Experts' Perceptions of Autocorrelation: The Hot Hand Fallacy Among Professional Basketball Players

Justin M. Rao*
UC San Diego

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Abstract

The hot hand fallacy is the perception positive autocorrelation when none is actually present. However, when mistaken beliefs do not affect the underlying success probability, then they come at zero cost if the underlying sequence truly exhibits independence. This paper studies an environment where success probabilities are a function of beliefs: shot selection in professional basketball. Beliefs are inferred through shot conditions such as time between shots, distance, defense, location, passes and touches. I find that a majority of the players in the sample significantly changed their behavior in response to hit-streaks by taking more difficult shots, while no player responded to miss-streaks. However, controlling for difficulty, shooting ability is not related to past outcomes. A quarter of the sample suffered a significant loss in shooting efficiency as a result of their mistaken responses. The remaining players either showed no response (3/8) or did so by substituting point value for difficulty leaving efficiency unchanged (3/8). Consistent performance is linked to heightened individual economic incentives.

1 Introduction

In many settings it is widely believed that past success is a good predictor of future success. Colloquially such sequential dependencies are referred to as having a "hot hand." There is a considerable evidence for belief in the hot hand. Basketball players and fans express the belief in surveys (Gilovitch, Villone and Tversky 1985, Burns 2004), mutual funds often advertise they have beaten the market in past years[1] and patterns in sports betting are consistent with bettors believing a team "gets hot" (Camerer 1989). If there exists an underlying serial dependency in the data, belief in the hot hand perfectly rational. For instance, given the strong serial correlation in GDP, a macro economist would hardly quibble at the common expression "the economy is heating up." However, many studies have found that people tend to infer positive autocorrelation when none in fact exists. This inference mistake is known as the "hot hand fallacy" (Tversky and Kahneman 1971).

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[1]In fact such advertising drew the ire of the SEC and lead to a change in the rules governing permissible advertising practices. The SEC 2003-122 states: "The amendments address concerns that, especially in times of strong market performance, some funds may use advertising techniques focusing on past fund performance that may create unrealistic investor expectations or may mislead potential investors."

However, studies which have found the hot hand fallacy have used novice experimental subjects or field subjects that had little to no financial incentive to have accurate beliefs. In contrast, this paper uses experts (professional basketball players) making decisions in a familiar environment (shot selection during games). In this setting, mistaken beliefs about serial dependence in ability can lead players to take shots that are too difficult, which can be costly for the team and individual. This paper addresses the questions: does the hot hand exist in professional basketball and do players respond appropriately to sequential dependencies (if any) in their ability? The goal is to further our understanding on the role of incentives in reducing inference mistakes and biases.

In a widely cited paper, Gilovitch, Vallone and Tversky (1985) study the hot hand in National Basketball Association (NBA) games. The authors present survey evidence that fans hold a strong belief in the hot hand.[2] The paper also surveys NBA players and finds that a majority (of the small sample) hold a belief in the hot hand. Contrary to the beliefs of players and fans, GVT fail to reject the hypothesis that shots are produced from a Bernoulli process with a constant success rate. In this paper I show that GVT's maintained assumption that players' shot selection is random (i.e. not dependent on past performance) is violated. If players take more difficult shots after a string of successful makes, then inference of autocorrelation in ability will be biased downwards if one fails to control for difficulty. A simple example is a player who is 5% better following a string of makes but adjusts by taking shots that are 5% more difficult – here one would erroneously find no hot hand effects.

Despite these shortcomings, the GVT finding has become a textbook example of a "behavioral bias." Agents, in this case basketball fans, (seemingly) commit mistaken inference and infer a pattern when none is in fact present. However, signal processing in a binary environment is a very difficult task and we might not expect unmotivated observers to do so following the edicts of Bayesian rationality.[3] On the other hand, professional players are the experts with multi-million dollar contracts. Inferring players' beliefs from questionnaires is unsatisfying from an economic perspective. Abstracting from the difficulty of eliciting true beliefs through a survey, economists are concerned with the behavioral implications of beliefs, not merely their subjective revelation. The standard method of analysis is to take observed behavior as the input and use it to define the set of action-consistent beliefs or preferences.

Using a rich dataset, I control for shot difficulty with shot conditions such as distance, defensive pressure and location and *find no evidence of the hot hand*. Given that shooting ability is not systematically related to past outcomes, I address the natural question: do players exhibit *through their actions* a belief in the hot hand, and if so, do the responses significantly impact shooting efficiency (points per shot)? Despite the fact that their ability does not predictably increase after made shots, some players shot selection indicates that they believe it does (i.e. they take signif-

[2]Fans belief in the hot hand also been found by (Burns 2004) which polled college students of varying basketball experience and (Rao 2009b) which examined the belief of "hardcore" fans found on Internet basketball message boards.

[3]The weak power of classical statistical tests of binary outcome streaks, such as the runs test, speaks to this difficulty (Wardrop 1995).

icantly more difficult shots but perform no better than their baseline skill level). However such a response is not universal. A majority of the sample has consistent shot selection across past outcomes or responds in a manner that does not impact shooting efficiency.

Laboratory and field studies using relatively inexperienced subjects are very useful in that they allow us to indentify errors in reasoning endemic to human psychology. The shortcoming is that they are unable to examine if these biases are present in the face of strong countervailing incentives. Field studies using expert practioners allow us to examine how deep behavioral biases run. Professional sports offer an attractive testing ground for economic theory because the stakes are high and payoffs can be objectively quantified and observed on the individual level. Unlike most industries, here the productive activities of the firm are on full display.

The literature on inference mistakes in the perception of covariation is deep. Studies have found experimental subjects display a positive bias in the perception of covariance (Kareev 1995), expect too much reversion in sequences (the "Gambler's Fallacy", Estes 1950) , lottery players are averse to choosing a number a week after it has won (Clotfelter and Cook 1993, Terrell 1994) and casino gamblers display both the hot hand fallacy and gambler's fallacy in roulette and craps (Croson and Sundali 2005). In all these cases, market forces do not provide a strong incentive for accurate inference. Experimental subjects are operating in an unfamiliar environment for low stakes, lottery players sacrifice a very small amount in expectation by avoiding previous winners[4] and all bets for given casino game have equal expected value. Further evidence of zero-cost mistaken perception of positive autocorrelation comes from financial markets. Sirri and Tufano (1998) find that investors are more likely to purchase top-performing mutual funds from the previous year despite the fact that there is little evidence of persistence in mutual fund performance.[5]

The dataset used in this paper comes from the 2007/08 Los Angeles Lakers NBA season.[6] The data set was constructed from NBA.com game logs and by actually watching the 60 games. It includes shot distance, defensive pressure, shot type, shot fouled, location, shot blocked, touches per player, time on the shot clock, double teams and if the shot was a turnaround or fadeaway. Observed shooting behavior following strings of makes and misses is analyzed to infer players' beliefs. I find heterogeneity of response to strings of successful shots; players fall into three groups: *sub-optimal responders*, *benign responders* and *consistent performers*. Both sub-optimal and benign responders react to past success by taking significantly more difficult shots, the difference is that benign responders do not show a significant drop in "points per shot" because they are shifting into

[4]In parimutuel lotteries a share of the proceeds from ticket sales is simply split among the winners, as such a player should try to choose numbers that others are averse to choosing. In non-parimutuel games there is no cost to mistaken beliefs. Players also make the mistake of not betting "unlucky" numbers such as 666 enough, and these mistakes are generally of a much larger magnitude than gambler's fallacy mistakes.

[5]Hendricks et al (1993) find evidence of persistence in mutual fund performance, but the persistence is generally short-lived and limited to the absolute best and worst funds in the sample. Carhart (1997) revisits the issue and concludes that overall the evidence does not support positive autocorrelation in mutual fund performance. Neither paper finds any evidence of negative autocorrelation. As such, the observed behavior of buying "hot" mutual funds comes at zero cost and potentially a small gain.

[6]The L.A. Lakers are one of teams in the National Basketball Association (NBA), which is the top professional basketball league in the world. NBA team salaries routinely exceed $80 million per team annually.

3 point shots, which offer increase value to offset the difficulty. Both groups of responding players also tend to pass the ball less and shoot more frequently. Consistent performers show no evidence of a belief in the hot hand.

The adjustments of the sub-optimal responders leads to significantly lower shot productivity and it is argued that these mistakes are of a costly, albeit not enormous, magnitude. That is they are large enough to alter game outcomes over the course of a season, but the net effect is likely in the range of one or two games (out of 82). I show that the players who sub-optimally respond to their perceived increase in ability had less economic incentive to optimally select shots due to contracts top-censored by the league's collective bargaining agreement. Whereas the players in the sample who adhere closest to the dictates of Bayesian rationality are young, unestablished players fighting for playing time and contracts.[7] The heterogeniety in response and link to economic incentives indicates that the while the hot hand fallacy is a robust behavioral bias, it is by no means universal or immune to incentives.

Of course to justifiably claim these predictable responses to past performance are mistakes, it must be adequately shown that ability following makes does not experience a concomitant increase.[8] Controlling for shot conditions, players show no evidence of ability changing as a function of past outcomes — this holds true for streaks of any length. I cannot reject that players in some rare instances have periods of higher ability, but it is shown that ability, in contrast to shooting behavior, does not systematically change as a function of past outcomes.

Interestingly, players respond far less to miss-streaks. Both groups of responding players show consistent performance across all streak lengths of misses. Their behavior after miss-steaks does not appear different than their baseline shot selection. For miss-streaks, all players in the sample have shot selection consistent with their observed performance as no player shows a decrease in ability following misses either. Inference mistakes in the serial dependence of ability are limited to the success domain. In the discussion section I present potential explanations for this asymmetry in response.

The rest of the paper proceeds as follows: Section 2 describes the data, Section 3 presents the main results of the paper, a discussion of the results follows in Section 4 and Section 5 concludes.

[7]NBA players enter the league on a standardized "rookie contract" the size of which depends on where they were selected in the annual draft. These contract are 3-4 years in duration. After this period, a player may become a "free agent" and sign contract dictated by his market value. Players who have performed well earn a contract often paying many times that of his rookie contract, while players who have not done so well might be unable to sign with any team and have to play in a lower paying league in Europe.

[8]I do not have to show that the hot hand does not exist per se, just that ability is not systematically related to past outcomes. There might be rare occurrences that players "get in the zone", but if they consistently respond to past outcomes by taking more difficult shots then ability should consistently respond as well. In section 3.3 I show that this is not in fact the case.

2 Data

The data used in the paper are 60 games from the Los Angeles Lakers 2007-08 National Basketball Association season. For each game, shot time, distance and outcome were first entered using the game logs (an online play-by-play including shot time and success/failure) available at espn.com and the NBA's official website.[9] Each game used in the study was recorded and the games were then watched by the author to record shot location, defensive pressure, touches for each player on the court, shot blocked/fouled, shot type and time on the shot clock.[10] The author performed all the game cataloging and did so in as objective a manner as possible.[11]

Table 1 describes the variables collected.

Table 1: Descriptions of the variables

Variable	Description
Shot Time	Time of the FG attempt,
	includes attempts when the player was fouled
Defended[12]	=1 if player was guarded at the time of the shot
Hit	=1 if shot is made
Double team	=1 if player was defended by 2 or more opponents
Touches	Number of touches on a possession, by player
Team touches	Total touches on a possession
Shot Zone	One of 14 zones giving location on the court
Turnaround	Fadeaway, turn-around jumper or hook shot
Distance	Shot distance in feet, =0 for dunks and 1 for layups
Pulled	Player removed from game
Fouled	=1 if shooter was fouled
Blocked	=1 if shot is blocked
Forced	=1 if shot is taken with less than 5 seconds on the shot clock
Shot clock	time on the shot clock
Offensive rebound	=1 if the shot resulted in an offensive rebound

The Lakers were chosen because they have two players Kobe Bryant and Derek Fisher who are known around the league as streaky shooters. Bryant is considered by many to be the leagues top player and was the league MVP for the year of the study. Data was collected only for the Lakers and not their opponents. The NBA season is 82 games long, given the lengthy nature of the cataloging process (4-5 hours per game) it was determined that 60 games provided a large enough sample. The data set covers more games and is much richer than any previous study.

[9] An example can be found at http://sports.espn.go.com/nba/playbyplay?gameId=280106013.

[10] For the first 34 games in the sample a binary variable was recorded when the shot clock was less than 5, for the remaining games the actual time was recorded.

[11] Many games have been transferred to .mpeg format and can be provided along with the coded spreadsheets to any parties interested in examining my cataloguing system.

[12] A shot is counted as defended if the defender is within 2ft of the shooter and actively guarding him when the shot is attempted, notably this excludes "close-outs" where a defender runs at an open shooter. The defended variable was the hardest to code, particularly difficult cases were watched many times. In these cases the motion of the shooter was examined in an effort to determine if the nearby defender affected the shot. Every effort was made to apply as objective a standard as the other measures used in the study.

The appendix further describes the collection process.

3 Results and analysis

The 8 players who took 300 or more shots during the sample period are included in the study. In the way of background, a basketball team consists of three types of players: guards, forwards and low-post. Guards bring the ball up the court and handle the ball on the perimeter during the offensive set. They are the primary ball handlers and long-range shooters. Low-post players are the tallest members of the team and generally take short-range shots near the basket and get rebounds. Forwards operate between the guards and the low-post. These distinctions are important because the range of shooting opportunities and accordingly the available responses to perceived "hotness" may differ across player types. Table 2 gives useful background information on the players in the study.

Table 2: Background on Players

Player	Description	Shots
Kobe Bryant	shooting guard, league MVP	1,418
Derek Fisher	point guard, good jump shooter	604
Lamar Odom	forward and low-post, decent jump shooter	677
Jordan Farmar	point guard, good jump shooter	455
Luke Walton	forward, "role player"	353
Vladimir Radmanovic	forward, long-range shooter	322
Ronny Turiaf	low-post, limited shooting range	334
Sasha Vujacic	shooting guard, Kobe's backup	359

3.1 Predicting shot probabilities

For each player, the data has a panel structure by games (i) and possessions within games (t). As such, the natural estimating procedure to formulate predicted probabilities is random-effects Probit by player. Appendix Table 2 provides the estimation results. A cubic in distance is used to account non-linear increases in shot difficulty with distance. For some players none of the three distance terms are statistically significant but a joint F-test of significance overwhelmingly rejects the null of joint insignificance for all players. *Defended* is interacted with both *layup/dunk* and *three-pointer* to allow for differential effects of defense depending on shot type. Unreported regressions including the zone dummies were run but interestingly including shot location did not significantly improve fit for any player (controlling for a cubic in distance).

The coefficients have the expected signs. Notably being defended leads to a large and significant drop in shooting percentage. Most players had a lower shooting percentage when they took a "turnaround" type shot - since these shots were nearly always taken when being defended the marginal effects are not pronounced. Figure 1 shows the predicted success rates as a function of distance for undefended standard shots for two players: Kobe Bryant and Lamar Odom. Both patterns are typical, shooting percentage falls rapidly for the first few feet of distance, levels off for a mid-range "comfort zone" and then falls rapidly again for longer range shots. For low-post players this second fall occurs at about 12ft (2ft less than a free throw), while for long-range specialists it occurs as far as 25ft from the basket (1ft more than the longest three pointer).

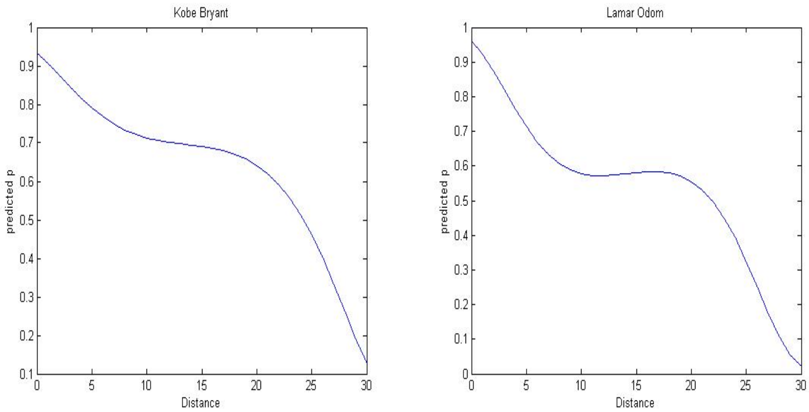

Figure 1: Success probability by distance for Kobe Bryant and Lamar Odom

3.2 Shooting performance as a function of past outcomes

The analysis of this subsection is done through Table 3 which relates shooting performance to past shot outcomes. The table is broken down by streak length and outcome (hit/miss). It allows for an easy comparison of behavior following a streak of X hits as compared to a streak of X misses. Note that the Table has telescoping structure. Columns 1 and 2 give all the outcomes after 1 hit and miss respectively, i.e. they include all shots taken by the player. Moving to columns 3 and 4 limits the sample to streaks of length 2 or more, and so on down the line.

A word of explanation is needed to understand the results presented in Table 3. "Hit rate" is the observed success rate for the shots in the column and "avg $\hat{p}$" is the average predicted success rate taken from the estimation of the previous subsection. Expected points for shot it are calculated as follows and then averaged across shots in the column:

$$\mathrm{E}_{it} = \begin{cases} \hat{p}_{it} * 2 + \hat{p}_{it}^{\text{off}}(1-\hat{p}_{it}) * \mathrm{EV}_{t+1} & \text{fouled=0, three=0} \\ \hat{p}_{it} * 3 + \hat{p}_{it}^{\text{off}}(1-\hat{p}_{it}) * \mathrm{EV}_{t+1} & \text{fouled=0, three=1} \\ \hat{p}_{it}(2 + f_i * 1) + (1-\hat{p}_{it}) * f_i * 2 & \text{fouled=1, three=0} \\ \hat{p}_{it}(3 + f_i * 1) + (1-\hat{p}_{it}) * f_i * 3 & \text{fouled=1, three=1} \end{cases}$$

where f_i is player i's free throw shooting success rate for the 2007/2008 season, EV_{t+1} is the expected value of a possession following an offensive respond, $\hat{p}$ is the predict shot success rate and $\hat{p}^{\text{off}}$ is the predicted probability of an offensive rebound for a given shot.

For the sample period the Lakers averaged 91.7 shots per game. Except in cases during the last minute of the game during close games, maximizing expected point value per shot is the optimal strategy because at the end of the game the team with the most points wins.[13] Rao (2009a) provides simulations that show that risk-neutrality maximizes the probability of winning the game. The intuition is that since there are a large number of possessions over the course of a game the law of large numbers implies that a risk-averse stance would lead to a much lower point total with probability near 1.

Significance levels shown in the tables are determined using t-tests which compare the hits section of each column with the miss section.[14] The observed success rate is never significantly different from the predicted performance.

The results are discussed player-by-player. The sheer amount of information can be initially overwhelming. Since Bryant takes over 1/3 of the shots when he is on the court and because he is the star player his table will receive the most attention.

[13] The last minute of play for games when the point margin was less than 5 were omitted

[14] There is one exception, the star on "42" in column 4 of Bryant's table. In this case the significance level indicates that Bryant has too few streaks of 4 makes given his overall shooting percentage. The significance was determined through simulations and maintains the assumption that success rate is constant. The result indicates that if we failed to account for shot difficulty we would (incorrectly) conclude that Bryant has a "oscillating" or "gambler's" hand.

Table 3: Shot selection by player as a function of past outcomes

Kobe Bryant	Consecutive Shots Made/Missed							
Outcome	1		2		3		4	
this period	Made	Missed	Made	Missed	Made	Missed	Made	Missed
Shots	645	706	291	387	119	205	42**	112
Hit Rate	0.422	0.424	0.399	0.434	0.353	0.459	0.405	0.438
Avg $\hat{p}$	0.408**	0.434**	0.399**	0.435**	0.382***	0.442***	0.410	0.422
Expected points	1.333**	1.394**	1.307**	1.397**	1.221***	1.379***	1.216	1.339
Derek Fisher								
	1		2		3		4	
Shots	240	304	91	157	31	78	11	52
Hit Rate	0.425	0.428	0.451	0.452	0.484	0.474	0.545	0.481
Avg $\hat{p}$	0.414	0.425	0.399	0.423	0.432	0.419	0.424	0.424
Expected points	1.291*	1.358*	1.190**	1.333**	1.170**	1.372**	1.195	1.443
Lamar Odom								
	1		2		3		4	
Shots	328	287	151	141	73	64	36	39
Hit Rate	0.451	0.443	0.477	0.468	0.521	0.438	0.556	0.436
Avg $\hat{p}$	0.444	0.465	0.446	0.481	0.430	0.463	0.454	0.509
Expected points	1.393	1.385	1.345	1.372	1.332	1.322	1.384	1.398
Luke Walton								
	1		2		3		4	
Shots	133	163	44	70	12	25	3	18
Hit Rate	0.368	0.472	0.364	0.529	0.333	0.600	0.333	0.556
Avg $\hat{p}$	0.394*	0.443*	0.394	0.444	0.367	0.424	0.263	0.438
Expected points	1.200	1.233	1.231	1.222	1.470	1.232	1.470	1.292
Vladimir Radmanovic								
	1		2		3		4	
Shots	130	146	49	68	26	29	13	18
Hit Rate	0.408	0.432	0.531	0.441	0.462	0.414	0.385	0.444
Avg $\hat{p}$	0.399**	0.444**	0.441	0.441	0.440	0.428	0.382	0.448
Expected points	1.324	1.375	1.379	1.357	1.339	1.343	1.301	1.359
Ronny Turiaf								
	1		2		3		4	
Shots	125	149	44	74	15	38	4	27
Hit Rate	0.368	0.383	0.318	0.351	0.267	0.447	0.250	0.481
Avg $\hat{p}$	0.371	0.387	0.370	0.380	0.387	0.421	0.415	0.451
Expected points	1.238	1.324	1.174	1.322	1.341	1.335	1.332	1.302
Jordan Farmar								
	1		2		3		4	
Shots	199	195	81	74	29	24	13	14
Hit Rate	0.427	0.503	0.383	0.514	0.517	0.375	0.615	0.429
Avg $\hat{p}$	0.463	0.477	0.448	0.493	0.494	0.496	0.496	0.493
Expected points	1.392	1.354	1.374	1.398	1.419	1.419	1.353	1.496
Sasha Vujacic								
	1		2		3		4	
Shots	133	172	54	84	22	36	10	23
Hit Rate	0.451	0.436	0.463	0.452	0.409	0.472	0.200	0.478
Avg $\hat{p}$	0.419*	0.457*	0.388	0.440	0.395	0.479	0.380	0.471
Expected points	1.368	1.446	1.312	1.417	1.295*	1.504*	1.280	1.524

*** p<0.01, ** p<0.05, * p<0.1

In column 4 of Bryant's table, we see he has "too few" streaks of 4 hits. Using GVT's methodology of assuming random shot selection, we would conclude that Bryant has a statistically signficantly worse following makes (a "gambler's hand"). This result highlights the importance of controlling for shot difficulty. The reason he has too few streaks of 4 hits is that he takes progressively more difficult shots, based upon observables, after strings of hits. For instance after 3 hits his average predicted success rate is .382 while after 3 misses it is a healthy 0.442. Similarly after two hits average $\hat{p}$ is 0.399 while after two misses it is 0.435. These differences are highly significant. One might argue, however, that since the prediction model only took shooting conditions into account, and not past performance, that while the shots appear harder they are not in fact more difficult because ability has temporarily increased or decreased. If this were the case and the hot hand does in fact exist (at meaningful levels) we would expect actual performance to exceed predicted performance after hits and fall short of predicted performance after misses. For Bryant we note that this is not in fact the case —- the model performs very well. There are not systematic "model beating" tendencies that would point to the existence of a hot hand that predictably follows from past success. The following subsection addresses this point in much more detail.

The increased shot difficulty leads to a decline in points per shot for Bryant. In NBA competition, small differences in shooting percentage matter because games are often decided by only a few points. For example, in the 2007/08 season the difference between the best Western Conference team and the team that just missed the playoffs (8 teams make the playoffs per conference) was a mere 6.1 point differential per game and 18 (of 82) games played by the Lakers during the 2007/08 season were decided by 4 points or fewer.[15] In Table 7, Bryant's outside options are analyzed and it is shown that the net cost to the team should be adjusted down by approximately 0.05 points per shot because the defense increases pressure on all players during longer hit-streaks. As such the mistakes are not as costly as they initially appear, although they are still economically meaningful. In the discussion section I quantify the cost of these mistakes over the course of the season.

Unlike Bryant, Fisher does not take systematically more difficult shots in terms predicted success rate, but expected points do tend to decline after successes. The reason, which is shown in Table A1, is that Fisher draws fewer fouls after past success(es). This is because he is more likely to "settle" for a jump shot rather than driving the lane to draw a foul. Given his high free-throw shooting percentage, fouls provide high expected point value for the field goal attempt. Fisher and Bryant comprise the sub-optimal responder group.

The two remaining guards are Farmar and Vujacic both of whom respond less than their veteran counterparts. Farmar's expected shot value is stable across columns — he takes slightly harder shots, but these shots are 3-pointers offering higher returns to offset the difficulty (see Table 6). There also does not exist a pattern of exceeding or falling short of model predictions. Interestingly, Farmar is the least experienced player in the sample. An explanation is that since he is a young player fighting for playing time and hoping for a large free-agent contract, mistakes are far more costly. The lack of wiggle room creates a strong incentive for optimal behavior. Appendix Table 3 shows that there was wide range of annual salary and years remaining on contracts. Younger players yet to sign a large (by NBA standards) contract generally performed in closer adherence to Bayesian rationality than their veteran peers. I elaborate on this point in the discussion section.

Returning to the discussion of Table 3, Vujacic shows a pattern of taking more difficult shots, based upon observables, after makes than misses. For length 3 the model matches the observed hit

[15] Making the playoffs allows the team to host lucrative home games and boosts the player's reputation for future contracts. The higher ranked a team is during the regular season, the more playoff games it gets to host. This provides both direct financial windfall and the benefit of increasing the chances the team will proceed in the playoffs because of the home court advantage.

rate for both cases and expected point value is significantly lower following 3 hits as compared to 3 misses. For length 4, the sample sizes are small — expected point value is lower following makes but the difference is not significant. His pattern of taking more difficult shots is not as pronounced as Bryant's as it only appears after strings of length 3 or more, whereas for Bryant even a single made shot has an effect.

In general forwards and low-post players respond less to past outcomes. One factor is that the unconditional variance in their success rate is lower as they have a more homogeneous shot repertoire. Another is that since they get far fewer touches per possession (see Tables 6 and A1), there are fewer opportunities to make a behavioral adjustment even if they held the hot hand belief.

Long-range shooter Radmanovic takes significantly more difficult shots following a hit as compared to a miss, but these changes do not lead to a significant decline in expected points because he is switching into 3-pointers (Table A1). His expected point values are stable across columns and the pattern of taking more difficult shots appears to only apply to the most recent shot. Walton has a similar pattern, he takes harder shots but experiences no drop in expected point value. Turiaf has stable shot difficulty and expected point values across columns. Odom displays a tendency to take slightly more difficult shots after hits as compared to misses, but in terms of expected shot value, his behavior does not trend up or down based up on past performance. These players make up the consistent performers group.

Interestingly, the patterns of response are driven only by streaks in the makes domain. For instance, the player who responded the most to his past success, Bryant, did not respond at all to miss-streaks. The predicted success rates of his shots for miss-streaks of length 1-4 were 0.44, 0.44, 0.43 and 0.45 respectively. His points per shot and other measures of shot selection given in Table 6 were stable as well. The results are similar for the remaining players in the sample.

3.3 Is ability systematically related to past outcomes?

One can observe from Table 3 that players do not exhibit a tendency to exceed the predictions of the model (based on observables alone) following makes as compared to misses. Put another way, there does not appear to be an unobserved change in ability. However, given the sheer amount of information contained in Table 3, it is useful to present aggregate analysis that makes the point more forcefully.

Table 4: Summary of Table 3

	Better than expected	Worse than expected	Sign Rank Test z-score
Following make(s)	19	13	0.90
Following miss(es)	17	15	0.90

The sign rank score indicates that players beat the model by roughly the same magnitude following makes and misses. In absolute terms, 19 of the 32 observations (8 players by 4 lengths) exceed the model expectations following makes while 17 do so following misses. The reason the sign rank score is the same is that it is weighted by the magnitude of the differences, meaning that the differences for the case of makes were somewhat smaller than those of misses.

Another way to attack the question at hand is to put lagged performance into the Probit model estimated in Appendix Table 2. Again, shot difficulty is controlled by the included conditioning variables. Table 5 reports the coefficient estimates and standard errors for "last shot made," "last 2 shots made," and "last 3 shots made" — which are added separately due to collinearity problems. If hot hand effects are systematically related to past outcomes, the estimates should display a positive trend (even if none are individually statistically significant). In fact such a trend is not present. The estimated coefficients are just as likely to be positive as they are negative and are generally quite close to 0.

Table 5: RE Probit Estimates of Shot Success on Lagged Performance Conditional on Observable Shot Conditions

Player	Last Shot Made	Last 2 Made	Last 3 Made
Kobe Bryant	0.06	-0.01	-0.09
	(0.07)	(0.09)	(0.13)
Derek Fisher	-0.01	0.16	0.12
	(0.13)	(0.15)	(0.25)
Lamar Odom	0.03	0.09	0.34**
	(0.12)	(0.15)	(0.18)
Jordan Farmar	-0.22	-0.27	0.02
	(0.15)	(0.17)	(0.25)
Luke Walton	-0.17	-0.11	-0.05
	(0.17)	(0.23)	(0.46)
Vladimir Radmanovic	-0.08	0.36	0.07
	(0.19)	(0.23)	(0.31)
Sasha Vujacic	0.18	0.3	0.04
	(0.16)	(0.21)	(0.30)
Ronny Turiaf	0.03	-0.03	-0.24
	(0.18)	(0.26)	(0.43)
Total (+)	4	4	5
Total (-)	4	4	3
$\sum z - score$	-0.56	2.36	1.08
$\sum z^2$	5.42	8.76	2.87

*** p<0.01, ** p<0.05, * p<0.1

The coefficient estimates are nearly evenly split between negative and positive. Out of 24 estimates, only 1 is significant at the 0.05 level, which is the expectation under chance. The second to last row gives the sum of the z-scores from the estimates. If there are significant underlying hot hand effects, then these values would be large and positive - they are not. The last row gives the sum of the squared z-scores, which under the null hypothesis that the coefficients equal to zero is distributed χ^2_8. The associated p-values are 0.81, 0.49 and 0.96 for columns (1), (2) and (3) respectively, which do not even approach conventional significance levels.

It is important to note that these results do not, and cannot, reject the notion that a player (very) occasionally drifts (i.e. unrelated to past performance) into a "hot state" and has period of improved performance. Rather the results show that ability is not *systematically* higher following makes as compared to misses. Conversely, it was shown in the past subsection that shooting decisions are, for a subset of players, systematically related to past outcomes and these changes lead to more difficult shots. We shall see in the following subsection that observable behavior is also systematically related to past outcomes and once again there is heterogeneity in the response ranging from none to quite large in magnitude.

3.4 Observable player behavior as a function of past outcomes

This section presents evidence on observed player behavior in the same format as the results from section 3.2. The purpose is two-fold. First, it provides a useful check of the results from 3.2 as it allows us to see the actual changes in shot conditions that led to the changes in difficulty and expected point value. Second, examining touches and the timing of shots allows us make further inference as to the beliefs of players.

Table 6 and Appendix Table 1 are the game conditions analog to Table 3. Given the sheer volume of information, the results are presented in the body of the paper for only two players (although they are discussed for all players), one sub-optimal responder and one benign responder. The remaining tables can be found in the appendix.

To understand the tables, recall that a "touch" is defined as holding the ball on a given possession in the offensive half of the court. For instance if a player brings the ball across half-court, passes and then later in the possession is passed the ball and shoots, then this counts as 2 touches for the player and 3 for the team. The results for touches include every possession during the streak, not just the ones the player took a shot. Hence sample sizes are much larger for this variable. A "one touch jumper" occurs when the player brings the ball up court and takes a shot that is not a lay-up or dunk (to rule out breakaways) without ever passing the ball. The decision of when to shoot over the course of possession is formalized in Rao (2009a) as an optimal stopping problem. The model predicts that shots are taken more quickly when the shooting opportunity offers a higher return. As such a player who believes he is hot may be more inclined to shoot the ball before passing to other teammates due to his perceived increase in ability. "Time gap" gives the elapsed game time in seconds between field goal attempts. Once again, statistical significance is determined using t-tests between makes and misses for a given streak length.

Table 6: Observable behavior as a function past outcomes

Kobe Bryant

Outcome	1		2		3		4	
	Consecutive Shots Made/Missed							
this period	Made	Missed	Made	Missed	Made	Missed	Made	Missed
One touch J	0.165**	0.126**	0.141	0.111	0.126	0.117	0.119	0.134
Touches	0.735***	0.679***	0.758***	0.677***	0.748**	0.660**	0.723*	0.624*
Distance	15.52***	11.76***	16.35***	11.98***	17.01***	11.73***	16.67**	12.19**
Turnaround	0.200	0.186	0.207*	0.158*	0.244**	0.151**	0.167	0.134
Three pointer	0.307***	0.166***	0.337***	0.178***	0.370***	0.156***	0.429***	0.179***
Defended	0.757	0.784	0.759	0.770	0.824	0.784	0.762	0.838
Fouled	0.146	0.177	0.134	0.171	0.101	0.161	0.048*	0.152*
Double team	0.089**	0.129**	0.076***	0.147***	0.084	0.127	0.071	0.134
Time gap	105.22**	120.7**	108.44	120.99	113.48	118.39	134.86	110.92
Obs	644	706	290	387	119	205	42	112

Jordan Farmar

Outcome	1		2		3		4	
	Consecutive Shots Made/Missed							
this period	Made	Missed	Made	Missed	Made	Missed	Made	Missed
One touch J	0.095	0.108	0.074	0.095	0.103	0.083	0.000	0.071
Touches	0.917	0.891	0.939	0.902	0.872	0.964	0.833	0.921
Distance	16.13	15.28	17.25*	14.07*	16.14	11.54	15.54	12.21
Turnaround	0.106	0.118	0.111	0.108	0.103	0.125	0.077	0.214
Three pointer	0.497	0.426	0.543**	0.378**	0.552	0.375	0.462	0.429
Defended	0.396	0.399	0.395	0.425	0.379	0.522	0.385	0.462
Fouled	0.075	0.046	0.074	0.068	0.034	0.083	0.000	0.143
Double team	0.020	0.026	0.012	0.014	0.000	0.042	0.000	0.000
Time gap	245.8*	312.94*	232.78**	398.41**	161.93*	298.29*	100.15*	278.5*
Obs	199	195	81	74	29	24	13	14

*** p<0.01, ** p<0.05, * p<0.1

Bryant is more likely to take a jump shot without passing after a single hit than a miss (significant at .05 level) but the difference is not significant for streaks of longer length. Bryant shots are roughly 4 ft longer following a hit than miss, this difference grows to over 6 ft for streak length 3. All the differences in distance are highly significant. Bryant is also significantly more likely to take a turnaround/fadeaway jumper when on hit streak as compared to a string of misses. Defensive attention does not seem to vary systematically across columns. However, Bryant does face significantly fewer double teams following hits as compared to misses. Initially this might seem counterintuitive, if the defense holds a hot hand belief they should double team more during hit-streaks. The finding is explained by the fact that most double teams occurs close to the basket and Bryant is taking longer shots on hit-streaks.

The touch data indicate that Bryant sees more of the ball during streaks of hits. His lowest touches per possession are during streaks of 4 misses, while they are highest after two makes, consistent with the notion that his teammates hold a belief in the hot hand. Time between shots is lower following 1 and 2 makes as compared to misses, but the difference is not significant for length 3 and in fact reverses sign for length 4. One possible explanation for the last finding is that defensive pressure steps up during long streaks (4 or more) forcing Bryant to wait longer between shots. Finally, Bryant is more likely to be fouled when on miss streak, the difference is significant at length 4, which can be attributed to taking closer range shots more likely to draw a foul. Overall the results for Bryant show that his behavior is significantly changing as a function of past outcomes. The differences are not only statistically significant but also of large magnitude.

Fisher, Vujacic and Farmar take more three-pointers following hits than misses. Fisher, like

Bryant, is also more likely draw a foul when on a miss streak. Touches for these players do not seem to be systematically related to past outcomes. Farmar and Vujacic have lower time gaps when on a hit streak as compared to a miss streak.[16]

Odom's behavior with respect to shot conditions and touches is remarkably consistent across past outcomes. Radmanovic's is similarly consistent. Walton tends to take longer shots and significantly more three pointers, for example half his shots are three pointers after 3 makes, far in excess of his baseline propensity to take a three.

3.5 Outside options

The largest departures from optimal shot selection were by the best player, and league MVP, Kobe Bryant. One explanation for this has already been offered. A superior player has a lower private incentive to make optimal shot choices because he is not fighting for playing time or on cusp of the level of performance necessary to secure a lucrative "free agent" contract or remain in the league. Salaries in second-tier leagues are far less lucrative than even the NBA minimum salary. In contrast, Bryant is signed to a censored "league maximum" contract.

There are two other possible explanations. The first is that Bryant does not hold a belief in the hot hand but his teammates do, so during a Bryant hit-streak they "lay back" and do not seek out good shooting opportunities for themselves forcing Bryant bear the offensive load. The second is that the defense increases overall pressure when he strings makes together because they either hold a hot hand belief, believe in team "momentum" or wish to avoid the Lakers getting too large a lead.[17] In either case, we would expect Bryant to take more difficult shots due to a decline in outside options (points per shot by his teammates on the court) and the increased personal pressure.

Table 7 summarizes the outside options for the 2 sub-optimal responders, Bryant and Fisher, during streaks of length 1-4. The first row simply compares the expected point value of teammates when the player is playing or not. The result indicates that Bryant does in fact "make his teammates better" as is commonly asserted.[18] This effect does not hold for Fisher. Rows 2 through 5 give the expected shot value of the other 4 players on the court broken down by streak length and hits/misses.

[16]This pattern of shooting naturally leads to temporally grouped hits. Due to memory constraints the temporal grouping can help explain hot hand beliefs among observers. Interested readers are referred to Rao (2009b) for a complete discussion.

[17]Note that if they increased pressure on just Bryant his teammates should have less pressure and therefore he should pass more and not experience a decline in performance. "Momentum" refers to a belief that a short run of good play by a team can have lasting effects in the game.

[18]This is effect is robust to controlling for the composition of players in the game.

Table 7: Expected shot values of teammates on the floor, by streak length

Streak length	Outcome	K. Bryant	D. Fisher
n/a	Off Court	1.288***	1.343
	On Court	1.346***	1.347
1	Missed	1.348	1.360
	Hit	1.348	1.336
2	Missed	1.347	1.366
	Hit	1.345	1.311
3	Missed	1.359	1.334
	Hit	1.323	1.293
4	Missed	1.370	1.329
	Hit	1.320	1.270

Table 7 shows that for streaks of length 1 and 2 outside options were very similar between makes and misses. For both players, the table does reveal a tendency for teammates' points per shot to be lower during strings of makes 3 or more. These differences reduce the net cost to the team — however, even after adjusting the magnitudes found in Table 3 down by the estimated margin (≈ 0.05 points), the statistical significance remains. It also lends support to the argument that defensive pressure applied to the whole team increases slightly when one player is on a streak of hits.

Comparing Tables 3 and 7 we notice that after 3 makes, Bryant's expected point value was 1.22 for his own shots, while his teammates averaged 1.32 — the difference is statistically significant. After 3 misses the difference between Bryant and his teammates was less that .02. The pattern is similar for streaks of length 4. As such, even though there is a difference in teammate performance when Bryant is on a lengthy streak hit-streak, these differences are not large enough to explain Bryant's shot choices. The same analysis can be applied to Fisher, but no other players in the sample made these mistakes.

4 Discussion

In this section I discuss the heterogeneity in response across players, provide back-of-the-envelope calculations on the true cost to the team of sub-optimal shot selection by Bryant and Fisher and discuss the interesting result that players only respond to hit-streaks.

4.1 Heterogeneity in response and economic incentives

In the previous section it was shown that some players in the sample responded to past success by taking sub-optimally difficult shots. Explanations based on improved ability or increased defensive pressure on the whole team were ruled out. These players made mistakes that detracted from both personal and team performance. In contrast, some players exhibited remarkable consistency in their shooting behavior. For guards, the player with the least NBA experience (and smallest contract), Jordan Farmar, was the most consistent. The second lowest paid and experienced guard, Sasha Vujacic, also behaved more in line with the normative edicts of Bayesian rationality than his more experienced counterparts Bryant and Fisher.

There is an interesting link between the behavioral responses of the players and the economic incentives they faced. NBA contracts are subject to the terms of the Collective Bargaining Agreement (CBA) between the NBA Players' Association and the league owners. While the CBA is far too complex to describe in detail here, there are two key features that are important to the individual incentives faced by players in the sample.[19] The first is that contracts for players in their first 3 years in the league (such as Vujacic and Farmar) are set at pre-determined levels based on the player's selection number in the annual draft. These contracts are far less lucrative than those of even moderately successful veterans. A young player must perform well in order to sign a "free agent" contract, the terms of which are (generally) dictated by market value. Young players who do not perform at a high level are quite often unable to secure a contract at even the league minimum and are forced to take a large pay-cut in a second tier league. The second is that the CBA sets a maximum salary any player can earn.

Bryant earned the league maximum during the sample period, indicating that his true market value is probably above this level. In contrast, the young players of the same position had very high economic incentives. The breakdown of individual incentives due to the maximum contract can help explain Bryant's sub-optimal shot selection and the heightened incentives of the artificially low "rookie" contracts can help explain the fact that the young players did not experience a drop in shooting efficiency.

The link between incentives and behavioral biases has important implications. In many market settings, there are underlying behavioral biases that lead to a divergence of individual actions from firm interests. If biases are immutable, then enhancing incentives comes at a cost but generates no gain. However, if experienced agents can eliminate biases when properly incentivized, then firms should be mindful of underlying behavioral biases and structure contracts to punish agents who fall prey to them. The NBA maximum salary is similar to executive pay caps proposed in the wake of the 2008 financial crisis. For executives, the relevant bias is not the hot hand fallacy but rather present bias. It is in the interests of shareholders to structure contracts to eliminate present bias, but a pay cap places some executives in the position of an NBA player (such as Bryant) with a top-censored salary. High ability executives would face very liqttle economic incentive to overcome behavioral tendencies damaging to the firm. The results of this paper suggest that without proper incentives, latent biases are more likely to manifest themselves.

[19]Interested readers can find the entire CBA at http://www.nbpa.com/cba_articles.php.

4.2 Quantifying costs

This subsection presents some conservative back-of-the-envelope calculations of the effective cost to the team of shot selection errors. In Table 3, I showed that two players, Bryant Fisher, took sub-optimally difficult shots following consecutive made shots. The most significant departures were streaks of length 3 and 4 (indeed these departures drove the differences in the whole table, given the telescoping structure of the presentation). For these streak lengths, Table 7 illustrated that the defense increased pressure on the entire team during these streaks. As such, the net cost to the team was lower, yet still significantly positive, than it initially appeared in Table 3.

For both players the net cost of their shot selection during hit-streaks of length 3 or 4 was approximately 0.12 points per shot. This value can used to calculate the aggregate cost. Bryant attempted 162 shots for streaks of length 3 or 4 and Fisher attempted 42. Using the value of 0.12 points per shot, this translates to about 25 total points for the 60 game sample or 34 point over the entire season. This estimate is conservative in that it excludes streaks of length longer than 4 (although there are very few of these). 34 points may not seem like a large value over the course of an 82 game season for a team that averages 90 points per game. However, NBA basketball is very competitive and many games are decided my slim margins. In the 2007/08 season the Lakers played 18 games that were decided by 4 points or less. As such, even using these conservative estimates it is likely that the shot selection mistakes cost the team 1 or 2 wins over the course of the season. For a playoff team, a single game usually determines if they get "home court advantage" — i.e. a single game translates to an economic loss through lost revenue in ticket sales.

4.3 The salience of the success domain

The results of Section 3.2, which showed that players tended to respond only to streaks in the makes domain (Section 3.4 showed some behavioral changes, but these did not impact shot difficult or shooting efficiency) . This result is consistent with the etymology and usage of the phrase "hot hand." Overestimating autocorrelation in general would also lead to a "cold hand" belief; however the focus of previous laboratory and field experiments and the colloquial usage is on past success predicting future success and not necessarily past failure predicting future failure. NBA players responses indicates that there is something more salient about successful outcomes that leads to mistaken inference.

The psychological salience of successful outcomes has intuitive appeal. It is a robust finding that people tend to accentuate the positive and downplay the negative in their recall of events and attributional judgment. There is also evidence that of hardwired optimism in our updating machinery. Eil and Rao (2009) show that subjects update there beliefs differently when the signal they receive is good as opposed to bad news. The authors use an objective signaling environment in which subjects receive binary signals (up/down comparisons to another subject) about there intelligence or physical attractiveness. They find that subjects tend to respond more to good news than bad news. This result can help explain why (some) players respond to hit-streaks of length 3 and 4 but not to miss-streaks of the same length.

5 Conclusion

This paper uses a rich data set to examine the beliefs of NBA players concerning the hot hand. The underlying methodology is that beliefs should be inferred from observed behavior. Using shot difficulty, touches per possession, passing behavior, and time between shots I find heterogeneity in players' hot hand beliefs. Broadly the players fall into three categories: *sub-optimal responders*, *benign responders* and *consistent performers*. The players who do respond to their past performance tended to take longer shots, were less likely to draw a foul, touched the ball more and passed the ball less following a make or string of makes. Interestingly, there is no evidence that any player responded to strings of misses. The analysis of Section 3.3 showed that, controlling for shot difficulty, players did not exhibit an increase in ability following strings of made shots or a drop in ability following misses; i.e. there is no serial dependence in ability (the hot hand does not exist for the players in my sample).

I argue that the significant change in behavior provides evidence of a belief in the hot hand. Given that players do not experience a concomitant increase in ability, the taking of difficult shots following a string of makes lead to a significant drop in expected shot value for *sub-optimal responders* (2 of 8 players). The most notable player in this group is 2007/08 League MVP Kobe Bryant. In sharp contrast, *consistent performers* (3 of 8 players) did not systematically respond to hit-streaks and as such do not suffer from reduced performance. These players observable actions are remarkably stable across past outcomes. A third group, *benign responders* (3 of 8), did significantly respond to past success by taking more difficult shots — but did so by switching into 3-pointers that provided increased returns, which offset the increased difficulty leaving points per shot stable. There is evidence that players with higher economic incentives (i.e. those with a low margin of error in performance) were more likely to occupy the latter two groups.

The finding that some players do in fact commit costly shot selection mistakes sets the result apart from other evidence of behavioral biases in Bayesian updating. These players exhibit a bias previously found amongst basketball fans, experimental subjects and field subjects (lottery, casino) but in contrast to these previous studies, here exhibiting the bias is costly. The result shows the robustness of the hot hand fallacy in human psychology. However, the fact that the players with greater economic incentive to perform consistently did not exhibit the bias indicates that it is by no means universal. Generalizing the results to other settings, they suggest that contracts should be structured to help eliminate behavioral biases.

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6 Appendix

6.1 Further description of the data

The exact schedule of games used is available from the author. As are tapes and the corresponding spreadsheets for certain games saved on the author's hard drive. For the purposes of this study an offensive possession was defined as possession of the ball in the offensive half resulting in a shot. If the team had an offensive rebound this started a new possession. If readers thought the touch numbers were lower than they might expect this is why. For instance, on a put-back the possession would only have one touch.

Buzzer beaters were omitted from the study (shots at the buzzer of length 30 ft or more).

6.2 Table A1

Derek Fisher

Outcome this period	1 Made	1 Missed	2 Made	2 Missed	3 Made	3 Missed	4 Made	4 Missed
One touch J	0.154	0.191	0.187	0.197	0.323	0.231	0.182	0.250
Touches	0.810	0.800	0.790	0.824	0.734	0.804	0.811	0.757
Distance	17.7***	15.72***	17.22	16.62	17.1	16.87	17.73	16.77
Turnaround	0.054	0.036	0.067	0.038	0.100	0.038	0.000	0.019
Three pointer	0.427***	0.309***	0.367	0.363	0.267	0.346	0.364	0.327
Defended	0.456	0.452	0.522	0.465	0.484	0.474	0.455	0.462
Fouled	0.059*	0.102*	0.022*	0.083*	0.000*	0.115*	0.000	0.154
Double team	0.046	0.043	0.056	0.032	0.033	0.026	0.091	0.019
Time gap	230.28	225.2	257.38	228.27	323.13	270.24	436.18	285.56
Obs	239	304	90	157	30	78	11	52

Consecutive Shots Made/Missed

Lamar Odom

Outcome this period	1 Made	1 Missed	2 Made	2 Missed	3 Made	3 Missed	4 Made	4 Missed
One touch J	0.018	0.017	0.020	0.014	0.027	0.016	0.000	0.000
Touches	0.534	0.567	0.522	0.557	0.540	0.524	0.560	0.510
Distance	7.8	7.58	9.03	7.37	9.63	8	9.81**	5.67**
Turnaround	0.101	0.091	0.099	0.128	0.110	0.125	0.139	0.103
Three pointer	0.137	0.115	0.159	0.113	0.151	0.156	0.139	0.051
Defended	0.657	0.644	0.622	0.626	0.634	0.656	0.571	0.667
Time gap	241.16	209.65	252.27	191.74	228.81**	182.89**	211.5	164.49
Fouled	0.180	0.153	0.139	0.128	0.151	0.109	0.167	0.128
Double team	0.098	0.066	0.099	0.064	0.068	0.047	0.056	0.000
Obs	328	287	151	141	73	64	36	39

Consecutive Shots Made/Missed

Luke Walton

Outcome this period	1 Made	1 Missed	2 Made	2 Missed	3 Made	3 Missed	4 Made	4 Missed
One touch J	0.008	0.025	0.023	0.014	0.000	0.000	0.000	0.000
Touches	0.539	0.553	0.502	0.510	0.474	0.516	0.609	0.520
Distance	11.32**	9.21**	13.30***	8.41***	14.17	9.84	17.33	10.33
Turnaround	0.135	0.123	0.159	0.100	0.083	0.000	0.000	0.000
Three pointer	0.195	0.160	0.250*	0.129*	0.500**	0.160**	0.667*	0.167*
Defended	0.515	0.547	0.409	0.580	0.333*	0.520*	0.333	0.444
Fouled	0.113	0.067	0.114	0.057	0.250	0.080	0.333	0.111
Double team	0.030	0.043	0.068	0.071	0.250	0.080	0.333	0.056
Time gap	379.58**	241.11**	366.05	261.33	206.75	197.08	132.33	226.94
Obs	133	163	44	70	12	25	3	18

Consecutive Shots Made/Missed

*** p<0.01, ** p<0.05, * p<0.1

Table A1 (cont.)

Vladimir Radmanovic

Outcome	Consecutive Shots Made/Missed 1		2		3		4	
this period	Made	Missed	Made	Missed	Made	Missed	Made	Missed
One touch J	0.031	0.048	0.041	0.044	0.038	0.069	0.077	0.056
Touches	0.434	0.441	0.486	0.421	0.545	0.446	0.607	0.461
Distance	15.67	14.21	14.98	14.09	13.81	16.03	13.23	14.72
Turnaround	0.085	0.068	0.041	0.088	0.038	0.103	0.077	0.167
Three pointer	0.523	0.479	0.531	0.515	0.500	0.621	0.462	0.556
Defended	0.430	0.427	0.375	0.455	0.440	0.393	0.500	0.412
Fouled	0.092	0.068	0.082	0.044	0.077	0.034	0.154	0.056
Double team	0.046	0.048	0.020	0.059	0.038	0.103	0.077	0.056
Time gap	289.61	271.25	255.92	264.43	207.81	268.55	192.69	341.44
Obs	130	146	49	68	26	29	13	18

Ronny Turiaf

Outcome	Consecutive Shots Made/Missed 1		2		3		4	
this period	Made	Missed	Made	Missed	Made	Missed	Made	Missed
One touch J	0.008	0.013	0.000	0.027	0.000	0.026	0.000	0.037
Touches	0.428	0.394	0.403	0.393	0.361	0.382	0.286	0.370
Distance	8.71	5.92	8.75	5.11	6.53	4.89	4.75	5.3
Turnaround	0.080	0.081	0.045	0.135	0.133	0.105	0.250	0.037
Three pointer	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Defended	0.610	0.703	0.674	0.743	0.733	0.684	0.750	0.63
Fouled	0.368	0.242	0.182	0.243	0.267	0.211	0.250	0.148
Double team	0.032*	0.081*	0.023	0.068	0.000	0.053	0.000	0.074
Time gap	327.26	308.6	378.82	287.93	266.33	313.37	116.5	350.78
Obs	125	149	44	74	15	38	4	27

Sasha Vujacic

Outcome	Consecutive Shots Made/Missed 1		2		3		4	
this period	Made	Missed	Made	Missed	Made	Missed	Made	Missed
One touch J	0.045	0.029	0.037	0.024	0.000	0.028	0.000	0.043
Touches	0.564	0.573	0.557	0.599	0.613	0.517	0.630	0.531
Distance	20.05	19.15	21.63**	18.06**	20.77	17.28	20.5	17.96
Turnaround	0.075*	0.029*	0.074	0.036	0.091	0.028	0.200	0.043
Three pointer	0.586	0.570	0.685*	0.524*	0.591	0.556	0.500	0.565
Defended	0.364	0.281	0.389	0.333	0.409	0.250	0.500	0.261
Fouled	0.053	0.052	0.037	0.071	0.045	0.056	0.100	0.087
Double team	0.008	0.023	0.019	0.036	0.000	0.056	0.000	0.043
Time gap	205.06**	303.92**	206.26	272.79	257	290.22	91.1	315.04
Obs	133	172	54	84	22	36	10	23

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

6.3 Table A2

Appendix Table 2: Random-effects probit for shot success, by player

	K. Bryant	D. Fisher	L. Odom	J. Farmar	L. Walton	V. Rad	S. Vujacic	R. Turiaf
Distance	-0.199***	-0.245**	-0.351***	-0.372***	-0.233*	-0.116	-0.385*	-0.530***
	(0.062)	(0.12)	(0.10)	(0.12)	(0.13)	(0.17)	(0.22)	(0.16)
Distance^2	0.0139***	0.0198**	0.0255***	0.0280***	0.0104	0.00143	0.0239	0.0467***
	(0.0047)	(0.0091)	(0.0085)	(0.0098)	(0.011)	(0.014)	(0.017)	(0.017)
Distance^3	-0.0003***	-0.0005**	-0.0006***	-0.0006***	-0.0002	0.0000	-0.0005	-0.0013**
	(0.00010)	(0.00020)	(0.00020)	(0.00021)	(0.00027)	(0.00031)	(0.00036)	(0.00049)
Fouled	-0.806***	-0.529**	-1.004***	-0.407	-0.786**	-0.721*	-0.258	-0.346
	(0.11)	(0.25)	(0.17)	(0.30)	(0.32)	(0.37)	(0.37)	(0.23)
Turnaround	-0.00484	0.110	-0.207	-0.00931	0.509**	-0.528	0.269	-0.312
	(0.10)	(0.29)	(0.20)	(0.25)	(0.24)	(0.36)	(0.36)	(0.32)
Double team	-0.219*	-0.622*	-0.313	-0.227	-0.372	-0.562	-0.276	-0.0710
	(0.12)	(0.33)	(0.22)	(0.41)	(0.42)	(0.44)	(0.70)	(0.37)
Forced	-0.190	0.179	0.0649	0.0330	-0.193	0.221	-0.178	0.314
	(0.15)	(0.23)	(0.26)	(0.23)	(0.35)	(0.35)	(0.36)	(0.32)
Defended	-0.822***	-0.561***	-0.749***	-0.762***	-1.052***	-1.058***	-0.834***	-0.728***
	(0.13)	(0.17)	(0.21)	(0.23)	(0.28)	(0.38)	(0.26)	(0.28)
Defended	-0.336*	-0.708**	-0.600**	-0.399	-0.585*	-0.450	-1.253**	-0.744**
Layup	(0.19)	(0.33)	(0.24)	(0.35)	(0.35)	(0.45)	(0.62)	(0.35)
Defended	0.211	-0.370	-5.588	0.403	-5.225	0.556	-0.261	(dropped)
Three	(0.17)	(0.31)	(8652)	(0.36)	(8311)	(0.50)	(0.40)	(dropped)
Constant	1.503***	1.003***	1.746***	1.585***	1.624***	1.503***	1.962***	1.593***
	(0.20)	(0.37)	(0.23)	(0.33)	(0.33)	(0.40)	(0.66)	(0.31)
Observations	1404	597	665	449	348	316	357	330
Games	60	60	57	60	54	45	51	56

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

6.4 Table A3

Appendix Table 3: Los Angeles Lakers Salaries 2007/08 Season

Player	Annual Salary	Contract Yrs Remaining	Yrs in NBA
Kobe Bryant	$19,490,000*	3	11
Lamar Odom	$13,248,596	1	8
Vladimir Radmanovic	$5,632,200	1	6
Derek Fisher	$4,352,000	2	11
Luke Walton	$4,000,000	5	4
Sasha Vujacic	$1,756,951	3	3
Jordan Farmar	$1,009,560	2	1
Ronny Turiaf	$770,610	0	2

* Maximum Permitable. Source: hoopsworld.com, espn.com