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THE HOT HAND PHENOMENON IN BASKETBALL REVISITED

A Thesis
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Master of Arts
Economics

by
Alexander T. Dahlstrom
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Accepted by:
Dr. Raymond Sauer, Committee Chair
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ABSTRACT

The focus of this paper is to summarize the economic literature of the hot hand phenomenon in basketball while adding in another study of my own. By using recent NBA statistical data, I will show the advancement and evolution of this widely held public belief that a certain number of makes or misses can alter the chances of the next attempt's success or failure. I start by recreating part of Gilovich, Valone, and Tversky's (1985) experiments with a larger set of data and finish by introducing Miller and Sanjurjo's fix to their method's biases(2015). The major finding is when a three and an eight percentage point correction for the bias from Miller and Sanjurjo's calculations are applied to my data set as well as many other studies, that a hot hand effect starts to surface more frequently. This important correction allows us to flip the hot hand myth from a "cognitive illusion" to a potentially significant effect on gameplay.

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I. INTRODUCTION

An exceptional player is performing uncommonly, historically well. He's on. He's in the zone. He has the "hot hand." The hot hand is a term often used to describe a player who is temporarily playing above his usual level of play with a string of shots that seem to be successful at a higher rate with each additional made shot.

To basketball fans, this scenario is familiar. It's what happened the night of Kobe Bryant's 81 point performance against the Toronto Raptors. An excellent player shot 16% better from the field than his career average. It's moments like these that sports fans live for. A game where an individual elevates his play to unprecedented levels. However, is it possible for players to really be "on," to "have the hot hand?" Is it really the case that making a few shots in a row statistically improves your chance to hit the next one?

Confidence is a clear factor in influencing the way the game is played, but the hot hand phenomenon is almost exclusively tied to this as the driving force making this such a popular expression with the public. Is confidence enough to make this "mind over matter" momentum boost into a statistically significant effect?

What sports economists have been searching for over the past thirty years has been a very slight effect compared to the public's perception of a hot or cold state. If shown plausible, such an effect even as slight as it may be on player performance could lead to major changes in coaching decisions in crunch time situations. Currently the question of giving the ball to the player who is hot versus the player who is consistent is unknown and a big part of why I did this study.

Randomness in sports has a massive effect on play, game, and even season outcomes for teams. Every time a team takes the court there is a chance for anything to happen, which can more or less be measured by player and team stats. Of course uncertainty is why we play the game and practice is how players attempt to lower this uncertainty. There will always be unexplained factors contributing to outcomes in either direction, but like in a coin flip, general tendencies of prediction tend to hold. The basic idea behind the "hot hand" though is that this uncertainty in skill and streakiness can overpower the randomness of a coin flip type hit or miss outcome.

In 1985, psychologists/behavioral economists Gilovich, Valone, and Tversky (GVT) investigated the validity of the "hot hand" in basketball. The underlying goal of their research was to examine whether our belief that the previous outcome affects the next "random" event. In their results, they "disproved" this commonly believed phenomena by examining the Boston Celtics' free throws and field goal records from 48 home games of the Philadelphia 76ers. Later, they conducted controlled experiments with student-athletes from Cornell University in which students attempted to make as many shots as possible and accurately predict the outcomes. Their data showed that there was little to no correlation between successful attempts and the subsequent attempts success. This paper has been extremely influential and is known to have popularized the idea of the "hot hand fallacy." Since its publication, there have been a number of major studies that have revisited the idea.

From here, the Hot Hand has been consistently labeled as nothing more than a "fallacy" seeing that GVT called it a mere "cognitive illusion" by the public. Based on common sense statistics, a player's odds at hitting a shot is simply his/her make percentage just as a coin has a 50/50 chance at being "heads" each flip. Rattle in a few shots in a row or land a few heads and the public deems it a hot streak. In reality, the odds of making those shots consecutively are high enough for it to be a rather regular occurrence; thus the public's willingness to deem a streak "hot" is usually premature.

GVT though had several errors in calculating the effect ranging from selection bias in the data to a lack of controls for coaches and players adjusting their strategy to the player who may be hot. This issue though is much bigger than just basketball, seeing that many economists and psychologists overstate this "myth" in showing how humans misjudge numbers, leading to many flawed spinoffs of anti-hot hand literature.

As recently as 2010, Rabin and Vayanos did a similar study of the hot hand within the scope of the "gambler's fallacy." This study used some coin flip scenarios and the main finding here was that people "underreact to short streaks and overreact to longer ones"(Rabin and Vayanos 2010). The psychology of this can be applied to areas of behavioral finance where people buy and sell in the stock market at these predicted rates.

Now to segway into the psychology side of the spectrum, it is believed that the public's conception of the hot hand's effect on performance is much greater in magnitude than it actually is. In a 2014 study by Blanchard, Wilke, and Hayden, it was noted that hot hand biased based tendencies are readily apparent in the foraging habits of Rhesus monkeys, meaning this “clumpy” autocorrelation in a series of binary outcomes may be more deeply ingrained into our psyche than previously thought(BWH 2014). As imperfect humans, we gain confidence with the smallest increases in the probability of success. Whether it is our human nature or not, the common person generally lacks a sound knowledge of statistics. Therefore, an increase of shooting percentage of five percentage points may cause an inflation of shooter and audience confidence as if it really were a fifty percentage point increase. Their point here is that our overestimations of such “hot” states is such a psychological illusion that it predates humankind as something hard-wired into our psyches as primates.

Daniel Kahneman shows us in his book, *Thinking Fast Thinking Slow*, is another prime example an economist/psychologist who took GVT’s work as fact.

“The hot hand is entirely in the eye of the beholders, who are consistently too quick to perceive order and causality in randomness. The hot hand is a massive and widespread cognitive illusion. [Could the same be said about much of the priming literature?]”

(Kahneman 2011)

On the other side of the spectrum, Dixit & Nalebuff in their 1991 book, *Thinking strategically: the competitive edge in business, politics, and everyday life,* show us that not everyone is completely on board for GVT’s fallacy as being concrete.

To expand on how widely held the idea is in the public sphere, we even see the term stretched into the context of team performance levels. Daniel Stone and Jeremy Arkes address this in their 2018 paper stating that the committee determining seeds for the NCAA Championship Basketball Tournament under reacts to teams with strong recent resurgences in performance going into the tournament even though these teams are statistically shown to do better in tournament play. Using Sagarin Ratings and point spreads, team performance vectors were heavily responding to hot hand stats and thus leading to the many upsets that help the credibility of the tournament's nickname, "March Madness."

The hot hand has been tested and yielded positive results in several other sports as well such as bowling, billiards. In a 1995 study by Robert Adams, it was found that professional billiards players had a significantly significant increase in their win percentage in best of 21 matches if they had won the previous game or two in a row(Adams 1995). It was noted mostly under the term "momentum," but a hot hand type effect nonetheless. As for bowling, Dorsey and Smith in 2004 found that professional bowlers were increasing their probability of throwing a strike with statistical significance as they had more strikes thrown immediately preceding an attempt from one to four. In short, a player's chances of throwing a strike after one to four previous strikes was increasing with streak size. This phenomenon was called a "hot hand," and rightly so was another instance of positive significance in its favor.

To revisit the most common way people like to test probability, a simple coin flip or game of matching pennies has been the focus of almost every hot hands paper. Taking a specific coin or event results where we know the absolute chances of it occurring and recording the results is by far the best way to start investigating how streakiness and how probabilities work on a fundamental level. Probabilities in these cases can be predetermined by the notion that only a set number of occurrences can happen and at these rates, therefore meaning that any combination of events will be within the ranges of the mean result's confidence interval. Taking events that do not have an absolutely black or white chance of happening and recording these results like in a basketball game or round of golf, on the other hand are much harder because the absolute chance of a result occurring is unknown and left only to our records of occurrences to interpolate an estimate of this value.

The idea of using a matching pennies type approach to this study has been criticized as a biased estimate due to the understatement in the weighting of longer make or miss streaks. Miller and Sanjurjo claim and show in their 2015 paper that "the expected proportion of successes, on those realizations that immediately follow a streak of successes, is strictly less than the underlying probability of success"(Miller and Sanjurjo 2015).

This makes results found in early papers like Gilovich, Valone, and Tversky(GVT)(1985) have estimates predicted to be between .08 and .12 percentage points underestimated on the changes between a player's normal state and a hot hand. Miller and Sanjurjo also actually devised a fix to this bias, which they used on older data sets like the GVT paper and yielded statistical significance for the hot hand. Here is where the argument of improved approaches to the hot hand question begins to emerge.

Many of the papers within the literature that have failed to find a “hot hand” correlation lacked a high enough powered model to test the idea. Lack of sample numbers, understated autocorrelation, and infrequent occurrences of true “hot hand” situations have limited many papers’ ability to find a hot state.(Arkes 2013)

The statistical range that randomness occupies is quite large in the probability spectrum, meaning that observations outside of this area are quite unusual in frequency. This occurrence may only happen twice during a player’s career and maybe a few times over a whole season, which makes a larger dataset more likely to find hot or cold states. Most early papers sacrificed their ability to find these occurrences by limiting their sample size to only one or two thousand observations(GVT 1985 had 887). In the 1980’s, shot data was not nearly as easy to come by as today where NBA.com or data mining websites like BigDataBall.com can give you every shot taken in a season by every player with intricate details like floor position, time on the clock, and even defenders on the floor. Thus, the studies of today have way more sample producing power than the studies of yesterday.

Arkes’s 2010 paper on free throws needed roughly 28,000 data points to find a three percentage point increase in make percentage between second free throw attempts if the first shot was a make. The paper was the first of any in the literature to find statistically significant evidence backing the hot hand’s existence. By using a “pooled, multivariate framework,” Arkes was able to increase the testing power for this hot hand effect. Aggregate shot data automatically gives more opportunities than regressing player by player independently and thus the small hot hand effects are shown within the results.

Conditional that a player has hit his previous shot, the probability of him making the next shot increases by 1.9 percentage points, which is significant at the 90% confidence level(Arkes 2010).

Andrew Bocskocsky, John Ezekowitz, and Carolyn Stein in their 2014 work took this type of analysis a step further by looking at everything from defender distance as streak numbers rise to the likelihood of a player taking the next shot in a streak. Their results also found statistically significant evidence in favor of the hot hand with roughly a 1.2% (.54 percentage points) increase in make percentage on shots occuring after a shot streak. The most important takeaway from their article though comes in the form of defining what a hot hand really is.

"A player who makes three out of his past four layups is not hot, but a player who makes three out of his past four three-point attempts is. In other words, being hot is not about the absolute number of shots a player has previously made, but rather is about how much he has outperformed, conditional on the types of shots he has taken."

(Bocskocsky, Ezekowitz, and Stein 2014)

Having thousands of observations for shots that occur after different types of makes and misses give this phenomenon new life and with the quality of game log shot data increasing steadily in quality over the past fifteen years, there is no place left for the hot hand to hide. On the other side of the spectrum, cold states are something that this paper will examine as well. Although they are not as popularly tested within the literature, part of this paper's hypothesis is that this cold state can be traced in a parallel fashion to hot streaks. If this holds true, the phenomena would be a seamless number check of our hot hand data.

With this notion of higher powered testing for the hot and cold hand in mind, this paper will revisit the original procedure of measurement used by GVT and then apply Miller and Sanjurjo's fix to further investigate this hot topic in sports economics.

II. THE SAMPLE

Our regressions were drawn from the 2016-2017 NBA regular season. Every shot taken from season tip-off to the final shot in the finals is tracked within the dataset. We attempt to find the probability of this phenomena being true in a relatively ordinary set of circumstances with many observations.

With historically unprecedented data at the public's disposal, we were able to find every imaginable stat recorded on NBA.com. A detailed description of every shot taken by every player in every game of the season was at our disposal. The meticulous, detailed, and abundant data available make it far more interesting and reliable to study this topic in 2018 rather than in 1985 with severe limitations to data. Players were selected based on field goal attempts per game (FGA per game). The top 17 players were chosen. A round number of twenty or fifteen players was also considered for this, but seventeen shots per game helped get a better mix of shot variety from these players without deflating the sample too much or increasing it to twenty with several players having never attempted any three pointers. At 17 FGA per game or greater, most of the top ten scorers in the league were captured along with a few other high-volume shooters. Overall this was a better methodology than picking players that were perceived to be "streaky" in their scoring patterns because the highest volume of shots is going to get the standard error to be the smallest and help our chances of finding statistically significant effects. With high volume of shot attempts also comes a larger amount of streaks that are within the confines of a single game.

From this selection of players, we get a whole range of variety in terms of shooting tendencies, while still having high shots per game averages. For example, Russell Westbrook is noted as being a very streaky jump shooter while still consistently shooting a league leading twenty three shots per game! Anthony Davis shoots roughly at the bottom threshold of our data, but has the second highest field goal percentage out of the seventeen. Either way and whichever tendency, these players are the cream of the crop and if anyone is going to produce games where the "hot" state is reached, it is these players.

Once the players were selected, game-logs were analyzed for each and every game played this year, gathering a mass collection of single game numbers. The players chosen on average took around nineteen shots per game and were generally efficient with the ball, boasting low turnover numbers and nearly fifty percent field goal percentage on average. Each specific log of the 80+ games per player selected contains the important order of shots taken, a description of the shot taken, and a whole mess of other information that helped in splitting up shots types into different groups.

Before getting into which types of shots were selected as subdivisions for this study, let's look at the shots not included. The first large omission from the study is free throws. This is not because they are not good for a hot hand study, but instead because of personal preference to actual field goals being evaluated. In the public's perception of a player being"hot," very rarely will we see free throws get mentioned. If anything, free throws are only mentioned when they are not hit particularly well and are usually the first thing an angry coach will mention in a loss if there were more misses here. Sure Dirk

Nowitzki and James Harden have had games where they have made twenty plus free throws in a row, but their free throw percentages are generally around ninety percent making even this seemingly impressive feat only two shots different from their typical outing. That being said, these shots are especially good for testing seeing that each player is taking the same uncontested shot from the charity stripe each time with the only thing varying is the pressure level in the game.

Specific zones for mid range jump shots were the other main omission from the study seeing that players at this level are capable of taking “hook shots” and “floaters,” which are very different from traditional jump shots and hard to differentiate without greatly shrinking the sample when looking at specific streaks of these shots.

In order to test shot type specific “hot/cold hands,” the subsections were divided into short two point field goals (0-5ft, medium two pointers(6-11ft), long two pointers(12-23ft), three pointers (24ft+), middle three pointers (at the top of the arc), and corner three pointers(along the 3ft between the end-lines and the flat sides of the 3 point arc). For each section, only shot streaks corresponding to each type leading up to another attempt in this category were used to count streak observations. For example, the result of the fourth medium two point attempt after three consecutive makes of medium twos. If the player attempted three pointers or dunks between these attempts, these would not be part of the streak nor the attempt being counted in the medium two pointer section. This allowed for a few more looks at different cross-sections within the dataset as well as addressed the problem of shot variety affecting streaks. (See Appendix A for shot selection diagram)

In separating the different shots from each other, a coordinate map provided with the data set I used from bigdataball.com was used to properly select shots to be used in each section. The shot distance metrics were easy to separate given that shots can easily be filtered by distance in the excel files. Location specific shots like the top of the key and corner threes were a little bit trickier seeing that two pieces of coordinates had to be used in filtering. Corner threes were all three pointers taken in the three foot space between the the three point line on parallel to the sideline and up to where this line becomes an arc fourteen feet from the baseline. These corner threes are of specific interest to the study because of some players including Stephen Curry having these as strategic shots that they attempt many times each game. Threes from the top of the key were chosen in a sixteen foot square reaching from the center point of the arc at 24 feet from the basket (eight feet on either side from the center). These also were chosen specifically for players using this area as a strategic shot area like James Harden.

Shot distances were chosen to separate dunks from jump shots as well as regular jump shots from longer distance attempts near the three point line. Dunks and layups are high percentage field goal attempts that are sure to differ from typical shot attempts since the only thing preventing a dunk and layup from going in usually is a block from a defender. As a result, these should definitely be considered a different shot group from the other categories.

The three pointers were divided into middle of the key and corner shots because of obvious differences in shot distance and difficulty for some players. Also, some players have set spaces that they really try to be especially good shooters from like Kevin Durant at the top of the three point arc and Steph Curry from each of the corners.

To mimic the data collected from GVT's experiment in 1985, a shot streak was defined as at least three makes in a row, with differences in means compared for attempts with three plus makes versus misses. This was tested on the individual player level as well as for the whole aggregate sample.

The second part of the study takes this classical approach to hot hands and applies a fix to the shot selection bias that Miller and Sanjurjo have been using in their forthcoming work. What they do is produce a randomized sample while generating a true streak statistic to be used in the measurement of the hot hand effect. To simplify this for the purpose of this study, the calculation for adjusting the conditional means observed to the true number from Miller and Sanjurjo (2016) of eight percentage points will be used to correct our initial findings under the GVT type procedure.

Below is a summary of the statistics for my dataset, as well as a frequency distribution of makes and misses.

27699 shots were taken with a make percentage of 46.13% and shots were tallied binarily with 1's as makes and 0's as misses.

III. THEORETICAL FRAMEWORK

The whole basis of the Hot Hand is dependent on a change within the player on his next attempt from his normal shot percentage, given that the past three or more shots have been successes. What could possibly change within a player that quickly though? Skills can take months or years to improve to the point where the impact could change one's shot percentage by enough to be statistically significant. Could it be an inflow of adrenaline within the player's system that improves his awareness and coordination? If so, this would be extremely hard to test and can be debunked in simple experiments like GVT's where a few college kids are shooting one hundred shots in the gym.

A strongly educated guess would indicate that the one thing that could improve a player's ability to make shots in such a short amount of time would be a boost in confidence. Yes, streakiness in the data, muscle memory, and a few other unmeasurable other factors to be a part of the error term influencing increased make percentage, but a perceived mind over matter factor like the hot hand definitely is likely to be heavily weighted in something emotional like a confidence boost.

Sports psychologists have tried to pinpoint the significance of confidence in preparing elite athletes for crucial contests and studies like Vealey's in 1986 have even put together instrumental frameworks for how confidence impacts performance. If anything, the general consensus among athletes is that focus and calmness that accompany confidence are beneficial to one's ability to perform at a high level(Hays, Maynard, Thomas, Bawden 2009).

From this notion of game performance comes the impact on strategy by coaches and general managers. If something is present that is going to help the team win, it is not just useful to the coaching staff, but perhaps the difference between them winning a championship or even keeping their jobs. This hot state is presented by evidence on the court though and not from anything a player has said or done off the court to indicate something is coming down the pipe. A way this could be investigated further on the sports psychology side would be to look at these body language and verbal nuances preceding potential hot streaks or cold streaks. The sports economics side of the spectrum is more concerned with the pure mechanics that make a series of observations a hot streak or cold streak and testing this possible effect on the player's overall shooting percentage.

What makes a hot streak important and pertinent to sports economics though? Just like how on base percentage was found to be an undervalued stat in major league baseball in the 1990's, finding players who can consistently dial in to these types of hot streaks may lead to an increase in value in their play services the next time their contracts need to be renewed(Hakes and Sauer 2006). This of course would be another expansion to this literature if a study were to come out showing players who consistently get into these streaks and their efficiency numbers versus other similar players in the league.

Confidence leading to hot streaks and hot streaks leading to team wins in an extremely competitive league of play even in small doses is enough to be a matter worth being looked into. The average margin of victory for winning teams in the NBA in the 2016-2017 season was a mere three points, meaning that in an 82 game season even as slight of an effect as Arkes's 1.9 percentage point hot hand in a player could cause a several game swing minimum in a team schedule of contests decided by two or three points. Such a swing could mean the difference between the playoffs and another long offseason from the outside looking in, not to mention millions of dollars in playoff ticket revenue missed for a franchise.

Is every shot going to make or cost a team millions of dollars and a chance to win the game? No way! What the hot hand does though is give players a better chance than usual in circumstances where a shot could be worth that or more in some cases, and therefore has been a valuable effect, if true, worth studying.

IV. PRELIMINARY EMPIRICAL ANALYSIS

In this study, it is important to note that this sample of roughly 28,000 shots is bound to have specific tendencies and trends, which is why this next section shows us a brief dissection of the data in the subsections that will later be used to compare conditional means.

To start off the methods used in analyzing the sample, we begin with a simple snapshot of how common certain streak lengths are up to four plus makes or misses in a row. This shows us that past three makes/misses, the number chosen as the main streak length used in the next section, the data shrinks down to the point where only ten percent of the sample remains.

Frequency Data (Misses)					
	All Shots	short 2s(0-5ft)	medium 2s (6-11ft)	long 2s(12-23ft)	3s(24ft+)
Observations	27699	8375	2753	9159	7955
Streak of 2+	7935	1338	969	3577	3190
Streak of 3+	4186	540	577	2221	1996
Streak of 4+	2228	217	355	1404	1254
% of total shots taken 2+	28.65%	15.98%	35.20%	39.05%	40.10%
% of total shots taken 3+	15.11%	6.45%	20.96%	24.25%	25.09%
% of total shots taken 4+	8.04%	2.59%	12.90%	15.33%	15.76%

(Table 1)

Frequency Data (Makes)					
	All Shots	short 2s(0-5ft)	medium 2s (6-11ft)	long 2s(12-23ft)	3s(24ft+)
Observations	27699	8375	2753	9159	7955
Streak of 2+	5789	3069	511	1328	1078
Streak of 3+	2615	1883	225	510	391
Streak of 4+	1167	1171	101	204	136
% of total shots taken 2+	20.90%	36.64%	18.56%	14.50%	13.55%
% of total shots taken 3+	9.44%	22.48%	8.17%	5.57%	4.92%
% of total shots taken 4+	4.21%	13.98%	3.67%	2.23%	1.71%

(Table 2)

In no way is this an evaluation of the hot or cold states in players, but an interesting prelude to the conditional mean comparisons to come. To summarize, short 2s had more long shot streaks than all other categories and everything else had more long magnitude miss streaks, which increased with distance from the rim.

What was found is that, as expected, frequency of shot make streaks decreased with distance away from the rim and miss streaks increased with distance. If anything, numbers were lower than expected in make streaks beyond three with only around five percent of observations fitting this criteria across the board. This surprisingly low amount of streaks is most likely due to the sheer difficulty for players in this league to make or miss more than four shots in a row seeing that the game situation is constantly changing. For example, Russell Westbrook could in the same game make three open dunks in a row with three missed three pointers in between and this swathe of data would count it as three 1 shot makes/misses instead of two one three shot streaks. In order to combat this, we broke the data down further and switched up the types of shots observed.

To further simplify what counts as a streak, it is a shot where the result of the attempted shot N+1 is different from shot N. In a sequence of fifteen shots looking like Hit, Hit, Hit, Miss, Hit, Hit, Miss, Hit, Miss, Miss, Hit, Hit, Hit, Hit, Hit, the results of what would be counted as streaks are described in the table below.

(Frequency Distribution of Streak Length in a 15 Shot Sequence)

Length	1	2	3	4	5+
Hits	1	1	1	0	1
Misses	2	1	0	0	0

(Table 3)

The short two pointers had the strongest and only case for something resembling good conditions for a hot hand within the data because of longer streak numbers of four plus being four times more frequent than the average for all shots. Of course shot miss streaks were very uncommon here being “easy” buckets, but these were decreasing at a similar rate to the make streak’s increasing. Here we see the number of players hitting four plus shots in a row skyrocket compared to the other subsections, but just because these shots are closer does not necessarily mean these are “gimme” buckets. Defense around the rim is very tight. (Just watch any bit of Lebron James’ or Anthony Davis’ defensive highlights) These shots can and do get blocked frequently and sometimes even the pros miss dunks. Of course, it makes sense that if hot hands were present in this data set it would be here at least because of the difficulty of being “cold” from five feet out! Also, no shots where players were fouled were included in this part.

Although these players’ averages do not really show it, many of these shots longer 2s and 3s are probably fifty percent more difficult than closer in attempts, making it much easier to get a miss streak going than closer inside. The players in the data set are also superstar caliber meaning that their consistency is by definition better than average, otherwise they would be the average NBA player. With this in mind, players of this skill level are able to recognize their cold states and refrain from shooting after two or three misses. So although we do have stronger evidence of cold streaks here in terms of available observations, these streaks are mitigated by player skills and awareness to their temporarily ineffective shooting.

V. RESULTS

To get into the process behind our GVT inspired two sample hypothesis testing of the means, first samples of shots attempted after specific numbers of makes and misses had to be evaluated. The intuition here is that make percentage after a make or miss streak should be the same as the regular overall make percentage, which was GVT's null hypothesis. If a difference is statistically significant between these means, the null is rejected and a hot state may exist. Through a use of dummy/categorical variables, shots were classified in the whole sample along with each smaller spot based pool of shots. From here, differences between attempts conditional on each streak magnitude were calculated and tested for statistical significance by player and as a whole.

	Difference in Means T-Test Results (Group)							
Shot type	**Obs(3+makes)**	**Obs(3+misses)**	**Mean(P)**	**Mean(P/3makes**	**Mean(P/3m**	**Difference**	**Significance level**	**T Value**
All	2619	2614	0.46131	0.4464	0.4678	-0.0214	10%	-1.55272
3s	390	1995	0.36731	0.346	0.3719	-0.0259	not	-0.970393
Middle 3s	76	503	0.36406	0.35555	0.3719	-0.01635	not	-0.276105
Right 3s	45	105	0.41176	0.6	0.4285	0.1715	10%	1.9557802
Left 3s	32	77	0.4406	0.4375	0.42185	0.01565	not	0.149878
Long 2s	509	2219	0.37722	0.3988	0.3677332	0.0310668	not	1.304209
Medium 2s	224	576	0.416636	0.4464	0.3854	0.061	not	1.5713462
Short 2s	1882	539	0.60334	0.6217	0.5993	0.0224	not	0.9372696

(Table 4)

As expected, filtering the data into shot categories and even further into three plus makes/misses shrinks the sample dramatically. With a sample of this size though, a reasonable amount of shots are still left to analyze even with some groups only having under 1% of the total data population. Only a few selected shot types yield anything close to a statistically significant hot hand effect with right corner three pointers having a massive seventeen percentage point difference in conditional means and medium length two pointers having a six percentage point difference. The rest of the other shot types were either not statistically significant or had magnitudes in the negative direction meaning that shot accuracy was seeming to increase after a miss streak and decrease after a make streak.

Short twos are especially hard to get a statistically significant difference because of the high make percentage relative to other shots. Making three layups in a row is obviously a different feat than three three pointers and thus a true hot streak of short ange attempts is bound to be higher and thus many non hot streaks are captured by using only three straight makes. Increasing the number of shot successes on these shots though increases the chances of stretching beyond the confines of a single game as well as borders on banking on a player having an especially high number of attempts in a row, when the data shows that there are very limited instances of make streaks over four shots.

	Difference in Means T-Test Results (Player)							
Player	**Obs(3+makes)**	**Obs(3+ misses)**	**Mean(P)**	**Mean(P/3makes**	**Mean(P/3m**	**Difference**	**Significance**	**T Value**
Stephen Curry	150	238	0.470119	0.38	0.521	-0.141	5%	-1.841542
Lebron James	269	131	0.551505	0.52044	0.62878	-0.10834	none	-1.171459
Kawhi Leonard	156	181	0.49009	0.397435	0.54696	-0.149525	5%	-1.771196
John Wall	146	273	0.451312	0.4452055	0.446886	-0.001681	none	-0.022956
Russell Westbrook	160	401	0.4221585	0.425	0.4239	0.0011	none	0.0173527
James Harden	127	274	0.43607	0.47244	0.474	-0.00156	none	-0.020873
Kyrie Irving	197	257	0.4717719	0.5076142	0.49085	0.0167642	none	0.2334665
Andrew Wiggins	146	236	0.4518802	0.4726027	0.5169492	-0.044347	none	-0.575698
Anthony Davis	178	162	0.5045872	0.4719101	0.5308642	-0.058954	none	-0.677266
CJ McCollum	181	239	0.4760026	0.5082873	0.4435146	0.0647727	none	0.8685029
Carmelo Anthony	119	238	0.4334053	0.4537815	0.4285714	0.0252101	none	0.3184969
Damian Lillard	129	251	0.4435995	0.379845	0.4501992	-0.070354	none	-0.916136
DeMar DeRozan	173	283	0.4633721	0.433526	0.4416961	-0.00817	none	-0.11588
DeMarcus Cousins	108	219	0.4518156	0.3703704	0.4840183	-0.113648	10%	-1.37219
Devin Booker	109	291	0.4234801	0.3761468	0.3676976	0.0084492	none	0.1121459
Isaiah Thomas	140	254	0.4573241	0.3857143	0.492126	-0.106412	10%	-1.408258
Kemba Walker	126	256	0.4434483	0.452381	0.4296875	0.0226935	none	0.2963246

(Table 5)

For the shot streaks divided up by players, results were even more disappointing with nobody having a statistically significant increase in make percentage after three plus makes and four players having decreases in make percentage by double digits at the 5 or 10% significance level.

At first glance, this looks dismal for the existence of the hot hand as it did in GVT's study in 1985(table 1 with 76ers numbers in their work) with only Daryl Dawkins having statistically significant differences in shot percentage, but in the wrong direction. Most people after reading these results immediately go to the intuition that in the NBA once a player makes three shots in a row defenses tighten to stop him and of course after three misses the defenses are more likely to let him shoot. What really is going on here is a selection bias in the data from looking only at shot streaks of either makes or misses. Intuitively, we could say that the logic behind comparing the pure conditional means between the two types of streaks is sound, but it is when we pick something "randomly" from this finite sample of "assigned" attempts to represent the whole population that the difference of means runs into some flaws(Miller and Sanjurjo 2015).

Although a coin has the 50/50 chance of being heads or tails, the arithmetic mean of the combinations is only 5/12 since instances where a certain number of heads are flipped in a row with more recorded observations are weighted the same as flips with more tails. For example, a streak of three straight flips resulting in heads is weighted the same as two straight or a single flip. In order to get this fair coin's arithmetic mean up to the correct 50/50 proportion, numbers of streaks were divided by streak opportunities instead of just the raw flip numbers. This way the problem of having all numbers represented as equally informative when streak values in reality are more informative by nature is corrected and the predicted probability is returned to its actual value.

Miller and Sanjurjo's forthcoming work that attempts to revive the existence of the hot hand not only accounts for this selection bias, but shows us that there is indeed a statistical explanation for the lack of significant coefficients as well as a few being significant in the wrong direction. It is because the actual mean of the next shot attempt after a miss is between eight and twelve percentage points on average below the raw average of makes from the whole population. With this in mind, a player in a hot state only needs to match his season average in the streaks for it to really be a statistically significant difference from the true expected value.

The size of the bias is at its greatest streak length of five successes or failures in Miller and Sanjurjo's study(See their size of the bias graph in figure 1 in their 2016 paper). At the streak length of three used for this study using the same rough expected shot value as GVT of .5, we see a bias size of around four to six percentage points. To find the exact size of the bias for each expected make percentage value, we would use the formula and equations that are also from Miller and Sanjurjo's forthcoming work.

After using this equation with the streak info of three shots equaling K in another study where Miller and Sanjurjo compiled twenty eight years of NBA shot data, they found roughly an 8 percentage point difference in the true conditional mean versus the initial calculations from the GVT methodology. Thinking back to the fair coin having a true arithmetic mean of .405, these shot attempts have similar numbers once adjusted using this 8 percentage point cushion. I use this amount to adjust for the bias in my study because if twenty eight years worth of data being used as their sample to calculate for this bias in NBA players is still yielding an eight percent difference, then this is a conservative estimation to be used for a smaller study with players of similar caliber.

The other main reason that eight percentage points is used is because nba three point shootout performers are all All Stars just like the seventeen players selected for this study. A an average shooting percentage of the top ten three point shooters in the league that get invited to the contest have around a .40-.46 three point field goal percentage, which is fairly similar to the shooting numbers of my sample's averages. Of course these numbers will not be perfect, but this number should get us close to the true biased adjusted effect of the hot hand. To further lowball the effect in estimation, I have also included a three percentage point correction to represent the bottom threshold that Miller and Sanjurjo make note of in their work. The results here are almost as impressive as they were in Miller and Sanjurjo's working paper.

	Difference in Means T-Test Results (Group)								
Shot type	**Obs(3+makes)**	**Obs(3+misses)**	**Mean(P)**	**Mean(P/3makes**	**Mean(P/3m**	**Difference**	**Adjusted (.03)**	**T Value**	**Significance level**
All	2619	2614	0.46131	0.4464	0.4678	-0.0214	0.0086	0.3935854	not
3s	390	1995	0.36731	0.346	0.3719	-0.0259	0.0041	0.123781	not
Middle 3s	76	503	0.36406	0.35555	0.3719	-0.01635	0.01365	0.1923797	not
Right 3s	45	105	0.41176	0.6	0.4285	0.1715	0.2015	1.6504014	5%
Left 3s	32	77	0.4406	0.4375	0.42185	0.01565	0.04565	0.3173718	not
Long 2s	509	2219	0.37722	0.3988	0.3677332	0.0310668	0.0610668	2.0219067	1%
Medium 2s	224	576	0.416636	0.4464	0.3854	0.061	0.091	1.7132775	5%
Short 2s	1882	539	0.60334	0.6217	0.5993	0.0224	0.0524	1.1768744	not

(Table 6)

	Difference in Means T-Test Results (Group)								
Shot type	Obs(3+makes)	Obs(3+misses)	Mean(P)	Mean(P/3makes	Mean(P/3m	Difference	Adjusted(.08)	T Value	Significance level
All	2619	2614	0.46131	0.4464	0.4678	-0.0214	0.0586	4.2518399	1%
3s	390	1995	0.36731	0.346	0.3719	-0.0259	0.0541	2.026959	1%
Middle 3s	76	503	0.36406	0.35555	0.3719	-0.01635	0.06365	1.0748686	not
Right 3s	45	105	0.41176	0.6	0.4285	0.1715	0.2515	2.8680975	1%
Left 3s	32	77	0.4406	0.4375	0.42185	0.01565	0.09565	0.9160277	not
Long 2s	509	2219	0.37722	0.3988	0.3677332	0.0310668	0.1110668	4.6626727	1%
Medium 2s	224	576	0.416636	0.4464	0.3854	0.061	0.141	3.6321281	1%
Short 2s	1882	539	0.60334	0.6217	0.5993	0.0224	0.1024	4.2846612	1%

(Table 7)

Starting with the group data, now all but two shot types are statistically significant and are positive in magnitude. Right three pointers is still the clear leader having a 25 percentage point increase in make percentage in the hot state. In the by player group below, we find similar results, with only Kawhi Leonard and Steph Curry having shot percentage decreases after three makes. The rest are generally around six percentage points better in make percentage after three makes and statistically significant. Dramatic results all around are to be expected when a bias this large is adjusted for and keep in mind that these are some of the lower level bias adjustments compared to the .10 used on GVT's work by Miller and Sanjurjo.

	Difference in Means T-Test Results (Player)								
Player	Obs(3+makes)	Obs(3+ misses)	Mean(P)	Mean(P/3makes	Mean(P/3m	Difference	Adjusted (.03)	T Value	Significance
Stephen Curry	150	238	0.470119	0.38	0.521	-0.141	-0.111	-1.449724	10%
Lebron James	269	131	0.551505	0.52044	0.62878	-0.10834	-0.07834	-0.847075	none
Kawhi Leonard	156	181	0.49009	0.397435	0.54696	-0.149525	-0.119525	-1.415832	10%
John Wall	146	273	0.451312	0.4452055	0.446886	-0.001681	0.0283195	0.3868475	none
Russell Westbrook	160	401	0.4221585	0.425	0.4239	0.0011	0.0311	0.4906074	none
James Harden	127	274	0.43607	0.47244	0.474	-0.00156	0.02844	0.3805229	none
Kyrie Irving	197	257	0.4717719	0.5076142	0.49085	0.0167642	0.0467642	0.6512614	none
Andrew Wiggins	146	236	0.4518802	0.4726027	0.5169492	-0.044347	-0.0143465	-0.186243	none
Anthony Davis	178	162	0.5045872	0.4719101	0.5308642	-0.058954	-0.0289541	-0.332625	none
CJ McCollum	181	239	0.4760026	0.5082873	0.4435146	0.0647727	0.0947727	1.270757	10%
Carmelo Anthony	119	238	0.4334053	0.4537815	0.4285714	0.0252101	0.0552101	0.697508	none
Damian Lillard	129	251	0.4435995	0.379845	0.4501992	-0.070354	-0.0403542	-0.525483	none
DeMar DeRozan	173	283	0.4633721	0.433526	0.4416961	-0.00817	0.0218299	0.3096237	none
DeMarcus Cousins	108	219	0.4518156	0.3703704	0.4840183	-0.113648	-0.0836479	-1.009969	none
Devin Booker	109	291	0.4234801	0.3761468	0.3676976	0.0084492	0.0384492	0.5103348	none
Isaiah Thomas	140	254	0.4573241	0.3857143	0.492126	-0.106412	-0.0764117	-1.011236	none
Kemba Walker	126	256	0.4434483	0.452381	0.4296875	0.0226935	0.0526935	0.6880551	none

(Table 8)

	Difference in Means T-Test Results (Player)								
Player	Obs(3+makes)	Obs(3+ misses)	Mean(P)	Mean(P/3makes	Mean(P/3m	Difference	Adjusted (.08)	T value	Significance
Stephen Curry	150	238	0.470119	0.38	0.521	-0.141	-0.061	-0.796695	none
Lebron James	269	131	0.551505	0.52044	0.62878	-0.10834	-0.02834	-0.306435	none
Kawhi Leonard	156	181	0.49009	0.397435	0.54696	-0.149525	-0.069525	-0.823557	none
John Wall	146	273	0.451312	0.4452055	0.446886	-0.001681	0.0783195	1.0698531	none
Russell Westbrook	160	401	0.4221585	0.425	0.4239	0.0011	0.0811	1.2793652	10%
James Harden	127	274	0.43607	0.47244	0.474	-0.00156	0.07844	1.0495153	none
Kyrie Irving	197	257	0.4717719	0.5076142	0.49085	0.0167642	0.0967642	1.3475861	10%
Andrew Wiggins	146	236	0.4518802	0.4726027	0.5169492	-0.044347	0.0356535	0.4628468	none
Anthony Davis	178	162	0.5045872	0.4719101	0.5308642	-0.058954	0.0210459	0.2417757	none
CJ McCollum	181	239	0.4760026	0.5082873	0.4435146	0.0647727	0.1447727	1.9411806	5%
Carmelo Anthony	119	238	0.4334053	0.4537815	0.4285714	0.0252101	0.1052101	1.3291932	10%
Damian Lillard	129	251	0.4435995	0.379845	0.4501992	-0.070354	0.0096458	0.1256054	none
DeMar DeRozan	173	283	0.4633721	0.433526	0.4416961	-0.00817	0.0718299	1.0187971	none
DeMarcus Cousins	108	219	0.4518156	0.3703704	0.4840183	-0.113648	-0.0336479	-0.406266	none
Devin Booker	109	291	0.4234801	0.3761468	0.3676976	0.0084492	0.0884492	1.1739829	none
Isaiah Thomas	140	254	0.4573241	0.3857143	0.492126	-0.106412	-0.0264117	-0.349534	none
Kemba Walker	126	256	0.4434483	0.452381	0.4296875	0.0226935	0.1026935	1.3409393	10%

(Table 9)

In terms of the cold state, the calculations would just flip between P/3make-P/3miss to P/3miss-P/make, yielding parallel flipped results. This makes sense because the best control of a shooting performance state is its counterpart because if a state truly exists, the difference would be greatest between these two scenarios leading into each attempt. A regular average here may be biased in either direction seeing that it could be at the beginning of a hot or cold state, and thus making the difference between conditional means artificially smaller just like how the coin flip numbers are artificially lowered by the .5 probability of an outcome being used instead of the arithmetic mean. As for the players with opposite signs on their hot versus cold data, a few factors may lead to a valid explanation of this occurrence. One is that the cold state may be more potent.

Between these two different states we tested, a few explanations can be made for why a cold state is in fact more potent than the hot state. First, is that it could be more psychologically draining for each miss accumulated on a cold streak than makes are empowering in a hot streak. This is consistent with psychological research that shows that negative emotions are more potent than neutral or positive ones (Negativity Bias). A large amount of misses in a row has the consequences of missed opportunity and creates a chance for the other team to pull ahead or drift away in the game. For example, let's say James Harden has missed four field goals in a row and the opposing team has now opened up a six point lead. That next shot he takes may have a little bit of a rattle of the the last few misses in it in terms of pressure of not letting the game slip beyond reach.

For a hot streak, that fourth shot may be more of a check to see if the magic is in fact there, like a Stephen Curry near half-court shot once a six point lead has been opened up thanks to his streak.

The second point is that it is overall much easier to play sloppy than it is to be at an above average level of play. With that being said, it is also harder to be absolutely perfect from the field than it is to be zero for fifteen. Of course there are diminishing returns to effort in either direction, but these players are the best in the business and are more than capable of making someone else look foolish on a bad day than anyone else on the planet.

Also, what is this decrease in shot percentage after make streaks and increase in shot percentage in miss streaks for a few players even after the fix has been made? A negative correlation here is not a "cold state, but a correction to what has transpired over the past few attempts. On make streaks it may be the defense tightening up on that player and on miss streaks it could be a player being extra careful before his next attempt to make sure that the miss streak ends.

Basketball in itself is a game with strategy and of course within the context of this, it is expected that tendencies and patterns are corrected for and adjusted by players and coaches to improve the chances of winning. Another large part of GVT's error in their original study was not controlling for this type of in game self correcting. Just because one looks at the result following a shot streak does not mean that the effect tested for is going to pop out when many other factors such as strategy may be cancelling it out. Dixit and Nalebuff mention this piece of game theory briefly in the first chapter of their 1991 book *Thinking Strategically: The Competitive Edge In Business, Politics, And Everyday Life.*

"While the statistical evidence denies the presence of streak shooting, it does not refute the possibility that a "hot" player might warm up the game in some other way. The difference between streak shooting and a hot hand arises because of the interaction between the offensive and the defensive strategies. Suppose [a player] does have a truly hot hand. Surely the other side would start to crowd him. This could easily lower his shooting percentage."

(Dixit and Nalebuff 1991)

Of course, this adjustment in strategy would almost never come into play with free throws, making Arkes' 1.9 percent still a solid estimation and the Celtic free throw part of GVT's study unaffected. The only time strategy could come into play on free throws is if a player needs a strategic miss to run out the clock at the end of a game that could break a shot streak continued otherwise. These scenarios are decently rare in close games given the exact timing this situation would play out.

To wrap up this defining part of the study, both effects are large enough to impact these star players, who are the picture of consistency given that scoring over twenty points per game in the most competitive basketball league out there is incredibly difficult to accomplish. If the effects are this large with the best of the best in the NBA right now, imagine the effects on regular starters, benchwarmers, or even you or me. Here we tested a realm in which the hot or cold state would be best showcased, but on the other hand hardest to attain. A truly amazing performance in pickup games, high school, and even college pale in comparison to one on this stage because of the competition, the viewing pressure, and money earning stakes are as large as they could ever be. Players and coaches' careers are determined by performance and victories. Inefficient strategies may shift the structure of a multi-billion dollar industry.

VI. CONCLUSIONS

In summary, we took the popular urban myth/ playing phenomenon of the “hot hand” in basketball and put it to the test at the highest level of competition in the NBA. What we found is that in a star player’s games, hot and cold streaks are a statistically different scenario from any other selection of shots. From here, the hot and cold state can be dissected further into two parts. The small version or microscale is a brief stint in which a player out shoots or undershoots his average by a substantial amount with k number of makes or misses in a row, but it is not a large enough set of shots to draw a statistical inference from on its own.

For example, the aforementioned perfect triple double by Russell Westbrook where he was six for six from the field can be considered a micro hot state because for those six shots he was almost sixty percent better from the field than his season average. However, so few shots were taken that it cannot be used for a statistical comparison unless of course he had several streaks within the same game. The Macroscale is what we tested which is a game to game measure of make percentage after a certain number of shots have been made or missed in a row. These games may include multiple instances of both states, but for it to be considered a true macro hot state, the hot effect has to dominate any coldness by enough to make it statistically different from the recent shooting averages on the positive end. Basically a hot state cannot just have three makes in a row and a regular amount of makes on the fourth attempt, but instead have enough fourth shot makes to make it statistically different from shots after a miss streak.

With Miller and Sanjurjo's correction on the means of hot and cold streak data, we then get a fair estimate of means for comparison. What was found is indeed an average statistical difference of roughly four percentage points in make percentage between hot states and cold states in player by player numbers and roughly a ten percentage point difference for players by shot specific groupings. Both are much larger than the 1.9 percentage point difference found in Arkes' 2010 study and certainly more than the 1.2 percentage point difference in Andrew Bocskocsky, John Ezekowitz, and Carolyn Stein's 2014 study. If anything, what is amazing is that these players are so consistent that most games in general fall within five percentage points of each player's average or less than half of a standard deviation, which makes either side of this a drastic change from the norm.

In conclusion, the best players in the world have good days and bad days like anybody. However, on a few days, a hot or cold state may make them a statistically different player on the next shot. Coaches and players should adjust their strategies accordingly to the in-game performance of players. Relying on season averages fails to maximize efficiency when considering the variability of player performances in a "hot" or "cold" state. Perhaps the final shot should be taken by the game's best player not the season's best player. The next time you see the star of your favorite NBA team rip up a defense for forty points and shoot fifteen for twenty two from the field, know that it is not magic, but a hot hand.

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APPENDIX A

Shot Selection Diagram