Like Mike or Like LeBron:
Do the Most Able Need College to Signal?

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October 31, 2013

Very Preliminary, Please Do Not Quote or Cite Without Permission

Abstract:
Do individuals with demonstrably high ability need to attend college to further signal their ability to potential employers? We examine the labor market entry decision for basketball players deciding to enter or return to college versus entering the labor market for professional basketball, specifically the National Basketball Association (NBA). Individuals in this market have significant financial incentive to forgo further schooling in order to pursue their careers immediately and therefore face a trade-off between possible immediate financial rewards and the acquisition of additional skill-related human capital or improving the signals regarding own productivity. We exploit the variation generated from three exogenous ability rankings of college prospects, the Scout 100, Rivals150, and ESPN 100, in order to document three key findings related to signaling and human capital accumulation. First, we find that players who were ranked as being of high ability before entering college systematically pursue fewer years of schooling than those who were not. Next, among those signaled to be most able, individuals who are ranked more highly—indicating the highest ability levels—are less likely to accumulate significant amounts of skill-specific human capital, as they opt to be professionals more quickly than those ranked less highly. Finally, we find that exogenous signals of ability are highly informative to potential employers: after controlling for other possible determinants of player quality, whether a player was identified as being of high ability in high school is both an economically and statistically significant determinant of draft position.

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Introduction

In 1981, basketball legend Michael Jordan graduated from high school in North Carolina and chose to pursue a basketball career at the University of North Carolina, despite being a heralded prospect. Likewise, in 2003, basketball star LeBron James graduated from high school in Ohio also as a lauded prospect, even appearing on the cover of *Sports Illustrated* as a high school junior with the caption "The Chosen One". Both Jordan and James had to decide whether or not to obtain additional years of schooling, despite the fact that both were nationally-recognized as being of high ability. Jordan chose to obtain three additional years of schooling, opting to exit North Carolina one year before he was due to graduate. James chose the option to directly enter the labor market after completing high school. Strikingly, although both James and Jordan were considered to be among the highest-ability players before they chose whether or not to attend college, their ultimate choices about the amount of schooling to pursue varied substantially, with one player (James) choosing to bypass college education entirely.

Are the years of schooling choices of the most able more similar to James or Jordan? This paper asks whether individuals who possess notable signals of high ability before college choose to pursue additional years of secondary schooling for either an additional signal of ability or additional human capital. The classic labor market signaling model formulated by Spence (1973) posits that high ability individuals may pursue secondary education regardless of whether any additional human capital accumulation takes place in order to signal higher productivity to employers. Empirically, it is well-established that individuals may receive higher wages from credentials that may be only loosely related to human capital accumulation (Hungerford and Solon, 1987; Belman and Heywood, 1991;

Weiss, 1995; Jaeger and Page, 1996; Tyler, et al., 2000; Flores-Lagunes and Light, 2010). Nonetheless, because individuals who choose to pursue secondary education usually also accumulate human capital, it is difficult to identify whether individuals pursue secondary education to obtain additional, productivity-enhancing human capital or to signal existing ability and productivity to potential employers.

We address the fundamental trade-off facing individuals to either acquire additional human capital or enter the labor force by examining the choices faced by basketball players who possess publicly-available signals related to own productivity *prior* to graduating from high school. Players who choose to enter college receive additional signals regarding their own productivity and thus face the choice between additional human capital accumulation and labor market entry following each season. Since individuals already have signals that communicate potential productivity to future employers, the incentives to pursue additional signals through secondary education are reduced such that the subsequent choice to pursue additional years of schooling is more plausibly framed as a choice to obtain additional amounts of human capital, rather than a choice to obtain an additional signal.

If a player believes himself to be of sufficiently high quality to obtain an NBA contract, then he has little monetary incentive to complete a college degree since the expected value of the initial contract outstrips the option value from remaining in school to pursue more basketball-specific human capital. Because of this, it is reasonable to think that most, if not all, of the players in our sample would pursue a career in the NBA if able to do so, since the pecuniary incentives of an NBA career are so strong. We examine labor market outcomes for these same individuals, specifically whether these individuals are hired and, if so, the extent to which teams value their skills. These labor market outcomes are observable to potential labor market participants, who must decide on a yearly basis whether to accumulate additional human capital via more years of schooling or to forgo that schooling to pursue their careers. We analyze the factors that lead to a player being selected in the draft as well as those factors which lead to a player being selected *more highly* in the draft, since players who are selected early are thought by teams to be more promising prospects and are paid more highly.

Hendricks, DeBrock, and Koenker (2003) examine data from the professional draft in the National Football League (NFL) in order to determine the impact of hiring uncertainty upon future productivity. They discuss the role of imperfect information and signaling of ability in these markets and that it is difficult to identify whether success arising from ability or arises from sorting of high ability individuals into environments in which they are likely to succeed. Our analysis takes this problem one step further in order to determine whether early indicators of ability, prior to the accumulation of additional skill-specific human capital, are sufficient for individuals to signal productivity. Therefore, our analysis, applied to professional basketball, allows us to extend the frame of reference examined in Hendricks, DeBrock, and Koenker (2003) in order to determine the importance of early signals of ability relative to acquired human capital.

The key data that we observe are the external assessments of ability that are generated *before* a player plays in college. Players are not exposed to collegiate coaching or collegiate experience when the assessments of ability are made. Player performance in college is correlated with both a player's inherent ability and investments made in human capital from coaching and experience. Because of this, one cannot use collegiate performance data to disentangle player ability from human capital obtained from the improved inputs that a player receives from improved competition, coaching, and teammate interaction. On the other hand, high school performances are incredibly noisy, as the quality of coaching, competition, and teammates varies substantially across players, making performance metrics generated from high school play unreliable predictors of a player's future performance. Moreover, while many talented high school players play each other in basketball camps and other informal tournaments, the quality of coaching, refereeing, and incentives to play well in these tournaments can vary substantially, making the results of these tournaments unreliable measures of player ability or player human capital accumulation. The variance in performances among high school players creates demand for external assessments of player ability from both fans of university programs and the universities themselves.

We observe three different external assessments of ability from three different scouting agencies—the Rivals 150, Scout 100, and ESPN 100—from 2002-2012 for over 5,000 different players. Each scouting agency publishes multiple ordinal lists which capture: (i) players with the overall highest ability identified as "top recruits"; (ii) players with the highest ability separated by position; and (iii) an overall assessment of ability which categorizes players according to four or five different levels of ability. Even though each list is produced by a separate organization, players are nonetheless ranked similarly across lists, providing consistent and multiple observations of player ability for a given year. We match the ability assessments to a wide battery of performance metrics for each season that a player played in both college and professional basketball. These metrics include all relevant in-game statistics, biographical data, and labor choice decisions.

To summarize, for each player we observe whether the player was rated as being of high ability in high school (and if so, how highly the player ranked relative to his peers), how the player performed in college for all seasons that the player played in college, how the player performed in all of his professional seasons, when (or if) the player chose to forgo additional schooling, where (or if) the player was selected in the NBA draft, and what compensation the player received if he played in the NBA. Moreover, we are able to observe a natural experiment in this labor market associated with an exogenous change in the restrictions governing player entry into the NBA draft. In 2005, the NBA and the National Basketball Players Association (NBPA) signed a new collective bargaining agreement which included a provision that raised the minimum age at which a basketball player can enter the NBA. Thus, players who once faced a choice to enter the NBA after high school graduation or pursue an additional year of schooling as a college freshman are now prohibited from entering the NBA as high school seniors.

We document three key sets of findings. First, using both a logistic regression and time-varying Cox proportional hazard approach, we find that players who are ranked as being of high ability are systematically more likely to enter the NBA draft, even after accounting for a myriad of performance metrics, such as the number of points a player scores in a game. Our findings are robust to three different assessments of ability by three separate agencies. Furthermore, *among ranked players,* players who are ranked among the Top 25 or Top 10 recruits are over five times more likely to enter the draft then their lesser-ranked counterparts.

Next, we find that professional teams are more likely to draft players that have external signals of ability. We estimate that the lowest-ranked player is 1.02-1.03 times more likely to be drafted (i.e., just marginally more likely), but that the top-ranked player is between 13 and 31 times more likely to be drafted. Finally, we find evidence that players who are drafted are selected more highly if they have external signals of ability. In our preferred specifications, increasing a player's rank by 10 slots can lead to a one-slot increase in selection, holding player production constant. For drafted players receiving a guaranteed rookie contract under the current rookie salary scale, the economic impact of a one-slot increase ranges between $19,400 to $1,414,800, with a median of $226,000, over a three year period. Taken together, we find substantial evidence that players with external signals forgo schooling and that employers both hire these players more frequently and select them earlier in the draft.

We proceed by describing the professional basketball labor market in the second section and describing the precise ranking and outcome data in the third section. The fourth section describes our empirical strategy and explores the natural experiment in more detail and the subsequent section discusses the results from our empirical estimation. The final section discusses the implications of our results within the specific context of this labor market and concludes.

Professional Basketball Labor Market

Studying the labor market decisions and outcomes of basketball players is attractive for several reasons. One primary benefit of utilizing professional sports to examine labor markets is the amount and detail of available information regarding worker characteristics, performance, and labor market outcomes. Moreover, the collectively-bargained provisions governing both the length and salary structure of worker contracts and worker movements between teams enables us to distinguish between alternative explanations for schooling choices, allowing the decision to enter the NBA draft to be plausibly framed as an option value decision for enrollment, as in Strange (2012). Finally, the economic importance of superstars in the NBA, identified by Hausman and Leonard (1997), creates incentives to identify these individuals at an early age for teams, advertisers, as well as the players themselves.

The study of labor market outcomes can be confounded by the presence of unobservable worker characteristics, such as soft skills, non-cognitive skills, personality traits, and external connections, which can jointly influence workers' entry decisions, firms' hiring decisions, and workers' long-term wages (Bowles, Gintis, and Osborne, 2001a; Bowles, Gintis, and Osborne, 2001b; Nyhus and Pons, 2005; Borghans, ter Weel, and Weinberg, 2008). Although some of the skills relevant to the professional basketball labor market remain unobservable, the majority of the most important factors influencing both worker and firm actions are observable. We are able to observe a wide variety of performance metrics for college basketball players directly correlated with player performance in the NBA. Coupling these metrics with external assessments of ability allows us to plausibly control for most relevant determinants of a player's selection.

Over the past fifteen years, the NBA and the NBA Players Association (NBPA) have negotiated three separate collective bargaining agreements (CBA); in 1999, in 2005, and most recently in 2011. Each CBA influences player contracts along several dimensions which impact players differentially depending upon years of experience in the league as well as years of experience with a particular team. Although detailing the differences across

CBAs is beyond the scope of this analysis, in some form each of the CBAs imposes the following structure upon labor contracts:

i) a wage floor governing minimum annual player salaries as well as the annual nominal changes in these salaries;

ii) a wage ceiling governing maximum annual player salaries based upon a player's experience, a player's experience with the team, the team's overall salary cap, as well as the annual nominal changes permitted in these salaries;

iii) maximum contract lengths; and

iv) a rookie salary scale and contract length which remains separate from that of all other players.

Because a player's decision to enter the draft is based primarily on the financial benefit from playing professionally, it is worthwhile to examine the changes in the rookie salary scale in more detail. For the 1999 CBA, the number one overall draft pick was guaranteed $2,679,300 for the 1998-99 season whereas the player selected with the 29th pick, the last pick to receive a guaranteed contract, earned $535,000 (NBPA, 1999). The same CBA guaranteed 5% nominal annual increases in rookie salaries through the 2004-05 season as well as guaranteed rookie contracts for three seasons with a fourth season team option. The addition of a 30th NBA team prior to the 2004-05 season implies the number of players receiving a guaranteed rookie contract at the draft increased by one to thirty total. The 2005 CBA kept the basic rookie pay scale structure in place, but gradually reduced the nominal salary increases from 3.7% per year to 3.1% per year for the 2011-12 season (NBPA, 2005). The 2011 CBA held rookie salaries constant and equal to the 2010-11 scale for two seasons, such that the first overall pick in the 2012-13 draft received a guaranteed

$4,286,900 and the 30th overall pick is guaranteed $850,800 (NBPA, 2011). The final major provision of the 2011 CBA was the change in guaranteed contract length for NBA rookies which were shortened to two guaranteed seasons with one-year team options for the third and fourth seasons.

The various CBAs also govern how player talent is allocated amongst the NBA teams either via free agency or the NBA draft. A basketball player who wishes to enter the NBA *for the first time* is restrained from initially signing with his preferred team, an option afforded to previously drafted players seeking new contracts via free agency. Rather, all players must agree to enter the NBA draft which occurs once a year in June. The draft is a modified reverse-order entry draft, implying that teams with poorer records during the previous season receive earlier selections, although the top selections are allocated via a weighted lottery. The draft consists of two rounds with one selection per round allocated to each team. Only players selected in the first round each year receive guaranteed contracts and draft pick spots as well as player rights can be, and frequently are, traded between teams. The draft is intended to improve competitive balance within the NBA by more allocating talent to the poorer performing teams. An individual's decision to enter the NBA draft is binding; a player that chooses to enter the draft may not return to college to play basketball and pursue additional levels of basketball-specific human capital, although nothing prevents the player from (re-)enrolling to finish his degree or from pursuing basketball career in a different professional league.

In previous literature, Li and Rosen (1998) identify the NBA draft as an example of unraveling in a matching market and note that in 1997, 17 of the 29 first round draft picks were not college seniors. Groothuis, Hill, and Perri (2007) build on this observation and find that the average age of first round picks declined substantially between 1989 and 2002. They identify that institutional changes incorporated in the 1999 CBA provided substantial incentives for early entry into the NBA draft. Specifically, the CBA was negotiated such that rookie players became contractually obligated to stay with their initial team for a longer period of time at lower salaries before they could seek higher salaries via free agency. Additional analysis by Eschker, Perez, and Siegler (2004) and Groothius, Hill, and Perri (2007) also examine the increasing presence of international players in the NBA draft and the implications upon team performance and early entry decisions.

Similarly, economists have examined the determinants of player draft position among NBA players as well as the long-term impact of relative draft position. Berri, Brook, and Schmidt (2007) and Berri, Brook, and Fenn (2011) find that points scored in college, player height, team success in the college basketball playoffs, and to a lesser extent shooting efficiency and measures of defensive performance positively impact draft position whereas player age has a negative effect. This study consists of cohorts of NBA players who have either been selected in the NBA draft or have playing time in the NBA. However, undrafted players with similar attributes to draftees are excluded from these samples and hence from the estimations. Bishop and Gajewski (2004) use data from a single season of college basketball and principal component analysis to find two sets of linear combinations that explain 67% of the variance in draft position. They broadly separate variables into those associated with in-game college performance (minutes, points, rebounds, etc.) and those associated with player body type (height, weight, etc.). We contribute to the sports economics literature by examining the entry decision faced by all college players, independent of the realized outcomes, using a panel of collegiate players across multiple seasons.

Finally, Staw and Hoang (1995) identify that an earlier draft position in the NBA is associated with greater player longevity, independent of actual performance. They attribute this result to teams escalating their commitment to early draft picks and thus falling subject to a fallacy regarding the sunk cost associated with these earlier draft picks. Camerer and Weber (1999) examine these conclusions under an alternate set of hypotheses regarding draft position and find that although evidence of escalation persists, the magnitude is decreased. They conclude that if the actual draft position contains prior information regarding player quality, that teams may imperfectly update their prior beliefs following the introduction of new signals regarding player quality (i.e., performance).

Data

Just as US high schools can vary in quality and characteristics, US high school basketball programs, and the leagues in which they participate, can also vary substantially in quality. Even though performance statistics for high school basketball games are readily observable, the heterogeneous quality of basketball programs and leagues introduces information asymmetries as university coaches and scouts can observe the player performance, but not necessarily the performance relative to the level of competition. Recruiting news agencies, which scout and rank high school basketball players according to observable characteristics, offer services to both universities and fans which reduce the information asymmetries regarding the quality of recruits. Since these agencies profit directly from the quality of the information that they provide, there are significant incentives to provide unbiased, truthful assessments of player quality (Bricker and Hanson (2013)).

Our sample includes data provided by three separate agencies – Rivals.com (Rivals) associated with Yahoo! Sports, Scout.com (Scout) associated with FoxSports.com, and ESPN.com (ESPN) – that rank high school basketball players based on perceived quality from 2002-2012. The publicly available information provided by these agencies affords us with an observable measure of ability for high school basketball players, in addition to other observable characteristics such as player height and weight. Although we focus exclusively on the final posted rankings, most of the top high school basketball players are initially ranked as freshman or sophomores, with the ranking agencies updating their information and their scouting reports as these players progress through high school.

All three agencies provide rankings for high school seniors on an ordinal scale regardless of the player's position. Both ESPN and Scout rank the top 100 high school prospects each year whereas Rivals ranks 150 prospects. We observe these overall rankings data for ten consecutive graduating classes for Rivals and for Scout for every class except 2004. ESPN only began to rank players in this fashion in 2007. Additionally, each of the agencies provide ordinal measures for each prospect class for each basketball position (i.e., point guard, shooting guard, small forward, power forward, and center) as well as "star" rankings which classify a sub-sample of prospects into broad categories of five-, four-, three-, two-, and one-star recruits. ESPN also attempts to provide a cardinal ranking of players which it characterizes as a prospect "grade".

Across the three agencies, it is possible for a player to have up to ten measures of observable basketball ability when they graduate high school. Although the top prospects typically are rated by all agencies, the vast majority of our sample is ranked by a single agency in a given year. In our present analysis, we identify ability using the ordinal "top" rankings for each of the agencies as well as the positional and "star" rankings by Rivals and report the number of prospects rated by each measure for each class year in Table 1.[3]

The rankings data provide us with metrics of player ability prior to entering collegiate or professional basketball. We match these data with player performance statistics, at both the collegiate and professional basketball level, available from Sports-Reference.com. The inclusion of collegiate-level performance data allows us to determine whether the prospect rankings are sufficient signals of ability or if observable, in-game performance is relevant in determining a player's entry decision and draft position. The performance data from the NBA allows us to control for in-game performance in determining player outcomes such as seasons, games, and minutes played, as well as salary, at the professional level.

We consider traditional statistics, both total and per game, measuring player performance including points, rebounds, assists, steals, blocks, three-point field goals, free throws, games played, minutes played, and turnovers. Furthermore, we also consider a handful of common advanced statistics designed to more accurately capture player contributions towards winning including PER, win shares, win shares per 48 minutes of playing time, and true shooting percentage.[4] Our sample of collegiate basketball players consists of all players who graduated high school between 2002 and 2012. The sample of professional basketball players consists of all players who graduated high school between

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[3] Due to double counting of players across class years and imperfect reporting by the ranking agencies, it is possible that the number of players ranked in a given year do not perfectly match with the stated number of rated players (i.e., there are not necessarily 150 players rated as "Top 150" by Rivals in a given year).
[4] Definitions of these variables and a brief discussion of their importance can be found in the appendix.

2002 and 2012, regardless of whether they attended college, as well as foreign-born professionals whose date of birth would place them within the same high school cohorts.

Table 2 presents the summary statistics for the college data. All ranking variables have been transformed so the highest-ranked player has the largest numerical ranking (i.e., if there are 100 players ranked, then the top player is ranked 100). This is done in order to generate an intuitive meaning of the ranking variable such that unranked players take the value of rank 0. Roughly 1.51 percent of our sample enters the draft early; 3.67 percent of our sample players are drafted, though this is biased upward since some drafted players play for multiple years in college. On average, players in our sample do not have prolific college seasons. Players score an average of 6.7 points per game, gather an average of 3.0 rebounds per game, and record an average of 1.3 assists per game.

Finally, Berri, Brook, and Fenn (2011) find that in addition to the performance metrics which impact draft position, height for position and team performance in the college basketball playoffs are also correlated with draft outcomes. In addition to these proposed determinants of player outcomes, we also control for other publicly available signals of player ability provided by third parties; namely, whether a player was selected as a McDonald's All-American in high school or an AP All-American in college.

Empirical Strategy

In order to determine whether or not external assessments of ability influence the decision to acquire additional human capital, we take advantage of several features unique to this specific labor market. We construct a panel from our player performance data and examine the labor market entry decisions that players face prior to the expiration of their collegiate eligibility. Moreover, we are able to observe an exogenous policy change in the labor market within our sample period. Specifically, the 2005 CBA, signed in June 2005, increased the minimum age of prospective draftees from 18 to 19 years old. This policy change implies that high school seniors could no longer declare for early entry into the NBA draft. Finally, we exploit the possibility that players receive multiple assessments of their ability as high school prospects in order to determine the impact of reinforcing or contradictory signals on the labor market entry decision.

We first analyze the draft entry decision facing collegiate players with remaining NCAA eligibility by estimating both a logistic and Cox proportional hazard model of entry. Entering the NBA draft causes a player to forgo his existing NCAA eligibility as well as any additional accumulation of basketball-specific human capital acquired by playing in NCAA-sanctioned competitions or from NCAA coaches. We estimate the probability of player i's entry following season j as:

$$\Pr\left(ENTER_{ijk} = 1 | ELIGIBLE_{jk} = 1\right) = f\left(HSRANK_{ik}, HSRANK_{ik} \times RANK_{ik}, X'_{ij}, Z'_{ik}\right) \quad (1)$$

where $ENTRY_{ijk}$ is a dummy variable set equal to 1 if player i enters the NBA draft in season j given that he is in high school class k and $ELIGIBLE_{jk}$ is a dummy variable set equal to 1 if high school class k is eligible to enter the draft following season j. Additionally, $HSRANK_i$ is a dummy variable indicating whether the player was ranked as being of high ability before entering college for *any* of the three rating agencies; $RANK_i$ are the ordinal measures of ability from the three ranking agencies (Scout 100, ESPN 100, Rivals 150), Z'_{ik} is a vector of observable characteristics for player i in high school class k, and X'_{ij} is a vector of observable statistics that measure player productivity for during a given season. Specifically, our controls are defined as:

$$Z'_{ik} = [POSITION_i, HEIGHT_i, MCDONALDS_{ik}]$$

and

$$X'_{ij} = [CLASS_{ij}, AP_{ij}, CONF_{ij}, PLAY_{ij}, STATS_{ij}],$$

where

$$STATS_{ij} = \begin{bmatrix} GAMES_{ij}, STARTS_{ij}, MINUTES_{ij}, POINTS_{ij}, REBOUNDS_{ij}, \\ ASSISTS_{ij}, STEALS_{ij}, BLOCKS_{ij}, TURNOVERS_{ij}, PERCENTAGES_{ij}, \end{bmatrix}.$$ [5]

Multiple prior studies have found that players who increase the number of points that they score in a season see their draft position improved. Given this finding, players who score a large number of points in a season may choose to enter the draft, and we expect scoring more points to positively influence the likelihood that a player enters the draft. Likewise, we expect other measures of productivity, such as the number of games played, games started, minutes played, rebounds, assists, steals, blocks, and field goal and free throw percentages to also positively affect a player's entry whereas turnovers to negatively affect entry, albeit perhaps not with the same magnitude as the number of points. We include conference fixed effects, captured by $CONF_{ij}$, to account for the fact that players who play in conferences where the quality of competition is higher may choose to enter the draft more frequently than players who play in lesser conferences.[6] We include class fixed effects, captured by $CLASS_{ij}$, to account for any systematic differences in entry based on the number of years a player attends college. Also, we include player position ($POSITION_i$), player height ($HEIGHT_i$), a dummy indicating if a player made a McDonald's All-American team in high school ($MCDONALDS_i$), a dummy indicating if a player made an AP All-

[5] All statistical in-game productivity measures are normalized to a per-game basis to account for the fact that teams play different numbers of games.

[6] Players in these conferences may be systematically more likely to enter the draft for other reasons, including increased television exposure, better coaching, etc.

American team in college (AP_i), and a dummy indicating whether a player's team advanced to the semi-finals of the college basketball playoffs in that season ($PLAY_{ij}$).

The primary coefficients of interest are related to $HSRANK_{ik}$, which captures whether or not a player is ranked by a rating agency. These rankings are determined for a player before he attends college. We ask first whether being judged as being of high ability *before* entering college is an important determinant of player entry after controlling for other determinants of performance. We then ask whether, conditional on being ranked, being ranked more highly (i.e., closer to the top of the ordinal ranking) impacts whether or not a player enters the draft. For intuition, a player who is ranked as the 100th-best player in the country as a freshman may not wish to enter the draft based solely on his ranking since only sixty players are chosen. On the other hand, a player who is ranked as the top player in his class may wish to enter the draft since he could not improve his ranking.

We estimate equation (1) using logistic maximum likelihood regression and the natural experiment which changed the eligibility requirements in the 2005 CBA. Unobserved factors may impact an individual player's decision to enter a draft across years. For example, a player may choose whether or not to enter a draft based on his perception of the quality of the other potential entrants in the draft, which varies from season to season. In this case the individual characteristics of a player may not fully capture the information that a player uses to decide whether or not to enter. We account for these characteristics by clustering our standard errors by the season when a player performs.

Although equation (1) is able to describe the behavior of any player within our sample, it may not adequately capture the underlying dynamics of each individual player's entry decision. For example, by estimating equation (1) without considering the panel structure of our data, we are assuming that a player's decision to enter the NBA draft as a junior is independent from his decisions to enter as a sophomore or freshman. These assumptions may be unreasonable since a player who considers enter the draft as a high school senior, college freshman, or college sophomore may strongly consider entering the draft again at a later date. As an example, a player who is highly ranked out of high school may not receive as much playing time in college during his freshman year because of inexperience, the difficulties of adjusting to college life, or competition for playing time with existing players on the team. Following the conclusion of the season, the player faces the trade-off of entering the draft and losing his college eligibility or remaining in school for an additional year and retain the option to enter the draft at a later date.

In order to account for the potential dynamics underlying the entry decision, we also consider a time-varying covariates Cox proportional hazard approach to estimate the relationship between early entry and whether or not a player is ranked of high ability. The hazard rate, *h(l),* is the likelihood that a player enters the draft as a freshman, sophomore or junior given that he has not yet entered the draft. The model takes the form:

$$\begin{aligned} &h\left(l \mid ELIGIBLE_{jk}, HSRANK_{ik}, HSRANK_{ik} \times \ RANK_{ik}, X'_{ij}, Z'_{ik}\right) \\ &= h_0(l)\exp\left(X'_{ij}\beta_1 \ + Z'_{ik}\beta_2 + HSRANK_i\beta_3 + HSRANK_i \times RANK_i\ \beta_4 + ELIGIBLE_{jk}\beta_5\right) \end{aligned} \quad (2)$$

where $ELIGIBLE_{jk}, HSRANK_{ik}, HSRANK_{ik} \times \ RANK_{ik}, X'_{ij}, Z'_{ik}$ are as described previously. We note that our formulation includes ability assessments, which do not vary over time, and productivity measures, which differ for each player by both class and season. We present results for all three rating agencies to account for any idiosyncratic differences in pre-college assessments of player ability.

We next assess whether, among those who possess external signals of ability, individuals who are ranked very highly choose to enter the draft earlier than those who are ranked less highly. Because only 60 players are selected in the NBA draft each year, players who are ranked as being of high, but not the highest ability may not possess a signal high enough to justify entry. If rankings do indeed serve as signals of ability to NBA teams, then stronger signals of ability may induce players to enter the draft more quickly, since the value of playing an additional season may be superseded by the existing signal of ability that players have to demonstrate to potential teams. We proceed by restricting our sample of players to include only those ranked by Scout, Rivals, or ESPN. We then re-estimate (1) and include dummy variables to denote whether a player was ranked as being among the top 10 or top 25 in ability by the three ranking agencies, again including the same productivity controls as before. Using the technique of maximum likelihood and logistic regression we again estimate:

$$\begin{aligned} &\Pr\left(ENTRY_{ijk} = 1 | ELIGIBLE_{jk}, HSRANK_{ik} = 1\right) \\ &= f\left(TOP25_{ik}, TOP10_{ik}, HSRANK_{ik} \times RANK_{i,}, X'_{ijk}, Z'_{ik}\right) \end{aligned} \tag{3}$$

where $TOP25_{ik}$ is a dummy variable equal to 1 if a player is among the top 25 players in the ability rankings and $TOP10_{ik}$ is a dummy variable equal to 1 if a player is among the top 10 players in the ability rankings.

Finally, we estimate two models that examine the extent to which high school rankings, as well as observable collegiate productivity measures, impact player outcomes in the NBA draft. We first estimate:

$$\Pr\left(DRAFT_{ijk} = 1 | ENTRY_{ijk} = 1\right) = f\left(HSRANK_{ik}, HSRANK_{ik} \times RANK_{ik}, X'_{ij}, Z'_{ik}\right) \tag{4}$$

where $ENTRY_{ijk}, X'_{ij}, Z'_{ik}, HSRANK_{ik},$ and $HSRANK_{ik} \times\ RANK_{ik}$ are as described previously and $DRAFT_{ijk}$ is a dummy variable equal to 1 if player i from high school class k was drafted following season j. We estimate (4) via logistic maximum likelihood and again include conference and class fixed effects to account for the possibility that teams prefer players who face a specified level of competition or wish to acquire players who have attained a certain amount of schooling, perhaps for human capital or maturity reasons. Finally, we cluster our standard errors by season to account for "stronger" or "weaker" drafts, since the pool of available basketball talent differs from year to year. As in previous models, a positive sign on a player's rank indicates that teams draft players with higher signals more often than those with lower signals or without signals.

Our final model follows Berri, Brook, and Schmidt (2007) and Berri, Brook, and Fenn (2011) and we examine whether, for players who have been drafted in our sample, external assessments of ability are important *in addition* to observable productivity characteristics. In this model, we include three additional measures of productivity, PER, usage rate, and true shooting percentage, that may convey a richer understanding of how well a player performs in college than traditional measures. Therefore, we estimate:

$$DRAFTPOS_{ijk} = f\left(HSRANK_{ik}, HSRANK_{ik} \times\ RANK_{ik}, X'_{ij}, Z'_{ik}\right) \tag{5}$$

where DRAFTPOS $_{ijk}$ is the draft position, 1-60, of player i in class k for season j. All measures of productivity are included in the vector $X^{'}_{ij}$. As players may be compared to peers who started college basketball at the same time, we include cohort-specific fixed effects. We estimate (5) as a censored Tobit model because the dependent variable, DRAFTPOS $_{ijk}$, is both left- and right-censored, and thus OLS is inconsistent. Since a value of 1 for draft position indicates that a player is the highest selection, if a player's rank is negative and significant after accounting for productivity characteristics, then this is strong evidence that teams consider external ability assessments as informative determinants of hiring decisions and players with higher assessments are drafted earlier.

(Preliminary) Results and Discussion

We first report our results for entry decisions, contained in Tables 3-5. Table 3 reports the results from the estimation for equation (1) examining the player entry decision. We report the results for three separate panels of ranking data for each of the ranking agencies. In all three specifications using the Rivals 150 rankings, the interaction term between a player being ranked with his number ranking in the Rivals 150 is significant. Whether a player is ranked or not is significant in specifications without conference and class controls, but becomes insignificant in our preferred specification, (III), which includes conference and class fixed effects. In (III), a player who has the top Rivals 150 ranking for a particular cohort enters the draft 12.807 times more frequently than a player who is unranked, conditional on other characteristics.

Our results confirm other studies in that higher levels of traditional measures of productivity, including points per game, rebounds per game, assists per game, and blocks per game, all positively influence a player's decision to enter the draft, with points per game being the most significant of all measures of whether or not a player enters the draft. Our findings complement previous studies which find that players who score more points are more likely to be selected higher in the draft as we find that players who score more points may be more inclined to enter the draft if they are aware of team preferences to select higher-scoring players.

Panels B and C repeat the analysis for both the Scout 100 and ESPN 100 rankings. Our preferred specification for the Scout 100 rankings, (VI), indicates that the top player in the rankings enters the draft 6.30 times more frequently than an unranked player, while a player ranked as the top player in the ESPN 100 rankings enters the draft 5.59 times as frequently as an unranked player (specification (IX)). As in the other specifications, the number of points per game, rebounds per game, assists per game and blocks per game all positively influence a player's decision to enter the draft, with points, assists and blocks all economically and statistically significant at the 99 percent level.

Table 4 reports the results for our time-varying characteristic Cox proportional hazard estimates of early entry. These results generally confirm our results for the maximum likelihood logistic estimates for the early entry decision from Table 3. In all specifications we find that more highly-ranked players enter the draft more quickly. Points per game are again the most significant determinant of whether or not a player enters the draft. However, in these specifications we find that one-unit increases in both rankings and points lead to similar magnitude increases in hazard rates, which contrasts the magnitudes from our logistic specifications, where per-unit increases in points led to much larger probabilities of entry than did per-unit increases in rankings. Regardless of these magnitude differences, we find strong evidence that exogenous signals of ability reduce the amounts of schooling that players choose, and that stronger signals are even more likely to induce entry. Interestingly, we do not find that rebounds per game continue to be a significant determinant of player entry.

In our estimations of equation(3), reported in Table 5, we restrict our sample to include only ranked players. As only 60 players are selected in each draft, a signal of ability while in high school may not be sufficiently strong to incentive entry. Thus, we examine whether the quality of the signal is more important than just receiving a signal by decomposing the signal into whether or not players are ranked in the Top 10 or Top 25 for each ranking agency in order to account for the possibility of a non-linear response to signal strength. Specification (I) only considers Rivals rankings, specification (II) only considers Scout rankings, specification (III) considers both Rivals and Scout rankings whereas specifications (IV) and (V) considers only ESPN rankings and all three agency rankings, respectively.

Specifications (I) and (II) indicate the possibility of such a non-linear response. When only one set of rankings are considered, players who are ranked more highly have an additional boost in the probability of entry outside of the linear relationship between their rank and entry, which is still significant and positive, albeit at reduced magnitudes when compared to Table 3. In addition to the linear relationship between rank and entry, a player who is a Top 10 recruit is 5.05 times more likely to enter the draft than a player ranked from 26-100 if ranked by Rivals, and is 5.58 times more likely to enter the draft if ranked by Scout. This indicates that, among players who possess external signals of ability, those who possess the best signals enter school much more frequently than those who have lesser signals. In the third specification, which includes both Rivals and Scout rankings, only the Rivals rankings have an appreciable effect on the entry decision by players. This may be due to high colinearity between the Rivals and Scout rankings. Our results in specification (V), including rankings from all three agencies, do not indicate any evidence of non-linearity between higher- and lower-quality signals. However, since the players who have higher signals are likely to be rated highly by all the ranking agencies simultaneously, we again have the possibility of colinearity between the rankings.

We next examine the extent to which NBA teams find external assessments of ability important in selecting players. Table 6 reports the results of equation (4), which is a logistic regression of the probability of being drafted on college statistics and high school rankings. Specifications (I)-(III) report the estimates for each of the three ranking agencies separately without class and conference fixed effects. In each of these specifications, a player's ranking appreciably improved his likelihood of being selected; compared with unranked players, the odds ratios of being drafted range from 1.023 to 1.033 for the lowest-ranked player compared to 13.599-31.500 for the highest-ranked player. When we include conference and class fixed effects, the results become insignificant for the Scout 100 and ESPN 100, but remain significant for the Rivals 150. Specifications (IV)-(VI) also include an additional, very visible, signal of ability; namely, whether or not a player was selected to the McDonald's All-America Team. In all three specifications, being selected to the McDonald's team appreciably improved a player's probability of being selected, with odds ratios of 1.37 to 1.92, significant at the 99 percent level. Finally, in every specification, collegiate measures of productivity appreciably improved a player's probability of being selected, which is consistent with previous findings. However, even after accounting for most observable determinants of productivity, a player's external signal of ability (in this case, being a member of the McDonald's All-American team or ranked in the Rivals 150) remains a significant factor in the hiring decision of NBA teams.

The final set of estimations examines only drafted players in order to determine whether signaling high ability influences when, within a draft, a player is selected. Table 7 presents the estimates of equation (5), which is a censored regression of draft position on high school rankings and observable measures of productivity. Because players can only be selected between #1 and #60, we impose an upper limit of 60 and a lower limit of 1 and estimate equation (5) via maximum likelihood. Additionally, as NBA teams potentially utilize more advanced performance metrics in order to evaluate players in the draft, we also consider usage rate, PER, and true shooting percentage as explanatory variables for player performance.

We find evidence that players who are ranked as being of high ability are more likely to be selected earlier in the draft. In all specifications, whether or not a player is ranked is negative and significant, indicating that a player who is ranked more highly is chosen earlier. Specifications (I)-(III) provide estimates of the relationship between draft selection and rankings without advanced metrics. In these specifications, points per game, blocks per game, and assists per game are negative and significant, indicating that higher amounts of these productivity measures cause players to be drafted earlier. However, when advanced metrics, particularly PER, are added in for specifications (IV)-(VI), we find that points per game, assists per game, and blocks per game are no longer significant, though the rankings remain significant. This may occur for two reasons. First, we lose a significant number of observations in (IV)-(VI). Second, PER is a linear combination of these variables and as such may capture the information contained in these measures. Regardless, in all specifications, we find that an increase in ranking by ten slots can lead to anything from a 0.4 decrease in draft slot for the Rivals 150 (being drafted one-half slot earlier) to a full decrease in draft slot for the Scout 100 and the ESPN 100 rankings. These findings indicate that employers both value signals and value higher signals more than lower signals.

Conclusion

Our research provides insight into how individuals make schooling decisions when they have observable, exogenous signals of career-specific ability before entering secondary education. If these signals are informative to potential employers, then these individuals would have less incentive to acquire additional, profession-specific human capital as well as less of an incentive to utilize education as a mechanism to signal ability. We find significant evidence that players with higher exogenous ability rankings pursue less school relative to those individuals with lower or no rankings, even after controlling for observable productivity characteristics. Our findings are robust to a large class of models and different ability assessments.

We also find evidence that employers value external signals of ability even after controlling for observable productivity measures. NBA teams systematically draft players with higher signals more frequently than those with lower or no signals. Moreover, for players who are drafted, being ranked of high ability appreciably improves the slot in which the player is selected, which further indicates that employers use signals of ability acquired before a player attends school. These rankings can have significant economic impacts upon the economic outcomes of these players. Specifically, only the first 30 selections in the NBA draft are offered a guaranteed labor contract for the first three years and within those first 30 picks the rookie salary scale varies substantially.

In additional research, we plan on examining the exogenous policy intervention which affected how basketball players decide to pursue additional years of schooling. Between the 2005 and 2006 NBA Drafts, the NBA imposed minimum age restrictions that forbid high school players from entering the draft directly; players had to have graduated from their high school at least one year prior to entering the draft. This minimum age restriction meant that college freshmen basketball players went from having a prior opportunity to enter the draft (when they were in high school) to having no prior opportunity to enter the draft due to the restriction. We intend to examine the effects of restricted entry into the workforce on worker decisions to pursue additional years of schooling once the restriction expires.

References

Belman, Dale and John S. Heywood. "Sheepskin Effects in the Returns to Education: An Examination of Women and Minorities." *Review of Economics and Statistics* 73(4): 720-724, 1991.

Berri, David J., Stacey L. Brook, and Aju J. Fenn. "From College to the Pros: Predicting the NBA Amateur Player Draft." *Journal of Productivity Analysis* 35(1): 25-35, 2011.

Berri, David J., Stacey L. Brook, and Martin B. Schmidt. "Does One Simply Need to Score to Score?" *International Journal of Sport Finance* 2(4): 190-205, 2007.

Bishop, Todd and Byron J. Gajewski. "Drafting a Career in Sports: Determining Underclassmen College Players' Stock in the NBA Draft." *Chance* 17(2): 12-15, 2004.

Bowles, Samuel, Herbert Gintis, and Melissa Osbourne. "Incentive-Earning Preferences: Personality, Behavior, and Earnings." *American Economic Review* 91(2): 155-158, 2001a.

Bowles, Samuel, Herbert Gintis, and Melissa Osbourne. "The Determinants of Earnings: A Behavioral Approach." *Journal of Economic Literature* 39(4): 1137-1176, 2001b.

Borghans, Lex, Bas ter Weel, and Bruce Weinberg. "Interpersonal Styles and Labor Market Outcomes." *Journal of Human Resources* 43(4): 815-858, 2008.

Bricker, Jesse and Andrew Hanson. "The Impact of Early Commitment on Games Played: Evidence from College Football Recruiting." *Southern Economic Journal* 79(4): 971-983, 2013.

Camerer, Colin F. and Roberto A. Weber. "The Econometrics and Behavioral Economics of Escalation of Commitment; A Re-Examination of Staw and Hoang's NBA Data." *Journal of Economic Behavior & Organization* 39(1): 59-82, 1999.

Eschker, Erick, Stephen J. Perez, and Mark V. Siegler. "The NBA and the Influx of International Basketball Players." *Applied Economics* 36(10): 1009-1020, 2004.

Flores-Lagunes, Alfonso and Audrey Light. "Interpreting Degree Effects in the Returns to Education." *Journal of Human Resources* 45(2): 439-467, 2010.

Groothuis, Peter, James R. Hill, and Timothy J. Perri. "Early Entry in the NBA Draft: The Influence of Unraveling, Human Capital, and Option Value." *Journal of Sports Economics* 8(3): 223-243, 2007.

Hausman, Jerry A. and Gregory K. Leonard. "Superstars in the National Basketball Association: Economic Value and Policy." *Journal of Labor Economics* 15(4): 586-624, 1997.

Hendricks, Wallace, Lawrence DeBrock, and Roger Koenker. "Uncertainty, Hiring, and Subsequent Performance: The NFL Draft." *Journal of Labor Economics* 21(4): 857-886, 2003.

Hungerford, Thomas and Gary Solon. "Sheepskin Effects in the Returns to Education." *The Review of Economics and Statistics* 69(1): 175-177, 1987.

Jaeger, David A. and Marianne E. Page. "Degrees Matter: New Evidence on Sheepskin Effects in the Returns to Education." *Review of Economics and Statistics* 78(4): 733-740, 1996.

Li, Hao and Sherwin Rosen. "Unraveling in Matching Markets." *American Economic Review* 88(3): 371-387, 1998.

National Basketball Players Association (NBPA). *1999 Collective Bargaining Agreement*, 1999. Last accessed October 23, 2013, University of New Hampshire Sports and Entertainment Law Institute, http://www.ipmall.info/hosted_resources/SportsEntLaw_Institute/1999NBA_NBPA_CBA.pdf.

National Basketball Players Association (NBPA). *2005 Collective Bargaining Agreement*, 2005. Last modified December 16, 2009, http://www.nbpa.org/cba/2005.

National Basketball Players Association (NBPA). *2011 Collective Bargaining Agreement*, 2011. Last modified January 1, 2012, http://www.nbpa.org/cba/2011.

Nyhus, Ellen and Empar Pons. "The Effects of Personality on Earnings." *Journal of Economic Psychology* 26(2): 363-384, 2005.

Spence, Michael. "Labor Market Signaling." *Quarterly Journal of Economics* 87(3): 355-374, 1973.

Staw, Barry and Ha Hoang. "Sunk Costs in the NBA: Why Draft Order Affects Playing Time and Survival in Professional Basketball." *Administrative Science Quarterly* 40(3): 474-494, 1995.

Strange, Kevin. "An Empirical Investigation of the Option Value of College Enrollment." *American Economic Journal: Applied Economics* 4(1): 49-84, 2012.

Tyler, John H., Richard J. Murnane, and John B. Willett. "Estimating the Labor Market Signaling Value of the GED." *Quarterly Journal of Economics* 115(2): 431-468, 2000.

Weiss, Andrew. "Human Capital vs. Signaling Explanations of Wages." *Journal of Economic Perspectives* 9(4): 133-154, 1995.

Table 1: High School Basketball Prospect Rankings

	Rivals Rankings			Scout Rankings	ESPN Rankings
Year	"Top 150"	Position	"Stars"	"Top 100"	"Top 100"
2002	-	95	254	-	-
2003	145	115	394	94	-
2004	150	159	313	3	-
2005	144	155	411	97	-
2006	143	154	419	96	-
2007	144	166	679	97	98
2008	145	157	713	93	94
2009	147	150	564	99	97
2010	149	151	421	97	100
2011	149	149	431	99	98
2012	150	156	467	100	100
Total	1466	1607	5066	875	587

Source: Authors' estimates using Rivals.com, Scout.com, and ESPN.com rankings databases.
1: Although Scout provides other rankings for 2004, it does not provide a separtely identified list for the "Top 100" prospects as it does in other years.

Table 2: Summary Statistics

Variable	N	Mean	Standard Deviation	Min	Max
College Productivity Measures					
Points per game	30538	6.754	4.816	0.00	28.86
Assists per game	30538	1.263	1.204	0.00	10.00
Steals per game	30538	0.648	0.497	0.00	3.91
Total Rebounds per game	30538	3.020	2.067	0.00	14.51
Blocks per game	30538	0.321	0.461	0.00	6.53
Advanced Productivity Measures					
PER	13308	13.873	7.052	-84.90	99.30
True Shooting Percentage	30535	0.520	0.097	0.00	1.36
Usage	13305	19.451	5.814	3.10	100.00
Decision, Draft, and Ranking Variables					
Entered Draft Early?	31297	0.015	0.122	0	1
Ranked * HS Rivals 150	31297	8.424	27.508	0	150
Ranked * HS Scout 100	31297	3.323	14.277	0	100
Ranked * ESPN 100	31297	2.000	11.297	0	100
Drafted?	31297	0.037	0.188	0	1

Source: Authors' estimates.

Table 3: Determinants of Player Entry

	Panel A: Rivals 150			Panel B: Scout 100			Panel C: ESPN 100		
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
Player Ranked?	-0.470	0.428	-0.234	1.107 **	1.536 **	0.536	1.793 **	1.783 **	0.615 **
	(0.456)	(0.457)	(0.403)	(0.351)	(0.435)	(0.381)	(0.221)	(0.213)	(0.194)
Rivals 150 ranking	0.031 **	0.022 **	0.017 **						
	(0.003)	(0.003)	(0.002)						
Scout 100 ranking				0.030 **	0.021 **	0.018 **			
				(0.005)	(0.005)	(0.005)			
ESPN 100 ranking							0.023 **	0.018 **	0.017 **
							(0.004)	(0.004)	(0.006)
Points per game		0.260 **	0.251 **		0.255 **	0.246 **		0.242 **	0.268 **
		(0.049)	(0.049)		(0.051)	(0.049)		(0.053)	(0.069)
Total Rebounds per game		0.165 **	0.147 **		0.153 **	0.138 **		0.147 *	0.151 *
		(0.045)	(0.042)		(0.042)	(0.042)		(0.062)	(0.067)
Field Goals per game		0.114	0.154		0.135	0.168		0.215	0.116
		(0.128)	(0.136)		(0.132)	(0.127)		(0.143)	(0.190)
Blocks per game		0.805 **	0.910 **		0.822 **	0.924 **		0.850 **	0.928 **
		(0.118)	(0.134)		(0.108)	(0.130)		(0.153)	(0.155)
Steals per game		-0.176	-0.013		-0.209	-0.029		-0.247	-0.150
		(0.182)	(0.186)		(0.198)	(0.192)		(0.202)	(0.188)
Assists per game		0.447 **	0.436 **		0.450 **	0.443 **		0.417 **	0.406 **
		(0.047)	(0.050)		(0.046)	(0.048)		(0.047)	(0.047)
McDonald's All-American			0.460 *			0.485 *			0.478 *
			(0.193)			(0.234)			(0.242)
Constant	-4.707 **	-10.637 **	-11.346 **	-4.707 **	-10.577 **	-11.395 **	-4.954 **	-10.589 **	-10.904 **
	(0.144)	(0.327)	(0.797)	(0.144)	(0.326)	(0.832)	(0.097)	(0.252)	(0.830)
Class Fixed Effects			X			X			X
Conference Fixed Effects?			X			X			X
Observations	24,497	24,023	20,885	24,497	24,023	20,885	15,029	14,807	11,731
Pseudo R-square	0.189	0.511	0.560	0.179	0.505	0.559	0.196	0.506	0.549

Source: Authors' estimates. ** $p<0.01$, * $p<0.05$, = $p<0.10$.
Table 3 presents the logistic regression coefficients associated with estimates of (1). Dependent variable: player enters NBA draft = 1, returns to college = 0. The Rivals 150, Scout 100, and ESPN 100 coefficients represent interaction terms of whether a player is ranked with (150-Rivals rank), (100-Scout rank), and (100-ESPN rank). Robust standard errors in parentheses; all standard errors are clustered by season.

Table 4: Cox Proportional Hazard Estimates of Entry

	Panel A: Rivals 150		Panel B: Scout 100		Panel C: ESPN 100	
	(I)	(II)	(III)	(IV)	(V)	(VI)
Player Ranked?	2.143 *	1.003	4.766 **	1.903 +	6.123 **	2.266 **
	(0.796)	(0.378)	(1.698)	(0.700)	(1.114)	(0.288)
Rivals 150 ranking	1.016 **	1.013 **				
	(0.002)	(0.002)				
Scout 100 ranking			1.016 **	1.012 *		
			(0.003)	(0.005)		
ESPN 100 ranking					1.013 **	1.010 *
					(0.003)	(0.004)
McDonald's All-American?		1.132		1.207		1.229
		(0.137)		(0.261)		(0.286)
Points per game	1.013 **	1.013 **	1.013 **	1.013 **	1.014 **	1.014 **
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total Rebounds per game	1.002	1.001	1.001	1.001	1.000	1.000
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Steals per game	0.995	0.998	0.994	0.998	0.992	0.994
	(0.005)	(0.007)	(0.007)	(0.008)	(0.008)	(0.010)
Assists per game	1.016 **	1.015 **	1.016 **	1.015 **	1.014 **	1.013 **
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Blocks per game	1.043 **	1.043 **	1.044 **	1.044 **	1.050 **	1.050 **
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Conference Fixed Effects?		X		X		X
Class Fixed Effects?		X		X		X
Observations	28,762	28,762	28,762	28,762	18,460	18,460

Source: Authors' estimates. ** p<0.01, * p<0.05, + p<0.10.
Table 4 reports the hazard rates associated with estimates of (2). Dependent variable: "Failure" is defined as a player leaves college to enter the NBA draft. Rivals 150, Scout 100, and ESPN 100 coefficients represent interaction terms between ranks and whether a player is ranked. Robust standard errors are clustered by season.

Table 5: Early Entry Decisions Among Ranked Players

	(I)	(II)	(III)	(IV)	(V)
Rivals 150 Ranking	0.010 **		0.008 **		0.006 +
	(0.002)		(0.002)		(0.003)
Player in Rivals Top 25?	1.012 **		0.787 *		0.507
	(0.309)		(0.371)		(0.381)
Player in Rivals Top 10?	0.614 *		0.187		0.255
	(0.265)		(0.417)		(0.631)
Scout 100 Ranking		0.010 **	0.004		0.003
		(0.003)	(0.002)		(0.005)
Player in Scout Top 25?		0.706 **	0.137		0.269
		(0.257)	(0.243)		(0.169)
Player in Scout Top 10?		1.017 *	0.725		1.196 +
		(0.433)	(0.633)		(0.663)
ESPN 100 Ranking				0.009	0.006
				(0.005)	(0.006)
Player in ESPN Top 25?				0.871 +	0.234
				(0.488)	(0.555)
Player in ESPN Top 10?				0.391	-0.668
				(0.582)	(0.601)
Points Per Game	0.290 **	0.290 **	0.290 **	0.287 **	0.292 **
	(0.024)	(0.026)	(0.025)	(0.029)	(0.029)
Assists Per Game	0.422 **	0.420 **	0.413 **	0.442 **	0.446 **
	(0.057)	(0.064)	(0.063)	(0.055)	(0.075)
Total Rebounds Per Game	0.087 *	0.068 +	0.070	0.114 +	0.056
	(0.037)	(0.041)	(0.043)	(0.058)	(0.059)
Blocks Per Game	1.001 **	1.029 **	1.017 **	0.969 **	1.024 **
	(0.158)	(0.154)	(0.157)	(0.175)	(0.175)
Steals Per Game	0.189	0.158	0.193	-0.116	-0.137
	(0.292)	(0.310)	(0.306)	(0.259)	(0.344)
Constant	-10.334 **	-9.855 **	-10.282 **	-9.601 **	-10.071 **
	(0.908)	(0.946)	(0.940)	(1.044)	(1.099)
Observations	2,749	2,749	2,749	1,920	1,920
Pseudo R-square	0.465	0.457	0.47	0.435	0.469

Source: Authors' estimates. ** $p<0.01$, * $p<0.05$, + $p<0.1$.

Table 5 presents the logistic regression coefficients associated with estimates of equation (3). Dependent variable: player enters NBA draft = 1, returns to college = 0. Sample includes only players ranked by a scouting service. Rivals 150, Scout 100, and ESPN 100 coefficients represent interaction terms between ranks and if a player is ranked. All specifications include a dummy for whether a player is ranked in any of the rankings and conference and class fixed effects. Robust standard errors clustered by season.

Table 6: Determinants of Whether a Player is Drafted

	(I)	(II)	(III)	(IV)	(V)	(VI)
Rivals 150 ranking	0.023 **			0.007 **		
	(0.001)			(0.001)		
Scout 100 ranking		0.033 **			0.005	
		(0.003)			(0.003)	
ESPN 100 ranking			0.026 **			-0.002
			(0.005)			(0.006)
Points per game	0.101 **	0.096 **	0.083 **	0.147 **	0.146 **	0.143 **
	(0.022)	(0.021)	(0.022)	(0.030)	(0.030)	(0.028)
Total Rebounds per game	0.104 **	0.093 **	0.102 **	0.145 **	0.147 **	0.154 **
	(0.019)	(0.018)	(0.018)	(0.020)	(0.020)	(0.018)
Field Goals per game	0.204 **	0.225 **	0.269 **	0.249 **	0.261 **	0.276 **
	(0.060)	(0.058)	(0.070)	(0.075)	(0.072)	(0.067)
Blocks per game	0.753 **	0.796 **	0.841 **	0.885 **	0.910 **	0.919 **
	(0.059)	(0.049)	(0.049)	(0.062)	(0.058)	(0.059)
Steals per game	-0.085 +	-0.138 *	-0.141 *	-0.046	-0.052	-0.057
	(0.049)	(0.062)	(0.067)	(0.060)	(0.060)	(0.058)
Assists per game	0.231 **	0.256 **	0.280 **	0.234 **	0.241 **	0.243 **
	(0.028)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
McDonald's All-American				0.370 **	0.619 **	0.917 **
				(0.109)	(0.172)	(0.156)
Constant	-6.917 **	-6.649 **	-6.567 **	-6.879 **	-6.874 **	-6.897 **
	(0.342)	(0.334)	(0.333)	(0.352)	(0.350)	(0.355)
Class Fixed Effects				X	X	X
Conference Fixed Effects?				X	X	X
Observations	30,522	30,522	30,522	22,102	22,102	22,102
Pseudo R-square	0.348	0.307	0.261	0.434	0.428	0.427

Source: Authors' estimates. ** p<0.01, * p<0.05, + p<0.1.
Table 6 presents the logistic regression coefficients associated with estimates of (4). Dependent variable: player drafted = 1, player not drafted = 0. Rivals 150, Scout 100, and ESPN 100 coefficient represent interaction terms between ranks and if a player is ranked. All specifications include a dummy for whether a player is ranked in any of the rankings. Robust standard errors are clusterd by season.

Table 7: Determinants of Draft Pick Number, Censored Model

	(I)		(II)		(III)		(IV)		(V)		(VI)	
Rivals 150 Ranking	-0.039	**					-0.050	**				
	(0.010)						(0.018)					
Scout 100 Ranking			-0.125	**					-0.104	**		
			(0.016)						(0.026)			
ESPN 100 Ranking					-0.122	**					-0.102	**
					(0.024)						(0.027)	
Points Per Game	-0.490	**	-0.515	**	-0.482	**	0.417		0.462		0.488	
	(0.142)		(0.139)		(0.141)		(0.470)		(0.463)		(0.465)	
Blocks Per Game	-3.957	**	-3.938	**	-3.694	**	-1.783		-1.878		-1.476	
	(0.860)		(0.842)		(0.856)		(1.591)		(1.567)		(1.573)	
Steals Per Game	-1.346		-0.867		-1.317		-6.347	*	-6.389	**	-6.154	*
	(1.394)		(1.366)		(1.385)		(2.484)		(2.445)		(2.453)	
Total Rebounds Per Game	0.053		0.165		0.052		0.277		0.222		0.083	
	(0.315)		(0.309)		(0.314)		(0.611)		(0.601)		(0.602)	
Assists Per Game	-1.286	**	-1.337	**	-1.241	**	-0.917		-1.140		-0.953	
	(0.478)		(0.469)		(0.476)		(0.809)		(0.800)		(0.799)	
PER							-1.553	**	-1.419	**	-1.389	**
							(0.498)		(0.488)		(0.489)	
Usage							-0.060		-0.181		-0.183	
							(0.481)		(0.475)		(0.477)	
True Shooting Percentage							10.500		-3.776		-3.399	
							(36.227)		(35.930)		(36.034)	
Constant	40.182	**	39.501	**	39.760	**	77.993	**	86.028	**	82.230	**
	(2.262)		(2.217)		(2.252)		(22.364)		(22.213)		(22.142)	
Observations	938		938		938		241		241		241	
Pseudo R-square	0.018		0.024		0.020		0.054		0.058		0.058	
Regression Standard Error	16.120	**	15.781	**	16.029	**	13.510	**	13.302	**	13.337	**
	(0.382)		(0.374)		(0.380)		(0.632)		(0.622)		(0.624)	

Source: Authors' estimates. ** $p<0.01$, * $p<0.05$, + $p<0.1$.

Table 7 presents the results of equation (5), a censored tobit model with upper limit of 60 and lower limit of 1. Dependent variable: draft position. Rivals 150, Scout 100, and ESPN 100 coefficients represent interaction terms between ranks and if a player is ranked. All specifications include a dummy for whether a player is ranked in any of the rankings. Robust standard errors are clustered by season.