Accuracy Under Pressure

By Mukund Madabhushi

Introduction:

At first glance, in basketball, the distance a defender is from a player attempting a shot may seem irrelevant if the shot has not been blocked. A defender who is guarding against a shot cannot physically disrupt the athlete's shot in any way. However, I believed there is a correlation between defensive pressure and shot success, or lack thereof. Possible reasons why a player's shot success might be affected by defensive pressure include the threat of blocking their shot and obstructed vision. When observing a basketball game, it appears there is an effect on players' shot success when a defender is closer by, and my aim was to find out to what degree. Therefore, my paper researched the effect of the nearest defender's distance from a player who is attempting a shot on the success of their shot.

To answer this question, we must first define "defensive pressure." My data set used NBA data from the 2014-2015 season. The data that I acquired have a column displaying the distance the nearest defender was from the player who attempted a shot. Using various distances, I created ranges of defender distance and ran an empirical analysis on the success rate of a shot across those ranges. Because extenuating factors that affect shots other than just defensive pressure exist, I controlled for these variables. Some of these variables are: distance from the hoop, time remaining in the game, time remaining on the shot clock, and player's season shot record.

There are advantages to using sport data rather than data from laboratory experiments or fieldwork. First, sports data have observability. Balafoutas, Chowdhury, and Plessner (2019) found that unlike "in business, politics, or other domains of public and economic life in which individuals can conceal their behavior (or are legally obliged to do so)," sporting events, especially professional sports, are well documented. Second, sports have clear rules, which allows consistent data across games. There are also strong monetary incentives for athletes to perform at their skill level. Therefore, observability, well-defined rules, and clear incentives make sports data advantageous to non-experimental field data.

I predicted that the closer a defender is, the more likely it is that the player attempting the shot misses. I predicted that the skill of the shooter measured in their current season shot average, time left in the game, time left on the shot clock, and distance from the hoop would all affect the success rate of the shots and, therefore, I controlled for those variables to minimize confounding variables.

Literature Review:

Earlier studies have not focused on the correlation between defender distance and shot outcome. Previous research examining athletes' performance under pressure in the NBA has largely examined free throw data, in which a player's shot is uncontested. Cao, Price, and Stone (2010) (18), all find evidence that athletes do tend to perform worse during periods of high pressure when their shots are unguarded. They define periods of high pressure to be times in which free throw shots are taken in close games or in the final 10 to 15 seconds of the game. However, rather than focusing on the impacts of pressure on unguarded shots, our study will choose to focus on the impact of guarded shots on a player's shot accuracy because the majority of shots taken during a game are guarded.

Ortega and Fernandez (2007) analyzed the factors contributing to the shot accuracy of 3-point shots, shots taken from outside the 23-foot 9-in line from the basket and controlled for various variables such as the number of defenders and level of defense at the time of shooting. The study examined the data from an individual game, U19 Spanish championship, in 2005. They concluded that 3-point shots were completed with greater accuracy when defensive pressure was minimal, and also determined that the majority of 3-point shots were taken under partial defensive pressure. However, a better understanding of the impact of defensive pressure can be found by examining the data from a larger sample of games from both 2-point and 3-point shots. Looking at data from a larger number of games allows our study to control for varying athletic performance for an individual performer across games.

Marcey and Lucy (2017) analyzed data from the 2015-2016 NBA season. They gathered data from 1.1 million 3 point shots and analyzed three attributes of shot entry: left-right entry value, entry depth and entry angle from the perspective of the shooter on the basket. Left-right entry value refers to the position to the left or right of the basket's center. Entry depth refers to the forward and backwards displacement from the basket's center, and entry angle refers to the incident angle with which the ball enters the basket. On average, the medium left-right value from the data was zero, but determined that athletes who had a consistent left-right aim, had a higher shot percentage. Similarly the entry depth value was evenly distributed around the center of the standard 9" basket. They also determined that the optimal entry angle for 3-point shots was 45 degrees. Similar to the left-right value, the study concluded that there was a positive relationship between angle shot consistency and shot percentage. Therefore, it is worthwhile to consider how defending pressure can impact a player's shot trajectory without making physical contact with the shot trajectory.

Daly-Grafstein and Bornn (2020) analyzed 50,000 shot trajectories from the NBA and found that guarding a shot has little impact on the left-right accuracy of shots. Yet, the study concluded that defending shots did have a statistically significant impact on shot entry angles and on entry depth. On average, shooters biased their shots short when experiencing defensive pressure. Therefore, defending a shot, even without making contact with the ball or the shooter, potentially impacts the shooter's shot trajectory.

Since defenders cannot make contact with the shooter when defending a shot, it is potentially relevant to consider the impacts of defensive pressure on an athlete's perceived level of difficulty. Dihoff and Epifanio (2007/8) analyzed the relationships of a task's perceived difficulty and an individual's performance. The study randomly distributed to students identical worksheets labeled easy, medium, and hard. They found that the students who received the worksheet labeled "easy," on average were more successful. Self reports of pierced competence were also higher for those students who received the "easy worksheets." While this study examined students, NBA data offers a window into how perceived difficulty of a shot based on the distance of the closest defender impacts an athlete's shot performance.

Despite the limited amount of time a player has to make the decision to shoot, it is important in this study to understand the decision making process behind shooting. "Basketball training influences shot selection assessment: a multi-attribute decision-making approach" analyzes the factors that impact shot selection and strategy. The study concluded that the four factors, physical defensive pressure, rebound, defensive balance and shooting distance, all were considered by study participants when taking a shot. While this study was conducted in a laboratory setting, by taking into consideration a player's touch time, this empirical analysis can take into account decision processing time when evaluating shots.

Finally, Chang, Hsu, and Liu (2019) examine the occurrence of “choking” in sports when athletes are under pressure. Specifically, the study examines the impact of situational pressures on field goal kickers performance in the NFL using data from 2000-2017. The study determined that the impacts of pressure on kickers’ performance was only distinguishable without poor environmental conditions. NBA games are played indoors. Therefore, by examining NBA data, this data exists in a quasi-vacuum, which allows the data to be unaffected by external environmental variables.

Dataset Description:

My dataset consisted of basketball shots taken by various NBA players over the course of the 2014-2015 NBA season. This study’s main focus was on examining the correlation between defensive pressure, represented by the distance away between the shooter and the nearest defender and the outcome of the shot represented by the dummy variable where 1 is a shot ‘made’ and 0 represents a shot ‘missed.’

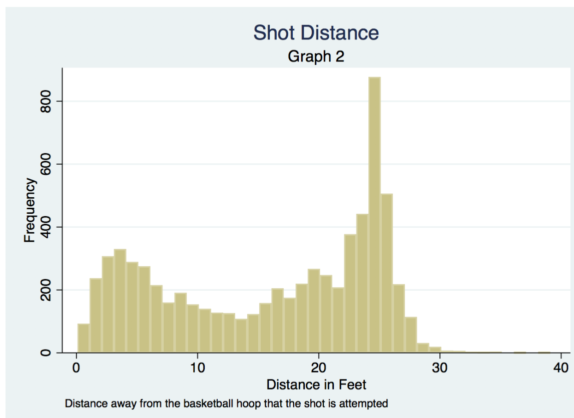
Since my paper aimed at identifying the effect of defensive pressure on the success of a shot, I accounted for confounding variables that could influence the success of the shot. I controlled for 1) the distance the player was from the basket when the shot was attempted, 2) how much time was left on the shot clock when the shot was taken, 3) the time left in the shot clock when the shot was taken, 4) the player’s overall season shot average calculated by averaging the total number of shots they have made in the season over the total shots attempted, and 5) an extra time component, represented by the dummy variables of fourth quarter, close game, and overall game clock.

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
margin	11.6	8.47	1	43
period	2.44	1.12	1	6
shot_clock	12.78	5.62	0	24
shot_dist	15.97	8.65	.1	38.6
def_dist	4.26	2.84	0	53.2
Outcome	.45	.50	0	1
fgpct	.45	.04	.37	.54

In basketball, the distance a player is from a basket varies, and likewise the level of shot difficulty varies along with it. As a player moves further away from a shot, the number of points awarded to a successful shot change to reflect the added level of difficulty. On the basketball court, there is an arc around the basket that designates the difference between a shot worth 2 points and 3 points - if the shot is attempted inside the arc, it counts for 2 points, and if it is outside the arc, it counts as 3 points. Therefore, controlling for the distance away from the hoop the shot is taken prevented the results of each shot from interfering with the other, and allowed me to make for a more accurate estimate on the effect of defensive pressure. In my data set, the average shot distance is 15.97ft. For comparison, the 3 point line is located 23ft, 9in away from the basket. Graph 2 shows the frequency of shots attempted from different distances. However, you can see the highest frequency of shots are taken right around the 3 point arc. Another interesting aspect is the large standard deviation. Shot distance had a wide standard deviation of 8.653ft.

Graph 2:



The second variable I controlled for is the shot clock. In basketball, there is a timer that counts down from 24 seconds, giving a team 24 seconds to shoot the ball. If the team isn't able to shoot the ball in that time, the ball is automatically given to the other team. It thus follows that the closer the shot clock is to 0 seconds, the more pressure is on the player to shoot the ball. I controlled for this and therefore, kept the effect of the shot clock on a player's shot out of the model so that the focus stayed on the effect of a defender on the player's shot. On average, shots are taken when the shot clock reads 12.78 seconds with a standard deviation of 5.62.

Finally, with regards to the time variable, this variable is similar to variable 1 in that players are under additional pressure the closer the game is to ending. According to studies of 7,000 basketball games collected over 6 seasons, moving into the 4th quarter, a game with a margin within 8 or less point difference had an 80% chance of winning (Goel, 2012). In other words, a game within 8 points, can be considered a close game. On average, the game margin in this sample is 11.61 and the period is 2.43. However, looking at Graph 3, the spread of the shots are fairly even across the fourth quarter with a slight inkling towards the first half of the game. The standard deviation is 1.120.

Methods:

The purpose of this study was to analyze whether there is a relationship between the distance away a defender is from a shooter and the chances that the player scores. In order to analyze the impact a defender's distance has on a player's shot accuracy, I tested the null hypothesis that there is no correlation between defender distance and the outcome of the shot which is represented by a dummy variable.

The first model I estimated by OLS is the model where outcome of the shot is the dependent variable, with defender distance as the independent variable controlling for the distance away from the basket the player is when shooting, the time on the shot clock and the player's season shot average.

In the next model, model 2, I explored the correlation of outcome with the square root of the defender distance. In basketball, as the defender moves further away from the shooter, the amount of pressure that is exerted on the shooter has the potential to diminish with each foot moved. Therefore examining a model that takes into consideration this theory nonlinearly given the relationship between the defender distance and shot outcome should follow the shape of a diminishing marginal utility curve. This model ran an OLS regression examining the outcome of the shot in relation to the square root of nearest defender distance, holding constant the shot distance, the shot clock, and the players' season average.

In the third model, I examined an additional time regressor. This variable time is the product of dummy variables of fourth quarter and close game margin multiplied by the quarter game clock. Therefore, if the game was in the fourth quarter and considered "close," then the game clock was added to the regressors and held constant in this model.

Results:

	Outcome	Coefficient	Std. error	t	P > | t |
Model 1	def_dist	.018	.002	8.01	0
	shot_dist	-.011	≈ 0	-14.93	0
	shot_clock	.005	.001	4.92	0
	fgpct	.827	.139	5.94	0
Model 2	√def_dist	.098	.011	8.89	0
	shot_dist	-.012	.001	-15.51	0
	shot_clock	.005	.001	4.92	0
	fgpct	.819	.139	5.88	0
Model 3	√def_dist	.097	.011	8.88	0
	shot_dist	-.012	.001	-15.50	0
	shot_clock	.005	.001	4.88	0

	fgpct	.809	.139	5.81	0
	time	-.098	.071	-1.38	0

Model 1:

Number of obs = 6,964
F(4, 6959) = 83.52
Prob > F = 0
R-squared = .0458
Adj R-squared = .0453
Root MSE = .4863

Model 2:

Number of obs = 6,964
F (4, 6959) = 87.37
Prob > F = 0
R-squared = .047
Adj R-squared = .047
Root MSE = .486

Model 3:

Number of obs = 6,964
F(5, 6958) = 70.28
Prob > F = 0
R-squared = .048
Adj R-squared = .047
Root MSE = .486

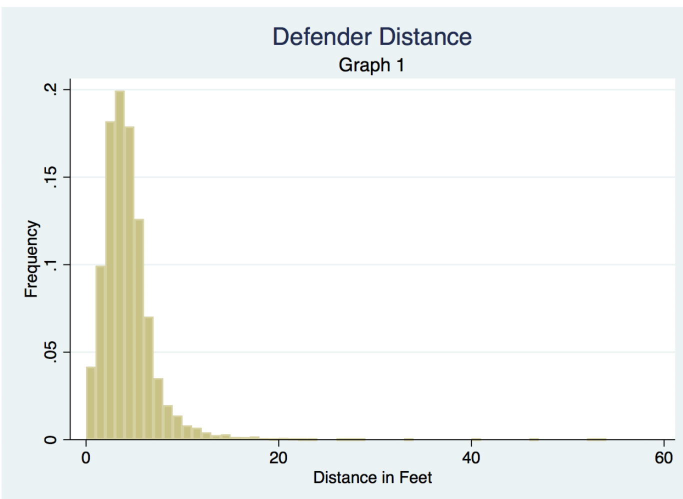
The main question of this study was to look at how the distance between a defender and a shooter impacts the success of a shot. I began by running the OLS regression analysis on the first model, (see Table 2) where outcome is the dependent variable, defender distance is the main regressor, and I controlled for shot distance, shot clock, and season average. The 95% confidence interval for this model indicated that holding all else equal, a change in defender distance by 1 foot on average was associated with an increase in probability of making the shot by .01376 to .02269. The R^2 value for this model is 0.0458, meaning that about 4.58% of the variation in the shot outcome could be explained by this model. The regressor with the largest slope coefficient was field goal percentage, which represents the players season shot average, with a value of .8279. This result indicates that holding all else equal that an increase in field goal percent by 1 is correlated to an increase in probability of making the shot by .8279.

In model 2, (see Table 3), which looks at the potential for a diminishing marginal utility to the amount of pressure a defender exerts on a shooter, I found that the coefficient for defender distance increased on average from .01823 to .09755 when I held constant the distance from the basket the shot was taken, the shot clock, and the players' season average. The 95% confidence interval for this model is .07603 to .1191. Therefore, on average, with this model, as the player moved 1 foot further away from the shooter, the probability that the basketball would enter the basket increased on average by .09755. Based on the R^2 value, 4.78% of the variation in the outcome could be explained by this model.

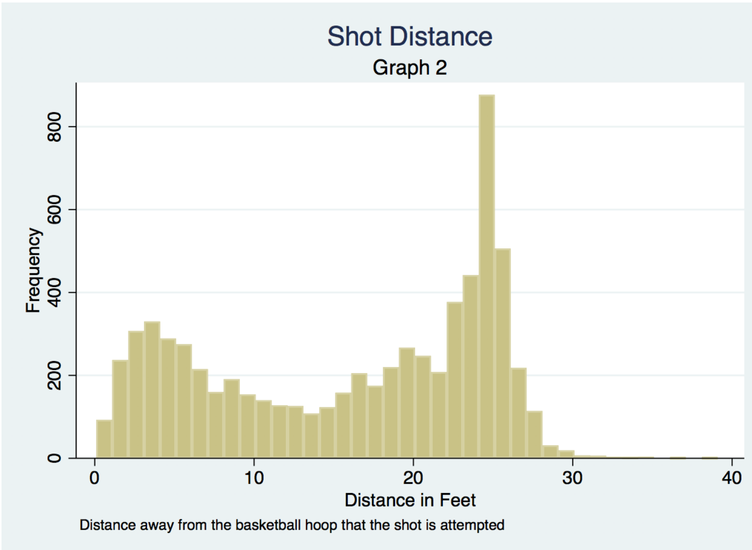
When I included the regressor game time in the model parameters as I did in model 3 (see table 4), the 95% confidence interval for defender distance changed only slightly to .0974 with a confidence interval of .0759 to .1190. The R^2 value did change to 0.0481, however this may have been a result of more regressors included in the model and not a better model specification.

Appendix:

Graph 1: Defender Distance



Graph 2: Shot Distance



Conclusion:

To conclude, I found that the distance a defender is from a player who is attempting a shot has an effect on the success of the shot. The further a defender is from a player, the greater the probability of that shot being successful. This lines up with what I hypothesized would happen. Because I am an avid basketball fan, I have seen countless examples of players shooting better when defenders are not present, and thus had a good idea of the results the tests would yield. I was predicting that with each additional foot a defender is away from a player attempting a shot, the success of the shot would go up by around 10%. The true change in shot success being an increase of 9.7% falls very close to my prediction. However, I was surprised by other results that I found. In particular, I found the results related to differences in skill level to be very intriguing. Seeing that a 1% difference in a player's season averages causes an ≈83% increase in the likelihood of a successful shot was very surprising. I knew that skill level would play a factor in the results, but the extent to which it did was intriguing. I thought that a 1% change in season averages was negligible, and that I would not see dramatic results unless there was a difference in season averages by >5%. Therefore, seeing such a stark increase in the likelihood of a successful shot from just a 1% change was the most surprising part of the results.

References

Balafoutas L, Chowdhury S, Plessner H. 2019. “Applications of Sports Data to Study Decision Making.” Journal of Economic Psychology Vol. 75. JOUR 10.1016/j.joep.2019.02.009

Cao Z, Price J, Stone DF. 2011. “Performance Under Pressure in the NBA.” Journal of Sports Economics.;12(3):231-252. doi:10.1177/1527002511404785

Chang, Hsu, Liu. 2019. “Choking under the pressure of competition: A complete statistical investigation of pressure kicks in the NFL, 2000–2017.” *PLoS One;* 14(4). https://doi.org/10.1371/journal.pone.0214096

Daly-Grafstein, Daniel and Bornn, Luke. 2020. “Using In-game Shot Trajectories to Better Understand Defensive Impact in the NBA.” 1 Jan. 2020 : 235 – 242.

Francis JW, Owen AJ, Peters DM. 2021. “Predicting field-goal success according to offensive, defensive and contextual variables in elite men's wheelchair basketball.” *PLoS One*;16(1): e0244257.. doi:10.1371/journal.pone.0244257

Llorca Miralles, Perales, Pinar, Sánchez-Delgado, Vélez. 2013. “Basketball training influences shot selection assessment: A multi-attribute decision-making approach.” Revista de Psicologia del Deporte. 33(1):223-226

Marty R, Lucey S. 2017 “A data driven method for understanding and increasing 3-point shooting percentage.” MIT Sloan Sports Analytics Conference. 2017 Research Papers Competition.

Orn A. 2017. “Effects of Pressure and Free Throw Routine on Basketball Kinematics and Sport Performance.” Theses and Dissertations. ARIZONA STATE UNIVERSITY.

Ortega, E. and Fernandez, R. 2007. “Differences in 3-point shots between winning and losing teams in formative years of basketball play.” Iberian Congress on Basketball Research, 4, 33-37.

Scasserra, Dominick. 2008. "The influence of perceived task difficulty on task performance" Theses and Dissertations. 756. https://rdw.rowan.edu/etd/756