AN ABSTRACT OF THE DISSERTATION OF

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Daniel F. Stone

This dissertation consists of two essays that address behavioral economics issues.

In first chapter we analyze the effects of psychological pressure on performance using National Basketball Association (NBA) free throw data from the 2002-2003 through 2009-2010 seasons. We find evidence that players choke under pressure – they shoot on average 5-10 percentage points worse than normal in the final seconds of very close games. Choking is more likely for players who are worse overall free throw shooters, and on the second shot of a pair after the first shot is missed. In general, performance declines as pressure increases (as game time remaining decreases, and as the score margin decreases, whether the shooter's team is winning or losing). However, we find no evidence of choking when games are tied in the final 15 seconds. We also fail to find evidence of performance under pressure being affected by home status, attendance, and whether or not the game is in the playoffs.

In second chapter we develop a simple estimable model that allows the effects of psychological and physical states on players' shooting performance to persist across multiple games. We use the model to test the existence of game-level hot hand and whether professionals believe in its existence using NBA game-level box score data from

the 1991-92 through 2006-07 seasons. We find no evidence for a game-level hot hand of a substantial magnitude for various subsamples. However, simulation result indicates that the measurement error caused by using shooting percentage as the proxy for shooting ability might significantly bias the estimate of hot hand effect towards zero. We find moderate evidences of coaches' belief in both within and game-level hot hand – "hot" players will play more minutes so that they will have more shot attempts. We also find the magnitude of the belief in within game hot hand is three times as large as that of the game-level hot hand.

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APPORVED:

Major Professor, representing Economics

Director of the Economics Graduate Program

Dean of the Graduate School

I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Zheng Cao, Author

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CONTRIBUTION OF AUTHORS

Dr. Daniel F. Stone was involved with the design, analysis and writing of every chapter.

TABLE OF CONTENTS

TABLE OF CONTENTS (Continued)

LIST OF FIGURES

LIST OF TABLES

LIST OF TABLES (Continued)

CHAPTER 1

INTRODUCTION

Behavioral economics has played an increased role in the research of economics over the past decades. This field uses psychology to study how human decision systematically deviates from those predicted by neo-classic economics. The recent financial crisis puts the behavioral economics in the spotlight – its principles can be seen all over the turmoil. In an interview, Daniel Kahneman, who was awarded Nobel Prize in Economics for the pioneering work in this field, says "the people who took on subprime mortgages were thoroughly deluded. One of the main ideas in behavioral economics that is borrowed from psychology is the prevalence of overconfidence."

However, testing theories of behavioral economics is subject to the availability of empirical data. So researchers have begun to use data that come from laboratory or controlled experiments. Sports games often serve as natural experiments, providing a very good data source to examine human behavior in well controlled settings. As Kahn (2000) says, "There is no research setting other than sports where we know the name, face, and life history of every production worker and supervisor in the industry." Sports games data has several strengths: 1) they are often abundant, which provide sufficient statistical power; 2) unlike the experimental data that are generated under created laboratory experiments, sports games data are collected from real life events, which makes the results more credible; 3) human behavior in sports games can often be observed clearly, which makes it easier to measure performance and identify individual decision; 4) since sports games are well controlled environments, indentifying the factors that might affect human behavior is relatively straightforward.

Due to the advantages of sports data, there has been a rapid growth of using sports data to address issues of behavioral economics in past decades. Romer (2006) uses National Football League (NFL) data to test whether coaches' choice on fourth down between kicking and trying for a first down maximizes teams' chances of winning. He argues that the coaches' choice is a case study of the basic assumption that firms make choices to maximize profit. Camerer(1989) shows that the belief that teams in the midst of a winning steak are more likely to win the next game cause inefficiency in betting market for basketball games. This provides insight into whether markets are efficient in general. Walker and Wooders (2001) use field data from Wimbledon tennis matches to test whether players use mixed strategy to win the games—that is, whether the mixed strategy equilibrium solution concept is an effective descriptive model. Besides behavioral economics, sports data is also useful in other fields. Price and Wolfers (2010) test the existence of racial discrimination among NBA referees by examining the effect of racial composition of the refereeing crew on the number of calling fouls on players of the opposite race. They argue NBA games provide a good place to evaluate implicit racial biases because referees often make split-second decisions under high pressure situations,

In chapter 2 we use play level NBA free throw data to analyze the effects of psychological pressure on performance. Economic incentive theory says that higher incentive will induce individuals to exert more effort, consequently resulting in better performance. On the other hand, folk wisdom tells us this high incentive might be perceived as pressure and lead to poor performance (choking under pressure). These two contrary arguments raise the questions: (a) To what extent do experienced professionals

choke or perform well when the performance really matters? (b) What are the factors that affect choking (if any)? Many of the existing works cited by Hilla et all. (2010) use experimental to test choking. Dohman (2008) uses penalty kick data, which suffers from two problems – the interaction between kicker and goal keeper and sample selection issue. Free throw in basketball provides a well controlled setting to test whether experienced professionals choke under pressure. We find that NBA players do indeed choke at the end of a close game, but only to a moderate extent. We also examine how players' characteristics affect the choking. We find better free throw shooter in general choke less when his team is losing by a small margin in the final seconds. We interpret this finding as a result of self-confidence – these shooters are more confident in their abilities, and self-confidence in turn moderates and potentially eliminates anxiety and choking. In addition, we examine the effect of attendance, home and playoff status on choking. Results indicate players' performance is immune to these factors.

The third chapter of this dissertation makes contributions to a well known research topic – belief in the hot hand. In basketball it often refers to the belief that a player is more likely to make a successful shot following a streak of hits. Although research provides strong evidence that fans and professionals believe in the basketball hot hand, most of previous research has also failed to find the positive autocorrelation in shot or game outcomes. This phenomenon illustrates that people tend to over-infer the correlation between shot outcomes as well as game outcomes. The false belief in the hot hand has economics implications, for example, over-inference of the past performance in stock market will cause stocks with high past return to be overpriced. However, none of

previous works uses game-level basketball data. We develop a simple estimable model and apply this model to test the existence of game-level hot hand and whether professionals hold belief in its existence using NBA game-level box score data. We find a small game-level hot hand effect in field goal percentage. However, since our result is affected by measurement error, endogeneity in shot selection and change in defense, we claim it could imply a relatively large hot hand effect in "true" shooting ability. We estimate the effect of field goal percentage on the number of shot attempts. The result shows some moderate evidences of coaches' belief in both within and game-level hot hand – "hot" players will play more minutes so that they will have more shot attempts.

The final chapter briefly discusses the implications of our findings.

CHAPTER 2

PERFOMANCE UNDER PRESSURE IN THE NBA

2.1 Introduction

Neoclassical economic theory predicts that individuals exert the most effort, and consequently produce their best performances, when the net returns to effort are highest. Folk wisdom and common sense suggest something different: when performance matters most individuals feel psychological pressure, and as a result often make uncharacteristic mistakes (i.e. "choke"), but sometimes rise to the occasion in the clutch. The degree to which experienced professionals choke or perform well in the clutch, and the factors causing or mitigating either type of behavior, are empirical issues that are still not fully understood.[1]

In this paper we analyze performance under pressure using free throw data from the National Basketball Association (NBA). Pressure and the potential for choking arise in all sports, and many contexts outside of sports as well.[2] The basketball variable free throw percentage is a measure of performance that is especially well-suited for the empirical analysis of choking for several reasons. First, each free throw attempt is taken from the same distance and location, so the physical difficulty of each shot is constant (as opposed to basketball field goal attempts or say, golf putts, which are taken from varying locations). Second, free throws are undefended, and so observed changes in performance are not confounded by simultaneous changes in offensive and defensive player behavior (in contrast to, e.g., soccer penalty kicks). Third, free throws occur very frequently—most players shoot over 100 in each season. This allows us to control carefully for the substantial heterogeneity across players in free throw shooting ability. Fourth, since most close games involve at least a few free throws being shot in the final seconds or minute,

we have access to the sample size necessary to obtain reasonably precise estimates of how performance changes as a function of time remaining in the game and score difference. Finally, shooting a free throw is a fairly easy, but still non-trivial, task for most NBA players (as opposed to, say, the trivial task of kicking an extra point in American football), so *a priori* it seems highly plausible that psychological factors may affect performance.

We find that NBA players do indeed choke, but not too badly. In fact, they are fairly immune to factors that we hypothesized may cause anxiety throughout games. In the first three quarters of games, being the home team has a statistically significant but very small (less than half a percentage point) positive effect, playoff status has no effect, and attendance has a significant, but also small effect (free throw percentage decreases by just over one percentage point when attendance increases by 10,000) for both home and away players. The score difference and time of shot have small and usually insignificant effects.

When the shot is taken at the very end of a close game, and thus is much more likely to change the game's outcome, the story is different. We find that expected free throw percentage declines by around 4 percentage points when the shooter's team is down by one or two points and the shot is taken in a game's final minute. The magnitude of the decline increases to 6.3 and 8.8 in the last 15 seconds, when down two and one points, respectively. There are also significant choking effects for players whose teams are up by one or two points, but they are substantially stronger for the second shot, when

pressure is likely higher.[3] Surprisingly, given these other results, we find that performance does not decline at all in the last 15 seconds when the score is tied.

We find that these choking effects are considerably larger for players who are worse free throw shooters in general. Since it is natural to think that these shooters are less confident in their abilities, we interpret this result to support the theory that self-confidence moderates, and potentially eliminates anxiety and choking. This result may also simply be due to the magnitude of choking being an increasing function of the variance of the outcome variable. We also find that choking declines when the previous free throw was made and increases when the previous shot was missed, which provides further support for the importance of confidence, since making the first free throw likely improves confidence.[4] We find that the effects of other variables that may be thought to affect the degree of choking in games' final seconds (experience, home and playoff status, attendance) are minimal and mostly insignificant.

2.2 Theory and Related Literature

The topic of choking under pressure has received substantial attention from the psychology literature. Hilla et al. (2010), a recent review, say that most of the literature defines choking (at least implicitly) as "any inferior performance under pressure."[5] We attempt to use this basic definition, which raises two questions: 1) What causes pressure? 2) Inferior performance as compared to what? Regarding the former, it is natural to think that pressure increases as the probability that the performance will affect which team wins the game increases, which occurs as both the score difference and time remaining in

the game decrease. Hilla et al. (2010) also discuss what they refer to as possible moderators of choking, including presence of an audience, whether that audience is supportive or not, self-confidence and skill level.[6] The answer to the second question is less straightforward, since it is not clear that pressure and performance have even a monotone relationship. Hilla et al. (2010) discuss the upside-down U curve theory of this relation: that increasing pressure first causes performance to improve, then decline. We take this into consideration in our empirical analysis.

Many of the papers cited by Hilla et al. (2010) use experimental data from controlled settings; one advantage of our paper is that we use non-experimental data.[7] The size of our dataset (discussed further below) also provides us with greater statistical power than that of many experimental studies. One especially closely related psychology paper is Worthy et al. (2009), which also analyzes NBA free throw performance and uses a fairly large dataset. Their results are fairly similar to some of ours, in that we both find performance worsens when the shooter's team is down by one or two points, or up one point with less than one minute remaining, but not when tied. However, there are numerous differences between our papers. We use a sample from eight seasons, while their sample only comes from one season, and we use a different empirical strategy. We also examine several issues outside of their scope, including pressure effects throughout the game, how the effects change as time remaining decreases during the last minute and depending on whether the shot is the first or last of the set, and how the effects vary for players with different characteristics.

There is a limited but growing economics literature on choking. Ariely et al. (2009) analyze experiments showing that individuals perform worse when stakes are higher, and Bannier and Feess (2010) and Rauh and Seccia (2010) study theoretical models that incorporate anxiety and choking. Dohmen (2008) is one of the few economics papers that uses non-experimental data to study choking.[8] Dohmen uses penalty kick data from the German Premier Football League over 40 seasons. He finds that while being the home team is associated with an approximately two conversion percentage point decline, neither the score difference at the time of the shot, nor attendance, have significant effects on performance. Our results differ in that we find that being the home team has a very small positive effect on performance, while score differences can have negative effects of larger magnitude. One reason being the home team may be more of an advantage in the free throw setting is that home fans may be able to distract shooters from the away team more in basketball than soccer. One reason Dohmen may not have found that choking increased when the score was closer was that his dataset may not have included a sufficient number of observations from the very final seconds of games. On the other hand, each penalty kick is much more important than most individual free throws, since scoring occurs much less frequently in soccer than basketball, which should mitigate the importance of time remaining on pressure.

2.3 Data and Empirical Strategy

We use play-by-play data from the 2002-03 through 2009-10 seasons obtained from ESPN.com. We use a play-level, rather than game-level, dataset because it allows us to

observe the time in the game at which the various shots were taken, and the score difference at the time of the shots. We convert the play-by-play data to a free throw attempt-level dataset with nearly 500,000 observations; however, the vast majority are shots taken throughout the game that are unlikely to directly cause the shooter's team to win or lose, and so pressure likely does not vary substantially across most of the observations. Summary statistics are presented in Table 2.1 and graphically in Figure 2.1 (all variables referred to are defined below).[9] We have over 700 and over 900 observations with the shooter's team losing by less than five points with 16-30 and 0-15 seconds remaining in the fourth quarter or overtime, respectively.[10] The table and figure also provide a preview of our econometric results, as they both show performance clearly declines as the score margin and game time remaining decrease in the final minute of games. Both indicate that choking is greater when teams are losing rather than winning (by the same margin), and Figure 2.1 indicates a lack of choking in the second to last minute of games, and that choking does not occur when the score is tied in the final 15 seconds.

There are two more subtle observations we can make from Figure 2.1. One is that since the major decline in "Actual" performance from "Normal" occurs only when the score is very close and in the last 30 seconds, this indicates that fatigue cannot be the main factor driving the decline. It is implausible that the players' physical condition changes substantially in the final 30 seconds, as compared to the previous 30 seconds. The second observation is the figure shows better overall shooters are more likely to be selected to shoot when the shooter's team is winning by at least one point, as compared to

when his team is tied or losing, in the last 30 seconds. The "Normal" plot for the bottom figures, which represents the overall free throw percentage of players shooting for each score difference, is approximately flat for score differences between -5 and 0, and also for score differences between 1 and 5. But the plot jumps when the difference increases from 0 to 1 (the jump is less pronounced when there are 16-30 seconds remaining). This likely reflects the fact that teams that are winning in the final seconds know they are likely to be fouled, and as a result attempt to give the ball to their players known to be relatively good shooters, and perhaps even players thought to perform especially well under pressure. This may bias our estimates of choking towards zero for situations in which the shooter's team is winning in the final 30 seconds.

Our empirical strategy is to use linear probability models to estimate the effects of several variables that may be associated with pressure on a binary dependent variable that equals one if the free throw is made (*FreeThrowMade*). We use player-season fixed effects, which means our estimates should be interpreted as deviations from player-season means, and should eliminate many possible selection biases (as discussed just above, shooters who are better—or worse—on average may be more likely to get fouled in certain situations).[11] However, our results may still be affected by changes in the composition of shooters in different situations. We discuss this further below in this section. We also include quarter dummies and dummies for whether the shot was from a one-shot set (*OneShot*, which usually occurs when the player was fouled during a successful field goal attempt), and whether the previous free throw was made

(*PrevMade*) and whether it was missed (*PrevMiss*) for the second or third free throw of a set, as controls (see Arkes, 2010).

We use linear models rather than logit or probit because most of our estimates of interest are coefficients on interaction terms, which are difficult to interpret for non-linear models (Ai and Norton, 2003). It is well known that the linear probability model generally yields results that are very similar to those of logit and probit, especially for dependent variables whose means are not too close to zero or one (see, e.g., Angrist and Pischke, 2009), and we have confirmed that results are very similar when we use logit and calculate marginal effects using the methods of Ai and Norton (2003) and Corneliben and Sonderhof (2009).[12]

We first estimate the effects of several variables, including home/playoff status (*Home, Playoff*); attendance (*Attend*), and score differences (*Up1*, *Down1*, *Up2*, …) on performance in the first three quarters of games, to examine the effects of factors that may affect anxiety throughout games. We drop the fourth quarter to ensure that our results are not affected by end-of-game effects. The theoretical effect of home status on performance here is ambiguous, as players may benefit from the support of fans at home and be harmed by distractions created by fans on the road, but may also feel more pressure to please home fans. Clearly, playoff games and games with higher attendance levels should involve higher pressure, even in the first three quarters. Smaller score differences should involve higher pressure, but the differences may not be substantial, since in the first three quarters of a game it is highly unlikely that any single free throw

will affect the game's outcome (and it is almost certain that fans and analysts will not attribute the game's outcome to a free throw taken before the fourth quarter).

We then analyze how the effects of the score difference variables may change in the final seconds when the game's outcome is on the line. To do this we interact dummies for various score differences with dummy variables for whether there is less than 60/30/15 seconds (*Last60, Last30, Last15*) left in the game (fourth quarter or overtime). We use interactions so that we can include the *Last* variables separately to control for fatigue and other changes that may result at the end of games for reasons other than pressure. We use dummy variables for different amounts of time remaining to transparently allow for a non-linear relation between score difference and pressure. We focus on the last minute since, as shown in Figure 2.1, there is little evidence of choking with greater than one minute remaining.

We also estimate coefficients on a number of triple-interaction terms involving score difference, the *Last* variables, and other variables. This allows us to gain insight into the importance of various factors that may affect responses to pressure, both internal (i.e., inside a player's head) and external. First, we look at interactions with *FinalShot*, a dummy for whether the free throw is the last of its set (usually second of two). In many situations the pressure will be higher when the shooter is down to his last shot. For example, if the shooter's team is up one point, then there is a large benefit to hitting one shot, since that puts his team up by a field goal.

We also examine interactions with shooter characteristics: free throw percentage for the season for shots taken with more than one minute remaining in the fourth quarter

or overtime (*FTPct*[13]), years of experience (*Exper*), number of attempts per game for the season (*Atts*) and number of attempts for the season in pressure situations (*PrAtts*), defined as attempts in the final minute when the shooter's team is tied or losing by up to four points. These interactions allow us to analyze the types of players who are more or less likely to choke. The natural hypothesis is that free throw shooting ability, years of experience, and free throw shooting experience are internal factors that would be positively associated with "mental strength" and thus better performance under pressure.[14]

The estimate for *PrAtts* may be most difficult to interpret. The variable is intended to proxy experience shooting free throws in high pressure situations. If its coefficient is positive, this could be caused by selection (players known to be better in the clutch may be given the ball more often in pressure situations) or could indicate that greater experience in the clutch causes clutch performance to improve. Thus, if we find the estimate is positive, it is not clear which of these factors would be responsible. On the other hand, if we find the estimate is insignificant, we could view this as evidence that selection does not substantially affect our overall results, at least for situations in which the shooter's team is losing or tied. When constructing our measure of previous shots, we exclude situations in which the shooter's team is winning by a small number of points because selection effects are likely more severe in those situations, since the shot is much more likely to be due to a strategically committed foul.

We use interactions with *Home*, *Playoff* and *Attend*, which all would be positively associated with pressure, to examine the importance of these external factors. We also

look at interactions with *PrevMade* and *PrevMiss*, which are likely more appropriately classified as internal factors, since conditional on other variables (score, time remaining etc.) they primarily affect a player's mindset. If we find performance improves when *PrevMade*=1, and declines when *PrevMiss*=1 (in high pressure situations, relative to regular situations), this would indicate confidence is affected by the outcome of the initial shot(s), which in turn affects performance on the later shot(s).

To elaborate on the potential sample selection issue alluded to just above—that teams may feed the ball to players thought to perform best in the clutch—this may not be too serious a concern since basketball teams tend to just give the ball to their best shooters in the most crucial situations, and not necessarily the players thought to be best in the clutch relative to their regular performance. However, if selection affects our results, it would likely bias our estimates of performance under pressure upward, since the shooting team usually has more control over the foul shooter than the defending team. We should thus view our estimates as conservative estimates of the amount of choking that occurs.[15]

The coefficient on each score dummy can be interpreted as the difference between expected free throw percentage when that dummy equals one, and the expectation conditional on the score difference being in the omitted category. Thus, the definition of the omitted category affects the interpretation of the results. To make results as transparent as possible we present results with two "baselines" (omitted categories): 1) down or up by 11+ points (11+ baseline), 2) down or up by five to 10 points (5-10 baseline). The 11+ baseline is intended to capture the lowest pressure situations, and the

5-10 baseline represents medium pressure situations. We combine situations in which a team is either winning or losing by the same range of points for each baseline because pressure, as determined by the expected effect of the shot on game outcome, should be similar in both cases. This approach enables us to easily allow for a non-linear (for example, inverse-U) relation between pressure and performance. The approach also allows us to test whether performance changes significantly when the score is very close as compared to both baselines (if we just used the 11+ baseline we would have to use F-tests to test the difference between estimates for small score margins and margins of five to 10 points), and to check that our results are not driven by changes in the composition of players that occur when the score difference takes different values.[16]

2.4 Results

Table 2.2 presents results for the analysis of the first three quarters. This analysis roughly parallels that of Dohmen (2008), who focused on the determinants of choking throughout games. The magnitude of the coefficients on the score difference are less than or equal to 1% and mostly insignificant, so we do not report them. There is a small positive effect to being the home team, and small negative effect of higher attendance, both of which are only significant when the data from all three quarters are pooled. The attendance effect is not significantly different for home or away teams, and playoff status does not have an economically or statistically significant effect. The estimates are generally similar for each of the first three quarters. Almost all of the effects are not significantly affected by player characteristics, but there is some evidence that the playoff

effect is increasing in overall shooting percentage, but decreasing in player experience (the coefficient on *Playoff*FTPct* is positive and significant at 10%, and on *Playoff*Exper* is negative and significant). The former is consistent with more confident players choking less in higher pressure situations, but the latter result is difficult to explain.

The paper's main results are presented in Tables 3 and 4. Both present estimated coefficients for interactions of the various score differences with the *Last* variables and, in separate specifications, whether the shot was the final shot from the set. In Table 2.3 the omitted score category is winning or losing by 11 or more points, and in Table 2.4 the omitted score difference is 5-10 points. The main effects for the score difference and *Last* variables are included in all of the regressions. Their coefficients are almost always less than 0.01 and insignificant.

The results indicate that during the last 15 seconds of the game, players shoot 8.8 percentage points worse than their season average when down one point, and 6.3 percentage points worse when down by two, as compared to when up or down 11 or more points, in the last 15 seconds. When we expand our window of pressure situations to the last 30 seconds or the last minute, we see the estimated effects are slightly smaller but continue to be statistically significant at the 5% level.

Players shoot around five percentage points worse when up one or two in the last 15 seconds on the final shot of a set, as compared to other shots in the same set. This is consistent with the choking hypothesis, since pressure should be higher on the final shot. On the other hand, players perform better on the initial shot of a set, as compared to the

final shot, when down by one point, which is puzzling, but the effect is insignificant so we should not put much weight on it. The estimates for interactions of dummies for down three and down four with *Last30* and *Last15* range from -1% to -5%, but are statistically insignificant and unreported.

Table 2.4 shows that players shoot 3.7 and 5.5 percentage points worse when down one and two in the last 30 seconds, respectively, as compared to when the score difference is five to 10. The numbers are 4.5 and 6.5, respectively, in the last 15 seconds, though only the latter is significant. Players again shoot around 5 percentage points worse on the final shot in the last 15 seconds when winning by one or two. These effects are smaller than those reported in Table 2.3 because players shoot 1-2 percentage points worse in the last 30 seconds, as compared to the rest of the game, when the score difference is five to 10, indicating there are small pressure effects for these moderate score differences. The estimates tend to be of much lower magnitude and insignificant for the *Last60* models, and for terms involving the variable representing the score being tied.[17]

Table 2.5 presents estimates of interaction terms involving player characteristics, for the +11 baseline.[18] To improve statistical power we combine some of the individual score difference groups into broader categories and report the coefficients for a dummy variable equal to one when the shooter's team is down by one to four points, *Down1_4*. We look at both the effect of shots taken during the last 30 seconds of the game (Panel A) and during the last 15 seconds (Panel B).

In columns 2-5, we examine whether the basic choking effect (column 1) differs based on player characteristics such as ability and previous experience. We find that players with higher shooting ability experience a smaller change in performance in high pressure situations. A 10 percentage point increase in a player's past free throw percentage is associated with a decrease in the choking effect of 5.6 percentage points in the last 30 seconds. However, we find that none of our measures of player experience were associated with lower choking effects. Our results are also similar when we include all of the interactions at the same time and when we narrow our analysis to look at the effect of the last 15 seconds. A very poor shooter who averages 60% (e.g. Shaquille O'Neal) would have an estimated choking effect for those situations of around 15 percentage points (from column 2 of panel b, -0.51+0.61*0.6).

Table 2.6 presents results for additional interactions with *Down1_4*. The most striking result is that performance in the final 30 seconds when the shooter's team is down up to four points improves by around five percentage points when the previous free throw was made, and declines by an even greater magnitude when the previous shot was missed, though these effects are not estimated precisely. As discussed above, this likely indicates the importance of a player's mindset, and how it can be influenced by success on the first shot. Although performance on the first/second shot may be correlated for other reasons, we control for this possible general correlation by including *PrevMade* and *PrevMiss* as non-interacted terms in the models.

Home status and attendance have no significant interaction effects (the direction of the home effect is positive but its magnitude is always less than 4%). Playoff status

does not interact significantly with *Down1_4* and *Last*, and the magnitudes of the effects are close to zero for models 3 and 4. We are somewhat surprised by this, and while it may be due to the relatively small playoff sample, we thought this may also be due to players gaining experience throughout the season, and consequently becoming less prone to choke later in the season, which could nullify increased choking in the playoffs. This does not appear to be the case, however, as when we include an interaction with a variable equal to month of season, which is highest in playoff months and should thus pick up the effect of declining within-season choking, results are similar (results not reported).

Pressure may also be relatively high for games that occur late in the regular season that are likely to affect playoff seeds. To account for this we estimate the models on a sub-sample without regular season games played in the final month (April); this should accentuate the difference in pressure between playoff and regular season games. Doing this does not substantially change the *Playoff* results, but does weaken the *PrevMade* and *PrevMiss* estimates (results unreported). Perhaps the lack of an observed increase in choking in the playoffs is caused by selection biases being exacerbated in the playoffs, which would occur if teams make more of an effort to get the ball to their best free throw shooters and/or clutch players in the playoffs, as compared to the regular season. Perhaps teams experiment more in the regular season, giving various players chances in clutch situations.

2.5 Discussion and Conclusion

The results of this paper indicate that NBA players do choke at the very end of games when their team is winning or losing by a small margin. Choking is more severe for players who are worse overall free throw shooters, and on the second shot if the first was missed. Choking effects are stronger for players whose teams are losing, which is unsurprising since the marginal effect of a foul shot on the probability of winning the game is likely greater for shooters whose teams are losing rather than winning. However, the choking estimates for players on winning teams may be biased slightly downward, as the shooters in those situations are slightly better than average.

In contrast, we find that players do not choke when the score is tied in the last 15 seconds, which is consistent with the findings of Worth et al. (2009). In these situations, players may perceive that even if the shot is missed the shooter cannot be held directly responsible for the game outcome—the shooter's opponent still needs to score in the final seconds to win, and if the opponent scores by making a two or three point field goal (as scoring usually occurs) a single free throw would not make a difference to the game outcome anyway. On the other hand, when the shooter's team is up by one or two, a single free throw could be the difference between a two or three point shot by the opponent leading to a win or overtime. However, these perceptions would be at odds with the empirical reality. We find that when games are tied in the last 15 seconds, after a made free throw the shooter's team has a 69.5% chance of winning in the current period, and only a 35.0% chance of winning after a miss. When up one point, the percentages are 71.1% and 67.7%, respectively. The numbers are similar for teams up two points. This indicates that the shot is very important to the team's outcome when the

game is tied, but is less likely to matter when the shooter's team is winning by a small margin.[19]

The behavioral economics theory of loss aversion also offers an explanation. The shooter might think the shot as gaining a win when the game is tied and avoiding a loss for other score differences. Since losses are painful, the pressure in the cases is higher.

Another possible explanation for the lack of a decline in performance in the last 15 seconds when the score is tied is that players are especially focused in those situations, while players do not exert full effort, i.e. they shirk, when there is more time left because they think there will be time to recover from missed shots. It is possible shirking, rather than choking, explains the negative performance effects we do observe in the last minute of games. See Berri and Krautmann (2006) for a recent study of shirking in the NBA. We do not think shirking can plausibly explain our results since we find for all scores other than ties, performance declines as time remaining decreases, and the decline is sharper when the score is closer. While this pattern is consistent with the choking hypothesis, we would expect shirking to cause the opposite pattern—for performance to be worst in the situations where it matters least.

We are also somewhat surprised that home and playoff status do not have substantial effects on choking (despite the ambiguous theory regarding home status, discussed above). Perhaps the lack of a home effect is due to players knowing their teammates, coach, and the vast majority of fans, will be aware of or learn about the performance (good or bad) whether it takes place at home or on the road, and so the effects of choking on the player's reputation are independent of home status. The lack of

a home effect (in the first three quarters and end-of-game choking) may also be due to competing forces; players may feel more pressure playing at home, but be more distracted by fans on the road, as they typically make extra noise and even wave objects to attempt to distract shooters from the opposing team. The lack of a playoff effect may be due to small sample size; although our dataset is large, the number of observations for very high pressure situations that occurred in the playoffs is still highly limited.

NBA players are highly-paid professionals, most of whom have substantial experience performing in front of thousands watching in person, and millions watching on television. Our findings that even NBA players choke lead us to believe that athletes across all sports, and workers in general, are likely subject to anxiety in pressure situations that cause them to perform less than optimally. An important topic for future sports economics research is the relation between performance under pressure and earnings. The most immediate questions to investigate are whether players who consistently choke more than average have lower pay or if playing time is affected by choking, and if so (for either), to what extent. Deutscher et al. (2010) take a step in this direction; they find that players who perform better than normal in the last five minutes of close games do receive substantially higher pay. A more difficult question to answer would be whether monetary compensation for choking/clutch performance is optimal from a profit-maximization perspective. One plausible alternative hypothesis is that pay may respond excessively to recent, salient performance under pressure. For example, if a player hits a last-minute winning shot in an important playoff game, that player may obtain greater pay as a free agent in the next off-season. But a single shot may provide

almost no information about the player's ability as a clutch performer in the future. Anecdotal evidence of this occurring in American football is Larry Brown, a previously unheralded player who had a very good performance in Super Bowl XXX causing him to win the game's MVP award and then one month later signed a relatively lucrative contract with the Oakland Raiders. He was released just two seasons after that due to poor performance (Kroichick, 1998).

2.6 Endnotes

[1] See Hilla et al. (2010) for a recent literature review.

[2] See Dohmen (2008) and Ariely (2010) for discussions of the relevance of choking in labor market contexts outside sports. One context particularly worth noting is finance, and perhaps day-trading in particular, since, like basketball players, traders sometimes have to make split-second decisions and the degree of pressure can be very high.

[3] Most free throws are shot in pairs.

[4] Arkes (2010) showed that free throw shooters perform better after making their previous free throw, as compared to after a missed free throw, which he interpreted as evidence of the hot hand. We find similar results, and find that the effect is exacerbated considerably in the final seconds of close games. It is also worth noting (estimates not reported) that players perform substantially (three to four percentage points) better on the second shot than the first even when the first was missed, indicating that even seasoned professionals benefit from a warm-up shot.

[5] Hilla et al (2010) provide a detailed discussion of alternative theories for exactly why, and how, anxiety may arise and worsen performance in pressure situations. Two primary classes of theories are distraction (that performers are distracted from their task when pressure is high) and self-focus (that performers become self-conscious under pressure). Distinguishing between these theories is beyond the scope of this paper; we refer the reader to their paper for more detail on those topics.

[6] Wallace et al. (2006) provides a review of the literature on the effects of performing in front of supportive and hostile audiences. They discuss the theory of how supportive audiences should improve performance for effort-based tasks, but increase pressure and worsen performance for skill-based tasks. Evidence of supportive audiences causing choking has been found in multiple contexts, such as golf and baseball. Free throw performance is likely more affected by skill than effort, however, basketball audiences can distract players from the opposing team, especially free throw shooters, more than audiences in other sports (such as golf), so the net theoretical effect of home status on performance in basketball is ambiguous.

[7] For example, Wang et al. (2004) examines choking using free throw data obtained from a controlled setting. Levitt and List (2007) provide a discussion of the advantages of data “from the field”.

[8] Ariely (2010) refers to research on clutch performance using NBA data currently in progress; see also Deutscher et al. (2010). There are also sabermetric studies on clutch performance, but they focus on the question of whether individual players are consistently good clutch performers; see, e.g., Neyer (1999). Two other very recent

papers that use soccer data and study a somewhat different form of psychological pressure are Apesteguia and Palacios-Huerta (2010) (who find substantial pressure effects) and Kocher et al. (2010) (who find weak and insignificant pressure effects).

[9] Attendance data are only available for the 2002-03 through 2007-08 seasons. We began this project during the 2009-10 season and added in all observations for the regular season as we proceeded, but exclude all observations from that season's playoffs.

[10] We drop observations for the last shot of a set (usually the second shot of two) with the shooter's team losing by two or three points with five or fewer seconds remaining, as players sometimes intentionally miss their shot in those situations in the hope that their team will rebound the missed shot and make a field goal, which is necessary to tie the game or take the lead. We examined the data closely, and found no evidence of these intentional misses for shots taken with greater than five seconds remaining.

[11] We experimented with alternative controls, including player fixed effects, and player 60-120 day moving averages, to allow for players' free throw percentage to vary less/more frequently than season to season, and obtained similar results.

[12] Results are not reported, but available on request. Another reason that we prefer linear models is that due to our large sample size and player-season fixed effect specification it is computationally extremely demanding to use the Ai and Norton (2003) approach.

[13] We exclude the current observation in the calculation of this variable.

[14] In all specifications with interaction terms we include all variables used in the interaction terms as separate regressors. We drop the player-season fixed effects in specifications involving *FTPct* to avoid perfect multicollinearity. The variable *FTPct* still provides a good control for overall free throw shooting ability.

[15] We considered examining shots caused by technical fouls separately. Teams can directly choose the shooter (i.e., the free throw shooter is not just the player who was fouled) for these shots, so positive selection bias should be most severe for these shots. However, we only have seven and three observations for technical shots take in the last 30 and 15 seconds, respectively, with the shooter's team down one to four points.

[16] It is well known that teams are more likely to play "scrubs" when losing or winning by a substantial margin at the end of the game. Scrubs may actually feel even less pressure than normal players in these situations (since they likely know they are not being evaluated by their coach and others as closely as they are evaluated in the middle of games), and will not be as fatigued, which could bias the estimates on the *Last* variables upward, and consequently the estimate on *Last* interacted with other score variables to be biased downward. We are confident our results are robust to this

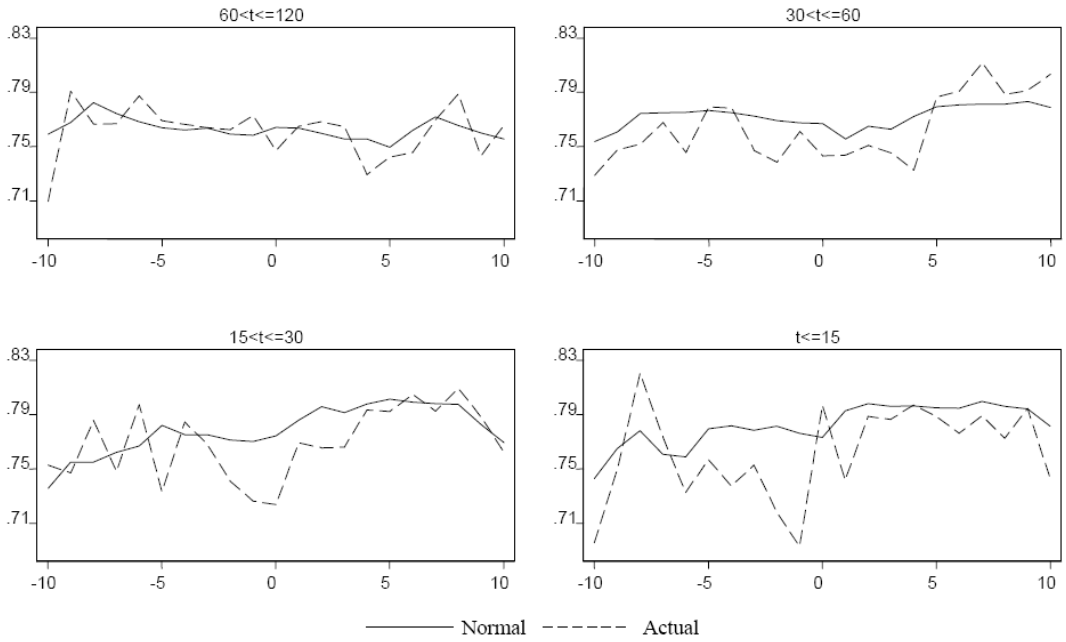
issue since results are similar when we use the 5-10 baseline, and we also found results are similar for the 11+ baseline when we drop scrubs (players who took most of their free throw attempts in the last minute when winning or losing by 11+ points).

[17] Figure 2.1 indicates that players perform worse when the score is tied when there are 16-30 seconds remaining; however, we find even these effects are insignificant when we test for them using this framework.

[18] In the interest of brevity we do not present results for the alternate 5-10 baseline for the remaining tables, as they are largely similar. We also do not report results for other score difference category interactions, although many are significant. It is worth noting in particular that the interaction of the category representing situations in which a team is tied or winning by a small margin with *FTPct* is also significant, but of a lower magnitude than the *Down1_4* estimate, which is consistent with choking being more likely when teams are losing by a small margin rather than winning for players of all abilities.

[19] The percentages are 28.7% and 5.5% when down one point, respectively.

Figure 2.1. Comparison of Free Throw Percentage in High ("Actual") and Low ("Normal") Pressure Situations.



Notes*:* *t* = seconds remaining in fourth quarter or overtime; X-axis = score difference (shooter's team's score minus opponent's score, prior to shot); Normal = mean *FTPct* (free throw percentage for the shooter in non-pressure situations); Actual = mean *FreeThrowMade* (percentage of shots made for given pressure situation--score difference/time remaining).

Table 2.1: Summary Statistics

	30<t<=60			15<t<=30			t<=15		
	mean	std error	N	mean	std error	N	mean	std error	N
Panel A: Summary Statistics for *FreeThrowMade*									
Home = 1									
Down1_4	0.769	0.017	585	0.739	0.024	341	0.729	0.021	468
Up0_4	0.755	0.015	867	0.774	0.011	1524	0.778	0.008	3007
Other	0.774	0.006	4423	0.779	0.007	3298	0.780	0.008	2431
Home = 0									
Down1_4	0.738	0.017	682	0.756	0.022	386	0.722	0.021	454
Up0_4	0.728	0.016	767	0.776	0.012	1128	0.791	0.008	2498
Other	0.760	0.006	4546	0.779	0.008	2876	0.771	0.009	2079
Playoff = 1									
Down1_4	0.816	0.042	87	0.830	0.052	53	0.687	0.057	67
Up0_4	0.738	0.047	88	0.735	0.035	162	0.755	0.022	376
Other	0.765	0.016	686	0.770	0.023	330	0.728	0.026	301
Panel B: Summary Statistics for Other Variables									
FTPct									
Down1_4	0.771	0.002	1354	0.772	0.003	780	0.779	0.003	989
Up0_4	0.765	0.002	1722	0.793	0.001	2814	0.795	0.001	5881
Other	0.762	0.001	9655	0.778	0.001	6504	0.782	0.001	4811
Exper									
Down1_4	5.375	0.094	1354	5.031	0.123	780	5.332	0.114	989
Up0_4	5.382	0.085	1722	5.550	0.066	2814	5.473	0.047	5881
Other	4.758	0.037	9655	4.908	0.045	6504	4.928	0.052	4811
Atts									
Down1_4	4.281	0.070	1354	4.139	0.087	780	4.182	0.086	989
Up0_4	3.926	0.061	1722	3.702	0.045	2814	3.648	0.031	5881
Other	3.193	0.025	9655	3.098	0.028	6504	3.159	0.033	4811
PrAtts									
Down1_4	5.756	0.108	1354	5.609	0.136	780	5.657	0.125	989
Up0_4	3.686	0.097	1722	3.460	0.074	2814	3.243	0.049	5881
Other	2.517	0.035	9655	2.514	0.041	6504	2.592	0.053	4811

Notes: The first two sections of panel A (*Home* = 1 and *Home* = 0) give the statistics for regular season games only. Observations for *OneShot*, second and third shot with team losing by 2 or 3 points and time remaining is less than 6 second are dropped. t = seconds remaining in fourth quarter or overtime.

Table 2.2: Analysis of Quarters 1-3

	(1) quarter 1	(2) quarter 2	(3) quarter 3	(4) quarter 1-3	(5) quarter 1	(6) quarter 2	(7) quarter 3	(8) quarter 1-3
Home	0.002	0.004	0.005	0.004**	-0.034	0.026	0.003	0.001
	[0.003]	[0.003]	[0.003]	[0.002]	[0.027]	[0.024]	[0.024]	[0.014]
*Home*FTPct*					0.052	-0.039	0.016	0.007
					[0.035]	[0.032]	[0.031]	[0.019]
*Home*Exper*					0.000	-0.000	-0.001*	-0.001
					[0.001]	[0.001]	[0.001]	[0.000]
*Home*Atts*					-0.001	0.003**	-0.001	0.000
					[0.001]	[0.001]	[0.001]	[0.001]
Attend	-0.013	-0.012	-0.008	-0.012***	-0.008	-0.016	-0.099	-0.044
	[0.009]	[0.008]	[0.008]	[0.005]	[0.072]	[0.063]	[0.060]	[0.038]
*Attend*FTPct*					0.023	-0.024	0.133*	0.045
					[0.096]	[0.084]	[0.080]	[0.050]
*Attend*Exper*					-0.003	0.004*	-0.002	-0.000
					[0.002]	[0.002]	[0.002]	[0.001]
*Attend*Atts*					-0.002	-0.000	-0.000	-0.001
					[0.004]	[0.003]	[0.003]	[0.002]
*Home*Attend*	-0.005	0.018	-0.016	-0.001	0.058	-0.025	-0.025	-0.002
	[0.013]	[0.012]	[0.012]	[0.007]	[0.097]	[0.086]	[0.084]	[0.052]
*Home*Attend*FTPct*					-0.085	0.084	0.012	0.015
					[0.129]	[0.115]	[0.111]	[0.069]
*Home*Atten*Exper*					0.002	-0.003	0.001	-0.000
					[0.003]	[0.003]	[0.003]	[0.002]
*Home*Atten*Atts*					-0.001	-0.002	0.001	-0.001
					[0.005]	[0.005]	[0.005]	[0.003]
Playoff	0.006	-0.006	0.008	0.004	-0.019	-0.047	0.011	-0.020
	[0.007]	[0.006]	[0.006]	[0.004]	[0.052]	[0.048]	[0.045]	[0.028]
*Playoff*FTPct*					0.096	0.087	0.000	0.060*
					[0.065]	[0.060]	[0.058]	[0.036]
*Playoff*Exper*					-0.006***	-0.004**	-0.000	-0.003***
					[0.002]	[0.002]	[0.002]	[0.001]
*Playoff*Atts*					-0.003	-0.000	-0.001	-0.001
					[0.002]	[0.002]	[0.002]	[0.001]
N	67,585	87,472	89,413	244,470	67,585	87,472	89,413	244,470
R-squared	0.003	0.003	0.002	0.003	0.043	0.042	0.045	0.043

Notes: All models include *OneShot, PrevMade, PrevMiss, Up5_10, Up4, Up3, Up2, Up1, Tied, Down1, Down2, Down3, Down4, Down5_10.* Model 4&8 also include dummies for quarter. *Attend* is measured in ten thousands. Models 1-4 include player-season fixed effects, and models 5-8 include *FTPct, Exper* and *Atts* as separate regressors. Robust standard errors given in brackets. *, **, *** denote 10%, 5% and 1% significance.

Table 2.3: Analysis of Last Minute Pressure Effects, 11+ Baseline

	(1) X=60	(2) X=30	(3) X=15	(4) X=60	(5) X=30	(6) X=15
*LastX*Down2*	-0.037**	-0.045**	-0.063**	-0.021	-0.034	-0.060
	[0.017]	[0.023]	[0.032]	[0.024]	[0.031]	[0.042]
*LastX*Down1*	-0.041**	-0.066***	-0.088***	-0.062**	-0.097***	-0.108**
	[0.016]	[0.022]	[0.030]	[0.024]	[0.032]	[0.043]
*LastX*Tied*	-0.015	-0.008	0.018	-0.011	-0.010	0.023
	[0.017]	[0.022]	[0.029]	[0.025]	[0.032]	[0.040]
*LastX*Up1*	-0.026**	-0.029**	-0.042**	-0.009	-0.015	-0.016
	[0.012]	[0.015]	[0.020]	[0.015]	[0.017]	[0.023]
*LastX*Up2*	-0.018*	-0.019	-0.018	0.001	0.002	0.008
	[0.011]	[0.013]	[0.019]	[0.014]	[0.017]	[0.022]
*FinalShot*LastX*Down2*				-0.029	-0.020	0.001
				[0.032]	[0.042]	[0.057]
*FinalShot * LastX*Down1*				0.043	0.060	0.042
				[0.031]	[0.041]	[0.053]
*FinalShot * LastX*Tied*				-0.006	0.005	-0.009
				[0.032]	[0.041]	[0.050]
*FinalShot * LastX*Up1*				-0.036	-0.031	-0.063**
				[0.023]	[0.026]	[0.032]
*FinalShot * LastX*Up2*				-0.034*	-0.039**	-0.046**
				[0.019]	[0.020]	[0.023]
N	436,898	424,167	414,069	436,898	424,167	414,069
R-squared	0.003	0.003	0.003	0.003	0.003	0.003

Notes: All models include *Up5_10, Up4, Up3, Up2, Up1, Tied, Down1, Down2, Down3, Down4, Down5_10, Last60/30/15, PrevMade, PrevMiss, Home, Playoff,* interaction of *Last60/30/15* and score dummies, dummies for quarter. Models 1-3 also include *OneShot*. Models 4-6 also include *FinalShot* and its separate interactions with *Last60/30/15* and score dummies. Observations with *FinalShot*=1 and less than 6 seconds remaining (in fourth quarter or overtime) are dropped, as are observations with *LastX*=0 with less than five minutes remaining (this is why N varies from model to model). All models include player-season fixed effect and use robust standard errors are given in brackets. *, **, *** denote 10%, 5% and 1% significance.

Table 2.4: Analysis of Last Minute Pressure Effects, 5-10 Baseline

	(1) X=60	(2) X=30	(3) X=15	(4) X=60	(5) X=30	(6) X=15
*LastX*Down2*	-0.033**	-0.035	-0.041	-0.018	-0.025	-0.039
	[0.016]	[0.021]	[0.029]	[0.024]	[0.030]	[0.039]
*LastX*Down1*	-0.037**	-0.055***	-0.065**	-0.059**	-0.087***	-0.087**
	[0.016]	[0.020]	[0.027]	[0.024]	[0.031]	[0.040]
*LastX*Tied*	-0.010	0.003	0.040	-0.008	-0.000	0.045
	[0.016]	[0.021]	[0.026]	[0.024]	[0.031]	[0.037]
*LastX*Up1*	-0.022*	-0.019	-0.019	-0.005	-0.005	0.005
	[0.011]	[0.012]	[0.015]	[0.014]	[0.015]	[0.018]
*LastX*Up2*	-0.013	-0.008	0.005	0.004	0.012	0.029
	[0.010]	[0.010]	[0.013]	[0.014]	[0.015]	[0.018]
*FinalShot*LastX*Down2*				-0.029	-0.019	0.002
				[0.032]	[0.042]	[0.057]
*FinalShot * LastX*Down1*				0.042	0.060	0.043
				[0.031]	[0.041]	[0.053]
*FinalShot * LastX*Tied*				-0.007	0.005	-0.008
				[0.032]	[0.041]	[0.050]
*FinalShot * LastX*Up1*				-0.036	-0.031	-0.062**
				[0.023]	[0.026]	[0.032]
*FinalShot * LastX*Up2*				-0.034*	-0.039*	-0.046*
				[0.019]	[0.020]	[0.023]
N	436,898	424,167	414,069	436,898	424,167	414,069
R-squared	0.003	0.003	0.003	0.003	0.003	0.003

Notes: All models include *Up5_10, Up4, Up3, Up2, Up1, Tied, Down1, Down2, Down3, Down4, Down5_10, Last60/30/15, PrevMade, PrevMiss, Home, Playoff,* interaction of *Last60/30/15* and score dummies, dummies for quarter. Models 1-3 also include *OneShot*. Models 4-6 also include *FinalShot* and its separate interactions with *Last60/30/15* and score dummies. Observations with *FinalShot*=1 and less than 6 seconds remaining (in fourth quarter or overtime) are dropped, as are observations with *LastX*=0 with less than five minutes remaining (this is why N varies from model to model). All models include player-season fixed effect and use robust standard errors are given in brackets. *, **, *** denote 10%, 5% and 1% significance.

Table 2.5: Player Characteristics Interactions

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: *Last30* Interactions						
*Last30*Down1_4*	-0.038***	-0.453***	-0.075***	-0.057**	-0.071***	-0.475***
	[0.014]	[0.121]	[0.025]	[0.023]	[0.021]	[0.122]
*FTPct*Last30*Down1_4*		0.557***				0.547***
		[0.155]				[0.159]
*Atts*Last30*Down1_4*			0.008			-0.002
			[0.006]			[0.008]
*Exper*Last30*Down1_4*				0.004		0.001
				[0.004]		[0.004]
*PrAtts*Last30*Down1_4*					0.007	0.003
					[0.004]	[0.006]
N	424,167	424,167	424,167	424,167	424,167	424,167
R-squared	0.003	0.04	0.003	0.003	0.003	0.04
Panel B: *Last15* Interactions						
*Last15*Down1_4*	-0.058***	-0.511***	-0.093***	-0.045	-0.086***	-0.546***
	[0.021]	[0.189]	[0.035]	[0.034]	[0.031]	[0.193]
*FTPct*Last15*Down1_4*		0.611***				0.648***
		[0.243]				[0.250]
*Atts*Last15*Down1_4*			0.008			0.008
			[0.009]			[0.013]
*Exper*Last15*Down1_4*				-0.004		-0.007
				[0.006]		[0.006]
*PrAtts*Last15*Down1_4*					0.002	-0.008
					[0.007]	[0.010]
N	414,069	414,069	414,069	414,069	414,069	414,069
R-squared	0.003	0.04	0.003	0.003	0.003	0.04

Notes: All models include *Up5_10, Up0_4, Down5_10, Last30/15, Oneshot, PrevMade, PrevMiss, Home, Playoff*, interaction of *Last30/15* and score dummies, dummies for quarter. Models with *FTPct, Atts, Exper* and *PrAtts* interactions include separate interactions of these varaibles with *Last30/15* and score dummies. Observations with *FinalShot*=1 and less than 6 seconds remaining (in fourth quarter or overtime) are dropped, as are observations with *LastX*=0 with less than five minutes remaining (this is why N varies from model to model). All models except 2 and 6 include player-season fixed effects; 2 and 6 include *FTPct* as non-interacted regressor. Robust standard errors are given in brackets. *, **, *** denote 10%, 5% and 1% significance.

Table 2.6: Other Interactions

	(1) X=30	(2) X=15	(3) X=30	(4) X=15
*PrevMade*LastX*Down1_4*	0.042	0.058	0.049**	0.045
	[0.026]	[0.036]	[0.023]	[0.031]
*PrevMiss*LastX*Down1_4*	-0.036	-0.046	-0.069*	-0.096**
	[0.041]	[0.053]	[0.035]	[0.047]
Home LastX*Down1_4*	0.016	0.032	0.004	0.022
	[0.025]	[0.034]	[0.022]	[0.029]
Playoff LastX*Down1_4*	-0.046	-0.108	0.036	-0.003
	[0.053]	[0.072]	[0.043]	[0.060]
Attend LastX*Down1_4*	0.012*	0.005		
	[0.007]	[0.009]		
*Home*Attend*LastX*Down1_4*	-0.008	-0.004		
	[0.009]	[0.013]		
N	308,176	300,664	424,167	414,069
R-squared	0.003	0.003	0.003	0.003

Notes: All models include *Up5_10, Up0_4, Close, Down5_10, Last30/15, Oneshot, PrevMade, PrevMiss, Home, Playoff,* interaction of *Last30/15* and score dummies, dummies for quarter, separate interaction of *Home* and *Playoff* with *Last30/15* and score dummies. Models 1-2 also include *Attend* and *Home*Attend* and their separate interactions with *Last30/15* and score dummies. Only observation from 02-03 to 07-08 season are used for models 1-2, as *Attend* is only available for those seasons. Observations with *FinalShot*=1 and less than 6 seconds remaining (in fourth quarter or overtime) are dropped, as are observations with *LastX*=0 with less than five minutes remaining (this is why N varies from model to model). All models include player-season fixed effect and use robust standard errors are given in brackets. *, **, *** denote 10%, 5% and 1% significance.

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CHAPTER 3

REVISITING THE HOT HAND: REALITY AND PERCEPTIONS

3.1 Introduction

In sports the conviction that "success breeds success" is known as the belief in the hot hand. One example in basketball is that fans and professionals believe that it is more likely that a player will make a successful shot following a string of hits.[1] Many existing studies test the validity of the hot hand belief by estimating the serial correlation between outcomes of adjacent shot attempts (shot-level hot hand), and use sequences of hits and misses in a basketball game to examine people's perception of randomness.

Although it is still unclear to what extent people think this idea (success breed success) is true even when it is not, previous research provides strong evidence that people believe in the basketball hot hand. Gilovich et al. (1985) present the result of a survey that 91 out of 100 basketball fans believe that players are more likely to make a successful shot after two or three hits than after two or three misses. Tversky & Gilovich (1989) analyze the data for 18 players in 39 NBA games in one season and demonstrate that the probability of a player taking the team's next shot after a hit is significantly higher than after a miss. Rao (2009) finds moderate evidence that some NBA players respond to a string of hits by taking tougher shots. Besides basketball fans and professionals, Camerer (1989) shows that gamblers betting on basketball games hold the belief that teams in the midst of a winning streak are more likely to win the next game.

However, most of previous research has failed to find evidence of the basketball hot hand, despite the common belief in it.[2] The pioneering work of Gilovich et al. (1985) analyzes a dataset containing field goal data for nine players of Philadelphia 76ers in 48 home games during the 1980-1981 season. They find the probability of hitting a shot is

independent of the performance of previous shots. The same results are found with respect to free throw shooting and a controlled shooting experiment dataset. Several subsequent studies argue that the power of the statistical tests of Gilovich et al. (1985) is too low to detect the existence of the hot hand.[4] As pointed out by Smith et al. (2003), one possible reason for the insufficient power of the tests is the limited number of observations available from only nine players. There are two recent works that use relatively large datasets. Huizinga and Weil (2008) examine a field goal dataset containing 200 times more data as Gilovich et al. (1985). They find some weak evidences of a negative serial correlation for consecutive shots, which implies a player is less likely to make his next shot if he made his last shot. They argue the result might be caused by endogeneity in shot selection and change in defense. Arkes (2010) provides supportive evidence for the existence of the hot hand. He uses a dataset containing the free throw attempts of all players during the 2005-06 NBA season and finds that making the first free throw in a set increases the probability of making the second one in the same set by two to three percentage points.[4]

Based on previous research, we can conclude that people over-infer the correlation between shot outcomes as well as game outcomes. This perception bias is known as the "hot hand fallacy"[5], which has economic implications. DellaVigna (2009) gives a good example: investors in stock market might over-infer the past performance, which will cause the stocks with high past return to be overpriced.

However, as far as we are aware of, none of the existing studies used game-level data. Our game-level data is useful for two main reasons: 1) the large sample size (we

have data on all games from 1991-92 through 2006-07 seasons) provides substantial statistical power; 2) game-level data reduces the measurement error problem that occurs in the analysis of the basketball hot hand. Since the shooting ability in a game is unobservable, we need to use other variables as a proxy for it. Stone (2011) shows that using the shot outcome as a measure of shooting ability leads to severe measurement error, which causes the hot hand in shooting ability to be significantly underestimated. Using field goal or free throw percentage as a proxy of shooting ability will also cause measure error. But it becomes more precise when players take more shots. In addition, we make three other new contributions to this literature; 1) instead of pooling the two- and three- point shots, we examine them separately; 2) we test whether good shooting performance can raise the free throw percentage in the same game; 3) we provide new tests of the beliefs of players and coaches in the hot hand's existence.

In this paper we first develop a simple estimable model that allows the effects of psychological and physical states on players' shooting performance to persist across multiple games. Then we use the model to analyze the serial correlation of players' shooting performance in successive games. We find no evidence for a game-level hot hand of a substantial magnitude. The estimated serial correlation between the shooting performances in consecutive games is sometimes positive and significant, but always close to zero. Furthermore, we investigate the subsamples based on the position a player plays in the game, the professional experience, and the number of games in a season in which the player has shot attempts, respectively. The estimated hot hand effect in all the subsamples is very close to zero. We also test the hypothesis that the "hotness" in field

goal shooting boosts players' free throw shooting performance. The result shows there is no evidence of correlation between performance of free throw and field goal shooting in the same game.

Since our result is subject to measurement error, we look at the subsamples of players who have more shooting attempts on average and use the regression that weighs the field goal percentage by the number of field goal attempts in corresponding games. Using these two approaches does not change our conclusion. To better understand the effect of measurement error on the estimate of the hot hand, we conduct a simulation. The simulation result shows that the measurement error can cause the hot hand effect to be significantly underestimated. The estimated autocorrelation in field goal percentage is very close to zero when autocorrelation in the shooting ability is 30 percentage points. The simulation result implies that our estimation results (small hot hand effect) have to be interpreted carefully.

Whether or not the hot hand exists, we are also interested in whether NBA professionals hold the belief that a game-level hot hand exists. We find that NBA professionals do believe in its existence – players tend to take more shot attempts in a game if they shoot well in the last game, but only to a moderate extent. This positive relationship between the number of attempts and shooting performance in the last game is larger for the players who take more shot attempts on average, but is not affected by the game outcome of the last game. We also find the NBA professionals believe in the existence of with-in game hot hand, and its magnitude is about three times as large as that of game-level hot hand. Moreover, for two-point field goal, the fact that "hot" players

get more attempts is mainly caused by coaches' belief in the hot hand – the "hot" player will play more minutes while the number of shot per minutes played is unaffected by the "hotness".

A number of studies have extrapolated the hot hand and hot hand belief into fields such as economics and finance. Benartzi (2001) shows that employees exhibit "over-inference" in investing in employ stock. Employees of the companies whose stock performance is in top quintile invest 39.7 % their savings in employer stock that is in the top quintile of performance, as a contrast, only 10.4 percent for the companies in bottom quintile. However, the companies in the bottom quintile have a better performance of the next year. Jegadeesh & Titman. (1993, 2001) find the momentum effect in the stock market – buying stocks that performed well over the previous 3-12 months and selling the ones performed poorly over the same period generates significant abnormal returns. Barber et al. (2009) find that individual US investors systematically buy stocks that have strong recent performance. The existence of the hot hand in mutual funds is still controversial. Hendricks et al. (1993) find evidence of the short-run persistence of mutual funds' performance – funds that performed well in the most recent year continue their superior performance in the near term, and this persistence is not caused by known anomalies or survivorship bias. On the other hand, Metrick (1999) analyzes the equity-portfolio recommendations of 153 investment newsletters and fails to find significant evidence of short-run persistence in superior stock-picking ability. Jagannathan et al., (2010) find strong evidence that performance among top hedge funds is persistent, but little evidence of persistence among bottom funds. An important issue in economics is the

implications of the hot hand fallacy. Camerer (1989) writes that "The important question for economics is whether mistaken beliefs like the hot hand fallacy make allocation of resources suboptimal." Sinkey et al. (2010) show that the betting market for American college football is inefficient and provide evidence that this inefficiency is attributable to bettors' belief in the existence of the hot hand.

The rest of the paper proceeds as follows: We discuss our data and empirical methods in Section 3.2, estimation results in Section 3.3. Section 3.4 concludes.

3.2 Data and Empirical Strategy

3.2.1 The Hot Hand Reality

We use game-level box-score data obtained from ESPN.com for all NBA regular season and playoff games from the 1991-92 through 2006-07 seasons. The unit of observation is a player-game, so there is a different observation for each player in each game (a total of nearly 370,000 observations). Summary statistics of the key variables are presented in Table 3.1.

The hot hand effect might only exist when two adjacent games happen within a few days and the magnitude might depend on the number of days between the consecutive games. So the estimates of the hot hand might be biased towards zero by the observations whose most recent game occurring more than a certain amount of days ago. For example, a player shoots well before he takes one week off due to injury. It is possible that he reverts to his normal level of performance after he recovers because the injury eliminates his "hotness". We restrict the sample to the observations such that their

most recent games occur within four, three and two days. And we compare the estimated hot hand of these three different cases.

In addition to pooling two- and three-point field goal attempts, we examine them separately. This is because they are of different difficulty levels. As showed in Table 1, average *FG2P* (two-point field goal percentage) is about 46%, much higher than that of *FG3P* (three-point field goal percentage), of 32%. If we simply pool all of the field goals as most previous studies do, there is a potential for the estimates to be biased.

We now define the game-level hot hand and develop a simple model to test its existence empirically.[6] We treat each player in each season as a unique panel "entity," indexed by i ($i = 1,\ldots, N$). A player's true shooting ability in t^{th} game of a particular season P_{it} is assumed to be determined in a linear fashion by his fundamental shooting ability in that season f_i, his psychological and physical state in that game u_{it} and other control variables that capture the state of that game X_{it}. So we can write:

$$P_{it} = \beta X_{it} + f_i + u_{it}, \qquad i = 1,\ldots, N,\ t = 1, 2,\ldots,T_i. \qquad (1)$$

The high level of a player's psychological and physical states reflects his "hotness" of shooting in a particular game. We use the first-order autocorrelation in $\{u_{it}\}$ as a measure of the game-level hot hand. If u_{it} is positively autocorrelated, i.e., $E(u_{it} \mid u_{i,t-1} > 0) > 0$ (as $E(u_i)=0$), performance in any game is positively associated with shooting performance in previous games. If we find significant and substantial evidence of first-order autocorrelation we can then examine higher-order correlation. But it is natural to begin by focusing on the first lag. So we can write:

$$u_{it} = \rho u_{i,t-1} + \varepsilon_{it}, \qquad i = 1,\ldots, N,\ t = 1, 2,\ldots,T_i. \qquad (2)$$

where ε_{it} is identically and independently distributed (IID) over t and i with mean zero and variance σ_ε. We will discuss why this assumption is needed when we discuss different estimation approaches of this model. ρ is the coefficient of interest and represents how psychological and physical conditions are autocorrelated. A positive and significant estimate of ρ implies the existence of the hot hand. Injuries might worsen player's shooting across games, which causes ρ to be positive. But we think this effect should be minimal. To estimate ρ, we can rearrange (1) and (2), and get

$$P_{it} = \rho\, P_{i,t-1} + \beta(X_{it} - \rho X_{i,t-1}) + (1-\rho)f_i + \varepsilon_{it}, \quad i = 1,\ldots,N, \; t = 1, 2,\ldots,T_i. \quad (3)$$

The "true" shooting ability is unobservable, and so we estimate it with natural measures of this ability, field goal and free throw percentage (FGP_{it} and FTP_{it}). This causes estimates of ρ to be biased towards 0, as we discuss. Two variables are included in X_{it}. The first one is a dummy variable for whether the shooter is on the home team. The effect of home status on shooting performance is of two facets. On one hand, players might benefit from the support of fans, and Price et al. (forthcoming) find evidence that referees make calls that favor home teams. On the other hand, players may feel more pressure to please fans, which in turn leads to inferior performance. The shooting performance is also affected by defense quality of opponent team, which varies significantly across NBA teams. Huizinga and Weil (2008) capture this effect by using a variable that equals the difference between the league average field goal percentage for each season and each opponent's average defensive field goal percentage. So the larger this variable, the better the defense. We adopt their method and add a variable that represents the defense quality in current game (DQ_{it}).[7] So we can rewrite the empirical model as below,

$FGP_{it}=\rho\ FGP_{i,t-1}+\beta_1 home_{it}+\beta_2 home_{i,t-1}+\beta_3 DQ_{it}+\beta_4 DQ_{i,t-1}+\eta_i+\varepsilon_{it}$,

$i=1,2,\ldots,N$, $t=2,3,\ldots,T_{i.}$(4)

Equation (4) is a dynamic panel model with player-season fixed effect η_i.[8] Using the player-season fixed effect allows a player's fundamental shooting ability to change over different seasons. The coefficient on the lagged dependent variable ρ estimates how deviations in field goal percentage from the player-season mean in a particular game affects field goal percentage in the next game. If equation (4) does not include player-season fixed effect, estimates on lagged dependent variables (OLS) will be biased due to the omitted variables. Specifically, since a player's field goal percentage of any particular game is positively related to his overall shooting ability in that season, omitting a player's overall shooting ability will cause the estimates to be biased upward, and this bias will not diminish as the number of games a player plays in each season or as the number of players increases.

The conventional approach estimates the coefficients by transforming the equation to eliminate η_i. After the transformation, we have:[9]

$$FGP_{it}-FGP_{i\cdot}=\rho(FGP_{i,t-1}-FGP_{i\cdot-1})+(\varepsilon_{it}-\varepsilon_{i\cdot});\ \ i=1,2,...,N;\ \ t=2,3,...,T_i\ . \qquad (5)$$

where $x_{i\cdot}=\frac{1}{T_i-1}(x_{iT_i}+...+x_{it}+...+x_{i2})$ and $x_{i\cdot-1}=\frac{1}{T_i-1}(x_{i,T_i-1}+...+x_{it}+...+x_{i1})$

This transformation causes a negative correlation between the independent variable and error term. Specifically, $-\frac{FGP_{it}}{T_i-1}$ in $FGP_{i\cdot-1}$ is correlated with ε_{it}, and $-\frac{\varepsilon_{i,t-1}}{T_i-1}$ is correlated with $FGP_{i,t-1}$, which both imply a negative correlation between transformed independent variable and error term. As pointed out by Bond (2002), this negative correlation will

dominate the positive correlation caused by the correlations of some other terms such as $-\frac{FGP_{i,t-1}}{T_i-1}$ and $-\frac{\varepsilon_{i,t-1}}{T_i-1}$. The OLS estimator of ρ in the transformed model (FE) is biased downward due to this negative correlation. Maddala and Rao (1973) show that the bias in this FE estimator is $O(1/T_i)$, i.e., it diminishes as T_i increases. For all regressions that use the lagged dependent variable as a regressor, we drop the observations of the players who have field goal attempts in less than 45 games in a season (i.e., T_i<45), which implies the bias is less of a concern according to Greene (2008) p.241. We also tried other two estimation approaches to minimize this possible bias in estimate. They are both based on the first difference of equation (3). Instead of taking group mean difference of equation (3), we take the first differences and get:

$$\Delta FGP_{it} = \rho \Delta FGP_{i,t-1} + \Delta\varepsilon_{it}\ ;\ i=1,\ldots, N;\ t=1,\ldots,T_i\ . \qquad (6)$$

Taking the first differences eliminates the player-season fixed effect, but causes another issue. $\Delta FGP_{i,t-1}$ is now correlated with $\Delta\varepsilon_{it,}$ because $FGP_{i,t-1}$ in $\Delta FGP_{i,t-1}$ is correlated with $\varepsilon_{i,t-1}$ in $\Delta\varepsilon_{it}$ by construction. Anderson and Hsiao (1981, 1982) propose a Two Stage Least Square approach (2SLS) that uses further lags of FGP_{it} as instruments for $\Delta FGP_{i,t-1}$. For example, under the assumption that ε_{it} is IID over i and t, $FGP_{i,t-2}$ will be a valid instrument of $\Delta FGP_{i,t-1}$. The resulting estimator is consistent for the dataset with large N and limited T, but it is not asymptotically efficient. Arellano and Bond (1991) suggest an asymptotically efficient Generalized Method of Moments estimator (AB).[10] This approach estimates the coefficients by using the moment conditions constructed from further lagged levels of FGP_{it} and first-differenced error terms.[11] To be specific, under

the assumption that ε_{it} is IID over i and t, the matrix of all the valid instruments for the ith group is of the form

$$M_i = \begin{bmatrix} FGP_{i1} & 0 & 0 & \dots & 0 & \dots & 0 \\ 0 & FGP_{i1} & FGP_{i2} & \dots & 0 & \dots & 0 \\ . & . & . & \dots & . & \dots & . \\ 0 & 0 & 0 & \dots & FGP_{i1} & \dots & FGP_{i,T_i-2} \end{bmatrix}, \quad (7)$$

which is a $(T_i\text{-}2)\times(T_i\text{-}1)(T_i\text{-}2)/2$ matrix. And the moment conditions are

$E[M_i'\Delta\varepsilon_i] = 0$ for i = 1, 2,…, N, where $\Delta\varepsilon_i = (\Delta\varepsilon_{i3}, \Delta\varepsilon_{i4}, ..., \Delta\varepsilon_{iT})'$. (8)

To compare the performance of these four different estimation methods we conduct a simple simulation analysis. For simplicity, field goal percentage is generated using (3) without including X_{it} and $X_{i,t-1}$. For various values of ρ, we generated 500 samples. In each sample, there are 100 players whose fundamental shooting ability is drawn from Uniform (0.4, 0.5),[12] and each player has 50 observations (i.e., 50 games). Table 3.2 shows the estimation results of four estimation methods. For all the values of ρ, the 2SLS and AB estimates are very accurate, while OLS and FE estimates are biased. The OLS estimate is always larger than the true parameter value and the FE estimates tend to be smaller, which is consistent with the theory discussed above. Two-period lagged dependent variable is used as instruments for 2SLS and AB. According to the simulation result, it seems that 2SLS outperforms other three estimation methods. We will just show the FE, 2SLS and AB estimation results for all the empirical analysis that uses the dynamic panel model.

Using the field goal data might mask the existence of the hot hand for a few reasons. One of them is the change in defense. If a player hits a shot, he might then face

a tighter defense, so that the chance of making the next shot might be lower. Free throw is undefended so the correlation between shots is not affected by the change in defense. So we also apply the same models to examine how free throw percentage of a game is affected by the free throw performance in previous games.

We also analyze different subsamples. First, we estimate the serial correlation for different positions. The hot hand might vary across different shot types. It is possible that a game-level hot hand exists only for a specific shot type, e.g., jump shot. And the compositions of shot types are different from position to position, for example, a center might have more layups while a guard and forward might have more jump shots. So the tests of the hot hand for different positions may yield different results. Second, we look at subsamples based on the number of games in which the player has shot attempts in a season (T_i). Players who have bad shooting performance might stay at the bench for the next game, which might bias the estimate of hot hand towards zero. Subsamples with large T_i (e.g., T_i >75) do not have this issue. Third, we investigate subsamples of players with different years of experience (*Exper*). Experience might affect the existence of the hot hand, for example, the confidence level of younger players may be more variable, causing their performance to be more subject to streaks.

One important issue is whether *FGP* can measure a player's "hotness" precisely if it exists. As we discussed, the real shooting ability in a game is an unobservable parameter, so *FGP* is always an imprecise estimate for this ability, therefore, also for "hotness". This implies that our empirical models are subject to the measurement error. But the precision of *FGP* increases as a player's number of field goal attempts (*FGA*)

increases. *FGP* is more likely to capture the hotness of a player when he takes more shots in a game, i.e., *FGP* might be too noisy if he only takes few shots. For example, one way to reduce this measurement error is to look at the subsample of the players with a relatively high player-season mean of number of shot attempts per game. We also tried another method that weights observations by the number of field goal attempts in the corresponding game.

To have a better understanding about how the measurement error affects estimates of the hot hand we also conduct simulations. For various values of ρ, we simulate three sets of samples using different uniform distribution for the number of field goal attempts, which enable us to examine how the estimates change as the number of attempts increases. Each set has 500 samples, and each sample has 500 players whose fundamental shooting abilities are randomly drawn from Uniform (0.4, 0.5), and each player has 50 observations (i.e., 50 games). The "true" shooting ability is generated using (3) without including X_{it} and $X_{i,t-1}$. The next step is to generate number of made shots. For each field goal attempt, we draw a Uniform[0,1] random variable, and each random variable whose value is smaller than corresponding true shooting ability would count as a shot made. By doing this, we actually generate a binary random variable that equals one with corresponding shooting ability and zero otherwise. The sum of the outcome of these binary random variables is the numbers of field goal made. So the observed field goal percentage is equal to the generated number of field goals made divided by the generated number of field goal attempts. Then, instead of true shooting percentage, we run regressions using the simulated observed field goal percentage. Table 3.3 gives the

estimation results, which implies that the measurement error can cause the hot hand to be significantly underestimated. When the "true" shooting ability exhibits some hot hand, e.g., ρ = 0.3, none of the estimated first autocorrelation of the observed field goal percentage exceeds 0.1. And the bias does not vanish as we increase the number of attempts. When we switch the data generating process for number of attempts from U(0,10) to U(10, 20), the mean of the number of attempts triples, but it only leads to a moderate increase in the estimates. And, the estimates are still much smaller than the 'true' hot hand effect for both the cases of ρ = 0.3 and 0.1. When ρ = 0, the estimates are close to zero, which implies that measurement is less of a concern when there is no hot hand effect in shooting ability. Stone (2011) uses similar data generating process to simulate shooting ability, but estimates the hot hand effect based on individual shot outcome. He shows that using second lagged shot outcome as instrument leads to an unbiased estimate of first autocorrelation. However, using second lagged dependent variable will not eliminate the bias for our dynamic panel data model. The reason is similar to why the FE estimator is biased, e.g., in equation (5), if we use $FGP_{i,t-2}$ as the instrument for $FGP_{i,t-1}$, the correlation between $\varepsilon_{i,t-2}/(T_i-1)$ in $\varepsilon_{t\cdot}$ and $FGP_{i,t-1}$ will cause the estimate to be biased.

We conduct one additional analysis of the hot hand's existence. If a player is in "hot" state of shooting in a game, this "hotness" might improve both his field goal and free throw performance. So we regress FTP_t on FGP_t and other control variables. If the estimated coefficient on FGP_t is significantly positive, then it provides some evidences for the existence of the hot hand. But if not, we should not draw the conclusion that the

hot hand does not exist, since the hot hand effect may only occur within each type of shot, i.e. the performance of field goal does not significantly affect the performance of free throw, and vice versa.

3.2.2 The Hot Hand Belief

The fact that field goal percentage might affect the number of field goal attempts is a curse and a blessing for our analysis. It is curse because it might bias the estimate for the hot hand. To be specific, if hitting a high percentage of the first few shots makes a player believe that he is in "hot" state, he might respond by taking more shot attempts during the rest of the game. But the "hot" state may just exist for a period that is shorter than a whole game, e.g., a quarter, so it is possible that his shooting ability already reverts to the normal level as he takes more shots. So the resulting field goal percentage would not be as high as if he didn't take more shots. Therefore, this possible issue might dilute our estimate for the game-level hot hand, if it exists. The issue is a blessing because we can test whether players believe in the hot hand by regressing the number of field goal attempts in any game on the field goal percentage in both the last and current game. If NBA professionals believe that they are more likely to shoot well after having a good performance in the last game, a player who shoots well in the last game will have more shot attempts in the current game. Meanwhile, a significantly positive estimate of the coefficient on FGP_t will imply that NBA professionals believe that the hot hand could happen within a game. However, as we discussed above, FGA_t in turn might affect FGP_t. So including FGP_t may cause the issue of simultaneity, which leads to biased estimate.

To know the effect of this simultaneity issue, we also try the regression without including FGP_t and see how the estimate of the coefficient on FGP_{t-1} changes. There are two possible ways for the "hot" players to have more attempts. First, if coaches believe in the hot hand, they would have players play more minutes when players shoot well. So, even if players take the same number of shots per minute, they will take more shots per game. Second, players could have minutes played unaffected and take more shots per minute. Adding minutes played in each game (Min_t) as a control regressor can tell us whether the increase in FGA_t is caused by only one of the two reasons or both. In addition, we believe that whether teammates pass the ball more often to a player who is "hot" in the last game also depends on the outcome of the last game. Specifically, if a player shoots well in one game and his team loses, his teammate might think that his "hotness" does not benefit the whole team and choose not to pass the ball to him in the next game as often as if his team had won the game. To capture this effect, we include a dummy for the outcome of last game (Win_{t-1}) and its interaction with FGP_{t-1}.

3.3. Results

3.3.1 Analysis of Hot Hand Reality

Table 3.4 – 3.6 present the estimates for the four different estimation approaches when we use the subsamples in which the number of days between two consecutive games (*gap*) is less than four, three and two. Different panels show the estimates for different shot types. All of the estimated coefficients on the one-period lagged dependent variable are very close to zero, and most of them are highly significant except AB

estimates, which imply the serial correlation between the shooting performances of two consecutive games is weak. For two-point field goal, the 2SLS estimate, which outperforms the other three methods in the simulation, even though positive and significant, implies shooting 10 percentage points above player-season mean in one game only causes expected improvement of 0.5 percentage points in next game for the subsample with *gap* is less than two. Moreover, the 2SLS estimates of the hot hand in two- point field goal of the subsample in which *gap* is less than two are slightly larger than when gap is less than three, while the estimates are the smallest when *gap* is less than four. The results show that OLS estimates are always positive and FE estimates are negative. This is consistent with what we discussed in previous section – FE estimates are biased downward while OLS estimates are biased upward. All 2SLS and AB estimates except one fall between FE and OLS estimates. According to the value of standard errors, it seems that AB estimator is less efficient than the other three. We used the two-period lagged dependent variable as the instrument for AB estimator, which is a subset of all available instruments. As equation (7) shows, the value of all the periods earlier than t-1, i.e., from $FGP_{i,t-2}$ to FGP_{i1}, are all valid instruments.[13] The Arellano-Bond test shows there is no serial correlation at 5% significance level up to the third order in the error terms except the free throw and three-point field goal in Table 3.6, which implies that the instrument we use is valid in most of the cases. For the other two cases, the moment condition for the AB estimator is not satisfied due to the correlation between two-period lagged dependent variable and first differenced error, which implies that the AB estimates are likely to be biased. We also report the estimates for $home_t$ and DQ_t. Most of

the estimates imply there is a small positive effect to be the home team, and a sizable negative effect for better defense quality, both of which are highly significant. All the estimated coefficients on $home_{t-1}$ and DQ_{t-1} are insignificant, so we do not report them in the tables. As equation (3) implies, the estimates of coefficients in the empirical model, equation (4), should satisfy the restriction $\rho * \beta_1 = \beta_2$ and $\rho * \beta_3 = \beta_4$. For the models in Table 3.4-3.6, most of the nonlinear restriction tests indicate we cannot reject the null hypothesis that $\rho * \beta_1 = \beta_2$ and $\rho * \beta_3 = \beta_4$ at 10% significance level.

FE, 2SLS and AB estimates for subsamples based on a player's position are given in Table 3.7. The results show that the estimates are similar across the three position types and close to zero, which somewhat implies that a game-level hot hand of a substantial magnitude does not exist in any specific type of field goals. Moreover, there is no hot hand effect for center at all (2SLS for two-point field goal is insignificant). The Arellano-Bond test shows there are no serial correlations at 10% significance level up to the third order in the error terms except the free throw models of center and guard. So the AB estimates inn these two cases are likely to be biased. Table 3.8 presents FE, 2SLS and AB estimates for different subsamples based on the number of games in which a player has field goal attempts in a season. All the estimates are close to zero, and do not indicate significant difference across subsamples. Table 3.9 shows the FE, 2SLS and AB estimates for subsamples of players with different years of experience. It seems that none of the groups experience the hot hand, and estimates of three subsamples are not significantly different in magnitude.

Table 3.10 presents the estimates for the weighted regression. We run the regression for each of the four shot types, and each regression is weighted by the number of attempts of the corresponding shot type in each game. Since it is extremely computationally demanding to use the fixed effect model in this case, we run the model by subtracting the player-season mean of corresponding variables from both sides of equation (4). The resulting estimates are actually the standard FE estimates, only the standard errors are different due to degree of freedom loss from de-meaning. The estimated coefficients on de-meaned lagged dependent variables are very close to zero and mostly significant, which implies the effect of the performance in last game is very small.

Table 3.11 presents FE, 2SLS and AB estimates for different subsamples based on the value of the player-season mean of the number of shot attempts per game. All the estimates are close to zero. Moreover, the estimates for players who take more shots in each game are not significantly different from those with fewer attempts.

The results of Tables 3.4 – 3.11 show consistent evidence of the hot hand in field goal percentage – most of the 2SLS estimates of different subsamples are statistically significant and positive. But the magnitude is very small – most of the 2SLS estimates of different subsamples range from two to three percent points. As we know, when the shooting ability exhibit some hot hand effect, the autocorrelation in field goal percentage might significantly underestimate the autocorrelation in shooting ability due to the measurement error. According to the simulation result, a 0.024 autocorrelation in field goal percentage could imply a hot hand of 30 percentage points in shooting ability, which

is quite sizable. Also, the result has a intuitive implication – the small increase in 2SLS estimates caused by restricting the sample with a smaller value of *gap* might indicate a much larger increase in the autocorrelation in shooting ability. We would expect the hot hand to have this property if it exists. Moreover, since the estimate of hot hand in field goal percentage might be muted by the endogeneity of shot selection (players might take tougher shots after a streak of hits) and change in defense, our estimate might imply an even larger hot hand in shooting ability.

Estimation results of regressing FTP_t on FGP_t are given in Table 3.12. The first column is for the whole sample, while the second and third columns give the results when the sample is restricted to players whose player-season mean of the number of free throw attempt (*SFTA*) is greater than 2.6 and 5, respectively. The magnitude of the coefficients on the FGP_t is very close to zero and insignificant, failing to support the hypothesis that performances for field goal and free throw are positively correlated. The weak correlation might be caused by the possibility that players' asymmetric correlation between the performances of these two shot types, in the sense that the free throw performance stays at the normal level when their field goal performance is worse than average, but it is boosted by relatively good field goal performance.

3.3.2 Analysis of Hot Hand Belief

Table 3.13 presents results for the analysis of professionals' belief in the hot hand. Two panels give the estimates for two- and three-point field goal, respectively. The dependent variable of all the regressions is the number of field goal attempts of the

corresponding shot type. When minutes played in each game (Min_t) is not included in regression, the estimates for $FG2P_{t-1}$ and $FG3P_{t-1}$ is about 0.3 on average and highly significant, which provides evidence that players or coaches believe that shooting performances of consecutive games are positively correlated. For example, a player whose *SFG2A* is greater than 7 takes about 0.1 more two-point field goal attempts if his 2-point field goal percentage in the last game is 20 percentage points higher than his season mean. Estimated coefficients on $FG2P_t$ and $FG3P_t$ are all significant and about three times as large as those on $FG2P_{t-1}$ and $FG3P_{t-1}$. So players take more shots during the game in which they are shooting well, which implies that there is belief in the existence of the within-game hot hand effect. The estimates of all the coefficients on field goal percentage are larger for players who take more shot attempts on average. We also run the regression without including $FG2P_t$ or $FG3P_t$, and the estimated coefficients on $FG2P_{t-1}$ and $FG3P_{t-1}$ not change significantly, which indicates simultaneity between number of attempts and the field goal percentage does not have strong effect on the estimate of game-level hot hand belief. So we do not report in the table. All of the coefficients on the interaction of $FG2P_{t-1}$ and Win_{t-1} except one are all small and insignificant, which implies that the outcome of the last game does not affect players' belief in the game-level hot hand. The estimated coefficients on $FG2P_t$ and $FG2P_{t-1}$ become insignificant and much smaller when the Min_t is added as a regressor. This implies that $FG2P_t$ and $FG2P_{t-1}$ do not affect the number of two-point field goal attempts given the amount of minutes played in the count, which might be caused by the change in defense. A player might face tighter defense when he become "hot", which makes it

harder for the players to get the ball and take a shot. The estimated coefficient on $FG3P_t$ and $FG3P_{t-1}$ are still significant and slightly smaller, which implies $FG3P_t$ and $FG3P_{t-1}$ have small effect on the number of shot per minutes played. The estimated coefficient on Min_t is highly significant and sizable for all the models, e.g., for the players whose *SFG2A* is greater than 7, one additional minute played will lead to about 0.3 more two-point field goal attempts.

Table 3.14 shows the results of regressing Min_t on $FG2P_t$ and $FG2P_{t-1}$. The estimated coefficients on $FG2P_t$ and $FG2P_{t-1}$ indicate that these two variables have some moderate effects on minutes played on the court, e.g., if a 20 percentage points increase in field goal percentage relative to season mean will make the player play about 0.3 more minute in the next game. The estimation result further implies that the effect of hot hand belief on two-point field goal is realized by letting the players who are "hot" play more minutes, which is a reflection of the coaches' belief in hot hand. And according to the results in Table 3.13, more minutes played, in turn, lead to more two-point field goal attempts. The extra minutes for the "hot" player might also be explained as the reward for the good shooting given by the coaches. Since coaches' objective is to maximize teams' chances of winning, this effect should be minimal.

3.4 Conclusion

In this paper we first develop a simple model that can be used to test the existence of game-level hot hand effect. Using box score data from the National Basketball Association (NBA), we find the correlations between shooting percentage in consecutive

games are very close to zero for various subsamples. However, due to the measurement error caused by using field goal or free throw percentage as proxy for shooting ability, the autocorrelation in shooting percentage could underestimate the autocorrelation in shooting ability. For example, according to the simulation results, the estimate in Table 3.5, 0.024 could imply a hot hand in shooting ability as large as 30%. Moreover, the endogeneity of shot selection and change in defense might cause the estimated hot hand in field goal percentage to be biased downward, which implies a even larger autocorrelation in shooting ability.

We find that NBA players take more field goal attempts if they shot well in the last game, but only to a moderate extent, which implies NBA professionals do believe in the existence of a game-level hot hand effect. We also find evidence for the belief of with-in game hot hand effect, of which the magnitude is three times large as the belief in game-level hot hand. Furthermore, we find "hot" players get more two-point field goal is only because coaches let them play more minutes and the attempts per minute are not affect by their "hotness", which implies the belief in the hot hand we find in this paper is mainly a reflection of coaches' belief.

Our paper has implications for cognitive errors. If the coaches' belief is just based on field goal percentage, their belief is a fallacy since the autocorrelation in field goal percentage is close to zero. However, our estimate of the hot hand might be muted by measurement error, endogeneity of shot selection and change in defense, the autocorrelation in the underlying shooting ability might exhibit some sizable hot hand effects even though the estimated correlation of shooting percentage is close to zero. So,

if coaches believe that the hot hand effect exists in underlying shooting ability, their hot hand belief might not just be a fallacy.

Since we use game-level data in this paper, it is possible that we miss the hot effect that only exists for a relatively short period of time, e.g., a quarter. With quarter-level data, we can also test whether the belief in hot hand effect is stronger over a shorter period of time. If professional believe that the “hotness” can only exist for a short period of time, he might just take more shots over the next a few minutes or next quarter, so the increase in number of attempts would not be that significant over the whole game, which implies using game-level data could dilute the estimate of hot hand belief.

3.5 Endnotes

[1] Purvis Short, of the NBA's Golden State Warriors, once said, "You're in a world all your own, it's hard to describe. But the basket seems to be so wide. No matter what you do, you know the ball is going to go in".

[2] See Bar-Eli et al. (2006) for a recent review.

[3] See Smith (2003), Frame et al. (2003), Miyoshi (2000) and Wardrop (1999).

[4] Studies of the hot hand can be also found in other sports, for example, baseball (Albert, 1993), golf (Gilden & Wilson, 1995), tennis (Klaassen & Magnus, 2001).

[5] One explanation for this fallacy is people's persistent misunderstanding of randomness. Tversky & Kahneman (1971) argue that people expect the properties of a random process to hold not only in large samples but also in small ones. For instance, if a coin is only tossed a few times, people expect roughly 50% of the outcomes to be tails and other 50% to come up heads. This perception is known as "the belief in the law of small numbers". So, when watching a random process, people might expect more alternations and fewer long streak than actually occur. Therefore if more or longer streaks of hits or missed are observed than is expected for a random process, people might infer that the sequence of shot outcomes is positively autocorrelated.

[6] For simplicity, we only show the model for pooling all the field goals, but the same model can be applied to any specific type of field goal and free throw.

[7] A better approach is to control for the defense quality is to create a dummy for each team in each season. But running regressions with such a large number of dummies is extremely computationally demanding.

[8] Arkes (2010) includes fixed effect in his model to estimate the hot hand using data of free throw outcome in a set.

[9] Other independent variables are omitted here for simplicity of exposition.

[10] See Bond (2002) for the detail of this approach.

[11] Although the AB estimator is generally more efficient than 2SLS estimator, AB estimators suffer from substantial finite sample biases. Given the large size of our dataset, we believe this problem is minimal.

[12] The mean of the two-point field goal percentage for all the NBA players is 46%.

[13] It would be extremely computationally demanding to use more valid instruments.

Table 3.1: Summary Statistics

	N	mean	std. dev.	max
FGA	364,227	8.072	5.860	49
FGP	345,440	0.437	0.237	1
FG2A	364,311	6.690	5.172	46
FG2P	339,511	0.458	0.258	1
FG3A	364,311	1.382	2.087	21
FG3P	168,712	0.315	0.330	1
FTA	364,311	2.563	3.06	31
FTP	226,490	0.735	0.28	1

Notes: *FGA*, *FG2A*, *FG3A* and *FTA* are the number of total field goal, 2-point field goal, 3-point field goal and free throw attempts that a player takes in each game, respectively. *FGP*, *FG2P*, *FG3P* and *FTP* are the total field goal, 2-point field goal, 3-point field goal and free throw percentage of each game respectively.

Table 3.2: Simulation 1 – Comparison of Four Estimation Methods

		OLS	FE	2SLS	AB
ρ=0.15	mean	0.215	0.126	0.151	0.147
	std. dev.	[0.016]	[0.014]	[0.026]	[0.023]
ρ=0.1	mean	0.170	0.078	0.099	0.097
	std. dev.	[0.016]	[0.015]	[0.027]	[0.023]
ρ=0.05	mean	0.123	0.028	0.048	0.046
	std. dev.	[0.016]	[0.015]	[0.025]	[0.023]
ρ=0	mean	0.078	-0.020	0.002	-0.001
	std. dev.	[0.017]	[0.015]	[0.024]	[0.021]
ρ= - 0.1	mean	-0.015	-0.118	-0.099	-0.102
	std. dev.	[0.017]	[0.015]	[0.023]	[0.020]

Note: Equation (3) without including X_t and X_{t-1} is used as the data generating process for the field goal percentage. The error term in equation (3) is drawn from $N(0, 0.1)$.

Table 3.3: Simulation 2 – Effect of Measurement Error

		OLS	FE	2SLS	AB
Panel A: ρ=0.3					
FGA~U(0, 10)	mean	0.048	0.018	0.026	0.023
	std.dev	[0.014]	[0.014]	[0.019]	[0.019]
FGA~U(0, 20)	mean	0.68	0.034	0.037	0.035
	std.dev	[0.015]	[0.014]	[0.021]	[0.020]
FGA~U(10, 20)	mean	0.123	0.080	0.065	0.065
	std.dev	[0.014]	[0.015]	[0.019]	[0.018]
Panel B: ρ=0.1					
FGA~U(0, 10)	mean	0.020	-0.009	0.009	0.006
	std.dev	[0.014]	[0.014]	[0.019]	[0.019]
FGA~U(0, 20)	mean	0.031	0.002	0.015	0.012
	std.dev	[0.014]	[0.014]	[0.020]	[0.019]
FGA~U(10, 20)	mean	0.056	0.014	0.026	0.024
	std.dev	[0.013]	[0.013]	[0.019]	[0.018]
Panel B: ρ=0					
FGA~U(0, 10)	mean	0.009	-0.020	0.000	-0.003
	std.dev	[0.014]	[0.014]	[0.019]	[0.019]
FGA~U(0, 20)	mean	0.013	-0.019	-0.001	-0.004
	std.dev	[0.013]	[0.013]	[0.018]	[0.018]
FGA~U(10, 20)	mean	0.025	-0.017	0.000	-0.002
	std.dev	[0.014]	[0.014]	[0.019]	[0.019]

Note: The error term in data generating process for shooting ability is drawn from $N(0, 0.1)$. Fixed effect is drawn from U(0.4, 0.6). *FGA* is the number of attempts.

Table 3.4: Analysis of Serial Correlation (gap<4)

	(1)	(2)	(3)	(4)
	OLS	FE	2SLS	AB
Panel A				
FGP_{t-1}	0.050***	-0.011***	0.015***	0.021
	[0.003]	[0.002]	[0.004]	[0.018]
$home_t$	0.014***	0.014***	0.014***	0.014***
	[0.001]	[0.001]	[0.001]	[0.001]
DQ_t	-1.076***	-1.064***	-1.047***	-1.046***
	[0.028]	[0.028]	[0.034]	[0.034]
N	251,177	251,177	242,977	242,977
R-squared	0.01	0.006	n/a	n/a
Panel B				
$FG2P_{t-1}$	0.033***	-0.012***	0.014***	0.022
	[0.002]	[0.002]	[0.004]	[0.018]
$home_t$	0.016***	0.016***	0.015***	0.015***
	[0.001]	[0.001]	[0.001]	[0.001]
DQ_t	-1.150***	-1.137***	-1.129***	-1.128***
	[0.031]	[0.031]	[0.039]	[0.039]
N	245,688	245,688	235,617	235,617
R-squared	0.008	0.006	n/a	n/a
Panel C				
$FG3P_{t-1}$	0.022***	-0.014***	0.024***	0.057**
	[0.003]	[0.003]	[0.005]	[0.024]
$home_t$	0.008***	0.008***	0.008***	0.008***
	[0.002]	[0.002]	[0.002]	[0.002]
DQ_t	-0.559***	-0.522***	-0.529***	-0.528***
	[0.061]	[0.061]	[0.080]	[0.081]
N	109,304	109,304	95,099	95,099
R-squared	0.001	0.001	n/a	n/a
Panel D				
FTP_{t-1}	0.111***	-0.011***	0.011	0.004
	[0.004]	[0.003]	[0.009]	[0.039]
$home_t$	0.004**	0.004**	0.002	0.002
	[0.001]	[0.001]	[0.002]	[0.002]
N	133,036	133,036	103,640	103,640
R-squared	0.01	0.008	n/a	n/a

Notes: Model 2-4 include player-season fixed effect. All models include $home_t$, $home_{t-1}$. All field goal models include DQ_t, DQ_{t-1}. Observations with *gap*>3 are dropped, as are observations of players who have less than 51 field goal attempts in a season or who have field goal attempts in less than 45 games in a season. For OLS, FE, 2SLS estimator, standard errors clustered by player-season are given in brackets. For AB estimator, robust standard errors are given in brackets. *, **, *** denote 10%, 5% and 1% significance.

Table 3.5: Analysis of Serial Correlation(gap<3)

	(1)	(2)	(3)	(4)
	OLS	FE	2SLS	AB
Panel A				
FGP_{t-1}	0.052***	-0.009***	0.024***	0.026
	[0.003]	[0.003]	[0.006]	[0.031]
$home_t$	0.014***	0.014***	0.014***	0.014***
	[0.001]	[0.001]	[0.001]	[0.001]
DQ_t	-1.065***	-1.055***	-1.052***	-1.051***
	[0.031]	[0.031]	[0.037]	[0.037]
N	206,499	206,499	199,524	199,524
R-squared	0.01	0.007	n/a	n/a
Panel B				
$FG2P_{t-1}$	0.035***	-0.009***	0.025***	0.015
	[0.003]	[0.003]	[0.005]	[0.030]
$home_t$	0.015***	0.016***	0.014***	0.015***
	[0.001]	[0.001]	[0.001]	[0.001]
DQ_t	-1.134***	-1.124***	-1.131***	-1.130***
	[0.034]	[0.034]	[0.042]	[0.042]
N	201,981	201,981	193,496	193,496
R-squared	0.008	0.007	n/a	n/a
Panel C				
$FG3P_{t-1}$	0.022***	-0.013***	0.019***	0.037
	[0.004]	[0.004]	[0.008]	[0.033]
$home_t$	0.009***	0.009***	0.010***	0.01***
	[0.002]	[0.002]	[0.003]	[0.003]
DQ_t	-0.546***	-0.508***	-0.534***	-0.535***
	[0.067]	[0.067]	[0.083]	[0.086]
N	90,174	90,174	78,337	78,337
R-squared	0.001	0.001	n/a	n/a
Panel D				
FTP_{t-1}	0.111***	-0.009***	0.006	-0.03
	[0.004]	[0.003]	[0.011]	[0.054]
$home_t$	0.003**	0.004**	0.001	0.001
	[0.002]	[0.002]	[0.002]	[0.002]
N	109,627	109,627	85,294	85,294
R-squared	0.01	0.008	n/a	n/a

Notes: Model 2-4 include player-season fixed effect. All models include $home_t$, $home_{t-1}$. All field goal models include DQ_t,DQ_{t-1}. Observations with *gap*>2 are dropped, as are observations of players who have less than 51 field goal attempts in a season or who have field goal attempts in less than 45 games in a season. For OLS, FE, 2SLS estimator, standard errors clustered by player-season are given in brackets. For AB estimator, robust standard errors are given in brackets. *, **, *** denote 10%, 5% and 1% significance.

Table 3.6: Analysis of Serial Correlation (gap<2)

	(1)	(2)	(3)	(4)
	OLS	FE	2SLS	AB
Panel A				
FGP_{t-1}	0.048***	0.001	0.045***	0.014
	[0.005]	[0.005]	[0.013]	[0.075]
$home_t$	0.016***	0.017***	0.018***	0.018***
	[0.002]	[0.002]	[0.002]	[0.002]
DQ_t	-1.014***	-0.982***	-1.054***	-1.051***
	[0.054]	[0.031]	[0.037]	[0.062]
N	67,334	67,334	64,427	64,427
R-squared	0.01	0.007	n/a	n/a
Panel B				
$FG2P_{t-1}$	0.029***	-0.002	0.050***	0.053
	[0.005]	[0.005]	[0.013]	[0.073]
$home_t$	0.017***	0.019***	0.019***	0.019***
	[0.002]	[0.002]	[0.002]	[0.002]
DQ_t	-1.064***	-1.040***	-1.153***	-1.153***
	[0.060]	[0.061]	[0.070]	[0.071]
N	65,938	65,938	62,559	62,559
R-squared	0.007	0.006	n/a	n/a
Panel C				
$FG3P_{t-1}$	0.016**	-0.001	0.010	-0.105**
	[0.006]	[0.006]	[0.013]	[0.053]
$home_t$	0.006	0.007*	0.010**	0.011***
	[0.004]	[0.004]	[0.004]	[0.004]
DQ_t	-0.645***	-0.645***	-0.445***	-0.461***
	[0.124]	[0.126]	[0.147]	[0.140]
N	29,037	29,037	25,052	25,052
R-squared	0.001	0.001	n/a	n/a
Panel D				
FTP_{t-1}	0.110***	0.012**	-0.006	-0.334
	[0.006]	[0.006]	[0.025]	[0.071]
$home_t$	-0.006**	-0.004	-0.000	-0.001
	[0.003]	[0.003]	[0.003]	[0.003]
N	35,519	35,519	27,280	27,280
R-squared	0.01	0.008	n/a	n/a

Notes: Model 2-4 include player-season fixed effect. All models include $home_t$, $home_{t-1}$. All field goal models include DQ_t,DQ_{t-1}. Observations with *gap*>1 are dropped, as are observations of players who have less than 51 field goal attempts in a season or who have field goal attempts in less than 45 games in a season. For OLS, FE, 2SLS estimator, standard errors clustered by player-season are given in brackets. For AB estimator, robust standard errors are given in brackets. *, **, *** denote 10%, 5% and 1% significance.

Table 3.7: Analysis of Serial Correlation of Different Position

	(1) FE	(2) 2SLS	(3) AB
Panel A: Forward			
$FG2P_{t-1}$	-0.005	0.036***	0.079
	[0.004]	[0.009]	[0.053]
N	73,601	70,627	70,627
R-squared	0.007	n/a	n/a
$FG3P_{t-1}$	-0.011	0.041***	-0.048
	[0.007]	[0.012]	[0.055]
N	25,323	21,353	21,353
R-squared	<0.001	n/a	n/a
FTP_{t-1}	-0.01**	0.018	-0.011
	[0.005]	[0.017]	[0.076]
N	41,910	33,054	33,054
R-squared	0.009	n/a	n/a
Panel B: Guard			
$FG2P_{t-1}$	-0.011***	0.024***	-0.045
	[0.004]	[0.008]	[0.044]
N	72,920	69,962	69,962
R-squared	0.006	n/a	n/a
$FG3P_{t-1}$	-0.012***	0.015*	0.045
	[0.005]	[0.008]	[0.044]
N	49,611	43,597	43,597
R-squared	<0.001	n/a	n/a
FTP_{t-1}	-0.012**	-0.003	-0.25***
	[0.005]	[0.02]	[0.074]
N	37,842	28,962	28,962
R-squared	<0.001	n/a	n/a
Panel C: Center			
$FG2P_{t-1}$	-0.015***	-0.005	-0.146**
	[0.007]	[0.015]	[0.067]
N	27,674	26,436	23,436
R-squared	0.005	n/a	n/a
FTP_{t-1}	-0.011**	-0.011	-0.217
	[0.008]	[0.027]	[0.088]
N	14,595	11,332	11,332
R-squared	0.002	n/a	n/a

Note: Data from the 1991-92 through 2003-04 seasons are used for this table. All models include player-season fixed effect, $home_t$ and $home_{t-1}$. All field goal models include DQ_t,DQ_{t-1}. Observations with gap>2 dropped, as are observations with players who have less than 51 field goal attempts in a season or who have field goal attempts in less than 45 games in a season. For FE, 2SLS estimator, standard errors clustered by player-season are given in brackets. For AB estimator, robust standard errors are given in brackets. *, **, *** denote 10%, 5% and 1% significance.

Table 3.8: Analysis of Sub-Sample Based on Number of Game Attended Per Season

	(1) FE	(2) 2SLS	(3) AB
Panel A: T_i>55			
$FG2P_{t-1}$	-0.007***	0.025***	0.018
	[0.003]	[0.006]	[0.034]
N	176,897	170,353	170,353
R-squared	0.007	n/a	n/a
$FG3P_{t-1}$	-0.01***	0.017**	0.012
	[0.004]	[0.007]	[0.034]
N	81,044	70,816	70,816
R-squared	<0.001	n/a	n/a
FTP_{t-1}	-0.01***	0.005	-0.081
	[0.003]	[0.011]	[0.056]
N	98,499	77,383	77,383
R-squared	0.01	n/a	n/a
Panel B: T_i>65			
$FG2P_{t-1}$	-0.008**	0.024***	-0.017
	[0.003]	[0.009]	[0.036]
N	146,822	142,316	142,316
R-squared	0.007	n/a	n/a
$FG3P_{t-1}$	-0.007*	0.020***	0.016
	[0.004]	[0.007]	[0.038]
N	69,063	60,807	60,807
R-squared	<0.001	n/a	n/a
FTP_{t-1}	-0.009***	-0.000	-0.092
	[0.004]	[0.012]	[0.061]
N	85,136	67,871	67,871
R-squared	0.009	n/a	n/a
Panel C: T_i>75			
$FG2P_{t-1}$	-0.003	0.027***	-0.054
	[0.004]	[0.008]	[0.044]
N	91,741	89,470	89,470
R-squared	0.008	n/a	n/a
$FG3P_{t-1}$	-0.007	0.025***	-0.009
	[0.005]	[0.008]	[0.045]
N	45,408	40,345	40,345
R-squared	0.001	n/a	n/a
FTP	-0.002	-0.012	-0.087
	0.004	[0.015]	[0.070]
N	55,531	45,100	45,100
R-squared	<0.001	n/a	n/a

Note: Data from the 1991-92 through 2003-04 seasons are used for this table. All models include player-season fixed effect, $home_t$ and $home_{t-1}$. All field goal models include DQ_t,DQ_{t-1}. Observations with *gap*>2 are dropped, as are observations with players who have less than 51 field goal attempts in a season. For FE, 2SLS estimator, standard errors clustered by player-season are given in brackets. For AB estimator, robust standard errors are given in brackets. *, **, *** denote 10%, 5% and 1% significance.

Table 3.9: Analysis of Sub-Sample Based on Player's Professional Experience

	(1) FE	(2) 2SLS	(3) AB
Panel A: *experience>4*			
$FG2P_{t-1}$	-0.010***	0.02***	-0.025
	[0.003]	[0.006]	[0.034]
N	159,631	153,317	153,317
R-squared	0.006	n/a	n/a
$FG3P_{t-1}$	-0.011***	0.022***	0.042
	[0.004]	[0.007]	[0.038]
N	71,919	62,763	62,763
R-squared	<0.001	n/a	n/a
FTP_{t-1}	-0.011***	0.001	-0.055
	[0.004]	[0.012]	[0.056]
N	88,628	69,644	69,644
R-squared	0.01	n/a	n/a
Panel B: *experience>8*			
$FG2P_{t-1}$	-0.006*	0.015**	-0.023
	[0.004]	[0.007]	[0.041]
N	107,896	103,861	103,861
R-squared	0.007	n/a	n/a
$FG3P_{t-1}$	-0.007	0.025***	-0.022
	[0.005]	[0.008]	[0.042]
N	47,824	41,586	41,586
R-squared	0.001	n/a	n/a
FTP_{t-1}	-0.012***	-0.003	-0.11**
	[0.004]	[0.015]	[0.060]
N	59,928	47,124	47,124
R-squared	0.008	n/a	n/a
Panel C: *experience>12*			
$FG2P_{t-1}$	0.000	0.026	0.026
	[0.006]	[0.012]	[0.065]
N	39,534	38,321	38,321
R-squared	0.008	n/a	n/a
$FG3P_{t-1}$	-0.011	0.008	-0.105**
	[0.008]	[0.014]	[0.051]
N	16,331	14,365	14,365
R-squared	0.001	n/a	n/a
FTP	-0.01	-0.029	-0.226***
	0.007	[0.022]	[0.074]
N	23,657	19,279	19,279
R-squared	0.004	n/a	n/a

Note: Data from the 1991-92 through 2003-04 seasons are used for this table. All models include player-season fixed effect, $home_t$ and $home_{t-1}$. All field goal models include DQ_t,DQ_{t-1}. Observations with *gap*>2 are dropped, as are observations with players who have less than 51 field goal attempts in a season or who have field goal attempts in less than 45 games in a season. For FE, 2SLS estimator, standard errors clustered by player-season are given in brackets. For AB estimator, robust standard errors are given in brackets. *, **, *** denote 10%, 5% and 1% significance.

Table 3.10: Analysis of Regressions Weighted by Number of Attempts

	(1) All field goal	(2) 2-point FG	(3) 3-point FG	(4) Free throw
de-meaned one-period lagged dependent variable	-0.009***	-0.007***	-0.007**	-0.001
	[0.002]	[0.002]	[0.003]	[0.003]
N	206,520	202,000	90,183	109,631

Notes: All models include de-meaned $home_t$ and $home_{t-1}$. Model 1-3 include de-meaned DQ_t and DQ_{t-1}. Observations with *gap*>2 are dropped, as are observations with players who have less than 51 field goal attempts in a season or who have field goal attempts in less than 45 games in a season. Robust standard errors are given in brackets. *, **, *** denote 10%, 5% and 1% significance.

Table 3.11: Analysis of Sub-Sample Based on Number of Attempts

	(1) FE	(2) 2SLS	(3) AB
Panel A: *SFG2A*>7			
$FG2P_{t-1}$	-0.011***	0.026***	-0.047
	[0.003]	[0.008]	[0.046]
N	100,992	99,150	99,150
R-squared	0.01	n/a	n/a
Panel B: *SFG2A*<=7			
$FG2P_{t-1}$	-0.008**	0.024***	0.013
	[0.003]	[0.007]	[0.037]
N	101,013	94,346	94,346
R-squared	0.003	n/a	n/a
Panel C: *SFG3A*>3			
$FG3P_{t-1}$	-0.01**	0.008	-0.021
	[0.005]	[0.009]	[0.045]
N	42,685	40,846	40,846
R-squared	<0.001	n/a	n/a
Panel D: *SFG3A*<=3			
$FG3P_{t-1}$	-0.014***	0.025***	0.031
	[0.005]	[0.009]	[0.042]
N	47,502	37,491	37,491
R-squared	<0.001	n/a	n/a
Panel E: *SFTA*>2.6			
FTP_{t-1}	-0.004	-0.007	-0.080
	[0.004]	[0.012]	[0.065]
N	73,854	63,852	63,852
R-squared	0.005	n/a	n/a
Panel F: *SFTA*<=2.6			
FTP_{t-1}	-0.017***	0.030	-0.120
	[0.005]	[0.021]	[0.068]
N	35,786	21,442	21,442
R-squared	0.007	n/a	n/a

Notes: *SFGA*, *SFG2A*, *SFG3A* and *SFTA* are player-season mean of number of all field goal, 2-point field goal, 3-point field goal and free throw attempts per game. All models include player-season fixed effect, $home_t$ and $home_{t-1}$.All field goal models include DQ_t,DQ_{t-1}. Observations with *gap*>2 are dropped, as are observations with players who have less than 51 field goal attempts in a season or who have field goal attempts in less than 45 games in a season. For FE, 2SLS estimator, standard errors clustered by player-season are given in brackets. For AB estimator, robust standard errors are given in brackets. *, **, *** denote 10%, 5% and 1% significance.

Table 3.12: Analysis of Relationship Between *FTP* and *FGP*

	(1) Whole Sample	(2) *SFTA*>2.6	(3) *SFTA*>5
FGP_t	0.001	0.007	0.001
	[0.003]	[0.005]	[0.008]
N	198,266	114,628	34,684
R-squared	<0.001	<0.001	<0.001

Note: All models include player-season fixed effect, $home_t$. Observations with players who have less than51 field goal attempts in a season and who have field goal attempts in less than 45 games in a season are dropped. Standard errors clustered by player-season are given in bracket

Table 3.13: Analysis of the Belief in Hot Hand (1)

	(1) Whole Sample	(2) *SFG2A*<= 7	(3) *SFG2A*>7	(4) Whole Sample	(5) *SFG2A*<= 7	(6) *SFG2A*>7
Panel A: 2-point FG						
Min_t				0.262***	0.214***	0.323***
				[0.002]	[0.002]	[0.002]
$FG2P_t$	1.152***	0.877***	1.88***	-0.021	0.022	0.026
	[0.037]	[0.035]	[0.092]	[0.027]	[0.025]	[0.069]
$FG2P_{t-1}$	0.370***	0.331***	0.476***	-0.001	0.041	-0.038
	[0.042]	[0.043]	[0.01]	[0.033]	[0.034]	[0.079]
Win_{t-1}	-0.162***	-0.162***	-0.165***	-0.064***	-0.062**	-0.090
	[0.031]	[0.032]	[0.07]	[0.025]	[0.026]	[0.057]
$FG2P_{t-1}$* Win_{t-1}	0.025	0.028	0.02	-0.016	-0.014	0.016
	[0.057]	[0.058]	[0.137]	[0.046]	[0.047]	[0.108]
DQ_t	-2.913***	-4.540	-0.745	-4.915***	-5.052***	-5.192***
	[0.534]	[0.596]	[0.877]	[0.442]	[0.487]	[0.734]
N	202,057	101,050	101,007	202,057	101,050	101,007
R-squared	0.011	0.011	0.01	0.453	0.297	0.331
	(1) Whole Sample	(2) *SFG3A*<= 3	(3) *SFG3A*>3	(4) Whole Sample	(5) *SFG3A*<= 3	(6) *SFG3A*>3
Panel B: 3-point FG						
Min				0.100***	0.072***	0.130***
				[0.001]	[0.001]	[0.002]
$FG3P_t$	0.736***	0.473***	1.226***	0.530***	0.353***	0.854***
	[0.024]	[0.02]	[0.053]	[0.021]	[0.019]	[0.048]
$FG3P_{t-1}$	0.264***	0.23***	0.332***	0.209	0.190***	0.257***
	[0.027]	[0.028]	[0.058]	[0.025]	[0.026]	[0.054]
Win_{t-1}	0.008	0.000	-0.002	0.036**	0.022	0.036
	[0.017]	[0.019]	[0.034]	[0.016]	[0.018]	[0.032]
$FG3P_{t-1}$* Win_{t-1}	0.028	-0.029	0.13*	0.033	-0.015	0.106
	[0.036]	[0.038]	[0.076]	[0.034]	[0.035]	[0.071]
DQ_t	-0.141	0.993**	-1.299	-0.886**	0.864*	-3.136***
	[0.455]	[0.476]	[0.799]	[0.424]	[0.443]	[0.733]
N	90,212	47,514	42,698	90,212	47,514	42,698
R-squared	0.023	0.021	0.021	0.161	0.07	0.15

Note: All models include player-season fixed effect. Observations with *gap*>2 are dropped, as are observations with players who have less than 51 field goal attempts in a season or who have field goal attempts in less than 45 games in a season. Standard errors clustered by player-season are given in brackets. *, **, *** denote 10%, 5% and 1% significance.

Table 3.14: Analysis of the Belief in Hot Hand (2)

	(1) Whole sample	(2) SFG2A<=7	(3) SFG2A>7
$FG2P_t$	4.426***	3.988***	5.610***
	[0.088]	[0.098]	[0.180]
$FG2P_{t-1}$	1.414***	1.357***	1.583***
	[0.106]	[0.126]	[0.194]
Win_{t-1}	-0.371***	-0.466***	-0.233*
	[0.076]	[0.093]	[0.136]
$FG2P_{t-1}$* Win_{t-1}	0.157	0.195	0.019
	[0.142]	[0.168]	[0.264]
N	202,038	101,031	101,007
R-squared	0.023	0.021	0.021

Note: All models include player-season fixed effect. Observations with *gap*>2 are dropped, as are observations with players who have less than 51 field goal attempts in a season or who have field goal attempts in less than 45 games in a season. Standard errors clustered by player-season are given in brackets. *, **, *** denote 10%, 5% and 1% significance.

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CHAPTER 5

CONCLUSION

This dissertation uses NBA data to address some issues of behavioral economics.

In the first chapter we use NBA free throw data to analyze the effect of pressure on players' performance. We find evidence that player choke under pressure – their performance deteriorates by 5-10 percentage points in the final seconds of very close games. The magnitude of choking is smaller for players who are better overall free throw shooting, and on the second shot of a pair after the first shot is missed. We claim that both of these phenomena are caused by self-confidence, which moderates and potentially eliminates anxiety and choking. However, we find no evidence of choking when games are tied in the final 15 seconds. We also fail to find evidence of performance under pressure being affected by home status, attendance and whether or not the game is in the playoffs. NBA players are highly-paid professionals who have many exposures to the pressure situations. Our findings that even NBA players choke lead us to believe workers in general perform less than optimally under pressure.

In second chapter, we use NBA game-level box score data to test the existence of game-level hot hand and whether professionals believe in its existence. We fail to find any evidence for a game-level hot hand of a substantial magnitude. Since our results are subject to measurement error, endogeneity in shot selection and change in defense, the small estimated autocorrelation in field goal percentage might imply a much larger hot hand in shooting ability. We also find the evidence for the existence of coaches' belief in hot hand – players who shoot well will play more minutes so that they will have more shot attempts. Our results imply that the hot belief might not just be a fallacy.

A topic of future research is to use women's basketball data to examine the performance under pressure and test the existence of hot hand and hot hand belief.

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