Moneyball to Moreyball: How Analytics Have Shaped the NBA Today

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Abstract

Moreyball is the concept of emphasizing three pointers and points in the paint over mid-range shots on offense, while forcing mid-range shots on defense. Understanding this concept is crucial not just for front office personnel, but the players and the coaches of the NBA. This research explored whether or not Moreyball accurately predicts success in the NBA. The methodology used multiple regressions between specific NBA statistics and the Win/Loss record of NBA teams. The results of this research showed that on its own, the main statistics of Moreyball were significant in predicting team success in the NBA. However when additional statistics were included, the strength of the model increases, demonstrating there is more than just the Moreyball variables that contribute to team success.
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The NBA is a league that has undergone many changing philosophies on both offense and defense. Over the decades there are many instances that show a change in how the game is played. Whether it is the installation of the three point line, or the introduction of the hand-check rule, the NBA has undergone many transformations since the league was formed in 1949 (Steca, Pala, Greco, Monzani, & D'Arrario, 2013). Defense in the NBA has shifted almost as much as offense in the NBA, and it is important to understand how these fads affect the league, and the success of the teams as well. The athletes in the NBA are stronger, quicker, and more athletic than their earlier counterparts (Mangine, Gonzalez, Jajtner, Scanlon, Rogowski, & Stout, 2014).

A transition from interior offenses to perimeter-based offensive game plans has caused a dramatic shift in the shot selection of players in the NBA, and as a result, new philosophical models have been created to benefit from this change. The concept of Moreyball has become the newest concept in the NBA, derived from this new-age, perimeter game, and the mastermind behind it is Daryl Morey, currently the Houston Rockets General Manager. His philosophy revolves around the idea that taking as many three point shots as possible, as well as many shots as possible close to the rim are the recipe for offensive success (Caporale & Collier, 2015). The defensive concept of Moreyball is centered on the idea of having a strong, interior defensive presence, and promoting the perimeter defenders to force their assignments to take mid-range jump-shots, statistically proven as the least efficient shot in basketball (Caporale & Collier,
2015). Doing so will reduce the chance of the opposing team taking three point shots or shots close to the rim.

The core concepts of the literature, which are analytics, factors influencing individual success and factors influencing team success allow a foundation of knowledge to understand the many complexities of the NBA. The research method used will give the reader a concrete understanding of the data collected and analyzed, allowing observations that can be drawn and discussed. The intention of this research is to educate the reader and enhance their knowledge on the current state of analytics in the NBA, and the potential for growth of analytics as well. What this research looks to answer is: does Moreyball accurately predict the success of NBA teams?

**Literature Review**

The use of new, advanced analytics in the NBA has proven quite useful, however they are not the end-all when it comes measuring success. A myriad of factors influence success in the NBA, and they extend further than just emphasizing threes and dunks on offense, or tilting the defense towards whatever side the other team’s best offensive players is standing (Bartholomew, & Collier, 2012). There are factors that influence the success of both the team and the individual.

Understanding the factors that influence both individual and team success is important because doing so can assist teams in pinpointing where a problem may exist on the team. According to Aicinena (2013), a good coach has the ability to understand that there will be outside variables affecting his/her team. Also, a good coach will not lose themselves
emotionally because of those variables, however a good coach will not ignore the outside variables that exist (Leite, Coelho, & Sampaio, 2011). Understanding the multiple variables influencing individual and team success is critical, as well as their positive and negative interactions.

**Analytics**

The increased literature on analytics in the NBA has opened the door for more tools to be used in the evaluation of players and teams. Wallace, Caudill, & Mixon Jr. (2013) were able to provide evidence that disproves the notion that NBA players elevate their level of performance in the playoffs, specifically during the fourth quarter, which is referred to as “crunch time”. Using the 2011 NBA playoffs as the source of data, Wallace et al. (2013) arrived to the conclusion that NBA players do not raise their performance levels in the fourth quarters of playoff games, but in fact their level of playing actually decreases in the fourth quarter compared to the first through third quarters of playoff games. Such a realization is compounded when you stop to consider some of the names that were measured in the 2011 playoffs: Tim Duncan, LeBron James, Kevin Durant, and Dirk Nowitzki to name a few. A common notion tied to these and several other superstars that participated in the 2011 playoffs is their ability to raise their performance levels in the fourth quarters of playoff games, however Wallace et al. (2013) were able to disprove this myth. Such a revelation will not change the opinion that diehard fans may have of these players, but when it comes to decision making by coaching staffs for and against these players, keeping this in mind can completely alter the game plan previously drawn up by the head coach.
This builds on the research conducted by Koehler and Conley (2003) regarding the debunking of the “hot hand” myth. Using the annual Three Point Contest held in the NBA and coding that is designed to alert the observers when an announcer makes a reference to the state of the athlete, Koehler and Conley (2003) came to the conclusion that shooters made a high percentage of their shots before the announcement that “X player is on fire!” However, their shooting percentages drop dramatically after the proclamation of their present state (“hot” or “cold”). Although this study is limited by the fact that it only observes the Three Point Contest, the contest itself was created for the NBA players that specialize in the three point shot to showcase themselves against others of the same mold, to compare who can stay hot the longest. Which is an interesting statement to say now that the whole idea has been disproven.

An example of defensive metrics comes from Csapo and Raab (2014), in which they measure the effect of defensive pressure on players that are considered to be on a “hot/cold streak.” Although the idea of the “hot/cold hand” is considered to be a myth, Csapo and Raab simplify it to a player that connects on consecutive shots or misses on consecutive shots. Csapo and Raab (2014) conclude that as a player hits more shots, the shot difficulty increases as the defensive pressure increases, and that a player will then miss more shots because of the increased defensive pressure. Also, when Csapo and Raab (2014) take into consideration field goal percentage, the offensive player’s performance is not increased during “hot streaks.” Together, the research of Csapo and Raab (2014), Koehler and Conley (2003), and Wallace, Caudill, &
Mixon Jr. (2013), we see a shift in the reality of the NBA, from a league dominated by stars going on “hot streaks” to a league that is educated as to why players seem to “raise their level of play.”

As a result, these pieces of literature can be used by coaches to preach to their teams to not lose focus when an opposing player strings together a few successful shots. A common occurrence in the NBA is when a superstar player is able to hit a few shots in a row, and on the following possession, the defender becomes too overzealous and overextends themselves, giving the offensive player an opportunity to bypass their primary defender and look for a high percentage shot, a theory reinforced by Koehler and Conley (2003).

However, these examples of advanced analytics are leaving out an area that has become highly desirable for measurement: defensive metrics. In the NBA, Blocks and Steals were the only concrete pieces of statistical information that measures a player’s defensive abilities. According to Franks, Miller, Bornn, & Goldsberry (2015, p.1), “While steals, blocks, and rebounds do provide some useful proxies for defensive skills, they represent small discrete signals within the perpetual broadcast of defensive play.” The work of Franks et al. (2015) resulted in five brand new defensive metrics: (1) Volume Score, which is the total magnitude of attempts a defender faces, (2) Disruption Score, defined as the degree to which an individual defender is able to reduce the effectiveness of his assignment’s shots, (3) Defensive Shot Charts, similar to shot charts, but for a visual depiction of an individual’s defensive prowess; both Volume Score and Disruption Score are mapped across the scoring area, (4) Shots Against,
described as a weighted average of the shots attempted against the defender per 100 possessions, and finally (5) Counterpoints, depicted as a weighted average of points scored against a particular defender per 100 possessions.

When these new metrics are put to use by Franks et al. (2015), we can see a clear image of a specific defender. For example, Kwahi Leonard, a small forward for the San Antonio Spurs, is establishing a reputation as one of the top overall defenders in the NBA today, and is a player analyzed using the new metrics of Franks et al. (2015). Kwahi Leonard’s Defensive Shot Chart shows the viewer a top-notch ability from Leonard to suppress the amount of three point shots against him, as well as a low-percentage of shots made against him as well from three point range (Franks et al., 2015). In fact, Leonard suppresses three point shots to the point where he actually faces a higher amount of mid-range jump shots than three point shots, when three point shots are being taken at an all-time high rate (Shortridge, Goldsberry, & Adams, 2014).

Another prominent NBA defender that is measured using the newly created defensive metrics of Franks et al. (2015) is the starting center for the Indiana Pacers, Roy Hibbert. For instance, he leads the league in the Shots Against metric. Also, the third ranked player for Shots Against is Ian Mahinmi, his backup. Furthermore, Indiana Pacers starting power forward David West is dead last in Shots Against. What kind of a story does this tell us? A reasonable conclusion we can draw from this is that Indiana Pacer’s Head Coach Frank Vogel’s defensive philosophy is centered on funneling the other team’s players towards their rim protectors in Hibbert and Mahinmi, based on the evidence provided by Franks et al. (2015). In conclusion,
the analytics provided by Franks et al. (2015), and Shortridge et al. (2014), demonstrate the potential growth of defensive metrics and how they can be interpreted by players, coaches, and management.

Kirk Goldsberry, a former professor from Michigan State, has teamed up with other specialists looking to create advanced metrics for the NBA, with a focus on the defensive end. In their paper titled *The Dwight Effect: A New Ensemble of Interior Defense Analytics for the NBA*, Goldsberry and Weiss (2013) use SportVu cameras in the arenas that have them and observed seventy five thousand NBA shots during the 2011-2012 and 2012-2013 seasons to create “spatial splits” for each NBA player. For example, Goldsberry and Weiss (2013) found that the frequency of the league average when shooting from inside, mid-range, and three point range to be: 35/41/24, with an efficiency from each area to be: 53/39/36. What these numbers tell us is that although the average NBA player only took 35% of their shots in the paint, they converted 53% of those shots into points, while they took 41% of their shots from mid-range and converted 39% of them, and 24% of their shots from three point range, converting 36% of them.

After arriving to these numbers, Goldsberry and Weiss (2013) used them to create new statistics to show the effectiveness of interior defenders in the NBA, from how they affect the field goal percentage of the offensive player to how they affect the location of the offensive player’s shot. The resulting information revealed that although Dwight Howard may not have the lowest field goal percentage against in the league, he lead the league in a statistic Goldsberry and Weiss call “The Dwight Effect,” which is the ability of the interior defender to prevent shots
close to the rim. When a defender was within five feet of the basket, the NBA average was 57.2% of shots taken close to the rim, but when Dwight Howard was on the floor, that number plummets to 45.7%, an 11.5% drop in efficiency. A statistic such as this can be utilized when coaching players, according to Ross-Stewart, Short, and Kelling (2014), who found that coaches that used some form of imagery were able to lessen the difficulty of certain concepts in basketball to their players. Doing so can make the transition from different strategies during a game much smoother for both coaches and athletes.

Analytics can also assist in reaffirming previous strategies in coaching. For example, Bartholomew and Collier (2012) examine the potential benefits of forcing ball handlers to their non-dominant side. As expected, the offensive player’s field goal percentage experienced a drop when forced to their weak side, as well as points scored, and assists as well, however, drawbacks do exist; according to Bartholomew and Collier (2012), while forcing the offensive player to their weak side is helpful, if it inhibits on the team’s ability to rebound a missed shot or if it interferes with defensive steals, then the team must pick and choose when to do so.

In conclusion, these new analytical tools are now available thanks to the advances in technology available to teams today. There were some limitations, since some of the arenas were not equipped with SportVu cameras in them when research was conducted. However, as NBA teams continue to implement the use of SportVu cameras, further research will be able to use this available data for all teams. Using these newly accessible tools helps eliminate some of the gray area when it comes to player/team evaluation, not just internally, but externally as well,
meaning these tools can be used to evaluate players on other teams as well. This opens doors
that lead to more than just player evaluation. What if a team is looking to compare one of their
players during contract negotiations, and they are looking for a comparable player to analyze and
determine whether the player deserves a large raise or a minimal one at best? Being able to go
beyond the basic box score statistics we see every day helps teams and players alike in
determining the true value of that player, which means utilizing these new tools for financial
management as well, not just the on-court production. Although statistics help to explain how
overrated or underrated a player can be, there are also factors that impact how successful the
individual athlete can be.

Factors Influencing Individual Success

An important concept that has a large impact on individual success is injuries. Injuries
are not just an important factor in basketball, but for all sports as well. Athletes are to be in peak
physical and mental state, according to Mangine, Gonzalez, Jaijtner, Scanlon, Rogowski, and
Stout (2014). However strong an athlete may be, injuries are an unavoidable aspect of sports,
with little to no indication on when they may occur, an observation made by Aicinena (2013).
Also, according to Gomes de Araujo, Manchado-Gobatto, Papoti, Camargo, and Gobatto
(2014), NBA players suffer the highest rate of injury to their lower extremities compared to
other sports such as football, baseball, and hockey. The literature revealed that even the most
physically fit athletes will always be susceptible to injury.
Kevin Durant, a former Most Valuable Player on the Oklahoma City Thunder is a good example regarding the uncertainty of injuries. Until the 2014-2015 season, Durant had played in 542 out of a possible 558 games, all starts (Durant, n.d.). A reasonable conclusion that can be drawn from that statistic is that Kevin Durant is an incredibly durable player. However, during the 2014-2015 season, Durant suffered multiple injuries to his lower extremity, an area with a high volume of recorded injuries to basketball players (Podlog, Buhler, Pollack, Hopkins, & Burgess, 2015). After suffering a Jones fracture in his right foot, a rolled right ankle, and a sprained right big toe, he had season ending surgery on his right foot to alleviate the Jones fracture, resulting in him playing in only 27 games for the season. Based on research conducted by Mangine, et al., (2014), this random spurt of injuries more than likely arose from a weakened limb (Durant’s right foot), combined with a heavy workload, as Durant had averaged 38.2 minutes from his rookie season in 2007 to 2014 (Sports Reference LLC., n.d.). An unfortunate situation where an athlete who had missed fewer than 8 regular season games had to endure an injury riddled season.

A second factor that influences individual success is the health of the player. According to Leite, Coelho, and Sampaio, (2011), if a basketball player is playing and they are physically exhausted, they will have a higher chance for injury since their bodies are not used to such stress. In other words, basketball players have to build their stamina to handle the stress of a basketball game, and it starts with proper aerobic training before practicing the fundamental aspects of basketball. Also, research conducted by Gomes de Araujo et al. (2014) indicates that because of
the size range of basketball players, the level of aerobic training will vary. Centers, Power Forwards, and Small Forwards are larger than Shooting Guards and Point Guards, therefore they will have a different aerobic training schedule compared to that of guards. Big men have to be able to train themselves to hand the grind of battling in the post, whereas guards have to be able to play on the perimeter, requiring a lot of quick movement and direction change (Drinkwater, Pyne, & McKenna, 2008). Appropriate aerobic training is necessary to promote strong fitness as well as building the appropriate physical structure to handle the rigor of the positions each player normally plays.

Another area that can influence individual success is team success. Research conducted by Yang and Shi (2011) showed that players considered to be a “rising star” (p 361) achieved such status at the quickest rate when both the individual and the team were successful. The “rising star” label is also associated with All-Star appearances, since All-Star appearances are based on fan voting (Yang & Shi, 2011). An important distinction discovered because of the research from Yang and Shi is that although individual success is an important factor in achieving “rising star” status, winning a championship provides players the best chance to display their abilities to the world, and therefore tabbed a “rising star.” Players such as Kwahi Leonard and Klay Thompson, young players on elite NBA teams have a noticeable advantage when it comes to acquiring the “rising star” label compared to players such as DeMarcus Cousins and DeMar DeRozan face an uphill climb when it comes to achieving the same status because of their teams’ lack of success (Aiken, Campbell, & Koch, 2013).
A fourth factor that had thought to have been an indicator of individual success was compensation. However, according to Bern, Brook, and Schmidt (2007), NBA players observed in a study from 1995-2005 showed little to no variation on whether pay inequalities affected their level of play. This may be a result of the additional revenue streams available for athletes in today’s world, where endorsements, sponsorships, and shoe brands such as Nike and Jordan sometimes pay the athlete more than their actual NBA contract (Yang & Shi, 2011). Instead, the research revealed that when a player is playing on a team that consists of highly paid players, the individual athlete raises his play in an attempt to justify his spot on the team (Bern, Brook, & Schmidt, 2007). This is also true in the opposite situation. If a player is on a team of players that are paid below market average, then the individual players will put forth only the necessary effort to maintain their spot on the team, rather than justify it by performing to the best of their abilities (Bern, Brook & Schmidt, 2007). This research was also used by Simmons and Berri (2011) when discussing the justification of pay inequality in the NBA. What Simmons and Berri (2011) found was that pay inequality was favorable in the NBA, as players believe that to earn the most amount of money possible, they must perform at their best to do so.

For example, the 2011-2012 and 2012-2013 Miami Heat Championship teams were made of a three-headed monster of LeBron James, Dwayne Wade, and Chris Bosh. All signed at slightly below maximum contracts, and the rest of the roster filled with players either finishing their rookie contracts, or veterans signed for the veteran’s minimum outlined in the Collective Bargaining Agreement (Sports Reference LLC, n.d.). Since the team had three of arguably the
best players in the league, the other players on the team raised their individual levels of play in order to justify their existence on the team, and the result was back-to-back NBA championships. However, even though the individuals on those Miami Heat teams raised their personal levels of play, there are many factors that influence the overall success of NBA teams as well, which will be discussed in the following section.

**Factors Influencing Team Success**

Team success takes into account the abilities of the players on the team, and combines them with the competency of the coaching staff to help generate wins, which lead to playoff appearances and hopefully NBA championships. This research looks to discuss the factors listed below, and hopefully serve as a resource for future measurements of factors that affect team success.

A common factor that has a hand in team success is the ability of players to positively interact with each other on the court, as well as the ability of teammates to interact with new players on the team. According to De La Torre-Ruiz and Aragón-Correa (2012), not only does the prior performance of the newcomer affect how the team may succeed or fail, but the prior performance of the current team members as well. De La Torre-Ruiz and Aragón-Correa (2012) found that a newcomer’s ability to adapt to the team can be stalled if the current members of the team already have strong prior performances playing together.

The existence of this phenomenon is best explained through the interdependence of team tasks, a concept examined by De La Torre-Ruiz and Aragón-Correa (2012), and briefly
discussed by Bern, Brook, and Schmidt (2007). The interdependence of NBA teams means that the players understand that they must develop a positive chemistry between each other, as doing so helps the offense run smoothly and assists in strengthening the team defense as well. When a newcomer is added to the equation, this disrupts that level of team chemistry. According to Bern, Brook, and Schmidt (2007), when the newcomer is factored into the team equation, it acts as a reset button for the level of team chemistry. If player X prefers to cut baseline without the ball on a certain offensive set, but new player Y prefers to fake a cut on the baseline, a consequence could be a pass that sails out of bounds for a turnover, because the primary ball handler was anticipating player Y making the full cut that player X normally takes. An intimate level of teammate chemistry has essentially been reset, as the pre-existing players on the team must combine their games with the newcomer as well, a process that may cost the team early wins in the regular season (Maymin, Maymin and Shen, 2013).

Another factor that can influence team success is coaching. According to Bern, Leeds, M.A., Leeds, E.M., and Mondello (2009), coaches such as Phil Jackson and Gregg Popovich, widely regarded as two of the greatest coaches in NBA history have a distinct advantage over the field. The problem however, occurs when it comes to separating the field based on the research by Bern, et al. (2009). According to their research, although coaches such as Larry Brown, Gene Shue, Chris Ford, Kevin Loughery, and Isiah Thomas had positive effects on player development on the teams they coached, only Larry Brown has an NBA championship to show for it. All five coaches were able to post success when it came to player development, but the
other four posted lifetime losing records, showing that they were unable to transfer their player
development benefits to on-court success (Bern, et al., 2009). This proved true for the coaches
who are considered better than the average NBA coach as well. The research of Bern, et al.,
(2009) showed that the effect of a player going to play for a new head coach such as Phil
Jackson resulted in an increase in that player’s performance, but at a 95% confidence interval it
was proven to be only slightly above the lowest ranked coach (Larry Brown) that had a positive
effect on players coming to the team.

In order to further understanding the concept of coaching affecting team success, we
must observe the Chaos Theory of Sports from Aicinena (2013). This theory states that coaches
must understand that although many aspects have become measurable via advanced statistics in
today’s modern age, there will always be grey areas that are unmeasurable. Aicinena (2013)
explains how smart coaches must understand that luck is a factor in sports and is uncontrollable,
as is the chaos/unpredictability of sports itself, as well as the human error that comes in to play
not just with athletes, but officiating as well. With all sports implementing some form of replay,
there are still cases where human error impacts officiating, which can greatly affect a game, or
affect with minimal impact. There are variations of the Chaos Theory, in particular the “luck”
aspect.

A variation of the “luck” aspect of the chaos theory proposed by Aicinena (2013) can be
seen through the research of Bern et al. (2009), when they discuss the credentials of Phil Jackson
and Gregg Popovich. Bern et al. (2009) propose that although both coaches have won several
championships and many regular season games as well, they both fell into very unique positions. Jackson was able to coach Michael Jordan, and then when he went to the Lakers he had Shaquille O’Neal and Kobe Bryant, and in Popovich’s case, he was able to coach David Robinson, and then Tim Duncan. All of these players are regarded as some of the greatest players to ever play in the NBA. This would be considered a characteristic of luck, in which the coaches benefited from teams that had young superstar talent before they arrived (Bern et al., 2009). Jackson and Popovich realized this and used it to their advantage, which resulted in many successful seasons for both the coaches and the teams as well.

A third potential factor of team success is the idea of home advantage. The research conducted by Swartz and Arce (2014) ranged from 1979-1980 to the 2011-2012 season of the NBA. The lower scoring rates were correlated by Swartz and Arce (2014) to home team advantage to show that as the years passed, officials scaled back their bias, reducing the number of scoring chances for the home team. They concluded that this occurrence may be due to reduced officiating bias as well as lower scoring rates as time progressed. Yubo, Hilsman, Caudill, and Mixon, (2014) discover that the bias shown towards home teams has decreased as the NBA has progressed from its inaugural season in 1949 to today. The research conducted by both Swartz and Arce (2014) and Yubo et al. (2014) also indicates that teams that play at higher elevation, which included the Denver Nuggets and Utah Jazz actually had home court advantage. Although the home records around the league have declined, the Nuggets and Jazz have had more consistent home records over time. Players traveling to either of these arenas most likely
struggle due to their bodies not adjusting to the higher altitudes, a reminder of the importance of good physical health for the athletes (Robazza, Gallina, D'Amico, Izzicupo, Bascelli, Di Fonso, & Di Baldassarre, 2012). This research however, only took into account regular season games. O’Reilly (2011) examines the concept of home court advantage in the playoffs. The end result was a highly significant relationship between home court advantage and wins in the playoffs as the NBA has aged over time from its first season in 1949. Although home court advantage has lessened in the regular season, the playoffs have proven that in order to achieve success in the postseason, teams must do their best to accomplish home court advantage.

The literature provided a plethora of concepts and theories of the many variables NBA teams must deal with. From the development of analytics to the examination of home court advantage, sports teams are constantly trying to find something they can use to beat the competition, although whatever it is, teams have yet to figure it out. New trends hit the league, and although they may be a new method previously unknown, teams are hoping that whatever they find can be used to increase their success in the NBA. However, in this study we will examine and analyze the impact of this research for on-court production purposes only, and we will tie it together with the newest fad sweeping the NBA: Moreyball, or simply put, the emphasis on three point shots and points in the paint, thereby de-emphasizing mid-range shots on offense. Defensively, this concept revolves around the concept of suppressing three point shots, emphasizing mid-range shots, and contesting or preventing shots in the paint. What this research looks to answer is: does Moreyball accurately predict the success of NBA teams?
Method

Subject Characteristics

For the characteristics of the subjects being examined, this research used the information from the 2014-2015 NBA season. In order to remove any bias, every team in the NBA was used for this process, to ensure the entire league is appropriately represented in this study. Using the most recent season gives the most updated state of the league and whether or not there may be a growing trend of shooting three point shots in the league. For this research, there will not be any past seasons included, as it is too difficult to find the first year where Moreyball may have started to gain traction in the league.

Operationalization of Variables

This statistical analysis included points per game, points allowed per game, turnovers per game, three point percentage, field goal percentage from zero to ten feet from the basket, opponent three point percentage, opponent field goal percentage from zero to ten feet from the basket, and the win/loss record of each team (Sports Reference LLC., n.d.). For this research, we are considering field goal percentage from zero to ten feet from the basket since the official width of the key in the NBA is sixteen feet wide, with the two-foot wide foul lanes increasing it to a ten foot radius to the basket from each baseline (Sports Reference LLC., n.d.). All totals will be for each team as a whole, and the data in this research is measured by a ratio scale of measurement, and the data will be rounded to one thousandth of a decimal point, since that is the rounding used by the database (Sports Reference LLC., n.d.).
Points per game, points allowed per game, and turnovers per game were included into the analysis as well. The reasoning for this was that this research wanted to include the factors of Moreyball that were discussed, but to also account for factors that others could potentially claim as factors influencing team success. In order to figure out what potential variables should be included, this research asked a basic question to general and highly interested basketball fans: “What statistics do you associate with a team that would have a high winning percentage?” Once we believed that we had enough variables, we included them into both the Excel Spreadsheet and SPSS as well. Such a small sample size of thirty two teams over one season does affect the results of this research, so in order to try to account for this, we used these additional variables to be used as controls on our data. These variables were selected to act as a guard against potential skeptics to this research who may view those variables as important factors in determining success in the NBA.

Data Entry Protocols

The IBM SPSS program was used to organize the information and prepare it for statistical analysis, since this program is capable of running the appropriate measurements this research is looking for. Using Microsoft Excel, the data was copied from basketball-reference.com onto a spreadsheet in order to use the features of Excel to organize the data before inserting it into SPSS. Each row represented each NBA team, and with the columns representing the statistics for each team.

Once organized on Excel, the data set was transferred to SPSS. Under the “TeamName” section of the Variable View, each team was coded simply by each team name, since they are easy to distinguish from one another, making it pointless to code them in any other manner. This
way, each team can be easily distinguished from each other so there cannot be any misinterpretation of the data. All variables were coded in order to comply with SPSS settings.

Data Analysis Plan

For this research, a significance level of .05 was used when analyzing results, meaning our research displayed a 95% confidence level. If at any point our measurements were above the .05 significance level, but lower than .1, this research still evaluated the data even though it may not have had a .05 significance level, since it still showed a strong relationship to our data.

Several descriptive and inferential statistics were used in order to discover some form of a connection with the data. For descriptive statistics, we used the mean, along with the maximum and minimum of each independent variable, as well as the standard deviation of each variable.

The inferential statistics that were used were a single regression as well as a multiple regression. Regressions are used to see if variables can be used in order to predict potential outcomes. Using a multiple regression means that we were looking to see if the ideas of Moreyball can be used to predict future team success, and again, we are looking for a statistically significant result to prove that it can predict team success.

Results

The purpose of this research is to see if it is possible to answer the question of whether Moreyball can accurately predict success in the NBA. Using the IBM SPSS program, this research was able to generate data that can be used in the discussion of Moreyball and its implications in the NBA. In this case, although our research did in fact show that Moreyball had
a strong connection to team success, however it does not mean it is the only predictor of team successs.

The descriptive statistics used in this research were the mean, as well as the minimum and maximum number of each data set. For example, in the category of “PTSinPaint,” the minimum is .455, and it has a maximum of .549, with a mean of .50610 (See Appendix A). A basic interpretation of this data is that the lowest field goal percentage from zero to ten feet from the basket from the previous season was 45.5%, while the highest percentage from that distance was 54.9%. The mean of .50610 represents the league wide average field goal percentage from zero to ten feet from the basket, which was 50.6%. An important reminder is that points per game, opponent points per game, and turnovers per game are all whole numbers, simply meaning that the value in the data tables do not need to be converted from a percentage.

Once the descriptive statistics were established, inferential statistics were also used through SPSS. Using a multiple regression, this research was able to see if the core concepts of Moreyball were accurate predictors to winning percentage in the NBA. To refresh, the independent factors in Moreyball are field goal percentage from zero to ten feet, three point percentage, opponent field goal percentage from zero to ten feet, and opponent three point percentage as well. Looking at Appendix B, we can see that Moreyball has a strong case when it comes to the influence it has on winning percentage, especially with an $R^2=.86$. However, when doing a multiple regression with these variables as well as the additional variables, which includes points per game, opponent points per game, and turnovers per game, we are provided with a brand new table (Appendix C), and this table yields even better results with an $R^2=.965$. 
These factors were included to assuage the average NBA fan who may believe the additional variables have a substantial impact in predicting success in the NBA.

**Discussion**

After running the calculations in SPSS, the overall concept of Moreyball was shown to be a major predictor of team success in the NBA. The four main factors of Moreyball, (field goal percentage in the paint, three point percentage, and opponent percentages from those areas) had a high with the least significant factor being team three point percentage, with a significance value of .006, as well as an $R^2=.86$ (See Appendix B). However, there are many other statistics that come into play when discussing team success, hence the inclusion of points per game, opponent points per game, and turnovers per game. Although these variables were included, these are not the only variables that could have been used in this research.

When the additional variables were present in the multiple regression, the data showed that team three point percentage hardly mattered, as well as opponent points in the paint, with each variable scoring a significance values of .980 and .716 respectively. Also, turnovers per game also had a .720, meaning these three variables meant very little when determining team success with these other factors included in SPSS. Points in the paint (.078), points per game (.000) and opponent points per game (.000) all had significance values that could be justified to be used in discussion, while opponent three point percentage was just on the fringe at .130. Also, the new model had an $R^2=.965$, meaning the newer model could explain more of the data in comparison to the Moreyball model (Appendix B&C). With the data collected from both descriptive statistics and multiple regressions, we can go a step further in showing how this data can be used.
What makes SPSS so useful is that it allows for further analysis using descriptive statistics in unison with inferential statistics as well. Let’s use the minimum and maximum data values for points in the paint, which are .455 and .549 respectively. Looking back at the multiple regression table with all independent variables included we see that points in the paint has a B value of .833. If we multiple the B value by both the minimum and maximum numbers, we get .379015 and .457317 respectively. If we subtract the minimum value from the maximum value, we get .078302. So what in the world does that number mean to us? This number indicates that if the team with the lowest field goal percentage in the paint from zero to ten feet increased it to the best team’s percentage, their winning percentage would increase by 7.8%, as shown by Appendix D. A negative percentage means that if the team who gave up the lowest three point percentage at .322 were to regress and allow opposing teams to shoot .38, then their winning percentage could drop by 7.6%. This can be done for any of the independent variables, since descriptive statistics were used on all independent variables.

These results should be explored more closely by coaches and general managers. Each year, there are always teams in the NBA that struggle and end the season with a bad record. When they look back on the season, they are going to be interested in the areas they struggled with, and the areas they found success. If teams were to utilize this research, they could copy this model to include variables that they are looking to see how they affect the bottom line, which is winning percentage. Although this research is not the one true answer to improving winning percentage, it gives teams a foundation to work with,

*Limitations and Direction for Future Research*

This research is not perfect. There are issues that could have a hand in the potential of this research skewing data, however minimal it may have been. Researcher bias is in play with
this research, since the additional variables were included in an attempt to think with the mindset of the average NBA fan. To enhance this research in the future, surveying GMs and coaches in the NBA could be done to decipher what additional variables could be included or excluded in any future research. If this research were to be done differently, perhaps Blocks and Steals could be included as well while excluding some statistics as well. If there are too many variables included, then you run the risk of presenting data that may appear to be definitive, but is actually misleading. This research did not include any advanced statistics, only using basic NBA statistics for comparison. Advanced statistics have been increasing in popularity, but this research looked to use statistics that were simpler to calculate and integrate into SPSS for comparison and analysis.

A final limitation was that this research only explored one season of data. If multiple seasons were to be used, a new question would arise: What year did Moreyball officially come into play for all thirty two teams? A nice aspect of this research is that these numbers can all be plugged into SPSS to calculate new findings that can be compared to these and any other efforts as well.

**Conclusions**

This research looked to see if Moreyball can accurately predict success in the NBA. On its own, the four variables of Moreyball were great indicators of team success in the NBA, but those alone were not statistically significant in a multiple regression to demonstrate great confidence in that model. However when additional variables were included in the calculations, the data showed that Moreyball lost a significant amount of importance when considering only a few additional factors. However, this may not be the case if other variables were included. This research is an additional stepping stone that could lead to the answer that people in the NBA are
looking for: What predicts success in the NBA? Although this research may not have made the
final call on that topic, hopefully it will spur future discussion and attempts at doing so.

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Appendix

Appendix A

Descriptive Statistics on Independent Variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>PTSinPaint</td>
<td>0.455</td>
<td>0.549</td>
<td>0.5061</td>
</tr>
<tr>
<td>FGPerct3P</td>
<td>0.318</td>
<td>0.398</td>
<td>0.3491</td>
</tr>
<tr>
<td>OppPTSinPaint</td>
<td>0.48</td>
<td>0.558</td>
<td>0.5063</td>
</tr>
<tr>
<td>Opp3PointPerct</td>
<td>0.322</td>
<td>0.38</td>
<td>0.3499</td>
</tr>
<tr>
<td>PPG</td>
<td>91.9</td>
<td>110</td>
<td>100.02</td>
</tr>
<tr>
<td>OppPPG</td>
<td>94.9</td>
<td>106.5</td>
<td>100.01</td>
</tr>
<tr>
<td>TNVPG</td>
<td>11.9</td>
<td>17.7</td>
<td>14.353</td>
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Appendix B

Multiple Regression with Moreyball Statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>B</th>
<th>Sig.</th>
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</thead>
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<tr>
<td>(Constant)</td>
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<td>0.109</td>
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<tr>
<td>PTSinPaint</td>
<td>3.4</td>
<td>0.000**</td>
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<td>FGPerct3P</td>
<td>2.5</td>
<td>0.006**</td>
</tr>
<tr>
<td>OPPPTSinPaint</td>
<td>2.5</td>
<td>0.001**</td>
</tr>
<tr>
<td>OPP3PointPerct</td>
<td>5.2</td>
<td>0.000**</td>
</tr>
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</table>

Note. *p<.05 **p<.01, R²=.86
Appendix C

Multiple Regression with all Included Variables

<table>
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<tr>
<th>Variables</th>
<th>B</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Constant)</td>
<td>0.933</td>
<td>0.037*</td>
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<tr>
<td>PTSinPaint</td>
<td>0.833</td>
<td>0.078</td>
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<td>FGPerct3P</td>
<td>0.014</td>
<td>0.98</td>
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<td>0.716</td>
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<td>OPP3PointPerct</td>
<td>-1.3</td>
<td>0.13</td>
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<tr>
<td>PPG</td>
<td>0.028</td>
<td>0.00**</td>
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<tr>
<td>OppPPG</td>
<td>-0.03</td>
<td>0.00**</td>
</tr>
<tr>
<td>TNVPG</td>
<td>0.002</td>
<td>0.72</td>
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</table>

Note. *p<.05 **p<.01. Model had significance of p=.000, and R²=.965

Appendix D

Change in Winning Percentage based on Appendix A & C

<table>
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<tr>
<th>Variables</th>
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<tr>
<td>PTSinPaint</td>
<td>7.8%</td>
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<tr>
<td>FGPerct3P</td>
<td>0.1%</td>
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<td>OppPTSinPaint</td>
<td>-1.5%</td>
</tr>
<tr>
<td>Opp3PointPerct</td>
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</tr>
<tr>
<td>PPG</td>
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</tr>
<tr>
<td>OppPPG</td>
<td>-36.0%</td>
</tr>
<tr>
<td>TNVPG</td>
<td>1.2%</td>
</tr>
</tbody>
</table>