DOES ATTENDING A MORE ELITE SCHOOL LEAD TO BETTER LABOR MARKET OUTCOMES? EVIDENCE FROM THE COLLEGE FOOTBALL LABOR MARKET USING SCREENING INFORMATION

by

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A thesis

submitted in partial fulfillment

of the requirements for the degree of

Master of Science in Economics

Boise State University

December 2020

BOISE STATE UNIVERSITY GRADUATE COLLEGE

DEFENSE COMMITTEE AND FINAL READING APPROVALS

of the thesis submitted by

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Thesis Title: Does Attending a More Elite School Lead to Better Labor Market Outcomes? Evidence from the College Football Labor Market Using Screening Information

Date of Final Oral Examination: 04 September 2020

The following individuals read and discussed the thesis submitted by student Kyle Brookman, and they evaluated their presentation and response to questions during the final oral examination. They found that the student passed the final oral examination.

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ABSTRACT

College football prospects in the market for an athletic scholarship face similar career-altering choices as traditional academic students when selecting a college, however, the market they operate in is very different. They are actively recruited by university coaches and closely observed by a college sports scouting industry. Their choice of school is highly anticipated and publicized within college sport culture. College football is no doubt a lucrative industry, particularly for the elite university football programs, but one may want to know if the athletic scholars themselves gain in any career measurable way by attending a more elite university football program. This analysis uses the scouting and coaches screening information to form a baseline control for pre-college ability and then estimates the value-added from choosing a more selective football program by measuring 3 observable football oriented career outcomes: 1) the probability of receiving an invite to the NFL Combine, 2) an objective metric for strength and conditioning, and 3) a player's overall order from the NFL draft. Evidence shows that recruits who choose a more selective university football program have a higher probability of receiving an invite to the NFL Combine. However, once at the Combine, there is no evidence that more selective university football programs produce better athletes based upon standardized strength and conditioning tests. Evidence also suggests that NFL employers utilize the objective information they gain at the NFL Combine in their draft decisions, in which case, the premium enjoyed from the initial Combine invite is attenuated. If NFL teams update the information obtained from the Combine into their

draft decisions, then there is no evidence attending a more selective football program generates value-added to a recruit's ability and thus, their post-college career. Additionally, there is suggestive evidence that highly sought after football recruits are made worse off by the recruiting process in general, holding objective measures of ability constant.

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LIST OF ABBREVIATIONS

NCAA	National Collegiate Athletic Association
FBS	Football Bowl Subdivision
FBS	Football Championship Subdivision
NFL	National Football League
EI	Emotional Intelligence
OLS	Ordinary Least Squares
BMI	Body Mass Index

CHAPTER 1: INTRODUCTION

Accumulating human capital through a college education is of ever-growing importance to ensure success and quality of life. Colleges offer programs to help individuals specialize in a particular set of skills that help them stand out in subsequent labor markets. Commonly, academic scholarships are awarded to students who show scholastic promise in the eyes of a university. Since hard-work and student aptitude are major inputs to a university's production function, schools compete for academic talent in a myriad of ways – such as student aid packages, housing amenities, unique customs, traditions, and other perks, like a quality athletic program. The better the student does, the better the university looks, which increases their reputation and propensity to garner more academic talent along with donor contributions.

Athletic scholarships, in particular football scholarships, work in a similar way. College teams compete for player talent (their primary input) in order to maximize wins and increase reputation and revenues, thus increasing their propensity to garner better athletic talent in the future.[1] In return, athletic scholars hope to gain practical knowledge and skills for their prospective career options. When individuals invest a considerable amount of time and effort into a specialized skill, and perform to a high degree, it reveals

[1] See Kesenne (2012) in the *Oxford Handbook of Sports Economics* for a theoretical model of a college football team's objective function and the effect on competitive balance and social welfare. The model can be used to argue that college football teams engage in a win-maximizing objective, in which case the distribution of talent across the league is consolidated into the larger market teams causing less competitive balance and lower overall social welfare. The results are reversed when football teams engage in a league-wide profit-maximizing objective.

motivation and intent to pursue careers based on those prior investments. For example, serious students in the market for academic scholarships likely have a good sense of the type of professional environment they'd like to pursue and will specialize in particular qualities to achieve those ends. In a similar fashion, it is reasonable to assume that college football recruits who have differentiated themselves on a high enough level to be in the market for a coveted athletic scholarship do indeed have the motivations and intentions of turning their specialized skills, hard-work, and talents into a professional athletic career.[2] Such crucial career influencing choices are made by individuals at a young age (generally between the ages of 17-18 years old) in which the full ramifications of their decisions may not be clear. If the question of school choice is important on a cost-benefit basis for the general academic minded student, then it is surely important for the athletic minded student, as well.[3] Indeed, a considerable amount of economic research has accumulated in estimating the value-added to labor market returns from attending elite university programs in the context of the academic scholar. I reintroduce this economic question through the perspective of the athletic scholar.

The underlying question in this research paper is: *Does choosing a more selective or elite university football program provide any value-added to a player's measurable career prospects?* An ideal analysis would take identical high school football recruits and randomly place them into schools with varying quality dimensions and then measure

[2] One doesn't question the motivations and intentions of the violinist who earns a music scholarship to approach her educational training with the hopes to play professionally. Or the culinary and automotive tech students looking for placement in their specific industry. Despite different odds of success due to supply and demand in professional markets, it would be a mistake to assume a high level football recruit would have a different approach to his human capital accumulation than that of a musician, mathematician, or other specialized vocational student – just because they are not in a typical job market.

[3] Possibly even more so on an individual basis due to the high opportunity costs associated with lucrative professional sports contracts.

the difference in outcomes that the labor market also rewards – such as strength and conditioning, draft position, career opportunities, and earnings. There are two serious econometric hurdles to address here: First, the double-sided selection bias due to higher ability players non-randomly selecting onto a more prestigious team, as well as more prestigious teams non-randomly sorting through recruits to award highly coveted athletic scholarships (i.e. roster spots) to the higher ability players. If these individual, pre-college ability characteristics are not accounted for, then estimates on returns to school quality will be biased upward. Second, potential bias accrues once an individual leaves the college environment and enters into a highly competitive professional football labor market in which small differences in each player's continual training may have confounding effects on the estimates for college quality.

To address the first concern, I utilize a matching on observables *and unobservables* method first presented in Dale and Krueger (2002) in order to circumvent the double-sided selection bias. This technique observes the set of teams in which a recruit conveyed interest (i.e. applied to), and which teams either offered (i.e. accepted) or didn't offer (i.e. rejected) each prospect an athletic scholarship. The observed results from the football recruit screening process allows me to utilize the privileged knowledge that individual market participants have, but would otherwise be unknown in the data.[4] The screening data and observed ability variables control for factors correlated with a football recruit's school choice and subsequent labor market outcomes. This technique creates a robust baseline for a recruit's fixed level of ability post-high-school and pre-college when the critical economic decision of school choice is made — allowing for a

[4] Hence the term, *matching on unobservables.*

natural experiment under the right set of conditions. More methodological details are discussed later in the paper.

To address the second econometric concern, I narrow the scope of analysis to measurable outcomes post-college and pre-professional career, effectively isolating measurable outcomes that may accrue solely through the university football program. For clean outcome variables, I use NFL Combine results as a standardized post-test score to measure differences in acquired skills through the university's often touted strength and conditioning programs. I also estimate an individual's probability of being invited to the NFL Combine, probability of being drafted, as well as their overall draft order – all conditional on a measure of school quality.

If there is evidence that recruits acquire higher skill sets from higher quality schools (i.e. value-added), then it would make sense that individuals who attend elite university football programs systematically receive better draft results and subsequently earn higher incomes. However, if there is no evidence that elite university football programs actually cause individuals to acquire greater skills and opportunities, then football recruits may enjoy greater flexibility in school choice without sacrificing potential career outcomes.

My thesis is structured in the following order: Section 2 reviews the economic literature regarding value-added from school choice, and also highlights the limitations and advantages of mapping this football specific micro-analysis into the econometric modelling assumptions found in the broader research. Section 3 describes the data and the environment the players and schools operate in. This section also builds an econometric model by detailing the theoretical framework, research design, and identification strategy to answer the value-added to school quality question. Section 4 presents the empirical results. Section 5 concludes with a discussion of the results in the context of the college football labor market.

CHAPTER 2: LITERATURE REVIEW

2.1 Circumventing Selection Bias

What are the effects of attending a more selective or elite school on future earnings and other labor market outcomes? The question is straightforward, but the empirical path has many potential confounding factors. Of these factors, the primary concern within the empirical strategy is to circumvent the double-sided selection bias that occurs when high ability students limit applications to more selective schools and the more elite schools select and admit students who they perceive to have greater abilities. It's well known that this selection process will upwardly bias a desirable outcome variable, such as career earnings, if there are unobserved higher ability traits within students who are admitted into elite schools. This is most certainly the case considering selective schools employ screening panels whose job and livelihood depends on picking the best and brightest students to admit. In other words, there is an entire market of economic agents who sort through the supply of students (i.e. a school's inputs) to find the potential highest achievers in order to enhance the school's reputation and prestige. Although many schools start their selection process using common observable metrics such as SAT scores, it often does not end there. College admission panels observe important ability traits through several sources, such as letters of recommendations, essays, interviews, evidence of community service, etc. – which provides important privileged information not made readily available for empirical analysis. Indeed, even the process of applying to a selective institution may reveal important ability characteristics about a student in and of itself. Thus, student "unobserved" ability that would otherwise bias econometric results is often observed in the school selection/admission process.[5]

Highly selective schools tend to have substantially higher costs of attendance and boast that their graduates make higher earnings in the labor market, thus paying the higher cost off over the medium-to-long run.[6] Indeed, evidence confirms that there is a large wage gap between those who attend a highly selective academic institution and those who attend less elite institutions.[7] However, it is an entirely different assertion whether a highly selective institution actually causes the earnings premium, or whether the same student would have those same earnings if they attended a less elite institution.

Early researchers investigated the question of increased earnings potential from attendance at elite universities by using naïve OLS models, confirming a positive and statistically significant return to attending an elite university (Kane, 1998; Brewer et al., 1999). However, these models do not address the double-sided selection bias. Several other empirical strategies have been utilized to correct the value-added estimates for endogeneity, in which the mixed results have led to a rigorous debate about best practices and assumptions. Hoekstra (2009) uses a regression discontinuity design to measure the effect of admissions to a top state university at the admission cutoff of the student composite high school GPA and SAT score. The study found a 20% increase in earnings for white-men who later earned wages between the ages of 28 and 33. A well-constructed

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[5] The caveat is that non-selective schools may not take the time to observe these non-obvious student characteristics.

[6] In the context of college football scholarship athletes, the players don't necessarily pay out of pocket for cost of attendance, but they do forgo the value they generate while at the school. This opportunity cost is estimated to be a sum at least comparable to college debt, and up to $4 million for star athletes (Goff et al., 2017).

[7] See https://collegescorecard.ed.gov/ for published data on cost of attendance, academic records, and earnings by school. Schools with higher student average SAT scores tend to have graduates with higher earnings.

regression discontinuity design will generate effective treatment-control groups for strong internal validity, however, the method is inherently narrow in scope as it only measures a very specific subset of the population around an arbitrary cut-off point. In this case, white-men who were barely admitted into their own state college, suggesting that a more selective college may improve earnings for the marginal academically inclined white-male student. It's less certain that this estimate applies to the general student population. Long (2007) uses an instrumental variable approach to measure 5 separate proxies for college quality on 4 different outcome variables and finds that only 3 of the 20 combinations produced statistically significant improvement in outcomes,[8] none of which were men's hourly earnings as Hoekstra (2009) suggests. Long (2007) also compared the instrumental variable approach to the naïve OLS model which only found 12 of the 20 college-quality-outcome combinations to produce statistically significant improvements – still not a clear cut effect despite the substantial upward bias a model without strong selection controls is presumed to produce. To say the least, results are mixed on both the individual proxies used to measure school quality, as well as the overall effects of value-added to school quality itself.

Some research suggests that the earnings premium exists through a signaling effect, as opposed to acquired human capital skills, in which an educational institution's prestige proxies for the individual's ability when employers make hiring decisions (Weiss, 1995; Bills, 2003; Tyler et al., 2000). For example, an employer looking at two

[8] The 5 proxies of school quality: median freshman SAT/ACT score, average net tuition, adjusted full professor salary, professor-student ratio, and an index of college quality. The 4 outcome variables: earned a bachelor's degree, men's hourly earnings, women's hourly earnings, and self + spouse's annual earnings. Significant results were: effect of median freshman SAT/ACT scores on earning a bachelor's degree, effect of adjusted full professor salary on women's log hourly earnings, and the effect of a college quality index rating on earning a bachelor's degree.

very similar job applicants for recent graduates who only vary by their academic institution's reputation may be swayed by the institution's prestige as the marginal factor in the hiring decision. Mountjoy and Hickman (2020) found evidence of a small earnings premium for recent graduates of more selective universities, but the earnings premium fell to zero within 2-3 years of graduation. Presumably, the "elite effect" fades as better information regarding merit, ability, and other hard to measure soft-skills are eventually observed and rewarded in the labor market.

One of the most compelling and highly cited studies in this field was delivered by Dale and Krueger (2002) where they were able to utilize individual level college admission screening data regarding student university applications and their acceptance and rejection status by each school, as well as the individual's college choice from their set of acceptance options.[9] As described above, they assume that through the matriculation process many student-ability characteristics that are unobservable to the econometrician are observed in detail by the college admission screening panels and subsequently reflected in their acceptance and rejection decisions. Dale and Krueger (2002) effectively controlled for student unobserved ability by matching them on identical acceptance and rejection outcomes, as well as commonly observed earnings covariates such as SAT scores, race, gender, and family background information. The treatment-control group identification happens when one otherwise identical 'matched-applicant' chooses a more selective school while the other chooses the less selective school, and the differences in outcomes are measured within each matched-applicant grouping. They argue that if the student's decision to attend the less (or more) selective

[9] The colleges in their dataset ranged from well-regarded to elite institutions. In other words, they were all selective, but to varying degrees.

school is not correlated with the labor market outcome variable and the error terms, then the method produces the causal impact from attending a more selective college. Their naïve model without the matched-applicant selection controls found a statistically significant and economically important 8% earnings premium from attending a more selective college, where school selectivity is measured by a latent variable for the institution's student body average SAT score. When applying the selection controls to measure earning outcomes *within* matched-applicant groups, the earnings premium coefficient falls to near zero, sometimes turning negative, and not statistically significant (Dale and Krueger, 2002). Dale and Krueger (2014) corroborate these results in their follow-up paper for the same individuals with a more detailed account of career earnings using administrative data.

Using the matched-applicant approach with college admissions screening data was novel and the results controversial as they contradicted much of the literature, as well as challenging preconceived notions of school quality, reputation, and elitism. After all, one would expect to get something in return for an additional payment. Mountjoy and Hickman (2020) also implement the matched-applicant method with the same identification strategy as Dale and Krueger (2002) using high quality administrative records for students attending one of thirty public schools in the Texas university system. They also find that there is no evidence of an earnings premium from attending a more selective school, holding pre-college ability constant. Furthermore, additional observable student and school covariates did not alter the earnings premium coefficient beyond what the pre-college ability fixed-effects had already explained. Mountjoy and Hickman (2020) were also able to utilize their rich dataset to alleviate concerns regarding potential threats to the identification process, namely showing that once students are matched *within* applicant groups, they did not further sort into colleges based on their own ability. Since the major appeal of the matched-applicant approach is to circumvent the double-sided selection bias due to non-random sorting, their evidence extends the econometric method by reinforcing both its internal and external validity.

2.2 Defining School Quality

Even if the endogeneity issues are effectively controlled, a second major concern within the literature is defining adequate measures of school "quality" that highly selective colleges purport to have. As Black and Smith (2006) point out, *"school selectivity"* and *"school quality"* are used synonymously as measurement devices for explanatory variables and caution that the two are similar, but not identical. The primary metric for school selectivity is a school's student body average SAT score since it identifies which schools have higher acceptance standards. A higher school average SAT score indicates an overall higher achieving student who themselves are more selective, and thus the presumption of a higher quality of education – *why would high achievers settle for less?* Other common measures of school quality include average teacher pay, expenditures per student, and student-teacher ratio. These other proxies translate into higher input costs that serve to improve school quality and thus create/attract higher ability students (i.e. the ones with higher average SAT scores). In a way, school selectivity is an earned outcome from input expenditures that promote the quality of human capital accumulation, and hence school selectivity is considered a latent variable for school quality. I will use the latent variable approach of school selectivity, as opposed to school expenditure categories, because it allows for individual schools to decide their own resource allocation process in order to generate a *quality* football program.

Black and Smith (2006) suggest that using the latent variable approach to estimate school quality, such as the school's average SAT score, has the benefits of simplicity and ease of interpretation, but lacks the important multidimensionality of quality between schools and the heterogeneous effects between student types. For example, some colleges excel (or lack) in particular programs that produce different levels of career earnings (e.g. engineering vs humanities or business vs art), and not letting the quality metric vary on multiple dimensions loses true explanatory power. This is a real concern when measuring returns with a latent variable for a diverse set of degree seeking students. For example, a large investment in the school of arts may or may not improve the quality of education for the average student, and likely have very little measurable effect on students in the nursing program. In short, the more heterogeneous the population of interest, the less effective the "catch-all" latent variable approach to estimate returns to school quality will be. This concern is not able to be addressed within the data from Dale and Krueger (2002, 2014), as well as many other studies in this field. However, if the population of interest is fairly homogenous, as is the case in this football-economy microanalysis, then using a latent variable to estimate school quality is quite advantageous. It allows schools to determine how quality is produced by not limiting the effects of any *value-added* to the explicit variables chosen by (or limited to) the researcher. The basis of the homogeneity argument is that every economic agent in the dataset are playing the same game, under the same set of rules, and maneuvering through the same process governed by the National Collegiate Athletic Association (NCAA). An additional assumption I'll make here is that the objective of the football recruits are also similar, in that every football player on an athletic scholarship has the intention to pursue a professional career in football. The amount of work and personal investment to earn a football scholarship suggests a motivation and intention to pursue it as a professional prospect. Although the odds of gaining entry into the professional football labor market will differ substantially between players, any given player would not turn down the opportunity for something else.

A university football program's production function is also relatively low-dimensional. In the absence of league-wide profit sharing, universities face a win-maximizing objective function that relies primarily on the accumulation of top player talent (Kesenne, 2006).[10] Since player compensation is capped at a scholarship across the board, regardless of talent, school-by-school differences in direct cost for player talent are trivial. University football programs also face the same capacity constraints of 85 football scholarships for any given roster year.[11] The important takeaway regarding the homogeneity assumption and non-random sorting is that the incentive for athletes to sort into schools to generate heterogeneous monetary opportunities from their name, image, and likeness is severely punished by threat of expulsion from the university and thus, their career track. Notice that the athletic scholar's path through the college football training program is well defined and enforced; however, the university itself faces relatively fewer NCAA regulations on how it chooses to spend its resources. Once

[10] Profits are shared within football conferences, but to varying degrees. This does not create an incentive to maximize profits across the FBS subdivision.

[11] However, the obvious economic response to both quantity and price controls for compensation to athletes is that schools use amenities as indirect (and less efficient) incentives to compete for talent – often with high fixed and sunk cost expenditures. The incentives have been described as an '*arms race*' that have larger ramifications to the university and public as a whole. See Leadley et al. (2015) for a detailed description of the incentives structures that arise in intercollegiate sports.

controlling for a recruits pre-college level of ability, the variation in outcomes will fall within the variation in the university's resource allocation decisions that drive school quality. Thus, the strict NCAA bylaws and enforcement mechanism creates a highly advantageous situation for a researcher in search of a treatment and control group.

Much of the school selectivity research uses individual SAT scores or other standardized aptitude tests as controls for pre-college ability which may take away important 'between' variation of specialized knowledge when students differ on many dimensions, such as college majors. For example, Black and Smith (2006) use the Armed Services Vocational Aptitude Battery (ASVAB) as their composite aptitude measurement. The components of this exam measures general academic knowledge in basic science and math, as well as additional comprehensions in subjects regarding mechanics, automotive information, and electronics knowledge. These ASVAB components measure very specific ability traits not necessarily important to many particular career paths (e.g. accounting or political science). OLS regressions of different student types along these standardized metrics means that people are being "matched" on erroneous composite measures which can lead to measurement error – possibly explaining some of the literatures mixed results. In this more narrow football labor market, college football prospects are associated with a standardized recruiting score that is analogous to an overall aptitude score, but along the dimensions of football related ability alone. This standardized metric makes measuring variations between individuals and outcomes more relevant and robust for inference. The standardized recruiting score will be further discussed in the next section as it happens to be a key metric in the value-added estimating equation.

After considering the key elements of the school quality research, the subsequent analysis will benefit from a fairly homogenous group of economic actors, low dimensionality in economic variables, and a highly controlled labor market structure. Importantly, rich datasets and fair assumptions do not create a natural experiment with a source of random assignment needed for causal inference. The typical research design without a random component to control for selection bias must assume that the observed characteristics, however accurate they may be, are similar and run in the same direction as unobservable characteristics.

2.3 Intangible Characteristics of Athletes

In the context of this research, it could be the case that some players have less than ideal observable characteristics and actively make up for it with highly prized intangibles. Conversely, some players may look so good on paper that they don't need to acquire certain intangible skills. It's important to consider that football is a highly competitive team sport in which success goes beyond individual skills and depends in part on team cohesion. To this end, the field of Sport Psychology provides evidence that emotional intelligence (EI) is a contributing factor to athletic performance (Laborde et al., 2016). The field further provides evidence that EI has even stronger correlations on performance outcomes in team sports, as opposed to individual, non-team sports (Crombie et al., 2009; Castro-Sánchez et al., 2018). These innate ability attributes that do not appear in the college football recruiting datasets may include communication skills, leadership, empathy, motivation, athletic IQ, intuition, and moxie.[12] Laborde et al. (2016) finds EI relates to emotions, physiological stress responses, successful psychological skill

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[12] Moxie is a term often used when describing athletes who may have less than ideal observable characteristics but display a sense of grit, drive, and determination to win.

usage, and more successful athletic performance. The authors find evidence that EI operates on several levels, specifically comprehension of athletic knowledge, the accumulation of athletic ability, and formation of valuable athletic characteristic traits such as leadership and communication skills. Castro-Sánchez et al. (2018) explore multiple dimensions of EI and finds that ego-centric traits are positively predictive of individual sport performance, but are negatively related in environments where team-cohesion is important. This suggests that an emotional capacity for oneself as well as empathy for others is a trait that will be rewarded in the football labor market.

These soft skills, personality traits, and other intangible ability characteristics that encompass emotional intelligence are not easily measured and likely correlate differently between individuals, positions, and their observable characteristics. However difficult to measure, these EI traits are sought after in the recruiting process. If coaching staffs observe these characteristics, then they will be reflective in the university's screening decisions. The next sections details the economic landscape in which our agents operate and the theoretical framework designed to control for unobserved ability, as well as the identification strategy to capture the *as-if* random assignment in the college football matriculation process.

CHAPTER 3: ECONOMIC ENVIRONMENT AND RESEARCH DESIGN

3.1 Economic Environment and Matriculation Process

There are roughly 900 college level football programs in the United States, where nearly ¾ of the teams are under NCAA authority.[13] Depending on the year, the NCAA sponsors about 250 Division-I football programs, over 170 Division-II, and nearly 250 in Division-III. This analysis will only observe individuals from Division-I football programs since they operate with a completely separate set of guidelines, rules, resources, and constraints than Division-II and Division-III schools. Furthermore, the 250 Division-I schools are split into two separate subdivision— teams in the Football Bowl Subdivision (FBS) and teams in the Football Championship Subdivision (FCS). These subdivisions are effectively 2 different leagues when it comes to selectivity, school quality, resources, and recruitment rules, and as such, I limit the subsequent analysis to the institutions that comprise the FBS.[14] The dataset consists of 13 years of college football recruiting cohorts between 2003 and 2015 for a yearly average of 116 FBS teams. Within the FBS, there are 10 football conferences as well as a few conference independent teams. It is common practice to refer to the top 5 elite conferences as the Power 5 and the less elite FBS conferences as the Group of 5. FBS football programs can have up to 85 scholarship players on their roster any given year. However, a maximum of 25 scholarships can be

[13] This includes NCAA Division I, II, and III schools. There exist a small non-NCAA sanctioned league, and about 120 2-year junior college teams not under direct NCAA authority.

[14] I also exclude military academies (Air Force, Army, and Navy) since they have separate recruiting guidelines. Furthermore, military cadets are not able to participate in professional sports until their service obligations are fulfilled.

awarded each year for any given team's incoming recruiting cohort. This constraint creates a highly competitive market for talent.

FBS football teams allocate a considerable amount of time, effort, and money into recruiting athletes.[15] University coaches and their assistants visit potential recruits to see them play in high school games. They may also do in-home visits and meet their families and high-school coaches. Schools often host football camps which potential recruits are invited to attend. Schools can even cover travel expenses to host a campus visit for up to 5 prospects per year. Additionally, any recruit can visit a school and meet with the athletic staff at their own expense. However, the timeframe in which coaches can communicate with recruits is tightly controlled. Contact and evaluation periods can happen freely in 4 months of the year, with restricted contact periods spanning another 4 months, and strictly forbidden contact periods the remaining 4 months. These time constraints necessitate a prioritization process that promotes selectivity on behalf of the recruiter and recruit.

The school admission screening data is available online by football recruiting outlets such as Rivals.com and 247sports.com. The private recruiting companies track potential FBS football prospects who are in the market for athletic scholarships. The recruiting agencies log the football programs each player is interested in, which of those interested schools extend scholarship offers, along with which schools who do not extend an offer, and ultimately the school the recruit chose to attend. Additionally, these private

[15] In the 2013-14 season the average FBS school spent over $700,000 on men's athletics recruiting expenses, ranging from $96,000 to $2,096,000 (U.S. Department of Education, 2020). The data comes from the U.S. Department of Education's Equity in Athletics Disclosure Act which only separates recruiting expenses by gender, but the lion's share of men's sports recruiting expenses is allocated to football and basketball. The stated figures do not incorporate coach salaries that in large part reward recruiting efforts, or other budget allocations such as marketing that also promote recruiting.

companies employ their own set of scouts to accumulate as much information on FBS recruits as possible.[16] Private scouts are active year-round and agglomerate specialized recruiting knowledge similar to coaching staffs. They primarily review live game footage in detail and some recruiting outlets even hold football camps. They contact recruits in a variety of ways to log additional information such as position, height, weight, hometown, and high school attended. Prospective recruits volunteer detailed information as they use the scouting platforms to market themselves to football programs. Every scouting agency uses their specialized market knowledge to establish overall recruiting scores in which players are rated, categorized, and ranked by ability relative to each other. In particular, 247sports.com publishes a composite recruiting score that equally weights the top scouting agency's individually determined recruiting scores. This standardized recruiting score encapsulates the specialized knowledge of an entire industry's measure of a recruit's overall pre-college football ability.

If a player chooses to accept a scholarship offer from a school, then they agree to the terms and conditions of NCAA eligibility as a student-athlete.[17] The student-athlete plays football for the school in the capacity the school wishes (they may play every game or zero games), while maintaining minimum behavioral and academic achievement standards. In turn, the student-athlete may attend college without paying the explicit cost of tuition.

[16] Private scouting agencies are not bound by any NCAA constraints and compete for information in a lucrative and expanding business model revolving around high school sports.

[17] Student-athlete is a legal term that was initially created to prevent football players from claiming employee status which would in turn allow them to collect workman compensation benefits in the case of a football related injury. The legal term was very successful and further evolved to give the NCAA exclusive rights over the student-athlete's name, image, and likeness (Leadley et al., 2015). Any personal profiteering on the student-athlete's part (e.g. signing an autograph for monetary gain, favor, or in-kind gift of any sort) can result in disqualification from the league and termination of scholarship.

3.2 Research Design and Identification Strategy

The university coaching staff's job is to observe the objective and subjective ability characteristics of recruiting prospects discussed above. Since accumulating talent is paramount to success for the university's football program and coaches wish to maximize wins in order to secure their jobs, the coaching staff's incentive structure is based around accurately gauging and attracting talented recruits. Additionally, the athletes themselves have knowledge about their own ability and how well their talents may project into the competitive football labor market. Both players and coaches have scarce resources and will attempt to optimize their own prospects. For example, coaches from mid-level schools want the best athletes, but they don't want to waste their resources recruiting top athletes who are likely to choose a more selective school. Athletes generally want to go to the top programs and get as much exposure as possible, but the top programs select the top athletes based on overall ability. Recruits must also limit their application process to the universities where they will be competitive in based on the knowledge of their own abilities and aptitudes. Matriculation happens once recruits and coaches have assessed the competitive landscape and determined their best fit. The university will either *offer* (i.e. accept) or *not-offer* (i.e. reject) an athletic scholarship to the interested recruit based on their ability characteristics. Recruits may receive multiple offers, or none at all from a wide array of teams of different quality.

Equation (1) models the football program's decision to offer a prospective recruit a scholarship.[18] The school's decision variable, Z_{ij}, to offer a recruit an athletic scholarship can be modelled as

$$upperC_j > Z_{ij} = \gamma_1 X_{1i} + \gamma_2 X_{2i} + e_{ij} > lowerC_j \qquad (1)$$

where school j offers player i if: $Z_{ij} > lowerC_j$ and $Z_{ij} < upperC_j$.

The variable X_{1i} represents a player's observable characteristics evaluated in the recruiting process known to both the recruiter at school j and the econometrician, while X_{2i} represents the unobservable characteristics not known to the econometrician, but observed by school j's recruiting staff. For example, highly regarded academic institutions who participate in FBS football (e.g. Stanford, Northwestern, Duke, Vanderbilt, and Rice) will likely put more relative weight on the characteristic of academic ability than the average institution. Since minimum thresholds of academic eligibility exist and grades are not observed in the recruiting data, then this information falls into X_{2i}. If, however, academic ability is not rewarded in the NFL labor market, then controlling for it is a moot point.[19] The school's decision thresholds $lowerC_j$ and $upperC_j$ represents each school's lower and upper cutoff threshold, respectively, which determines whether the school offers a prospective recruit an athletic scholarship. All gamma coefficients in equation (1) are added up to calculate a decision variable Z_{ij} to offer or not-offer a scholarship to the recruit based on the school j's perceived cutoff that maximizes their objective function and subject to their own set of

[18] This model is nearly identical to the matriculation decision used by Dale and Krueger (2002). It is only modified to include an upper cutoff threshold ($upperC_j$) to describe the situation in which a less endowed team would not find it rational to recruit and offer player "out of their league".

[19] This is an arguable consideration. The NFL accepts individuals without degrees, as well as those who went to Junior College due to academic restrictions. However, invitations to the NFL Combine and draft are rewarded conditional on NCAA eligibility rules which means those particular outcome variables are most likely dependent in part on academic ability.

constraints. An important assumption is that e_{ij} in equation (1) is not correlated with any outcome variable, Y_i, and is assumed independent across teams.

The last step of the matriculation process occurs when the athlete examines their set of offers and commits to a school of a particular quality based upon their own objective function. Dumond et al. (2008) models a college football recruit's commitment decision and finds certain school characteristics that are predictive of their school choice. Their model suggests that recruits are more likely to choose a school that has a large stadium and updated facilities, is a successful bowl eligible Power 5 team, has good (but not too good) academic ratings, offers an official campus visit, and has higher media exposure – which are general characteristics of more selective schools. That said, Dumond et al. (2008) found that the commanding source of variation in their model for a football recruit's school choice was a negative relationship with distance from their hometown. This makes sense on two levels: one) a player is more likely to be a fan of a team closer to their hometown, and two) the demanding schedule of being a full-time student and a full-time college football player leaves little room for wage earning opportunities that won't violate NCAA rules. Thus, being closer to home for any type of support, financial or otherwise, is likely an important consideration.

The following model estimates the value-added from attending a higher quality football program using a latent variable of school selectivity:

$$Y_i = \beta_0 + \beta_1 Q_{j^*} + \beta_2 X_{1i} + \beta_3 X_{2i} + \varepsilon_i \qquad (2)$$

where Y_i represents a professional career related outcome such as an NFL Combine invite, strength and conditioning metrics, or draft results. The coefficient of interest is β_1 which represents the value-added from attending a more selective football program –

measured by the latent variable Q_{j^*} which is the school average recruiting score for the incoming recruiting cohort of school j. The term X_{1i} captures pre-college player observables that influence earnings. The term X_{2i} is the otherwise unobserved ability characteristics in the absence of scouting and university screening information.

Estimating the naïve model without X_{2i} will upwardly bias the value-added coefficient on Q_{j^*}. Even if X_{2i} is properly measured and defined in the model, Q_{j^*} will still be biased upwards if higher ability players never applied to less selective schools to begin with, or less selective schools didn't even attempt to recruit them. To this point, Dale and Krueger (1999) run several simulations and show that a variable to control for unobserved ability alone will not fully correct the double sided selection bias. Ultimately, a source of random assignment into a treatment group for school quality is needed for a causal interpretation.

To explore possible sources of random variation that might place recruits into treatment and control groups, consider the simple latent variable model for a recruit's commitment decision:

$$Max\ Q_j = \boldsymbol{q_j} + \epsilon_{ij} \tag{3}$$

where $\boldsymbol{q_j}$ is a vector of school quality characteristics (discussed above) that generates a process for football programs to be more selective in their scholarship offers. Individual recruits will examine each school's set of $\boldsymbol{q_j}$ characteristics and commit to the offering team that maximizes their future prospects. The random disturbance term ϵ_{ij} represents factors that influence the commit decision but are necessarily uncorrelated with any outcome variable. As previously stated, Dumond et al. (2008) found the distance between a recruit's hometown and offering school accounts for the majority of variation in the school choice model. Since a recruit's hometown is unlikely to be correlated with labor market outcomes, then proximity to a school is a likely source of random variation to identify treatment into a particular school type defined by the latent variable Q_j. Furthermore, Dumond et al. (2008) finds that their highly specified model only accounts for 63% of the variation in school choice, leaving a considerable amount of additional random factors to potentially identify subjects into treatment and control groups. The key assumption regarding these random factors that determine treatment groups is that they are not correlated with any outcome variable, yet determines, in part, which school a player chooses.

In the following empirical analysis I estimate equation (2) in two ways. In the first method I use the scouting industry's composite recruiting score described above[20] as a measure of X_{2i} and run a regression with other pre-college observable covariates, X_{1i}. The results will indicate that this is a good control for overall ability, but the model still lacks a source of random assignment for reliable estimates. In the second method I implement the matched-applicant model by generating a set of dummy variables that match individuals on nearly identical levels of pre-college ability. To achieve this baseline, I parse each individual into narrowly defined ability groups based on their own composite recruiting score. From there, individuals within each narrowly defined ability group are further parsed into subgroups based on a narrow range of the average school selectivity score from their top 5 offers.[21] Table 1 provides an illustration and a more detailed description of how the

[20] This is the recruit's average ability score determined by the leading college football scouting companies in the industry. Largely based on personal observations, viewing game video, communication with recruits, and observations made in mini-camps, among other sources of information.

[21] This matching technique utilizes two measures of ability, one from the private scouting industry and one from each coaching staff's screening panels. Even though both likely capture much of the same ability measures, the composite recruiting score is more likely to pick up on raw and technical athletic ability,

matched-applicant groups were constructed. This second method can be expressed by a slight modification of equation (2),

$$Y_i = \beta_0 + \beta_1 Q_{j^*} + \beta_2 X_{1i} + \alpha_i + \varepsilon_i \qquad (4)$$

where α_i represents a set of matched-applicant dummy variables assigning each individual to a fixed effect, pre-college ability group. The fixed effect dummies provide a baseline in order to estimate the value-added coefficient, β_1, *within* groups of nearly identical ability characteristics. The natural expectation is that each athlete will commit to the highest quality team from which they received an offer. Although this happens in many cases, some athletes within matched groups choose a less selective team for reasons unrelated to ability and outcomes. This is the random variation the matched-applicant model seeks to exploit. If the error terms in equations (1) and (3) are uncorrelated with the outcome variable, Y_i, in equation (4), then a natural experiment arises due to the otherwise random assignment into a university's football program and β_1 can be interpreted as the causal effect of school selectivity on the player's professional career outcome.

Since this natural experiment depends on treatment into a particular school type, all players who transferred schools in their college career are excluded from the analysis. Even though transferring schools is not typical due to the barriers set in the NCAA regulations that restrict player mobility, it is still a necessary option for some players, most commonly in transition to and from a junior college due to academic or behavioral issues. With these exclusions, the sample data may not exactly capture the *average*

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while the measure from coaches (who actually offer the scholarships) likely have more intimate knowledge of factors such as emotional intelligence and academic ability due to a more personal communication channel, as well as having the additional incentives to acquire such knowledge.

Table 1 Illustration of Matched-Applicant Groups Used in Logit Models

Match Group	Recruit Score	Top 5 Offers Team-average	Group Count	Position	School Choice	School Selectivity Score	Year
1	88.0	82.8	5	DB	TCU	84.6	2013
1	87.8	82.6	5	LB	California	85.9	2008
1	87.5	82.9	5	DL	Stanford	90.5	2012
1	88.2	82.9	5	OL	Kansas	85.5	2008
1	88.1	82.5	5	WR	Virginia Tech	86.2	2008
2	83.54	79.54	7	WR	Iowa State	81.22	2006
2	81.85	79.75	7	TE	NC State	84.44	2014
2	81.74	78.65	7	DB	Cincinnati	83.99	2012
2	83.33	79.79	7	OL	Alabama	85.48	2004
2	81.85	78.82	7	LB	SMU	78.55	2014
2	83.33	79.13	7	LB	Boston College	82.53	2004
2	82.94	79.96	7	DB	Buffalo	77.75	2014
3	95.5	88.1	4	DL	Georgia	90.4	2010
3	95.3	87.9	4	OL	LSU	91.3	2014
3	96.0	89.0	4	OL	Notre Dame	93.0	2008
3	95.6	88.2	4	OL	Florida State	92.5	2015
4	85.12	88.98	3	RB	South Florida	82.99	2013
4	85.06	87.67	3	LB	Texas A&M	89.21	2013
4	84.83	87.60	3	DL	Southern Miss	79.63	2013
5	95.3	90.9	2	DL	Michigan	90.4	2009
5	95.6	91.4	2	WR	Texas	91.4	2011

Notes: Each row of this table shows a hypothetical player is first parsed into groups based on a narrow range of their own recruit score, and then matched into groups by a narrow range of the team-average recruit score from their top 5 offers. Specifically, recruits were coarsened into 30 similar groupings based on a 1 point parsing (0.16 of a standard deviation) of their own composite recruiting score. From there, recruits within these 30 initial groupings were further matched into very similar parsing of the team-average recruit score of their top 5 offers. The average spread in recruit score within matched groups is 1.47 (or 0.23 of a standard deviation) and the average spread in team-average recruit score of their top 5 offers with matched groups is 1.47 (or 0.34 of a standard deviation). This generated a total of 247 matched dummy sets over the 21,251 recruits in the sample. The median number of observations within each matched group is 238, with an average of 283, a standard deviation of 207, and a range between 1 and 812. All regressions using the matched-applicant dummies use frequency weights to account for the variation in group size. The dummy groups illustrated here are only used in the logit regressions and are not position specific.

football recruit, but it does capture the *typical* football recruit – or the one for which the NCAA system was designed.[22] The following empirical section uses both the composite recruiting score and the matched-applicant method to control for unobserved ability in order to estimate the value-added from attending a more selective college football

[22] A major reason to transfer between schools is for academic eligibility concerns, so excluding these transfers further increases the homogeneity of college football players in this analysis. In other words, the sample data only includes individuals who maintain NCAA academic eligibility standards above the minimum threshold throughout their college career.

program on 1) probability of receiving an NFL Combine invite, 2) the probability of being drafted into the NFL, 3) objective measures of strength and conditioning, and 4) overall pick in the NFL draft.

CHAPTER 4: EMPIRICAL RESULTS

4.1 Probability of Receiving an NFL Combine Invite

Table 2 presents summary statistics for the full sample of FBS college football recruits who committed to a team between 2003 and 2015. The restricted sample provides a subset of summary statistics for the set of observations who meet identification criteria for the matched-applicant model. There are two reasons for the difference in sample sizes – one being methodological and one being empirical. First, some players did not match on the coarsening parameters and fell into an ability group by themselves. Since the natural experiment depends on variation of school choice *within* matched groups, non-matches are dropped from the matched-applicant model. Second, the likelihood function from the logit regression can only converge when there is variation in outcomes within matched groups. Matched groups that did not have any *within* variation of outcomes were also dropped from the matched-applicant logit model. The two samples differ by 556 observations and the summary statistics remain qualitatively similar.

Each year the NFL extends Combine invites to about 320 draft eligible football players who have officially exhausted their NCAA eligibility.[23] After the Combine, the 32 NFL teams officially draft 256 players into the league each year. The order in which they are drafted primarily determines their rookie contract and pay-scale; players picked

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[23] NCAA eligibility is typically 4 years. There are circumstances in which players may be granted extended eligibility. Players can choose to prematurely terminate their NCAA eligibility to gain NFL Combine and draft consideration as long as they are at least 3 years removed from high school.

Table 2 Summary Statistics: College Football Recruits 2003-2015

	Full Sample				Restricted Sample			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Outcomes								
Combine invite	0.123	0.33	0	1	0.126	0.33	0	1
Drafted	0.094	0.29	0	1	0.096	0.29	0	1
Invite or drafted	0.132	0.40	0	1	0.135	0.34	0	1
School Quality								
Team-average recruit score	81.99	4.75	70.0	96.4	82.11	4.68	70	96.4
Ability and Screening Panel Covariates								
Own recruit score	82.17	6.30	70	100	82.29	6.29	70	100
Top 5 offers team-average	81.62	4.40	70.9	93.6	81.74	4.32	70.9	93.6
Offers received	4.68	4.90	1	53	4.74	4.91	1	53
Rejection-rate	0.31	0.30	0	1	0.31	0.30	0	0.94
Official visits	0.80	0.91	0	6	0.81	0.91	0	6
BMI in HS	28.42	4.42	18.2	46.3	28.42	4.42	18.2	46.3
Height in HS (inches)	74.03	2.55	61	82	74.04	2.55	61	82
Weight in HS (lbs.)	222.70	43.0	139	410	222.77	43.02	140	410
Chose in-state school	0.42	0.49	0	1	0.42	0.49	0	1
Ivy interest	0.04	0.29	0	7	0.04	0.29	0	7
N	21,251				20,695			

Notes: The sample includes FBS athletic scholarship recipients for incoming recruiting cohorts between years 2003-2015 who did not attend multiple schools. Outcomes include NFL Combine and draft years up until the year 2020. The restricted sample excludes recruits who did not match on the defined parameters or were included in the 61 dummy groups that were dropped due to insufficient variation in outcomes within groups required for a logit regression.

sooner get paid more than players picked later. Not everyone who receives a Combine invite gets drafted, and not everyone who gets drafted attended the Combine. However, nearly every official Combine invite is eventually signed as an undrafted free agent if they are not officially drafted. Thus, the Combine invite alone is a “foot in the door” with a high likelihood of some sort of payout, if not a contract for at least the league minimum wage.[24] The simple mean of the sample indicates that 12.3% of FBS scholarship recruits get an NFL Combine invite.

Table 3 presents the average marginal effects of value-added from school quality on the probability of receiving an NFL Combine invite using a logit regression. The marginal effects are computed for each individual and then averaged across the sample. Column 1 is a simple logit regression on the school selectivity score (*team-average recruit score*) from the football program each individual chose to attend. The simple model predicts the average marginal effect from attending a school with a 1 point increase in selectivity score will increase the probability of an invite by 1.92%, averaged across all individuals in the sample. This accounts for 15.6% (1.92/12.3) of the overall sample predicted probability of an invite. Column 2 is still a naïve model since it only accounts for basic observable characteristics of a football recruit. Here, it includes their body mass index in high school (*bmiHS*),[25] if they chose an in-state school (*in-state*), the number of schools that extended an official visit (*visits*), if they had interest in an Ivy League school (*Ivy interest*), as well as fixed effect controls for their position, home state, and recruiting year cohort. The average marginal effect from a 1 point increase in school selectivity decreases slightly to 1.8%, but is qualitatively similar to model 1. Column 3 adds the composite recruiting score (*recruit score*) which is a convenient measure for overall ability characteristics found in both $X_{1i} + X_{2i}$ in equation (2) above. After pulling unaccounted measures of innate ability from the error term, the value-added coefficient

[24] The NFL Players Association's collective bargaining agreement stipulates a rookie minimum salary at $375,000 in 2011 and increased to $510,000 by 2020 (NFLPA, 2011). Prior to the 2011 collective bargaining agreement, draftees were able to separately negotiate initial rookie contracts. This analysis does not quantitatively measure salary as an outcome, but simply uses the overall draft pick as an ordinal measure for outcomes. In other words, draft order is a qualitative measure of initial salary.

[25] Along with its square term (*bmiHS2*) and an interaction on position (*bmiHS*pos*).

on *team-average recruit score* drops by 2/3 compared to the estimate in model 1 and remains statistically significant. The average marginal effect from attending a more selective school increases the probability of an invite by only 0.70%, which now accounts for only 5.7% of the overall predicted probability of receiving an invite.

Column 4 adds college admission screening controls to the estimation, specifically the number of scholarship offers received (*offers*), a square term for the number of offers (o*ffers2)*, the average team selectivity score from the top 5 offers the recruit received (*top 5 offers team-average*), and the recruit's rejection rate (*rejection rate*).[26] These ability measures provided through the admissions screening process continue to decrease the value-added coefficient on school quality. The results in column 4 indicate that the average player has a 12.3% chance of getting an NFL Combine invite, but only 0.64% of that probability is attributed to attending a more selective school. The reduction of the coefficient on *team-average recruit score* is in line with the general notion that unaccounted ability will bias the value-added estimates upward. However, using the players own recruiting score to control for pre-college football ability does not account for any non-random sorting by both players and schools.

Equations 5 – 7 in Table 3 implement the matched-applicant method to estimate the returns to school quality outlined in equation (4) above. The model in column 5 runs a logit regression on the player's school selectivity score with no additional control variables other than 185 dummy variable groupings for pre-college ability fixed effects and a case for a natural experiment within those groups. The results show an average marginal effect from a 1 point increase in school selectivity will increase the probability

[26] Rejection rate is defined as the number of non-offers relative to the number of schools the recruit expressed interest in.

Table 3 Average Marginal Effects for Probability of NFL Combine Invite

Selection control	None	Recruit score			Matched-applicants		
	1	2	3	4	5	6	7
Team-average recruit score	0.0192*** (0.000871)	0.0180*** (0.000827)	0.00703*** (0.000974)	0.00639*** (0.00110)	0.00642*** (0.00116)	0.00645*** (0.00105)	0.00637*** (0.00104)
Recruit score			0.0110*** (0.000589)	0.00978*** (0.000725)			0.00712** (0.00311)
bmiHS		-0.0297*** (0.00855)	-0.0352*** (0.00778)	-0.0358*** (0.00782)		-0.0474*** (0.00777)	-0.0473*** (0.00773)
bmiHS2		0.000359*** (0.000116)	0.000400*** (0.000107)	0.000411*** (0.000107)		0.000556*** (0.000114)	0.000554*** (0.000114)
bmiHS*pos		0.000442 (0.000297)	0.000531* (0.000281)	0.000542* (0.000281)		0.000863*** (0.000279)	0.000868*** (0.000278)
Visits		0.0240*** (0.00259)	0.0135*** (0.00249)	0.0110*** (0.00241)		0.00673*** (0.00241)	0.00666*** (0.00240)
In-state		0.0125** (0.00532)	0.00349 (0.00511)	0.00546 (0.00519)		0.00758 (0.00508)	0.00724 (0.00508)
Ivy interest		-0.0167* (0.00998)	-0.00874 (0.00858)	-0.00745 (0.00808)		-0.00792 (0.00782)	-0.00782 (0.00787)
Offers				0.00187 (0.00130)		0.00519*** (0.00146)	0.00487*** (0.00148)
Offers2				-0.0000255 (0.0000367)		-0.000120** (0.0000517)	-0.000110** (0.0000518)
Rejection rate				-0.0340*** (0.00995)		-0.0116 (0.0112)	-0.0128 (0.0113)
Top 5 offers team-average				0.000962 (0.00133)		-0.00897* (0.00483)	-0.00930* (0.00482)
Year FE	x	x	x	x		x	x
Position FE		x	x	x		x	x
State FE		x	x	x		x	x
Prediction	0.123*** (0.00395)	0.123*** (0.00356)	0.123*** (0.00339)	0.123*** (0.00335)	0.0905*** (0.00340)	0.0905*** (0.00297)	0.0905*** (0.00297)
N	21,251	21,251	21,251	21,251	20,695	20,695	20,695

Standard errors in parentheses. Data from recruiting cohorts 2003 - 2015 and NFL Combine years up to 2020. Marginal effects are computed for each individual and then averaged across the sample. Predictions computed at sample means. Fixed effects include year, player's home state, and position where indicated. There were a total of 247 successfully matched dummy sets, while only 185 of the matched sets met the identification strategy, thus restricting the sample size by 556 observations. Frequency weights were applied to regressions using matched-applicant method to account for the wide range of observations within each matched set. Standard errors clustered at the team level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

of receiving an NFL Combine invite by 0.64%. This reduced the value-added coefficient by 2/3 when compared to the estimates in column 1 and remains statistically significant at the 1% level. The estimate is nearly identical to the highly specified model in column 4. When adding additional recruit characteristics and screening controls in columns 6 and 7, the value-added estimates from school quality remain robust regardless of the specifications. Column 7 highlights the robustness of the matched-applicant estimates by adding the player's own recruit score, which was just shown to have a major effect on the value-added from school quality as well as other covariates in the model. Since the matched dummies already control for observed and unobserved ability, the recruit score variable does little to affect overall results, yet remains statistically significant at the 5% level. This indicates that both measures of pre-college ability are capturing similar variation, but the matched-applicant method is much more robust to model specification which suggests that there is a source of random variation assigning treatment.

The results in Table 3 are computed using the average prediction across all individuals in the sample. However, there are different marginal effects in the predictive probability of receiving an NFL Combine invite at various levels of school quality. Figure 1 plots the average marginal effects from the model in column 1 and column 7 at various team-average recruiting scores. The information college coaching staffs are likely pitching to prospective recruiting talent is shown in Model 1, the value-added without selection controls, while Model 7 controls for baseline ability under the conditions of a natural experiment. The evidence shows that the most elite football programs can overstate their value-added to a player's labor market outcomes by up to 4 times their actual value once holding predetermined ability constant. Although both models are

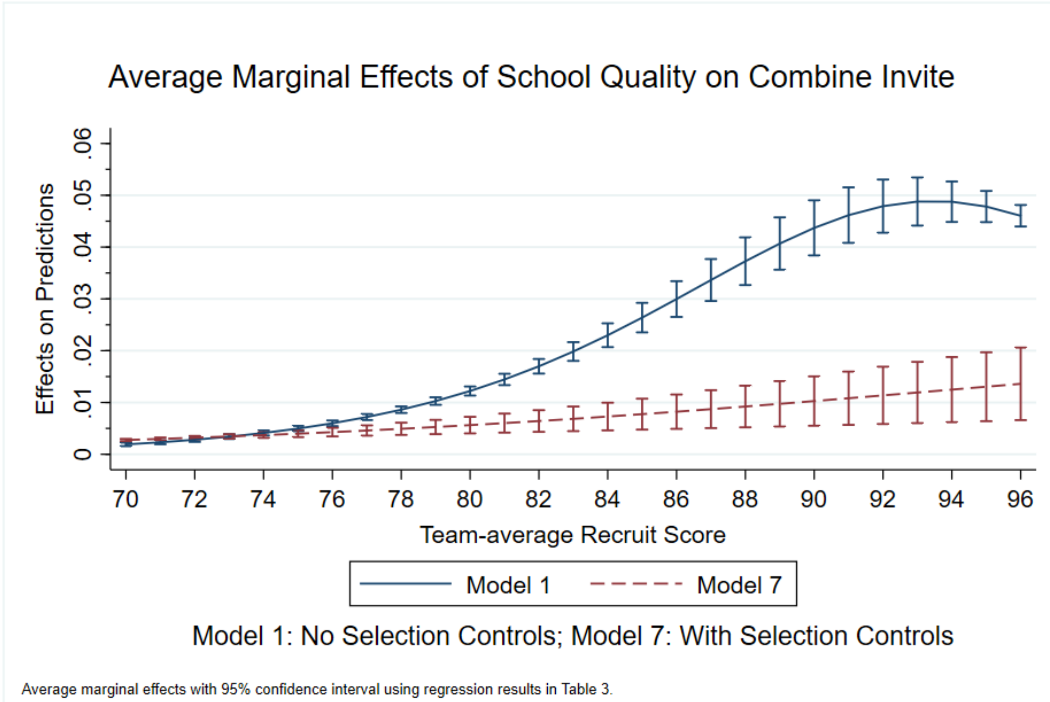

Figure 1 Average Marginal Effects of School Quality on Combine Invite

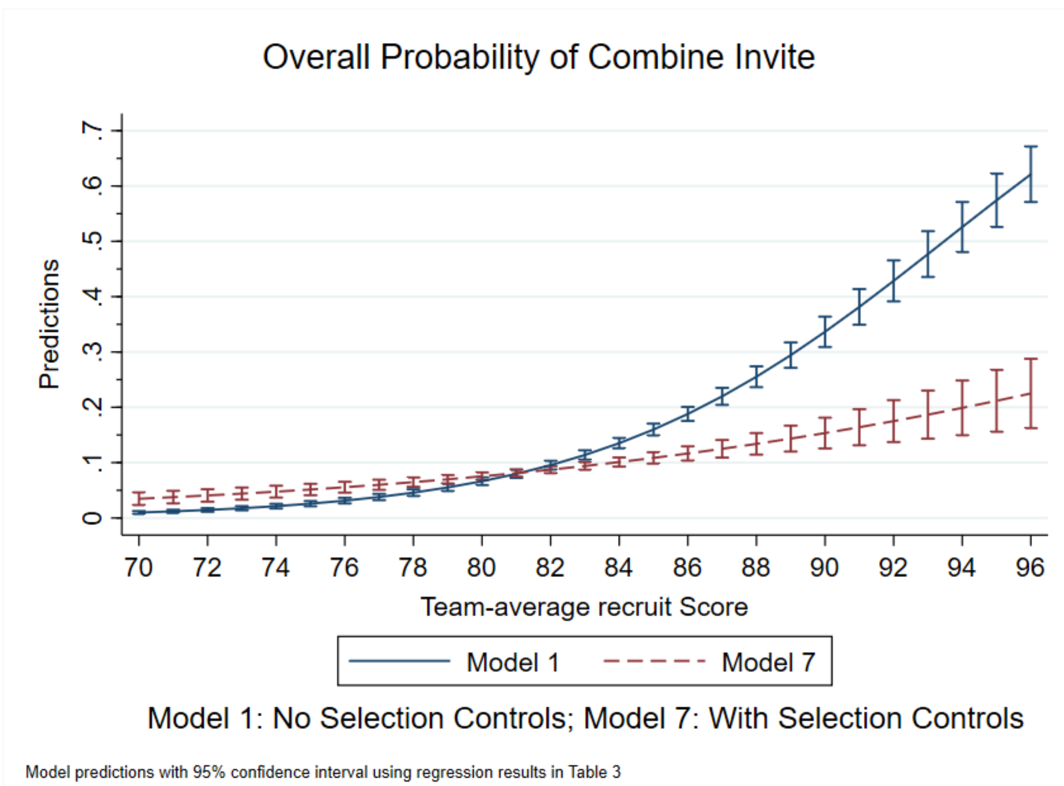

Figure 2 Overall Probability of Combine Invite

increasing, the 95% confidence interval widens with increases in school quality which suggests that any marginal gains from attending a more elite school is more tenuous than the average school in the sample.

To make things more concrete, consider the average player in the sample with a recruit score of 82 who is deciding whether to attend the average school in the sample (Q_{j^*} = 82) or a school that is 1 standard deviation above the average (Q_{j^*} = 87). Figure 2 also uses the regression results from Table 3 to show the overall predictive probabilities at various school quality levels. Using the estimates in Model 1, the probability of receiving a Combine invite is 22% when attending the above average school and only 9.54% for the same player at the average school. According to Model 1, attending the above average school more than doubles the odds of a Combine invite compared to the average school – which would be a hard thing for a recruit to pass up. However, the selection corrected value-added estimates from Model 7 predicts attending a school that is 1 standard deviation above average is associated with a 12.5% overall probability of an invite, while the average school predicts an invite probability of 8.73%. Conditional on the recruit's pre-college ability, the additional gains of moving from one school type to the next is relatively small, however, it is a statistically significant gain nonetheless.

There are several other observations between the two methods worth noting. First, there is a sign reversal on the coefficient for the average selectivity score of the recruit's top 5 offers. This ability measure is observed in the college admissions screening process which more directly emphasizes the value coach's place on a recruit and the caliber of the typical football program that was actively recruiting them. The higher the score on the top 5 offers, the more recruitment from more elite university coaching staffs. Although it's only marginally significant at the 10% level, the negative sign is counter-intuitive and continues to show up in the subsequent analysis. Second, the overall average probability of receiving an invite falls from 12.3% in the models without selection controls to 9% in the matched- applicant models. Keep in mind that the average player receiving an invite to the NFL Combine is well above average in ability from the overall sample and typically attends a more selective football program.[27] It would make sense that the 'true' predicted probability of the model is actually lower for the average recruit than the simple mean in the sample suggests. The matched dummies are effectively weighting the overall predicted results by ability. Third, the overall prediction for the matched-applicant models have lower standard errors despite the loss in degrees of freedom when adding 185 additional dummy variables to the regression. To compare goodness of fit, the matched-applicant model in column 7 classifies 91.1% of the sample correctly while the similar model in column 4 correctly classifies 88.5% of the sample. Although not too dissimilar in estimating coefficients, the additional inference checks and signs of robustness indicate greater efficacy for the matched-applicant model. That said, the recruiting score as a single measure for pre-college baseline ability does some serious heavy lifting on its own.

4.2 Probability of Being Drafted Into the NFL

Table 4 presents the value-added from school quality on the probability of being drafted into the NFL using the same covariates used to estimate columns 1, 4, and 5 of Table 3. The trend is similar to the previous Combine invite results in that the controls for baseline player ability attenuate the effect of school quality on labor market outcomes.

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[27] See Table 5 summary statistics

One noticeable difference is that the average marginal effects are even smaller than the Combine invite results. The matched-applicant estimates for school quality are just ¼ the size of the estimates without selection controls. This suggests that NFL employers are more likely to extend a Combine invite to a player from a more selective school, but relatively less likely to draft a player from a more selective school. It is helpful to acknowledge that the NFL is likely aware of the market distortions that may occur when pulling an entire labor supply from a monopsony market, and hence the reason to host the Combine in the first place – to sort out the lemons from the cherries in order to avoid a potential draft bust. The next set of empirical results explore what kind of information is accumulated by NFL employers once the job applicants participate in the NFL Combine.

Table 4 Average Marginal Effects for Probability of Being Drafted into NFL

Selection control	None 1	Recruit score 2	Matched-applicant 3
Team-average recruit score	0.0147*** (0.000685)	0.00480*** (0.00106)	0.00382*** (0.00104)
Recruit score		0.00791*** (0.000625)	
Year FE	x	x	x
Position FE	x	x	x
State FE	x	x	x
Prediction	0.0941*** (0.00302)	0.0941*** (0.00258)	0.0699*** (0.00250)
N	21,251	21,251	20,843

Notes: This table presents the average marginal effects on being drafted into the NFL give a 1 point increase in team-average recruit score. Columns 1, 2, and 3 are estimated using the same covariates as columns 1, 4, and 7 of Table 3, respectively, except year, position, and state fixed effects were included in all models to make for better comparisons. Marginal effects are computed for each individual and then averaged across the sample. Predictions computed at sample means. There were a total of 247 successfully matched dummy sets, while only 182 of the matched sets met the identification strategy, thus restricting the sample size by 408 observations. Frequency weights were applied to regressions using matched-applicant method to account for the wide range of observations within each matched set. Data from recruiting cohorts 2003 - 2015 and NFL draft years up to 2020. Standard errors in parentheses. Standard errors clustered at the team level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.3 Strength and Conditioning Evidence Using NFL Combine Results

The NFL Combine is a weeklong athletic skills showcase that takes place each year one month before the draft. The 32 NFL club teams collectively fund the event and invite about 320 draft eligible players in order to get a better look at the talent entering the professional landscape. A variety of standardized skills tests are administered in a heavily controlled environment each year.[28] Any given test is voluntary and players occasionally opt out of particular tests for a variety of reasons. However, there are 3 recorded metrics that nearly every Combine participant logs at the event: height, weight, and 40 yard dash time. These 3 metrics on their own don't seem like much, especially since every position has a different ideal distribution of each of these 3 random variables.[29] When combined in a particular way, they can form a measure sometime referred to as *explosive power*, *speed-strength*, or *horizontal-force*. For the purposes of this analysis, I simply refer to the measure as *force* since the calculation is derived from Newton's Laws of Physics: $force\ =\ mass\ x\ acceleration$. A variable for a player's body mass index (BMI) is derived from their height and weight measured at the NFL Combine. Technically acceleration is a rate of change at a specific moment in time, however, I am able to calculate an average acceleration measurement given the 40 yard dash time. The metric used in the following estimations multiplies each individuals BMI by their average acceleration to form an outcome measure of *force*. Table 5 provides the

[28] The location of the NFL Combine for all cohorts in the sample was Indianapolis's Lucas Oil Stadium, which is a dome able to replicate identical environmental settings between each cohort.
[29] Receivers are tall and lean, running backs are short and stalky, while linemen are big and bulky. Taken separately, height, weight, and speed characteristics will have confounding differential effects between positions.

means and standard deviations for all inputs to *force*, as well as the other NFL Combine related variables in the models.

Table 5 Summary Statistics: FBS Recruits Participating in the NFL Combine

	Full Sample				Restricted Sample			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Combine variables								
Force	50.19	4.230	29.9	66.1	50.23	4.174	29.9	66.1
40 yard dash time	4.77	0.304	4.2	6.0	4.76	0.303	4.2	6.0
Average acceleration	1.63	0.195	1.0	2.1	1.63	0.194	1.0	2.1
BMI at Combine	31.25	4.406	21.6	44.7	31.23	4.391	21.6	44.5
Height at Combine	73.8	2.657	65	82	73.8	2.662	65	82
Weight at Combine	243.4	44.846	160	369	243.3	44.811	160	369
School Quality								
Team-average recruit score	85.56	4.594	71.7	96.4	85.62	4.562	71.7	96.4
Ability and Screening Panel Covariates								
Own recruit score	87.68	7.174	70	100	87.82	7.098	70	100
Top 5 offers team-average	84.98	4.396	71.7	93.2	85.05	4.357	71.7	93.2
Offers received	7.47	6.511	1	49	7.58	6.509	1	49
Rejection-rate	0.21	0.255	0	1	0.21	0.252	0	1
Official visits	1.20	1.147	0	5	1.21	1.149	0	5
BMI in HS	28.19	4.463	18.8	46.3	28.17	4.448	18.8	46.3
Height in HS (inches)	74.3	2.554	66	82	74.3	2.559	66	82
Weight in HS (lbs.)	222.6	43.408	141	370	222.4	43.334	141	370
Chose in state school	0.46	0.498	0	1	0.46	0.499	0	1
Ivy interest	0.025	0.237	0	5	0.025	0.239	0	5
N	2,470				2,402			

Notes: This table presents the subsample of FBS athletic scholarship recipients who were invited to the NFL Combine and have an official record for height, weight, and 40 yard dash time. The restricted sample excludes 68 observations who did not match on the defined parameters.

Figure 3 provides a visual inspection of how *force* is correlated with the players' ultimate goal – getting drafted at the lowest pick possible. There is a clear association that exists no matter the position; increasing ones *force* is strongly correlated with a better draft outcome. This is intuitive for a high impact sport such as football and it's reasonable to assume college programs will teach to this standardized test.[30] FBS universities expend large allocations to their athletic training facilities and staff, and the quality of a team's strength and conditioning program is a key feature in the recruiting pitch to the prospective college recruit. Since *speed-strength*, measured by *force*, is a well-known characteristic the labor market rewards, it is reasonable for a recruit to believe that an elite football program will produce this purely objective metric at a premium.

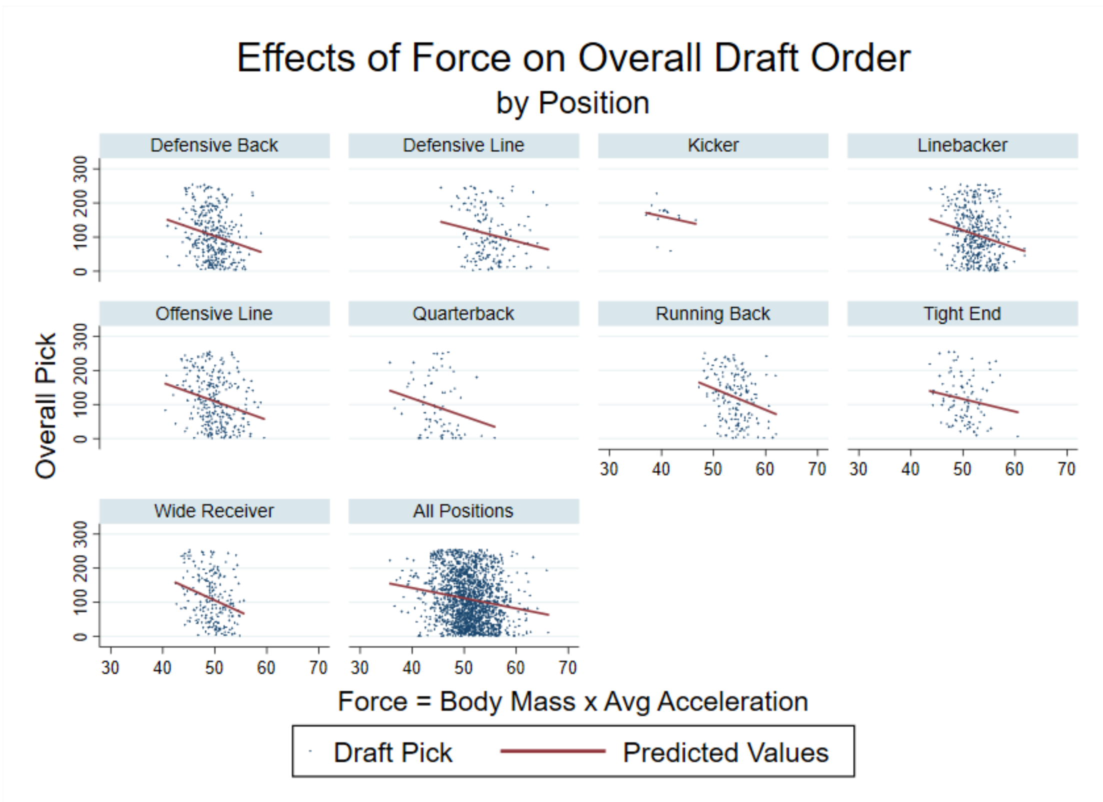

Figure 3 Effects of Force on Overall NFL Draft Order

[30] It's instructive to note that one can increase their *force* in two ways: 1) increasing their body mass, and 2) increasing their acceleration. This allows every position to adopt a strength and conditioning routine that can target the same outcome metric in a heterogeneous way. Large lineman may want to focus on building body mass, while wide receivers may want to focus on speed. More of both is even better as it would compound to greater *explosive power*. However, there is a tradeoff in that the larger the mass the lower the acceleration, and vice-versa. A player will benefit from strength and conditioning training that helps them optimize this tradeoff.

Table 6 provides OLS estimates for the value-added from school quality on *force*. The regression in column 1 estimates a model without a control for selection bias or baseline levels of ability. It shows that more selective schools produce players with greater *explosive power*. Column 1 indicates that choosing a school with a 1 standard deviation higher *team-average recruit score* will increase *force* by 9% of a standard deviation. This may not seem like much, but football is a ‘game of inches’ and any competitive edge is highly rewarded.

After adding the player’s own *recruit score* and other pre-college characteristics to the regression, the value-added coefficient on *team-average recruit score* turns negative and is not statistically different from zero. Column 3 shows that initial high-school measures of BMI increases *force* at a decreasing rate – confirming the tradeoff athletes make when building *speed-strength*. When height and weight enter the equation separately, we see that height is associated with an increase in *force* and weight is associated with a decrease, holding high-school BMI constant. This indicates a premium on the speed side of the equation since increasing weight slows a body down and increasing height typically comes with longer legs and thus an advantage in running. An interaction on high-school BMI and position shows that there is no significant difference in the marginal effect on *force* between position and different body types. This suggests that the intensity of the measure of *force* is equally important for all positions, and all types of players are able to produce *force* to their particular strength and conditioning needs.

Column 4 estimates the value-added from school quality with additional screening controls. The *team-average recruit score* coefficient turns back positive, but is still less than a ¼ of the size from column 1 and not statistically different form zero. The change in sign on *team-average recruit score* only happens when allowing a measure for the average recruiting score of the player's top 5 offers to enter the equation. The coefficient on *top 5 offers team-average* is negative, statistically significant, and economically important. This implies that the players recruited from more elite universities perform worse on strength and conditioning tests – holding their raw-ability *recruit score* and college quality constant. It could be that high profile players feel that they don't need to work as hard to hit the standardized marks the NFL is looking for. It could also be the case that coaches are placing a high value on certain intangible skills unrelated to physical strength and conditioning training that are not being factored in by the private scouting industry. It's also entirely possible that all the highly recruited players agglomerate into a select few teams and receive relatively less individual coaching attention regarding strength and conditioning. However, one would expect the sign on the total number of scholarship offers to run in the same direction as *top 5 offers team-average* since they are both indicators of a more highly recruited player.

If the natural experiment described above truly captures a source of random variation, and pre-college ability fixed effects can be held constant within groups, then the matched-applicant method should be able to produce robust estimates for a school's value-added on *force*. The matched dummies in this model were constructed with an extra layer to match on that was not present in the logit model from the previous section. The difference is that all observations are first matched into position groups. From there, each player within their position group is parsed into subgroups by a narrow range of their recruiting score. Within these position-recruit-score groups, players are even further

Table 6 OLS Estimates on Strength and Conditioning Measure of Force

Selection control	None	Recruit score			Matched-applicants		
	1	2	3	4	5	6	7
Team-average recruit score	0.0820***	-0.0207	-0.0160	0.0171	0.0235	0.0232	0.0214
	(0.0220)	(0.0221)	(0.0208)	(0.0214)	(0.0262)	(0.0247)	(0.0250)
Recruit score		0.0388***	0.0283**	0.0512***			0.0843
		(0.0116)	(0.0120)	(0.0157)			(0.0696)
bmiHS			3.439***	3.440***		3.439***	3.456***
			(0.443)	(0.445)		(0.512)	(0.517)
bmiHS2			-0.0175***	-0.0178***		-0.0205***	-0.0206***
			(0.00318)	(0.00321)		(0.00377)	(0.00378)
bmiHS*pos			-0.0000857	-0.000243		-0.000344	-0.000350
			(0.00767)	(0.00775)		(0.000977)	(0.000974)
heightHS			1.045***	1.040***		0.939***	0.950***
			(0.280)	(0.280)		(0.310)	(0.314)
weightHS			-0.270***	-0.267***		-0.237***	-0.238***
			(0.0497)	(0.0498)		(0.0534)	(0.0540)
Visits			0.00638	0.0311		0.0830	0.0776
			(0.0581)	(0.0563)		(0.0670)	(0.0680)
In state			0.211	0.220		0.272*	0.264*
			(0.138)	(0.139)		(0.157)	(0.156)
Ivy interest			0.0904	0.0703		0.0872	0.0967
			(0.242)	(0.238)		(0.282)	(0.280)
Offers				0.00693		-0.0430	-0.0440
				(0.0399)		(0.0442)	(0.0436)
Offers2				-0.000451		0.000806	0.000823
				(0.000996)		(0.00106)	(0.00105)
Rejection Rate				-0.129		-0.0644	-0.0476
				(0.330)		(0.389)	(0.390)
Top 5 offers team-average				-0.0837***		-0.0399	-0.0491
				(0.0309)		(0.108)	(0.108)
Year FE	x	x	x	x		x	x
State FE		x	x	x		x	x
Position FE		x	x	x	within	within	within
Constant	43.28***	47.87***	-52.11**	-49.95**	47.97***	-46.03*	-52.04*
	(1.942)	(1.459)	(21.07)	(21.19)	(2.669)	(25.77)	(27.00)
N	2,470	2,470	2,470	2,470	2,402	2,402	2,402
adj. R^2	0.012	0.410	0.487	0.488	0.321	0.453	0.454

Notes: Standard errors in parentheses. Data from FBS recruiting cohorts 2003 - 2015 and NFL Combine years up to 2020. Force = Body Mass x Acceleration. FE include year cohort and the player's home state where indicated. Position is held constant within the matched-applicant groups. That is, every dummy category is matched on the same position and very similar recruiting score measuring pre-college ability and are further matched on very similar scholarship offers measured by average school selectivity of the recruit's top five offers. Standard errors clustered at team level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

parsed and matched by the team-average selectivity score of their top 5 scholarship offers.[31] After dropping 68 observations who did not match, there are 248 dummy variables for pre-college ability fixed effects, each holding position constant within groups. Table 7 provides an illustration of how these dummy groups were constructed. It's worth pointing out that simply being invited to the NFL Combine puts the sample into a more narrow ability range to begin with.

Columns 5-7 in Table 6 implement the matched-applicant method with robust results for all coefficients in the model regardless of specification. The value-added coefficient on school quality remains low and not statistically different from zero. It is again worth pointing out the counter-intuitive negative signs on *top 5 offers team-average*, as well as the total number of *offers*. One would expect these recruitment measurements to run in the same direction since they both come directly from the university coaching staff's assessment of a higher quality player, but one would not expect the sign to remain negative across specification and models. At best, they are not statistically different from zero. Even though the matched dummies already control for baseline ability, adding the player's own recruit score highlights the robustness in the matched-applicant model, as shown in column 7. Most of the covariation happens between the players' ability measures and the constant term which houses the pre-college ability fixed effects from the matched dummies. This is further evidence that the assignment of variation within the model is well specified – presumably due to a random factor identifying treatment. In short, there is no evidence that elite schools produce

[31] The parsing of *recruiting score* within each matched group have an average spread of 2.6 recruiting points, or 0.36 of a standard deviation. The parsing of *average recruiting score of the top 5 offers* within each matched group have an average spread of 2.1 points, or 0.48 of a standard deviation.

football players with higher levels of strength and conditioning once controlling for pre-college player characteristics.

Table 7 Illustration of Matched-Applicant Groups (Position Held Constant)

Match Group	Recruit Score	Top 5 Offers Team-average	Group Count	Position	School Choice	School Selectivity Score	Year
1	84.17	82.48	5	WR	Kentucky	81.29	2008
1	84.62	84.97	5	WR	Stanford	87.83	2011
1	85.56	84.15	5	WR	Michigan State	83.75	2008
1	84.97	83.09	5	WR	Houston	82.6	2013
1	85.76	82.88	5	WR	USF	78.5	2006
2	83.33	78.52	6	LB	Nevada	75.24	2005
2	80.62	78.12	6	LB	Utah State	78.12	2012
2	82.19	79.58	6	LB	Boston College	80.98	2013
2	83.33	78.93	6	LB	Wake Forest	76.58	2004
2	81.11	79.13	6	LB	N. C State	82.15	2006
2	81.11	77.99	6	LB	Iowa State	82.28	2009
3	98.17	87.81	3	QB	LSU	89.84	2003
3	97.40	86.53	3	QB	Washington	82.83	2006
3	98.06	86.93	3	QB	Missouri	85.82	2008
4	99.24	88.25	2	QB	Michigan	90.09	2004
4	99.27	89.63	2	QB	Penn State	86.2	2013

Notes: Each row of this table shows a hypothetical player is first matched into groups by position. They are then parsed into groups based on a narrow range of their own recruit score, and then matched into groups by a narrow range of the team-average recruit score from their top 5 offers. Specifically, recruits were split by nine different position groupings. From there, they were parsed into dummy groups by their recruit score with an average spread of 2.57 points (or 0.36 of a standard deviation) within groups. These groups were further matched on team-average recruit score of their top 5 offers with an average spread within the group of 2.11 points (or 0.48 of a standard deviation). This generated a total of 316 matched dummy sets over the 2,470 recruits in the sample.

4.4 Career Placement Using NFL Draft Results

Is there a career placement premium from attending a more elite football program once NFL employers have assessed the pool of job applicants at the NFL Combine? Recall from section 4.2 that there is evidence more selective football programs provide additional value-added in the probability of being drafted into the NFL, albeit seemingly small. One can assume that the high cost of putting on the NFL Combine is an attempt to avoid draft busts by gaining additional information at the individual level. The following section estimates the value-added from school quality on NFL draft order. Table 8

presents summary statistics for the subsample of FBS recruits who were selected into the NFL draft up until the year 2020. I constructed 303 matched-applicant dummies which holds position constant within groups in the same way described in section 4.3.[32]
Table 9 displays the OLS regression results for the value-added equation on overall draft order.[33] A basic model without controls for pre-college ability or selection bias show a statistically significant improvement in draft order from attending a more elite football program. The results from the naïve regression in column 1 state that a 1 standard deviation increase in school selectivity is associated with a 12.5 spot improvement in draft position. For context, using the 2011 rookie pay scale, a mid-3rd round improvement of 12 spots increases the rookie contract value by about $280,000. Column 2 adds the player's recruit score to the model and the value-added coefficient on school quality decreases by over 80% and is not statistically different from zero. The regression in column 2 states that a 1 standard deviation increase in a player's own recruit score improves their overall draft order by 16 spots, on average. Column 3 shows that pre-college physical characteristics such as high school BMI no longer enter the model with statistical significance as they did in the regressions from the previous sections. This is evidence that NFL employers have been updated on new information at the Combine and the older information is no longer correlated with outcomes. By not explicitly controlling for the updated information that happened during a player's college tenure, it allows the latent variable for school quality (i.e. *team-average recruit score)* to pick up any potential

[32] The parsing of *recruiting score* within each matched group have an average spread of 2.45 recruiting points, or 0.34 of a standard deviation. The parsing of *average recruiting score of the top 5 offers* within each matched group have an average spread of 1.75 points, or 0.4 of a standard deviation.
[33] The lower the number the better the outcome; 1st pick overall being the most rewarded and 256 being the least.

value-added attributed to the school's football program. However, the regressions in columns 2 and 3 do not provide evidence of any labor market returns attributed to attending a more selective football program.

Table 8 Summary Statistics: FBS Recruits in NFL Draft

	Full Sample					Restricted Sample				
	N	Mean	Std. Dev.	Min	Max	N	Mean	Std. Dev.	Min	Max
Draft and Combine variables										
Overall pick	2,000	118.69	73.73	1	256	1,905	118.67	73.60	1	256
Force	1,711	50.90	3.99	35.7	66.1	1,633	50.96	3.93	35.7	66.1
BMI at Combine	1,805	31.37	4.35	22.6	44.7	1,723	31.36	4.33	22.6	44.5
40 yard dash time	1,711	4.74	0.30	4.2	5.9	1,633	4.74	0.30	4.2	5.9
Average acceleration	1,711	1.64	0.20	1.1	2.1	1,633	1.65	0.20	1.1	2.1
Height at Combine	1,805	73.92	2.64	65	81	1,723	73.90	2.65	65	81
Weight at Combine	1,805	245.17	44.57	166	358	1,723	244.97	44.57	166	358
School Quality										
Team-average recruit score	2,000	85.59	4.68	71.7	96.4	1,905	85.71	4.62	71.7	96.4
Ability and Screening Panel Covariates										
Own recruit score	2,000	87.75	7.18	70	100	1,905	87.97	7.08	70	100
Top 5 offers team-average	2,000	85.03	4.44	71.7	93.2	1,905	85.13	4.37	71.7	93.2
BMI in HS	2,000	28.18	4.38	18.8	46.3	1,905	28.18	4.38	18.8	46.3
height in HS (inches)	2,000	74.35	2.56	66	82	1,905	74.34	2.57	66	82
weight in HS (lbs.)	2,000	222.69	42.76	141	361	1,905	222.63	42.85	141	361
Offers received	2,000	7.78	6.81	1	49	1,905	7.95	6.84	1	49
Rejection-rate	2,000	0.21	0.25	0	1	1,905	0.21	0.25	0	1
Official visits	2,000	1.23	1.17	0	5	1,905	1.24	1.18	0	5
Chose in state school	2,000	0.46	0.50	0	1	1,905	0.46	0.50	0	1
Ivy interest	2,000	0.03	0.25	0	5	1,905	0.03	0.25	0	5

Notes: Table includes recruiting cohorts between 2003 and 2015 and draft year outcomes up until 2020.

Table 9 OLS Estimates on Overall Draft Pick

Selection control	None	Recruit score		Matched-applicants			
	1	2	3	4	5	6	7
Team-average recruit score	-2.681*** (0.370	-0.128 (0.568)	0.00801 (0.686)	-1.658** (0.836)	-1.548* (0.848)	-1.492* (0.841)	-0.664 (0.781)
Recruit score		-2.265*** (0.360)	-2.315*** (0.444)			-4.781** (1.925)	-4.083** (1.907)
bmiHS			4.384 (6.005)		2.849 (6.715)	3.797 (6.638)	11.59 (7.110)
bmiHS2			-0.0874 (0.0908)		-0.0499 (0.100)	-0.0595 (0.0997)	-0.137 (0.108)
bmiHS*pos			0.168 (0.256)		-0.00339 (0.319)	-0.0404 (0.313)	-0.191 (0.311)
Visits			-0.991 (1.581)		-2.005 (1.774)	-1.854 (1.763)	-2.287 (1.776)
In state			-3.288 (3.358)		-4.109 (3.263)	-3.944 (3.270)	-3.855 (3.556)
Ivy interest			1.877 (5.556)		5.818 (4.358)	5.600 (4.439)	4.943 (3.597)
Offers			2.299*** (0.690)		2.700*** (0.839)	2.545*** (0.847)	1.935** (0.905)
Offers2			-0.0385** (0.0191)		-0.0498** (0.0234)	-0.0472** (0.0232)	-0.0252 (0.0251)
Rejection Rate			9.273 (6.364)		16.32* (8.526)	14.00 (8.782)	1.731 (8.663)
Top 5 offers team-average			-1.088 (0.960)		0.933 (3.181)	1.360 (3.222)	1.356 (3.400)
Force							-5.625*** (0.595)
State FE	x	x	x	x	x	x	x
Position FE	x	x	x	within	within	within	within
Constant	303.3*** (95.75)	288.5*** (94.73)	319.1*** (98.97)	335.0*** (69.27)	218.4 (274.0)	508.1* (294.7)	497.2 (308.9)
N	2000	2000	2000	1,905	1,905	1,905	1,633
adj. R^2	0.047	0.068	0.069	0.157	0.166	0.170	0.205

Notes: Standard errors in parentheses. Data from recruiting cohorts 2003 - 2015 and draft years up to 2020. All models include FE for player home state and position. Position is held constant within the matched-applicant groups. That is, every dummy category is matched on the same position for a similar recruiting score measuring pre-college ability and are further parsed into groups with similar scholarship offers measured by average school selectivity of the recruit's top five offers. Year FE were dropped from the draft pick model due to a lack of significance given a standard F-test. Position FE were marginally significant and often failed a standard F-test once excluding the position for Kicker. However, given the strong intuition to control for position and maintaining consistency between models and methods, position FE were left in the estimating equation. Standard errors clustered at team level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Columns 4 – 7 implement the matched-applicant model using 303 groupings of pre-college ability fixed effects while holding position constant within groups. The model in column 4 only uses the ability dummies and state level fixed effects. The coefficient on *team-average recruit score* is nearly 60% the size from column 1 and statistically significant at the 5% level. The estimates decrease slightly in magnitude as more pre-college individual characteristics enter the model, but become marginally significant at the 10% level. Interpreting the school quality coefficient in column 6 suggests the premium from attending a more selective football program is a 7 spot draft improvement given a 1 standard deviation in *team-average recruit score*. The value-added effect is not immaterial considering the large average payout draft order is associated with, however, it is marginally insignificant at conventional levels and warrants a cautious interpretation.

Given the results in Section 4.3, we know that NFL employers have updated information through a standardized college exit exam that is the NFL Combine – particularly along the strength and conditioning measure of *force*. Additionally, we found strong evidence that this measure was not correlated with variations in school quality and is driven by one's own pre-college individual ability characteristics; thus, it is not appropriate to let the *force* variable remain in the error term and be absorbed by the latent variable for college quality. Column 7 allows *force* to enter the model, and in turn, the value-added to attending an elite football university decreases to ¼ of the size from column 1 and is not distinguishable from zero. Both *force* and *recruit score* remain statistically significant and economically important.

If NFL employers are not incorporating the objective information they learn at the Combine, then it is likely the case that attending an elite football program can generate some marginal gains in the NFL draft, as indicated in columns 4 – 6 of Table 9. If NFL teams do utilize the Combine information, then there is no evidence of value-added from school quality as indicated by draft outcomes. That being said, this evidence was conditional on receiving a Combine invite to begin with, which was shown in Section 4.1 to have a causal impact, albeit small, through school selectivity. In other words, even if NFL employers are able to objectively sort out the talent through the Combine and utilize the information in the draft, there may still be a positive effect on career outcomes attributed to school selectivity if selection into the Combine is due to market distortions created by university football programs.

4.5 Evidence of Market Distortions

Lastly, Table 9 shows a statistically significant and robust counterintuitive sign on the coefficient for number of scholarship offers received during the recruiting process. This does not appear to be a one-off specification error since the sign on both the number of *offers* and *top 5 offers team-average* have been working in the opposite direction of positive outcomes throughout the analysis. This suggests that high school players who are more heavily recruited by university coaches are associated with worse draft results, holding school quality and raw-ability measures constant. The results in column 7 imply that a highly sought after recruit who receives an additional 7 scholarship offers (i.e. a 1 standard deviation increase) can expect to fall in the draft by 13 spots. It's worth speculating on these coach's assessment variables from the admission screening data since the effect is robust and highly significant across the draft specifications, as well as having some corroborating evidence of a similar pattern in Table 3 (see columns 6 and 7) and Table 6 (see columns 4, 6, and 7).

It could be the case that the extra recruiting attention these individuals receive are ego inducing, which Castro-Sánchez et al. (2018) have shown to detract from athletic performance in a team setting. That said, the R-squared for emotional intelligence is not particularly high in the determination of overall athletic performance and it would be surprising for the single dimension of ego to emerge as such a strong effect. It could also be the case that the increase in *offers* were awarded because of valuable intangible skills, such as emotional intelligence, observed by the university recruiting staff despite lower physical ability traits. However, it is likely the case that NFL programs would also reward those same intangibles, so the compensating intangible skills theory seems to be an unlikely explanation for the counter-intuitive effects associated with *offers* and *top 5 offers team-average*. A more likely (and economic) explanation considers the incentive structure of the recruiting process. If highly sought after recruits are agglomerating into more selective programs, and those programs have a fixed capacity in which to put their talent to use, then elite teams can essentially hoard the more valuable players. Since there are indeed a fixed number of games, positions, players on the field, and years of NCAA eligibility, it is likely the case that the more highly prized talent are – literally – sitting on the sidelines rather than putting their resources to best use. If elite university football coaches are selling high-school recruits on the idea that playing for their program is in their best interest for reasons causal of their program's quality, then the evidence above suggests that such a marketing ploy is a disingenuous claim. The commanding share of labor market outcomes are attributed to pre-college ability a recruit brings to the football program to begin with.

CHAPTER 5: DISCUSSION AND CONCLUSION

The evidence here indicates that college football recruits receive limited value-added from attending a more selective football university. The results come in 3 parts. First, the average football recruit who chooses a more selective football university enjoys a small increase in the probability of receiving an invitation to the NFL Combine. It is not clear on how much the small marginal increase in probability translates to in the labor market, or if the effect is nothing more than a short-lived signal once labor market experience comes into play. Second, there are no measurable premiums from attending a more elite football university on the strength and conditioning measure of *force*. More selective schools are not turning out faster and stronger athletes above and beyond what less selective schools would have done, once controlling for the athlete's baseline skill level. Football is an incredibly physical job and the data show that physical force is statistically and economically important in the recruit's career prospects – arguably the most important considering the NFL pays a steep price just to assess at the Combine. Third, results from Table 9 show that if NFL employers fully factor in the objective skills tests they observe at the Combine, then there is no value-added to draft outcomes from attending an elite football university. However, NFL employers are not purely objective decision makers. Massey and Thaler (2013) provide statistical evidence that NFL teams consistently over-value top draft prospects relative to the player's later observed professional performance outcomes.[34] Given this, it is unlikely that NFL teams are looking at a purely objective world described by column 7 in Table 9, despite having a multi-million dollar incentive to do so. It's more likely the case they are looking at the signal of school quality described by column 5 or 6 in Table 9, or something in between. If players from elite football institutions systematically end up going earlier in the draft due in part to school quality signals as opposed to objective performance measures, then they will likely end up being overvalued on the field. If this is the case, then it is a reasonable explanation to the results in Massey and Thaler (2013).

The evidence presented here also indicates a negative effect specifically for highly recruited players, holding ability and school quality constant. This suggests that there is something in the institutional design of the college football recruiting process that is making highly sought after players worse off. In particular, the NCAA's win-maximizing incentive structure (as opposed to the NFL's maximizing league-wide profits incentive structure) described in Fort and Quirk (2004) and Kesenne (2006) theorizes that the larger market college football programs will indeed hoard talent because it is financially in their interest. It isn't unreasonable that any team would want to do that, however, it is unreasonable that the NCAA punishes their student-athletes when they attempt to move to a team that will better utilize their hard earned talents. Sutter and Winkler (2003) provide evidence that the more elite football universities tend to vote for more restrictive price and quantity controls, such as capping the number of scholarships and limiting compensation, because it reduces competitive balance for smaller market teams. Restricting players from transferring schools keeps other schools from gaining

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[34] The researcher's advice is that NFL teams should more readily trade away their early picks for later ones because they are likely to end up with an over-valued player.

talent and becoming more competitive. Furthermore, this restraint of trade lowers overall welfare in the market, not just for athletes, but also the spectators, universities, and communities that the athletic departments are financially tied in with. Several economists have elaborated on the negative externalities created by the NCAA cartel structure (Becker, 1987; Eckard, 1998; Kahn, 2007; Humphreys and Ruseski, 2018), and several other authors have expanded on the “arms race” for athletic talent that exist within the university system (Grant et al., 2014; Clotfelter, 2011). The overarching economic issue is that the price mechanism is not allowed to work in the college athlete’s favor, so universities precariously expend resources to indirectly woo athletic talent – typically on sunk and high fixed cost expenditures. Universities that are hindered from competing for talent due to restraints on trade can’t compete for wins and revenues, and thus unable to spend at the levels to attract top recruits. If athletes believe their future success is related to university athletic spending, then they are more likely to see their set of options as more limiting to the fewer amount of schools who can afford to signal an elite status. However, the evidence presented here suggests that the objective labor market characteristics the NFL is looking to employ is not deterministic on school status and heavily recruited players may benefit from not choosing the more selective school. The idea that more heavily recruited athletes are made worse off, holding talent constant, may be a symptom of the NCAA cartel structure.

Lastly, it should be made clear that the literature and evidence discussed above in no way suggests that academic or athletic education is unimportant, however, the evidence merely suggests that a more elite university does not systematically produce human capital gains at a higher level than a less elite institution. This research adds to the body of evidence that it is indeed important to have put oneself in a position to be accepted by a selective university, but it isn't important to actually attend an elite university. It does appear that some signaling effects from high resource schools do benefit the players who choose to attend those institutions. The measurable premiums in the college football labor market is small and marginal, which is in-line with the signaling effect found with academic institutions, which tend to be short lived.

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