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Essays on the Economics of the National Basketball Association (N.B.A.): Testing for Inefficiencies in the N.B.A. Labor Market

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Approval of the Dissertation Committee

This dissertation has been duly read, reviewed and critiqued by the Committee listed below, which hereby approves the manuscript of Samuel Lee as fulfilling the scope and the quality requirements for meriting the degree of Doctor of Philosophy in Economics.

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Abstract

Essays on the Economics of the National Basketball Association (N.B.A.):

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This dissertation is comprised of three economic essays, that each examine the labor market for players in the National Basketball Association (N.B.A.). Neoclassical economics often incorporate models that assume individuals are utility-maximizing agents who behave rationally. However, many studies in the field of behavioral economics have found evidence of irrational decision making, both within laboratory environments as well as in natural settings. The objective of this paper is to provide additional research to this growing body of literature by using empirical data collected from the N.B.A. to conduct quasi-field experiments. Although some may question their generalizability, one of the main advantages of using professional sports data is due to the abundant amount that is meticulously collected and regularly updated. Additionally, the enormous financial incentives rewarded to professional athletes make a strong case for the validity and reliability of the results.

The first chapter of this paper looks at whether the quality of program a basketball player chooses to play while in college, has any significant effects on their future professional careers. The paper uses salary and performance data from both Division I Men's N.C.A.A. Basketball as well as the N.B.A. to compare players who attended what I consider to be "elite college basketball programs" to those who had offers to play at one of these elite programs but instead

chose to attend another school. The research was partially motivated by an earlier study that looked at the financial effects of attending more academically selective colleges. Despite the common belief that academically elite schools would offer greater financial benefits upon graduation, the researchers found no significant differences in the career earnings of students who attended elite schools to those who were accepted to elite schools but chose to attend other, less selective schools. Using several econometric models, the results from this chapter indicate that players who attended elite basketball programs played fewer minutes in college and delayed their entrance to the N.B.A., compared to the group that attended non-elite programs. Furthermore, the career earnings of the group that attended elite schools are found to be significantly lower when adjusting for relevant variables.

The second chapter uses a sharp regression discontinuity design to examine whether an N.B.A. player's career is significantly affected by which side of the round cutoff they were selected during the league's annual rookie draft. Traditional economic theory would argue against any significant differences around this arbitrary cutoff point – one that has been artificially constructed by the league. Rather, financial compensation and playing time should be primarily based on a worker's expected productivity, regardless of where they were selected in the draft. However, earlier studies that looked at the National Football League (N.F.L.) have found evidence of substantial differences in compensation, as well as the perceived value of football players who were chosen before the round cutoffs compared to those selected immediately after. These initial differences in compensation and perception could create long term effects on a player's future productivity. Behavioral economics would attribute these findings to cognitive biases that humans are vulnerable to when decision making. Contrary to my initial hypothesis, that results similar to that of the N.F.L. would also occur in the N.B.A., the findings from this study fail to find any significant differences in player earnings and productivity at the round cutoffs. These results help support previous studies that found that earlier inefficiencies that had existed in the N.B.A. labor market, have since disappeared over the years.

The final chapter of this paper examines the effects the 1995 N.B.A. rookie wage scale had on the salaries and productivity of players who entered the league after its implementation. The rookie wage scale was introduced as a means of reducing the guaranteed salaries rookie players could receive upon entering the league. Using a fixed effects model, the initial test results show that the rookie wage scale did indeed have a significant negative impact on rookie salaries. The efficiency wage model of worker productivity predicts that an increase in salaries should incentivize workers to put forth more effort. If the efficiency wage model is accurate in describing the behavior of N.B.A. rookies, players who entered the league after the rookie wage scale will exert less effort because of a decline in their salaries relative to their peers. Assuming that effort is an important component in a player's production function, their productivity should therefore decline compared to similar players who entered the league prior to the wage scale. To test for this, I compare the career performances of players who entered the league before and after the rookie wage scale. The results fail to find evidence of a significant difference in performance; both during the immediate years after signing as well as in overall career performance. However, results from additional regressions comparing the two groups of players indicate that the rookie wage scale significantly lowered the average age of incoming players as well as increased the length of their professional careers.

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To my dearest wife, Caroline, and to my two boys, Adam and Evan. You guys brighten my life and motivate me to be a better person each and every day.

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The Best May Not Always the Best:

Does "Quality" of School Matter to Basketball Players?

Abstract: This chapter examines the career effects of playing at an "elite basketball school". The subjects in this study were all nationally ranked basketball players in high school, who were highly recruited by Men's Division I college basketball programs. Each member in the data set received at least one scholarship offer to attend an elite basketball school, yet some of them decided to play for other programs. By segmenting the players into two groups, I test whether there are any noticeable advantages of playing basketball at an elite program. Although many players from elite programs do go onto have successful professional basketball careers, there could also be less salient benefits of playing at a non-elite program. Using several econometric models, I compare the career outcomes of the two groups of basketball players during their time in college as well as in the National Basketball Association (N.B.A).

The dependent variables I use to compare the two groups of players are: the number of minutes they played during their freshman year in college, the number of years players stayed in college, the likelihood of being drafted in the N.B.A., the average pick they were selected in the draft, and finally the number of years played in the N.B.A. and the average salaries accumulated over the course of their careers. Despite commonly held beliefs that elite basketball colleges better prepare players for future success - when controlling for relevant individual, team and time variables - the regression results indicate that there are no significant differences between the two groups of players. Furthermore, additional regression results show that when controlling for those players ranked at the very top of their recruiting class,

from non-elite schools had more successful careers than their counterparts. A possible explanation for the findings may be a result of players overestimating the benefits of playing at an elite school as well as a demonstration of overconfidence in their abilities.

1.1 Introduction

The concept of rational, utility maximizing agents plays an integral role in many neoclassical economic models (Robbins, 1932; Becker, 1991). However, studies in behavioral economics have found that humans often demonstrate behaviors that are described as contrary to this axiom (Camerer, 1999; Mullainathan, 2000). Simon (1982) explains that humans are rationally bounded by the constraints they must face; specifically, information and time. Therefore, heuristics – a simplified rule of thumb – are commonly used to assist individuals in making complicated economic decisions (Tversky and Kahneman, 1975). Though often unlikely to produce optimal results, the use of heuristics generally produces outcomes that provide the individual enough utility to exceed a minimum threshold, known as satisficing (Simon, 1972). However, in many important life decisions - such as saving for retirement, selecting a health insurance plan or choosing a career – the act of satisficing would hardly seem appropriate. Yet, researchers find instances where even in critical decisions, people tend to make choices using irrational thought processes that can result in significant negative outcomes (Thaler and Benartzi, 2004; Choi, 2002).

The field of behavioral economics has played an important role in identifying and explaining many types of irrational behavior. An example of this is the tendency for people to use what is readily available in their minds to disproportionately influence their decision (Taylor, 1982). Experiments have shown that an irrelevant piece of information given by the researcher can be used as an anchor for subjects in their decisions without other information is available (Tversky, 1974). In addition, there is evidence that younger, less experienced decision makers are more vulnerable to committing irrational behaviors (List, 2003; Scheibehenne, 2005).

Although there are many studies that find examples of irrational decision making, many of these studies have been performed in the laboratory setting. This paper focuses on an important decision many teenagers must face in the real world.

For the average high school student, several factors might be considered in choosing a college to attend, such as the academic quality of the school, the distance from home as well as the financial costs (Gabert, 1999). Under a rational decision-making model, students should properly weigh all relevant factors and then select the school they believe maximizes their expected utility. The more colleges a student applies and is accepted to, should increase their expected utility by reducing their constraints on their choices. However, considering the number of students who transfer schools, change majors and drop out of school every year, it seems that many students fail to choose optimally. Research indicates that college students report being overwhelmed by the number of decisions they are required to make (Scott-Clayton, 2006). As an example of using heuristics, students may consider school rankings in their decision. Although useful, many have criticized how these rankings are constructed. Students who overestimate the importance of these rankings may end up choosing a school that is not in their best interest (Gnolek, 2014).

The group of basketball players examined in this study must also select a college to attend. However, due to their athletic abilities, they are afforded different opportunities and objectives than the typical student. Rather than having to deal with the process of applying to colleges and anxiously waiting for letters of acceptance, many schools will offer them full-ride athletic scholarships for their services to the school. These scholarships cover the out of pocket expenses associated with attending college - such as tuition and room and board. While this greatly reduces their opportunity costs of going to college, there are also significant implicit costs they must bear as well. Due to their amateur status, student-athletes are prohibited from receiving any compensation from their athletic talents.[1] Additionally, there are enormous financial incentives for college basketball players to leave school early to play professionally.

The National Basketball Association (N.B.A.) is widely considered the premiere professional basketball league in the world. In 2017, the average salary of an N.B.A. player was more than $5 million; with the minimum yearly salary set at more than $200,000 (Basketball-reference.com, 2018). Although there could be other factors that a player may consider in choosing a school, I assume that their decision will be based primarily off maximizing their career success in the N.B.A, due to the immense financial incentives. However, this decision could prove difficult when a player has many college offers to choose from. The number of options the players have available should not only be limited to the schools that have formally offered them scholarships, but also to schools that have not offered scholarships simply because of the unlikelihood of the player choosing to attend the school. This number could theoretically be in the hundreds. Therefore, players may end up using some form of heuristics to help guide their decision that could ultimately have negative effects on their career objectives.

It is difficult to parse the financial effects of attending a particular school in collegiate sports. One major hurdle is that every school has a different standard in the types of student athletes that are accepted. To mitigate this issue of selection bias, this paper uses a similar approach to an ingenious method that was done by Dale and Krueger in 2006, to look at the financial effects of attending more academically selective colleges. The researchers limited their data comparison to students that were accepted into both types of schools. Similarly, this paper

[1] Although there have been call for changes to this rule, the NCAA have not shown indications that they are interested in compensating student-athletes (Sanderson, 2015).

looks at athletes that chose to attend less prestigious basketball schools despite receiving offers from the elite programs.

Here is the structure for the remainder of the paper. Section 2 of this paper will provide a brief overview with respect to college basketball and the N.B.A. In Section 3, I will provide an extensive literature review of studies that are relevant to this paper. Section 4 provides descriptions and summarizes the data as well as the methodology used for the studies. Section 5 will provide the empirical models and an interpretation of the results. Lastly, Section 6 will provide a conclusion to the paper.

1.2 N.C.A.A. College Basketball and the N.B.A.

To understand the context of this paper, it is important to mention the current landscape of college basketball in the United States. The National Collegiate Athletic Association (N.C.A.A.) acts as the governing body of Men's Division I College Basketball, the highest level of collegiate basketball in the country. The N.C.A.A. has established rules that are intended to create a competitive market for schools to recruit players. One important rule is that colleges are unable to compete for players by offering financial compensations, which would give resource rich programs an unfair advantage. Despite these rules, the distribution of talent is not evenly distributed among the participating schools. In general, a handful of "elite basketball programs" are known to consistently recruit the highest ranked players. As an example, in 2016, the University of Kentucky had a recruiting class that was comprised of five players that were all ranked in the Top 50 in the entire nation. Considering that there are over 300 Division I basketball schools, for a single team to acquire ten percent of the top incoming players clearly shows that there are high levels of talent inequity among schools. Table-1 shows a list of the Top 30 ranked high school basketball players in 2016. Of the 30 players listed, 24 of them chose to attend an elite program.[2] The players who decide to play for an elite school must believe there are significant advantages for their future success compared to all other programs.

As noted before, talented college basketball players have strong financial incentives to play in the N.B.A. as soon as they are prepared to do so. A player who remains in school for all four years of their collegiate eligibility are thought to have stayed, not out of choice but because they would most likely not have been drafted had they left school earlier.[3] For many years, colleges have had to deal with the risk of losing players early to the N.B.A. However, recent changes to the N.B.A. collective bargaining agreement have heightened the effects. Under previous league rules, the most talented high school players were able to enter the league as soon as they had completed high school.[4] This allowed the most talented high school players to bypass college altogether. However, in 2006, the N.B.A. imposed a controversial rule that made it mandatory for all incoming players to have been at least one year removed from playing in high school.[5] The rule was created to mitigate concerns that high school players were not physically nor mentally mature enough to head directly to the N.B.A.[6] Since most of the players who might have gone directly to the N.B.A. otherwise, will disproportionately now choose to

[2] Although every school is unique and a standard definition of what an elite basketball school does not exist, I will give a more detailed explanation of how I define an elite school later in this paper.
[3] There are notable exceptions, such as Tim Duncan, who played in college all four years and was selected first in the NBA draft.
[4] Some of the most notable players who have played in the league, such as Kobe Bryant, Lebron James and Kevin Garnett, all went directly from high school.
[5] Prior to the rule, there were several notable players who announced their intention to forego college and go straight to the NBA.
[6] Those who supported the rule used previous cases of players who had skipped college and were unsuccessful in the league.

play for the elite schools, these programs must deal with the risk of losing their players even earlier.[7]

College basketball programs try to counteract the problem of early player attrition by often recruiting more players than there are available minutes for all their players. There are typically thirteen players on a college basketball team, yet only five of them can play at any given time. Each player is further constrained for playing time by the position they play.[8] In general, the starters on a team end up playing the majority of available minutes, while the remaining players are forced to sit on the bench. Schools may recruit additional players to sit on the bench to have quality players ready to replace starters when they are fatigued. Recruiting extra players can also act as a form of insurance in the case starters get injured. However, coaches may also be incentivized to recruit players without having any intention of playing them significant minutes during their freshman year. Instead, they may choose to keep them on the bench in hopes of convincing them to return for another year. Although this will help the program by retaining talented players, it may prevent certain players from optimizing their career objectives by keeping them in college longer.

Prospective players who are uncertain of their draft status must consider the risks involved in leaving school too early. Until recently, by declaring for the N.B.A. draft and signing a sports agent, a player would permanently lose their amateur status and not be able to return to school if they ended up deciding they would like to go back. As a result, players who were not selected during the draft are unable to improve their draft stock by returning to play in college but must find another route to make it to the league. Even if a player is confident that

[7] Although Kobe Bryant never went to college, he said he would have gone to Duke; one of the elite schools.
[8] There are five positions in basketball and most players are confined to playing one or two positions.

they will be selected in the draft, he could find it beneficial to return to school in order to improve his draft stock for the following draft. The N.B.A. draft is comprised of two rounds – players selected in the first round have guaranteed offers, while second rounders are not given any contract guarantees. Elite schools that could benefit from players returning may use this fact to convince players that did not receive much playing time during their first year into staying in school for another year. In a counterfactual scenario, where a player had gone to another school, they may have been able to start immediately.[9] If on court experience is a significant factor in a player's future success, players talented enough to be recruited by an elite school but not likely to start early on, would be better off playing for a less prestigious school.

Since college programs are unable to compete for players financially, another approach in recruiting players might be to emphasize the successful careers previous players from their program have gone on to have in the N.B.A. Recruiters may attribute this to their schools having better resources such as – superior coaches, the latest state of the art facilities, higher levels of competition, more recognition and a culture of winning– that help prepare players for the N.B.A. However, all this salient information could be misleading and inaccurate. Even though there are actual benefits these elite programs offer, they should also be weighed against the costs associated with playing at a more competitive school. Since an elite program begins with a greater number of highly ranked players playing for their schools compared to other schools, we would expect to see more successful players coming for these schools independent of any effects the school itself had on a player's future outcome. A greater number of players who played at

[9] A relevant situation comes from college football. In 2009, Pete Carroll, the coach of the University of Southern California, criticized his quarterback at the time, Mark Sanchez for leaving school early for the NFL. Carroll stated that he thought the quarterback was not prepared for the league. Sanchez was selected fifth overall in that year's NFL draft.

elite schools may have also gone on to have unsuccessful careers. Without taking this into consideration, players may overestimate the benefits an elite program contributes to their future success.

If there are indeed overall net positive effects of attending an elite basketball school, the data should show that players who played at these schools were better off than had they chosen to play at a non-elite school. Although a method for testing the counterfactual is not possible for this study, I use similarly ranked high school players that were also recruited by elite schools but chose not to attend, as a control group for comparison. Although there could be unobservable differences between the groups of players, this will significantly reduce the selection bias that would result if simply comparing the careers of all the players in Division I basketball. Based off previous research, I hypothesize that the results will indicate that the benefits of playing at an elite basketball program are highly overestimated. The following section provides a literature review of previous work relevant to this paper and that will help support my hypothesis.

1.3 Literature Review

Sports and behavioral economics are both relatively new topics of research in the field of economics. The rise in their popularity coincides with improvements in technology that have allowed for researchers to probe more finely into the area of sports economics. Despite criticisms about the generalizability of sports to the broader world, one of its main benefits is the abundance of accurate and up to date data that researchers have available. Additionally, the high salaries of professional athletes create a natural environment combined with strong financial incentives that make the observations reliable. The field of behavioral economics has used sports to find many evidences of irrational behavior despite the competitive nature of professional leagues. The following section describe several earlier studies in the field and their findings.

One of the earliest studies that incorporated sports and behavioral economics in its research examined the concept of the “hot hand” in the N.B.A. (Gilovich, Tversky, 1985). Prior to the paper’s findings, it was thought that N.B.A. players experienced episodes of “hot” and “cold” streaks of shooting during games. A player who made several baskets in a row was considered more likely to make his next shot than if he had previously missed consecutive shots. However, when the researchers looked at shot data from one of the league’s teams and controlled for each player’s individual shooting ability, they found no evidence of the hot hand. One explanation the researchers gave as to why casual observers were susceptible to this false belief was due to the “availability bias” (Tversky, 1974). The availability bias states that humans often overweight memory that is easily available and most recent in our minds to construct a future probability of likelihood that is inaccurate. However, some later studies have criticized the methodology of the paper and have tried to account for important variables that the initial study did not measure, such as the increased amount of attention that a player would get from the opposing team when he makes consecutive shots. When controlling for these variables, the researchers find evidence supporting the idea that players do in fact experience streaks of being “hot” and “cold” (Camerer, 1989; Ayton, Fischer, 2004).

Studies have also used data from the N.B.A. to study a wide variety of economic topics, ranging from racial discrimination to problems of moral hazard. In an early study, Kahn (1988) found evidence of salary discrimination. The study showed that black players were paid significantly less than their white counterparts. However, a following study showed that discrimination in salaries against black players have since disappeared (Bodvarsson, 1999). The researchers claimed this was due to greater strength in the league's players union that made it more difficult for owners from discriminating on race.

Another study found evidence of racial discrimination amongst N.B.A. referees (Price, 2010). The findings showed that referees called more fouls against players of the opposite race. This would seem like an irrational behavior since referees are evaluated on their performance and should not have any incentive to discriminate. Not only has there been evidence of discrimination but studies also finding evidence of referees point shaving (Gibbs, 2007). This is not surprising since a referee by the name of Tim Donaghy was found guilty and sentenced to prison for having engaged in point shaving.

Sports also provides a useful area of research in looking for evidences of moral hazard since there are quantitative methods available to measure player productivity. One related study found evidence of moral hazard behavior among N.B.A. players. The paper found that a player's performance declines the further they are away from their next contract. Additionally, a player's performance significantly improves the year prior to becoming a free agent (Stiroh, 2007). The research attributes this to the fact that N.B.A. player contracts are fully guaranteed regardless of future productivity. Another paper by Staw and Hoang (1995), finds evidence that N.B.A. teams are guilty of incorporating "sunk costs" in their decision making. The researchers found that teams will give more minutes to a player simply because they were selected earlier in the draft rather than based strictly on their productivity. A team's inability to remove the memory of sunk costs that were already paid and cannot be reimbursed will continue to have negative effects into the future. Finally, studies have looked at college data to determine a player's future outcome in the N.B.A. A study by Berri (2006) showed that players who scored more in college were likely to be drafted earlier, even though scoring is not a great measure of future performance. Another study found that the conference a player played in has a significant effect on their future draft status (Coates, 2010). This paper looks to add to this growing body of literature by looking at the effects the quality of the college program has had on the careers of basketball players.

Another motivation for this paper comes from earlier research performed by Dale and Krueger (2002), that compared the career earnings of graduates from Ivy League schools to those of less selective state schools. Unsurprisingly, an Ivy League graduate earns significantly more on average than a state school graduate. However, the researchers wanted to look at whether the qualities of schools contributed to the difference in earnings, or if higher earning members more often self-selected themselves to better schools. The researchers obtained access to data that allowed them to focus their study on students who were granted admission to both types of schools. The researchers found that when limiting their observations to these students, the quality of school had no significant effect on average earnings between the two groups. The results supported the hypothesis that the institution one attends has less importance on future earnings compared to one's own ability. It could also be the case that there are benefits of attending a less selective school that people often overlook. The current study takes this concept and tests whether it could be generalizable to sports.

Relative Deprivation and the "Big Fish Little Pond Effect" (B.F.L.P.E)

In his book, "David and Goliath", the author Malcolm Gladwell discusses the concept of "relative deprivation." The term, originally coined by early sociologist Samuel Stouffer, states that humans are not accurate calculators of absolute measurements. Instead, we often use those immediately around us to gauge are relative circumstance. The book cites a study that found that top academic researchers at lower ranked schools were shown to produce a higher score in journal publications compared to peers at more prestigious programs but who were not among the elite researchers at their respective schools (Conley and Onder, 2014). One theory that is proposed by the authors states that students at the less prestigious schools receive more mentoring and care from their colleagues. On the other hand, at prestigious schools, competition for limited resources will go disproportionately to those at the very top, leaving the remaining researchers relatively deprived. In the context of this paper, the limited resources could be in the form of the amount of attention given by their coaches, access to trainers and facilities, and the amount of playing time.

Another similar concept that discusses the negative effects of greater competition is known as the Big Fish, Little Pond Effect (BFLPE) (Marsh and Parker, 1984). The researchers looked at the self-perceived academic ability of similarly abled students who attended different quality schools. The researchers found that those who attended the better-quality schools self-reported lower levels of academic ability. The study provides further evidence that humans use others around them as a reference for their own overall ability. Additionally, the researchers performed a longitudinal study that showed that the students who reported lower perceived ability demonstrated lower performances in subsequent performances.

Researchers later looked at whether the BFLPE had any role in one's own perception of athletic ability (Chanal, Marsh, 2006). The study asked children to rate their gymnastic ability after they had participated against different levels of performers. Here, the results showed similar findings. Those competing against better competition, self-reported a lower overall ability. This was considered the first study that looked at the relationship between BFLPE and sports. The current paper tries to expand the literature by using college athletes to look at actual outcomes rather than simply their self-perceptions.

There is also an abundance of research that have looked at the benefits of being around a more competitive environment. The environmental press theory states that attending a more selective college can benefit students by increasing one's motivation through greater competition. Wert and Watley (1969) compared the effects of relative deprivation to that of the environmental press theory and found evidence that showed the former had a greater effect. In an experiment that compared the preference for competition, Niederle (2007) found that men prefer more competitive environments to women. However, the study also found men to have more overconfidence, which leads to them engaging in competition that goes beyond the optimal amount.

Another robust finding in behavioral economics, is that people often demonstrate overconfidence in their own abilities (Kahneman, 1997). Players may select an elite school if they overestimate their likelihood of becoming a starter. One study finds that participants, when asked to evaluate the performance of average driver's or the likelihood for a business to fail, have an accurate understanding of the statistics. Despite having this information, they will overestimate the likelihood of their own success (Camerer, 1999). Furthermore, men are more likely to be overconfident in their abilities (Barber, 2001 Malmendier, 2005). This is further exasperated when the task is one that the participant feels they are good at (Spiers-Bridge, 2010). In college sports, the problem has been addressed by Mark Emmert, the NCAA's president. In one of his speeches, he is quoted as saying "athletes often have incredibly unrealistic perceptions of their professional prospects."

The Effects of Choice Overload

In traditional economics, choices are often thought of as goods that are utility improving. A decision maker should not have any negative effects if they are offered additional choices, since all previous options remain available. However, studies have shown that consumers are less satisfied with their purchases when offered too many choices (Iyengaar, 2000). Schwartz (2004) found that subjects describe having higher expectations and more regret when given more choices. Researchers have used several terms such as "choice overload", "the paradox of choice" and "decision paralysis" to describe these effects. A meta-analysis found that choice overload can be exacerbated if the decision maker is inexperienced and unable to easily compare the different options (Scheibehenne, 2010). This can be applicable to this study, since every player will have many schools to choose from. If a player is uncertain which school is best suited for them, they may try to simplify their decision by using whatever is most salient. This would cause players to overlook many benefits other schools would have to offer.

1.4 Data and Methodology

All relevant data used in this paper comes from the following websites: Sports-reference.com, Basketball-reference.com and 247sports.com. Sports-reference.com is one of the leading websites in collecting and updating individual player and team data for N.C.A.A. Men's Division I college basketball. 247sports.com is one of the premiere websites for ranking high school basketball prospects by class. The website ordinally ranks the Top 100 high school basketball players every year. In addition, since certain classes of players are considered to be stronger than other years, it also provides a cardinal rating of each individual player on a scale from 0 to 1. Lastly, the website, Basketball-reference.com, was used to collect player performance as well as player salary data for the N.B.A.

The complete data set is comprised of 210 high school basketball players who were ranked in the Top 30 of their recruiting class according to 247sports.com from the years, 2006 to 2012. I chose to limit the data to these years since prior to 2006, high school players were not required to attend college and could go straight to the N.BA. Every one of the players were recruited by at least one elite school. This information is verifiable since the website 247.com lists all the schools that officially offered an athletic scholarship to each of the players. This information is critical because it implies that players who did not attend an elite school chose to do so voluntarily. Although thirty could be considered an arbitrary number, I chose this figure as the cutoff as it coincides with the current number of first round selections in the N.B.A. draft. If the high school rankings are highly accurate, each player would have a realistic chance of playing in the N.B.A. and therefore provide a sufficient sample size for conducting the study. Additionally, even among these top recruits, there are certain players that are ranked considerably higher than their peers. Therefore, I further segment some of the players at the very top of their class who were rated at least .999 by 247Sports.com and list them as, *super recruits*.

Unfortunately, a precise definition of what constitutes as an "elite basketball school" does not exist and can be debatable. For the sake of this paper, I created a list of schools that fall into this category based off a criterion which used the following factors - championships won, recent and overall program success, program revenue and recruiting rankings. Based off this methodology, there were ten schools that were considered elite programs. The schools that were selected are: Duke, North Carolina, Michigan State, UCLA, Villanova, Syracuse, Kentucky, Arizona, Kansas and Indiana. Table-2 shows the list of schools with the highest winning percentage of all time. Six of these programs rank in the Top 7 of all time wins, while all of them are in the Top 15. The other schools were left off due to their lack of recent success. Every school has won multiple NCAA championships and has had many of their players play in the N.B.A.[10] Another note of importance is that all the schools listed are considered primarily basketball schools and compared to another major sport such as football. All other schools that are not included are considered non-elite. Although there could be an argument for significant disparities even among non-elite schools in terms of basketball quality, I do not segment the quality of schools any further. The outcome measurements I use as dependent variables are: the amount of playing time during their freshman season, the likelihood of being drafted in the N.B.A, the draft pick they are selected, the average number of seasons played in the N.B.A. and their career earnings in the N.B.A.

1.5 Empirical Models and Results

Table-3 provides descriptive statistics that compares the players that attended an elite school to those who attended all other programs. Of the total, 210 players in the data set - 106 of them attended an elite school and 104 played at other schools. This provides us with a balanced number of data points for each group. The average career earnings of players in the data set is \$15.64 million. Those who attended elite schools earned slightly less, \$15.33 million, compared to \$15.94 million for those who went to all other schools. The results from the statistics show

[10] One exception is Syracuse, which has only won one NCAA championship. However, considering the other factors used in comprising the list, I believe they fall into the elite school category.

that there are no significant differences in the observable characteristics between the two groups of players.

Effects of Attending an Elite School on Freshman Playing Time

The first test I conducted looked at the immediate effects the quality of school had on the players. I assume that an important factor in selecting the ideal basketball program to play for involves the amount of playing time one initially receives. I hypothesize that players attending non-elite schools will receive more playing time compared to those who attend elite schools due to less competition from teammates. To confirm my hypothesis, I used a fixed effects model to test for any significant differences in playing time between the two groups of players during their freshman year in college. The log-linear regression model I used was

$$\ln(playingtime_{it}) = \alpha_i + x'\beta_{it} + \gamma_i elite + \delta_t + \varepsilon_{it}$$

where $x'\beta_{it}$ indicates a vector of control variables such as a player's race, position, the class year and other important factors that would affect playing time such as injuries or academic ineligibility. Additionally, the variable, $\gamma elite$, indicates a dummy variable, where $\gamma = 1$ if a player attended an elite school and 0 if they did not. δ_t , indicates a year fixed effects term. The last term,ε_{it} is the idiosyncratic error term. The results from the model are reported in Table-4. The initial results indicate that players at non-elite school's players play 19.6% more minutes compared to those who attend elite schools. The results are statistically significant at the 1% level and consistent with my earlier hypothesis. Players at elite schools are less likely to be a starter during their freshman year since there are other highly recruited players that are fighting for limited playing time.

I then controlled for players who I considered to be super recruits by incorporating the dummy variable, *super recruit*, where a value of 1 is given if a player is a super recruit and 0 otherwise. The following formula describes the model:

$$\ln(playingtime_{it}) = \alpha_i + x'\beta_{it} + \gamma_i elite + \theta_i superrecruit + \delta_t + \varepsilon_{it}$$

Table-4 also shows the results of controlling for super recruits on freshman playing time. Column (3) includes an interaction term between elite schools and super recruits as well. The results show that super recruits received more playing time regardless of the school they attended. This will further negatively impact playing time for the remaining freshman players at the elite schools. Those attending non-elite schools now have 32.9% more playing time. The results from both models - with and without controlling for super recruits - were significant at the 1% level. These findings are important if on-court minutes are critical for players to gain experience in preparation for their professional careers.

The Effects of Playing at an Elite School on Years in College

The next test was to determine whether there were any differences in the amount of years a player stayed in college between the two groups. As explained earlier in this paper, I assume that highly ranked players want to play in college for the minimum amount of time that is necessary. The longer a player stays in college indicates that they are not considered ready to play professionally. To test this, I ran a fixed effects model using the number of years a player stayed in college as the dependent variable:

$$YearsinCollege_{it} = \alpha_i + x'\beta_i + \gamma elite_i + \delta_t + \varepsilon_{it}$$

The variables on the right-hand side are identical to the ones used in the previous model. The results are listed in Table-5. The figures show that when controlling for individual variables, the players who attended elite schools stayed in college on average 0.275 years longer. The results are significant at the 1% level. Next, I again control for players that I consider to be super recruits. When controlling for super recruits, the findings show the difference between groups is even greater. Non-super recruit players who choose to attend elite college players remain in college 0.528 years longer than their counterparts, which is also statistically significant at the 1% level. Although considered an advantage for most students, to these basketball players this is an indication that they are concerned over their readiness to play in the N.B.A. The longer they remain in school, increases their opportunity cost due to foregone earnings they could be making in the N.B.A.

<u>The Effects of Elite Schools on the Likelihood of Being Drafted in the N.B.A.</u>

I then tested to see how school differences effected the next stage in the player's careers by examining the likelihood of being drafted in the N.B.A. The next study was to see whether there were any differences in the likelihood of being selected in the N.B.A. draft, regardless of where a player was drafted. Every year there are 60 players selected in the N.B.A. draft. Although there are significant differences in being selected early in the draft compared to being selected near the end, I do not distinguish by round or selection number. I test this using a logit model where the dependent variable is the probability of being drafted as follows:

$$\boldsymbol{logit(Drafted \mid \gamma = 1) = \alpha_i + x'\beta_i + \gamma elite_i + \delta_t + \varepsilon_{it}}$$

The logit model has advantageous properties that limit the probability from being between 0 and 1. I first include all players in the data set, controlling for several variables including year, race and whether there were any other issues such as injuries that would influence the dependent variable. As shown in Table-6, there is a negative effect elite schools have on the likelihood of being drafted. The results indicate they are 0.00329 times less likely to be drafted, but this is a small discrepancy that is not significant at any level. Additionally, Table-7 shows the log odds ratio of the likelihood of being drafted between players who attended elite schools to non-elite ones.

I then control for super recruits adding the dummy variable, *super recruit*. Although the results show an even greater effect, players who attend elite schools are now 0.407 times less likely to be drafted, it did not reject the null hypothesis at the 10% level. It is clear though that the super recruits have a much higher likelihood of being drafted compared to the rest of the group.

The Effects of School Quality on Draft Position

The fourth test I performed looked at whether there were any differences in the draft number a player was selected. For an N.B.A. prospect, it is not only important to be drafted, but selected early. The N.B.A. plays their rookies using a wage scale system where players selected early in the draft make significantly more compared to those at the very end. Also, those selected in the first round are guaranteed contracts, while second rounders do not. Therefore, a player may get selected in the second round but never sign an N.B.A. contract. I use an ordinary least squares (OLS) model where the dependent variable is the draft number.

$$\boldsymbol{draftnumber_i = \alpha_i + x'\beta_i + \gamma elite_i + \delta_t + \varepsilon_{it}}$$

A positive value on an independent variable would indicate that a player will be selected later in the draft, which will have a negative effect on career outcome. The results are listed in Table-7. The initial results, without controlling for super recruits indicate that players who attended elite schools were taken 0.299 picks later. Further, controlling for super recruits, the results showed that players who attended elite schools were drafted 4.1 picks later. However, these results did not reject the null hypothesis that elite schools had no effect on where a player was drafted. I also incorporated a Tobit model to control for the fact that the draft is limited to 60 players. I give a player that is not chosen in the draft a selection number of 61 as the upper limit. Although, this distorts the data, I propose it is not significant considering the number of players given this value. Also, I expect there to be a small difference of having had been the 61^{st} versus a later number to a player's career. Columns (3) and (4) in Table-8 are the results from the Tobit model, with and without controlling for super recruits. When controlling for super recruits, the Tobit model shows that players attending elite schools are drafted 6.7 positions later. However, this too is not considered significant at any level.

<u>The Effects of School Quality on N.B.A. Career Earnings</u>

Finally, in order to test the career financial impact of playing at an elite school, I compared the career earnings of the two groups using the following structural earnings models.

$$\boldsymbol{CareerEarnings_{it} = \alpha_i + x'\beta_i + \gamma elite_i + \delta_t + \varepsilon_{it}}$$

The initial results that are listed in Table-8 show that the players from elite schools earned on average \$1.107 million less, but the difference was not considered statistically significant. The insignificant results are still noteworthy because common perception would assume that there would be a significantly positive effect of playing at an elite school.

Furthermore, when controlling for the super recruits, the remaining players saw a decrease in earnings of $6.64 million that was significantly different at the 5% level. This indicates that most of benefits of going to an elite school are gained by the elite players of that school, while the remaining players are negatively affected. A Tobit model to control for the fact that some players will have a lower bound at $0 for those who did not play in the league is also listed. This increases the discrepancy of the two groups of non-super recruit players to $10.63 million, which is also significant at the 5% level.

To address concerns of heteroskedasticity in the error term, I also ran a log-linear model that uses log earnings as the dependent variable.

$$\ln(careerearnings_{it}) = \alpha + x'\beta_{it} + \gamma elite_i + \delta_t + \varepsilon_{it}$$

When controlling for super recruits as well as the other independent variables, there is a significant decrease in the log salary of player's attending an elite school compared to those who did not. Table-10 shows the regression results. On average, players who attended elite programs were shown to have career earnings that are 42,4% lower compared to those who attended non-elite programs, that is significant at the 10% level. A Tobit model on the lower bound of log earnings is also calculated. The results show that the difference is 35% but no longer considered statistically significant.

Overall, there are strong indications that players are negatively affected by attending elite programs compared to players who attended other non-elite schools. The results show that players who attend elite school are likely to stay in school longer and have a decline in earnings over the course of their N.B.A. career. The results may be a consequence of many high school players overestimating their abilities by choosing to play at an elite school when they would be better off elsewhere.

1.6 Conclusion

One of the main axioms in neoclassical economics is the belief that people are generally rational decision makers. However, experiments and empirical data indicate that this is often not the case. Research in behavioral economics has made it apparent that humans are susceptible to cognitive biases such as the availability bias and the overconfidence bias. Irrational behavior becomes more evident and harmful when dealing with significant life altering decisions that can have large financial implications, such as selecting a college to attend. Additionally, external effects such as the feeling of “relative deprivation” and “the Big Fish, Little Pond Effect” can have significant impact on one’s outcomes.

This paper looked specifically at the effect’s college choice had on highly recruited basketball players. The results from this study finds evidence that college basketball players may overweight the benefits of attending elite basketball schools. Ultimately, this results in negative effects to their career outcomes, especially for those not at the very top of their class. Players who attend elite programs do not play as many minutes during their freshman year, which likely diminishes their probability of being drafted and playing in the N.B.A. The results also show that this decision leads players to spend extra time in college when they could be playing professionally. Finally, their career earnings are substantially lower compared to similarly ranked players who did not attend elite schools. As shown by the data, the consequences are not trivial. The results cast doubt on the idea that elite programs better prepare their players for success in the N.B.A.

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Table-1. Rankings of High School Basketball Players in 2016

Rank	Player	Pos	School	State	College
T1	**Harry Giles**	**PF**	**Oak Hill**	**VA**	**Duke**
T1	**Josh Jackson**	**SF**	**Prolific Prep**	**MI**	**Kansas**
3	**De'Aaron Fox**	**PG**	**Cypress Lakes**	**TX**	**Kentucky**
4	**Jayson Tatum**	**SF**	**Chaminade**	**MO**	**Duke**
T5	Dennis Smith Jr.	PG	Trinity Christian	NC	NC State
T5	**Malik Monk**	**CG**	**Bentonville**	**AR**	**Kentucky**
7	**Lonzo Ball**	**PG**	**Chino Hills**	**CA**	**UCLA**
8	Markelle Fultz	CG	DeMatha Catholic	MD	Washington
T9	**Edrice Adebayo**	**PF**	**High Point Christian**	**NC**	**Kentucky**
T9	Jonathan Isaac	SF	IMG Academy	FL	Florida St.
11	**Miles Bridges**	**SF**	**Huntington Prep**	**WV**	**Michigan St.**
12	Terrance Ferguson	SG	Advanced Prep	TX	Alabama
13	**Frank Jackson**	**PG**	**Lone Peak**	**UT**	**Duke**
14	**Rawle Alkins**	**SG**	**Word of God**	**NC**	**Arizona**
15	**Wenywen Gabriel**	**PF**	**Wilbraham & Monson**	**MA**	**Kentucky**
16	**T.J. Leaf**	**PF**	**Foothills Christian**	**CA**	**UCLA**
17	**Kobi Simmons**	**CG**	**St. Francis**	**GA**	**Arizona**
18	**Josh Langord**	**CG**	**Madison Academy**	**AL**	**Michigan St.**
19	**Marques Bolden**	**C**	**DeSoto**	**TX**	**Duke**
20	Jarrett Allen	PF	St. Stephen's	TX	Texas
21	**Omari Spellman**	**C**	**McDuffie**	**MA**	**Villanova**
22	Dewan Huell	PF	Norland	FL	Miami
23	Mustapha Heron	SF	Sacred Heart	CN	Auburn
24	V.J. King	SF	Paul VI	VA	Louisville
25	**Sacha Killeya-Jones**	**PF**	**Virginia Episcopal**	**VA**	**Kentucky**
26	**Tyus Battle**	**SG**	**St. Joseph**	**NJ**	**Syracuse**
27	**Udoza Azubuike**	**C**	**Potters House**	**FL**	**Kentucky**
28	**Cassius Winston**	**PG**	**University Detroit**	**MI**	**Michigan St.**
29	**Tony Bradley**	**C**	**Bartow**	**FL**	**North Carolina**
30	Juwan Durham	PF	Tampa Prep	FL	Connecticut

Table-2. Overall Winning Percentage of Division 1 Basketball Programs

1	Kentucky*	1903	114	2,237	688	.765
2	North Carolina*	1911	107	2,206	781	.739
3	Kansas*	1899	119	2,217	841	.725
4	Duke*	1906	112	2,115	873	.708
5	UCLA*	1920	98	1,805	824	.687
6	Syracuse*	1901	116	1,755	880	.666
7	Western Kentucky	1915	98	1,724	901	.657
8	Arizona*	1905	112	1,750	923	.655
9	Louisville	1912	103	1,680	901	.651
10	Notre Dame	1898	112	1,845	994	.650
11	Villanova*	1921	97	1,709	920	.650

* These are all teams that I consider to be elite schools.   Indiana was 20th and Michigan St., though not listed in the Top 20 has won 2 NCAA championships and has consistently been one of the best teams over the past decade.

Table-3. Descriptive Statistics by Schools

	(1) Overall	(2) Elite	(3) Non-Elute
Earnings	15.64	15.33	15.96
	(26.73)	(27.34)	(26.23)
YearsinNBA	3.367	3.302	3.433
	(3.258)	(3.249)	(3.282)
Drafted	0.667	0.670	0.663
	(0.473)	(0.473)	(0.475)
YearsinSchool	2.600	2.736	2.462
	(1.179)	(1.221)	(1.123)
MinFresh	758.6	706.9	811.3
	(315.6)	(330.3)	(292.2)
Black	0.881	0.868	0.894
	(0.325)	(0.340)	(0.309)
N	210	106	104

mean coefficients; sd in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4. Regression Results – Freshman Playing Time

VARIABLES	(1) LN(FreshMin)	(2) LN(FreshMin)	(3) LN(FreshMin)
Elite School	-0.196***	-0.253***	-0.319***
	(0.0743)	(0.0751)	(0.0808)
Super Recruit		0.345***	0.118***
		(0.0919)	(0.0153)
Super Recruit * Elite School			0.354*
			(0.190)
Black	-0.023	-0.032	-0.045
	(0.0342)	(0.0573)	(0.0473)
Position	-0.055	-0.063	-0.075
	(0.0732)	(0.0886)	(0.0895)
Foreign	-0.0686	-0.119	-0.110
	(0.129)	(0.125)	(0.125)
Issues	-0.699***	-0.662***	-0.633***
	(0.123)	(0.119)	(0.120)
Year	0.162	0.137	0.127
	(0.107)	(0.104)	(0.104)
Constant	6.537***	6.475***	6.502***
	(0.120)	(0.117)	(0.117)
Observations	210	210	210
R-squared	0.206	0.260	0.272

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. OLS Regression – The Effect of Attending an Elite School on Years in College

VARIABLES	(1) YearsinCollege	(2) YearsinCollege	(3) YearsinCollege
Elite School	0.275*	0.468***	0.528***
	(0.165)	(0.152)	(0.173)
Super Recruit		-1.284***	-1.019***
		(0.190)	(0.323)
Elite School * Super Recruit			-0.390
			(0.403)
Position	-0.230	-0.180	-0.192
	(0.225)	(0.203)	(0.206)
Black	0.0108	-0.0800	-0.0415
	(0.257)	(0.233)	(0.239)
Issues	0.185	0.0440	-0.00238
	(0.269)	(0.244)	(0.254)
Year	-0.219	-0.120	-0.0995
	(0.239)	(0.217)	(0.219)
Foreign			-0.103
			(0.264)
Constant	2.493***	2.730***	2.676***
	(0.262)	(0.239)	(0.249)
Observations	210	210	210
R-squared	0.025	0.206	0.207

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6. Logit Regression – Probability of Being Drafted in the N.B.A.

VARIABLES	(1) Drafted	(2) Drafted	(3) Drafted
Super Recruit		2.174***	1.223
		(0.630)	(0.825)
Elite School	-0.00329	-0.261	-0.487*
	(0.300)	(0.315)	(0.337)
Position	0.458	0.434	0.459
	(0.431)	(0.447)	(0.459)
Black	-0.762	-0.605	-0.625
	(0.533)	(0.555)	(0.560)
Issues	-0.0676	-0.00918	0.0355
	(0.480)	(0.496)	(0.504)
Year	0.899*	0.880*	0.784
	(0.521)	(0.534)	(0.541)
Foreign	0.045	0.027	-0.738
	(0.834)	(0.643)	(0.556)
Elite School * Super Recruit			1.878
			(1.335)
Constant	1.211**	0.912	1.045*
	(0.536)	(0.558)	(0.569)
Observations	210	210	210

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table-7.Log Odds Ratio

	(1) Drafted
Elite School	0.502
	(1.43)
Position	0.169
	(1.26)
Black	-0.890
	(-1.49)
Issues	0.768
	(1.29)
Foreign	-0.592
	(-1.06)
MinFresh	0.00357***
	(5.38)
_cons	-1.888
	(-1.89)
N	204

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table-8. OLS Regression – The Effect of Elite School on Draft Pick

VARIABLES	(1) DraftPick	(2) DraftPick	(3) DraftPick	(4) DraftPick
Super Recruit		-23.41***		-31.84***
		(3.679)		(5.496)
Elite School	0.299	4.100	0.809	6.727
	(3.139)	(2.935)	(4.835)	(4.531)
Position	-2.584	-2.086	-4.924	-4.075
	(4.286)	(3.924)	(6.525)	(5.949)
Black	6.769	3.885	12.37*	8.314
	(4.904)	(4.512)	(7.336)	(6.685)
Issues	11.73**	10.44**	13.62*	11.50
	(5.134)	(4.704)	(8.042)	(7.321)
Year	-10.13**	-9.245**	-14.23**	-12.69**
	(4.574)	(4.189)	(6.861)	(6.244)
Constant	30.75***	35.98***	34.39***	40.82***
	(5.002)	(4.651)	(7.465)	(6.889)
Observations	210	210	210	210
R-squared	0.064	0.219		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Columns (3) and (4) are Tobit Models that use 61 as the upper limit for draft picks.

Table-9 : The Effects of Elite Schools on Career Earnings

			Tobit	Tobit
	(1)	(2)	(1)	(3)
VARIABLES	earnings	Earnings	earnings	earnings
Super Recruit		34.08***		43.26***
		(3.932)		(5.201)
Elite School	-1.107	-6.640**	-2.593	-10.63**
	(3.586)	(3.137)	(4.975)	(4.326)
Position	4.718	3.994	5.037	4.163
	(4.896)	(4.194)	(6.784)	(5.733)
Black	-3.255	0.943	-8.006	-2.544
	(5.603)	(4.823)	(7.550)	(6.359)
Issues	-14.30**	-12.42**	-17.01**	-13.93**
	(5.865)	(5.028)	(8.306)	(6.997)
Year	17.13***	15.84***	21.19***	19.15***
	(5.225)	(4.477)	(7.052)	(5.930)
Constant	17.42***	9.796*	13.83*	5.162
	(5.713)	(4.972)	(7.683)	(6.548)
Observations	210	210	210	210
R-squared	0.089	0.335		

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Career Earnings Figures Represent Millions of $.

Table-10. The Effects of Attending an Elite School on Log Earnings

VARIABLES	(1) Ln(Earnings)	(2) Ln(Earnings)	(3) Ln(Earnings)	(4) Ln(Earnings)
Super Recruit		1.625***		1.544***
		(0.281)		(0.256)
Elite School	0.0177	-0.424*	0.0637	-0.352
	(0.271)	(0.254)	(0.252)	(0.233)
Position	0.397	0.365	0.368	0.320
	(0.374)	(0.335)	(0.345)	(0.305)
Black	-0.225	-0.169	-0.150	-0.0829
	(0.384)	(0.344)	(0.354)	(0.313)
Issues	-1.606***	-1.389***	-1.505***	-1.307***
	(0.457)	(0.411)	(0.436)	(0.388)
Year	0.966***	0.926***	0.940***	0.889***
	(0.367)	(0.329)	(0.338)	(0.298)
Constant	2.279***	1.969***	2.227***	1.939***
	(0.388)	(0.352)	(0.359)	(0.321)
Observations	141	141	141	141
R-squared	0.156	0.325		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

On the Wrong Side of the Cutoff:

Using Sharp Regression Discontinuity to Test for

Effects of Round Cutoffs on the Careers of N.B.A. Players

Abstract: This chapter examines the effects league imposed, arbitrary round cutoffs have had on the career outcomes of basketball players in the National Basketball Association (N.B.A.). The N.B.A. created these cutoffs to distinguish players who were selected in the first and second round in their annual rookie draft. According to traditional economic theory, these round cutoffs should not have any significant effects on the compensations and productivity of the players. However, previous studies have shown that round effects do in fact exist in the National Football League (N.F.L.) labor market. By using a sharp regression discontinuity design, I test to see whether players selected at the end of the first round are significantly more productive and earn more in player salary compared to the players chosen at the beginning of the second round. The results from the model indicate that are no significant differences in either compensation or productivity. A pooled cubic regression on the dependent variables is also conducted to further verify the results. The findings support previous research that indicate that the market for N.B.A. players has become more efficient.

2.1 Introduction

The National Basketball Association (N.B.A.) is widely considered the premiere basketball league in the world. Although there are many other professional basketball leagues throughout the world, none of them can compete with the N.B.A. in terms of popularity, revenue and player salary. In 2017, the average N.B.A. player earned approximately $6 million a year (Basketball-reference.com, 2018). Unsurprisingly, the odds of making it to the N.B.A. are incredibly low. Of all the prospective basketball players around the world competing for a roster sport, roughly only 450 players make it to the league in a given year. The path most players take to reach the N.B.A. is to first play collegiately and perform well enough to get recognized by N.B.A. teams. The next step is to eventually enter their names in the N.B.A. draft and hopefully get selected by one of the teams.

The N.B.A. Draft is held annually prior to the beginning of the new season. Each of the 30 teams currently in the league are awarded two draft picks; one in the first round and another in the second. Therefore, the 31st player chosen in the draft is the first player selected in the second round [11]. The order of the first three picks in the draft are determined ahead of time by a lottery system. The odds of winning the lottery is based inversely off the team's previous year's regular season win-loss record. The system was developed in hopes of creating competitive balance within the league but also, simultaneously to prevent teams from deliberately losing; otherwise known as tanking. The remaining picks in the draft are then ordered beginning with

[11] Teams are not required to keep these picks and are able to use them as trade assets.

the team with the worst record that did not acquire one of the first three picks. The second round begins again with the team with the worst record receiving the first pick. This fact could potentially create some concerns of selection bias if teams selecting at the cutoff were consistently the same team(s). Fortunately, the most any team had selected last in the first round or first in the second round was twice.[12] Additionally, issue could be that second round players are different from first round players because they are the second player chosen for each individual team. However, this is not necessarily the case because teams often trade away or trade for first round picks.

There are no apparent reasons to believe a significant drop off in player productivity should occur at the arbitrary round cutoff the league has established. After all, the number of players chosen in the first round are simply determined by the number of teams in the N.B.A. This number has changed whenever the league has expanded. The most recent case was in 2002, when the New Orleans Pelicans became the 30th team in the league. Also, teams often select players based on their needs and not necessarily the best available player. Discontinuities in outcomes at the cutoff should only exist if there are other factors that are causing them to occur. One of the possible factors could be the differences in the contract terms of players chosen in the first round to those of players selected in the second round.

In 1995, the N.B.A. created a rookie wage scale that granted all first-round selections a three-year guaranteed contract - with a team option for the fourth year - from the team that selected or traded for them. These contracts are set annually by the N.B.A., using a sliding wage scale that pays the first selection the highest salary on the wage scale and continuously decreases

[12] This was by the Cleveland Cavaliers, and they had traded to get those picks.

for each player selected afterwards. Although this gave first rounders job security, the wage scale created a ceiling on the number of years and money in a rookie's contract. On the other hand, players selected in the second round are not offered any guaranteed contracts and must negotiate a contract with a team – first rights going to the team that selected them - or could otherwise be cut before ever playing in the league. Despite this drawback, some overlooked second-rounders can benefit by not having to submit to a rookie wage scale. Players selected in the second round could potentially sign a short-term rookie deal and - if they perform exceptionally well - can then sign a long-term contract that is worth significantly more what first rounders would be earning under the rookie wage scale. An example of this occurred in 2003, when Gilbert Arenas - the first player selected in the second round that year, signed a 6-year deal worth $60 million after only his second year in the N.B.A.[13] Had he been a first round pick, he would have still been under contract for the next year, where he would have been paid roughly $1 million. Still, these cases are an exception rather than the norm. This paper will look at whether this arbitrary discrepancy in pay structure results in significant differences in player outcomes.

Here is the structure for the rest of the paper. Section 2 of this paper will provide a brief overview of relevant information regarding N.C.A.A. college basketball and the N.B.A. Section 3 will provide an extensive literature review of previous papers related to this study. Section 4 will describe and summarize the data as well as the methodology used for the study. Section 5 will provide the empirical models and an interpretation of the results. Finally, Section 6 will provide a conclusion to the paper.

[13] Arenas selected the number 00 to wear on his jersey as a reminder of how many teams selected him in the first round.

2.2 Literature Review

Despite the different contract rules regarding first round and second round rookies, classical labor theory suggests that N.B.A. teams will end up paying each player according to their expected marginal productivity of labor regardless of which round they were selected (Becker, 1989). Although the round a player was selected can provide value in determining a player's expected productivity with limited information, a player's overall selection number provides strictly dominated information that would make round information redundant and unnecessary in the production function. This can be explained using the following model that comes from the Keefer (2015) in describing the compensation of N.F.L. players:

$$\boldsymbol{salary_i = f[E(P_i)\,,\ X_i]}$$

where $E(P_i)$ indicates Player i's expected future productivity and X_i indicates other relevant variables that determine a player's salary. Included in $E(P_i)$ is information regarding both the round number and selection number of Player i.

$$\boldsymbol{E(P_i) = g(r_i, s_i)}$$

where r_i, indicates the round Player i was chosen and s_i is the overall selection number. Since s_i already includes information that r_i provides, the function should simply be

$$\boldsymbol{E(P_i) = g(s_i)}$$

Therefore, in a competitive market, a reduction in player salaries due to a drop off in expected productivity should come from a change in selection number rather than round differences.

I assume that the labor market for players is very competitive since every team must abide by the league's salary cap. Therefore, teams in the N.B.A. are unable to simply overpay for better players unlike some other professional sports leagues. If teams can pay significantly less for a player simply because he was drafted in the second round, they would look to trade away their overpriced first round picks and acquire more picks in the second round. The market should eventually reach an equilibrium where any initial effects round cutoffs may have caused, are no longer present. Yet, there are evidences in highly competitive markets, where studies have found inefficiencies to persist.

In a paper by Bondt and Thaler (1985), the researchers found that investors overreacted to news regarding the stock market. Their research showed that the performance of portfolios comprised of previous losers significantly outperformed ones comprised of previous winners. This is an indication that losing stocks were being underpriced compared to winners. If true, this study would argue against the efficient market hypothesis (EMH), which states that arbitrage opportunities quickly disappear because stocks quickly adjust to their appropriate value (Fama, 1998). Another study showed that stock investors sell winners too early and hold on to losers too long (Barberis, 2001). Studies from the field of behavioral economics attribute this behavior to people's tendencies to use mental accounting and exhibit loss aversion in their decisions (Thaler, 1999). Thaler has created his own asset management company that tries to take advantage of these types of behavioral biases.

Research using the field of sports have also found evidence of irrational behavior. Several studies involving the National Football League (N.F.L.), found that there are significant differences in the perceived value and compensations between players selected in the first and second round. Teams in the N.F.L. often overvalue first rounders and are willing to pay a significant premium in order to trade up for them (Massey and Thaler, 2010). The researchers believe that this is a result of general managers displaying overconfidence in their ability to find talent. Another relevant study showed that there are significant round effects in NFL rookie compensation. The study uses a sharp regression discontinuity model to find that players selected at the end of the first round are paid significantly more compared to those selected at the beginning of the second that cannot be attributed to productivity (Keefer, 2016). Therefore, not only are teams N.F.L. giving up more assets to acquire earlier picks, they also give more financial compensation to players selected earlier. Another paper by Keefer and Rustamov (2015), finds evidence that may help explain this type of irrational behavior. The study used energy consumption data to show that people are prone to focus most on the left-most digit to determine their usage. Likewise, teams that focus more on the round that a player was selected rather than the overall number, many overvalue information that is insignificant.

There have also been several studies looking at whether market inefficiencies exist in the N.B.A. Previous studies found evidence of racial discrimination in the N.B.A. by looking at the relationship between salary and performance for black and white players (Kahn, 2009). However, more recent studies have found that racial discrimination has since disappeared. Basketball, like many other professional sports, offer players contracts that are essentially guaranteed ahead of time. A group of studies have looked at whether this causes N.B.A. teams to be susceptible to the sunk cost fallacy with mixed results. An initial study, showed that rookies selected earlier in the draft are given significantly more playing time compared to those chosen later when adjusting for performance (Staw and Hoang, 1995). However, a later study that identified flaws to the original study found that there was no evidence of the sunk cost fallacy (Leeds and Motomura, 2006). The researchers used a sharp regression discontinuity model to look at whether round changes had any effects on playing time. While the results from the paper looked at playing time, the goal of this paper is to examine the effects on player performance and career earnings. If players that are equally productive but compensated significantly different by round, teams would be able to benefit by acquiring more second round players.

2.3 Data and Methodology

The data collected for this study is comprised of all 612 N.B.A. players selected in the league's draft between the years, 2004 to 2015. The data consists of performance as well as compensation data of the players. Any player that was not on an NBA roster during the period is considered missing. The source of the data comes from basketball-reference.com, a website that keeps meticulous data on the NBA.

Currently, there are a total of 60 players selected in the two rounds of the NBA Draft. Consequently, the 31st player selected is the first player chosen in the second round. Some years may have less than 60 players selected due to teams having to forfeit picks for violating league rules. This has occurred a total of three times over the course of the periods examined. Each time it has been the Minnesota Timberwolves who were forced to forfeit their pick. For these years, there are only 29 players selected in the first round. However, regarding a player's draft number, it skips the Timberwolves pick and therefore the last player chosen in the first round is still considered to be the 30th pick in the draft.

For each of the dependent variables that was tested, I used a pooled cubic regression model that allows for interaction terms that combine both the round number as well as the overall draft number into the equation. However, the model may not be ideal if values that are far away from the cutoff are heavily affecting the results. Therefore, a sharp regression discontinuity design model is included as well for comparison. A sharp regression discontinuity model is an effective means of looking at data where an arbitrary cutoff has led to a discontinuous jump in the dependent variable, y_i. In this study the dependent variables looked at are a player's productivity and career earnings. In the model, t_i , acts as a binary dummy variable which will assign a value of 1 to a treatment variable, in this case players selected after the round cutoff, and 0 for players selected before the cutoff. The cutoff value in this paper is, $x_i = 31$, any player whose draft number is 31 or later, will be assigned a value of 1. The sharp regression discontinuity model will only work under the circumstance that there are no other observables that are significantly different between players around the cutoff. Another criterion requires that no other confounding factors are affecting the groups. Finally, the last requirement when using sharp regression discontinuity is for players to be unable to self-select themselves to either side of the cutoff. Considering the format of the N.B.A. draft, there is no reason to believe any differences of these sort would exist (Imbens and Lemieux, 2008; McCrary, 2008). The average treatment effect (ATE) when using sharp regression discontinuity is therefore

$$\boldsymbol{ATE} = \lim_{\epsilon \to 0^+} \boldsymbol{E}[\boldsymbol{y}|\boldsymbol{x_i} = \boldsymbol{\pi} + \epsilon_i] - \lim_{\epsilon \to 0^-} \boldsymbol{E}[\boldsymbol{y}|\boldsymbol{x_i} = \boldsymbol{\pi} + \epsilon_i]$$

$$\boldsymbol{ATE} = \boldsymbol{E}[\boldsymbol{y}(\boldsymbol{t} = \boldsymbol{1}) - \boldsymbol{y}(\boldsymbol{t} = \boldsymbol{0}) \mid \boldsymbol{x} = \boldsymbol{c}]$$

2.4 Empirical Models and Results

The summary statistics in Table-1 compares players by the round they were selected. The data shows that there is a clear distinction in earnings between the two groups. Players selected in the first round have average career earnings that are $32.91 million compared to those selected in the second round, where average career earnings are $11.16 million. The career earnings of first round picks are on average, $22 million more. The number of Win Shares are also significantly different between the two groups. On average, first rounders contribute 18.61 Win Shares over the course of their career, while second rounders only contribute 6.935. These results are both significant and unsurprising since these numbers include all the players selected in either round. However, the objective of this paper is to focus only on the players chosen near the round cutoffs.

Round Cutoff Effects on Player Productivity

The first test I performed looked at whether there were any significant differences in the productivity of players around the cutoff. Selecting an objective measure of player performance can be difficult. A player's overall contribution to a team's success cannot be quantified by simply using one statistical variable, such as scoring. Other offensive statistics such as assists along with defensive statistics such as blocks and steals should be incorporated into the performance measurement. Also, it is important that a productivity metric take into consideration a player's efficiency by adjusting for playing time and field goal percentages since a player's scoring average can be upwardly biased if they are given more opportunities to shoot. Lastly, there are many important contributions that a player makes that are not recorded by traditional stats, typically on the defensive side of the game. As a result, I use the amount of Win Shares (WS) a player contributes as the dependent variable to measure productivity. Win Shares uses a formula that addresses many of the issues mentioned previously. Win Share data is collected by Basketball-reference.com, where the formula is also listed. A player who has a Win

Share of 0 is considered to not add or subtract any value compared to the average N.B.A. player. Therefore, more Win Shares will be considered as an indicator of higher productivity.

The first test uses the following pooled cubic regression models

$$\boldsymbol{WinShares(WS) = a + \vartheta round + \sum_{1}^{3} \beta_i (x - c)^i + \sum_{1}^{3} \delta round\,(x - c)^i + \varepsilon}$$

where Win Shares (WS) is the dependent variable. The main independent variable of interest is whether the player was selected before or after the cutoff value of 31. Round, is a dichotomous dummy variable, where a player selected before the cutoff is given a value of 0, or a value 1 if the player was selected at or beyond the cutoff. Table-2 shows the results from the pooled cubic regression model. Having been selected in the second-round accounts for a 0.470 decline in Win Share. This number is quite small and statistically insignificant. Table-2 also shows the results from including fixed effects. Although including fixed effects causes a greater effect of 0.508 less Win Shares, it is also not considered statistically significant.

I then used a local linear regression model to compare and confirm the initial findings. The model uses the optimal bandwidth with triangle kernels that is recommended by Imbens and Kalyanaraman (2009). There are three bandwidths that are tested; none find any significant differences in Win Shares. The results that comes from the 100% bandwidth indicate a decline of .408 Win Shares of being selected after cutoff. This number is in line with the results from the earlier model. The results of the regressions fail to reject the null hypothesis that there are no significant differences in the performances of players at the cutoff.

An alternative measure of productivity can be measured by using Win Shares per 48 minutes (WS48). This looks at a player's contributions adjusted for the number of minutes played. If there are significant differences in playing time given to earlier drafted players as a result of the sunk cost fallacy, WS48 would be a more accurate comparison of productivity. The model can be expressed by the following:

$$\boldsymbol{WinShares48(WS48) = a + \vartheta round + \sum_{1}^{3} \beta_i (x - c)^i + \sum_{1}^{3} \delta round\,(x - c)^i + \varepsilon}$$

The results are listed for the pooled cubic regressions in Table-5 and the local linear regression in Table-7. The numbers indicate that there is virtually no difference in WS48 among players at the cutoff. On average, being selected in the second-round decreases WS48 by -0.00759 and -0.00542 when including fixed effects. To put into perspective, the summary statistics show that the average WS48 off all players in the sample was 0.0638. The results from the local linear regression model indicate that there is a decline in WS48 of -.0147 of being selected in the second round. Although, far higher than the previous results, this is still considered to be statistically insignificant. Therefore, the results are statistically insignificant. This would support the assumption that players on both sides of the cutoff are similar in their productivity.

Round Effects on Players Earnings

The next test I conducted looked for any difference in career earnings between those near the cutoff. Due to differences in contract structure among first and second rounders as well as evidence from earlier studies, there are reason to believe there will be significant differences.

$$\boldsymbol{RookieEarnings = a + \vartheta round + \sum_{1}^{3} \beta_i (x-c)^i + \sum_{1}^{3} \delta round\,(x-c)^i + \varepsilon}$$

$$\boldsymbol{CareerEarnings = a + \vartheta round + \sum_{1}^{3} \beta_i (x-c)^i + \sum_{1}^{3} \delta round\,(x-c)^i + \varepsilon}$$

$$\boldsymbol{\ln(CareerEarnings) = a + \vartheta round + \sum_{1}^{3} \beta_i (x-c)^i + \sum_{1}^{3} \delta round\,(x-c)^i + \varepsilon}$$

The variables on the right-hand side are identical to ones used in the previous models. The results from the first model is listed in Table-6. The results show that the round effect has an impact of $202,796 on rookie earnings. The local linear regression results are listed in Table-7 and show that at the 100% bandwidth, rookie effects had a negative effect of $13,711 for players chosen in the second round. Both results indicate that there are no significant differences in rookie earnings for players on either side of the cutoff. The next model looked at the result of round effects on the overall career earnings of players. The results indicate a positive coefficient of $3.561 million associated with being selected in the second round. Although surprising, this could be explained by the fact that second rounders are not subjected to a rookie wage scale and are able to enter free agency much earlier. The initial local linear regression model also shows that there are no differences in pay between players on both sides of the cutoff, with second round contributing $2.788 million. The findings are consistent with the earlier results. Table-8 shows the results of the local linear regression model with three bandwidths.

To take into consideration concerns over heteroskedasticity, I also tested the log career earnings of players. The results were mixed in terms of the pooled cubic regression and the local linear regression. Table-7 shows the results from the pooled regression model and finds that being selected in the second round earns 22.7% more in career earnings, however, this number is insignificant. Finally, Table-9 shows the results from the local linear regression and finds that second round players earn roughly 11% less than first rounders, also considered insignificant. Overall, the results fail to find any significant difference of being selected beyond the round cutoff. This could indicate that the labor market for NBA players is efficient.

2.6 Conclusion

This paper looked at whether league established round cutoffs had any significant effects on player performance and earnings in the N.B.A. The hypothesis that there would be differences was based off previous findings that showed significant round effects on player compensation in the N.F.L. Additionally, other studies involving the N.B.A. have found evidence of other examples of irrational behavior, such as the use of sunk costs in allocating playing time. Despite my initial hypothesis, the results of my paper have failed to reject the null hypothesis. One explanation could be that the N.B.A. labor market has become more efficient compared to earlier years. Previous studies have found that racial discrimination in N.B.A. player salaries have disappeared over time. Another explanation could be a result of the subjective nature in evaluating player productivity. Earlier studies have found evidence of moral hazard when using one performance measure but not when using another measure. The objective of this paper was to provide additional literature to the area of sports and behavioral economics.

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Table-1: Summary Statistics by Rounds

	1^{st} Round	2^{nd} Round	Total
Earnings	32.91	11.16	23.80
	(35.33)	(20.93)	(31.98)
Games	352.6	170.9	276.5
	(230.2)	(200.0)	(235.6)
WS	18.61	6.935	13.72
	(22.00)	(13.26)	(19.69)
WS48	0.0780	0.0441	0.0638
	(0.0562)	(0.134)	(0.0981)
Age	20.53	21.61	20.98
	(1.331)	(1.296)	(1.420)
Position	3.045	3.094	3.065
	(1.358)	(1.217)	(1.300)
N	612		

mean coefficients; sd in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table - 2: Pooled Cubic Results of Round Effects on Win Share

VARIABLES	(1) WS	(2) WS
Second Round	-0.470	-0.508
	(5.641)	(5.546)
Pick-31	-1.550	0.352
	(1.220)	(1.084)
$(\text{Pick-31})^2$	-0.129	-1.779
	(0.0900)	(1.617)
$(\text{Pick-31})^3$	-0.00375**	-0.0417
	(0.00190)	(0.0936)
Round*Pick-31	1.871	-0.0763
	(1.652)	(0.129)
$\text{Round*}(\text{Pick-31})^2$	0.0843	0.000983
	(0.132)	(0.00223)
$\text{Round*}(\text{Pick-31})^3$	0.00488	-0.00448
	(0.00297)	(0.00291)
Team		-2.421
		(3.791)
Position		6.448***
		(2.051)
Year		9.794***
		(2.731)
Constant	8.052*	6.032*
	(4.505)	(3.338)
Observations	612	612
R-squared	0.173	0.204

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table -3: Local Linear Regression of Round Effects on Win Shares

Bandwidth	(1) WS
100%	-0.408
	(5.252)
50%	-4.154
	(9.875)
200%	-2.480
	(3.247)
Observations	612

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Table-4: Pooled Cubic Regression of Round Effects on WS48

VARIABLES	(1) WS48	(2) WS48
Second Round	-0.00759	-0.00542
	(0.0303)	(0.0303)
Pick-31	-0.00221	-0.00173
	(0.00655)	(0.00593)
$(\text{Pick-31})^2$	-0.000203	-7.45e-05
	(0.000483)	(0.000513)
$(\text{Pick-31})^3$	-6.41e-06	-1.54e-06
	(1.02e-05)	(1.22e-05)
Round*Pick-31	0.00115	-0.000623
	(0.00887)	(0.00884)
Round*(Pick-31)^2	0.000225	-0.000287
	(0.000707)	(0.000707)
Round*(Pick-31)^3	6.08e-06	-5.04e-06
	(1.60e-05)	(1.59e-05)
Team		-0.00107
		(0.0207)
Position		-0.000547
		(0.0112)
Year		-0.0126
		(0.01409)
Constant	0.0614**	0.0566***
	(0.0242)	(0.0182)
Observations	612	612
R-squared	0.043	0.044

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table -5 Local Linear Regression of Round Effects on WS48

	(1)
Bandwidth	WS48
100%	-0.0147
	(0.0362)
50%	0
	(0)
200%	-0.0343
	(0.0495)
Observations	611

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table-6 Round Effects on Rookie Earnings

VARIABLES	(1) RookieEarnings
Second Round	-202,976
	(194,110)
Pick-31	-47,132
	(42,581)
$(\text{Pick-31})^2$	-108,174*
	(55,368)
$(\text{Pick-31})^3$	-4,799
	(3,158)
Round*Pick-31	14,832***
	(4,307)
$\text{Round*}(\text{Pick-31})^2$	-236.2***
	(66.94)
$\text{Round*}(\text{Pick-31})^3$	26.48
	(94.56)
Team	-107,719
	(128,758)
Position	-5,337
	(71,819)
Year	-376,741***
	(92,803)
Constant	1.060e+06***
	(155,941)
Observations	612
R-squared	0.726

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table-7 Local Linear Regression of Round Effects on Rookie Earnings

	(1)
Bandwidth	RookieEarnings
100%	-13,112
	(219,109)
50%	106,029
	(312,047)
200%	296,745*
	(156,672)
Observations	612

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table - 8 : Pooled Cubic Regression on Career Earnings

VARIABLES	(1) Earnings	(2) Earnings
Second Round	-4.152	-3.789
	(7.921)	(7.877)
Pick-31	-0.884	-0.734
	(1.466)	(1.455)
$(\text{Pick-31})^2$	0.0320	0.0233
	(0.120)	(0.120)
$(\text{Pick-31})^3$	-0.000591	-0.000459
	(0.00276)	(0.00274)
Round*Pick-31	-1.808	-1.818
	(2.270)	(2.254)
Round*$(\text{Pick-31})^2$	-0.255	-0.234
	(0.176)	(0.175)
Round*$(\text{Pick-31})^3$	-0.00628	-0.00613
	(0.00388)	(0.00385)
Team		-3.634
		(5.178)
Position		6.973**
		(2.901)
Year		10.02***
		(3.516)
Constant	15.59***	13.71***
	(6.347)	(5.968)
Observations	700	700
R-squared	0.302	0.316

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table-9: Local Linear Regression of Round Effects on Career Earnings

Bandwidth	Earnings
100%	-2.788
	(6.808)
50%	-4.028
	(11.90)
200%	-1.115
	(4.444)
Observations	612

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table-10: Pooled Cubic Regression of Round Effects on Log Earnings

VARIABLES	(1) Ln(Earnings)	(2) Ln(Earnings)
Second Round	-0.201	-0.181
	(0.372)	(0.372)
Pick-31	-0.0280	-0.0264
	(0.0728)	(0.0727)
$(\text{Pick-31})^2$	-0.00147	-0.00135
	(0.00628)	(0.00628)
$(\text{Pick-31})^3$	5.36e-05	4.64e-05
	(0.000150)	(0.000149)
Round*Pick-31	-0.0684	-0.0696
	(0.109)	(0.108)
$\text{Round}*(\text{Pick-31})^2$	-0.00336	-0.00332
	(0.00866)	(0.00866)
$\text{Round}*(\text{Pick-31})^3$	-0.000190	-0.000177
	(0.000196)	(0.000195)
Team		-0.282
		(0.254)
Position		0.287**
		(0.138)
Year		0.207
		(0.183)
Constant	1.722***	1.678***
	(0.222)	(0.224)
Observations	612	612
R-squared	0.367	0.374

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table -11: Local Linear Regression of Round Effects on Log Earnings

VARIABLES	(1) Ln(Earnings)
100%	0.118
	(0.622)
50%	-0.564
	(0.976)
200%	-0.115
	(0.386)
Observations	612

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Measuring the Impact of the National Basketball Association (N.B.A.)

Rookie Wage Scale on the Careers of N.B.A. Players

Abstract: The final chapter of this paper looks at the impact the National Basketball Association (N.B.A.) rookie wage scale had on subsequent player earnings and on-court performance. In 1995, a new collective bargaining agreement (C.B.A.) - that was agreed upon by the league's owners and players - implemented a rookie wage scale that created a ceiling on the number of years as well as the amount of money players could earn under their rookie contract. The wage scale was introduced to address growing concerns voiced by N.B.A. teams over the substantial bargaining power incoming players had even before they had played a professional game.

In this chapter, I first tested to see whether the rookie wage scale fulfilled the objective of reducing the compensation of rookies. The following test looked at whether the rookie wage scale had any additional effects on player performance and overall compensation. By using several econometric models, I compare the overall careers of players who entered the league before its implementation to those who entered after the rookie wage scale was introduced. Afterwards, I compare the average number of years played in the league as well as the average age of draft picks between the two groups of players. As expected, rookies who entered under the new C.B.A. earned significantly less during their first year in the league compared to their counterparts. However, the findings also indicate that there were no significant differences in career earnings and overall differences in player performance; both in the short and long run. Finally, the results indicate that the average career length significantly increased for players who entered after the rookie wage scale was implemented due to players entering the league at an

earlier age. This could be explained by assuming that N.B.A. teams that are generally risk averse, are more likely to take a chance on a younger prospect now that the costs associated with doing so have substantially fallen.

3.1 Introduction

The National Basketball Association (N.B.A.) began as a professional basketball league in 1946. Since its inception, the popularity of the league has significantly increased, both in the United States as well as globally. This has led to a dramatic increase in N.B.A. player's salaries over the years. To put into perspective, the average N.B.A. player salary has risen from approximately $1 million in 1985 to nearly $6 million in 2018 (Basketball-reference.com, 2018). Additionally, the share of basketball related income that goes towards player's salaries has gone up from approximately 51% in 2005 to 57% in 2016. This is a strong indication that the bargaining power of the National Basketball Players Association (N.B.P.A.) - the league's players union - has also been increasing overtime. Despite this general trend upwards in salary, there have been occasions where specific groups of players within the league have had their salaries negatively affected by changes to the league's collective bargaining agreement.

The labor market for N.B.A. players does not operate under a free market system. All current players are members of the N.B.P.A., which negotiates with N.B.A. teams via collective bargaining. The N.B.A. Collective Bargaining Agreement (C.B.A.) establishes frameworks for important agreements between the N.B.A. owners and the N.B.P.A. such as player salaries, trades between teams and rule changes to the game. Over the years, the two sides have been involved in disagreements that have led to a total of four lockouts.[14] As a result, significant changes to the C.B.A. have been made, establishing changes to league rules and regulations.

[14] The most recent was during the 2011-12 season. The lockout lasted for 161 days and cost the league 16 regular season games for each team.

This paper looks at how one of these changes - the introduction of a rookie wage scale - impacted the careers of N.B.A. players who entered afterwards.

Prior to 1995, N.B.A. rookies were granted much more flexibility in negotiating the terms of their rookie contracts. Many of them were able to sign long term guaranteed deals with the team that drafted them or traded for the rights to their services. As an example, in 1994, Glenn Robinson was the first player selected by the Milwaukee Bucks. Initially, both sides could not come to an agreement to the terms of the contract. Eventually, there were rumors that Robinson would threaten to sit out the entire season if he did not receive the thirteen-year, $100 million contract he was asking for. After many months of negotiations, the two sides eventually agreed to a ten-year deal worth $68 million. Until today, this is the largest rookie contract in the league's history and considered by many to be a risky move at the time. [15] Unlike most professions, the contracts of most N.B.A. players are fully guaranteed regardless of their future performance. A common argument given in favor of these guaranteed contracts views them as a necessary form of insurance due to the uncertain nature of the profession. The average length of an N.B.A. career is approximately only five years and sustaining a significant injury could jeopardize a player's entire career. Another supporting argument claims that guaranteed contracts counteract the monopsony power that teams in professional sports league initially have in the labor market (Neale, 1964).

Therefore, N.B.A. teams must face high levels of uncertainty when evaluating and drafting players. Although there is evidence indicating a positive correlation between a player's draft number and their future productivity, there is a great amount of variance between each

[15] Looking back, some say this was an unfavorable deal to Robinson because of substantial increases in the league's salary cap. Players on short term deals could become free agents earlier and sign for significantly more than those on long term deals that could not benefit from the increase.

individual pick. There are numerous examples of early draft picks who have failed to live up to their lofty expectations (Yukari, 2017). Furthermore, the league operates under a salary cap system that limits the amount of money teams can spend on players. Teams that have invested a significant portion of their salary cap on an underachieving rookie could suffer the negative consequences of their selection for many years. Another note of importance is that the N.B.A. grants the teams with the worst records from the previous season a higher chance of selecting early in the league's annual draft. Therefore, overpaying rookies could also lead to greater imbalances between the teams at the top and bottom of the league. A study by Szymanksi (2001) has shown that popularity begins to decline in sports leagues that have greater inequality in team performance within the league.

To address their concerns, N.B.A. owners proposed adding a rookie wage scale under the league's 1995 collective bargaining agreement. The player's association agreed to the new deal when owners were willing to make concessions that increased the percent of league revenue that veteran players would receive. This is line with traditional union strategy, where the voting power is more heavily favored by those who have been in the organization longer (Hill, 2008). The rookie wage scale capped the maximum number of years a player could sign at three years - with a team option for the fourth year. It also incorporated a sliding scale system, where the salary of every player selected is less than that of the players chosen before them. The league has the authority to adjust the scale on an annual basis to factor in changes to the league's salary cap. In this paper, I look at whether the implementation of the rookie wage scale had any significant impacts on player earnings and productivity. The following section will look at previous studies that are relevant to this paper. The structure of the remaining sections is as follows: Section 2 will provide a literature review of relevant papers. Section 3 describes and summarizes the data as well as the methodology used in this paper. Section 4 will provide the empirical models and an interpretation of the results. Lastly, Section 5 will be a conclusion to the paper.

3.2 Literature Review

The traditional economic model of worker productivity assumes that workers are utility-maximizers whose utility has a function that increases with compensation and diminishes from exerting additional effort. Workers are therefore inclined to shirk from their responsibilities whenever the marginal benefit of doing so is greater than the marginal cost (Becker, 1985; Shapiro, 1984). To combat this, employers must create an incentive-compatible compensation system to prevent this example of moral hazard from occurring. One possible strategy would be to use a piece-work pay system where each worker is paid according to their individual output. However, this type of system can be difficult to monitor and often ineffective in its objective (Gibbons, 1985). Another method is for employers to offer efficiency wages that are above the market equilibrium wage to increase the opportunity costs of losing their job (Yellen, 1995). Many companies have benefited from increased productivity when giving their workers efficiency wages. However, laboratory experiments find that contrary to expectations, any initial increases in worker productivity that are gained when subjects are given more compensation gradually disappear over time (Fehr and Gachter, 2000). Workers seem to quickly adjust to a new baseline of compensation.

Generally, guaranteed contracts are not thought of as an effective method of compensation since the principal must compensate the agent regardless of future performance.

In a one-shot game, every worker will have an incentive to shirk from their responsibilities. However, under a finitely repeated games scenario, players may be incentivized to exert high effort up until the last interaction (Rubinstein, 1983). Previous studies that have looked at the effects guaranteed contracts have had on player performance indicate mixed results. One study found that the performances of N.B.A. players worsen the further away they are from free agency and improve significantly the season prior to becoming a free agent (Sen, 2011). The paper uses a 3-period model to describe an N.B.A. player's career. The results showed that the overall effort of a player who signs a 2-period contract will be significantly greater in the second period to that in the first. In another paper by Berri and Krautman (2006), the researchers found that shirking amongst N.B.A. players existed when they used the N.B.A.'s method of measuring productivity. However, when they used an alternative measure of performance, that the researchers felt were more in line with economics' definition of productivity, they were not able to find shirking to exist. This indicates that performance measures can be highly subjective.

Previous studies that have focused specifically on rookie athletes have led to useful findings. A paper by Staw and Hoang (1995), used N.B.A. rookie data to find that teams exhibit sunk cost behaviors by unjustifiably investing more resources to players simply because they were selected earlier in the draft. The researchers found that teams gave earlier draft picks more playing time, were less likely to be traded, and remained in the league longer when controlling for productivity measures. Keefer (2013), using National Football League (N.F.L.) rookie data, finds evidence supporting an efficiency wage model of worker productivity. The paper shows a positive relationship between increased compensation and player performance among rookies. However, a major difference in player contracts between the N.F.L. and the N.B.A. is that the former does not have fully guaranteed contracts and therefore N.B.A. players may have less incentive to exert additional effort.

Since athlete salaries generally increase over time, it is rare to find studies that look at the effects of a decline in player earnings. A study by Keefer (2012), finds that the N.F.L. rookie wage scale that was implemented in 2011, significantly reduced rookie earnings. Additionally, studies have shown that people generally are concerned with their relative income rather than their absolute income (Clark, 2008). Despite earnings salaries that are far greater than the median worker in the United States, a rookie wage scale that leads to a loss in wages relative to their peers may cause players to reduce their effort. In this paper, I look at whether the implementation of the rookie wage scale had a significantly reduced player earnings and whether this effected player performance in their first year as well as to their overall career.

3.3 Data and Methodology

All relevant data collected for this paper - such as player salaries and performance statistics - comes from the websites, Basketball-reference.com and NBA.com. Basketball-reference.com, which began in 2004, is a website that collects and continually updates a wide variety of data regarding the N.B.A. Many studies that have looked at the N.B.A. collected their data from the website. NBA.com is the official website of the N.B.A. - where player statistics and facts are listed for every current as well as former N.B.A. player.

Included in the data set are a total of 278 N.B.A. players selected in the first round of the N.B.A. draft between the years, 1990 and 1999. A few players are missing from the data set because teams drafted overseas players that never came to the N.B.A. The period of years was chosen to allow for a significant sample size as well as to balance the number of years that are before and after the rookie wage scale was implemented. It is important to note, however, that the number of draft picks increased from 27 to 29 in 1995 due to the league adding two expansion teams; therefore picks 28 and 29 are not used for comparison. Although the N.B.A. Draft consists of two rounds, I limited my research on the first round since the wage scale only applied to first round selections. As a result, without guaranteed contracts, many of the players selected in the second round did not receive a contract. Additionally, I expect the differences in earnings and performance to be most significantly impacted for the players chosen early in the draft. I control for other individual and time variables such as the year a player entered the league, the league's salary cap for the year, the team that drafted them as well as the position that they played.

As mentioned in an earlier chapter, finding an objective measure of N.B.A. player performance can prove to be difficult. Although many measurements have been developed to evaluate player productivity, each one has its advantages and disadvantages. For this paper, I use the number of Win Shares (WS) a player contributed to his team as well as his Win Share Per 48 Minutes (WS48) as measures of productivity. Win Shares is a method of attributing credit for a team's success based off a player's contribution. It was originally developed for baseball by Bill James, the father of Sabermetrics (James, 1988), and later transferred to measure basketball performance. Win Shares is commonly used because it includes both offensive and defensive measures that players contribute. I also use WS48 as a performance measure since it adjusts for the playing time of each player. To compare earnings of players from different years, I use earnings that are adjusted for the salary cap that year.

3.4 Empirical Models and Results

The summary statistics listed in Table-1 compares observable characteristics of players that were drafted before and after the rookie wage scale. The summary indicates that players who were rookies prior to the rookie wage scale earned on average 7.3% of the league salary cap compared to 4.2% for those who entered the league after. Figure-1 shows by year, the mean percentage of the salary cap first round rookies earned.

The Effects of the Rookie Wage Scale on Rookie Earnings

To test for changes in initial compensation, I first looked at the effects the rookie wage scale had on a player's earnings during their first year in the league. To measure the effects on rookie wages, I use the following fixed effects model:

$$\boldsymbol{RookieEarnings_{it} = \alpha + x'\beta_{it} + \gamma_i\, scale + \delta_t + \varepsilon_{it}}$$

The dependent variable, *rookie earnings*, takes into consideration the increases in the NBA salary cap over time by measuring the percentage of the league's salary cap a player earned rather than their actual overall earnings. The vector, $x'\beta_{it}$, is comprised of control variables such as a player's position and the team that they played for during their rookie year. The variable, *scale*, is a dichotomous dummy variable that gives a value of 1 to a player who entered after the rookie wage scale and 0 to those who were rookies prior to the wage scale. The variable δ_t, represents year fixed effects. The model includes an interaction term between the draft number of a player and the rookie wage scale variable. The last variable, ε_{it} , is an idiosyncratic error term.

Table-2 presents the findings from the model, with and without the control variables. The findings indicate that the rookie wage scale had a substantial negative impact on N.B.A. rookie earnings. When controlling for the other variables, players who entered the after the rookie wage scale was implemented saw their earnings decline by 2.82% of the league's salary cap. To put into context, the salary cap for each N.B.A. team in 1995, was $23 million. Therefore, the average rookie earned approximately $648,600 less under the rookie wage scale. This result was significant at the 1% level. The findings are consistent with the intended objectives of the new collective bargaining agreement.

<u>The Effects of the Rookie Wage Scale on Rookie Productivity</u>

Considering the significant decrease in earnings rookies experienced after the rookie wage scale, I predicted that it would have also caused a decrease in player productivity during their rookie year. For the second test, I examined whether the rookie wage scale had any effects on rookie productivity by using the following fixed effects model:

$$\boldsymbol{RookieWS_{it} = \alpha + x'\beta_{it} + \gamma_i\, scale + \delta_t + \varepsilon_{it}}$$

I use a player's overall number of Win Shares (WS) they contributed during their rookie season as the dependent variable. The variables on the right side of the equation are identical to that of the previous model. Table-3 display the statistical results from the regressions. Surprisingly, the results show a slight increase in the rookie year win share of players who entered after the rookie wage scale. However, when adjusting for the control variables the average Win Share was 0.0252 higher, an amount that is statistically insignificant. The only variable that was significant was the player's draft number. The findings indicate that the reduction in rookie salaries did not noticeably diminish the productivity of players during their rookie season. This is somewhat surprising considering the standard view that decreased compensation will result in lower worker productivity. However, the result could be due to N.B.A. teams unwilling to give rookies in general enough playing time to notice a difference.

The Effects of the Rookie Wage Scale on Overall Career Productivity

I next tested to see if a decline in their rookie salary had any effects on a player's overall career. To test overall career productivity, I use the following fixed effects models

$$\boldsymbol{CareerWS_{it} = \alpha + x'\beta_{it} + \gamma_i\, scale + \delta_t + \varepsilon_{it}}$$

$$\boldsymbol{CareerWS48_{it} = \alpha + x'\beta_{it} + \gamma_i\, scale + \delta_t + \varepsilon_{it}}$$

Table-4 shows the results from the first model. Players that entered post-rookie wage scale had a career averages of 8.75 more Win Shares compared to players that entered before, a figure that is significant at the 10% level. This is approximately 25% more Win Shares over the course of their careers. However, this increase in overall productivity could have been spread over a longer time-period. If players who entered after the rookie wage scale had longer careers, then their actual productivity would be overestimated due to having played more games. Therefore, it is also important to compare the Win Share per 48 Minutes (WS48) of players. WS48 adjusts for the number of minutes a player accrues over the course of a season and averages it out amongst all players. The findings are listed in Table-5 and show that players that entered after the rookie wage scale produced .00816 more WS48. This figure was not significant at any level. Combining both results, it would indicate that players were not performing better but playing longer.

The Effect of the Rookie Wage Scale on the Career Length and Entering Age of Players

The next tests looked at the effects the rookie wage scale had on the number of years players played on average as well as the average age a player entered the league. To test this, I use the following fixed effects model:

$$\boldsymbol{YearsinLeague_i} = \boldsymbol{\alpha} + \boldsymbol{x'\beta_{it}} + \boldsymbol{\gamma_i\, scale} + \boldsymbol{\delta_t} + \boldsymbol{\varepsilon_{it}}$$

$$\boldsymbol{EnteringAge_{it}} = \boldsymbol{\alpha} + \boldsymbol{x'\beta_{it}} + \boldsymbol{\gamma_i\, scale} + \boldsymbol{\delta_t} + \boldsymbol{\varepsilon_{it}}$$

Where the first dependent variable measures the average years played in the N.B.A. The right-hand side of the equation is identical to the previous models. Table-6 shows the results of the model, with and without the control variables. The results from the fixed effects model shows that players who were selected after the implementation of the new collective bargaining agreement, played on average 1.070 years longer. The results however, fail to reject the null hypothesis that there are no differences in the length of careers between the two groups. Although the results are not considered significant, it is surprising considering players with similar performances should exit the league around the same time. Therefore, I next tested to see whether players entering post-rookie wage scale did so at a younger age. Players who would normally wait to enter the league may be more compelled to enter under the new agreement.

The variables controlled for are identical to the earlier models. The findings show that players selected after the rookie wage scale were approximately .743 years younger when controlling for position, time and year variables. The findings are significant at the 1% level. Table-7 shows the results of the model with and without the control variables. This data set only includes the players who were drafted, and not all players that were eligible to be selected.

Therefore, it does not tell the average age of all the players who entered the draft. However, this is strong indication that players were choosing to enter the league earlier. Another possibility is that risk averse teams are now more willing to invest in younger players. Younger players are considered riskier because they are being selected based off potential rather than on court productivity. Therefore, in the years prior to the rookie wage scale, team may have been less likely to select younger players when force to invest a significant portion of their salary cap. However, if there is a rookie wage scale that limits not only the pay, but the length of the rookie contract that a player signs, teams may be more likely to draft on potential.

3.5 Conclusion

In this chapter, I examined the effects the 1995 N.B.A. rookie wage scale had on subsequent player earnings and performance. As expected, the rookie wage scale led to a substantial loss in rookie earnings. However, contrary to classical economic theory, a significant reduction in first year wages did not result in a noticeable negative effect on player performance; both in the short and long run. One possibility could be that early on in their careers, N.B.A. players are limited in contributing on the court due to N.B.A. coaches having hesitancy in playing them. This may underestimate the relationship the effects earnings had on rookie performance. Another possibility could be that players, with shorter contracts players may have stronger incentives to perform well to maximize their earnings for future contracts.

I then tested to see whether the new collective bargaining agreement effected the age when players entered the league. The findings showed that the rule changes significantly reduced the average age of N.B.A rookies. This also led to players remaining in the league longer than their counterparts who enter before the rookie wage scale. I propose that this could have been due to a greater willingness for teams to take chances on younger players now that their salaries were lower. The aim of this paper was to contribute to the growing literature in the field of sports economics.

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List of First Selections in the NBA Draft

Year	First	Last	Rookie Salary
1985	Patrick	Ewing,	$1,250,000
1986	Brad	Daugherty,	$500,000
1987	David	Robinson,	$1,046,000
1988	Danny	Manning,	$1,650,000
1989	Pervis	Ellison,	$2,300,000
1990	Derrick	Coleman,	$2,100,000
1991	Larry	Johnson,	$1,955,000
1992	Shaquille	O'Neal,	$3,000,000
1993	Chris	Webber,	$1,600,000
1994	**Glen**	**Robinson,**	**$2,900,000**
1995	**Joe**	**Smith,**	**$2,473,000**
1996	Allen	Iverson,	$2,267,000
1997	Tim	Duncan,	$2,967,840
1998	Michael	Olowokandi,	$2,700,000
1999	Elton	Brand,	$3,375,960
2000	Kenyon	Martin,	$3,536,640
2001	Kwame	Brown,	$3,697,400
2002	Yao	Ming,	$3,858,240
2003	LeBron	James,	$4,018,920
2004	Dwight	Howard,	$4,179,720
2005	Andrew	Bogut,	$4,340,520
2006	Andrea	Bargnani,	$4,501,200
2007	Greg	Oden,	$4,662,000
2008	Derrick	Rose,	$4,822,800
2009	Blake	Griffin,	$4,983,480
2010	John	Wall,	$5,144,280
2011	Kyrie	Irving,	$5,144,280
2012	Anthony	Davis,	$5,144,280
2013	Anthony	Bennett,	$5,324,280
2014	Andrew	Wiggins,	$5,510,640
2015	Karl-Anthony	Towns,	$5,703,600

Table – 1. Summary Statistics

	Pre-Wage Scale	Post-Wage Scale	Total
Age	22.03	21.31	21.66
	(0.897)	(1.367)	(1.215)
Years	9.37	10.36	9.85
	(0.85)	(1.83)	(1.24)
Games	539.3	599.6	570.4
	(333.8)	(389.8)	(364.4)
MPG	21.65	22.26	21.97
	(8.552)	(8.921)	(8.734)
WS	29.29	38.49	34.04
	(32.79)	(44.01)	(39.19)
WS48	0.0737	0.0812	0.0775
	(0.0452)	(0.0595)	(0.0531)

mean coefficients; sd in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Table-2. Estimates of Rookie Wage Scale on Rookie Earnings

VARIABLES	(1) Rookie Earnings	(2) Rookie Earnings
Draft Pick	-0.0592***	-0.0587***
	(0.0148)	(0.0147)
Scale	-0.0295***	-0.0282***
	(0.00396)	(0.00418)
Draft Pick*Scale	-0.0393*	-0.0391*
	(0.0209)	(0.0207)
Position		-0.0124
		(0.00917)
Team		-0.00490
		(0.00535)
Years		0.00736
		(0.00693)
Constant	0.0396***	0.0411***
	(0.00275)	(0.00293)
Observations	278	278
R-squared	0.312	0.327

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table-3. Estimates of Rookie Wage Scale on Rookie Win Shares

VARIABLES	(1) Rookie WS	(2) Rookie WS
Draft Pick	-.1323***	-.1328***
	(.0220)	(.0223)
Scale	0.0681	0.0252
	(0.247)	(0.263)
Draft Pick*Scale	-.0143	-.0124
	(.0302)	(.0298)
Position		-0.666
		(0.578)
Team		-0.280
		(0.337)
Years		-0.253
		(0.437)
Constant	1.594***	1.678***
	(0.172)	(0.184)
Observations	278	278
R-squared	0.186	0.193

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table-4. Estimates of Rookie Wage Scale on Career Win Shares

VARIABLES	(1) Career WS	(2) Career WS
Draft Pick	-2.102***	-2.093***
	(0.373)	(0.377)
Scale	9.613**	8.750*
	(4.575)	(4.829)
Draft Pick*Scale	-0.458	-0.550
	(0.510)	(0.504)
Position		-17.38
		(10.58)
Team		-14.07**
		(6.230)
Year		-6.296
		(7.994)
Constant	36.42***	39.67***
	(3.186)	(3.377)
Observations	278	278
R-squared	0.097	0.122

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table-5. Estimates of Rookie Wage Scale on Career WS48

VARIABLES	(1) Career WS48	(2) Career WS48
Draft Pick	-0.0406*	-0.0394*
	(0.0239)	(0.0236)
Scale	0.00892	.00816
	(0.00641)	(0.00674)
Draft Pick*Scale	-0.0213	-0.0218
	(0.0338)	(0.0334)
Position		-0.0332**
		(0.0148)
Team		-0.0175**
		(0.00869)
Years		-0.00593
		(0.0112)
Constant	0.0798***	0.0845***
	(0.00446)	(0.00471)
Observations	278	278
R-squared	0.039	0.070

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table-6. Estimates of Rookie Wage Scale on Years Played in the League

VARIABLES	(1) Years	(2) Years
Draft Pick	-0.299***	-0.291***
	(0.0463)	(0.0464)
Scale	1.298*	1.070*
	(1.001)	(1.016)
Draft Pick*Scale	-0.00252	0.00412
	(0.0625)	(0.0629)
Position		-2.042*
		(1.196)
Team		-0.756
		(0.699)
Year		-0.655
		(0.898)
Constant	10.19***	10.60***
	(0.402)	(0.425)
Observations	278	278
R-squared	0.261	0.268

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table-7. Estimate of Rookie Wage Scale on Average Age of Draft Picks

VARIABLES	(1) Draft Age	(2) Draft Age
Draft Pick	-0.0370***	-0.0368***
	(0.0126)	(0.0126)
Scale	-0.764***	-0.743***
	(0.278)	(0.284)
Draft Pick*Scale	-0.000198	-0.00128
	(0.0169)	(0.0171)
Position		0.120
		(0.325)
Team		0.154
		(0.190)
Year		0.0230
		(0.244)
Constant	21.51***	21.48***
	(0.200)	(0.209)
Observations	278	278
R-squared	0.149	0.152

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1