Decision Theory in Sports: How Does Uncertainty Aversion Impact NBA Draft Performance?

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Introduction

We as humans must make hundreds, if not thousands of decisions every day. While some decisions are more difficult than others, attached to each of them are varying degrees of uncertainty over what their outcomes will be. In the economic field of decision theory, "uncertainty aversion" is a preference for risks with known probability distributions over those with unknown probability distributions. Thus, all else being equal, it is fair to expect that when forced to choose between two distinct options, we will favor the option that is more transparent in the odds of its outcome. These deductions in decision theory are thanks in large part to American economist Daniel Ellsberg, whose 1961 paper "Risk, Ambiguity, and the Savage Axioms" contextualizes this behavior in an experimental setting: people try to avoid situations in which they cannot attach a probability to an outcome. The paper's most famous test lays out two urns in front of the participant, urn A containing 50 red balls and 50 black balls, and urn B containing an unknown number of each colored ball. The following four bets are then offered to the participant:

Bet 1A: receive $1 if ***red*** is drawn from urn ***A***, receive nothing otherwise

Bet 2A: receive $1 if ***black*** is drawn from urn ***A***, receive nothing otherwise

Bet 1B: receive $1 if ***red*** is drawn from urn ***B***, receive nothing otherwise

Bet 2B: receive $1 if ***black*** is drawn from urn ***B***, receive nothing otherwise

Ellsberg found that while people were indifferent to the color of the ball they selected (1A ~ 2A), the majority of respondents strictly preferred choosing balls from urn A (1A, 2A > 1B, 2B), the urn in which the probability of selecting either a red or black ball was a known 50%. He also went on to conclude that even in instances where bets 1B and 2B could have offered a larger payout (more utility) if won, participants were more likely to favor the "known risk." Our uncertainty aversion makes us all the more cognizant of worst-case scenarios, and the absence of definitive odds often skews behavior conservatively.

Applying Uncertainty Aversion to Sports

Sports is an intriguing, accessible industry in which to both model and better understand uncertainty aversion. General managers and coaches of sports franchises must constantly make decisions under the weight of uncertainty in the form of setting lineups, trading and acquiring talent, and determining which players are worthy of contracts. Should too many of those decisions prove unwise, it can cost a team their season, a player their contract, and a team official their job—when the stakes are that high, second-guessing is a very real thing in the business of sports. Drafting, however, is likely the most difficult responsibility a general manager has. Premature injuries, contract holdouts, and players not meeting expectations are all things that can quickly derail what seemed like a surefire draft selection. Just looking across 10 full NBA seasons, (beginning in 2009-2010 and ending in 2018-2019) 9% of all NBA draftees (54 players) were out of the league after their first season, and in that same time period, almost 12% of draftees (69 players) had yet to play a single minute. On a team scale, consistency is no easier to find. The Sacramento Kings, for example, have sent just two home-grown players (originally drafted to the Kings) to the annual All-Star Game in the last *forty* seasons. Assessing talent from the collegiate level is incredibly hard, especially when organizations lack the ability to obtain "perfect information"—complete and instantaneous knowledge—about an incoming draft class. Such knowledge could surely reduce the deleterious effects of uncertainty and ease concerns over worst-case scenarios (Congdon-Hohman et al. 2015). The talent gap between amateurs and professionals along with artificial, competition-less environments like the NFL Scouting

Combine can make this pursuit of perfect information even more precarious (Berri and Simmons 2009). As it pertains to basketball specifically, however, some believe the NBA Draft Combine can be a useful platform for weeding out talent, especially when designating player length, size, and upper-body strength as the focus of your evaluations (Teramoto et al. 2017).

In order to combat uncertainty in the hiring process, firms (sports franchises especially) at times will turn to "group identification," a method that evaluates talent based on the past performance of particular labor pools that the applicant shares traits with (Hendricks et al. 2003). Where white-collar job markets likely judge applicants by the success of prior workers with similar education and work history, soon-to-be professional athletes would be likened to former/current players who were of similar height, weight, collegiate talent, etc. The hope in this strategy is that not only will the group-based evaluation provide an accurate, historically-proven assessment of the candidate, but also serve as a reliable basis for future appraisals. In other words, the size of the uncertainty surrounding a candidate is tempered knowing that individuals like them have already performed well in comparable situations.

As Hendricks et. al continue, however, they note such an approach can breed statistical discrimination, where the potential of an applicant is overlooked and undervalued based on their preparation in a less attractive, less established background (a community college education, for example). This leads to players from established backgrounds to be more heavily pursued and sometimes overvalued. Berger and Daumann (2021) argue that a rooted interest in certain traits of high school basketball stars can lead to "anchoring bias," a psychological event in which an individual relies too heavily on an initial piece of information, distracting them from other valuable, but contradicting insights that would better clarify how good the player truly is. Thus, the key to understanding how sports franchises draft becomes a question of what traits they truly value in their pursuit of amatuer talent.

Motivating Questions

While there have been considerable amounts of literature on how collegiate performance impacts the draft stock of soon-to-be NBA players, there have been no known analyses on how franchises respond to and measure uncertainty throughout the drafting process. The aim of this paper is to explore how the size of uncertainty associated with a draftee affects where they are selected in the NBA Draft. The size of uncertainty surrounding a given college player will in this case be determined by the university they attended, specifically the success of NBA players who came from that same institution.

To contextualize this, consider Brooklyn Nets star Kevin Durant, a University of Texas alum. Ignoring his performance in college along with his height, weight, age, etc., how did the fact Durant attended Texas change the uncertainty surrounding him as an NBA prospect? Did his enrollment at a Power 5 school shrink that uncertainty to the point where he could become the second overall selection in the 2007 Draft? Would attending a more prestigious university have reduced the ambiguity even more, perhaps making him the #1 overall pick? Was there a chance NBA executives would've balked on Durant had he attended a mid-major school such as Butler University? Thus, the basketball prestige of a player's alma mater will represent *hypothetically* how comfortable an NBA front office would be using their selection on him. What defines the term "prestige" will be discussed later in this paper.

Existing Literature

As stated before, there are few, if any, examples of studies that explore the effect of uncertainty on where amateurs get drafted. The closest-related study finds “players who competed on high-achieving college teams and in major conferences typically played more [NBA] minutes than otherwise similar players” (Evans 2017). Though it has little to say about how confident franchises are in drafting players from certain basketball programs, it does speak to the inherent value they place on such athletes once they’re in the league.

There is a score of literature attempting to draw connections between the traits of collegiate players and their position in the NBA Draft, as well as how well they perform after making it to the professional level. While such investigations may not be entirely relevant in answering the specific question of this paper, they can provide supplemental information on the mindset of NBA franchises when it comes to drafting, a much broader question that is still of great interest. If the uncertainty surrounding a soon-to-be NBA rookie is not a significant predictor of their draft position, these papers may grant us insight on some of the other factors sports organizations truly care about when scouting the amatuer talent market.

The academic consensus appears to be that high-volume scorers in college basketball are rewarded the most when it comes to draft stock, just as talented scorers in the NBA are the regular recipients of higher salaries and end-of-season rewards (Berri et al. 2010). This strategy, however, does not usually bode well for “lottery” teams trying to improve upon last season's failures; Coates and Oguntimein (2008) find college scoring only weakly related to professional scoring, and that collegiate rebounds, assists, blocks, and steals are more highly correlated to professional productivity. Yet, those same statistics do not financially compensate NBA talent in the same way scoring does, likely misguiding college players to believe it is the only skill worth developing. The Evans (2017) study finds similar evidence suggesting that scoring improves a player's draft selection, but does not seem to correlate with his subsequent NBA performance, possibly indicating that NBA franchises are mistakenly selecting high-scoring players early in the draft and giving them too much playing time. Staw and Hoang (1995) actually affirm this hypothesis of overvalued draftees, finding that "teams granted more playing time to their most highly drafted players and retained them longer, even after controlling for players' on-court performance, injuries, trade status, and position played." Therefore, a sunk cost fallacy arises where teams try to recoup value that has already been lost.

Performance in the annual NCAA "March Madness" Tournament has been found to be yet another indicator of where amateurs fall in the draft. The same Berri et. al (2010) paper found players on teams that reached the Final Four see their draft position improve by twelve slots, incentivizing them to leave school after a deep playoff run. Unexpected success, a hallmark of March Madness, is significant in its own regard. Ichniowski and Preston (2017) find players who score four or more points than their regular season average during an NCAA tournament win improve their draft standing by five slots. It is also found that contrary to popular belief, there is no evidence to claim front offices who make selections with the recent tournament results in mind are choosing incorrectly. In fact, the authors assert that conventional basketball wisdom is "masking" the importance of tournament performance on how successful a future NBA career can be, for "the glare of intense media attention and large arena crowds in a lose-and-go-home championship tournament provides important information about the true potential of these players" (Ichniowski and Preston 2017). Consequently, March Madness is often a setting in which lesser known schools can stand out on the national stage, perhaps reducing the uncertainty surrounding non Power-5 players and acting as a shield from the statistical discrimination they often face.

Theory

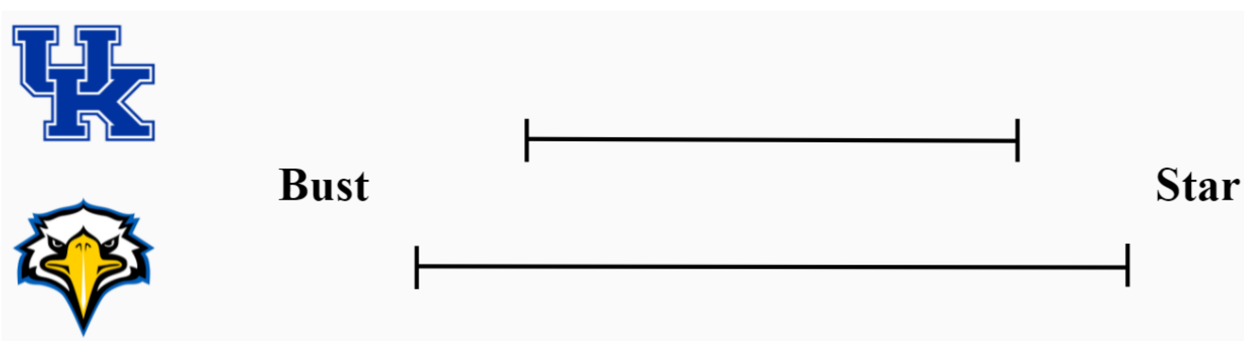
Before analyzing this paper's empirical model and data set, it is important to understand the theoretical assumptions it will make in addition to the expectation of the model's results. Consider two collegiate basketball players preparing to enter the NBA Draft, Player A and Player B. Aside from the school they attended, these players are identical; their height, weight, collegiate basketball performance, GPA, age, position, and whatever else NBA franchises evaluate pre-draft is the same:

Player A	**Player B**
University of Kentucky Wildcats	Morehead State University Eagles
Point Guard	Point Guard
20 years old	20 years old
2021: 15.7 PPG, 7.6 RPG, 4.3 APG*	**2021:** 15.7 PPG, 7.6 RPG, 4.3 APG*
6'4", 205 lbs	6'4", 205 lbs
Cumulative GPA: 3.5	Cumulative GPA: 3.5

*PPG = college points per game, RPG = rebounds per game, APG = assists per game

Returning to this paper's earlier discussion of uncertainty aversion and the findings of Ellsberg, the NBA career of Player A will be taken as the outcome with a more transparent probability distribution, whereas the result of drafting Player B is from an ambiguous distribution. This is because Player A comes from Kentucky, a prestigious basketball school that has sent 99 players to the NBA via the draft, forty of them since 2010. Kentucky has bred five NBA Hall of Famers, won 8 national championships, and won 2,237 games as a program, the most in NCAA Men's Division I history. In the eyes of a general manager, the size of the uncertainty surrounding Player A shrinks knowing Player A has graduated from a more decorated basketball program that is a regular producer of major-league talent. Morehead State, meanwhile, has sent just six players to the NBA via the draft, only one coming after 2010. Player B is then seen as the "uncertain gamble" coming from a school that has cultivated few professional draftees and has never advanced to the second weekend of an NCAA Tournament. It is reasonable to then assume that a team will make the conservative choice and select Player A, even if Player B has a wider range of outcomes and could end up being more talented on average. It is the relatively small, unknown history of Morehead State players that dissuades the general manager in the presence of a "safer" and "less risky" Kentucky alternative.

<u>Hypothetical Range of Outcomes for Player A (Kentucky) and Player B (Morehead St.)</u>



The price of Player B would have to fall in order for the general manager to be more willing to select them. Making such an "ambiguous lottery" less costly may be one of the only ways to convince someone to actually participate in one (Segal 1987). The "price" in this case could be the amount of draft capital required to select Player B (ex. a first-round pick), or perhaps the salary owed to Player B over the course of their rookie contract. Regardless, these two measurements of cost are almost always positively proportional.

Of course, this entire line of reasoning easily gives way to statistical discrimination; NBA scouts will continue giving plenty of attention to Kentucky ballplayers (even if some aren't good enough to deserve it), which in turn increases the pool of alumi that play in the NBA, reduces uncertainty, and makes it even easier for future Wildcats to play professionally. The cycle is far less forgiving for Morehead State players: each year without an alum drafted to the NBA creates more uncertainty about the Eagles' basketball program, further deterring teams from spending draft capital on future players from the university.

Data Collection

Data used in this study was collected from sports-reference.com, a database of both basic and advanced statistics for baseball, football (college and professional), basketball (college and professional), ice hockey, and soccer. Data currently enompasses draftees from every NBA draft class from 1999 to 2019, providing 21 full years of data. Players who were selected from overseas and/or out of high school will not be considered in this study, though the growing presence of the NBA's international and non-collegiate talent is not to be understated. Data in a variety of categories will be collected on relevant players via Excel:

Personal and Physical Metrics

Name	Position	School	*Power 6 Conference?	Draft Year	**Age When Drafted	Height	Weight	BMI
Elton Brand	Center	Duke	Yes	1999	20.30 years	80 in	275 lbs	30.21

* The "Power 6" is a collection of what are widely considered the best conferences in college basketball (Big 10, Big 12, Big East, Pac-12, Atlantic Coast Conference (ACC), and the

Southeastern Conference (SEC). These conferences are where the majority of the nation's top players compete.

**For precision purposes, the exact decimal age of the player is calculated.

Collegiate Performance and Accolades

Games Played	Seasons	Minutes Played Per Game	*Strength of Schedule	Consensus All-American?	AP Player of the Year?
60	2	29.3 (final season) 27.3 (career average)	10.14 (final season) 9.73 (career average)	Yes	Yes

* The SOS score is calculated by sportsreference.com and quantifies the quality of opponents faced throughout the season "in points above/below average, where zero is average."

High School All-American?	NCAA Tournament Appearances	NCAA Champion?	NCAA Tournament Awards?	*Offensive Win Shares	**Defensive Win Shares
Yes	2	No	All-Regional Team All-Tournament Team	5 (final season) 6.8 (career total)	5 (final season) 7.7 (career total)

*A statistic to credit a player's total measurable offensive contribution to his team's win total during the season.

**A statistic to credit a player's total measurable defensive contribution to his team's win total during the season.

Stats Regarding Alma Mater and Alumni in NBA

# of NBA Players from (Duke) since ('89-'90)	# of College Teammates in (1999) Draft Class	Off. Win Shares of (Duke) Alumni since ('89-'90)	Def. Win Shares of (Duke) Alumni since ('89-'90)
12	3	75.8 (cumulative) 6.32 (per player)	81 (cumulative) 6.75 (per player)

For regression calculations in STATA, these categories will be renamed.

Summary Statistics

There are 952 NBA draftees having their data recorded for this study, spanning from 1999 all the way to 2019, the last full season of NBA and NCAA basketball before the onset of the COVID-19 pandemic. Figure 1 demonstrates how many of the 952 observations possess a particular designation. Figure 2 summarizes the continuous variables that were measured across each of the 952 available players. Averages, standard deviations, maximums, and minimums are shown.

Methods and Empirical Models

This study will use ordinary least squares regression models in order to determine how the draft position of a collegiate player is impacted by the uncertainty attached to him. The size of uncertainty surrounding the player will be proxied for through the cumulative win shares of all professionals coming from that player's school across the previous NBA ten seasons. The assumption is the greater the number of NBA win shares a school has accumulated, the less uncertainty there is over the draftee. As explained earlier, win shares are an advanced metric that aims to quantify a player's contribution to his team's win total during the regular season. It essentially acts as a "catch-all" statistic that communicates how valuable someone was to their team's success that season, with negative win shares reflecting detrimental on-court performance. To contextualize this process, take Emeka Okafor, a University of Connecticut alum that was taken 2nd overall in the 2004 NBA Draft. In the ten-year period prior to Okafor's selection (the 1994-1995 season to the 2003-2004 season), UConn had 13 former players in the NBA appear in at least one game:

Player	From ▲	To
Clifford Robinson	1990	2007
Tate George	1991	1995
Chris Smith	1993	1995
Scott Burrell	1994	2001
Donyell Marshall	1995	2009
Donny Marshall	1996	2003
Travis Knight	1997	2003
Ray Allen *	1997	2014
Kevin Ollie	1998	2010
Richard Hamilton	2000	2013
Jake Voskuhl	2001	2009
Khalid El-Amin	2001	2001
Caron Butler	2003	2016

*** Denotes member of NBA Hall of Fame.**

Chris Smith, Clifford Robinson, Donyell Marshall, Tate George, and Scott Burrell were all active during the 1994-1995 NBA season; below are their individual offensive and defensive win shares for the year:

Player ▼	OWS	DWS
Chris Smith	1.0	0.3
Clifford Robinson	5.4	3.3
Donyell Marshall	-0.9	1.2
Tate George	0.0	0.0
Scott Burrell	2.8	2.9

Therefore, the University of Connecticut was responsible for 8.3 offensive win shares and 7.7 defensive win shares across the 1994-1995 NBA season. This method is repeated for the next nine years (up to 2003-2004), which eventually shows that UConn alumni generated 139.5 offensive win shares and 107.2 defensive win shares across the ten years before Emeka Okafor's draft. The 246.7 combined win shares were behind only Arizona (303.7), Michigan (284.8), and Duke (267.9) in the 2004 class, which gives reason to speculate that UConn's rich basketball tradition perhaps played a large role in Okafor being the #2 pick (and his college teammate Ben Gordon being #3). It should not be ignored, however, that Okafor was a Consensus All-American, national champion, and NCAA Tournament Most Outstanding Player in his final season, all factors that could have contributed to his draft performance.

Below are the three models that will be utilized in this analysis:

$$\textit{Selection(i)} = \alpha + (\beta_1 * \textit{TotalCollege\_WinShares}_i) + (\beta_2 * \textit{TotalNBA\_WinShares}_i) + \beta_3 (\textit{TotalCollege\_WinShares}_i * \textit{TotalNBA\_WinShares}_i) + (\beta_4 * \textit{other\_covariates}_i) + \varepsilon_i$$

$$\textit{Selection(i)} = \alpha + (\beta_1 * \textit{OffCollege\_WinShares}_i) + (\beta_2 * \textit{OffNBA\_WinShares}_i) + \beta_3 (\textit{OffCollege\_WinShares}_i * \textit{OffNBA\_WinShares}_i) + (\beta_4 * \textit{other\_covariates}_i) + \varepsilon_i$$

$$\textit{Selection(i)} = \alpha + (\beta_1 * \textit{DefCollege\_WinShares}_i) + (\beta_2 * \textit{DefNBA\_WinShares}_i) + \beta_3 (\textit{DefCollege\_WinShares}_i * \textit{DefNBA\_WinShares}_i) + (\beta_4 * \textit{other\_covariates}_i) + \varepsilon_i$$

The *Selection* variable is of utmost importance in this model, as it shows where in their respective draft class a player was selected, as well as implies how much value they carried in comparison to their counterparts. The first overall selection (*Selection* = 1) will obviously be far more coveted than, say, the 18th selection in the second round (*Selection* = 48). There are typically 60 selections in an NBA Draft class, two rounds with a pick for each of the league's 30 teams. Based on the nature of *Selection*, a negative coefficient will represent a positive effect on the player's draft position. In the first model, the Total*College_WinShares* variable demonstrates the total number of win shares $Player_i$ accrued over the final season of his collegiate career, and will tell us how highly franchises value college performance in their drafting strategy. As previously discussed, *TotalNBA_WinShares* will track the cumulative number of NBA win shares of every player that attended $Player_i$'s university across the ten years before $Player_i$ was drafted. The *TotalCollege_WinShares* and *TotalNBA_WinShares* will then be interacted, which looks to measure how the size of uncertainty changes across players of different collegiate performance levels: does the size of uncertainty impact draft position more for high-performance players, or are low-performance players more susceptible? The next two regression models will behave very similarly to the first, yet they work to determine how the offensive and defensive output of college alums impacts $Player_i$'s draft selection as opposed to solely aggregate output. Covariates regarding physical metrics and collegiate accolades will also be included, which hopefully can shed light on how NBA scouts value things like height, BMI, and performing well on the national stage.

Results and Discussion

The first regression was built around the *TotalCollege_WinShares* variable, which measured $Player_i$'s generation of total win shares during his final collegiate season. This was run alongside and eventually interacted with *TotalNBA_WinShares*, which measured the cumulative win shares generated by alumni of $Player_i$'s college during the ten NBA seasons prior to $Player_i$'s draft. Looking at the output (see Figure 3), it can be said with confidence that a strong overall performance in one's final collegiate season was rewarded in the NBA Draft. All else equal, $Player_i$ increasing their total college win shares in their final season by one point increased their draft position on average by 2.9 spots. In the early stages of the first round, moving from the 6th pick, for example, to the 3rd pick can make the modern NBA athlete an additional $3-4 million over the life of their rookie contract.[1] Meanwhile, the NBA performance of $Player_i$'s fellow college alumni does not appear to have a significant effect on where $Player_i$ is drafted, suggesting for the time being that perhaps the school he attended is not of particular interest to professional scouts. The interaction term was also found to be insignificant, implying that the size of uncertainty surrounding a player is not responsive to how well or how poorly they performed in college.

There were four significant covariates in this model: *DraftAge*, *CollegeGamesPlayed*, *AvgCollegeMinutesFinalSeason*, and *ConsensusAA*. The coefficient on *DraftAge* shows that with every year added onto a player's age by the time they're drafted, their selection increases by a little under four picks on average. In short, being an older prospect makes you less attractive to NBA scouts. This at first, may sound surprising, considering older draftees likely have more experience, better leadership qualities, and a higher basketball I.Q. Yet, if a veteran college player was not able to break through into the NBA until after his third or fourth college season, front offices will likely conclude that he lacks the potential to be developed into an all-star caliber player. Especially in the age of "one-and-done" players as well as the recent advent of the G-League (a developmental league that some highly-recruited high school players have chosen in lieu of collegiate basketball), younger players have increasingly appealed to NBA scouts in that they will have an extra two to three years to learn from professional coaches, trainers, teammates, etc.

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[1] Spotrac.com, NBA 2021-2022 Rookie (Contract) Scale

The significance of the *CollegeGamesPlayed* variable is in alignment with this idea of a "youth movement" taking over the NBA Draft, as there is a strong association between playing more games in college and seeing your draft stock fall. The coefficient on *CollegeGamesPlayed*, however, is not very economically significant as every additional appearance in a college game only raises *Selection* by an average of 0.22 slots. *AvgCollegeMinutesFinalSeason* has an opposite effect, as every additional minute Player_i logged in their final NCAA season improved their draft positioning. This suggests that the more playing time (per game) Player_i got across his final collegiate season, the more likely he'd be selected with a higher pick. For every additional minute of playing time per contest, Player_i saw on average his draft position improve by a little less than a quarter of a slot (not a very economically significant impact). This is not a groundbreaking revelation, but it validates the rather unsurprising notion that college starters have less draft uncertainty surrounding them in comparison with their teammates who come off the bench. Thus, this collection of observations suggest that NBA scouts are most interested in young, talent-rich players with little overall mileage but who were still key contributors to their collegiate squads. Unsurprisingly, the last 12 top overall picks have been "one and done" players, as have an increasingly large percentage of other first round draft selections in recent years.

The *ConsensusAA* variable measures the impact of being selected as a Consensus All-American. The Consensus All-America first and second teams (each made up of five players) is determined by a point system that awards three points for a first-team selection, two points for a second-team selection, and one point for a third team selection to any of the four major All-American teams (Associated Press, US Basketball Writers Association, National Association of Basketball Coaches, and Sporting News). The points granted to each player are then aggregated, with the top five point-getters earning a spot on the Consensus All-America first team and the next five landing on the second team. In 2021, each first team player was a unanimous selection, receiving a first team vote (three points) in each of the four major All-American polls:

2020-2021 Consensus All-America 1st Team

Player	School	Points from *Associated Press*	Points from USBWA	Points from NABC	Points from *Sporting News*	Total Points (out of 12 possible points)
Jared Butler	Baylor	3	3	3	3	12
Cade Cunningham	Oklahoma State	3	3	3	3	12
Ayo Donsunmu	Illinois	3	3	3	3	12
Luka Garza	Iowa	3	3	3	3	12
Corey Kispert	Gonzaga	3	3	3	3	12

Each second team player was "unanimously selected" to their respective team, with each player receiving two points in every major poll after all the first team players received three:

2020-2021 Consensus All-America 2nd Team

Player	School	Points from *Associated Press*	Points from USBWA	Points from NABC	Points from *Sporting News*	Total Points (out of 12 possible points)
Kofi Cockburn	Illinois	2	2	2	2	8
Hunter Dickinson	Michigan	2	2	2	2	8
Evan Mobley	Southern Cal.	2	2	2	2	8
Jalen Suggs	Gonzaga	2	2	2	2	8
Drew Timme	Gonzaga	2	2	2	2	8

According to the model, a Consensus All-America selection improves one's draft performance by an average of over 6 slots, further supporting the assertion that elite collegiate play is critical when being evaluated for the professional level.

The next model, almost identical to the first, focuses on offensive win shares, simply a quantification of a player's season-long contribution to his team while on offense (points, assists, offensive rebounds, limiting turnovers, etc.). The results (see Figure 4) remain fairly consistent. An increase by one offensive win share positively moves $Player_i$'s draft selection by a little less than three spots, suggesting effective play on offense is seen as an admirable trait in the eyes of NBA scouts, findings that echo the conclusions of the Berri (2010) and Evans (2017) studies. The cumulative NBA win share metric is still insignificant, as is the interaction term. Again, the process of examining collegiate talent does not seem to take into account how their contemporaries (fellow alumni) perform in the NBA, nor does the uncertainty about a draftee change across different amateur performance levels. Covariates *DraftAge*, *CollegeGamesPlayed*, *AvgCollegeMinutesFinalSeason*, *ConsensusAA* all stay statistically significant. Increased age is still a detriment to draft status (loss of ≈ 4 slots) while being a Consensus All-American stands to improve $Player_i$'s draft stock considerably (gain of almost 8 slots). *CollegeGamesPlayed* and *AvgCollegeMinutesFinalSeason* still work in opposite directions and are still of little economic significance.

NCAA-AllTourney was another covariate found to be significant; a member of the NCAA All-Tournament team saw an enhancement in their draft performance by over 4.5 selections on average. The team (five players) is selected soon after the conclusion of the NCAA Tournament and typically consists of players from the tournament's finalists and semifinalists, underscoring their excellent performance in a deep postseason run:

2021 NCAA All-Tournament Team

Player	Team
Jared Butler (Most Outstanding Player)	Baylor (Champion)
Davion Mitchell	Baylor (Champion)
Jalen Suggs	Gonzaga (Runner-Up)
Drew Timme	Gonzaga (Runner-Up)
Johnny Juzang	UCLA (Semifinalist)

Being a member of an All-Region team in the NCAA Tournament also has a significant impact on *Selection* (improvement of 3 slots). The All-Region teams (five players each) are made up of the top performers in each of the four quadrants of the bracket, usually players whose teams made it to the "Sweet 16" or "Elite 8" rounds of the tournament:

2021 NCAA All-South Region Team

Player	Team
Davion Mitchell (South Region MOP)	Baylor (South Region Champion)
Jared Butler	Baylor (South Region Champion)
MaCio Teague	Baylor (South Region Champion)
Max Abmas	Oral Roberts (South Region Semifinalist)
Jalen Tate	Arkansas (South Region Runner-Up)

The results associated with *NCAAAllTourney and NCAAAllRegion* results bear resemblance to the aforementioned Berri et. al (2010) and Ichniowski and Preston (2017) papers that explored the outsized value NBA teams place on collegiate players delivering when the lights are at their brightest.

The final model sets out to find if analyzing prospects and their fellow college alumni in the NBA through a defensive lens presents any real changes to the drafting process (see Figure 5). It was found that defensive collegiate output was significant, boosting Player$_i$'s draft stock by an average of over two slots. Once more, the *DefNBA_WinShares* metric and the interaction term are insignificant. *DraftAge*, *CollegeGamesPlayed*, *AvgCollegeMinutesPlayedFinalSeason*, *ConsensusAA,* and *NCAAAllRegion* all had their typical impact on *Selection*. To some surprise, *NCAAAllTourney* was just barely statistically insignificant. Finally, *APPOY* turned out to be a reliable predictor of how being the nation's top player impacted your draft stock. If you were voted the Associated Press Player of the Year, you should expect to see your positioning improve by an average of just over seven draft picks (all else equal).

Shortcomings

A source of bias stemming from this paper's procedure is that draft-eligible college graduates who were not selected by an NBA team aren't included in the data. This potentially undermines the assertion that the size of uncertainty about a particular player is generated via where they went to school. Since the majority of observations in this study came from Power 6 institutions, the lack of data on non-Power 6 players (or Power 6 players who weren't drafted) makes it difficult to see where the true differences lie between athletes who were good enough to join the NBA and those who weren't. There may be challenges in the way of seeing why exactly a player from UCLA is a more attractive candidate than one from Assumption University (a Division II school in Worcester, MA) if data about players from Assumption-like backgrounds are scanty. Therefore, this paper can be more aptly described as one that examines how NBA draftees separate themselves from one another—"what traits are most efficient at moving oneself up the draft order?"

Still, tracking the cumulative NBA win shares of college alumni was designed to avoid such biases: while the distinction between Power 6 and non-Power 6 may be elusive, identifying the best Power 6 programs (Duke, North Carolina, UCLA, Kentucky) is possible, as they are typically the year-on-year leaders in NBA win shares produced. The likely explanation for a lack of significant results is that yes, schools like Duke and Kentucky send multiple players to the league each year and boast the best cumulative win share figures, but their draftees are not always concentrated around the top percentile of the draft order; they are often scattered throughout the board:

University of Kentucky - 2012 NBA Draftees

Name	Selection
Anthony Davis	Round 1, Pick 1 (#1 Overall)
Michael Kidd-Gilchrist	Round 1, Pick 2 (#2 Overall)
Terrence Jones	Round 1, Pick 18 (#18 Overall)
Marquis Teague	Round 1, Pick 29 (#29 Overall)
Doron Lamb	Round 2, Pick 12 (#42 Overall)
Darius Miller	Round 2, Pick 16 (#46 Overall)

This reality makes it difficult for a linear relationship to be established between the size of uncertainty (which is typically very low for these schools) and where players get selected (which fluctuates). While players like Anthony Davis and Michael Kidd-Gilchrist provide evidence to suggest having successful Kentucky alumni (high level of *NBA_WinShares*) does improve positioning, the existence of a Doron Lamb or Darius Miller says the opposite.

Although *NBA_WinShares* was not shown to be significant in improving draft stock across a twenty year data set (1999-2019), approaching the analysis through another lens could produce a different result. College basketball (and college sports in general) have become increasingly commercialized and top-heavy as of late; money continues to flow into the nation's top programs, and so do the most talented recruits. As of 2018, the 43 college programs with the most expensive budgets were all from "Power 6" conferences, the lone exception being Gonzaga, who is an emerging powerhouse in their own right.

1	Duke	ACC	22,178,473
2	Kentucky	SEC	20,202,558
3	Louisville	ACC	19,180,078
4	Florida St.	ACC	16,773,013
5	Alabama	SEC	15,966,875
6	TCU	Big 12	15,718,763
7	UCLA	Pac 12	15,468,381
8	Marquette	Big East	14,979,149
9	Syracuse	ACC	14,845,555
10	Villanova	Big East	14,428,932
11	Michigan St.	Big Ten	14,395,851
12	Georgetown	Big East	13,573,946
13	Virginia	ACC	13,400,721
14	Indiana	Big Ten	13,230,211
15	Kansas	Big 12	12,547,439
16	Texas Tech	Big 12	12,338,645
17	Texas A&M	SEC	11,818,860
18	Texas	Big 12	11,649,912
19	UNC	ACC	11,204,115
20	Providence	Big East	11,117,186
21	Pitt	ACC	11,013,283
22	Ohio St.	Big Ten	10,996,364
23	West Virginia	Big 12	10,798,893
24	Northwestern	Big Ten	10,646,711
25	Tennessee	SEC	10,554,613
26	Auburn	SEC	10,536,653
27	Gonzaga	WCC	10,496,251
28	Illinois	Big Ten	10,480,939
29	Arkansas	SEC	10,440,326
30	Arizona	Pac 12	10,383,630

Per U.S. Department of Education, 2018

With the recent legalization of NIL (Name, Image, and Likeness) sales/licensing in the NCAA, big schools with outsized budgets can now offer even greater incentives like the opportunity to create corporate sponsorship deals for incoming recruits. This further shifts the balance more towards state universities and/or those with massive basketball budgets. For example, Duke's Paolo Banchero (a projected top-five selection in the 2022 Draft) recently agreed to an NIL deal with 2K Sports, making him the first collegiate athlete to appear in a video game.[2] Thus, the next decade of NBA draft classes (especially the lottery picks) may reflect a higher concentration of athletes from America's "blue bloods," finally showing that the size of uncertainty surrounding prospects *does* shrink as they attend more prestigious schools and that they are in fact rewarded for doing so. In the context of this paper, of course, the size of uncertainty would still be contingent upon how well those players performed *after* they were drafted, but the absolute number of win shares they'd accrue would still grow with every additional draftee. Unfortuntely, this dynamic could reinforce the afformentioned cycle of statistical discrimination against less pretigious basketball schools like Morehead State, where non-Power 6 or low-end Power 6 players are increasingly phased out of the drafting process. Therefore, it is only logical to say that the majority (or at least a large plurality) of the best players in the league could soon hail from blue blood programs given the growing "wealth and resource gap" in college basketball.

Areas of Further Interest

It is still a possibility that one's alma mater impacts their draft stock—perhaps using cumulative NBA win shares from $College_i$ was an inappropriate proxy for the size of uncertainty surrounding a potential draftee. There are a number of ways to approximate the level of prestige for a collegiate basketball program, yet the challenge remains whether or not such measures of

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[2] Polygon.com, "College basketball star makes NBA 2K debut on Friday," Feb 2022.

prestige provide long-term value for players who attended the institution. Some additional metrics that could be considered are:

- $College_i$'s all-time win percentage (in the regular season and postseason)
- $College_i$'s win percentage in Year X
- Number of conference/national championships $College_i$ has won
- Number of NBA All-Stars that $College_i$ has produced
- Number of NBA MVPs that $College_i$ has produced
- Number of NBA Champions that $College_i$ has produced
- Number of players $College_i$ has sent to the NBA

The same thinking can be applied to finding additional covariates with explanatory power: "what elements of $Player_i$'s *individual* effort could improve his draft stock?"

- $Player_i$ points per game, rebounds per game, assists per game, blocks per game, etc.
- $Player_i$ accolades (All-Conference Team, Conference Rookie of the Year, etc.)
- Advanced statistics
  - $Player_i$ Box Plus-Minus
  - $Player_i$ Player Efficiency Rating
  - $Player_i$ True Shooting %

It is also possible that *TotalNBA_WinShares*, *OffNBA_WinShares*, and *DefNBA_WinShares* should have been tracked differently. While this paper believed the ten seasons prior to $Player_i$'s draft was a relevant range across which to track cumulative NBA win shares, maybe such an estimate was misguided and needed to be smaller (3-7 years)/larger (12-15 years) in order to show a significant result.

Conclusion

This project has served to reinforce some of the more obvious assumptions associated with uncertainty in the NBA draft. Collegiate output, both in the aggregate, on offense, and on defense reassures scouts in their selection of players, findings that are largely consistent with the current literature. Younger draftees with more perceived upside and Consensus All-America selections who dominated the NCAA landscape are also consistently rewarded by seeing their draft stock rise. The number of college games an athlete plays (slightly negative impact) and their average minutes played per college game (slightly positive impact) were also variables significant across each of the three regressions, but were not economically relevant. Certain covariates that tracked Player_i's accolades like *NCAAAllTourney*, *NCAAAllRegion*, *APPOY*, and *NCAATournamentAppearances*, while significant in some cases, were not reliable predictors of *Selection* in each model. Such results imply that there may be a noteworthy value that NBA scouts place on postseason performance and individual regular-season awards, but further investigation is required to come to a more polished conclusion. Lastly, physical predictors like *Height* (in), *Weight* (lbs), and *BMI* were never shown to be significant, going against the grain of the Teramoto (2017) study that suggested such attributes were worth giving some attention.

Yet, the focal point of this paper was to determine if Player_i's alma mater significantly reduced the uncertainty involved with selecting them in the draft. The theory was that as the number of cumulative NBA win shares (across ten seasons) from athletes who attended College_i increased, that would represent the diminishing uncertainty surrounding Player_i, eventually resulting in him being selected higher in the draft. As an extension to this hypothesis, this "school effect" was to be monitored at varying collegiate performance levels as well to see if high-quality players saw a larger (or smaller) boost from their college compared to those of lesser caliber. This was done through an interaction term between the *College_WinShares* and *NBA_WinShares* variables in each of the three models used. Upon completion of testing, it was found that cumulative NBA win shares were not a reliable predictor for how much the draft position of a prospect improved/suffered. Furthermore, the lack of statistical significance meant the interaction term was also not important.

While this paper did not see its expected result, the hope was that it generated a better understanding of how NBA franchises approach amateur drafting and the ambiguity that comes with it. This paper can also serve to demonstrate the effects of group identification, specifically in the sporting job market. Perhaps further research and/or the implementation of new methods could expand on the field of uncertainty aversion in athletic settings.

Figure 1

N=952

Trait	Count	Percentage
College Position = Guard	414	43.49%
College Position = Forward	426	44.75%
College Position = Center	112	11.76%
Voted AP Player of the Year	21	2.21%
Winner of Naismith Award	21	2.21%
Winner of Wooden Award	22	2.31%
NCAA Champion	90	9.45%
NCAA Tournament Most Outstanding Player	18	1.89%
Member of NCAA All-Tournament Team	81	8.51%
Member of NCAA All-Regional Team	228	23.95%
Consensus All-American	179	18.8%
Played at "Power 6" School	757	79.52%

Figure 2

N = 952

Trait	**Mean**	**St. Deviation**	**Minimum**	**Maximum**
Age When Drafted	21.58 years	1.38 years	18.57 years	27.39 years
College Games	Played: 90.28 Started: 71.12	Played: 37.05 Started: 33.31	Played: 3 Started: 0	Played: 152 Started: 147
Minutes Played	Career: 28.18 Final Season: 31.27	Career: 4.75 Fin. Season: 4.35	Career: 7.5 Fin. Season: 1.3	Career: 38.3 Fin. Season: 39.3
Height	78.8 inches	3.26 inches	68 inches	86 inches
Weight	217.23 pounds	25.23 pounds	155 pounds	300 pounds
BMI	24.54	1.79	19.29	32.15
College Offensive Win Shares	Career: 6.18 Final Season: 3.01	Career: 3.51 Final Season: 1.33	Career: -0.2 Final Season: -0.3	Career: 21.6 Final Season: 7.3
College Defensive Win Shares	Career: 5.18 Final Season: 2.19	Career: 2.95 Final Season: 0.96	Career: 0.1 Final Season: 0.1	Career: 18.9 Final Season: 6.7
College Total Win Shares	Career: 11.36 Final Season: 5.20	Career: 5.46 Final Season: 1.72	Career: 0.1 Final Season: 0.1	Career: 31.7 Final Season: 11.3
Strength of Schedule Metric	Career: 6.90 Final Season: 6.99	Career: 3.23 Final Season: 3.35	Career: -9.85 Final Season: -9.3	Career: 12.8 Final Season: 12.8
# of College Alumni in NBA Over 10Y Span	11.96	9.19	0	48
NBA Off. Win Shares of Alumni	72.14	74.40	-4.7	290.2
NBA Def. Win Shares of Alumni	64.41	62.29	0	270.9
NBA Total Win Shares of Alumni	136.56	134.57	-0.8	545.4

Figure 3

Source	SS	df	MS
Model	124160.501	21	5912.4048
Residual	153558.218	930	165.116363
Total	277718.718	951	292.028095

Number of obs	=	952
F(21, 930)	=	35.81
Prob > F	=	0.0000
R-squared	=	0.4471
Adj R-squared	=	0.4346
Root MSE	=	12.85

Selection	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
TotalCollege_WinShares_Final	-2.906659	.3920502	-7.41	0.000	-3.676065	-2.137254
TotalNBA_WinShares	-.0056448	.0103533	-0.55	0.586	-.0259634	.0146737
Interact_FCollNBA	-.00011	.0018857	-0.06	0.954	-.0038106	.0035907
G	-.8915738	2.237959	-0.40	0.690	-5.283608	3.500461
F	1.138506	1.622095	0.70	0.483	-2.044886	4.321898
DraftAge	3.936957	.5057606	7.78	0.000	2.944393	4.929522
Seasons	-2.641913	1.477776	-1.79	0.074	-5.542075	.2582487
CollegeGamesPlayed	.2116932	.0463223	4.57	0.000	.1207849	.3026015
AvgCollegeMinutesFinalSeason	-.2584915	.1256059	-2.06	0.040	-.5049954	-.0119876
APPOY	-4.082479	3.0558	-1.34	0.182	-10.07954	1.914583
NCAAChamp	-2.187461	1.84314	-1.19	0.236	-5.804656	1.429733
NCAAMOP	2.421251	3.613902	0.67	0.503	-4.671097	9.513599
NCAAAllTourney	-3.525227	2.000785	-1.76	0.078	-7.451805	.4013507
NCAAAllRegion	-1.979022	1.176979	-1.68	0.093	-4.288865	.33082
ConsensusAA	-6.37091	1.301694	-4.89	0.000	-8.925508	-3.816312
Power6	-.9465201	1.023754	-0.92	0.355	-2.955656	1.062616
NCAATournamentAppearances	-.7778684	.5210182	-1.49	0.136	-1.800376	.2446393
Height	-.9507731	2.0159	-0.47	0.637	-4.907014	3.005467
Weight	.0488313	.3693271	0.13	0.895	-.6759798	.7736425
BMI	-.1491159	3.296644	-0.05	0.964	-6.61884	6.320608
SOSFinalSeason	-.2337903	.171027	-1.37	0.172	-.5694338	.1018532
_cons	30.45048	159.9819	0.19	0.849	-283.517	344.4179

Figure 4

Source	SS	df	MS
Model	117946.851	21	5616.51672
Residual	159771.867	930	171.797707
Total	277718.718	951	292.028095

Number of obs	=	952
F(21, 930)	=	32.69
Prob > F	=	0.0000
R-squared	=	0.4247
Adj R-squared	=	0.4117
Root MSE	=	13.107

Selection	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
OffCollege_WinShares_Final	-2.626577	.4876206	-5.39	0.000	-3.583541	-1.669612
OffNBA_WinShares	-.0126484	.0152529	-0.83	0.407	-.0425826	.0172857
Interact_FOffCollNBA	.0002483	.0045421	0.05	0.956	-.0086657	.0091623
G	.1937103	2.283621	0.08	0.932	-4.287937	4.675357
F	1.642732	1.653647	0.99	0.321	-1.602581	4.888045
DraftAge	3.958795	.5157856	7.68	0.000	2.946557	4.971034
Seasons	-1.566333	1.494454	-1.05	0.295	-4.499225	1.366559
CollegeGamesPlayed	.1812929	.0470346	3.85	0.000	.0889866	.2735992
AvgCollegeMinutesFinalSeason	-.3653951	.1267717	-2.88	0.004	-.6141868	-.1166033
APPOY	-4.915512	3.120951	-1.58	0.116	-11.04043	1.20941
NCAAChamp	-1.801164	1.882107	-0.96	0.339	-5.494834	1.892506
NCAAMOP	1.113603	3.668795	0.30	0.762	-6.086473	8.313679
NCAAAllTourney	-4.502452	2.036388	-2.21	0.027	-8.498901	-.5060027
NCAAAllRegion	-2.980683	1.191216	-2.50	0.013	-5.318466	-.6429007
ConsensusAA	-7.680122	1.320819	-5.81	0.000	-10.27225	-5.087991
Power6	-.9268959	1.045613	-0.89	0.376	-2.978931	1.125139
NCAATournamentAppearances	-1.132175	.5325314	-2.13	0.034	-2.177277	-.0870723
Height	-.8164194	2.056571	-0.40	0.691	-4.852476	3.219638
Weight	-.0093404	.3765844	-0.02	0.980	-.7483941	.7297132

Figure 5

Source	SS	df	MS
Model	115824.964	21	5515.47449
Residual	161893.754	930	174.079306
Total	277718.718	951	292.028095

Number of obs	=	952
F(21, 930)	=	31.68
Prob > F	=	0.0000
R-squared	=	0.4171
Adj R-squared	=	0.4039
Root MSE	=	13.194

Selection	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
DefCollege_WinShares_Final	-2.433437	.6995271	-3.48	0.001	-3.806271	-1.060602
DefNBA_WinShares	.0039462	.0189052	0.21	0.835	-.0331556	.041048
Interact_FDefCollNBA	-.006724	.0080817	-0.83	0.406	-.0225845	.0091366
G	-1.882396	2.309306	-0.82	0.415	-6.414451	2.649659
F	.5302455	1.668207	0.32	0.751	-2.743642	3.804133
DraftAge	4.103783	.5188549	7.91	0.000	3.085521	5.122045
Seasons	-1.033829	1.502863	-0.69	0.492	-3.983226	1.915568
CollegeGamesPlayed	.1436067	.0466914	3.08	0.002	.0519739	.2352394
AvgCollegeMinutesFinalSeason	-.5040297	.1230927	-4.09	0.000	-.7456013	-.262458
APPOY	-7.276481	3.112239	-2.34	0.020	-13.38431	-1.168657
NCAAChamp	-2.73874	1.888491	-1.45	0.147	-6.444937	.967457
NCAAMOP	2.53004	3.703099	0.68	0.495	-4.737359	9.797438
NCAAAllTourney	-3.938288	2.05264	-1.92	0.055	-7.966632	.0900557
NCAAAllRegion	-2.450381	1.208923	-2.03	0.043	-4.822914	-.077849
ConsensusAA	-9.476232	1.26201	-7.51	0.000	-11.95295	-6.999514
Power6	-.6809804	1.050618	-0.65	0.517	-2.742837	1.380876
NCAATournamentAppearances	-.5696842	.5402193	-1.05	0.292	-1.629874	.490506
Height	.0586592	2.068788	0.03	0.977	-4.001374	4.118692
Weight	-.1528233	.3787657	-0.40	0.687	-.8961578	.5905112
BMI	1.543087	3.382932	0.46	0.648	-5.095979	8.182153
SOSFinalSeason	-.1047973	.1739937	-0.60	0.547	-.4462631	.2366685
_cons	-50.98176	164.2063	-0.31	0.756	-373.2396	271.2761

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