The Decline of the Mid-Range Jump Shot in Basketball: A Study of the Impact of Data Analytics on Shooting Habits in the NBA

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ABSTRACT

The purpose of this thesis paper is to investigate the strategic shift away from the mid-range jump shot in basketball over the past decade. This paper will cover the rationale for the decline of the mid-range, as well as the general impact of data analytics on the way the game of basketball is played at the professional level. Following a review of the existing literature relating to the use of analytics in the NBA, this paper will analyze the differences in shooting habits between two seven-season periods. Data visualization tools, including boxplots, statistical trends, and distribution plots, will be used to illustrate the changes in shooting habits from the 2005-06 season through the 2018-19 season. Additionally, a predictive statistical model will be used to identify the variables that are most important to winning in the NBA, including shot locations, defensive rating, and pace of play.

INTRODUCTION

The game of basketball is constantly evolving. Data analytics has overhauled the way players and teams are evaluated, focusing more on statistics and quantitative measures rather than evaluating players purely on subjective opinion. The impact of data analytics is most profound on the shooting habits of both individual players and teams. In the NBA, there has been a drastic shift in shooting habits over the past decade as a result of the three-point revolution. The way the game is played in the NBA today is completely different than the way it was played in the early 2000s. The main difference? The absence of the mid-range shot.

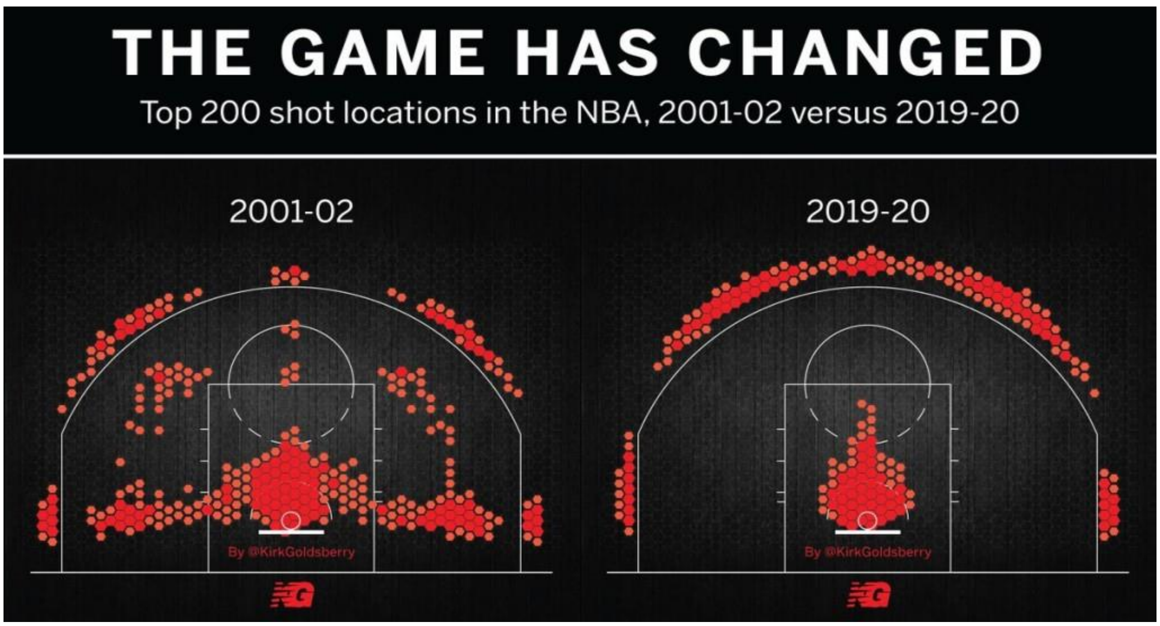


Figure 1: Shot Locations 2001-02 vs 2019-20 (Goldsberry)

The "mid-range" is the area of the court between the three-point line and the area immediately surrounding the basket, commonly referred to as "the paint". The charts above depict the shift in shot locations over the past 20 years in the National Basketball Association (NBA). The chart on the left shows the 200 most frequent shot locations over the course of the 2001-02 NBA season, while the chart on the right depicts the top 200 shot locations for the 2019-20 NBA season. The mid-range jump shot is now a rarity in the NBA, and league offensive strategies have changed accordingly. Nowadays, players are primarily encouraged to do one of two things on offense: drive all the way to the basket or shoot a three-pointer. This has resulted in the death of the mid-range jump shot.

This phenomenon is not only evident in the strategies of teams. The shot makeup of a current-day NBA superstar greatly differs from the superstars of the past. For example, the jump shot habits of Michael Jordan (1996-1998) and James Harden (2018-2020) are essentially inverted, despite each of them being arguably the greatest scorer of their era.

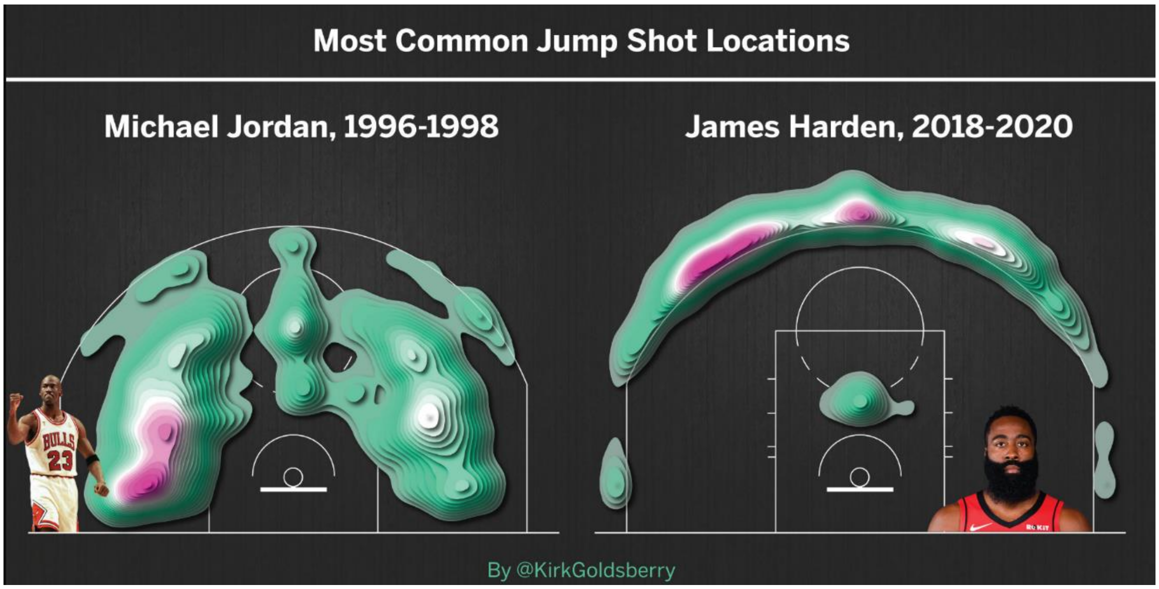


Figure 2: Jordan vs Harden Jump Shot Locations (Goldsberry)

This paper will explore the rationale behind the decline in the mid-range jump shot, explaining the inefficiency of the shot using NBA data. The paper will provide a brief history of the use of data analytics in the NBA and how it led to a shift in league-wide shooting habits. Using datasets of two seven-year periods, shooting trends will be analyzed using statistical visualization tools, including boxplots, statistical trends, and distribution plots. Additionally, a statistical model will be used to analyze the impact of numerous variables on winning in the NBA, including shooting locations, defensive rating, and pace.

Analytics in the NBA

The National Basketball Association has embraced analytics unlike any other professional sports league. Whether it is the tracking of player movement, analysis of specific shot locations on the court, or lineup analysis to identify a team's most effective combination of players, analytics are a major driver behind almost every basketball-related decision an NBA organization makes.

Matt McLaughlin captures the rise of data analytics in the NBA in his BizTech article *How Data Analytics Is Revolutionizing Sports*: "The NBA has embraced data analytics in a way that surpasses most other major U.S. sports leagues… Nearly every team in the NBA has hired data analysts as full-time staff members to work with coaches and front office staff. These analysts help teams identify trends that may improve" (McLaughlin 1). Data analytics is crucial for success in today's NBA, and teams such as the Golden State Warriors and Houston Rockets have taken the lead in the NBA's recent data analytics revolution.

NBA Commissioner Adam Silver says it himself: "Analytics are part and parcel of virtually everything we do now… I think it is part of the result" (Wharton School). No league in the world has embraced the recent data analytics movement like the NBA. From analyzing ticket sales in order to increase team revenue, to using wearables in order to monitor players' sleep schedules, the NBA has incorporated analytics into nearly every aspect of its product.

NBA front offices, coaches, and fans have always used statistics to supplement their evaluation of players. That said, until the mid-2010s, those statistics were predominantly basic box score numbers: points, rebounds, assists, steals, blocks, field goal percentage, etc. One of the major breakthroughs that helped start the current data analytics revolution is the league's investment in video tracking technology. At the start of the 2013-2014 season, the NBA implemented SportsVu software into every NBA arena, a brand specializing in video tracking tools (Mudric 1). Since the initial investment into video tracking, the NBA has only expanded its partnerships with data-focused companies, including SecondSpectrum and Sportradar. The league's six-year partnership with Second Spectrum and Sportradar are "worth in excess of $250 million to the NBA" according to Forbes (Heitner 1).

The leading pioneer for the NBA's data revolution is former Houston Rocket's General Manager Daryl Morey. Coming from an analytical background, Morey was hired as GM of the Rockets in 2007. Following three consecutive losing seasons, Morey upheaved the Rocket's offensive strategy prior to the 2012-2013 season, installing a system centered around taking highly efficient shot attempts, predominantly three-pointers and layups. Morey also traded for budding star James Harden and reconstructed the Rocket's roster to complement his star guard. In his development of the Rocket's groundbreaking strategy, Morey took advantage a simple reality: three is more than two. With the rationale that the 50% increase in points for a three-pointer outweighs the increased difficulty of a three-point attempt, nearly all jump shots that the Houston Rockets attempted moving forward have come from behind the three-point line. Morey's Rockets are the first example of a team abandoning the mid-range jumper, the main topic that this paper focuses on. Houston's strategy has resulted in sustained success; to date, the team has the third-best record in the NBA since 2012, with only the Golden State Warriors and San Antonio Spurs posting more wins. The Rocket's strategy has been dubbed *Moreyball*, a reference to the Oakland Athletics infamous *Moneyball* strategy.

The Evolution of the Three-Point Shot

Out of all the strategic adjustments that have been made since the beginning of the analytics revolution, the increasing reliance on the three-point shot is the most staggering. In the modern NBA, teams such as the Houston Rockets and Golden State Warriors structure their entire offensive attack around the three-point shot. The current reality of the NBA would have been unimaginable 40 years ago, when the three-point line was first introduced.

The use of the three-point shot increased only marginally over the first decade and a half of its existence following its introduction prior to the 1979-1980 season. The league average for attempts per game remained under 10 attempts per game through the 1993-1994 season. The early 1990s was also a time of decreased scoring across the league. For this reason, the NBA decided to move the three-point line closer to the basket, from 23 feet, 9 inches and 22 feet at the corners to a uniform 22 feet around the arch, in an attempt to increase scoring across the league. The first season after this change, the 1994-1995 season, was subsequently the first major jump in three-point attempts in league history, to 15.3 attempts.

As it turns out, the change in the three-point line did not stick, as the move did not result in the increased scoring that the league anticipated:

> Though the average number of 3-point attempts per game increased by over 50 percent, the line was moved back to the original distance after the 1996-97 season because the change had actually *lowered* the average score of games. In the three seasons leading up to the new rule, teams averaged 105.6 points per game. In the three seasons with the shorter 3-point line, that average fell to 100.8. (Pierson 1)

Although the league moved the three-point line back, this three-year experiment did have some lasting influence on team shot selection. Coaches had begun to incorporate the three-point shot into their offensive strategies, while players who specifically excelled in three-point shooting, dubbed three-point specialists, became more commonplace across the league.

Following the move of the three-point line back to its original distance, three-point attempts across the league increased slightly each year from 1997 through 2008, but then leveled out at roughly 18 attempts per team per game for each season through 2012. The 2012-2013 season represents the real beginning of the three-point revolution, as it was the first season in NBA history in which the average number of three-point attempts across the league eclipsed 20 attempts per game. That figure rose exponentially over the next 7 seasons, and during the 2018-2019 season, teams attempted 32 three-pointers per game on average (Basketball Reference).

If one player can be credited with spurring this three-point barrage, it is Golden State Warriors' superstar Stephen Curry. Drafted out of Davidson College in 2009, Curry is largely considered the greatest three-point shooter of all time. At the time of this writing, he ranks 6th in NBA history in three-point percentage, despite the absurd level of difficulty of many of his attempts. Curry has broken the record for most three-pointers in a single season three times, setting the current record of 402 in the 2015-2016 season. Prior to that season, no player had even eclipsed 300 three-pointers in a season. The adjacent shot chart

Figure 3: Curry Jump Shot Locations (Goldsberry)

depicts Curry's jump shot activity during his 2015-2016 MVP campaign, which features almost exclusively three-point attempts (Goldsberry, 2020).

Curry's impact on the game of basketball is historic. As the Ringer's Kevin O'Conner highlighted in his 2019 article *It's More Than Just the Shot*, Curry's influence on younger generations is the greatest since Michael Jordan, arguably the best player of all time:

> Kids used to lower their hoops or use trampolines to dunk like Michael Jordan. Now they shoot from deep like Stephen Curry. Whether it's good or bad for the game is moot; it's happening no matter what. Players of all shapes and sizes are entering the league with shooting skill. This season, 20 teams attempt over one-third of their shots from 3. (O'Conner 1)

Curry's shooting prowess has helped him capture two NBA MVP awards, as well as three NBA championship rings, while inspiring an entire generation and effectively changing the game.

Curry's coach, Steve Kerr, who was hired by the Warriors in 2014, ushered in a system of fast pace and three-point shooting that maximized Curry's skillset. In fact, Kerr, a former player himself, shot 45.4% from behind the three-point line over the course of his career, the best percentage of any player in NBA history. Kerr, who won 5 championships as a player, has coached the Warriors to three championships in the 2010s behind the shooting of Curry. The Warriors broke the typical prototype of a championship team; the team played at a fast pace, shot 30+ three-pointers per game, and utilized a lineup of undersized players. Golden State proved that the three-point shot is not a gimmick, but instead an efficient tool that, if utilized correctly, can be the driving force behind a dynasty.

The Decline of the Mid-Range Shot

Given the dramatic increase in three-point shots attempted, shots from other locations on the court have declined as a result. The primary victim of the rise of the three-pointer has been the mid-range shot. The mid-range is the area of the court between the paint and the three-point line; the shot is too close to the basket to be a three, but is far enough way that it is not considered a layup or floater. As the graph to the right indicates, since 2003, teams have steadily moved away from the mid-range jump shot in favor of taking more 3s. As one of the leading teams behind the three-point revolution, the Warriors 2015 championship coincides with when the three-point shot overtook the mid-range shot in terms of percentage of league shot attempts.

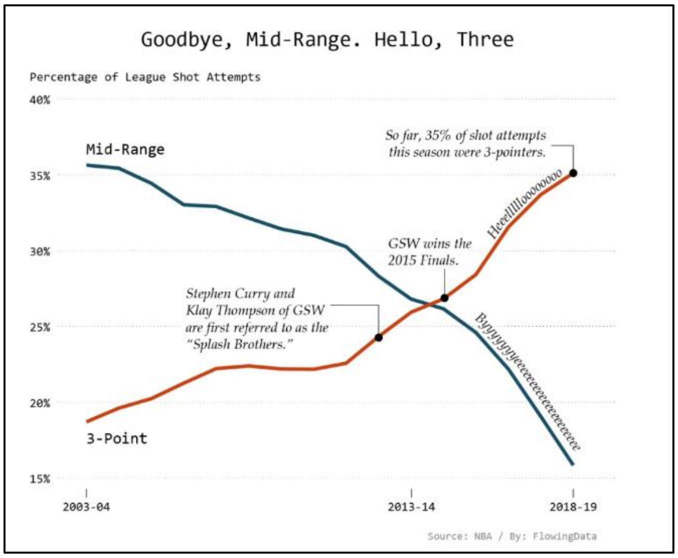


Figure 4: The Rise of the Three & Decline of the Mid-Range (FlowingData)

The decline of the mid-range is rooted in analytical research. As Wade McCagh synopsizes in his article *How Spatial Analytics Killed The Mid-Range Jump Shot:* “It took the most advanced spatial tracking technology we've seen in sports to reveal a simple truth: 3 points are more than 2” (McCagh 1). The decline of the mid-range is truly that simple; if a player gets three points for making a 23.8 foot jump shot, but only two points for a 23.7 foot jump shot (assuming they are shooting from straightaway), the three-point shot is undeniably the more efficient shot.

To put it another way, if a player manages to shoot 50% from mid-range in a season, they are considered an extremely good shooter. Despite that, over the course of that season, that shooter will only average 1 point per shot from the mid-range. If this shooter were to aim to score 1 point per shot while attempting three-pointers, they would only have to make 33.33% of their shots to reach this level of efficiency. The difference between these percentages is huge; if the shooter can shoot within 16.67% of their mid-range percentage on three-pointers, they will be a more efficient scorer of the basketball. The additional point for a three-point shot more than compensates for the increased difficulty of the deeper shot attempt, therefore teams have almost completely abandoned the mid-range attempt as part of their offensive strategy.

All in all, there has been a staggering shift in strategy in basketball over the past few decades, and it is rooted in data analytics. Statistical analysis has helped reveal the inefficiency of the mid-range jump shot and has spurred the three-point revolution that has overtaken basketball at all levels.

LITERATURE REVIEW

With the rise of data analytics and the three-point revolution in the NBA, a multitude of scholarly research has been conducted examining player and team performance, as well as shot selection and spatial analysis. This section of the paper will examine these past studies to provide an overview of the prior research completed in this area of study.

Utilizing Analytics to Evaluate Individual Player Performance

The first area in which several studies have been completed is using data analysis to evaluate individual player performance. Points, assists, rebounds, and other basic counting stats are the typical metrics used to evaluate players, yet they do not encapsulate all the potential impact, positive or negative, a player can have on the court. For this reason, researchers have developed different, more advanced metrics for evaluating individual performance that consider more than just basic statistics.

A 2011 study, *Evaluating Basketball Player Performance via Statistical Network Modeling*, introduces new metrics to evaluate player performance that considers the interaction effects by teammates. The study was presented at the 2011 MIT Sloan Sports Conference by James Piette, Lisa Pham, and Sathyanarayan Anand. The goal of the study is to evaluate how effective certain combinations of players are while measuring the contributions of each individual player using statistics. The study acknowledges that the commonly used plus-minus statistic inherently has biases, and the metric the researchers use attempts to correct for this.

The study evaluates players based on three areas, offense, defense, and total efficiency, and computes player centrality scores to measure the importance of each player to their respective teams. Using those scores, the researchers identified several players that overperform on offense, but underperform on defense, as well as those who underperform on offense, but overperform on offense. One of the advantages to the study is that it identifies players who are currently under-utilized by their teams; they overperform in one or multiple areas of the game, yet their centrality scores are low. Generally, the study contributes an algorithm to the growing body of metrics used to evaluate individual player performance, taking the contribution of teammates into account. (Piette, et al. 1)

In another study, Cervone et al. (2014) incorporate other factors into individual player evaluation. While most analytical models focus on the results of the end of a possession, such as points, turnovers, or assists, this model considers players' decisions to pass, dribble, or shoot over the course of the possession. By using the metric of expected possession value (EPV), this source offers a different type of analysis of offensive play in basketball.

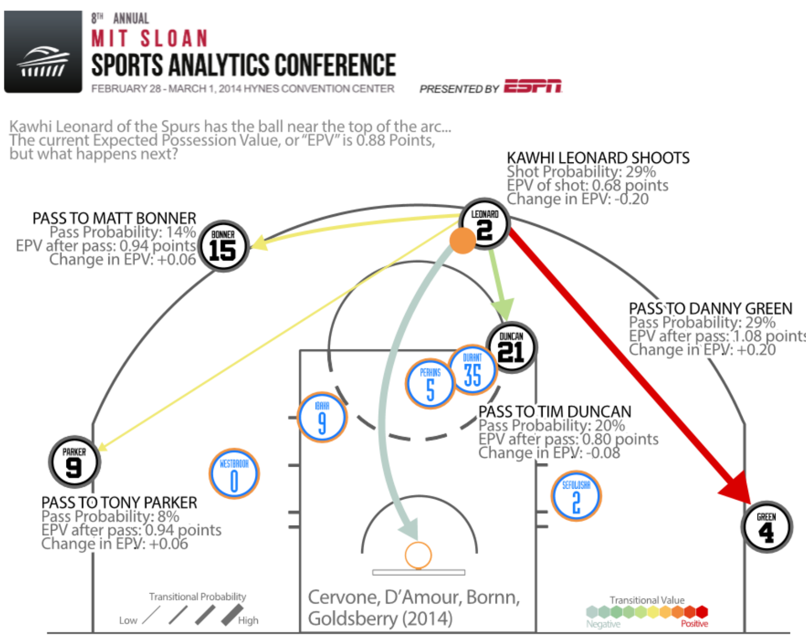


Figure 1. Diagram of EPV as a weighted average of the values of the ballcarrier's (Leonard's) decisions and the probability of making each decision. We also consider the possibility of Leonard dribbling to a different area or driving toward the basket, as well as turning the ball over, but these are omitted from the above diagram for conceptual clarity.

Figure 5: EPV of Spur's Possession (Cervone et al.)

The graphic above visually conceptualizes EPV. At this given point in the San Antonio Spurs' possession, Kawhi Leonard, the player with the ball, must decide whether to shoot or pass, and if he passes, which player to pass to. The EPV metric evaluates the probable points that result from each of his options, highlighting that the smartest play is to pass the ball to Danny Green for a corner 3. Typical statistical analysis would only acknowledge Leonard's decision if he either scored or assisted a teammate's made shot. The EPV metric instead evaluates Leonard's decision making; if he passes the ball to Danny Green, regardless of whether or not Green makes the shot, Leonard is credited with making the best play. This study, and the introduction of EPV as a metric, further contributes to the tools used to evaluate individual performance, and "overcomes many shortcomings of the conventional boxscore approaches to analyzing the game" (Cervone, et al. 1).

In evaluating player performance in basketball, most studies and metrics focus on a player's contributions on the offensive side of the game. *The Dwight Effect: A New Ensemble of Interior Defense Analytics for the NBA*, a 2013 study by Kirk Goldsberry and Eric Weiss, instead introduces spatial and visual analytics that evaluate multiple aspects of defensive play. The study investigates "The Dwight Effect", named after dominant defender Dwight Howard, which is defined as "the ability of an interior defender to reduce the efficiency of an opponent's shooting behavior" (Goldsberry & Weiss 3). Common statistics, such as steals and block shots, do not always accurately correlate to a player's defensive effectiveness; this study accounts for both the efficiency and frequency of shot attempts of opposing players. The incorporation of frequency as a key variable is relatively unprecedented, as it attempts to account for the fear factor of great defenders. Some interior defenders, such as Dwight Howard, have a presence that deters opposing players from attempting shots around them, which the frequency variable attempts to account for.

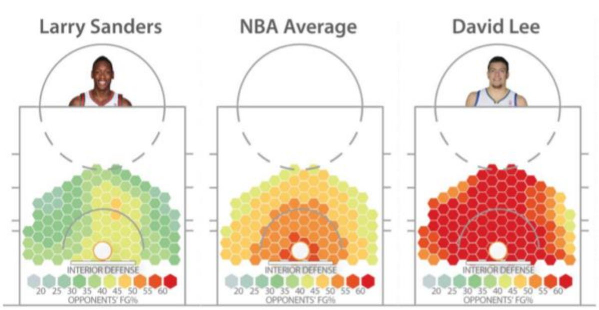


Figure 6: Opponent Field Goal Percentage by Individual Defender (Goldsberry & Weiss)

The study seeks to accomplish two goals: to present new metrics to evaluate defensive effectiveness in the NBA, and to acknowledge the challenges of measuring defensive performance. By comparing the efficiency and frequencies of opposing offenses when a certain player defends the interior, the researchers were able to identify the best, as well as the worst, interior defenders in the NBA over the course of the 2011-2012 and 2012-2013 seasons.

Utilizing Analytics to Evaluate Shot Selection

Another major area in which data analytics has had a distinct impact is shot selection. Recent studies have used advanced metrics to evaluate the efficiency of shots from certain positions on the court and have brought about increased emphasis on the importance of shot selection in basketball. Other studies have focused on spatial analysis, which takes into account both the location of shots taken and the distance of defenders.

A 2012 study, *The Problem of Shot Selection in Basketball*, by Brian Skinner, offers interesting insight into shot selection in the NBA. Skinner investigates the decision making of players, particularly their decision of whether to take a shot or pass the ball. The analysis explores what shots are worth taking and which shots should be passed up and takes extraneous factors such as time left on the shot clock and probability of a turnover into the analysis. In the NBA, teams have 24 seconds to attempt a shot and if the team does not attempt a shot within the shot clock, it expires and the team loses possession of the ball. Skinner uses a theoretical model of the shot selection process in hopes of answering the question "how likely must the shot be to go in before the player should take it?" (Skinner 1).

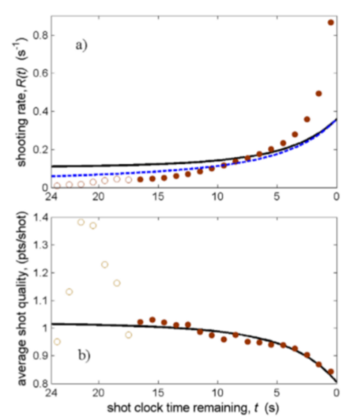


Figure 7: Shooting Rate by Shot Clock Time (Skinner)

As Skinner finds, the shot clock has a large impact on shooting habits. As the charts to the right depict, as the shot clock gets closer to expiring, teams attempt shots at a higher rate (out of necessity), but the quality of those shots decreases. For the games in his dataset, Skinner's analysis finds that: "For NBA teams, the expected number of points per possession is 0.86, or 0.83 if one considers only possessions lasting past the first seven seconds of the shot clock" (Skinner, 6). If teams were to employ the optimal shooting strategy identified by Skinner's model, that expected number of points per possession would rise to 0.91, or 0.88 if one only considers possessions that last past the first seven seconds of the shot clock. The rise from 0.86 to 0.91 is hugely impactful: "This improvement of 0:05 points/possession translates to roughly 4.5 points per game… such an improvement could be expected to produce more than 10 additional wins for a team during an 82-game season" (Skinner 6). In short, Skinner's study highlights the importance of shot selection in basketball and how it can have a profound impact on winning.

Another study, *Quantifying Shot Quality in the NBA*, evaluates shot quality in a different way. This Second Spectrum study introduces two new metrics in effective shot quality (ESQ) and EFG+, effective field goal percentage minus effective shot quality, which computes shooting ability above expectation. As the study highlights, the current advanced metric to evaluate shooting efficiency is effective field goal percentage (EFG%), which accounts for the reality that three-pointers are worth 1 more point than two-point shots. The study introduces ESQ and EFG+ to offset the fact that EFG% confounds the quality of any shot attempted and the ability of a player to make that shot.

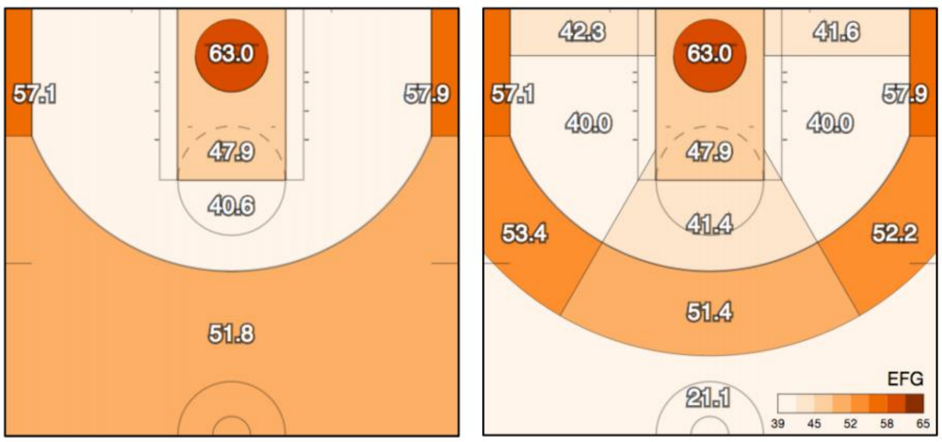


Figure 8: ESQ and EFG+ (Chang et al.)

The charts above depict EFG% for different locations on the court. The mid-range area is by far the least efficient area on the court according to the effective field goal percentage metric. The issue with EFG% is that it does not account for shot quality. If Player A attempts significantly harder shots than Player B, and as a result Player B makes more shots than Player A, Player B will have the higher EFG%. That is not necessarily a fair evaluation of Player A, because if Player B was able to take the same quality shots that Player B attempts, Player A may very well be a better shooter.

This is where ESQ and EFG+ come in. The following graphic depicts ESQ and EFG+ applied to NBA players:

	All Shots		
	EFG	ESQ	EFG+
Kyle Korver	63.3	48.6	14.7
Jose Calderon	60.7	47.7	13.1
LeBron James	62.9	50.5	12.5
Andre Iguodala	65.7	53.9	11.8
Marco Belinelli	61.6	49.9	11.7

	Three Pointers		
	EFG	ESQ	EFG+
Kyle Korver	69.6	53.1	16.5
Jose Calderon	67.1	52.7	14.4
Damian Lillard	64.4	50.4	14.0
Spencer Hawes	68.7	56.1	12.5
Kevin Durant	62.1	50.1	12.1

	Mid-Range		
	EFG	ESQ	EFG+
Gerald Green	59.8	42.0	17.8
Kyle Korver	55.9	41.7	14.3
Isaiah Thomas	54.0	41.1	12.9
Marco Belinelli	54.9	42.0	12.9
Damian Lillard	50.0	38.6	11.4

	Paint		
	EFG	ESQ	EFG+
LeBron James	75.6	56.7	19.0
Manu Ginobili	68.1	54.1	14.0
Kevin Durant	62.7	51.6	11.2
Boris Diaw	67.2	56.0	11.2
Al Horford	67.4	56.4	11.0

Figure 9: Player Specific ESQ and EFG+ (Chang et al.)

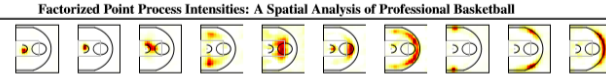
This graphic proves that some players must take much more difficult shots than others. For three-pointers for example, Spencer Hawes has an effective field goal percentage of 68.7%, while Kevin Durant has an EFG% of 62.1%. That said, Kevin Durant, a former NBA league MVP, faces much tougher defense every game than Spencer Hawes, a career role player. The ESQ metric takes this into account and shows that Hawes takes significantly easier three-pointers than Durant (Chang et al. 6). All in all, this study introduces two new metrics useful for evaluating shot quality and efficiency at the NBA level.

Utilizing Analytics to Evaluate Shot Quality by Location

Another study by Kirk Goldsberry, *CourtVision: New Visual and Spatial Analytics for the NBA*, introduces a "new ensemble of analytical techniques designed to quantify, visualize, and communicate spatial aspects of NBA performance with unprecedented precision and clarity" (Goldsberry, 2012). In this study, Goldsberry also introduces new metrics in an attempt to make up for the oversimplifying nature of commonly used statistics. Goldsberry's CourtVision metrics account for spatiality, clarifying that "although conventional metrics are simple ways to summarize the probability of a shot attempt resulting in a made basket, they fail to expose true differences in shooting ability across the league" (Goldsberry, 2012). In this particular study, Goldsberry uses the CourtVision model to identify the best shooters in the NBA during the 2010-2011 NBA season, pinpointing Ray Allen and Steve Nash as the league's best shooters.

Goldsberry also contributed to Andrew Miller, Luke Bornn, and Ryan Adams' research on spatial analysis of professional basketball. In that study, the researchers conducted a spatial pattern analysis to identify to the best shooters from different locations on the court. Based on the results, Miller et al. discovered great variety in shot selection, as well as effectiveness on those shots, amongst NBA players. In summary, "some shooters specialize in certain types of shots, whereas others will shoot from many locations on the court" (Miller et. al 5).

Factorized Point Process Intensities: A Spatial Analysis of Professional Basketball



LeBron James	0.21	0.16	0.12	0.09	0.04	0.07	0.00	0.07	0.08	0.17
Brook Lopez	0.06	0.27	0.43	0.09	0.01	0.03	0.08	0.03	0.00	0.01
Tyson Chandler	0.26	0.65	0.03	0.00	0.01	0.02	0.01	0.01	0.02	0.01
Marc Gasol	0.19	0.02	0.17	0.01	0.33	0.25	0.00	0.01	0.00	0.03
Tony Parker	0.12	0.22	0.17	0.07	0.21	0.07	0.08	0.06	0.00	0.00
Kyrie Irving	0.13	0.10	0.09	0.13	0.16	0.02	0.13	0.00	0.10	0.14
Stephen Curry	0.08	0.03	0.07	0.01	0.10	0.08	0.22	0.05	0.10	0.24
James Harden	0.34	0.00	0.11	0.00	0.03	0.02	0.13	0.00	0.11	0.26
Steve Novak	0.00	0.01	0.00	0.02	0.00	0.00	0.01	0.27	0.35	0.34

Figure 10: Factorized Point Process (Goldsberry, Miller, Bornn, Adams)

Another study, *Live by the Three, Die by the Three? The Price of Risk in the NBA* by Matthew Goldman and Justin M. Rao, looks into how a team determines the right proportion of two-point and three-point shots to take over the course of a game. In determining the best combination of shot attempts, a trade-off exists between risk and reward. Goldman and Rao highlight that early in a game, teams should maximize points per possession, regardless of risk, and therefore should attempt more three-pointers. That said, late in a game, the winning team should pursue low risk, "predictable scoring opportunities", while the trailing team must shoot more threes in order to tighten the score (Goldman & Rao 2).

One of the main takeaways from this study is that the leading team takes more three-pointers when the best play would be to take more high percentage shots. This trend continues as the winning team's lead decreases: "As a lead decreases, the leading team should become more risk-neutral, but teams in this circumstance actually tighten up and become more risk averse, contrary to what their risk preferences ought to be to maximize the chance of winning the game" (Goldman & Rao 8). This is an important finding; the statistics show that teams that are trying to solidify a win do not shoot the shots that would give the team the best chance of winning. Further research needs to be done to see if the mid-range jump shot could be an effective shot for the winning team late in games.

Paul Zuccolotto, Marica Manisera, and Marco Sandri also conducted a study on shooting performance of players in high-pressure game situations. Using data from the Italian Serie A2 Championship, the researchers identified that the situation "most impacting the scoring probability is when the shot clock is about to expire and, for free throws, when the player has missed the previous shot" (Zuccolotta et al. 587). The study investigates players' personal reactions in the last two seconds before the shot clock expires, as well as when the score is within a reasonable range within the last five minutes of a game. The findings of this study contribute to the growing body of analytics research related to basketball that are increasingly used to measure and evaluate player and team performance.

The existing body of research highlights the impact the rise of data analytics has had on player evaluation in the modern NBA. While the current research covers how analytics are used to evaluate individual player performance, shot selection, and shot quality by location, the research focusing specifically on the mid-range is not extensive. This paper aims to add to the existing body of research while identifying the key contributing factors to the decline of the mid-range jump shot in the modern NBA.

DATA ANALYSIS

Data:

The data analysis in this paper is based on a dataset of statistics gathered from fourteen seasons worth of NBA data. The larger dataset is split into two equally sized data sets of seven seasons. The first dataset is made up of NBA statistics from the 2005-2006 season through the 2011-12 season. The second dataset is made up of NBA statistics from the 2012-2013 season through the 2018-2019 season. As identified in the literature review, the 2012-2013 NBA season represents the beginning of the three-point revolution, making it a logical split for evaluating the shift in shooting habits in the NBA.

The data was retrieved from NBA.com/statistics. Microsoft Excel was used to organize the data. See Appendix A for a snippet of the dataset. Most of the values in the dataset are based on season totals, such as the total amount of shot attempts from designated areas on the court over the course of a full season. For this study, shot attempts are specified as coming from one of five areas on the court: the restricted area, the paint, the mid-range, corner three-pointers, and above the break three-pointers; see Appendix B for a visual illustration of these shot locations.

It is important to note that there are a few outlier data points that deviate from the typical 82 game NBA season. The 2011-2012 NBA season was only 66 games due to the lockout shortened season following disputes between players and owners regarding the league's collective bargaining agreement. All data points for the 2011-2012 season are based on 66 games, therefore the 2011-2012 season represents an outlier datapoint for some charts used in the analysis. Also, the Boston Celtics and Indiana Pacers only played 81 games each in the 2012-2013 season due to the tragic events of the Boston Marathon bombing leading to the teams' April 15, 2013 game being cancelled.

The dataset includes the following 30 variables:

Variable:	Description:
Year	NBA Season
GP	Games Played
RAFGM	Restricted Area Field Goals Made
RAFGA	Restricted Area Field Goals Attempted

PFGM	Paint Field Goals Made (Non Restricted Area)
PFGA	Paint Field Goals Attempted (Non Restricted Area)
MRFGM	Mid-Range Field Goals Made
MRFGA	Mid-Range Field Goals Attempted
C3FGM	Corner Three-Point Field Goals Made
C3FGA	Corner Three-Point Field Goals Attempted
ATB3FGM	Above the Break Three-Point Field Goals Made
ATB3FGA	Above the Break Three-Point Field Goals Attempted
FTM	Free Throws Made
FTA	Free Throws Attempted
PF	Personal Fouls
PFD	Personal Fouls Drawn
OFFRTG	Offensive Rating
DEFRTG	Defensive Rating
AST%	Assist Percentage
AST/TO	Assist to Turnover Ratio
PACE	Pace of Play
OREB	Offensive Rebounds
DREB	Defensive Rebounds
TREB	Total Rebounds
AST	Assists
TOV	Turnovers
STL	Steals
BLK	Blocks
Wins	Games Won
Rank	League Standing (based on Wins)

Methodology:

The two datasets are analyzed by two primary methods. First, visualization tools will be used to illustrate the statistic trends in shooting habits over the past 14 years. Graphs highlighting the trend over the years, boxplots based on variables such as offensive strength and league rank, and distribution plots based on league rank are used to visualize the data. Secondly, a linear regression model will be used to measure the effect selected variables have on an NBA team's chance of winning. Python is the primary software with which this analysis was completed.

For the visualization tools, each type of chart displays different measures of the data. The statistics trending graph simply showcases the totals for a selected variable each year. When graphed together, the trend of the data can be seen visually. Boxplots are used to identify the interquartile range, which is the 25th to the 75th percentile of the data. The middle line highlights the median of the selected data set. Scatterplots are used to observe the relationship between two variables; the dots represent individual datapoints, while the accompanying line graphs highlight the strength of the relationship between the two variables. The distribution plots identify the most common count of the data, as well as the shape of the sample distribution.

The linear regression model is used to predict the number of wins a team will have based on selected variables from the dataset. The model is computed using ten variables, as opposed to the 30 variables that influence the visualization charts. The use of fewer variables simplifies the model and gives a general idea of the variables that impact winning. See Appendix C for a snippet of the simplified database. The ten variables are:

Variable:	Description:
RAFGA	Restricted Area Field Goals Attempted
PFGA	Paint Field Goals Attempted (Non Restricted Area)
MRFGA	Mid-Range Field Goals Attempted
C3FGA	Corner Three-Point Field Goals Attempted
ATB3FGA	Above the Break Three-Point Field Goals Attempted
DEFRTG	Defensive Rating
PACE	Pace of Play
TREB	Total Rebounds
AST	Assists
TOV	Turnovers

Visualization Findings:

The initial findings focus on the change in shooting distributions for teams over the 14-year period analyzed. A statistics trending analysis was completed for the field goals attempted by teams on average over the course of each season from the 2005-06 season through the 2018-19 season. The number of field goal attempts from each of the major areas on the court was analyzed: the restricted area, the paint outside the restricted area, the mid-range, the corner three pointer, and the above the break three pointer. Again, it is crucial to note that only 66 games were played in the 2011-12 season, so this represents an outlier data point on each graph.

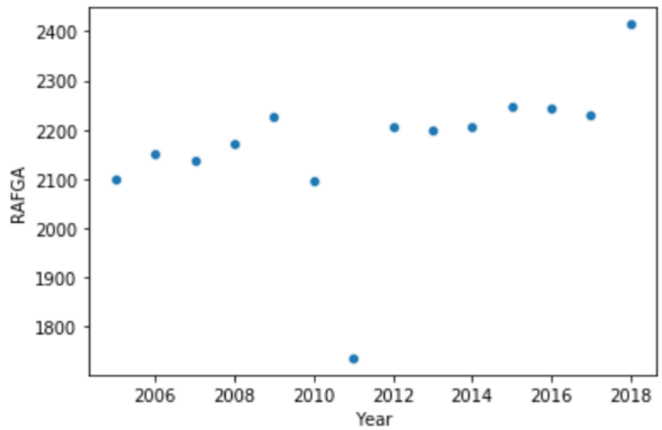


Figure 11: Restricted Area Field Goal Attempts by Year

Over the period analyzed, there is a slight positive trend in number of restricted area field goals attempted. In the 2005-06 season, teams averaged 2100.6 restricted area field goal attempts over the course of the season, compared to 2414.2 attempts in the 2018-19 season, a 313.7 shot increase. That change represents a 14.9% increase from the restricted area attempts in 2005-06.

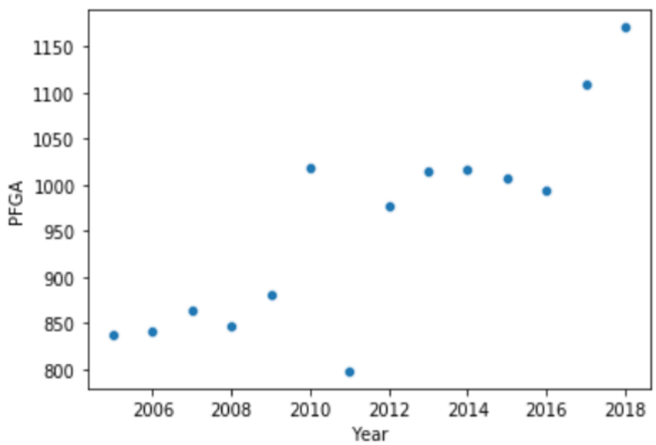


Figure 12: Paint Field Goal Attempts by Year

There is a clear positive trend in the number of paint field goal attempts (non-restricted area). In the 2005-06 season, teams averaged 836.9 paint field goal attempts, compared to 1170.7 attempts in the 2018-19 season, a 333.8 shot increase. That change represents a 39.9% increase from the paint attempts in 2005-06.

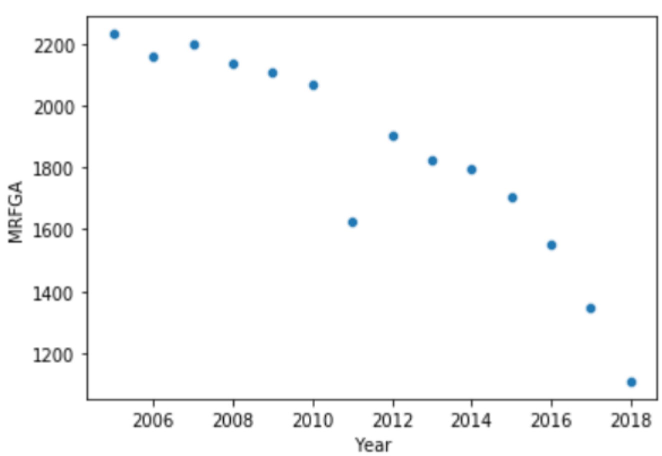


Figure 13: Mid-Range Field Goal Attempts by Year

There is a clear negative trend in the number of mid-range jump shot attempts. In the 2005-06 season, teams averaged 2230.9 mid-range attempts over the course of the season, compared to 1109.2 attempts in the 2018-19 season, a 1121.7 shot decrease. That change represents a 50.3% decrease from the mid-range field goal attempts in 2005-06.

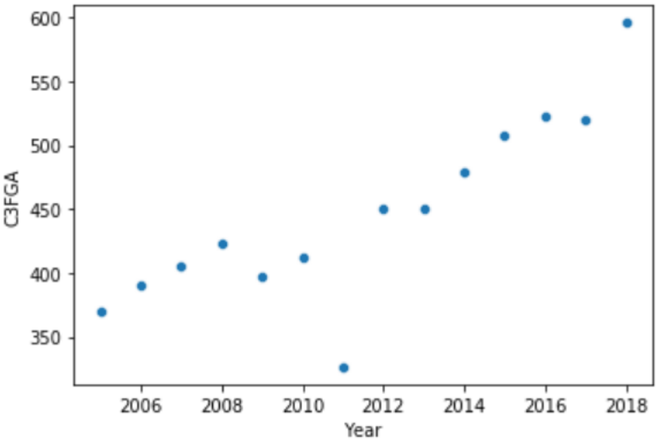


Figure 14: Corner Three-Point Field Goal Attempts by Year

There is a clear positive trend in corner three-point attempts. In the 2005-06 season, teams averaged 369.2 corner three-point attempts, compared to 596.1 in the 2018-19 season, a 226.9 shot increase. This change represents a 61.4% increase in corner three-point attempts since the 2005-06 season.

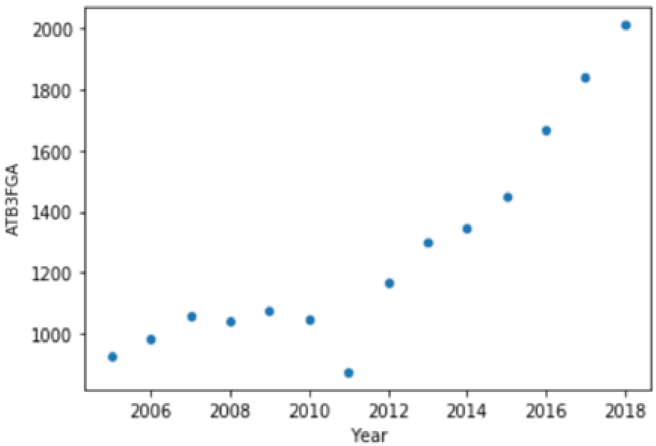


Figure 15: Above the Break Three-Point Field Goal Attempts by Year

There is a very clear positive trend in above the break three-point attempts. In the 2005-06 season, teams attempted 927.2 above the break three-point shots, compared to 2009.5 attempts in the 2018-19 season, a 1082.3 shot increase. This change represents a 116.7% increase from the average number of above the break three-point attempts in 2005-06. Furthermore, the average number of attempts in the 2012-13 season was 1170.0, a 242.8 shot increase from 2005-06. The average number of attempts then increased by 839.5 attempts from 2012-13 to 2018-19.

The next stage of the analysis focuses on looking at how these shooting habits differ based on the strength of a team's offense, as well as how these shooting habits translate to winning. Boxplots and distribution plots were used in this part of the analysis. For many of the boxplots, the data is dispersed based on a team's offense being neutral, weak, or strong; in this analysis, offense strength is quantified using Offensive Rating, a metric which measures a team's offensive points produced per 100 possessions. For the boxplots that deal with rank, the rank is based on where a team finished in terms of number of wins relative to all 30 teams.

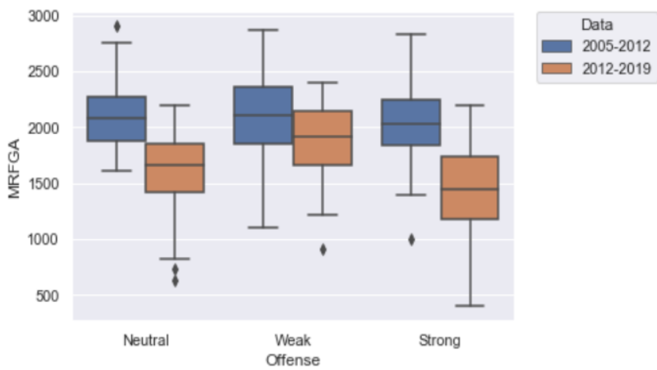


Figure 16: Mid-Range Attempts by Strength of Offense

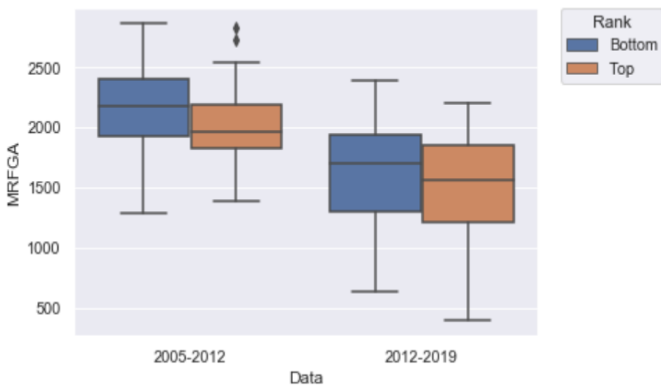


Figure 17: Mid-Range Attempts by Team Rank

As the boxplots to the left depict, the frequency of mid-range jump shot attempts clearly decreased in the 2012-2019 data compared to the 2005-2012 data. Interestingly, there was no major difference in mid-range field goals attempted for teams with strong or weak offenses. On the other hand, there are clear differences in the offensive strength of teams in the 2012-2019 dataset based on mid-range field goal attempts. Strong offensive teams attempted the least amount of mid-range shots, while the weakest offenses utilized the highest number of mid-range attempts.

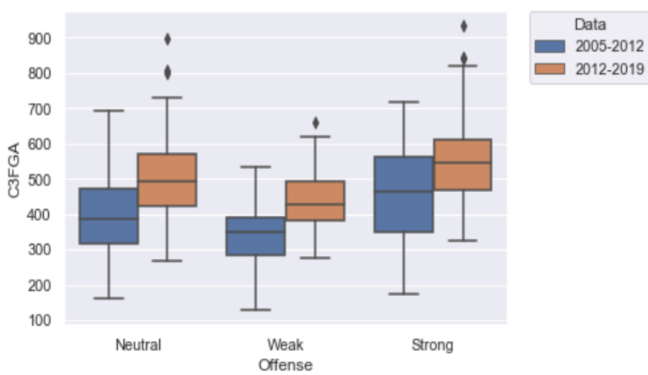


Figure 18: Corner Three-Point Attempts by Strength of Offense

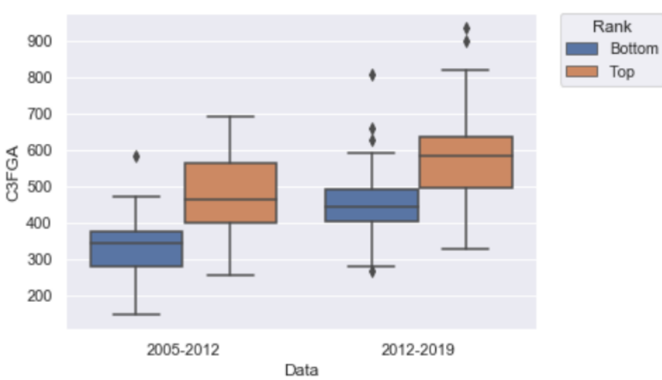


Figure 19: Corner Three-Point Attempts by Team Rank

The use of the corner three-point shot has changed over the past 15 years. As depicted by the boxplots to the left, teams in the 2012-2019 dataset attempted more threes across the board than the 2005-2012 teams, regardless of the strength of a team's offense. That said, the strongest offenses attempted the most corner three-pointers on average, although it was close to the level of league average (neutral) offenses. The weak offenses lagged farther behind, clearly attempting the least corner three-point shots over the course of a season.

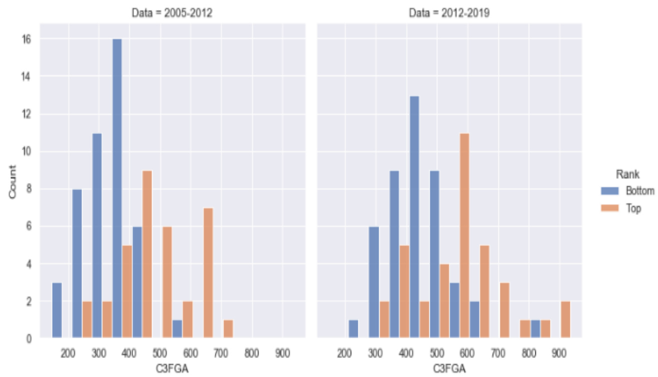


Figure 20: Corner Three-Point Attempts Distribution Plot by Rank

The frequency of corner three-point shooting directly correlates with winning. As the rank boxplot and distribution plot show, regardless of the dataset, top ranked teams utilized the corner three-pointer much more than lower ranked teams. The corner three-point shot is a staple of winning teams.

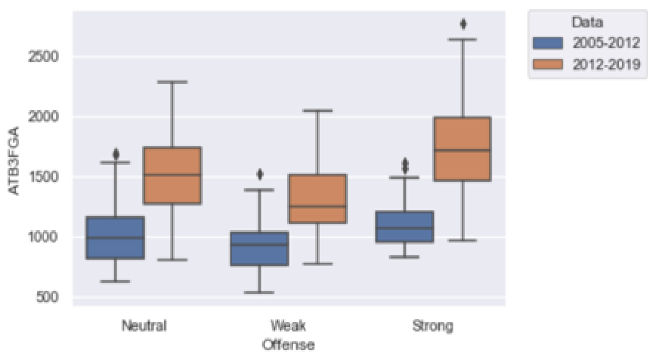


Figure 21: Above the Break Three-Point Attempts by Strength of Offense

The use of the above the break three-pointer has changed. Teams with strong offenses attempt the most above the break three pointers, while weak offenses shoot the least amount. The number of above the break three-point attempts is significantly higher in the 2012-2019 dataset than the 2005-2012, regardless of offensive strength. Although it is not a large difference, teams that attempt more above the break three-pointers rank higher in league standings on average.

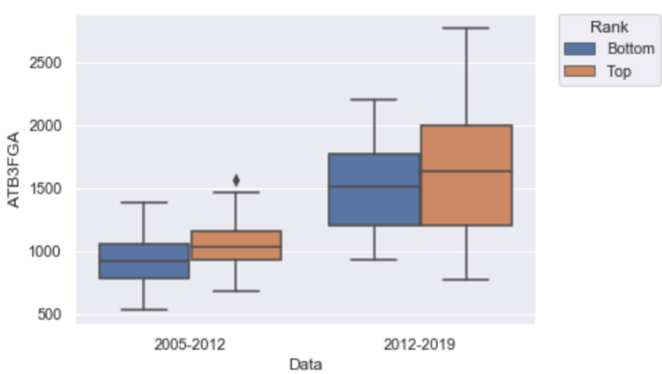


Figure 22: Above the Break 3-Point Attempts by Team Rank

In looking for variables that help explain the shift in shooting habits in the NBA over the 14-year period analyzed, a surprising variable presented itself as a factor: pace. Pace, a metric that simply measures the number of possessions a team has over the course of a game, is typically used to measure how often a team gets out in transition and pushes the ball down court. After looking at the pace variable in comparison with the shooting statistics in the datasets, specifically the mid-range field goal attempts, it seems that there is a relationship between pace of play and a team's shooting habits.

First, there seems to be a relationship between mid-range jump shooting and team pace of play. For the 2005-2012 data, the teams are heavily concentrated in the 1500-2500 MRFGA, 89.0-95.0 PACE area. On the other hand, the 2012-2019 teams are concentrated in the 1000-2250 MRFGA, 92.5-100.0 PACE area. Teams in the 2012-2019 data set are evidently shooting less mid-range jump shots and playing at a faster pace of play.

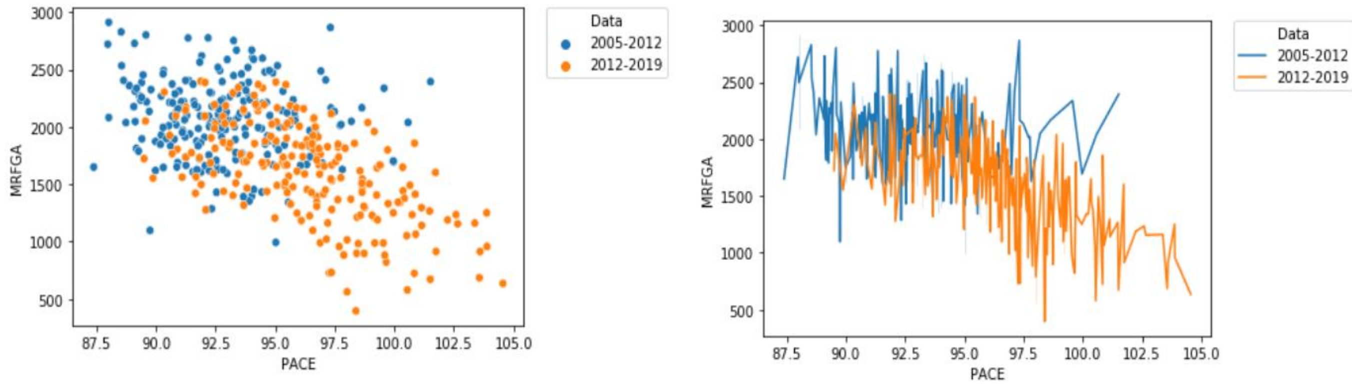


Figure 23: Correlation Between Mid-Range Field Goal Attempts and Pace

After the realization that pace of play is a variable that may influence a team's shooting habits, the relationship between pace and the strength of team's offense and defense, respectively, was looked at. As the boxplots below show, teams that have a strong offense play at the highest pace on average. Also, teams with a weak defense seem to play at the highest pace, while strong defenses play at a slower pace. Across the board, teams in the 2012-2019 data play at a higher pace than teams from the 2005-2012 dataset. That said, pace itself does not necessarily relate to winning. As the distribution plot depicts, pace increased across the league from the 2005-2012 period to the 2012-2019 period, but an even distribution of top and bottom ranked teams played at all different levels of pace.

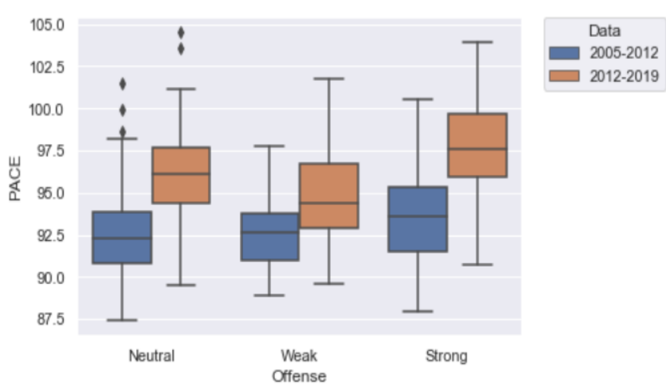


Figure 24: Pace by Strength of Offense

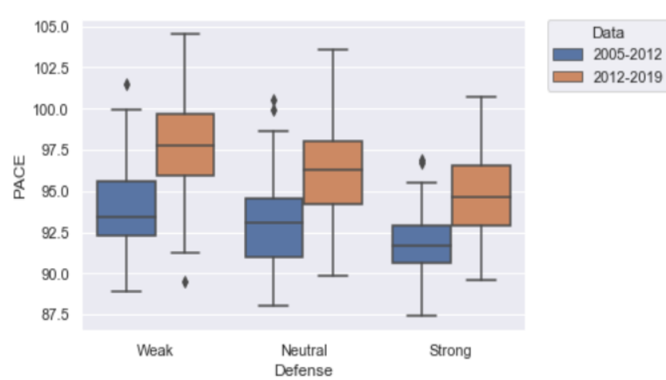


Figure 25: Pace by Strength of Defense

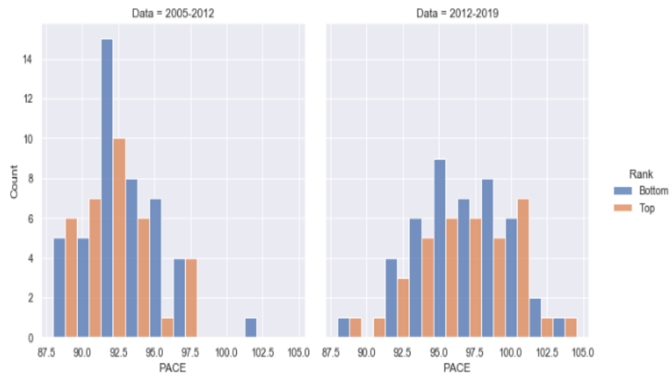


Figure 26: Pace Distribution Plot

Linear Regression Model Findings:

The second focus of the data analysis is to develop a model that predicts winning. A linear regression model using the nine variables identified in the methodology section produced the following results:

	Variable	Coef	Absolute Coef	Effect
0	DEFRTG	-1.735851	1.735851	Negative
1	PACE	1.139783	1.139783	Positive
2	TOV	-0.068601	0.068601	Negative
3	MRFGA	-0.029247	0.029247	Negative
4	TREB	0.026744	0.026744	Positive
5	ATB3FGA	-0.024948	0.024948	Negative
6	AST	0.024347	0.024347	Positive
7	PFGA	-0.019370	0.019370	Negative
8	RAFGA	-0.018780	0.018780	Negative
9	C3FGA	-0.014118	0.014118	Negative

Figure 27: Output for 2005-2012 Data

	Variable	Coef	Absolute Coef	Effect
0	DEFRTG	-1.710764	1.710764	Negative
1	PACE	0.763791	0.763791	Positive
2	TOV	-0.065177	0.065177	Negative
3	PFGA	-0.030204	0.030204	Negative
4	MRFGA	-0.029666	0.029666	Negative
5	ATB3FGA	-0.028590	0.028590	Negative
6	TREB	0.027096	0.027096	Positive
7	AST	0.026620	0.026620	Positive
8	RAFGA	-0.023731	0.023731	Negative
9	C3FGA	0.002366	0.002366	Positive

Figure 28: Output for 2012-2019 Data

The coefficient measures the impact of the variable on the expected number of wins in a season. For example, a one-point increase in defensive rating (DEFRTG) would result in 1.174 less expected wins in a season for the 2005-2012 data. It is important to note that defensive rating measures the number of points a team allows over 100 possessions. By this logic, a one-point increase in defensive rating signifies a weaker defensive team.

The two variables that impact winning the most, based on the model, are defensive rating and pace. These variables are measured differently than the other seven, as defensive rating and pace are measured on a possessions basis, as opposed to season totals. For this reason, it makes sense that an increase in one of these variables would have a more profound impact on winning than the same increase in one of the season-total based variables. Defensive rating had about the same impact on winning for both datasets. Pace had a stronger impact on winning for teams in the 2005-2012 dataset than teams in the 2012-2019 dataset.

Turnovers had the strongest impact on winning out of the season-total variables, with the impact being negative for both datasets. Mid-range field goal attempts had a nearly identical negative impact on winning for both datasets. Corner three-point attempts had a negative impact on winning for the 2005-2012 dataset, and a positive impact on winning for the 2012-2019 dataset.

DISCUSSION

The initial trending analysis highlights the major focus of this paper. Shot attempts from the mid-range have consistently declined across the NBA over the past 14 years, with a significant plummet in mid-range shot attempts from the 2012-2013 season on. This analysis confirms the statistical decline of the mid-range, as well as the types of shot attempts that have replaced those mid-range shots. Above the break and corner three-pointers have both increased exponentially since 2012. On top of that, paint attempts outside the restricted area, which are typically floaters and short pull-ups, have increased over this time period, with a significant spike between 2016 and 2019. Restricted area field goal attempts, which include essentially only layups and dunks, have also increased marginally over the time period.

These trends are indicative of the league-wide change in offensive strategy between the two time periods. Numerous teams in the mid-2000s focused on playing through star players that thrived in the mid-range, including league leading teams like Tim Duncan's Spurs, Kobe Bryant's Lakers, and Paul Pierce and Kevin Garnett's Celtics. From 2012 on, teams evolved to create pace-and-space offenses that focused on shooting almost exclusively three-pointers and layups. Teams in this new era surrounded backcourt and/or wing stars with shooters, such as LeBron James' Heat and Cavalier teams, James Harden's Rockets, and Steph Curry's Warriors.

That said, not all teams enacted this new focus on three-pointers and layups to the same degree. Some teams, such as the Houston Rockets, fully embraced this analytics-based strategy, and almost completely removed the mid-range jump shot from their team offensive attack. The Rockets only attempted an astonishingly low 5.5% of their shots from the mid-range during the 2018-19 season (the league average was 15.2%). Other teams, such as the San Antonio Spurs, still heavily depended on the mid-range jump shot as an integral part of their team's offensive strategy. With Kawhi Leonard and Tim Duncan leading the team in the early part of the 2010s, followed by LaMarcus Aldridge and DeMar DeRozen in the latter part of the decade, the Spurs have structured their attack around their star players, who all excel as individual mid-range shooters. The Spurs attempted a league-leading 28.2% of their shots from the mid-range in the 2018-19 season. Despite their conflicting offensive strategies, the Spurs and Rockets are both top three in the NBA in wins since 2012, suggesting that there are ways to win with and without the mid-range shot.

The boxplots in the data findings echo this sentiment, as there were no major differences in mid-range frequency between teams with strong offenses and those with weak offenses. The highest ranked teams did shoot less mid-range attempts than low ranked teams, but the difference was not as profound as it was with other shot attempt types. This suggests that the decline of the mid-range is a league-wide trend regardless of team strength.

Corner three-point attempt frequency did vary by team strength. Top ranked teams attempted significantly more corner three-pointers than low ranked teams. The corner three-pointer, which is a shorter distance from the hoop than above the break three-pointers, is an asset of strong teams. As mentioned, many teams in the new era have focused on surrounding star players with shooters, and the corner is an essential spot on the court to place a shooter. When a player drives to the basket, the kickout to the corner is one of the easiest passes that player can make, so it makes sense that strong teams heavily rely on corner three-point attempts.

Additionally, over 90% of corner three-pointers are assisted. Teams in this era highly value three-point specialists, such as the Rocket's PJ Tucker, whose sole purpose on the offensive end of the floor is to stretch the floor by spacing to the corner.

Above the break three-point shooting also did vary by team. Teams with strong offenses heavily incorporate the above the break three into their offensive strategy, while teams with weak offenses do not attempt nearly as many of these threes. The above the break three is not strongly related to team rank, but higher ranked teams did shoot slightly more above the break threes than low ranked teams.

The league-wide shift to play at a faster pace certainly impacts the changes in shot distribution. Although pace by itself was not related to team rank, strong offenses played at the fastest pace when compared to weak offenses. Weak defensive teams also played at a higher pace than strong defensive teams. Logically this makes sense, as teams that allow a lot of points need to play at a faster pace so that they get more possessions and have a greater chance of outscoring their opponent.

The league-wide increase in pace and league-wide decrease in mid-range shooting are not coincidental. As teams have changed to play at a faster pace, they get out in transition more often, and have less possessions in the half-court. When out in transition, a player is more likely to attempt to drive all the way to the basket, pull-up for an above the break three, or kick out to a corner 3-point shooter. At the same time, players are less likely to take a mid-range shot when in transition, as that shot is more typical in a slowed down, half-court style offense. For the 2012-2019 data, pace was positively correlated with restricted area field goal attempts, above the break three-point attempts, and corner three-point attempts, but negatively correlated with mid-range attempts. See Appendix D for the correlations between pace and the five types of shot attempts.

The linear regression model gives an interesting look into the variables that impact winning in the NBA. For this model, defensive rank and pace were the two most important variables for predicting winning. This finding follows classic logic in NBA history: offense wins games, defense wins championships. Teams that play at a high pace attempt a lot of shots and therefore score more points, which translates positively to winning. That said, the most important variable to winning in the model is the strength of a team's defense. This model used defensive rating as a blanket metric to measure team defense, so additional research would need to be done to identify the specific factors that contribute to strong defense. It is important to note that the model simply suggests that defensive rating and pace are the biggest predictors of winning of only the nine variables tested. It showcases their importance relative to the other variables but is not meant to claim that they are the end-all-be-all predictors for team success in the NBA.

CONCLUSION

This paper sought to investigate the strategic shift away from the mid-range jump shot in the National Basketball Association in the last decade. The findings of the data analysis statistically confirmed the decline in mid-range jump shot attempts from the 2005-06 season through the 2018-19 season. The visualization tools also highlighted the rise in paint field goal attempts, corner three-point attempts, and above the break threes over the time period. Another main takeaway of the study is the relevance of pace of play in the shift in shooting behavior in the NBA in the past decade. Pace, which measures the number of possessions a team has a game, has increased league-wide over the time period, regardless of the strength of the team. The increase in pace signifies an increase in transition opportunities, in which teams focus on getting all the way to the basket for a layup or finding a shooter for an open three-pointer. The style of play of this new pace-and-space era differs significantly from that of the mid-2000s and heavily contributes to the decline of the mid-range jump shot.

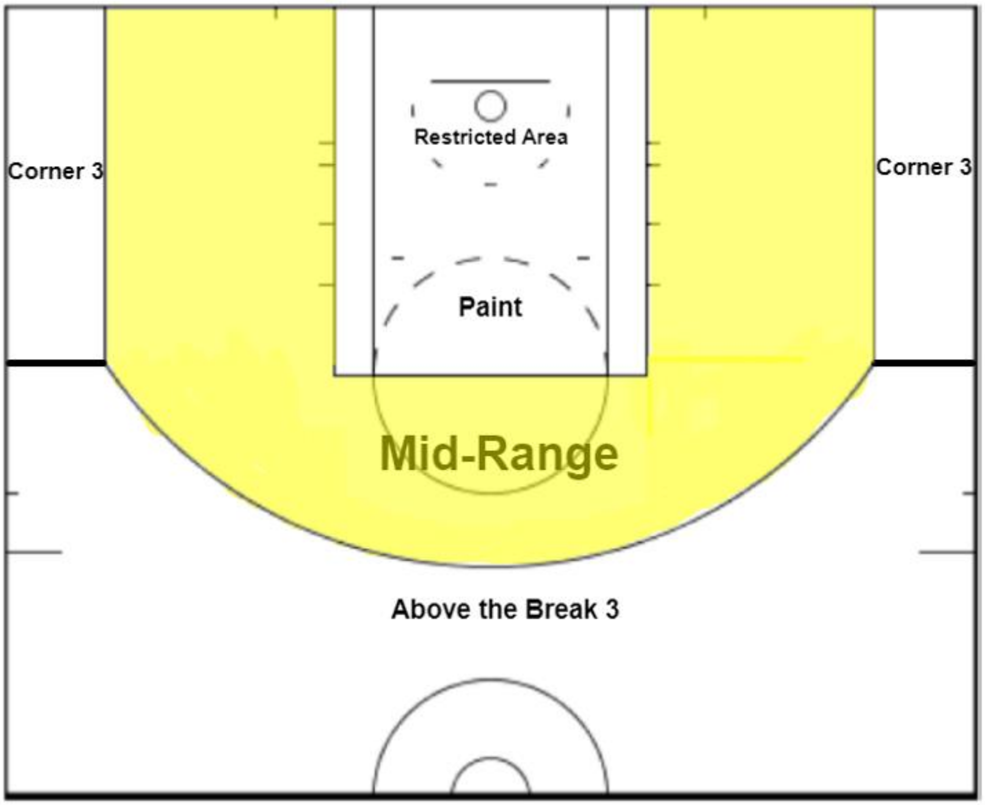
APPENDICES

Appendix A – NBA Database Snippet – 2005-06 Season:

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Year	GP	RAFGM	RAFGA	PFGM	PFGA	MRFGM	MRFGA	C3FGM	C3FGA	ATB3FGM	ATB3FGA	FTM	FTA	PF
8	2005-06	82	1529	2506	230	619	970	2472	111	339	237	716	1721	2312	1863
9	2005-06	82	1087	1793	235	589	1104	2723	183	455	374	994	1418	1950	1513
10	2005-06	82	1318	2195	274	775	723	1987	190	512	434	1303	1573	2190	1941
11	2005-06	82	1042	1815	347	850	852	2178	149	381	318	1019	1502	1980	1863
12	2005-06	82	1155	1963	294	753	801	2021	142	382	394	1143	1591	2158	1821
13	2005-06	82	979	1667	652	1345	1072	2589	74	195	216	633	1694	2142	1872
14	2005-06	82	1236	2076	377	853	826	2094	119	311	434	1260	1618	2172	1894
15	2005-06	82	1250	2089	288	810	619	1651	189	489	400	1078	1476	2077	1757
16	2005-06	82	1497	2264	406	1004	640	1649	168	422	327	1000	1616	2310	1871
17	2005-06	82	1336	2362	321	826	812	2044	166	409	341	923	1561	2115	1902
18	2005-06	82	1114	1868	317	730	1148	2803	79	192	230	728	1436	1895	1889
19	2005-06	82	1096	1947	272	707	934	2222	152	414	323	1011	1658	2187	1903
20	2005-06	82	1219	2164	330	885	982	2494	83	218	217	659	1649	2176	1786
21	2005-06	82	1392	2469	382	942	728	1910	135	344	185	525	1878	2587	2157
22	2005-06	82	1356	2296	300	762	957	2314	73	161	225	622	1663	2277	1908
23	2005-06	82	1312	2232	418	1019	897	2267	116	287	258	735	1770	2330	1712
24	2005-06	82	1233	1877	301	706	1060	2488	259	631	577	1455	1189	1475	1683
25	2005-06	82	1208	2057	303	806	917	2362	113	311	249	715	1339	1944	1828
26	2005-06	82	1176	1888	320	752	963	2448	130	363	365	1040	1704	2173	1672
27	2005-06	82	1305	2035	422	1053	744	1897	244	571	278	778	1327	1891	1714
28	2005-06	82	1193	2010	439	1013	840	2059	147	357	458	1252	1652	2104	1933
29	2005-06	82	1109	1913	349	811	949	2299	223	582	382	1021	1653	2089	1965
30	2005-06	82	1290	2222	250	676	892	2389	49	127	262	784	1774	2466	2032
31	2005-06	82	1279	2102	356	936	843	2226	92	262	405	1120	1889	2496	1855

P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD
PFD	OFFRTG	DEFRTG	AST%	AST/TO	PACE	OREB	DREB	TREB	AST	TOV	STL	BLK	Wins	Rank
1911	104.4	104.1	62.4	1.58	94.9	903	2486	3389	1921	1216	698	463	44	11.5
1710	109.3	101.7	66.1	2.12	87.98	975	2347	3322	1971	931	580	490	64	1
1918	103.5	104.9	57.6	1.47	94.43	980	2485	3465	1694	1156	604	356	34	22.5
1716	100.4	102.1	58.3	1.32	89.07	849	2565	3414	1580	1193	588	320	34	22.5
1800	103.1	101	58.5	1.3	90.85	898	2559	3457	1631	1254	598	409	41	15
1777	103.8	102.2	57.1	1.44	92.99	828	2704	3532	1708	1185	534	503	47	9
1925	106.8	104.2	58	1.52	92.22	970	2488	3458	1734	1143	628	350	45	10
1867	104.5	100.4	57.8	1.4	87.39	834	2379	3213	1586	1134	600	442	49	7.5
1938	107.5	103.4	55.7	1.43	92.56	858	2675	3533	1692	1186	522	442	52	5
1937	104.9	105.9	59.4	1.48	92.45	929	2448	3377	1769	1197	597	270	40	17
1736	101.5	103.5	59.4	1.44	89.58	811	2422	3233	1716	1189	559	471	33	24.5
1889	102.4	100.9	67.8	1.68	91.17	822	2539	3361	1884	1119	558	278	49	7.5
1910	102.3	105.1	53.7	1.39	90.32	918	2379	3297	1519	1095	611	311	38	18.5
2051	102.7	109.3	52	1.01	92.03	1033	2360	3393	1468	1449	555	271	23	29
1899	105.3	106.6	51.4	1.21	89.12	892	2402	3294	1495	1240	532	362	36	20
1898	104.7	106.5	55.1	1.43	93.91	873	2425	3298	1653	1159	651	404	38	18.5
1623	110.2	104.7	63.5	2	96.92	778	2650	3428	2179	1088	549	412	54	4
1704	99.7	110.3	53.4	1.24	88.88	886	2203	3089	1490	1205	529	435	21	30
1870	105.3	103.5	61.8	1.52	93.26	852	2473	3325	1825	1199	608	299	44	11.5
1689	106.2	98.7	57.4	1.52	89.41	851	2548	3399	1717	1126	543	467	63	2
1820	109.4	112.7	55.1	1.4	93.04	1013	2233	3246	1696	1208	622	306	35	21
1834	107.9	111.2	52.9	1.49	92.33	864	2291	3155	1593	1071	529	272	27	26
2104	102.4	105.1	64.6	1.37	89.4	1071	2380	3451	1772	1290	524	492	41	15
2053	107.7	105.8	51.2	1.33	93.68	1035	2344	3379	1523	1143	658	339	42	13

Appendix B – Visual Illustration of 5 Primary Shot Locations



Appendix C – Simplified NBA Database Snippet – 2005-06 Season:

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Year	GP	RAFGA	PFGA	MRFGA	C3FGA	ATB3FGA	DEFRTG	PACE	TREB	AST	TOV	Wins	Rank
4	2005-06	82	2306	797	2481	409	832	105.6	94.57	3260	1717	1167	26	27.5
5	2005-06	82	2031	769	2463	439	1023	102.7	93.59	3508	1804	1224	41	15
6	2005-06	82	2353	700	1894	553	897	104.4	90.77	3470	1560	1137	50	6
7	2005-06	82	1886	1101	2275	266	828	103.2	89.3	3461	1473	1112	60	3
8	2005-06	82	2506	619	2472	339	716	104.1	94.9	3389	1921	1216	44	11.5
9	2005-06	82	1793	589	2723	455	994	101.7	87.98	3322	1971	931	64	1
10	2005-06	82	2195	775	1987	512	1303	104.9	94.43	3465	1694	1156	34	22.5
11	2005-06	82	1815	850	2178	381	1019	102.1	89.07	3414	1580	1193	34	22.5
12	2005-06	82	1963	753	2021	382	1143	101	90.85	3457	1631	1254	41	15
13	2005-06	82	1667	1345	2589	195	633	102.2	92.99	3532	1708	1185	47	9
14	2005-06	82	2076	853	2094	311	1260	104.2	92.22	3458	1734	1143	45	10
15	2005-06	82	2089	810	1651	489	1078	100.4	87.39	3213	1586	1134	49	7.5
16	2005-06	82	2264	1004	1649	422	1000	103.4	92.56	3533	1692	1186	52	5
17	2005-06	82	2362	826	2044	409	923	105.9	92.45	3377	1769	1197	40	17
18	2005-06	82	1868	730	2803	192	728	103.5	89.58	3233	1716	1189	33	24.5
19	2005-06	82	1947	707	2222	414	1011	100.9	91.17	3361	1884	1119	49	7.5
20	2005-06	82	2164	885	2494	218	659	105.1	90.32	3297	1519	1095	38	18.5
21	2005-06	82	2469	942	1910	344	525	109.3	92.03	3393	1468	1449	23	29
22	2005-06	82	2296	762	2314	161	622	106.6	89.12	3294	1495	1240	36	20
23	2005-06	82	2232	1019	2267	287	735	106.5	93.91	3298	1653	1159	38	18.5
24	2005-06	82	1877	706	2488	631	1455	104.7	96.92	3428	2179	1088	54	4
25	2005-06	82	2057	806	2362	311	715	110.3	88.88	3089	1490	1205	21	30
26	2005-06	82	1888	752	2448	363	1040	103.5	93.26	3325	1825	1199	44	11.5
27	2005-06	82	2035	1053	1897	571	778	98.7	89.41	3399	1717	1126	63	2
28	2005-06	82	2010	1013	2059	357	1252	112.7	93.04	3246	1696	1208	35	21
29	2005-06	82	1913	811	2299	582	1021	111.2	92.33	3155	1593	1071	27	26
30	2005-06	82	2222	676	2389	127	784	105.1	89.4	3451	1772	1290	41	15
31	2005-06	82	2102	936	2226	262	1120	105.8	93.68	3379	1523	1143	42	13

Appendix D – Pace Correlations:

	A	B	C	D
1	x1	x2	Correlation (2005-2011)	Correlation (2012-2019)
2	PACE	TOV	0.387357059	0.221873931
3	PACE	RAFGA	0.445988917	0.46653575
4	PACE	PFGA	0.046746199	0.202867309
5	PACE	MRFGA	-0.180338473	-0.59897789
6	PACE	C3FGA	-0.014619506	0.350158562
7	PACE	ATB3FGA	0.472281561	0.697157214
8			NOTE: 2011-2012 season EXCLUDED	

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