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Don't Worry, College Doesn't Make You Successful In the NBA

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Abstract

This paper explores the value of attending college to Division I National Collegiate Athletic Association (NCAA) basketball players in terms of future success in the NBA. Future success is measured by both salary and minutes played per game. A dataset of 660 athletes from the 2006 through 2016 drafts was collected from Basketball-Reference. An empirical model is estimated using this data in order to identify the determinant factors in a player’s success in the NBA. It is found that college is not a determinant of success in the NBA.

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I. Introduction

Dorfman (2013) argues that student athletes are compensated between $50,000 and $125,000 a year. Dorfman arrived at these figures by compiling the value of athletes' scholarship, room, board, and coaching.[1] Dorfman alleges that athletes would pay $2,000-$3,000 a week for training similar to what they receive while in college. Not only do athletes receive compensation according to Dorfman, but they also gain national publicity, which may be even more valuable than the direct compensation itself. He elaborates, saying that the NCAA puts athletes into the national spotlight, whereby professional teams can easily both evaluate and track athletes' performance nationwide. However, Dorfman does not attempt to quantify publicity, noting the difficulties concerned with this, but he does postulate that it could be considered "pay." That is not to mention that the athletes are getting paid in a four- year education from some of the best colleges in the nation. He continues, saying that basketball, along with football, brings in money to their respective colleges. Dorfman concludes that college athletes are adequately compensated for their efforts.

Ramogi Huma, president of National College Players Association, also weighs in on athlete compensation, saying that, "athletes in the revenue-producing sports of football and men's college basketball are less likely to receive their diplomas than any other group of athletes while also bearing the burden of financing a college sport enterprise that

[1] Jeffrey Dorfman, "Pay Colleges Athletes? They're Already Paid Up to $125,000 Per Year," *Forbes Magazine* (August 2013).

has resulted in highly lucrative compensation packages for high profile coaches, athletics administrators, conference commissioners, and football bowl executives."[2] Huma's study found that in 2009-10 basketball players with the top 10 highest estimated fair market values are worth around $620,000 to $1,000,000. The report also found that the average NCAA basketball athlete is worth $289,031, while only earning $23,204 in scholarship money.

Huma came to these figures by following the NBA model, reached through collective bargaining, of establishing a 50% revenue-sharing standard. Huma applied said standards to reported college revenues to create an adequate value of the student athletes. Among said student athletes, although they received scholarships, 80% lived below the federal poverty line with an average shortfall of $3,098 in 2010-11. Despite this, in that same year, the athletes' respective coaches had an average salary of $2.5 million, excluding bonuses. Huma concludes her study by asserting that student-athletes are undercompensated and recommends that the US Department of Justice should file an antitrust lawsuit against the NCAA in order to protect student athletes.

There is an obvious lack of consensus on how to place a monetary value to college athletes, which extends to the specific case Division 1 NCAA basketball players. However, fair market valuations seem to be the best method. Irrespective of this, there is still much debate as to whether athletes should be compensated, or should be considered

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[2] Rumoji Huma, Ellen J Staurowsky, Ed. D, "The Price of Poverty in Big Time College Sports," *National College Players Association* (September 2011).

“amateurs,” who are not entitled to a salary. However, reports of student athletes getting paid for receiving a medal in the Olympics has added a wrinkle to the debate of student-athlete compensation.[3] Student athletes will receive $25,000, $15,000, and $10,000 for Gold, Silver, and Bronze respectively. This is important because it shows that athletes are already allowed to be paid for their efforts, creating a precedent that may ultimately change the NCAA’s rules on compensation altogether. However, the key question is, what, is a collegiate basketball player is really worth, and whether college has any impact on said athlete’s future value.

[3] Steve Berkowitz, “Olympics Offer Rare Chance for NCAA Athletes to Be Paid,” *USA Today*, (August 2016).

II. Literature Review

The question of what drives success in the NBA is hotly contended in both the scholarly and sports world. When it comes to the NCAA and NBA, there have been numerous studies conducted ranging from the economics, health, and social consequences that are attached to said associations. Ichniowski and Preston (2012) looked into, between the 1997-2010 seasons, whether performance in the NCAA "March Madness" annual tournament affects NBA team's draft decisions, and whether these biases would overpower overall player performance.[4] March Madness is an extremely publicized tournament and as such researchers looked into both its effect on draft stock and whether these biases are justified or not based upon future performance. Ichniowski and Preston found that unexpected team wins and player scoring in March Madness is directly linked to NBA teams' draft decisions, which persisted even after reviewing differences between mock drafts pre and post March Madness. Moreover, Ichniowski and Preston that March Madness information is actually undervalued by NBA executives, pointing to the fact that players who have a March Madness bump due to unexpectedly high performance are more likely to become a superstar in the NBA than those who do not. It seems as though superstars show up big in March Madness, the NCAA's biggest stage for collegiate basketball athletes. That being said, do the top schools themselves, that not only often make it to but are favorites in the March Madness tournament, churn

[4] Ichniowski, C., Preston, A. E., & National Bureau of Economic Research. (2012). Does March Madness lead to irrational exuberance in the NBA draft: High-value employee selection decisions and decision-making bias *NBER working paper series*, no. 17928; Working paper series (National Bureau of Economic Research), no. 17928. Cambridge, Mass.: National Bureau of Economic Research.

out more successful NBA athletes than other colleges that are not frequent March Madness contenders? That is to say, is there a strong causal correlation between these NCAA basketball powerhouses, like that of Duke or Kentucky, and successful NBA careers? That is one of the main aims of my thesis.

Staw and Hoang (1995)[5] conducted one of the first quantitative studies looking into the sunk-cost affect in the NBA in 1995.[6] Staw and Hoang looked into whether the salary NBA teams paid for players influenced the amount of minutes the players played and longevity in the NBA. Staw and Hoang used draft order in the NBA draft to predict playing time, whether a player would be traded, and longevity in the NBA. They found teams gave significantly more minutes to and retained the longest their highest drafted players, which held true even after controlling for player performance, injuries, trade status, and position of the player. NBA teams seem to be stuck in losing courses of action, that is to say, stuck in sunk-cost motives of action. This study suggests that success in the NBA is not driven by minutes played, nor by salary, but instead a sort of dogma of playing players that had high draft stock in the past. The implications of this study suggest that success in the NBA is much harder to find than what common sense would advise. Staw and Hoang could point to continual mediocrity of NBA franchises like the Philadelphia 76ers, Sacramento Kings, and New York Knicks to further prove their point. An especially relevant case would be that of the Los Angeles Lakers, whose adoration for Kobe Bryant led to his being grossly overpaid and contributed to their worst

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[5] Staw, B., & Hoang, H. (1995). Sunk Costs in the NBA: Why Draft Order Affects Playing Time and Survival in Professional Basketball. *Administrative Science Quarterly, 40*(3), 474-494. doi:1. Retrieved from http://www.jstor.org/stable/2393794 doi:

season of record as they did not have salary space for another high caliber player. However, these situations are likely outliers, as most NBA executives do not allow blind adoration to get in the way of their business. For example: Pat Riley did not cave and overpay Dwyane Wade in his later years when his statistics took a slump, which has likely been an overall positive move for his franchise, the Miami Heat. I aim to prove Staw and Hoang wrong by showing that success in the NBA is driven by these common sense measures, and to take the study a step further by assessing whether college attended before being drafted is a solid predictor itself for success in the NBA.

In that same line of thinking about underperforming relative to their expectations, Cao, Prince, and Stone (2011) looked into the psychological pressure on performance in the NBA.[7] Cao et al. used free-throw data from 2002-2010 season to quantify, and specifically high pressure moments when an NBA athlete is out on the line to make critical free-throws for his team to be successful. Cao found that there is a quantifiable choke factor when in these high pressure situations. On average Cao found that when under pressure i.e. the final seconds of a close game, athletes shoot on average 5-10 percentage points worse than their averages. Moreover, choking is more likely in players who are statistically worse in free-throws overall, as well as missing the second if the first is also missed when given a pair of free-throws. While Cao et al. did find a correlation between diminishing game time remaining, being in a close game, and choking, there was no evidence of choking specifically when games are tied with 15 seconds left. There was also no evidence of choking being affected by being home or away, attendance, and

[6] Zheng Cao, Joseph Prince, Daniel F. Stone (2011). Performance Under Pressure in the NBA. *Journal of Sports Economics.*

whether the game is in the regular season or playoffs. There is therefore a quantifiable "choke factor" that may be able to explain why some players underperform relative to their average play. Continual underperformance should likely lead to a reduction in salary and success overtime, despite what Staw and Hoang found in their study regarding sunk-costs. In fact, a lack of reliability down the stretch would likely lead to a reduction of salary, playing time, and statistical averages, leading to the devaluing of a player.

There is a widely held belief that colleges with big sports teams often bring in high- caliber applicants with high grades and SAT scores, directly due to the success of their sports program. Proponents of the behemoth that is the NCAA point the aforementioned idea, saying that these successful programs will promote the mission of these schools by attracting high caliber students. McKormick (1987) explored this phenomenon, known as the "advertising effect."[8] McKormick found evidence for a symbiotic relationship between a colleges athletics and academics, as the removal of significant athletic involvement leads to a significant decrease in SAT scores. Smith (2007)[9] challenged the validity of the advertising effect in his article Smith cites several

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[7] McCormick, Robert E., and Maurice Tinsley. "Athletics versus Academics? Evidence from SAT Scores." *Journal of Political Economy* 95, no. 5 (1987): 1103-116.

[8] Smith, D. Randall Big-Time College Basketball and the Advertising Effect: Does Success Really Matter? *Journal of Sports Economics August 2008 9: 387-406,* first published on December 21, 2007

studies including: Bremmer (1993)[10], Chressanthis and Grimes (1993)[11], Frank (2004)[12], Mixon (1995)[13], and Coughlin and Erekson (1985)[14], all of whom show that the advertising effect has no significant effect for big-time basketball schools, as most of these studies looked at every Division I college. However, Smith surveyed all Division I schools over a 12-year panel, testing assessing how closely performance is related to academic quality in the first-year class. Smith found that neither, the amount of first-years in the top 10th of their high school class, the amount of students with an average grade point average of 3.0 or above, nor the number of National Merit Scholars are at all significantly related to big-time basketball success. However, Smith did find that SAT scores are marginally correlated to basketball performance. Nevertheless, Smith concludes that the advertising effect in big-time basketball schools is miniscule at best.

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[9] Bremmer, D.S., & R.G. Kesselring. (1993). The advertising effect of university athletic success: A reappraisal of the evidence. *Quarterly Review of Economics and Finance,* 33, 409-421

[10] Chressanthis, G.A., & P.W. Grimes. (1993). Intercollegiate sports success and first-year student enrollment demand. *Sociology of Sport Journal,* 10(3), 286-300.

[11] Frank, R.H. (2004). Challenging the myth: A review of the links among college athletic success, student quality, and donations. *Paper commissioned by the Knight Foundation Commission on Intercollegiate Athletics. Retrieved Nov. 29,* 2005

[12] Mixon, F.C., Jr. (1995). Athletics versus academics? Rejoining the evidence from SAT scores. *Education Economics*, 95(3), 277-283.

[13] Coughlin, C.C., & O.H. Erekson. (1985). Contributions to intercollegiate athletic programs: Further evidence. *Social Science Quarterly*, 66(1), 194-202.

III. Data Review

There are 660 National Basketball Association athletes in my data set, each with 31 player specific data points. I collected said player specific data from Basketball-Reference.com, which is a subsidiary of sports-reference.com.[15] Basketball Reference is largely considered to be the most exhaustive, reputable, and easiest to use basketball statistics database. It was started by Justin Kubatko in April of 2004, and has been part of Sports Reference LLC, with seven full-time employees as of 2007. Basketball Reference has all of the available statistics on every NBA, WNBA, ABA, D-League, college, and Euro basketball teams, leagues, and players ranging from 1946-47 to the present. The database holds all players, teams, seasons, leaders, scores, playoffs, drafts, and even a play index which can find specific games, winning and losing streaks, and a "Head2Head Finder" where specific player matchups are reported. It is safe to say that there is no website more complete than Basketball Reference in terms of college and professional basketball statistics. In terms of statistics, it is even more complete than the official NBA website itself, which does not have many of the advanced statistics contained in Basketball Reference.

I use all available data from the 2006 through 2016 NBA draft classes. Each draft class has a first and second round, each consisting of 30 players, with 60 in total. I have selected these years because, as of 2006, the NBA enacted its highly controversial "one and done" rule. This rule mandates that in order for an athlete to be eligible for the NBA

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[14] Sports Reference LLC Basketball-Reference.com (NBA Draft Index)- Basketball Statistics and History. http://www.basketball-reference.com/.

draft, they must complete at least one year of college, or come from an international team or country. Before this ruling, players could elect to go straight from high school to the pros. Notable players who came straight out of high school are: LeBron James, Kobe Bryant, and Kevin Garnett, all unanimously believed to be future Basketball Hall of Fame inductees. Young basketball athletes must now go to college if they hope to make it in the NBA, however, and it therefore seems only natural to have 2006 as the starting point of the data set.

It is important to note that a player can be drafted into the NBA but not actually play in the NBA the year they were drafted in due to injury, such as the case of Joel Embiid who, while drafted in 2014, will be playing his first game this 2016 season. Another reason that a player may not play is because they elect to defer entering into the NBA in order to finish out their contracts on their current team. For example: Ricky Rubio who had his rights acquired by the Minnesota Timberwolves in 2009, but played out his contract on his Euro league team and had his first NBA game in 2011. Moreover, some players may have been drafted, but never actually played in the NBA due to their being released from the team before the subsequent season starts and not being able to find another team to pick them up, such as Josh Smith who as of the 2016 NBA Season has yet to be picked up by an NBA team and will likely play internationally. Many of these players will either stay in the NBA Development league, play internationally, or simply not play at all. These players will have empty data sets, but it is still important to leave them in the data set as they were at least drafted into the NBA, whether or not they have actually played in the league. I have also elected to leave out the 2016 NBA draftees' statistics from both NBA and college, as their NBA statistics would not be from a complete season as I am writing this in the beginning of the young 2016-2017 season, and their college statistics are not comparable with the other NBA specific statistics.

The 26 statistical categories are as follows in order as they are in the data set:

- Pick: Referring to when in the draft the player was drafted. Each draft has 2 rounds, each consisting of 30 players, 60 in total, from players in college, or from abroad. It is important to note that some players can go undrafted, and still be picked up by an NBA team, and may even be successful like the case of Tyler Johnson who went from being undrafted and in the NBA development league in 2014, to signing a 4 year, $50,000,000 contract with the Miami Heat in 2016.
- Team: Which NBA team the player currently on, or if no longer in the NBA, the last known NBA team the player was on.
- School: Where the player went to college. There is a space for those who played internationally instead of going to college in the United States.
- Years: Years in the NBA.
- Games Played: Total number of games a player has played in their NBA career.
- Minutes Played: Total number of minutes a player has played in their NBA career.
- Points: Total number of points scored by a player in their NBA career.
- Total Rebounds: Total number of rebounds a player has amassed in his NBA career.

- Assists: Total number of assists a player has amassed in his NBA career.
- Field Goal Percentage: A statistic measuring overall shot accuracy where the ratio is taken of shots a player has made over the shots he has taken throughout his NBA career.
- Three Point Percentage: A statistic measuring three-point accuracy where the ratio is taken of three-point shots a player has made over the shots he has taken throughout his NBA career.
- Free Throw percentage: A measurement of free throw accuracy where the ratio of free throws made over taken is measured.
- Minutes Per Game: The average minutes a player is in a game, over his whole career.
- Total Rebounds Per Game: Average number of rebounds a player grabs per game, over his whole career.
- Assists Per Game: Average number of assists a player dishes per game, over his whole career.
- Win Shares: Estimates the amount of wins contributed by each player.
- Win Shares per 48 minutes – estimates the number of wins contributed by a player per 48 wins (league average .100).
- Box Plus Minus: A box score estimate of the points per 100 possessions a player contributed above an average player, translated to an average team.
- Value Over Replacement Player – a box score estimate of the points per 100 team possessions that a player contributed over a replacement translated to an average team over an 82 game season.

- ACC: The Atlantic Coast Conference, one of the two consistently highly regarded Division I collegiate basketball conferences.
- Big 12: one of the two consistently highly regarded Division I collegiate basketball conferences
- Salary: Each players' yearly salary as of the 2016-2017 NBA season.
- Position: Each players' specific position. A guard is a point guard or shooting guard, a forward is a player who can play small forward or power forward, and a center is a player who plays center and who is generally over 6'10.
- Top5P: This is a dummy variable describing whether a player was a top 2 draft pick in his draft class. This is important because the first 5 picks get paid between three to five million dollars a year, while the bottom 25 range from one to under three million dollars a year.
- Top10: The top 10 historically dominant NCAA Division I basketball teams. These teams, in no particular order, consist of: Duke University, Michigan State University, Syracuse University, University of Arizona, University of Connecticut, University of Kansas, University of Kentucky, University of North Carolina, Villanova University, and Xavier University.
- Inter: Players coming from countries other than the United States.
- US: Players coming from the United States.

Table 1. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Pk	660	30.5	17.33124	1	60
Tm	0				
Player	0				
College	0				
Yrs	559	3.610018	2.547394	1	10
G	499	216.3687	184.7503	1	768
MP	499	4948.489	5413.729	0	25802
PTS3	499	6.89499	4.746082	0	27.4
TRB	499	875.3387	1080.153	0	6066
AST	499	430.0762	699.0865	0	5614
FG	496	.4347137	.0870634	0	1
P	456	.2696294	.1372262	0	1
FT	484	.7134112	.1287533	0	1
MP2	499	17.69439	8.675121	0	37.8
PTS3	499	6.89499	4.746082	0	27.4
TRB4	499	3.136273	2.123314	0	12.6
AST5	499	1.416834	1.448957	0	9
WS	499	10.10301	14.94454	-2.1	107.9
WS48	498	.0620181	.0784555	-.597	.343
BPM	498	-2.369679	3.515356	-23.2	6.2
VORP	499	2.28016	5.902687	-5.7	41.7
ACC	660	.1030303	.304229	0	1
Big12	660	.0909091	.2876978	0	1
Salary	334	6304715	6472391	25000	2.65e+07
Position	0				
Top5P	660	.9333333	.249633	0	1
Top10	660	.2136364	.4101839	0	1
Inter	660	.2106061	.4080483	0	1
US	660	.7893939	.4080483	0	1
lnSalary	334	15.07278	1.195374	10.12663	17.09417
lnMP2	498	2.722204	.6062705	.6931472	3.632309

Utilizing the above variables, examine the relationships between, college, a player's worth to their college, a players' salary, as well as their overall success. It is worth noting that the summary statistics for TM, Player, and College are not numeric values and as such Stata considers them zero when summarizing the statistics.

IV. Results

In order to find the correlation between an athlete's minutes played, salary, win shares, win shares per 48 minutes, box plus minus, value over replacement player, and international; I created a correlation matrix:

Table 2. Advanced statistics correlation matrix

	MP2	Salary	WS	WS48	BPM	VORP	Inter
MP2	1.0000						
Salary	0.0482	1.0000					
WS	0.7235	0.0572	1.0000				
WS48	0.5101	0.0550	0.5711	1.0000			
BPM	0.7128	0.0732	0.6660	0.8649	1.0000		
VORP	0.6285	0.0830	0.9194	0.4959	0.6459	1.0000	
Inter	0.0001	0.0420	-0.0241	-0.0258	-0.0172	-0.0370	1.0000

The matrix above shows that minutes per game is highly correlated with WS, and BPM, as well as relatively highly correlated with WS48 and VORP -which is to be expected. There is an expectation that the advanced stats favor good players, who in turn, will play more minutes per game over their other teammates. However, interestingly enough, MP2 is not highly correlated with Salary, suggesting that players who receive large salaries are not necessarily all getting heavy minutes. VORP is very highly correlated with both Salary and WS, which too is to be expected as the better the player, reflected in Salary and WS, the more the player would be valued over their replacement. WS48 is also highly correlated with BPM, which is also to be expected, as a player with a high BPM will likely contribute more to a team's win, and therefore have a higher WS48 than other players with lesser BPM statistics.

Table 3. Salary regressed on advanced statistics 1

Source	SS	df	MS		
Model	1.1706e+14	7	1.6723e+13	Number of obs =	253
Residual	1.0159e+16	245	4.1465e+13	F(7, 245) =	0.40
Total	1.0276e+16	252	4.0778e+13	Prob > F =	0.8998
				R-squared =	0.0114
				Adj R-squared =	-0.0169
				Root MSE =	6.4e+06

Salary	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
MP2	4624.708	77460.07	0.06	0.952	-147947.9	157197.3
WS	-64279.61	76810.08	-0.84	0.403	-215571.9	87012.73
BPM	101195	192534.4	0.53	0.600	-278038.8	480428.8
VORP	200440.8	178576.6	1.12	0.263	-151300.3	552182
ACC	118216.3	1476917	0.08	0.936	-2790858	3027291
Big12	488315.6	1357553	0.36	0.719	-2185649	3162280
Top10	-234259	998658.5	-0.23	0.815	-2201311	1732792
_cons	6801900	1564439	4.35	0.000	3720434	9883367

Table 4. Salary regressed on advanced statistics 2

Source	SS	df	MS		
Model	1.4037e+14	8	1.7546e+13	Number of obs =	253
Residual	1.0136e+16	244	4.1540e+13	F(8, 244) =	0.42
Total	1.0276e+16	252	4.0778e+13	Prob > F =	0.9070
				R-squared =	0.0137
				Adj R-squared =	-0.0187
				Root MSE =	6.4e+06

Salary	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
MP2	1848.74	77618.1	0.02	0.981	-151038.3	154735.7
WS	-63715.88	76882.67	-0.83	0.408	-215154.3	87722.53

BPM	102471	192714.6	0.53	0.595	-277125.6	482067.6
VORP	202679.8	178761.8	1.13	0.258	-149433.4	554792.9
ACC	185530.3	1480972	0.13	0.900	-2731590	3102650
Big12	603161.5	1367396	0.44	0.660	-2090244	3296567
Top10	-99955.37	1015511	-0.10	0.922	-2100241	1900331
Inter	985234.4	1315417	0.75	0.455	-1605786	3576255
_cons	6675069	1574973	4.24	0.000	3572792	9777346

I tested the predicting power of the advanced statistics, as well as college and national dummies. I ran three regressions to see the significance of the international and US dummies on the independent variable Salary. As shown in Tables 3 and 4 there are no significant variations between the regressions, so it is safe to say that a player's nationality does not significantly affect their Salary. The same can be said about MP2 (see appendix Table 19-23). Therefore, as they do not explain both Salary and minutes per game in any significant capacity, I dropped the International and U.S. dummies, as well as Top5P as it is highly correlated with PK and is an undesirable alternative to Pk as it may be less significant.

Table 3 shows the relationship between an athlete's salaries, and the advanced metrics. However, the R-squared value is very low (.011). As such, it would seem as though an athlete's salary is more difficult to explain. This may be due to MP2 being more of an outcome than an explanatory variable, or simply there is something not captured in the regression that can better explain an athlete's salary. In order to resolve this issue, I dropped MP2, WS48, and Top5P as well as adding PK, as shown in Table 4. This new regression is only a marginal improvement, with an R-squared value of .013. However, interestingly enough, WS has a negative value, suggesting that players who contribute more to their team's win tend to be paid less than those who do not contribute as much. However, the t-value is only significant at the 41% level (t-value -.83).

This phenomenon can be explained by looking at players like Stephen Curry, the reigning league MVP by unanimous vote and who was named MVP the year prior as well. Curry, despite having a staggering WS value of 17.9 last season (Kevin Durant had the second most with 14.5), is the fourth highest paid player on his team, the Golden State Warriors[16]. This would suggest that salary is not a good predictor of current success, but a bet on future success, a bet that seemingly is often not fruitful. According to Basketball-Reference, the current salary cap for each NBA team is $94,143,000, with a minimum of $80,021,550 per year. With 30 teams each working with upwards of eighty million dollars, each team should be able to afford a max-contract level player ($30,000,000 per year). This is important because when in rebuilding mode, teams will often pay a star player a max contract just to keep him, such as Mike Conley of the Memphis Grizzlies who despite never being selected as an All-Star, signed a 5-year $152,605,576 maximum contract. The only two other players who have earned $30 million a year are Kobe Bryant and Michael Jordan, both of whom are in the conversation for some of the greatest players of all time. With all due respect, Mike Conley is likely not on the same level as Jordan or Bryant. Conley simply is benefiting from the artificial cap on salary, where less than superstar players hit an earnings ceiling, after which, they can no longer receive a raise in salary irrespective of increase in skill. As a result, player performance does not adequately explain player salary, which is reflected in the R-

[16] Sports Reference LLC Basketball-Reference.com (NBA Draft Index)- Basketball Statistics and History. http://www.basketball-reference.com/.

squared value. Not surprisingly, Pk is also negatively correlated with salary, as the players picked earlier in the draft will naturally earn more than the later ones. However, it is important that Pk is also not very explanatory, with a t-value of -1.16 (see appendix table 21). VORP also falls in line with expectations as it is relatively highly correlated with salary, as the player with a high value over their replacements should be adequately compensated as such. Moreover, ACC, Big12, and Top10 colleges are all insignificant, showing that they are not good predictors of monetary success in the NBA. In light of these findings, it is safe to say that the independent variables are not very strong indicators of success in the NBA in terms of salary, as they are not very explanatory.

While the aforementioned variables are not very explanatory of salary, they are remarkably better causal predictors of current success in the NBA which can be reflected in minutes per game played, as better players will naturally play more minutes.

Table 5. MP2 regressed on advanced statistics 1

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   Source |       SS           df       MS      Number of obs   =       253
-------------+----------------------------------   F(9, 243)       =     71.20
       Model |  13935.3329         9  1548.37033   Prob > F        =    0.0000
    Residual |  5284.18216       243  21.7456056   R-squared       =    0.7251
-------------+----------------------------------   Adj R-squared   =    0.7149
       Total |  19219.5151       252  76.2679171   Root MSE        =    4.6632
------------------------------------------------------------------------------
         MP2 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      Salary |  -2.55e-08   4.64e-08    -0.55   0.583    -1.17e-07    6.59e-08
          WS |   .2954827   .0525379     5.62   0.000     .1919949    .3989705
         BPM |   1.007614   .1246226     8.09   0.000     .7621352    1.253092
        VORP |  -.2560316   .1296494    -1.97   0.049    -.5114116   -.0006516
         ACC |  -.4529088   1.072824    -0.42   0.673     -2.56613    1.660313
       Big12 |  -.0698344   .9903013    -0.07   0.944    -2.020505    1.880836
```

Top10	.3214464	.7412167	0.43	0.665	-1.138583	1.781476
Inter	-.1160088	.9577848	-0.12	0.904	-2.002629	1.770611
Pk	-.1775343	.0206271	-8.61	0.000	-.218165	-.1369036
_cons	22.20045	.9869219	22.49	0.000	20.25644	24.14447

Table 6. MP2 regressed on advanced statistics 2

Source	SS	df	MS			
				Number of obs	=	253
				F(8, 244)	=	80.43
Model	13935.0139	8	1741.87674	Prob > F	=	0.0000
Residual	5284.50118	244	21.6577917	R-squared	=	0.7250
				Adj R-squared	=	0.7160
Total	19219.5151	252	76.2679171	Root MSE	=	4.6538

MP2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Salary	-2.57e-08	4.63e-08	-0.56	0.579	-1.17e-07	6.55e-08
WS	.2955992	.0524229	5.64	0.000	.19234	.3988585
BPM	1.007657	.1243702	8.10	0.000	.762681	1.252633
VORP	-.2559324	.1293847	-1.98	0.049	-.5107859	-.0010789
ACC	-.4443233	1.068316	-0.42	0.678	-2.548622	1.659976
Big12	-.0559094	.9816173	-0.06	0.955	-1.989434	1.877616
Top10	.338285	.7265911	0.47	0.642	-1.092906	1.769476
Pk	-.1772543	.0204557	-8.67	0.000	-.2175465	-.136962
_cons	22.17318	.9589556	23.12	0.000	20.2843	24.06207

Table 5 and 6 firstly, much like for salary, show that the international dummy is not a significant determinant of MP2. Therefore, as done with salary, the international dummy may be dropped.

Table 6 shows that interestingly, Salary, ACC, Big12 are all insignificant when it comes to explaining MP2. This would suggest that these variables have no meaningful effect on MP2. Coupled with Top10’s positive, but still insignificant effect on MP2, it would seem as though college, and Salary which I have shown above to not be a good predictor of current success, altogether has no bearing on MP2. However, WS and BPM are significant at the 99 percentile, with t-values of 5.64 and 8.10 respectively. This means that a player with high WS and BPM values, will play more minutes, suggesting that their overall success is dependent upon their current contribution to their team, which is absolutely to be expected.

Table 7. MP2 regressed on advanced statistics 3

MP2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Salary	-1.57e-08	6.22e-08	-0.25	0.800	-1.38e-07	1.07e-07
WS48	49.60947	5.911855	8.39	0.000	37.96516	61.25378
ACC	-.4084419	1.441298	-0.28	0.777	-3.247301	2.430417
Big12	.6693	1.323637	0.51	0.614	-1.937808	3.276408
Top10	.0471062	.9766027	0.05	0.962	-1.876463	1.970676
Pk	-.2698977	.0257097	-10.50	0.000	-.3205369	-.2192584
_cons	21.56976	1.096594	19.67	0.000	19.40985	23.72967

Table 8. MP2 regressed on advanced statistics 4

MP2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Salary	-4.54e-08	4.90e-08	-0.93	0.355	-1.42e-07	5.11e-08
BPM	1.1417	.1295224	8.81	0.000	.8865805	1.39682
VORP	.3754414	.0687841	5.46	0.000	.2399577	.510925
ACC	-.6099013	1.133042	-0.54	0.591	-2.841648	1.621845
Big12	-.037041	1.041478	-0.04	0.972	-2.088434	2.014352
Top10	-.0269635	.7678349	-0.04	0.972	-1.539363	1.485436
Pk	-.2103995	.0207878	-10.12	0.000	-.2513452	-.1694538
_cons	25.22946	.8393321	30.06	0.000	23.57623	26.88269

WS48, VORP, and Pk are very negatively correlated with MP2, again, at the 99 percent level, with t-values of 8.39, 5.46, and -10.12 respectively. While Pk's sign is correct, WS48 and VORP are highly correlated with MP2, as shown in the correlation matrix with values of .51 and .63 respectively. It is clear that the advanced statistics best explain a player's current success, reflected in their explanatory power with respect to MP2.

To ensure that these advanced variables truly do capture a player's success in the NBA, I regressed them on more conventional statistics consisting of: Salary, Pk, years in NBA, games played, total minutes played, 3-point percentage, rebounds per game, assists per game, field-goal percentage, 3-point make per game, free-throw percentage, minutes per game, total career assists, and total career rebounds.

As such, in Tables 12-19 I regress the conventional statistics on the advances ones:

Table 9. WS regressed on conventional statistics 1

```
  Source |       SS       df       MS              Number of obs =     227
-------------+------------------------------           F( 14,   212) =  134.51
       Model |  50810.4589    14  3629.31849           Prob > F      =  0.0000
    Residual |  5720.24055   212  26.9822668           R-squared     =  0.8988
-------------+------------------------------           Adj R-squared =  0.8921
       Total |  56530.6995   226  250.135838           Root MSE      =  5.1944

------------------------------------------------------------------------------
          WS |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      Salary |   3.77e-08   5.43e-08     0.69   0.488    -6.93e-08    1.45e-07
          Pk |   .0721963   .0275512     2.62   0.009     .0178869    .1265057
         Yrs |   .4366828   .4622355     0.94   0.346    -.4744837    1.347849
```

	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
G	-.0347023	.011097	-3.13	0.002	-.0565769	-.0128277
MP	.0014512	.0005298	2.74	0.007	.0004069	.0024955
PTS3	.8397573	.2211175	3.80	0.000	.4038867	1.275628
TRB	.0082565	.0014036	5.88	0.000	.0054896	.0110233
AST	.0074092	.0023436	3.16	0.002	.0027895	.0120288
FG	28.00546	7.703798	3.64	0.000	12.8196	43.19132
P	.5302031	2.662595	0.20	0.842	-4.718349	5.778755
FT	6.080554	4.220846	1.44	0.151	-2.239649	14.40076
MP2	-.2814386	.202433	-1.39	0.166	-.680478	.1176009
TRB4	-1.012857	.5641001	-1.80	0.074	-2.124821	.0991068
AST5	-1.397201	.8731715	-1.60	0.111	-3.118411	.3240099
_cons	-15.94134	5.138959	-3.10	0.002	-26.07134	-5.811334

Table 10. WS regressed on conventional statistics 2

Source	SS	df	MS		
Model	57383.1959	2	28691.5979	Number of obs	499
Residual	53839.7696	496	108.547923	F(2, 496)	264.32
Total	111222.965	498	223.339288	Prob > F	0.0000
				R-squared	0.5159
				Adj R-squared	0.5140
				Root MSE	10.419

WS	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
TRB4	3.592146	.2253193	15.94	0.000	3.149448	4.034844
AST5	4.188389	.3301848	12.68	0.000	3.539655	4.837122
_cons	-7.097194	.8895676	-7.98	0.000	-8.844979	-5.349409

Table 11. WS48 regressed on conventional statistics 1

Source	SS	df	MS		
Model	.606796027	14	.043342573	Number of obs	227
Residual	.222588176	212	.001049944	F(14, 212)	41.28
Total	.829384203	226	.003669842	Prob > F	0.0000
				R-squared	0.7316
				Adj R-squared	0.7139
				Root MSE	.0324

WS48	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Salary	2.99e-10	3.39e-10	0.88	0.378	-3.69e-10	9.67e-10
Pk	.0004339	.0001719	2.52	0.012	.0000951	.0007726
Yrs	.0023345	.0028834	0.81	0.419	-.0033494	.0080183
G	.0000465	.0000692	0.67	0.503	-.00009	.0001829
MP	-1.98e-06	3.30e-06	-0.60	0.549	-8.50e-06	4.53e-06
PTS3	.0015903	.0013793	1.15	0.250	-.0011286	.0043093
TRB	-6.17e-06	8.76e-06	-0.70	0.482	-.0000234	.0000111
AST	.0000193	.0000146	1.32	0.187	-9.47e-06	.0000482
FG	.5653995	.0480561	11.77	0.000	.4706704	.6601286
P	.0528422	.0166092	3.18	0.002	.0201018	.0855825
FT	.0672008	.0263295	2.55	0.011	.0152996	.119102
MP2	-.0001711	.0012628	-0.14	0.892	-.0026603	.0023181
TRB4	.0084929	.0035188	2.41	0.017	.0015565	.0154293
AST5	-.0004167	.0054468	-0.08	0.939	-.0111535	.0103202
_cons	-.3040863	.0320567	-9.49	0.000	-.3672771	-.2408956

Table 12. WS48 regressed on conventional statistics 2

Source	SS	df	MS		
Model	.897899857	2	.448949928	Number of obs =	498
Residual	2.16126698	495	.004366196	F(2, 495) =	102.82
Total	3.05916684	497	.006155265	Prob > F =	0.0000
				R-squared =	0.2935
				Adj R-squared =	0.2907
				Root MSE =	.06608

WS48	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
TRB4	.0190414	.0014314	13.30	0.000	.016229	.0218539
AST5	.0049323	.0020951	2.35	0.019	.000816	.0090486
_cons	-.0048232	.0056625	-0.85	0.395	-.0159487	.0063023

Table 13. VORP regressed on conventional statistics 1

Source	SS	df	MS
Model	6853.20277	14	489.514484
Residual	1907.94472	212	8.99973924
Total	8761.14749	226	38.7661393

Number of obs	= 227
F(14, 212)	= 54.39
Prob > F	= 0.0000
R-squared	= 0.7822
Adj R-squared	= 0.7678
Root MSE	= 3

VORP	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Salary	2.64e-08	3.14e-08	0.84	0.401	-3.54e-08	8.82e-08
Pk	.0428933	.0159117	2.70	0.008	.0115279	.0742587
Yrs	.488063	.2669556	1.83	0.069	-.0381644	1.014291
G	-.0364272	.0064089	-5.68	0.000	-.0490605	-.023794
MP	.0005879	.000306	1.92	0.056	-.0000152	.0011911
PTS3	.1244594	.1277024	0.97	0.331	-.1272697	.3761885
TRB	.0045629	.0008106	5.63	0.000	.002965	.0061609
AST	.005345	.0013535	3.95	0.000	.002677	.008013
FG	11.9606	4.449187	2.69	0.008	3.190289	20.73091
P	.7432713	1.537733	0.48	0.629	-2.287933	3.774476
FT	2.008208	2.437672	0.82	0.411	-2.796972	6.813388
MP2	.0194624	.1169115	0.17	0.868	-.2109955	.2499203
TRB4	-.6355684	.3257856	-1.95	0.052	-1.277763	.0066258
AST5	-.5787644	.5042841	-1.15	0.252	-1.572818	.4152891
_cons	-7.362479	2.967911	-2.48	0.014	-13.21288	-1.512082

Table 14. VORP regressed on conventional statistics 2

Source	SS	df	MS
Model	8011.95753	2	4005.97877
Residual	9339.21605	496	18.8290646
Total	17351.1736	498	34.841714

Number of obs	= 499
F(2, 496)	= 212.76
Prob > F	= 0.0000
R-squared	= 0.4618
Adj R-squared	= 0.4596
Root MSE	= 4.3392

VORP	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
TRB4	1.114152	.093843	11.87	0.000	.9297734	1.298531
AST5	1.907101	.1375184	13.87	0.000	1.63691	2.177291
_cons	-3.916169	.3704952	-10.57	0.000	-4.644103	-3.188236

Table 15. BPM regressed on conventional statistics 1

Source	SS	df	MS		
				Number of obs =	227
				F(14, 212) =	38.03
Model	1337.48258	14	95.5344698	Prob > F =	0.0000
Residual	532.513369	212	2.51185552	R-squared =	0.7152
				Adj R-squared =	0.6964
Total	1869.99595	226	8.27431835	Root MSE =	1.5849

BPM	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Salary	1.54e-08	1.66e-08	0.93	0.355	-1.73e-08	4.80e-08
Pk	.0207344	.0084062	2.47	0.014	.0041639	.0373048
Yrs	.2267314	.1410332	1.61	0.109	-.0512757	.5047385
G	-.0025701	.0033858	-0.76	0.449	-.0092442	.0041041
MP	.0000296	.0001616	0.18	0.855	-.000289	.0003483
PTS3	-.0986251	.0674654	-1.46	0.145	-.2316141	.0343639
TRB	-.0001608	.0004283	-0.38	0.708	-.001005	.0006834
AST	.0004282	.000715	0.60	0.550	-.0009813	.0018377
FG	17.41045	2.350515	7.41	0.000	12.77708	22.04383
P	2.056238	.8123874	2.53	0.012	.4548466	3.65763
FT	1.914246	1.287827	1.49	0.139	-.6243403	4.452833
MP2	.1456493	.0617646	2.36	0.019	.0238979	.2674006
TRB4	.3432326	.1721133	1.99	0.047	.00396	.6825052
AST5	.3279631	.2664144	1.23	0.220	-.1971974	.8531237
_cons	-16.30292	1.567954	-10.40	0.000	-19.39369	-13.21214

Table 16. BPM regressed on conventional statistics 2

Source	SS	df	MS		
Model	2896.77789	2	1448.38895	Number of obs =	498
Residual	3245.01426	495	6.55558436	F(2, 495) =	220.94
Total	6141.79215	497	12.3577307	Prob > F =	0.0000
				R-squared =	0.4717
				Adj R-squared =	0.4695
				Root MSE =	2.5604

BPM	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
TRB4	.9015003	.0554662	16.25	0.000	.7925221	1.010478
AST5	.771333	.0811802	9.50	0.000	.6118328	.9308332
_cons	-6.297752	.2194132	-28.70	0.000	-6.728848	-5.866656

Each advanced statistic regression is coupled with a smaller regression on just rebounds and assists per game in order to show that they are truly positively correlated with the advanced statistics. As before, TRB4 and AST5 are correlated with the other variables, namely total career rebounds and assists, and as such, produce a negative relation owing to multicollinearity. In light of this, the R-squared values of WS, WS48, VORP, and BPM are .90, .73, .78, and .72 respectively, showing that the conventional statistics explain the advanced statistics very well. Total games played is insignificant. Despite the multicollinearity, most of the conventional statistics are explanatory for WS, WS48, BPM, and VORP, suggesting that these advanced statistics do truly capture the conventional ones, and are sufficient enough to predict an athlete's success in the NBA.

But can an athletes original draft order be explained by their later success? That is to say, do the advanced statistics explain where a player was drafted? In Tables 20-21 I show the causal relationship between the two:

Table 17. PK regressed on advanced statistics

Source	SS	df	MS		
Model	26028.9931	8	3253.62414	Number of obs =	253
Residual	39579.1887	244	162.20979	F(8, 244) =	20.06
Total	65608.1818	252	260.349928	Prob > F =	0.0000
				R-squared =	0.3967
				Adj R-squared =	0.3770
				Root MSE =	12.736

Pk	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Salary	-1.59e-07	1.26e-07	-1.26	0.210	-4.08e-07	9.02e-08
MP2	-1.327577	.1532064	-8.67	0.000	-1.629352	-1.025801
WS	-.1707056	.1521366	-1.12	0.263	-.4703743	.128963
BPM	.6700807	.3810208	1.76	0.080	-.0804291	1.42059
VORP	.6984531	.3541066	1.97	0.050	.0009573	1.395949
ACC	-2.250714	2.921175	-0.77	0.442	-8.004651	3.503223
Big12	-.9412179	2.68576	-0.35	0.726	-6.231451	4.349016
Top10	-3.671632	1.975429	-1.86	0.064	-7.562702	.2194385
_cons	53.35215	3.211397	16.61	0.000	47.02656	59.67775

Table 18. Top5P regressed on advanced statistics

Source	SS	df	MS		
Model	4.15096439	8	.518870549	Number of obs =	253
Residual	18.3786799	244	.075322459	F(8, 244) =	6.89
Total	22.5296443	252	.08940335	Prob > F =	0.0000
				R-squared =	0.1842
				Adj R-squared =	0.1575
				Root MSE =	.27445

Top5P	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]

Salary	-4.12e-10	2.72e-09	-0.15	0.880	-5.78e-09	4.95e-09
MP2	-.017213	.0033014	-5.21	0.000	-.0237159	-.01071
WS	-.0012134	.0032784	-0.37	0.712	-.0076709	.0052441
BPM	.0193433	.0082106	2.36	0.019	.0031707	.0355159
VORP	.0006809	.0076306	0.09	0.929	-.0143493	.0157112
ACC	-.0317166	.0629479	-0.50	0.615	-.1557072	.0922741
Big12	-.0915119	.057875	-1.58	0.115	-.2055103	.0224864
Top10	.007722	.0425682	0.18	0.856	-.076126	.0915701
_cons	1.275949	.0692019	18.44	0.000	1.139639	1.412258

Interestingly, the advanced statistics do not explain Pk nor Top5P as well, with an R-squared value of .39 and .18 respectively. This shows that, while the advanced statistics, encompass the impact of conventional statistics, they do not explain the draft order as well, possibly because there may be more that goes into a draft pick, especially a top 5 draft pick. For example: the subjective needs of a team, such as the need for a scorer or a distributer, may cause a team to draft a lesser player simply to fill a void that the team has. Moreover, there is likely multicollinearity occurring again, as all of the advanced statistics explain success in the NBA in some way. It is safe to say that the advanced statistics do help explain a player's draft order, yet it is not the whole story. However, a person's college has only a very small part in their draft order. Big 12 is negatively tied to Top5P, but not strongly, being significant at the 20% level. Moreover, Top10 also negatively affects Pk at the 10% level. All of this is to say that, Pk and Top5P, are not completely explained by the advanced and conventional statistics, nor well explained by which college the player attended. All in all, college is shown to not be a major predictor of success in the NBA in either current success, measured in MP2, or future success, measured in Salary.

V. Conclusion

As a direct result to the NBA's "one and done" rule, most players come from the NCAA. According to The Wall Street Journal, here is each of the top 50 basketball colleges' individual worth[17]:

Nothing but Net (Revenue)

The 50 most valuable college-basketball programs (figures in millions):

SCHOOL	VALUATION	SCHOOL	VALUATION	SCHOOL	VALUATION
1. Louisville	$301.3	18. N.C. State	$85.2	35. Marquette	$59.6
2. Kansas	$258.2	19. Tennessee	$84.5	36. Missouri	$58.3
3. Kentucky	$244.3	20. Alabama	$83.4	37. St. John's	$55.0
4. Indiana	$243.8	21. Michigan	$82.1	38. Oklahoma State	$54.0
5. Ohio State	$240.4	22. UCLA	$81.7	39. Oklahoma	$51.2
6. Arizona	$235.4	23. Northwestern	$81.5	40. VCU	$50.1
7. North Carolina	$221.6	24. Dayton	$80.6	41. Florida	$49.6
8. Wisconsin	$206.9	25. Virginia	$79.2	42. Gonzaga	$48.6
9. Syracuse	$203.9	26. Xavier	$78.1	43. Auburn	$46.7
10. Duke	$203.9	27. Pittsburgh	$77.2	44. Washington	$46.5
11. Connecticut	$137.9	28. Texas	$77.1	45. Virginia Tech	$46.4
12. Michigan State	$126.6	29. Kansas State	$76.7	46. UNLV	$46.0
13. Maryland	$123.9	30. Penn State	$68.7	47. South Carolina	$45.6
14. Purdue	$109.6	31. South Florida	$66.8	48. Miami	$44.2
15. Illinois	$109.1	32. Iowa	$62.9	49. Florida State	$43.8
16. Minnesota	$99.7	33. Iowa State	$62.7	50. Arizona State	$43.1
17. Arkansas	$97.4	34. California	$59.7		

Source: Ryan Brewer, IU-Purdue Columbus — The Wall Street Journal.

The basketball players on each of these 50 teams inevitably have great value to these schools, as they are the center-point of the basketball program. These college athletes quite literally bring in millions to their respective schools. However, there seems to be no

[15] Andrew Beaton, "How Much is Your College Basketball Team Worth? *Wall Street Journal*, (March 2016).

connection between a player's college they attended and their future success, reflected in both Salary and minutes per game. According to the Wall Street Journal, the best 13-15 players at each of these 50 schools are worth millions. Following the same system the NBA has adopted, where the collective players are valued at half of the total revenue, the players at the 50th ranked school, Arizona State, are worth $21.55 million collectively, holding all players equal. Clearly, there is a discrepancy between what these players are worth at their respective schools, what they are worth in the NBA, and what they are getting out of their colleges, both in scholarship and experience.

Moreover, the relationship between an international player and success was negligible at best, suggesting that success, both in Salary and MP2, does not, in any significant part, depend upon whether the player came to the NBA from a U.S. college or abroad. This is important because, coupled with the information from the other regressions that showed that a player's college they attended is not strongly correlated with either of the two measures of success, it suggests that college is not significant in terms of a player's success. Due to there being no significant correlation between international and success, there seems to be no discernable advantage to going to college over playing internationally and entering the NBA afterwards. However, NCAA proponents would likely respond by saying that collegiate athletes obtain world class training in world class facilities. This training, they would say, is imperative to their growth as a basketball player, and these players would likely have not been drafted as high without said training. However, this is not likely, as many players are one and done players, who would likely be able to learn just as much in one year abroad as they could in the U.S., that is to say, not very much as it is only one year. One season. It is clear that these collegiate athletes are grossly undervalued when playing for their colleges, as their values, both current and future, show that they are worth millions, and receive small fractions of their actual worth, all while benefiting little if anything from their respective colleges in the meantime.

VI. Limitations

There are some limitations to this study and I would be remiss if I did not mention them. Firstly, the data set used is of 660 athletes is of only NBA players, and as such, is comprised of "success stories." That is to say, the data does not reflect those who did not make it to the NBA from college. However, while not all 18,697 NCAA basketball athletes (Division I-III) aspire to and declare for the NBA draft for various reasons (117 declared according to the NCAA website), some will, and as a result, most of these athletes will not make the NCAA, as each draft has only 60 players. Furthermore, the sample is somewhat self selective, as the people who declare for the draft are most likely the best of the best in terms of college players.

Nevertheless, the study does not take into account those non-successful players who declared but did not make the draft. However, all things considered, not all college numbers are created equal. That is to say, not all college divisions and conferences are on the same level. As a result of this incongruity, some player's statistics are not as impressive as they seem as they are in lesser conferences, and the inverse is also true for players in more competitive conferences. As a result, it seemed a better option to use the success stories from the NBA in order to better standardize the statistics.

VII. Appendix

Table 19. Salary regressed on advanced statistics 3

Source	SS	df	MS		
Model	1.1193e+14	7	1.5990e+13	Number of obs =	253
Residual	1.0164e+16	245	4.1486e+13	F(7, 245) =	0.39
Total	1.0276e+16	252	4.0778e+13	Prob > F =	0.9104
				R-squared =	0.0109
				Adj R-squared =	-0.0174
				Root MSE =	6.4e+06

Salary	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
WS48	-847744.3	1.20e+07	-0.07	0.944	-2.45e+07	2.28e+07
BPM	56947.77	296066.8	0.19	0.848	-526213.3	640108.8
VORP	57190.15	90797.68	0.63	0.529	-121653.5	236033.8
ACC	91749.81	1479633	0.06	0.951	-2822673	3006173
Big12	441432	1360982	0.32	0.746	-2239287	3122151
Top10	-298397.2	1002865	-0.30	0.766	-2273735	1676941
Pk	-22208.81	27156.04	-0.82	0.414	-75697.91	31280.28
_cons	7089734	1675280	4.23	0.000	3789945	1.04e+07

Table 20. MP2 regressed on advanced statistics 5

Source	SS	df	MS		
Model	14792.954	10	1479.2954	Number of obs =	253
Residual	4426.56109	242	18.2915748	F(10, 242) =	80.87
Total	19219.5151	252	76.2679171	Prob > F =	0.0000
				R-squared =	0.7697
				Adj R-squared =	0.7602
				Root MSE =	4.2769

MP2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Salary	-1.98e-08	4.26e-08	-0.47	0.642	-1.04e-07	6.41e-08
WS	.3928786	.0502406	7.82	0.000	.2939138	.4918433
WS48	-56.89163	8.308569	-6.85	0.000	-73.25798	-40.52529

BPM	2.117389	.1983225	10.68	0.000	1.72673	2.508047
VORP	-.533154	.1256065	-4.24	0.000	-.7805756	-.2857324
ACC	-.7481061	.9848834	-0.76	0.448	-2.688144	1.191932
Big12	-.516861	.9105969	-0.57	0.571	-2.310569	1.276847
Top10	.1466767	.6802849	0.22	0.829	-1.193359	1.486712
Inter	-.4025065	.8794271	-0.46	0.648	-2.134815	1.329802
Pk	-.1576347	.01914	-8.24	0.000	-.195337	-.1199324
_cons	27.64916	1.2052	22.94	0.000	25.27514	30.02318

Table 21. MP2 regressed on advanced statistics 5

Source	SS	df	MS		
				Number of obs =	253
				F(10, 242) =	0.48
Model	1.9795e+14	10	1.9795e+13	Prob > F =	0.9051
Residual	1.0078e+16	242	4.1645e+13	R-squared =	0.0193
				Adj R-squared =	-0.0213
Total	1.0276e+16	252	4.0778e+13	Root MSE =	6.5e+06

Salary	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
MP2	-42283.91	98027.74	-0.43	0.667	-235380.4	150812.6
WS	-71854.43	84496.27	-0.85	0.396	-238296.5	94587.59
WS48	1498696	1.37e+07	0.11	0.913	-2.55e+07	2.85e+07
BPM	87963.43	364904.1	0.24	0.810	-630830.1	806757
VORP	234647.6	195909.1	1.20	0.232	-151257.1	620552.3
ACC	-36361.37	1396300	-0.03	0.979	-2786815	2714092
Big12	543677.1	1371747	0.40	0.692	-2158412	3245766
Top5P	345870.6	1594136	0.22	0.828	-2794283	3486024
Pk	-39420.71	34096.69	-1.16	0.249	-106584.9	27743.46
Inter	875476.4	1304387	0.67	0.503	-1693925	3444878
_cons	8056685	3530746	2.28	0.023	1101769	1.50e+07

Table 22. MP2 regressed on advanced statistics 6

Source	SS	df	MS		
				Number of obs =	253
				F(9, 243) =	66.58
Model	13674.3983	9	1519.37758	Prob > F =	0.0000

Residual	5545.11684	243	22.8194109	R-squared	=	0.7115
				Adj R-squared	=	0.7008
Total	19219.5151	252	76.2679171	Root MSE	=	4.777

MP2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Salary	-4.55e-08	4.74e-08	-0.96	0.339	-1.39e-07	4.79e-08
WS48	-38.49694	8.900418	-4.33	0.000	-56.02875	-20.96512
BPM	1.922342	.2197539	8.75	0.000	1.489476	2.355207
VORP	.3279779	.067485	4.86	0.000	.1950477	.4609081
ACC	-.8639474	1.099923	-0.79	0.433	-3.030548	1.302653
Big12	-.3637413	1.01684	-0.36	0.721	-2.366686	1.639203
Top10	-.2607096	.7576006	-0.34	0.731	-1.753012	1.231593
Inter	-.43048	.982252	-0.44	0.662	-2.365295	1.504335
Pk	-.2048684	.0202857	-10.10	0.000	-.2448267	-.1649102
_cons	29.65102	1.315409	22.54	0.000	27.05996	32.24208

Table 23. lnsalary regressed on advanced statistics

Source	SS	df	MS			
				Number of obs	=	253
				F(8, 244)	=	0.27
Model	2.89093213	8	.361366516	Prob > F	=	0.9748
Residual	325.170181	244	1.33266468	R-squared	=	0.0088
				Adj R-squared	=	-0.0237
Total	328.061113	252	1.30182981	Root MSE	=	1.1544

lnSalary	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
MP2	.0093858	.0146398	0.64	0.522	-.0194507	.0382223
WS	-.0040821	.0137738	-0.30	0.767	-.0312128	.0230485
BPM	.0023642	.0349055	0.07	0.946	-.0663904	.0711189
VORP	.0119526	.0320146	0.37	0.709	-.0511076	.0750128
ACC	-.0226205	.2649112	-0.09	0.932	-.544425	.499184
Big12	.1423297	.2446239	0.58	0.561	-.3395143	.6241737

Top5P	-.0212142	.2692669	-0.08	0.937	-.5515984	.5091699
Top10	-.0654271	.179046	-0.37	0.715	-.4181001	.2872459
_cons	15.00797	.4429255	33.88	0.000	14.13553	15.88042

Table 24. lnMP2 regressed on advanced statistics

Source	SS	df	MS		
				Number of obs =	253
				F(8, 244) =	50.64
Model	54.8792133	8	6.85990167	Prob > F =	0.0000
Residual	33.0503244	244	.135452149	R-squared =	0.6241
				Adj R-squared =	0.6118
Total	87.9295377	252	.348926737	Root MSE =	.36804

lnMP2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Salary	5.97e-10	3.65e-09	0.16	0.870	-6.60e-09	7.79e-09
WS	.0281935	.0040315	6.99	0.000	.0202525	.0361344
BPM	.1035281	.0097338	10.64	0.000	.0843551	.1227012
VORP	-.0566822	.0100219	-5.66	0.000	-.0764226	-.0369417
ACC	.0143769	.0844501	0.17	0.865	-.1519673	.1807211
Big12	-.0253938	.0779847	-0.33	0.745	-.179003	.1282153
Top5P	-.2755656	.0814327	-3.38	0.001	-.4359664	-.1151649
Top10	.0893463	.0568086	1.57	0.117	-.0225515	.2012441
_cons	3.018883	.0984227	30.67	0.000	2.825016	3.212749

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