender's name and defender distance which are important to our analysis. Finally, we merge in player characteristics and game characteristics from `http://www.basketball-reference.com`. We use the `bbr` package in R, available here: `https://github.com/mbjoseph/bbr`, to obtain and merge in player characteristics for both the offense and defense, including position, height, and weight, number of seasons in the NBA, and age from `http://www.basketball-reference.com`. Additionally, we add game characteristics, also from `http://www.basketball-reference.com`, including which team was the home team and away team and the crowd size.

2.2 Methods

2.2.1 The Determinants of Made Shots

To examine the effects of previous shot success on current shot success, we estimate variations on the following regression model:

$$s_{p,i,g} = \alpha_0 + \alpha_s s_{p,i-1,g} + \boldsymbol{v_{p,i,g}} \boldsymbol{\alpha_v} + \bar{s}_{p,-g} + \epsilon_{p,i,g}, \tag{1}$$

where the dependent variable, $s_{p,i,g}$, is an indicator variable equal to 1 if player p makes shot i in game g, and the independent variable of interest, $s_{p,i-1,g}$ is an indicator variable for whether the same player made the previous shot in the same game. If α_s is positive and statistically significant, it provides evidence for the hot hand effect, and if α_s is negative and statistically significant, it not only provides evidence that a hot hand does not exist, but that making the previous shot actually decreases the probability of making the current shot.

We begin these analyses by estimating naive models using the lagged shot indicator as the only independent variable. It is plausible that this naive regression does not properly test for the hot hand, as consecutive shots are not likely identical. Thus, we add in additional controls in $\boldsymbol{v_{p,i,g}}$. For both free throws and field goals, we include controls for the game situation, including indicators for the 2013/2014 season, month, and day of the week of the game, and the shooting player being on the home team interacted with the crowd size. We also interact indicators for the quarter with the minutes remaining in the quarter and with the point differential before the field goal attempt or current set of free throws. We also include controls for player characteristics, including indicators for player age, experience, team, and position, and the player's height in inches and weight in pounds.

We additionally control for free throw or field goal characteristics. For free throws, we include an indicator for whether there was a substitution between free throws, the type of foul (personal foul, shooting foul, and one, vs. technical foul), and the free throw number in that set. For field goals, we control for the number of points the opposing team scored on their last possession, time remaining on the shot clock, the number of dribbles the player took and touch time prior to the shot, an indicator for if the shooting player also took his team's previous shot and the natural log of the time between the player's shots, shot distance (and its square), indicators for and the interaction between shot types and shot distance, and indicators for and the interaction between the angle of the shot to the rim and whether it was on the left side of the court. For field goals, we also control for defensive characteristics. We include indicators for the opposing team, defensive player's position, defensive player's age, and for a new defender covering the shooting player compared to the shooting player's previous shot. We also include defender distance from the shooting player (and its square), and the height and weight difference between the shooting and defensive player and their interactions with defender distance.

Finally, it is important that we control for a player's underlying probability of making a shot and Simpson's Paradox (Wardrop, 1995). To this end, we adapt the methodology employed by Chen et al. (2016) and control for the player's "leave-out" field goal or free throw percentage, denoted by $\bar{s}_{p,-g}$. We include two measures, the player's field goal or free throw percentage in the relevant season, excluding the current game, and a four week moving average of the player's field goal or free throw percentage, including two weeks on either side of the current game, again excluding the current game. One other strategy for controlling for player ability could be to replace the observable player characteristics with player fixed effects, which would control for all time-invariant player characteristics. Including fixed effects with a lagged dependent variable would bias our coefficients downward (Nickell, 1981; Arellano and Bond, 1991; Nerlove, 1967, 1971). However, this bias becomes small as the number of observations for each panel unit increases. The average number of free throws for each player is approximately 106, and the average number of field goals for each player is approximately 204, so any bias introduced here would likely be small. We show in Appendix Tables B1 to B5 that including fixed effects in our regressions instead of the leave-out field goal or free throw percentages does not meaningfully impact our results. In all shooting models, we cluster our standard errors at the shooting player level.

2.2.2 Changes in Behavior Following Made Field Goals

When examining field goals, we additionally examine whether making field goals induces changes in offensive and defensive behaviors. To this end, we estimate fixed effects panel data regression models as follows,

$$y_{p,i,g} = \beta_0 + \beta_s s_{p,i-1,g} + \boldsymbol{w_{p,i-1,g}}\boldsymbol{\beta_w} + \boldsymbol{x_{p,i,g}}\boldsymbol{\beta_x} + \psi_p + \epsilon_{p,i,g}, \tag{2}$$

where $y_{p,i,g}$ is a shot-related outcome for player p's shot i in game g. We examine shot-related outcomes for both offensive and defensive players. We create three variables measuring the confidence of offensive players: an indicator for whether the same player who took the previous shot takes the next shot, the time before taking the next shot, and the shot distance in feet. Relatedly, we create an indicator variable for whether the player has an assist in the next play to measure whether, if players are guarded more closely by the defense, they respond by passing to increasingly open teammates. We also create four variables measuring possible defensive adjustments: the distance from the shooter to the nearest defender in feet, whether or not a new defender covers the shooting player, whether the defending team substitutes a player in the next two minutes, and whether the defending team calls a timeout in the next two minutes.

The independent variable of interest is again, $s_{p,i-1,g}$, the indicator for player p making shot $i-1$ in the same game. The vector $\boldsymbol{w_{p,i-1,g}}$ includes controls for the game characteristics of the lagged shot (indicators for the 2013/2014 season, month, and day of the week of the game, the shooting player being on the home team interacted with the crowd size, and indicators for the quarter interacted with the minutes remaining in the quarter and with the point differential before the previous field goal attempt). The vector $\boldsymbol{x_{p,i,g}}$ includes additional controls relevant to the current outcome related to field goal attempt i. When the dependent variable is an indicator for whether the same player who took the previous shot takes the next shot, the time before taking the next shot, whether the player has an assist in the next play, whether the defending team substitutes a player in the next two minutes, and whether the defending team calls a timeout in the next two minutes, $\boldsymbol{x_{p,i,g}}$ additionally includes indicators for the opposing team. When the dependent variable is the shot distance for field goal attempt i, we additionally include controls for the opponent characteristics of field goal attempt i (indicators for opposing team, defensive player's position, defensive player's age, and for a new defender covering the shooting player compared to the shooting player's previous shot, defender distance from the shooting player in feet (and its square), and the height and weight difference between the shooting and defensive player and their interactions with defender distance). Finally, in the specifications where the dependent variable is the defender distance or an indicator for a new defender for field goal attempt i, we additionally control for the shot controls for field goal attempt i (the number of points the opposing team scored on their last possession, time remaining on the shot clock, the number of dribbles the player took and touch time prior to the shot, an indicator for if the shooting player also took his team's previous shot and the natural log of the time between the player's shots, shot distance (and its square), indicators for and the interaction between shot types and shot distance, and indicators for and the interaction between the angle of the shot to the rim and whether it was on the left side of the court). In all specifications, ψ_p represents player fixed effects for the player who took shot $i-1$, which account for time-invariant observable and unobservable differences across players, allowing us to examine changes *within* players *across* shots. Including fixed effects will not bias our coefficients here, as we do not have a lagged dependent variable. In all offensive and defensive response models, we cluster our standard errors at the shooting player level.

2.2.3 Extensions to Baseline Specifications

We extend our baseline specifications to broaden our analysis of the hot hand in the NBA. First, we examine the effects of made field goals separately by types of previous shot attempts. We hypothesize that 3-point field goals are much more salient to teams, and offenses and defenses are more likely to respond to 3-point field goals than 2-point field goals. To this end, we separate previous field goal attempts into four different shot types. We first split previous field goal attempts by whether they are 2-point or 3-point attempts. Then, to alleviate concerns that many 2-point attempts are very different than 3-point attempts, we also examine previous field goal attempts which are within two feet on either side of the 3-point line.[4]

Second, we expand on Bocskocsky et al. (2014) to analyze whether the difficulty of previous field goals affects the estimation of the hot hand. The intuition is that making a more difficult shot, like a long-range jump shot, is a stronger indication of shooting success than making an easier shot, like a layup. To this end, we additionally estimate specifications which include lagged time-varying controls in addition to our contemporaneous controls.

Finally, we expand our definition of previous shooting success to examine streaks of shooting success for both free throws and field goal attempts. While our analysis focuses on testing for independence between consecutive shots, success from previous shots further back in a shooter's history may impact the probability of making the current shot as well. To this end, we modify equation 1 as follows,

$$s_{p,i,g} = \gamma_0 + \sum_{j=-4}^{-1} \gamma_{sj} s_{p,i-j,g} + \sum_{j=-4}^{-1} \sum_{\substack{k=-4,\\ k>j}}^{-1} \gamma_{sjk} s_{p,i-j,g} \times s_{p,i-k,g} + \boldsymbol{v_{p,i,g}\gamma_v} + \bar{s}_{p,-g} + \epsilon_{p,i,g}. \quad (3)$$

Here, our independent variables of interest are the first through fourth lagged shot indicators and their interactions. We calculate linear combinations of the lagged shot coefficients to measure the additional impact that comes from making several shots consecutively. Thus, we can separately estimate the effect of one shot, two shot, three shot and four shot streaks on the probability of making the next shot.[5] Our strategy here follows from Chen et al. (2016)'s analysis of the gambler's fallacy, and to our knowledge, it has not been adopted to examine the hot hand hypothesis in basketball shooting. We show these results in Section 3.6.

2.3 Summary Statistics

The free throw data covers 114,227 free throws during the 2013-2014 and 2014-2015 NBA regular seasons. To be in our analysis, free throws cannot be a player's first free throw of a game, which removes 29,796 free throws. Thus, our final sample for the free throw analysis is 84,431 free throws.

[4]Additionally, offensive and defensive players may react differently to 3-point field goals that are close to the 3-point line compared to those further away from the basket. To examine these responses, we choose a subset of previous 3-point field goal attempts that are at least 26 feet from the basket. We discuss these results in footnote 13.

[5]For example, the effect of making two shots in a row is the sum of the coefficient on the indicator for making the previous shot, the twice lagged shot, and the interaction of the previous and twice lagged shot.

Table 1 shows summary statistics for our free throw sample.[6] Some of our results are previewed by the difference between free throw success following a made and a missed free throw. The percent of free throws made following a made free throw is approximately 78 percent but only 72 percent following a missed free throw.[7] Many of the other observable characteristics, however, are similar between a previously made and missed free throw.

The field goal data covers 409,742 field goals during the 2013-2014 and 2014-2015 NBA regular seasons. To be in our analysis, field goal attempts cannot be a player's first field goal attempt of the game, which removes 49,080 field goal attempts. We remove an additional 3,305 field goal attempts which do not have a named defender (including 21 field goal attempts corresponding to one defender which we cannot match to player characteristics). Finally, we drop 772 field goal attempts which have negative values for players' time touching the ball before shooting. Our final sample contains 356,585 field goal attempts over the two seasons.[8] Table 2 shows summary statistics for our field goal sample.[9] Of our sample of field goal attempts, about 46 percent came after that player made his previous field goal in the same game. Here again, the differences between field goals following a made and a missed field goal preview some of our main results. First, the field goal percentage following a made field goal is about 45 percent, lower than the field goal percentage after a missed field goal of 46 percent.[10] Following a made field goal, players shoot from nearly a foot farther away, take their next field goal about 20 seconds sooner, are five percentage points more likely to take the next field goal on their team, are slightly more likely to be guarded by a new defender, and the opposing team is about two percentage points more likely to substitute in the next two minutes and six percentage points more likely to call a timeout in the next two minutes.

A strength of our paper is the controls we bring to estimating both the free throw and field goal specifications. We include a wide variety of controls in our model and clearly demonstrate how these controls affect the estimation of the hot hand effect. Moreover, we do not limit our setting to a single team, single player, or single shooting event, but instead examine both free throws and field goals to comprehensively study the hot hand in basketball.

[6] Appendix Table A1 additionally displays the medians, minimum and maximum values of these variables.

[7] Since these are averages, the bias identified by Miller and Sanjurjo (2018) may affect these averages.

[8] Importantly, field goal attempts are not recorded if there is a shooting foul and the field goal attempt is missed. Field goal attempts are counted if there is a shooting foul and the shot is made.

[9] Appendix Table A2 additionally displays the medians, minimum and maximum values of these variables.

[10] Since these are averages, the bias identified by Miller and Sanjurjo (2018) may affect these averages.

Table 3 compares the control variables used in our free throw and field goals with the previous studies most similar to ours, Arkes (2010) for free throws, and Bocskocsky et al. (2014), and Rao (2009) for field goals. Table 3 shows that we add in several additional game controls not found in Arkes (2010) when estimating the hot hand for free throw shooting. For field goals, we are able to match all game and shot controls used in the other two studies, except an indicator for a "fast break." We additionally include many controls that the previous studies did not, including many controls for the game situation. Our data did not provide several of the defensive controls found in the other two papers, however, we were able to include several controls they did not, including defender fixed effects.

3 Results

3.1 The Hot Hand Hypothesis in Free Throws

We begin by examining free throws. Results from estimating equation 1 for our sample of free throws are shown in Table 4. The first six columns show regressions estimated over all free throws. We add in different levels of controls, culminating in the addition of the leave-out free throw percentages in Column (5) and lagged controls in Column (6). In Columns (7) to (9) we exclude the first free throw in any set, keeping the same levels of controls as in Column (6). Thus, we are only examining free throws immediately following another free throw by the same player to focus on the physiological aspects of repeated motions.

In Columns (1) to (3), making the previous free throw increases the probability of making the next free throw by about six percentage points. However, once we control for player characteristics in Column (4) the effect drops to four percentage points. Including the leave-out free throw percentages decreases the size of the effect to 1.6 percentage points, which illustrates the importance of accounting for Simpson's Paradox. Column (6) demonstrates that the hot hand effect is not meaningfully impacted by including lagged free throw controls. In Column (7), the effect size increases slightly from 1.6 to 2.0 percentage points, consistent with the hypothesis of physiological mechanisms leading to changes in the success of repeated motions. In Columns (8) and (9) we restrict our focus to players taking a small number and large number of free throws, similar to Arkes (2010). As in Arkes (2010), our aggregate free throw results are driven by players who take large numbers of free throws.[11]

3.2 Offensive and Defensive Adjustments to Field Goals

We next examine potential offensive and defensive adjustments to field goals. Table 5 shows results from these regressions. We examine four outcomes for offensive responses, whether the player that took the previous field goal attempt takes the next field goal attempt, the seconds before the player takes his next field goal attempt, the shot distance of the next field goal attempt, and whether the player who took the previous field goal attempt creates an assist on the next play. We examine four outcomes for defensive responses, the distance between the defender and the shooting player, whether a new defender guards the player on his next field goal attempt, whether the defending team substitutes a player in the next two minutes, and whether the defending team calls a timeout in the next two minutes.

Starting with offensive adjustments, if a player makes his previous field goal attempt, he is about five percentage points more likely to take the next field goal attempt on his team, the time before he takes his next field goal attempt decreases by about 20 seconds, and he takes his next field goal attempt nearly one foot further away from the basket. Additionally, a player is 0.9 percentage points more likely to make an assist on the next play. Combining this result with the increased probability of taking the next field goal attempt, a player is more likely to be involved in his team's next scoring attempt if he makes his previous field goal attempt. Defenses also react to made field goals. Defenders guard about 0.06 feet closer and defenses are almost three percentage points more likely to have a new defender after a field goal. Additionally, defenses are 2.7 percentage points more likely to make a substitution and six percentage points more likely to call a timeout in the next two minutes.[12]

Below the coefficients and standard errors, we report the means of the dependent variables to help put the coefficient sizes into context. Roughly translating our marginal effects into semi-elasticities, the size of the effects of field goals on the offensive adjustments are substantial. Players are about 25 percent more likely to take the next field goal attempt, decrease the time between

[11] In results not shown but available upon request, we re-estimated the models in Columns (7) - (9) for players who shot at least 200 free throws in a season. The results are very similar to the results in Columns (7) - (9).

[12] In results not shown but available upon request, we also estimate the effect for timeouts within the next five seconds. A field goal raises the probability that the opposing team calls a timeout in the next five seconds by two percentage points, and the coefficient is statistically significant at the 1% level.

their field goal attempts by about nine percent, and increase their shooting distance by about seven percent. The size of the defensive adjustments are smaller, although still notable. Defenders decrease their distance by about one percent and are four percent more likely to change defenders. Teams are about five percent more likely to make a substitution and 25 percent more likely to call a timeout.

3.3 The Hot Hand Hypothesis in Field Goals

Next, we examine the hot hand hypothesis for field goals in Table 6. As mentioned in Section 2.2, we begin our analysis of the hot hand with a pared back specification where we only include whether or not the player in question made his previous field goal attempt as the independent variable. As seen from the results in Table 5, this is unlikely to be an accurate test of the hot hand hypothesis. As both offenses and defenses make adjustments to field goals, omitting player, team, and game characteristics may lead to biased coefficients. Thus, moving from left to right, we add in additional controls to create a more apples-to-apples comparison between field goal attempts. In Columns (2) through (5), we sequentially add in controls for the game situation, player characteristics, opponent characteristics, and shot characteristics. In Column (6) we add controls for the player's leave-out field goal percentages, and in Column (7) we additionally replace time invariant defender and opponent controls with defender-level fixed effects. Finally, in Column (8) we additionally add in lagged shot characteristics to further control for the difficulty of the previous shot.

Across all of our estimates, we find a negative and statistically significant relationship between making the previous field goal attempt and making the next field goal attempt, however the magnitude of the effect differs based on the included controls. In Columns (1) through (4), we find fairly stable coefficients suggesting that making the previous field goal attempt decreases the probability of making the next field goal attempt by between 0.9 and 1.5 percentage points. Thus, we find that game situation, player and opponent controls are fairly orthogonal to the underlying relationship between making consecutive shots. However, we find that controlling for other offensive characteristics such as shot distance, whether the shooting player took the previous field goal attempt on the team, and the time between field goal attempts, weakens the effect of a previous field goal on the probability of making the current field goal attempt. Accounting for the player's shooting ability with controls for their leave-out field goal percentages and including defensive player fixed effects do not change the magnitude or statistical significance of our estimates. Finally, including lagged shot controls reduces the magnitude of the negative effect. Specifically, once these characteristics are accounted for, making the previous field goal attempt reduces the probability of making the current field attempt goal by 0.4 percentage points, or about one percent.

3.4 Heterogeneity by Previous Shot Type

To further examine the hot hand hypothesis and offensive and defensive adjustments to field goals and the negative effects of making a previous field goal on future shooting success, we examine the effects of field goals separately by previous shot types as described in Section 2.2.3. The results in Table 7 indicate that players respond more strongly to 3-point field goals. Players are more likely to take the next field goal attempt, decrease the time between field goal attempts, and increase shot distance after making a 3-point field goal compared to after making a 2-point field goal. The defensive results are somewhat more mixed. Defender distance decreases much more after a 3-point field goal than a 2-point field goal, although defenders are more likely switch after a 2-point field goal. Teams are more likely to substitute and call a time out in the two minutes after the opposing team makes a 3-point field goal.

To alleviate concerns that many 2-point shots are very different than 3-point shots, we also examine shots which are within two feet on either side of the 3-point line. Here again we see that offenses respond more strongly to 3-point shots. Players are about one percentage point more likely to take the next shot and increase the distance of their next field goal attempt by about half a foot more after a made 3-point shot than after a similar 2-point shot. Moreover, defender distance decreases by roughly 0.18 feet after a made 3-point shot while not statistically significantly changing after a made 2-point shot just inside the 3-point line, and defenses are more likely to assign a new defender or call a timeout in the following two minutes following a made 3-point shot.[13]

[13] In results not shown but available upon request, we compare offensive and defensive responses for 3-point shots taken at least 26 feet away from the basket. Comparing the estimated effects to those found for three point shots within two feet of the three point line we find no statistical difference in any of the defensive adjustments to a made three point shot at least 26 feet from the basket, with the exception that they are nearly twice as likely to make a substitution within two minutes of the made shot. However, relative to the responses shooters make to a made three point shot close to the three point line, when they make three point shots of at least 26 feet their subsequent shot is further from the basket, they take the shot approximately eight seconds sooner, and the increase in the probability they earn an assist on the next play is no longer statistically different than zero. The probability that a player takes their team's next shot is also two percentage points higher when their previously made shot was a longer three point shot relative to a three point shot closer to the three point line.

The stronger offensive and defensive adjustments to made 3-point shots affect the probability of making the next shot, as shown in Column 9 of Table 7. There is very little relationship between making a previous 2-point field goal attempt and the probability of making the next field goal attempt, but we find large, negative effects of a previously made 3-point field goal attempt on the probability of making the next field goal attempt. Furthermore, these results persist when examining 2-point shots close to the 3-point line and 3-point shots close to the 3-point line in Panels C. and D. The point estimate of the effect of a previous 2-point field goal close to the the 3-point line on the probability of making the next field goal attempt is very small and not statistically significant. However, a previous 3-point field goal near the 3-point line reduces the probability of making the next field goal attempt by about two percentage points, despite controlling for all of the offensive and defensive adjustments shown in Table 7.

3.5 Robustness Checks and Heterogeneity

To ensure the robustness of our estimates of the hot hand and examine any further heterogeneity in our findings, we examine a large number of robustness checks for both our free throw and field goal samples. For free throws, we impose additional restrictions on the four specifications found in Columns (5) through (8) of Table 4. We estimate these specifications separately for each of the following restrictions: home team only, away team only, excluding free throws from overtime, excluding free throws within the last two minutes of the game, excluding free throws with substitutions made in between them, using only free throws from shooting fouls, and using only free throws from personal fouls. Finally, we also include controls from the previous free throw in the last set of results, following our discussion in Section 2.2.3.[14] We show these results in Appendix Table A3 and briefly describe them here. Across the different sub samples, we find similar coefficient sizes and statistical significance levels as in the baseline results in Table 4 for player's taking over 100 free throws. For players taking less than 100 free throws our estimates remain statistically insignificant, partly due to limited sample sizes and partly due to a smaller hot hand effect, although magnitudes remain fairly consistent to those found in Table 4 across the different specifications.

Next, we impose several additional restrictions on the field goal sample. We estimate equations

[14]More specifically, we additionally control for the time-varying game and shot controls for the previous free throw.

1 and 2 separately for each of the following restrictions; home team only, away team only, shots within the same half, shots within the same quarter, no overtime shots, no shots within five seconds of each other, no shots within the last two minutes of the fourth quarter of the game, and shots only within two minutes of each other. We show these regression results in Appendix Table A4 and briefly describe them here. The effect of making the previous shot on the likelihood of that player taking their team's next shot and the following shot's distance from the rim are robust to the different sub samples, each with a few exceptions. Excluding shots within five seconds of each other increases the effect of making the previous shot increases the probability of taking the next shot by about eight percentage points, as many shots within five seconds of each other are rebounds. We find the distance of a player's shot increases to an even greater degree under the restrictions of only using shots within the same half, only shots within the same quarter and only shots within two minutes. Defenses also consistently adjust for made shots across the different sub samples. Across each sub sample we find that the negative effect that exists from prior field goal success on the probability of making the current field goal is relatively similar, and consistent with our results in Table 6.

We additionally re-estimate our results in Tables 4, 6, 7, 8 and 9 using player fixed effects instead of controlling for the leave-out free throw or field goal percentage. We display these results in Appendix B. In general, these results are very similar to our main results in terms of coefficient magnitude and statistical significance. In results available upon request, we demonstrate that our results for models with a dichotomous dependent variable are robust to a probit specification (Spector and Mazzeo, 1980). Calculated average marginal effects are nearly identical to the OLS coefficients and levels of statistical significance are nearly identical as well.

As our final robustness check, we estimate our results over single players to more closely mimic the experimental settings in Miller and Sanjurjo (2018) and Miller and Sanjurjo (2014). Our preferred specifications provide an average effect across all players, but our average effect may hide hot hands for certain players. To this end, we estimate our results for the ten starters for the 2014 NBA All Stars game, LeBron James, Paul George, Carmelo Anthony, Dwyane Wade, Kyrie Irving, Kevin Durant, Stephen Curry, James Harden, Blake Griffin and Kevin Love. We estimate the hot hand effect for each player in separate regressions using all game situation and free throw situation controls. We do not include player controls, because they are invariant when only examining one player at a time, and we additionally exclude the leave-out free throw and field goal percentages, since we no longer are concerned with differing shooting percentages across players. Appendix Table A5 shows results for free throws and field goals. We find little evidence to suggest that these players have a hot hand for either free throw or field goal shooting. Notably, the only statistically significant coefficients we find are negative, suggesting the past shooting success decreases the probability of making the next shot.

3.6 Streaks of Previous Success

Thus far, our analysis focuses on testing for independence between consecutive shots. Next, we expand our definition of previous shot success to include streaks of shots as described in Section 2.2.3. Tables 8 and 9 present estimates for the effect of making the previous shot, the previous two shots, the previous three shots, and finally making the previous four shots.[15] Comparing these estimates will show whether the effect of previous success on the current shot varies with the the length of consecutive previous successes.

Table 8 shows results estimating the effects of streaks in past free throw shooting on current free throw shooting success. Column (1) of Table 8 replicates the results from Column (6) of Table 4, and Columns (2) through (4) show estimates for players who took two, three, and four previous free throws within the same game.[16]

We find that when only including success in the previous two free throws that there is no significant difference in our estimate of the effect of making only the previous free throw. However, we find larger coefficients and stronger evidence of a free-throw hot hand when we examine the sub-samples of players taking at least three and four free throws in a game. For example, for players taking at least four free throws in a game, making the previous free throw increases the probability of making the next free throw by about 10 percentage points. The differences across the estimated effects of different numbers of consecutive successes, within each model, vary little in magnitude

[15] Specifically, we present linear combinations of the coefficients which represent the effect of making a specific number of consecutively made shots. For example, the effect of making the previous three shots in Column (3) of Tables 8 and 9 is calculated by $\gamma_{L1} + \gamma_{L2} + \gamma_{L3} + \gamma_{L1,L2} + \gamma_{L1,L3} + \gamma_{L2,L3} + \gamma_{L1,L2,L3}$, where γ_{L1}, γ_{L2}, and γ_{L3} refer to the coefficient of the indicator for making the first second and third lagged shots, respectively, and $\gamma_{L1,L2}$, $\gamma_{L1,L3}$, $\gamma_{L2,L3}$, and $\gamma_{L1,L2,L3}$ represent interactions. Point estimates for any combination of makes and misses in the previous four shots can be calculated, but are not presented.

[16] The specifications in Table 4, which identify off of free throws within the same set (Columns (7)-(9) in Table 4), do not allow us to identify how consecutive successes effect the probability of the current free throw. Thus, we cannot estimate these specifications in Table 8.

and none are different at standard statistically significant levels.[17]

In Table 9 we repeat the analysis for field goal attempts. Column (1) of Table 9 replicates the estimates from Table 6, Column (8), and the additional columns show the results from progressively adding in additional lags of previously made field goals and their interactions terms. We do not find statistically significant relationships between streaks of shots and the probability of making the next shot, although the majority of the coefficients remain negative and of similar magnitude to the coefficient in Column (1).[18]

4 Conclusion

We use detailed data on the universe of free throw shots and field goal attempts during the 2013-2014 and 2014-2015 NBA regular seasons to investigate the hot hand hypothesis. Free throws are a more controlled shooting environment, allowing a closer examination of the possible physiological mechanisms at play in repeated shot motions, but they are not the setting most relevant to answering the question originally posed in Gilovich et al. (1985). Rather, field goals are the setting that observers most often refer to when describing a player's shooting performance as "hot" or "streaky." However, it is more difficult to determine whether a player exhibits a hot hand in this situation because many factors may be different for two successive field goal attempts, including the characteristics of the game, shot, offense, and defense. Examining both free throws and field goal attempts together within the same players in the same games allows us to more directly compare the results of hot hand analyses in each setting.

We find consistent evidence of the existence of a hot hand effect in free throw shooting. Among all players and all free throws, if a player makes his previous free throw, he is about 1.6 percentage points more likely to make his next free throw. We find considerable heterogeneity in our results,

[17] A concern is how quickly our sample size falls due to many players not having the required number of free throws in a game, especially in Columns (3) and (4). The selection of players that may exist into these sub-samples may be a result of defenses' fouling behavior responding to the successes in prior free throw shooting or in offenses' behavior in getting the ball into the hands of players having free throw success. Our detailed game, player and season/moving average free throw shooting percentage controls should mitigate these concerns.

[18] One possibility is that the large number of controls added in for previous shot difficulty increases the standard errors of our estimates. In Appendix Tables A6 and A7 we re-estimate Tables A6 and 9 without including the lagged shot characteristics. While our results for free throws are very similar, we do find negative and statistically significant results for field goals. Specifically, the small negative effect of making a field goal on the probability of making the next field goal grows slightly in magnitude for longer streaks. These differences are not statistically significant, except for the difference between making the previous four shots and just making the previous shot in Column (4), which is statistically significant at the 10 percent level.

and the effect is concentrated in free throws taken within the same set of awarded free throws, in players who shoot a large number of free throws each season, and especially in games where a player shoots more free throws. Our free throw results are much smaller than previous studies, notably Arkes (2010). Among players taking at least 100 free throws per season, making the previous free throw in a set results in a two percentage point increase in the probability of making the next free throw in that set. In contrast, Arkes (2010) suggests the effect size is roughly a five percentage point increase among players making at least 200 free throws in a season. These results demonstrate the important role that omitted variable bias plays, even in a fairly controlled setting like free throw shooting. Additionally, the size of our hot hand effect for all players and free throws is much smaller than effects from experimental studies. For example, Miller and Sanjurjo (2018) reevaluate the controlled shooting experiment in Gilovich et al. (1985) and find that a player who has made three shots in a row is 13 percentage points more likely to make his or her next shot than if the player missed three shots in a row. However, we find that the effect of making the previous free throw grows in magnitude to 10 percentage points, approaching the results in recent experimental settings, when we examine players who shoot at least five free throws in a game.

In stark contrast to free throws, we find that if a player makes a field goal, he is about 0.7 percentage points less likely to make his next field goal attempt. Additionally, we show that introducing controls for the game situation and difficulty of the current and previous shots does not produce a hot hand effect, as previous research suggests (Bocskocsky et al., 2014). Moreover, this effect is concentrated in players who have made streaks of previous field goal attempts and in players who just made 3-point field goals, compared to players who just make long 2-point field goals. However, both offenses and defenses respond to made field goals as if the hot hand effect exists. Following a made shot, players are more likely to make an assist on their team's next made shot, take their team's next shot, and take that shot quicker and from a further distance. Defenses are more likely to take a time out, make a substitution, assign a new defender to that player, and defend that player closer. We find these responses are much stronger when the previous field goal is just outside the 3-point line compared to just inside the 3-point line. Put together, our results reinforce the suggestion that, while the physiological mechanisms behind repeated shot success found in experimental settings do exist in game situations, they are easily overwhelmed by other factors.

Recent hot hand research has focused on experimental settings due to their ability to remove external factors (see Miller and Sanjurjo (2014) for more on the argument that controlled shooting experiments are preferred to in-game data). However, the original question posed by Gilovich et al. (1985) was whether observers' perceptions of shooting success *in game situations* is correct. Thus, although controlled experiments can uncover whether a physiological mechanism for repeated shot success, controlled experiments cannot directly speak to perceptions regarding in game performance. While omitted variable bias is always a concern in applied microeconomics, we take a number of steps to minimize potential omitted variable bias. As shown in Table 3, we include a larger set of controls than in previous studies. Additionally, while our results show the importance of controls in both free throw and field goal settings, many of our results are fairly stable when adding additional controls. For example, in Table 6 our results are consistent once controlling for shooting player behaviors. Additional controls for individual shooting ability, shot controls, defensive player controls, and even defensive player fixed effects do not markedly change our results.

To further examine omitted variable bias, we follow a method outlined in Oster (2019) to create a bounding set for what the true effect of making the previous shot on current shot success for both free throws and field goals. For free throws, we find that the bounded set for the effect of making the previous free throw on the probability of making the current free throw using the regression found in Column (9) of Table 4 is $[0.007; 0.022]$, which suggests that unobservable variables may be biasing our estimated hot hand effect for free thows downward. For field goals, the bounded set for the effect of making the previous field goal attempt on the current probability of making the next field goal attempt using the regression found in Column (8) of Table 6 is $[-.004; .001]$.[19] Thus, it is unlikely that unobservable variables are masking a true positive hot hand effect and biasing our field goal coefficients so strongly as to become negative and statistically significant. Furthermore, we find that the estimate would still be negative as long as the unobservables were 75% as important as the observables we included in the regression. The extensive set of controls we are able to include in our regression alleviate concerns that there are unobservables which would be able to explain 75% of what our observables can. Thus, we believe that omitted variable bias is unlikely to explain why our results differ from those in controlled shooting experiments.

[19] For both free throws and field goal attempts, we use the method for the selection of R_{Max} suggested by Oster (2019) which uses the R^2 found from the controlled model multiplied by 1.3.

One further potential issue is whether our analyses have enough statistical power to detect a hot hand effect under different potential data generating processes (DGPs). To further examine this issue, we conduct simulations described in Appendix C. We adapt DGPs from Wetzels et al. (2016) and Stone (2012), and the results of these exercises suggest that our models have sufficient power to detect hot hand effects, should they exist in the true data generating process.

Another concern is measurement error in our dependent and independent variables. As previous research points out, making a shot is a noisy indicator of changes in the underlying probability that a player makes a shot (e.g. Stone, 2012; Arkes, 2013). This measurement error may affect both our dependent variable, whether a player makes his current free throw attempt or field goal attempt, and also our independent variable of interest, whether a player made his previous free throw attempt(s) or field goal attempt(s). We take a number of steps to reduce this possible measurement error. First, we include a number of controls for game, player and shot characteristics to control for the difficulty of making a player's current shot, and we additionally control for the characteristics of a player's previous shot. We also examine streaks of made shots in Table 8 and 9 to examine different measures of previous shot success. We find that our findings of a positive correlation between free throw success and a negative correlation between field goals persists, although the correlations are not statistically significant once we add controls for lagged shot characteristics. Additionally, if making the current shot is a noisy but unbiased measure of the underlying probability of making a shot, our coefficients will be unbiased but our standard errors will likely increase. If making the previous shot is a noisy but unbiased measure of the player's previous shooting performance, this will generate attenuation bias and our coefficients will be biased towards zero. Since the coefficients in our main results in Tables 4, 5 and 6 are statistically significant, this indicates that neither classical measurement error nor attenuation bias are driving our results.

It is unclear how analyses of the hot hand should control for shot difficulty or examine the underlying probability of making a shot versus the observed outcome of a made or missed shot. The original question posed by Gilovich et al. (1985) is whether the widespread belief in the hot hand among players, coaches, announcers and fans is correct. Answering this question necessitates a correct interpretation of what these beliefs are. It is unclear to what extent players, coaches, announcers and fans "control" for external factors when evaluating the hot hand effect in game situations and whether players, coaches, announcers and fans evaluate the probability of making a shot versus the observed outcome of whether a shot is made. In this paper, we have focused on observable outcomes, as we believe this is the most relevant for examining perceptions regarding the hot hand.

An important question is where this leaves the original hypothesis in Gilovich et al. (1985). Our results suggest that the original hypothesis posed by Gilovich et al. (1985) is largely correct for field goals, but not for free throws. Our findings support the hypothesis of a hot hand existing due to muscle memory of repeated physical movements in free throw shooting. But this muscle memory appears to dissipate quickly, as evidenced by the hot hand effect in free throws being driven by repeated free throws in a set and by players who take more free throws in a game. Given the size of the hot hand effect, a two percentage point increase in the probability of making the next free throw, it is unclear whether casual fans can discern an effect of this magnitude. But we also find that the size of the hot hand effect grows for players taking more free throws in a game, and it is plausible that observers may be able to discern a 10 percentage point increase in the probability of making the next free throw. However, we do not find a hot hand in the most important setting, the run of play. In fact, we find that current shot success is negatively correlated with future shot success. Thus, our results suggest that the widespread belief in the hot hand in the run of play is incorrect, supporting the original hypothesis in Gilovich et al. (1985).

We believe that our paper calls for more work connecting results from controlled settings to the run of play and for connecting spectators' beliefs with shooting success. For example, controlled experiments could be conducted which more closely mimic the run of play, varying the time in between shooting attempts the types of shots, adding in defenders. While some experiments have been conducted along these lines (e.g. Miller and Sanjurjo, 2018), we believe more work is called for in this area to further examine the conditions under which the hot hand effect emerges.

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Table 1: Summary Statistics for Free Throw Sample

Variable	All Free Throws		Made Prev. Free Throws		Missed Prev. Free Throws	
	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev
Made Prev. Free Throw (Y/N)	0.750	0.433				
Free Throw Made (Y/N)	0.766	0.423	0.781	0.414	0.721	0.448
Sub. Before Free Throw (Y/N)	0.249	0.432	0.247	0.431	0.254	0.435
Personal Foul Free Throw (Y/N)	0.147	0.354	0.150	0.357	0.136	0.343
Shooting Foul Free Throw (Y/N)	0.634	0.482	0.629	0.483	0.648	0.478
Free Throw Number	1.620	0.513	1.609	0.519	1.654	0.493
And One Free Throw (Y/N)	0.057	0.231	0.058	0.233	0.054	0.227
N	84,426		63,356		21,070	

Notes: Data from `http://www.bigdataball.com`, `http://www.nbasavant.com`, and `http://www.basketball-reference.com` for the 2013-2014 and 2014-2015 regular seasons.

Table 2: Summary Statistics for Field Goals Sample

	All Shots		Made Prev. FG		Missed Prev. FG	
Variable	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev
Made Prev. FG Att. (Y/N)	0.459	0.498				
Made FG Attempt (Y/N)	0.454	0.498	0.449	0.497	0.458	0.498
Shot Distance (Ft.)	12.760	9.939	13.142	9.860	12.435	9.993
Defender Distance (Ft.)	4.145	2.760	4.173	2.699	4.121	2.811
Time b/t FG Att. (Sec.)	222.543	292.162	211.091	277.436	232.276	303.778
Player Took Prev. FG Att. (Y/N)	0.213	0.409	0.240	0.427	0.190	0.392
Assist on Next Shot	0.051	0.220	0.055	0.228	0.047	0.212
New Defender (Y/N)	0.728	0.445	0.736	0.441	0.721	0.448
Sub w/in Two Min	0.505	0.500	0.519	0.500	0.494	0.500
Timeout w/in Two Min	0.235	0.424	0.268	0.443	0.207	0.405
Shot Clock (Sec.)	11.884	6.320	11.810	6.149	11.947	6.461
Dribbles	2.019	3.491	2.063	3.556	1.982	3.436
Touch Time (Sec.)	2.733	2.983	2.796	3.031	2.679	2.940
N	356,585		163,817		192,768	

Notes: Data from http://www.bigdataball.com, http://www.nbasavant.com, and http://www.basketball-reference.com for the 2013-2014 and 2014-2015 regular seasons.

Table 3: Comparison of Controls by Type

Panel A. Free Throws

Control Type	Control	Arkes (2010)	Our Paper
Game	Day and Month Indicators	-	X
Game	Home Team, Attendance, Attendance × Home Team	-	X
Game	Opposing Team Indicator	-	X
Game	Quarter	X	X
Game	Minutes Remaining	-	X
Game	Minutes Remaining × Quarter	-	X
Game	Point Gap	-	X
Game	Point Gap × Home Team	-	X
Game	Time Variant Player Controls$^\flat$	-	X
Game	Foul Type Indicators	-	X
Game	Sub. Before Free Throw	-	X
Game	# of FT in last set	X	-
Game	# of FT Made in Last Set	X	-
Game	Controls for FT% (Excluding Current Game)	-	X
	Player Fixed Effects	X	X*

Panel B. Field Goals in the Run of Play

Control Type	Control	Bocskocsky et al. (2014)	Rao (2009)	Our Paper
Game	Quarter	X	-	X
Game	Point Gap	X	-	X
Game	Point Gap × Quarter	X	-	X
Game	Minutes Remaining	-	X	X
Game	Day and Month Indicators	-	-	X
Game	Home Team , Attendance, Attendance × Home Team	-	-	X
Game	Opposing Team Indicator	-	-	X
Game	Minutes remaining × Quarter	-	-	X
Game	Point Gap × Home Team	-	-	X
Game	Time Variant Player Controls$^\flat$	-	-	X
Game	Took Previous Shot	-	-	X
Game	Time in Between Shots	-	-	X
Game	Opposing Team's Points on Previous Possession	-	-	X
Shot	Fast Break	X	-	-
Shot	Shot Type Indicators	X	X††	X
Shot	Shot Distance × Shot Types	X†	-	X
Shot	Shot Clock	-	X	X
Shot	Shot Distance, Shot Distance Squared	X†	X‡	X
Shot	# of Dribbles, Touch Time	-	-	X
Shot	Shot Angle, Side of Court, Shot Angle × Side of Court	-	-	X
Defensive	Angle of Closest Defender	X	-	-
Defensive	Defender Distance × Defender Angle	X	-	-
Defensive	Double Team	X	X	-
Defensive	Fouled	-	X	-
Defensive	Defended, and Defended Shot Type Indicators	-	X	-
Defensive	Forced Shot Indicator	-	X	-
Defensive	Height and Weight Difference with Defender	X	-	X
Defensive	Defender Distance × Height Difference	X	-	X
Defensive	Defender Distance, Distance Squared	X†	-	X
Defensive	New Defender	-	-	X
Defensive	Defender's Position, Defender's Age	-	-	X
Defensive	Defender Fixed Effects	-	-	X
	Controls for FG% (Excluding Current Game)	-	-	X
	Player Fixed Effects	X	RE	X*

$^\flat$-See Section 2.2 for a list of the player controls we include.
†-Uses dummies for all 2x2 locations on the court instead of distance.
‡-Does not include the squared term of the variable indicated.
††-Includes only if a turnaround shot.
*-Includes player's season shooting percentage excluding the current game's shots. Also robustness checks using player fixed effects.

Table 4: Effects of Making Previous Free Throw on Probability of Making Next Free Throw

	All Free Throws & All Players						Only 2nd and 3rd Free Throws		
	(1)	(2)	(3)	(4)	(5)	(6)	All Players	Players Taking <100 FTs	Players Taking ≥100 FTs
Made Prev. Free Throw (Y/N)	0.060***	0.059***	0.060***	0.040***	0.016***	0.016***	0.020***	0.013	0.022***
	(0.008)	(0.008)	(0.008)	(0.004)	(0.003)	(0.003)	(0.004)	(0.009)	(0.005)
Sub. Before Free Throw (Y/N)			-0.005*	-0.005	-0.005	-0.004	-0.008**	-0.003	-0.009**
			(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.008)	(0.004)
Personal Foul Free Throw (Y/N)			0.010*	0.005	-0.001	0.000	-0.005	0.015	-0.016
			(0.006)	(0.005)	(0.005)	(0.007)	(0.057)	(0.014)	(0.061)
Shooting Foul Free Throw (Y/N)			-0.005	-0.003	-0.004	0.001	-0.071	-0.170	-0.028
			(0.005)	(0.004)	(0.004)	(0.005)	(0.110)	(0.210)	(0.128)
Free Throw Number			0.034***	0.033***	0.035***	0.024***	0.830***	0.039**	0.790***
			(0.004)	(0.003)	(0.003)	(0.005)	(0.070)	(0.019)	(0.081)
And One Free Throw (Y/N)			0.001	0.001	-0.000	-0.001			
			(0.007)	(0.007)	(0.007)	(0.007)			
Dep. Var. Mean	0.766	0.766	0.766	0.766	0.766	0.766	0.777	0.740	0.792
Adjusted R-Squared	0.004	0.004	0.006	0.025	0.047	0.047	0.049	0.039	0.050
N	84,431	84,431	84,426	84,426	83,800	83,797	50,717	13,933	36,784
Game Controls		X	X	X	X	X	X	X	X
Player Controls				X	X†	X†	X†	X†	X†
Leave-Out FT%					X	X	X	X	X
Lag Controls						X	X	X	X

Notes: Data from `http://www.bigdataball.com`, `http://www.nbasavant.com`, and `http://www.basketball-reference.com` for the 2013-2014 and 2014-2015 regular seasons. The dependent variable is an indicator equal to one for a made free throw and zero for a missed free throw. Standard errors, clustered by player, are in parentheses. Game controls include indicators for the 2013/2014 season, month, and day of the week of the game, the shooting player being on the home team interacted with the crowd size, indicators for the quarter interacted with the minutes remaining in the quarter and with the point differential before the current set of free throws. Player controls include indicators for player age, experience, team, and position, and the player's height in inches and weight in pounds. FT% (Excluding Current Game) controls include the player's free throw percentage in the relevant season, excluding the current game, and a four week moving average of the player's free throw percentage, including two weeks on either side of the current game, again excluding the current game. Lagged controls include all time-varying controls for the previous free throw. Stars denote statistical significance levels: *: 10%, **: 5%, and ***: 1%.

Table 5: Offensive and Defensive Adjustments to Field Goals

	Offensive Adjustments				Defensive Adjustments			
	Take Next Field Goal Attempt	Time b/t Field Goal Attempts	Shot Distance	Assist on Next Play	Defender Distance	New Defender	Sub w/in Two Mins.	Time Out w/in Two Mins.
Made Prev. FG Att. (Y/N)	0.054***	-20.842***	0.951***	0.009***	-0.061***	0.028***	0.027***	0.061***
	(0.004)	(1.512)	(0.037)	(0.001)	(0.009)	(0.002)	(0.002)	(0.002)
Dep. Var. Mean	0.211	222.543	12.760	0.051	4.145	0.728	0.505	0.235
Adjusted R-Squared	0.014	0.053	0.322	0.001	0.279	0.027	0.090	0.027
N	356,585	356,585	356,585	356,585	356,585	356,585	356,585	356,585

Notes: Data from `http://www.bigdataball.com`, `http://www.nbasavant.com`, and `http://www.basketball-reference.com` for the 2013-2014 and 2014-2015 regular seasons. The dependent variable is given by the column title, and standard errors, clustered by player, are in parentheses. All models control for the game characteristics of the previous field goal attempt, including indicators for the 2013/2014 season, month, and day of the week of the game, the shooting player being on the home team interacted with the crowd size, and indicators for the quarter interacted with the minutes remaining in the quarter and with the point differential before the previous field goal attempt. The Take the Next Field Goal Attempt, Time b/t Field Goal Attempts, Assist on Next Play, Sub w/in Two Mins. and Time Out w/in Two Mins. specifications additionally include indicators for the opposing team. The Shot Distance specification additionally includes controls for the opponent characteristics of the current field goal attempt (indicators for opposing team, defensive player's position, defensive player's age, and for a new defender covering the shooting player compared to the shooting player's previous shot, defender distance from the shooting player in feet (and its square), and the height and weight difference between the shooting and defensive player and their interactions with defender distance). The Defender Distance and New Defender specifications additionally control for the shot controls of the current field goal attempt (the number of points the opposing team scored on their last possession, time remaining on the shot clock, the number of dribbles the player took and touch time prior to the shot, an indicator for if the shooting player also took his team's previous shot and the natural log of the time between the player's shots, shot distance (and its square), indicators for and the interaction between shot types and shot distance, and indicators for and the interaction between the angle of the shot to the rim and whether it was on the left side of the court). Stars denote statistical significance levels: *: 10%, **: 5%, and ***: 1%.

Table 6: Effects of a Previous Field Goal on Probability of Making Next Field Goal Attempt

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Made Prev. FG Att. (Y/N)	-0.009***	-0.010***	-0.015***	-0.015***	-0.006***	-0.007***	-0.007***	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dep. Var. Mean	0.454	0.454	0.454	0.454	0.454	0.454	0.454	0.453
Adjusted R-Squared	0.000	0.001	0.007	0.008	0.137	0.137	0.137	0.139
N	356,585	356,585	356,585	356,585	356,585	356,277	356,277	310,635
Game Controls		X	X	X	X	X	X	X
Player Controls			X	X	X	X	X	X
Opponent Controls				X	X	X	X‡	X‡
Shot Controls					X	X	X	X
Leave-Out FG%						X	X	X
Def. Player FE							X	X
Lag Controls								X

Notes: Data from `http://www.bigdataball.com`, `http://www.nbasavant.com`, and `http://www.basketball-reference.com` for the 2013-2014 and 2014-2015 regular seasons. The dependent variable is an indicator equal to one for a made field goal attempt and zero for a missed field goal attempt. Standard errors, clustered by player, are in parentheses. Game controls include indicators for the 2013/2014 season, month, and day of the week of the game, the shooting player being on the home team interacted with the crowd size, and indicators for the quarter interacted with the minutes remaining in the quarter and with the point differential before the current field goal attempt. Player controls include indicators for player age, experience, team, and position, and the player's height in inches and weight in pounds. Opponent controls include indicators for opposing team, defensive player's position, defensive player's age, and for a new defender covering the shooting player compared to the shooting player's previous shot, defender distance from the shooting player in feet (and its square), and the height and weight difference between the shooting and defensive player and their interactions with defender distance. Shot controls include the number of points the opposing team scored on their last possession, time remaining on the shot clock, the number of dribbles the player took and touch time prior to the shot, an indicator for if the shooting player also took his team's previous shot and the natural log of the time between the player's shots, shot distance (and its square), indicators for and the interaction between shot types and shot distance, and indicators for and the interaction between the angle of the shot to the rim and whether it was on the left side of the court. FG% (Excluding Current Game) controls include the player's field goal percentage in the relevant season, excluding the current game, and a four week moving average of the player's field goal percentage, including two weeks on either side of the current game, again excluding the current game. Lagged shot controls include all time-varying controls for the previous shot except for lagged defender fixed effects. Stars denote statistical significance levels: *: 10%, **: 5%, and ***: 1%. ‡ When including defensive player fixed effects we do not include any time-invariant player characteristics for the defensive player (e.g. position).

Table 7: Offensive and Defensive Adjustments to Field Goals by Previous Shot Type

	Offensive Adjustments				Defensive Adjustments				
	Take Next Field Goal Attempt	Time b/t Field Goal Attempts	Shot Distance	Assist Next Play	Defender Distance	New Defender	Sub w/in Two Mins.	Time Out w/in Two Mins.	Prob. Make Next Shot
A. Prev. 2-Point Shots (N=264,440)									
Made Prev. FG Att. (Y/N)	0.046***	-14.068***	0.670***	0.011***	-0.019*	0.031***	0.023***	0.055***	0.001
	(0.004)	(1.571)	(0.040)	(0.001)	(0.010)	(0.002)	(0.002)	(0.002)	(0.002)
Dep. Var. Mean	0.216	218.209	11.870	0.049	4.017	0.727	0.504	0.233	0.460
Adjusted R-Squared	0.012	0.049	0.317	0.001	0.291	0.027	0.095	0.027	0.145
B. Prev. 3-Point. Shots (N= 92,145)									
Made Prev. FG Att. (Y/N)	0.076***	-38.039***	1.757***	0.007***	-0.178***	0.012***	0.035***	0.081***	-0.018***
	(0.005)	(2.374)	(0.080)	(0.002)	(0.017)	(0.003)	(0.003)	(0.003)	(0.004)
Dep. Var. Mean	0.197	234.981	15.314	0.055	4.511	0.733	0.510	0.241	0.432
Adjusted R-Squared	0.020	0.067	0.343	0.001	0.258	0.031	0.075	0.030	0.122
C. Prev. 2-Point Shots Close to 3-Point Line (N= 5,131)									
Made Prev. FG Att. (Y/N)	0.062***	-34.119***	1.257***	0.004	-0.000	0.005	0.051***	0.039***	-0.002
	(0.011)	(8.035)	(0.215)	(0.007)	(0.073)	(0.013)	(0.014)	(0.013)	(0.017)
Dep. Var. Mean	0.195	225.987	14.833	0.059	4.444	0.700	0.479	0.206	0.431
Adjusted R-Squared	0.012	0.049	0.343	0.006	0.268	0.040	0.084	0.024	0.130
D. Prev. 3-Point Shots Close to 3-Point Line (N= 64,557)									
Made Prev. FG Att. (Y/N)	0.072***	-37.352***	1.704***	0.005***	-0.180***	0.013***	0.025***	0.079***	-0.019***
	(0.005)	(2.780)	(0.081)	(0.002)	(0.021)	(0.004)	(0.004)	(0.004)	(0.004)
Dep. Var. Mean	0.195	238.576	15.219	0.055	4.529	0.734	0.517	0.246	0.433
Adjusted R-Squared	0.018	0.066	0.348	0.001	0.264	0.031	0.082	0.028	0.119

Notes: Data from `http://www.bigdataball.com`, `http://www.nbasavant.com`, and `http://www.basketball-reference.com` for the 2013-2014 and 2014-2015 regular seasons. The dependent variable is given by the column title, and standard errors, clustered by player, are in parentheses. Columns (1) - (8) use the same specifications as Table 5, while Column (9) uses the specification from Column (8) of Table 6. Stars denote statistical significance levels: *: 10%, **: 5%, and ***: 1%.

Table 8: Effects of Making Consecutive Free Throws on Probability of Making Next Free Throw

	(1)	(2)	(3)	(4)
Made Prev. FT (Y/N)	0.016***	0.019**	0.039***	0.103***
	(0.003)	(0.008)	(0.014)	(0.032)
Made Prev. Two FTs (Y/N)		0.041***	0.065***	0.095***
		(0.007)	(0.013)	(0.032)
Made Prev. Three FTs (Y/N)			0.053***	0.073**
			(0.012)	(0.031)
Made Prev. Four FTs (Y/N)				0.069**
				(0.031)
Dep. Var. Mean	0.766	0.766	0.772	0.771
Adjusted R-Squared	0.047	0.049	0.050	0.053
N	83,797	57,050	40,925	27,442

Notes: Data from `http://www.bigdataball.com`, `http://www.nbasavant.com`, and `http://www.basketball-reference.com` for the 2013-2014 and 2014-2015 regular seasons. The dependent variable is an indicator equal to one for a made free throw and zero for a missed free throw, and standard errors are clustered at the player level. The independent variables of interest are indicators for whether or not a player made the lagged, twice lagged, third lagged and fourth lagged free throw, as well as all the possible interactions between these indicators. We create linear combinations of the relevant coefficients to calculate the effect of only making the previous free throw, only the previous two free throws, only the previous three free throws and making all of the previous four free throws. The controls included are the same as in Column (5) in Table 4, with the addition of time-varying controls for the relevant lagged free throws. Stars denote statistical significance levels: *: 10%, **: 5%, and ***: 1%.

Table 9: Effects of Consecutive Field Goals on Probability of Making Next Field Goal Attempt Controlling for Previous Shot Characteristics

	(1)	(2)	(3)	(4)
Made Prev. FG (Y/N)	-0.004**	-0.003	-0.001	-0.006
	(0.002)	(0.003)	(0.004)	(0.006)
Made Prev. Two FGs (Y/N)		-0.001	0.002	-0.001
		(0.003)	(0.004)	(0.006)
Made Prev. Three FGs (Y/N)			-0.002	-0.002
			(0.004)	(0.006)
Made Prev. Four FGs (Y/N)				-0.004
				(0.007)
Dep. Var. Mean	0.453	0.452	0.451	0.451
Adjusted R-Squared	0.139	0.139	0.140	0.140
N	310,635	268,192	229,238	193,921

Notes: Data from `http://www.bigdataball.com`, `http://www.nbasavant.com`, and `http://www.basketball-reference.com` for the 2013-2014 and 2014-2015 regular seasons. The dependent variable is an indicator equal to one for a made field goal attempt and zero for a missed field goal attempt, and standard errors are clustered at the player level. The independent variables of interest are indicators for whether or not a player made the lagged, twice lagged, third lagged and fourth lagged field goal attempts, as well as all the possible interactions between these indicators. We create linear combinations of the relevant coefficients to calculate the effect of only making the previous field goal attempt, only the previous two field goal attempts, only the previous three field goal attempts and making all of the previous four field goal attempts. The controls included are the same as in Column (7) of Table 6, with the addition of time-varying controls for the relevant lagged shots. Stars denote statistical significance levels: *: 10%, **: 5%, and ***: 1%.

Appendices

A Appendix Tables

Table A1: Additional Summary Statistics for Free Throw Sample

Variable	Mean	Min	Median	Max
Made Prev. Free Throw (Y/N)	0.750	0.000	1.000	1.000
Free Throw Made (Y/N)	0.766	0.000	1.000	1.000
Sub. Before Free Throw (Y/N)	0.249	0.000	0.000	1.000
Personal Foul Free Throw (Y/N)	0.147	0.000	0.000	1.000
Shooting Foul Free Throw (Y/N)	0.634	0.000	1.000	1.000
Free Throw Number	1.620	1.000	2.000	3.000
And One Free Throw (Y/N)	0.057	0.000	0.000	1.000
N	84,426			

Notes: Data from `http://www.bigdataball.com`, `http://www.nbasavant.com`, and `http://www.basketball-reference.com` for the 2013-2014 and 2014-2015 regular seasons.

Table A2: Additional Summary Statistics for Field Goal Sample

Variable	Mean	Min	Median	Max
Made Prev. FG Att. (Y/N)	0.459	0.000	0.000	1.000
Made FG Attempt (Y/N)	0.454	0.000	0.000	1.000
Shot Distance (Ft.)	12.760	0.000	13.000	87.000
Defender Distance (Ft.)	4.145	0.000	3.700	70.700
Time b/t FG Att. (Sec.)	222.543	0.000	110.000	3084.000
Player Took Prev. FG Att. (Y/N)	0.213	0.000	0.000	1.000
Assist on Next Shot	0.051	0.000	0.000	1.000
New Defender (Y/N)	0.728	0.000	1.000	1.000
Sub w/in Two Min	0.505	0.000	1.000	1.000
Timeout w/in Two Min	0.235	0.000	0.000	1.000
Shot Clock (Sec.)	11.884	0.000	12.000	24.000
Dribbles	2.019	0.000	1.000	34.000
Touch Time (Sec.)	2.733	0.000	1.600	24.900
N	356,585			

Notes: Data from `http://www.bigdataball.com`, `http://www.nbasavant.com`, and `http://www.basketball-reference.com` for the 2013-2014 and 2014-2015 regular seasons.

Table A3: Robustness Checks: Free Throws

	All Free Throws & All Players	Only 2nd and 3rd Free Throws: All Players	Only 2nd and 3rd Free Throws: Players Taking <100 FTs	Only 2nd and 3rd Free Throws: Players Taking ≥100 FTs
Home Team Only	0.016***	0.021***	0.015	0.022***
	(0.005)	(0.006)	(0.013)	(0.007)
	[0.768]	[0.778]	[0.737]	[0.793]
	N=42,888	N=25,867	N=7,033	N=18,834
Away Team Only	0.014***	0.018***	0.010	0.022***
	(0.005)	(0.006)	(0.012)	(0.007)
	[0.764]	[0.777]	[0.744]	[0.790]
	N=40,909	N=24,850	N=6,900	N=17,950
No Overtime Free Throws	0.017***	0.021***	0.014	0.023***
	(0.003)	(0.004)	(0.009)	(0.005)
	[0.766]	[0.777]	[0.740]	[0.791]
	N=82,638	N=50,122	N=13,812	N=36,310
No Last 2 Minutes of End of Game	0.016***	0.018***	0.008	0.020***
	(0.004)	(0.005)	(0.009)	(0.005)
	[0.765]	[0.775]	[0.739]	[0.790]
	N=74,622	N=46,087	N=13,273	N=33,576
No Sub. Between Free Throws	0.019***	0.021***	0.016	0.023***
	(0.005)	(0.005)	(0.011)	(0.006)
	[0.770]	[0.781]	[0.744]	[0.795]
	N=49,115	N=33,243	N=9,184	N=24,059
Shooting Fouls Only	0.015***	0.019***	0.008	0.022***
	(0.004)	(0.006)	(0.010)	(0.007)
	[0.763]	[0.776]	[0.738]	[0.790]
	N=53,137	N=32,988	N=9,106	N=23,882
Personal Fouls Only	0.011	0.021*	0.012	0.021*
	(0.009)	(0.012)	(0.025)	(0.013)
	[0.781]	[0.790]	[0.759]	[0.800]
	N=12,254	N=7,469	N=1,900	N=5,569

Notes: Data from `http://www.bigdataball.com`, `http://www.nbasavant.com`, and `http://www.basketball-reference.com` for the 2013-2014 and 2014-2015 regular seasons. The dependent variable is an indicator equal to one for a made free throw and zero for a missed free throw. Each cell represents the estimate for the effect of a previously made free throw on the probability of making the current free thow under the restrictions denoted by the row and column headings. Standard errors clustered at the player level are shown in parentheses and dependent variable means are shown in brackets. The controls included are the same as in Columns (5) through (8) in Table 4, except for the last row of results which additionally includes time-varying game and shot controls for the previous free throw. Stars denote statistical significance levels: *: 10%, **: 5%, and ***: 1%.

Table A4: Robustness Checks: Field Goals

	Offensive Adjustments				Defensive Adjustments				
	Take Next Shot	Time b/t Shots	Shot Distance	Assist Next Play	Defender Distance	New Defender	Sub w/in Two Mins.	Time Out w/in Two Mins.	Prob. Make Next Shot
Home Team Only (N=178,030)	0.054***	-19.092***	0.924***	0.010***	-0.050***	0.031***	0.027***	0.064***	-0.003
	(0.004)	(1.822)	(0.045)	(0.001)	(0.012)	(0.002)	(0.002)	(0.002)	(0.003)
	[0.212]	[222.866]	[12.635]	[0.052]	[4.150]	[0.728]	[0.506]	[0.237]	[0.459]
Away Team Only (N=178,555)	0.054***	-22.420***	0.989***	0.009***	-0.073***	0.025***	0.027***	0.057***	-0.008***
	(0.004)	(1.744)	(0.047)	(0.001)	(0.011)	(0.002)	(0.002)	(0.002)	(0.003)
	[0.211]	[222.221]	[12.885]	[0.050]	[4.140]	[0.729]	[0.505]	[0.233]	[0.447]
Shots w/in Same Half (N=315,551)	0.056***	-9.899***	1.071***	0.009***	-0.070***	0.029***	0.026***	0.061***	-0.005**
	(0.004)	(1.254)	(0.040)	(0.001)	(0.010)	(0.002)	(0.002)	(0.002)	(0.002)
	[0.234]	[166.492]	[12.675]	[0.051]	[4.128]	[0.720]	[0.501]	[0.236]	[0.455]
Shots w/in Same Quarter (N=261,941)	0.058***	-1.161	1.218***	0.009***	-0.084***	0.032***	0.025***	0.065***	-0.006***
	(0.004)	(0.712)	(0.044)	(0.001)	(0.011)	(0.002)	(0.002)	(0.002)	(0.002)
	[0.274]	[109.291]	[12.651]	[0.051]	[4.132]	[0.699]	[0.496]	[0.247]	[0.457]
No Overtime Shots (N=353,385)	0.054***	-20.672***	0.955***	0.010***	-0.063***	0.028***	0.027***	0.061***	-0.004**
	(0.004)	(1.514)	(0.037)	(0.001)	(0.009)	(0.002)	(0.001)	(0.002)	(0.002)
	[0.211]	[222.706]	[12.749]	[0.051]	[4.146]	[0.728]	[0.506]	[0.233]	[0.454]
No Shots w/in 5 Seconds (N=350,104)	0.081***	-28.785***	0.827***	0.008***	-0.073***	0.023***	0.028***	0.062***	-0.003
	(0.003)	(1.429)	(0.037)	(0.001)	(0.009)	(0.002)	(0.002)	(0.002)	(0.002)
	[0.198]	[226.613]	[12.906]	[0.052]	[4.169]	[0.732]	[0.505]	[0.234]	[0.452]
No Last 2 Minutes of 4th Qtr. (N=339,159)	0.052***	-19.521***	0.965***	0.010***	-0.062***	0.028***	0.027***	0.062***	-0.004**
	(0.004)	(1.511)	(0.038)	(0.001)	(0.010)	(0.002)	(0.002)	(0.002)	(0.002)
	[0.211]	[222.728]	[12.687]	[0.051]	[4.144]	[0.728]	[0.506]	[0.228]	[0.455]
No Shots over 2 Minutes (N=189,416)	0.078***	4.576***	1.435***	0.004***	-0.079***	0.027***	0.027***	0.059***	-0.008***
	(0.005)	(0.302)	(0.055)	(0.001)	(0.013)	(0.003)	(0.002)	(0.002)	(0.003)
	[0.384]	[57.751]	[12.408]	[0.042]	[4.100]	[0.681]	[0.499]	[0.247]	[0.459]

Notes: Data from `http://www.bigdataball.com`, `http://www.nbasavant.com`, and `http://www.basketball-reference.com` for the 2013-2014 and 2014-2015 regular seasons. Each cell presents the estimate for the effect of making the previous shot on the dependent variable identified by the column title, but under the restriction identified by the row heading. Standard errors clustered at the player level are shown in parentheses and dependent variable means are shown in brackets. Columns (1) - (8) use the same specifications as Table 5, while Column (9) uses the specification from Column (8) of Table 6. All controls are the same as in the relevant specifications in Table 5 or Table 6, except for the last row of results which additionally includes time-varying game, shot, and defender controls for the previous field goal attempt. Stars denote statistical significance levels: *: 10%, **: 5%, and ***: 1%.

Table A5: Free Throw and Field Goal Shooting Results for NBA All Stars

	Free Throws		
	All Free Throws	Only 2nd and 3rd Free Throws	Field Goal Attempts
LeBron James	-0.117***	-0.052	-0.061***
	(0.030)	(0.049)	(0.021)
Carmelo Anthony	-0.111**	-0.024	-0.040*
	(0.055)	(0.094)	(0.024)
Stephen Curry	-0.063	-0.032	-0.029
	(0.040)	(0.064)	(0.023)
Kevin Love	0.007	0.065	-0.049*
	(0.053)	(0.061)	(0.027)
Dwyane Wade	0.025	0.069	-0.014
	(0.051)	(0.060)	(0.029)
Kevin Durant	-0.025	-0.010	-0.029
	(0.035)	(0.058)	(0.024)
Russell Westbrook	-0.004	-0.014	-0.086***
	(0.037)	(0.043)	(0.023)
Chris Paul	-0.014	0.050	-0.071**
	(0.025)	(0.044)	(0.028)
James Harden	-0.013	0.008	-0.072***
	(0.038)	(0.047)	(0.021)
Tim Duncan	-0.005	-0.014	-0.042
	(0.034)	(0.041)	(0.030)

Notes: Data from `http://www.bigdataball.com`, `http://www.nbasavant.com`, and `http://www.basketball-reference.com` for the 2013-2014 and 2014-2015 regular seasons. Regressions are run over each player individually, and thus do not include player controls. Regressions do include the same game and shot controls as the regressions in Table 4 for free throws and Table 6 for field goals. Standard errors are clustered at the game level. Stars denote statistical significance levels: *: 10%, **: 5%, and ***: 1%.

Table A6: Effects of Making Consecutive Free Throws on Probability of Making Next Free Throw Not Controlling for Previous Shot Characteristics

	(1)	(2)	(3)	(4)
Made Prev. FT (Y/N)	0.016***	0.020**	0.039***	0.103***
	(0.003)	(0.008)	(0.014)	(0.032)
Made Prev. Two FTs (Y/N)		0.042***	0.065***	0.097***
		(0.007)	(0.013)	(0.032)
Made Prev. Three FTs (Y/N)			0.053***	0.074**
			(0.012)	(0.030)
Made Prev. Four FTs (Y/N)				0.070**
				(0.030)
Dep. Var. Mean	0.766	0.765	0.772	0.771
Adjusted R-Squared	0.047	0.048	0.050	0.053
N	83,800	57,056	40,931	27,448

Notes: Data from `http://www.bigdataball.com`, `http://www.nbasavant.com`, and `http://www.basketball-reference.com` for the 2013-2014 and 2014-2015 regular seasons. The dependent variable is an indicator equal to one for a made free throw and zero for a missed free throw, and standard errors are clustered at the player level. The independent variables of interest are indicators for whether or not a player made the lagged, twice lagged, third lagged and fourth lagged free throw, as well as all the possible interactions between these indicators. We create linear combinations of the relevant coefficients to calculate the effect of only making the previous free throw, only the previous two free throws, only the previous three free throws and making all of the previous four free throws. The controls included are the same as in Column (5) in Table 4. Stars denote statistical significance levels: *: 10%, **: 5%, and ***: 1%.

Table A7: Effects of Consecutive Field Goals on Probability of Making Next Field Goal Attempt Not Controlling for Previous Shot Characteristics

	(1)	(2)	(3)	(4)
Made Prev. FG (Y/N)	-0.007***	-0.006***	-0.006*	-0.007
	(0.002)	(0.002)	(0.004)	(0.005)
Made Prev. Two FGs (Y/N)		-0.009***	-0.006*	-0.006
		(0.002)	(0.003)	(0.005)
Made Prev. Three FGs (Y/N)			-0.014***	-0.012**
			(0.004)	(0.006)
Made Prev. Four FGs (Y/N)				-0.018***
				(0.006)
Dep. Var. Mean	0.454	0.453	0.452	0.451
Adjusted R-Squared	0.137	0.139	0.139	0.139
N	356,277	310,820	268,549	229,700

Notes: Data from `http://www.bigdataball.com`, `http://www.nbasavant.com`, and `http://www.basketball-reference.com` for the 2013-2014 and 2014-2015 regular seasons. The dependent variable is an indicator equal to one for a made field goal attempt and zero for a missed field goal attempt, and standard errors are clustered at the player level. The independent variables of interest are indicators for whether or not a player made the lagged, twice lagged, third lagged and fourth lagged field goal attempts, as well as all the possible interactions between these indicators. We create linear combinations of the relevant coefficients to calculate the effect of only making the previous field goal attempt, only the previous two field goal attempts, only the previous three field goal attempts and making all of the previous four field goal attempts. The controls included are the same as in Column (7) of Table 6. Stars denote statistical significance levels: *: 10%, **: 5%, and ***: 1%.

B Results Using Player Fixed Effects

Table B1: Effects of Making Previous Free Throw on Probability of Making Next Free Throw

	All Free Throws & All Players						Only 2nd and 3rd Free Throws		
	(1)	(2)	(3)	(4)	(5)	(6)	All Players	Players Taking <100 FTs	Players Taking ≥100 FTs
Made Prev. Free Throw (Y/N)	0.060***	0.059***	0.060***	0.040***	0.006	0.006*	0.013***	0.001	0.018***
	(0.008)	(0.008)	(0.008)	(0.004)	(0.003)	(0.003)	(0.004)	(0.008)	(0.005)
Sub. Before Free Throw (Y/N)			-0.005*	-0.005	-0.004	-0.003	-0.007**	-0.002	-0.009**
			(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.008)	(0.004)
Personal Foul Free Throw (Y/N)			0.010*	0.005	-0.003	-0.001	-0.021	0.013	-0.025
			(0.006)	(0.005)	(0.005)	(0.007)	(0.062)	(0.014)	(0.063)
Shooting Foul Free Throw (Y/N)			-0.005	-0.003	-0.004	0.001	-0.070	-0.175	-0.020
			(0.005)	(0.004)	(0.004)	(0.005)	(0.112)	(0.223)	(0.125)
Free Throw Number			0.034***	0.033***	0.034***	0.023***	0.776***	0.026	0.760***
			(0.004)	(0.003)	(0.003)	(0.005)	(0.070)	(0.019)	(0.077)
And One Free Throw (Y/N)			0.001	0.001	-0.001	-0.001			
			(0.007)	(0.007)	(0.007)	(0.007)			
Dep. Var. Mean	0.766	0.766	0.766	0.766	0.766	0.766	0.777	0.740	0.792
Adjusted R-Squared	0.004	0.004	0.006	0.025	0.002	0.002	0.001	0.001	0.001
N	84,431	84,431	84,426	84,426	84,426	84,423	51,212	14,405	36,807
Game Controls		X	X	X	X	X	X	X	X
Player Controls				X	X†	X†	X†	X†	X†
Player FE					X	X	X	X	X
Lag Controls						X	X	X	X

Notes: Data from `http://www.bigdataball.com`, `http://www.nbasavant.com`, and `http://www.basketball-reference.com` for the 2013-2014 and 2014-2015 regular seasons. The dependent variable is an indicator variable equal to one for a made free throw and zero for a missed free throw, and standard errors, clustered by player, are shown in parentheses. In general, models include the same controls as described in Table 4. Stars denote statistical significance levels: *: 10%, **: 5%, and ***: 1%. † When including offensive player fixed effects we do not include any time-invariant player characteristics for the offensive player (e.g. position).

Table B2: Effects of a Previous Field Goal on Probability of Making Next Field Goal Attempt

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Made Prev. FG Att. (Y/N)	-0.009***	-0.010***	-0.015***	-0.015***	-0.006***	-0.008***	-0.008***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dep. Var. Mean	0.454	0.454	0.454	0.454	0.454	0.454	0.454	0.453
Adjusted R-Squared	0.000	0.001	0.007	0.008	0.137	0.131	0.140	0.142
N	356,585	356,585	356,585	356,585	356,585	356,585	356,585	310,836
Game Controls		X	X	X	X	X	X	X
Player Controls			X	X	X	X†	X†	X†
Opponent Controls				X	X	X	X‡	X‡
Shot Controls					X	X	X	X
Player FE						X	X	X
Def. Player FE							X	X
Lag Controls								X

Notes: Data from `http://www.bigdataball.com`, `http://www.nbasavant.com`, and `http://www.basketball-reference.com` for the 2013-2014 and 2014-2015 regular seasons. The dependent variable is an indicator variable equal to one for a made shot and zero for a missed shot, and standard errors, clustered by player, are shown in parentheses. In general, models include the same controls as described in Table 6. Stars denote statistical significance levels: *: 10%, **: 5%, and ***: 1%. ‡ When including offensive player fixed effects we do not include any time-invariant player characteristics for the offensive player (e.g. position). † When including defensive player fixed effects we do not include any time-invariant player characteristics for the offensive player (e.g. position).

Table B3: Determinants of Made Field Goals by Shot Type

A. Prev. 2-Point Shots (N=230,698)	
Made Prev. FG Att. (Y/N)	-0.003
	(0.002)
Dep. Var. Mean	0.460
Adjusted R-Squared	0.148
B. Prev. 3-Point. Shots (N= 80,138)	
Made Prev. FG Att. (Y/N)	-0.021***
	(0.004)
Dep. Var. Mean	0.432
Adjusted R-Squared	0.123
C. Prev. 2-Point Shots Close to 3-Point Line (N= 4,335)	
Made Prev. FG Att. (Y/N)	0.001
	(0.018)
Dep. Var. Mean	0.431
Adjusted R-Squared	0.135
D. Prev. 3-Point Shots Close to 3-Point Line (N= 55,907)	
Made Prev. FG Att. (Y/N)	-0.022***
	(0.004)
Dep. Var. Mean	0.433
Adjusted R-Squared	0.120

Notes: Data from `http://www.bigdataball.com`, `http://www.nbasavant.com`, and `http://www.basketball-reference.com` for the 2013-2014 and 2014-2015 regular seasons. The dependent variable is an indicator variable equal to one for a made shot and zero for a missed shot, and standard errors, clustered by player, are shown in parentheses. In general, models include the same controls as described in Table B2. Stars denote statistical significance levels: *: 10%, **: 5%, and ***: 1%. ‡ When including offensive player fixed effects we do not include any time-invariant player characteristics for the offensive player (e.g. position). † When including defensive player fixed effects we do not include any time-invariant player characteristics for the offensive player (e.g. position).

Table B4: Determinants of Free Throws for Consecutive Successes

	(1)	(2)	(3)	(4)
Made Prev. FT (Y/N)	-0.001	0.002	0.026*	0.089**
	(0.004)	(0.008)	(0.015)	(0.035)
Made Prev. Two FTs (Y/N)		0.012	0.038***	0.063*
		(0.008)	(0.015)	(0.036)
Made Prev. Three FTs (Y/N)			0.018	0.035
			(0.014)	(0.035)
Made Prev. Four FTs (Y/N)				0.020
				(0.035)
Dep. Var. Mean	0.766	0.766	0.772	0.771
Adjusted R-Squared	0.060	0.058	0.059	0.062
N	83,797	57,050	40,925	27,442

Notes: Data from `http://www.bigdataball.com`, `http://www.nbasavant.com`, and `http://www.basketball-reference.com` for the 2013-2014 and 2014-2015 regular seasons. The dependent variable is an indicator equal to one for a made free throw and zero for a missed free throw. The independent variables of interest are indicators for whether or not a player made the lagged, twice lagged, third lagged and fourth lagged free throw, as well as all the possible interactions between these indicators. We create linear combinations of the relevant coefficients to calculate the effect of only making the previous free throw, only the previous two free throws, only the previous three free throws and making all of the previous four free throws. The controls included are the same as in Column (5) in Table B1. Stars denote statistical significance levels: *: 10%, **: 5%, and ***: 1%.

Table B5: Determinants of Field Goals for Consecutive Successes

	(1)	(2)	(3)	(4)
Made Prev. FG (Y/N)	-0.009***	-0.009***	-0.006	-0.011*
	(0.002)	(0.003)	(0.004)	(0.006)
Made Prev. Two FGs (Y/N)		-0.011***	-0.007*	-0.010*
		(0.003)	(0.004)	(0.006)
Made Prev. Three FGs (Y/N)			-0.015***	-0.015**
			(0.004)	(0.006)
Made Prev. Four FGs (Y/N)				-0.020***
				(0.007)
Dep. Var. Mean	0.453	0.452	0.451	0.451
Adjusted R-Squared	0.144	0.143	0.143	0.143
N	310,635	268,176	229,207	193,885

Notes: Data from `http://www.bigdataball.com`, `http://www.nbasavant.com`, and `http://www.basketball-reference.com` for the 2013-2014 and 2014-2015 regular seasons. The dependent variable is an indicator equal to one for a made field goal attempt and zero for a missed field goal attempt. The independent variables of interest are indicators for whether or not a player made the lagged, twice lagged, third lagged and fourth lagged field goal attempts, as well as all the possible interactions between these indicators. We create linear combinations of the relevant coefficients to calculate the effect of only making the previous field goal attempt, only the previous two field goal attempts, only the previous three field goal attempts and making all of the previous four field goal attempts. The controls included are the same as in Column (7) of Table B2, with the addition of time-varying controls for the relevant lagged shots. Stars denote statistical significance levels: *: 10%, **: 5%, and ***: 1%.

C Description and Results of Simulations

In this Appendix, we create simulated data to test the statistical power and accuracy of our estimation strategies. We construct data generating processes (DGP) of three models of shot success and show how our models perform in estimating each DGP. We calculate average coefficients across the simulations, the percent of the coefficients that are statistically significant to examine the statistical power of our estimation strategy, and the percent of the coefficients that are negative to examine how likely the results in our paper would be for each DGP. The first DGP comes from a Markov switching model similar to Wetzels et al. (2016) where both a hot and cold state exist, however, we simplify the model so that the state a player is in is solely dependent on the outcome of the previous shot.[20] The second model expands on the first, where entering the hot state is dependent on the outcome of the previous three shots. The third model is taken directly from Stone (2012), however, we report results for fewer values of the model's parameters.

Our simulation results suggest that, if in fact a hot hand effect exists, our estimation strategy would likely be able to identify it. Our estimation strategy is able to pick up even relatively low magnitudes of the hot hand, and it is unlikely to find a negative effect if in fact a positive relationship exists. Our coefficients are unbiased for the first DGP, although if instead the true DGP is one of the second two DGPs, our strategy results in attenuated coefficients. However, it performs better than simply controlling on observables or using fixed effects, as has been done in previous work. We also show that even if one of the second two DGPs is in fact the true DGP, we would still be unlikely to find the negative coefficients from our in game field goal data. We explain each data generating process and present the results of our estimation strategy below.

C.1 Simulated Data

We begin by creating a simulated data set of 100 players with different underlying probabilities of shot success, coming from a normal distribution with a mean of 0.73 and a standard deviation of 0.105, corresponding to the mean and standard deviation field goal percentage from our field goal data. In order to show bias that could exist from omitted variables we also generate two additional variables, W and Z, each with their own mean, standard deviation, and covariances with the underlying probability of shot success for players.[21]

Next, we generate a different number of shots per game for each player for 82 games, the number of shots are generated from a distribution matching that found in the field goal data, with a mean of 5.312, standard deviation of 8.361, skewness of 0.824 and kurtosis of 3.553. The above process results in 8,200 unique player game combinations and 66,069 total shots. Each of our three data generating processes for shot success start with this generated data.

We run 1,000 iterations of the above data. For each iteration, we create three DGPs of shot success and then estimate statistical models on each of these DGPs as described below.

C.2 Regime Shift Model 1

The first model of shot success uses a regime shift model, where a player enters a hot state if he makes his previous shot. The probability of success on the first shot of each game is equal to the player's underlying probability of shot success, μ_p. For each subsequent shot the probability of success, $P(s_{t,p} = 1)$, is the player's underlying probability of shot success, μ_p, plus the hot hand

[20] We use the model outlined in Wetzels et al. (2016) with α=1 to make this simplification.

[21] The mean, standard deviation and covariance of W were set to 5, 2 and 0.25, while the mean, standard deviation and covariance of Z were set at 50, 20 and 0.75.

parameter, δ if the previous shot was made. Therefore, the probability of success for player p current shot t is as follows,

$$P(s_{p,t} = 1) = \mu_p + \delta * \mathbb{1}\{s_{p,t-1} = 1\}, \tag{4}$$

where $\mathbb{1}\{s_{p,t-1} = 1\}$ is an indicator function for whether player p made his previous shot $t-1$. We repeat this process for five values of the hot hand parameter, δ = (-0.10, -.01, 0.00, 0.01 , 0.10). These values correspond to no hot hand existing, and an increase (decrease) in a player's probability of shot success of approximately $1/10^{th}$ of a standard deviation, and an increase (decrease) of approximately one standard deviation.

C.3 Regime Shift Model 2

The second model of shot success uses a regime shift model where the probability of entering the hot state is 1 only if the previous three shots were made, which reflects a common theme in the hot hand literature that the search for the hot hand should not solely extend to success from the previous shot but success in several of the previous shots. Therefore, we alter Model 1 such that the probability of success on the current shot is as follows:

$$P(s_{p,t} = 1) = \mu_p + \delta * \mathbb{1}\{s_{p,t-1} = s_{p,t-2} = s_{p,t-3} = 1\}, \tag{5}$$

where $\mathbb{1}\{s_{p,t-1} = s_{p,t-2} = s_{p,t-3} = 1\}$ is an indicator that takes on the value of one only if the previous three shots were all successful. We then repeat the simulation process used for Model 1, but replace the probability of shot success on the current shot with the above equation. We also use the same three values of δ that were used in Model 1.

C.4 Model 3

Finally, our third model uses a data generating process that follows a data generating process outlined by Stone (2012), in which the probability of success on every shot depends not on whether the previous shot was made, but is generated by the following AR(1) process:

$$P(s_{p,t} = 1) = \rho P(s_{p,t-1} = 1) + (1-\rho)\mu_p + \epsilon_t, \tag{6}$$

where $\epsilon_t | P(s_{p,t} = 1) \sim U[-\alpha\delta_t, \alpha\delta_t]$ and $\delta_t = min\{\rho P(s_{p,t-1} = 1) + (1-\rho)\mu_p, 1 - (\rho P(s_{p,t-1} = 1) + (1-\rho)\mu_p)\}$. We use the same underlying player's probability of shot success as the previous two models, and set $\alpha = 0.5$.[22] We use the same simulation process as Model 1 and 2, however, we replace the probability of shot success on the current shot with equation 6. We run Model 3 for five values for ρ =: 0, 0.1, 0.5, 0.9, and 1. As the values of ρ increase, the probability of making the current shot increasingly depends on the probability that the player made the previous shot instead of the player's underlying probability of shot success, μ_p.

C.5 Regression Models

For each of the three models discussed above we estimate the following regression for each iteration of the 1,000 simulations, and for each value of δ in Model 1 and 2, and each value of ρ in Model 3:

$$s_{p,i,t} = \alpha + \beta s_{p,t-1}\gamma W + \chi Z + \phi \bar{s}_{p,-i} + \epsilon, \tag{7}$$

[22]For more values of α and ρ see Stone (2012)

where $s_{p,t}$ is an indicator for player p making his shot t in game i. We begin by estimating a model only including the lagged shot indicator, $s_{p,t-1}$. We then estimate a second model where we add in the control variables W and Z and a third model which includes these controls as well as the player's field goal percentage excluding the current game, $\bar{s}_{p,-i}$. To further mimic our regression results, we cluster our standard errors at the player level. Finally, to highlight the differences between a player's leave out field goal percentage and fixed effects models, we estimate a fourth regression which includes the two control variables, W and Z, as well as player fixed effects.

C.6 Simulation Results

We estimate these four models across each value of either δ or ρ for 1,000 simulated datasets. We store the coefficient estimate and associated p-value for each iteration. We average the coefficients across all 1,000 simulations and present them in Table C1. We also report the number of statistically significant coefficients and the number of coefficients that were negative of the 1,000 simulations.

For the first regime shift model the estimate of β should be very close to the value of δ in the model. Our results show that our estimation strategy of controlling for observables and the leave out field goal percentage performs best for this data generating process. Additionally, it highlights the negative bias that exists when using player fixed effects instead of the leave out field goal percentage. If the parameter δ is in fact zero, reflecting no existence of a hot hand, the leave out field goal percentage model results in an average β coefficient of 0.001, and 388 of the 1,000 iterations were negative. Additionally, if Regime Shift Model 1 is the true DGP, we can accurately estimate both relatively small and large hot hand effects. If $\delta = -0.01$, representing an extremely small negative autocorrelation in shot success, 979 of the 1,000 iterations result in negative coefficients and 517 coefficients are statistically significant. If instead there is a small positive hot hand effect and $\delta = 0.01$, only four of the 1,000 iterations are negative and not statistically significant, and 714 of the coefficients are statistically significant and positive. Importantly, this demonstrates that under this DGP, our negative and statistically significant coefficients would be extremely unlikely. For larger magnitudes of δ, every single coefficient is statistically significant. Put together, these results suggest that the leave-out field goal percentage performs very well both in terms of generating unbiased coefficients and sufficient statistical power.

In the second regime shift model, we expect the average estimate of β to be lower in magnitude compared to the actual value of δ. Because the hot hand depends on three shots made in succession, and the regression model only examines the last shot, this measurement error in the independent variable of interest will attenuate the β coefficients. Once again if there is in fact no hot hand, when $\delta = 0$, our estimation strategy of controlling on observables and including the leave out field goal percentage results in an average estimate of approximately zero. As in Regime Shift Model 1, just under 400 of the estimates are negative, and only 15 are statistically significant. The attenuated coefficients here do affect the performance of the leave-out field goal percentage model for extremely small positive and negative values of δ. However, once again, for larger absolute values of δ, every single iteration resulted in statistically significant coefficients.

Finally, we present the estimates for the data generating process outlined by Stone (2012). Here again, the leave-out field goal percentage regression specification performs relatively well. Even when 90% of the probability of current shot success is determined by a player's underlying shooting percentage, μ_p, we only find 133 negative coefficients, and just 2 of them are statistically significant, while 182 coefficients are statistically significant and positive. Thus, even here it is unlikely to find a consistently negative and statistically significant coefficient if this is the true DGP. Additionally, our estimates from the field goal data suggest that higher values of ρ are even less likely to be the true parameter values if in fact this is the correct DGP, because we find no negative coefficient estimates from any of the simulations for the higher values of ρ. Finally, these results suggest that our results found for free throws may be understating the true autocorrelation in the probabilities of shot success, since for higher values of ρ our strategy has a negative bias.

Table C1: Simulated Estimates of the Hot Hand

	No Controls			Control Variables			Leave Out FG %			Player FE		
	Avg. Coef.	# Stat. Sig.	# Neg.	Avg. Coef.	# Stat. Sig.	# Neg.	Avg. Coef.	# Stat. Sig.	# Neg.	Avg. Coef.	# Stat. Sig.	# Neg.
A. Regime Shift Model 1												
δ = -0.10	-0.054	1000	1000	-0.084	1000	1000	-0.099	1000	1000	-0.101	1000	1000
δ = -0.01	0.045	1000	0	0.010	449	16	-0.009	517	979	-0.012	773	997
δ = 0.00	0.057	1000	0	0.020	988	0	0.001	72	388	-0.002	72	666
δ = 0.01	0.068	1000	0	0.030	1000	0	0.011	714	4	0.008	466	31
δ = 0.10	0.173	1000	0	0.126	1000	0	0.101	1000	0	0.098	1000	0
B. Regime Shift Model 2												
δ = -0.10	0.012	269	2	-0.018	970	1000	-0.033	1000	1000	-0.035	1000	1000
δ = -0.01	0.052	1000	0	0.016	912	0	-0.002	68	709	-0.005	233	909
δ = 0.00	0.057	1000	0	0.020	982	0	0.001	65	388	-0.002	70	647
δ = 0.01	0.062	1000	0	0.025	1000	0	0.005	201	109	0.002	82	295
δ = 0.10	0.115	1000	0	0.069	1000	0	0.044	1000	0	0.040	1000	0
C. Stone DGP												
ρ = 0.0	0.057	1000	0	0.020	989	0	0.002	63	360	-0.001	63	623
ρ = 0.1	0.060	1000	0	0.023	994	0	0.005	184	133	0.002	79	362
ρ = 0.5	0.076	1000	0	0.040	1000	0	0.022	1000	0	0.019	992	0
ρ = 0.9	0.133	1000	0	0.100	1000	0	0.082	1000	0	0.079	1000	0
ρ = 1.0	0.197	1000	0	0.166	1000	0	0.150	1000	0	0.146	1000	0

Notes: Each panel represents results from a different data generating process. Each individual row of a panel represents results for the specified value of the relevant parameter of that model for the four different regression equations. Each different regression specification shows the average coefficient, number of statistically significant coefficients, and number of negative coefficients across 1,000 simulations of the data generating process named. The Leave Out FG % and Player FE columns also include the two control variables. Panel A an Panel B correspond to a modified model from Wetzels et al. (2016). Panel C corresponds to the model outlined by Stone (2012).