Do the Rich Get Richer?
Competitiveness in the Student-Athlete Market under NIL

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The introduction of Name, Image, and Likeness (NIL) rights within college athletics has sparked a significant debate about the future of college sports. This article investigates the impact of NIL on the recruitment of high school football players to college programs, with a particular focus on whether the new policy leads to an increased concentration of talent among top-ranked institutions, potentially disrupting competitive balance. Our empirical analysis draws from a dataset that encompasses pre- and post-NIL recruitment patterns to examine the distribution of 3, 4, and 5-star recruits in different levels of football programs. Our findings suggest a nuanced impact of NIL on recruitment. Contrary to the hypothesis that NIL would lead to a "rich get richer" dynamic, our results indicate a notable increase in the dispersion of talent. Post-NIL, we observe a tendency for lower-ranked football programs to attract higher-quality recruits, especially among 5-star and 3-star athletes. This trend is consistent across various model specifications and robustness checks. For college sports stakeholders, from administrators and coaches to fans, these findings underscore the potential of NIL to enhance the competitiveness of college football. Our analysis informs strategic decision-making by athletic programs and offers a template for other industries where non-pecuniary benefits and brand associations play significant roles in talent acquisition and retention. Ultimately, this study offers a comprehensive examination of NIL's short-term effects on competitive balance and sets the stage for ongoing research into the long-term consequences of this landmark policy change.

Keywords: Assortative Matching, College Football, NIL

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1 Introduction

"You're going to create a caste system where the rich will get richer and the poor get poorer"- Nick Saban on NIL, in a March 2024 congressional hearing[1]

The introduction of Name, Image, and Likeness (NIL) rights in July 2021 has catalyzed fervent discourse in sports media regarding its impact on collegiate athletics. Before this time, student-athletes were not allowed to earn money for any use of their name, image, or likeness. Yet, in 2019, Division 1 university athletic departments generated more than $15.8 billion in revenue.[2] With NIL now permissible and with student-athletes such as the 2022 Heisman Trophy winner Caleb Williams earning roughly $10 million in NIL money at USC, critics have begun to speculate that NIL could exacerbate existing disparities within college sports, enhancing the dominance of already prosperous programs. The central concern is whether NIL arrangements could create an uneven playing field in which top-tier football programs leverage the wealth of their alumni to accumulate elite talent. On the contrary, proponents argue that NIL democratizes player recruitment by offering athletes from all ranks more control over their economic prospects, potentially dispersing talent more evenly across programs. How future student-athletes sort among college programs has enormous consequences for program profitability, entertainment value, and competitive balance in college athletics.

In this paper, we focus on the impact that NIL has had on the largest college sport, American football. College football is the ideal setting due to large roster sizes and being a predominantly American sport.[3] Specifically, we seek to determine whether more top-rated football recruits are matching with the top-tier football programs after NIL. Simply put, has NIL led to the "rich" (the top-tier programs) getting richer (in talent)?

We determine that the "rich" are NOT getting richer. Instead, we see an extensive increase in the mixing of recruits. Lower-ranked programs match more with higher-quality players in a post-NIL world, so NIL decreases the degree to which matching is positively assortative. This holds for all but the local measure of three- (3*) and four-star (4*) recruits matching with programs ranked

[1] `https://theathletic.com/5339689/2024/03/13/nick-saban-nil-college-sports-congress/?campaign=9248378&source=untilsaturday_newsletter&userId=437916`

[2] https://www.pbs.org/newshour/economy/analysis-who-is-winning-in-the-high-revenue-world-of-college-sports

[3] NIL is less applicable to international students because of visa restrictions. For example, `https://www.espn.com/mens-college-basketball/story/_/id/39882011/purdue-zach-edey-missing-profits-due-us-nil-law`

outside the top 10 or in the aggregated case of those outside the top 25. Our results further show that post-NIL five-star (5*) recruits choose schools with worse historical performance. They take advantage of their existing talent and celebrity status, choosing the most profitable NIL contract while minimally sacrificing player development, as these athletes have a 59% probability of being drafted into the NFL.[4] We find behavior from 3* recruits that is also consistent with maximizing NIL money - they choose schools with worse historical performance, weaker recruiting classes, and lower coach pay post-NIL. Unlike 5* recruits, 3* have a much lower probability of making it into the National Football League (6.9%), so they look to capitalize with NIL money rather than develop their skills to increase their NFL draft chances. We thus determine that NIL is likely beneficial for the competitive balance of college football.

The implications of NIL extend beyond collegiate athletics and should be relevant to hiring managers, who can view NIL as a natural experiment in labor markets characterized by significant non-wage benefits and restrictions. Studying NIL provides insights into the choices workers make when wage-like payments become available, contributing to a broader understanding of how workers value immediate financial compensation versus nonpecuniary benefits. Additionally, our findings can be applied to labor markets where talent development is necessary to maximize delayed payoffs, such as the market for doctoral students.

The academic literature on labor economics is a suitable starting point for our research. We draw from this literature to understand student-athlete behavior and infer its impact on the competitiveness of college football. Recognizing the similarities between college football recruiting and labor matching with firms is important. Just like workers and firms, the sorting of athletes amongst football programs matters for the production of output (wins). The similarities also extend to the marriage markets, where "the degree of homogamy in marriage - defined as people's tendency to'marry their own' - has important consequences for family inequalities and intergenerational transmission of human capital" (Chiappori et al. (2021)). Given this connection, our initial research leverages the literature on the measurement of assortative matching to assess the degree of sorting that occurs within college football.

We also pull from the treatment effect literature to dive deeper into the effects of NIL. This line of research allows one to assess the causal impact of interventions or treatments on the outcomes

[4]From our own analysis in Section 3.1

of interest. By employing numerous methodologies (regression models, propensity score techniques such as doubly robust augmented IPW (AIPW), and matching procedures), we ensure that we determine the causal impact of the NIL policy change. Leading research in this field originates from the pioneers of Rubin (1974), Rosenbaum and Rubin (1983), and Imbens and Angrist (1994). More recently, advances from Ho et al. (2007) have showed the value of preprocessing data to reduce the model dependence in parametric causal inference. Hansen (2004) illustrates the value of complete matching in understanding the impact of coaching on SAT scores. Athey et al. (2019) and Athey and Wager (2021) present an approach on how to estimate conditional means and propensity scores using random forests, which allows research to take a non-parametric position on how the model characteristics X affect both.

In addition to the methodological research, we highlight several important papers in the field of the economics of sports. The first is David Romer's paper on whether or not firms profit maximize (Romer, 2006). He leverages data and evidence from Professional Football to address this question. Chung (2013), which empirically investigates the "Flutie" effect to determine the relative importance of a school's athletic success compared to other factors on admissions. Papers from Chung et al. (2013) and Derdenger et al. (2018) study athlete endorsements with Chung et al. (2013) addressing the simple question of whether endorsements have a causal impact on product sales by shifting consumer behavior. Derdenger et al. (2018) "investigates how [athlete] endorsements affect consumer choices during new product introductions, the roles of planned advertising and unplanned media exposure, and how firms can strategically leverage the unplanned component" to increase new product sales.

2 Institutional Detail

2.1 Name, Image, and Likeness (NIL)

Name, Image, and Likeness (NIL) in college athletics refers to the ability of student-athletes to profit from their name, image, and likeness while maintaining their eligibility to participate in collegiate sports. Athletes profit from their NIL by signing sponsorship deals with brands and local businesses, exchanging social media posts or advertising appearances for money. Colleges and their collective of boosters (i.e. super fans/donors) facilitate these deals for athletes. Traditionally, National Collegiate Athletic Association (NCAA) rules prohibited athletes from earning compensation beyond their scholarships and stipends, citing the preservation of amateurism as a fundamental principle of college athletics.

NIL opportunities encompass a wide range of potential income streams for student-athletes. These include endorsement deals with brands, appearances, autograph signings, social media sponsorships, and monetization of personal merchandise or content. With the rise of social media platforms and influencer marketing, student-athletes have become increasingly valuable assets for brands seeking to reach young and engaged audiences. In addition, it has allowed student-athletes to leverage their athletic achievements and social media presence to generate income and pursue entrepreneurial opportunities.

To put the monetary potential of NIL in perspective for the reader, Arch Manning, who attends the University of Texas at Austin and is the nephew of famed QBs Eli and Payton Manning, has an estimated NIL valuation of $3.8 million. Manning is ranked above the likes of former USC quarterback Caleb Williams ($2.6 million), CU Buffs QB Shedeur Sanders ($1.6 million) and former Ohio State receiver Marvin Harrison Jr. ($1.3 million).[5] Just how much is this? The starting QB for the Super Bowl runner-up San Francisco 49ers, Brock Purdy, earned $870,000 in 2023. NIL is not only for 5* recruits. A 4* receiver landed a deal that will pay him more than $1 million over the next four years in exchange for his exclusive NIL rights. Furthermore, a 3* defensive tackle secured $500k over four years for his NIL rights.[6]

Below, we provide a timeline covering key events leading up to the regulation of Name, Image, and Likeness (NIL) in college athletics.

- March 9, 2019: The NCAA announces the formation of a working group to examine issues related to the name, image, and likeness of student-athletes.
- October 29, 2020: The NCAA Division I Council introduces proposed NIL legislation, but delays voting.
- June 21, 2021: The US Supreme Court delivers its ruling in NCAA v. Alston unanimously affirms a lower court decision that the NCAA's restrictions on education-related benefits for

[5] https://broncoswire.usatoday.com/2023/02/17/highest-paid-nil-athletes-arch-manning-bronny-james/
[6] https://theathletic.com/3256808/2022/04/19/college-football-recruiting-nil/

college athletes violate antitrust laws.

- June 30, 2021: The NCAA Board of Governors adopts an interim NIL policy that allows athletes to profit from their name, image, and likeness without jeopardizing their eligibility. This move is partly in response to the impending implementation of various state NIL laws.

- July 1, 2021: NIL laws go into effect in several states, including Alabama, Florida, Georgia, Mississippi, and New Mexico, allowing college athletes to profit from their name, image, and likeness.[7]

The important date is July 1, 2021. We use this policy intervention to study the impact of NIL.

2.2 College Football and Recruiting

College football is one of the largest sports in the United States and the single largest revenue driver in collegiate athletics. In Division 1 FBS, the highest level of collegiate competition, the average school generates $31 million dollars in revenue per year from college football.[8] This is more than the revenue generated by the next 35 largest college sports combined.[9] In 2017, college football was responsible for at least $4 billion in revenues in D1 FBS alone, a number that has certainly grown since then as media deals and the college football playoff have expanded. Moreover, these numbers do not account for the indirect benefit college football has on local economies and businesses through increased tourism. Among all Division I athletics, $15.8 billion in revenues were generated in 2019 according to the NCAA.[10]

Participation in football at the high school and college level is high. More than 1 million high school students participate in football each year in the United States[11]. More than 75,000 of these high school athletes end up playing football at some level in college; 30,000 of them compete in Division 1 (D1), and 20,000 compete in Division 2 (D2). Table 1 provides some characteristics of

[7] These laws were to force the NCAA to permit NIL for athletes. It is important to note that it was not illegal to make profit from your NIL in any state. Rather, if one did so before the June 30th NCAA decision, a student-athlete would be ruled ineligible for competition.

[8] Revenue streams include ticket sales, merchandise, TV media rights, etc.

[9] https://www.businessinsider.com/college-sports-football-revenue-2017-10

[10] https://www.pbs.org/newshour/economy/analysis-who-is-winning-in-the-high-revenue-world-of-college-sports

[11] https://ncaaorg.s3.amazonaws.com/research/pro_beyond/2020RES_ProbabilityBeyondHSFiguresMethod.pdf

college football in D1 and D2.[12].

	Division 1	Division 2
Teams	254	170
Players	30,722	20,414
Scholarships Per Team	85	63

Table 1: Characteristics of D1 and D2 college football programs

Athletes are sorted into colleges through a practice known as recruiting. A highly simplified explanation of recruiting is as follows. College coaches (assistant or head) allocated their limited time to visit high schools throughout the high school football season and scout potential recruits.[13] If a school likes an athlete enough, they can make an offer. Athletes then decide which school they would like to attend given their offers. Before NIL, this decision could be based on coaching, scholarships/academics, facilities, playing time, and other nonpecuniary factors. After NIL, money could also be used as a deciding factor. To help make their decision, athletes can visit interested schools on a limited basis.[14]

The recruiting process is extremely decentralized and difficult for fans (and even coaches) of schools to keep track of. As a result, over the past few decades, third-party websites have established themselves in the grading and ranking of high school recruits. These websites include *Rivals, 247Sports, ESPN,* and more. Each website independently rates and ranks thousands of high school football players yearly. The website *247Sports* assigns a *247 Composite Score* to each player, aggregating ratings across all major recruiting websites into one consensus score for each player on the interval $[0, 1]$. The 247 Composite score can then be ordered to determine the top recruits in each high school class.

Traditionally, recruits have been subdivided into a discretized five-star system that assigns a star rating based on the perceived quality of the recruit. Five-star recruits are foundational building block players for a college football program. These players have an excellent chance of becoming a professional football player in the National Football League (NFL). 59% of 5* high school football recruits end up being drafted by an NFL team (Table 3). Four-stars are slightly less prestigious

[12] `https://www.ncaa.org/sports/2018/10/10/ncaa-sports-sponsorship-and-participation-rates-database.aspx`

[13] Colleges are constrained on which months and the number of days they can use to visit high schools

[14] Before April 13, 2023, athletes were limited to 5 school visits. Today, athletes can visit unlimited schools, but are still restricted to one visit per school. `https://www.ncaa.org/news/2023/4/13/media-center-di-council-adopts-proposal-for-student-athlete-representation.aspx`

than five-stars, but are still considered excellent prospects. Three-stars are good players that may develop into solid players at the college level. Two-stars and below rarely make it to the NFL. The 247 Composite Score maps onto the five-star scale. Table 2 shows the number of recruits grouped by stars in each year according to the 247 Composite Score: Assuming 20,000 of the 75,000 athletes

	Year	3 Stars	4 Stars	5 Stars
Pre NIL	2017	1856	320	33
	2018	1955	347	29
	2019	2292	388	34
	2020	2604	378	32
Post NIL	2021	2083	365	35
	2022	1707	392	34
	2023	1826	411	39
	2024	2048	440	37

Table 2: Number of 3, 4, and 5-star recruits each year

are freshmen,[15] four and 5* recruits compose the top 2-3% of all high school recruits; including 3* recruits we have about the top 10% of high school recruits. To put things into perspective, about 250 college players are selected each year to become professional football players through the NFL Draft. So while the dream of many high school and college football players is to play professionally, the reality is often very different.

2.3 College Football Division I FBS

Division I Football Bowl Subdivision (FBS) is the highest level of college football in the United States. We provide additional context on D1 FBS because over 99% of 3* or better recruits end up in a D1 FBS program. As of the 2024 season, there are 134 teams split into 10 conferences in D1 FBS. The five historically most dominant and the largest, most athletically-relevant D1 FBS conferences during this period were called the "Power 5" conferences. They consisted of the Southeastern Conference (SEC), Big Ten, Big 12, Pac-12, and the Atlantic Coast Conference (ACC).[16]

The FBS season begins in late August or early September, with each school playing just one game per week, usually on Saturdays. Most FBS schools play 12 regular season games per year,

[15] Given an average of four years of college and students quitting to focus on academics as they get older, this number is likely a conservative estimate

[16] The Pac-12 has dissolved with notable schools like USC and UCLA leaving for the other Power 5 conferences

with eight or nine of those games coming against intra-conference schools. After the regular season games, each conference selects the two teams with the best intra-conference record to play in a conference championship game. Once the conference champions are decided, a third-party committee chooses their perceived four best teams in the country to compete in the College Football Playoff.[17] The four teams compete in a semi-final game and then the championship game to determine the national champion.

Crucial to our analysis, coaches and media outlets rank who they believe are the top 25 college football teams after each week, including after the national championship game. These rankings are aggregated into two main polls: the Coaches' Poll and the Associated Press (AP) Top 25 Poll. D1 FBS teams are the only teams that have ever been ranked, even though theoretically non-D1 FBS teams can also be ranked. A team rank 1 implies that they are the best in the country, while teams below the top 25 are not ranked. Rankings are sticky within a season; a team's rank in week $t + 1$ is heavily dependent on their rank in week t, but ranks reset at the beginning of the next season. For the purposes of this paper, our analysis uses just the AP rankings after the national championship game. We refer to a team being "Top X" if the team is ranked X or better in the previous season. For example, if a class of 2024 recruit chooses a top 25 school, then that school was ranked 25 or better at the end of the 2023 college football season.[18]

2.4 Data

Our data comes from the College Football Data API which scrapes *247Sports*. Figure 1 shows the available data, including the location of the high school athlete, physical attributes, rating, choice set of schools, and school decision. We have additional data on each recruit's outcomes in the NFL draft, and have data on each school's historical performance and rankings, location, and facilities. College football coaching salaries come from USA Today. We augment our data with DMA-level data on DMA rankings and number of households.

Our data sample is split into two periods: three recruiting classes before the NIL policies went into effect (2018 - 2020) and three recruiting classes after the NIL policies went into effect (2022 - 2024). We start with the class of 2018 because that class was the first class affected by major

[17]This playoff expanded to 12 teams in the 2024-25 season.

[18]Note: the national championship game for the 2023 season is played in January 2024.

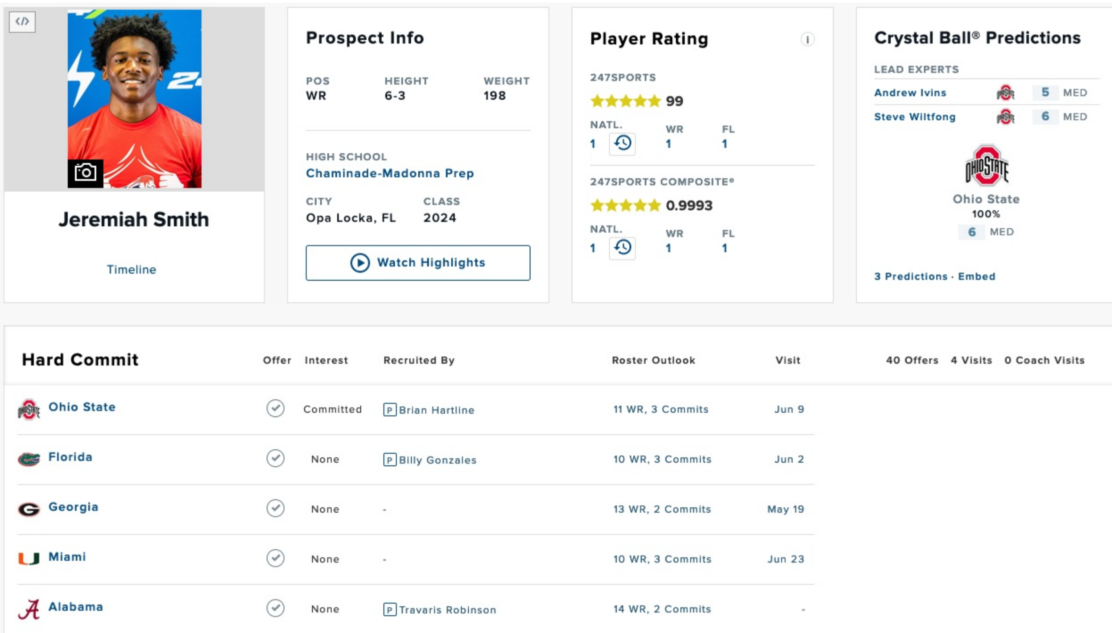

Figure 1: A screenshot of the *247Sports* website for Jeremiah Smith, the #1 ranked recruit in the class of 2024. Everything observable in this screenshot is available in our data.

recruiting changes implemented in 2017.[19] These changes, including the introduction of an early signing period in December the year before graduation as well as another visiting period, greatly impacted how schools could influence recruits' choices. We dropped the class of 2021 which was most affected by COVID. Many school visits were canceled late 2020 and every collegiate conference had different rules regarding the COVID-affected seasons.[20] We also drop international recruits, Army/Navy/Air Force commits, and rated prospects who ultimately committed to another sport. Lastly, we filter on recruits 3* or above because 247Sports stops ranking two-star and one-star players in this period. Our cleaned data set has over 13,000 recruits spread over six recruiting classes.

[19]See `https://www.ncaa.com/news/football/article/2017-04-14/college-football-di-council-adopts-new-recruiting-mo`

[20]Meanwhile, class of 2020 recruits had already committed to colleges in December 2019 and February 2020 before COVID restrictions were implemented.

3 Competitive Effects from NIL

3.1 Theory: Impact of NIL

To understand the possible impact of NIL, we provide a scholarship choice model for high school recruits. We ignore the college program's choice of whom to offer scholarships to as college football programs are unable to work with NIL collectives to offer NIL contracts or guarantee any monetary income from those contracts. Thus, NIL regulation has not changed the incentives of a college football program or the levers they can pull to recruit. Its objective has remained constant, that is, to field the best possible team.[21]

We now present our theoretical choice model and make several simplifying assumptions from the above setting to articulate the new NIL forces in a college choice decision. A high school recruit i of quality $q_i \in (5*, 4*)$ receives scholarship offers from two college football programs. A program's quality is $R_t \in (h, l)$ and captures the ranking of a program. Program 1 is initially of high quality (h) and can be thought of as being ranked in the top 25 in practice and program 2 is of initial low quality (l) (and is not ranked among the top 25) in period t. Recruits are forward-looking. They take an action $a_t \in 1, 2$ that indicates the program choice. For simplicity, we note the state variables as $z_t = (q_i, R_t)$ which includes player and program quality in period t, and where program quality is allowed to transition over time.[22] If recruit i decides to accept the scholarship offer from football program j in time period t, he obtains the utility given by

$$u_{i,j,t}(z_t, a_t) = f(z_t, a_t) + \beta \mathbb{E}[V_i(z_{t+1}|z_t, a_t)] + \epsilon_{i,j,t}, \tag{1}$$

where $f(z_t, a_t)$ is the flow utility associated with choice a in period t, $\beta \mathbb{E}[V_i(z_{t+1}|z_t, a_t)]$ represents recruit i's discounted expected future value of choice a_t in period $t+1$ conditional on being in state z_t, while β is the discount factor. We assume that the flow utility captures the prestige of the high-quality program (being ranked in the top 25 in practice). For any quality recruit, the flow utility associated with a low-quality (unranked) program is normalized to 0. Those same recruits,

[21] In 2024, the NCAA has allowed direct payments from schools to students. These changes occurred after the class of 2024 had committed to colleges.

[22] We do not explicitly model the transition here, but historically it has remained quite sticky (i.e. high quality teams usually remain high-quality and vice versa).

regardless of quality, value a high-quality (ranked) program at $\alpha > 0$.[23]

$$f(z_t, a_t) = \begin{cases} \alpha, & R_t = h \\ 0, & R_t = l \end{cases}$$

$\beta\mathbb{E}[V_i(z_{t+1}|z_t, a_t)]$ is an important term for our model, as it captures the discounted expected future value a recruit receives by playing on a high-quality (ranked) team in the future, his development over time in college and playing in the NFL. Finally, we view $\epsilon_{i,j,t}$ as the fit between recruit i and program j at time t.

We focus our attention on a high school recruit's first college decision at $t = 1$. Abstracting away from the player-program fit ($\epsilon_{i,j,t}$) for simplicity, we see that the initial choice of the program is driven in large part by the prestige of the program and the player's expected future value from choice a_1. A high school recruit will select the low-quality program ($a_1 = 2$) over the high-quality ($a_1 = 1$) when $u_{i,j,1}(z_1, a_1 = 2) > u_{i,j,1}(z_1, a_1 = 1)$ which leads to the condition of

$$\mathbb{E}[V_i(z_2|z_1, a_1 = 2)] - \mathbb{E}[V_i(z_2|z_1, a_1 = 1)] > \frac{\alpha}{\beta}.$$

Here the recruit will choose the initial low-quality program when the difference in the expected future value of attending the initial low-quality (unranked) program from the high-quality (ranked) program is greater than the prestige of attending a (ranked) high-quality program.

To glean insight into the sign of the left-hand side term, we analyze a player's likelihood of being drafted into the NFL based on his and the school's quality (Table 3). We construct a dataset with 10 years worth of NFL draft data (2012 - 2021),[24] tracking the universe of high school recruits 3* and above throughout college and into the NFL.[25] We observe their 247 Composite Score and star rating, the school they initially committed to, the last college they played football at before they were drafted or completed their eligibility, and when they were selected in the NFL Draft, if at all. Our empirical analysis indicates that conditional on player quality the difference in expected value

[23]See Table 14 in the appendix for empirical support that prior season performance is indicative of performance in the subsequent season.

[24]The most recent ten NFL drafts unaffected by NIL

[25]The universe of 3+ stars recruits according to 247Sports Composite Rating. We use three stars and above because we have all 3+ star high school recruits throughout the 10-year panel, but we do not necessarily have every recruit ranked lower than 3 stars.

Y: 1{Selected in NFL Draft}	3 Star	4 Star	5 Star
Height	0.115***	0.096**	−0.004
	(0.032)	(0.038)	(0.067)
Weight	−0.000	0.002	0.002
	(0.001)	(0.003)	(0.005)
School top 25 before recruit	0.441***	0.267***	0.109
	(0.078)	(0.103)	(0.244)
Num. obs.	13518	2980	323
Position FE	Y	Y	Y
Recruit Year FE	Y	Y	Y
Mean Y:	0.069	0.229	0.592

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 3: NFL Draft logit regressions by stars; 2012 - 2021 NFL drafts, all 3-5 star recruits from 247Sports

functions is likely either negative or near zero. For instance, conditional on player quality (star rating), 5* recruits do not benefit from an increased NFL draft probability by playing for a ranked program. 3* and 4* stars, however, do.[26] Such analysis would indicate that 3* and 4* recruits have an incentive to attend the highest quality school possible to increase their likelihood of being drafted into the NFL and thus their expected future value. For these recruits, $\mathbb{E}[V_i(z_2|z_1, a_1 = 1)]$ would be larger than $\mathbb{E}[V_i(z_2|z_2, a_1 = 2)]$. For 5* recruits, the difference in expected values appears negligible resulting in their decisions being driven by each player's prestige effect for ranked teams (α). Given our analysis, we hypothesize that players match with like-quality programs without NIL.

Under NIL, the state variables that enter the decision processes for a high school recruit change. High school recruits now also incorporate the impact of NIL income in their flow utility and in their expected value function. Naturally, NIL impacts their flow utility through multi-year NIL contracts at the time or shortly after signing with a college football program. NIL also impacts a recruit's future value through the potential of additional NIL contracts above and beyond the initial ones.

Below, we highlight the choice decision with NIL. The utility for player i with NIL now takes the form:

$$u_{i,j,t}(z_t, NIL_t, a_t) = h(z_t, NIL_t, a_t) + \beta\mathbb{E}[V_i(z_{t+1}, NIL_{t+1}|z_t, NIL_t, a_t)] + \epsilon_{i,j,t}, \qquad (2)$$

[26] Table 3

Where $h(z_t, NIL_t, a_t) = f(z_t, a_t) + g(z_t, NIL_t, a_t)$ includes the program prestige, $f(z_t, a_t)$, and the impact of NIL income, $g(z_t, NIL_t, a_t)$. Like before, the recruit must evaluate the differences in the expected value between each program, but with the added layer of NIL income. The choice of program 2 under NIL requires the following condition.[27]

$$\begin{aligned} &\underbrace{\frac{1}{\beta}\Big\{g(z_1, NIL_1, a_1 = 2) - g(z_1, NIL_1, a_1 = 1)\Big\}}_{\text{Difference in flow util as a function of NIL payments}} + \\ &\underbrace{\mathbb{E}[V_i(z_2, NIL_2|z_1, NIL_1, a_1 = 2)] - \mathbb{E}[V_i(z_2, NIL_2|z_1, NIL_1, a_1 = 1)]}_{\text{Difference in future value in presence of NIL}} > \frac{\alpha}{\beta} \end{aligned} \tag{3}$$

This condition differs from the earlier one without NIL in that the choice depends on the difference in expected values, $\mathbb{E}[V(z_t, NIL_t, a_t)]$, and the difference in NIL income, $g(z_t, NIL_t, a_t)$, across programs at time t. Moreover, the expected value functions differ from those presented without NIL. The sign of this difference and the difference in NIL income in period t is unclear. For high-quality 5* recruits, it could be the case that both are positive, which is attributed to the fact that the low-quality program could generate larger deals now and in the future for athlete i (e.g. due to being in a larger media market and/or valuing the player relatively more) and that the impact of program quality on NFL draft likelihood is statistically insignificant for 5* athletes. Both terms could also be negative, where the higher quality program with its "rich" collectives are able to incentivize top players to accept the program's scholarship offer with larger NIL contracts.

The difference in present and expected value terms is also unclear for 3* and 4*. For these athletes, program choice (quality) affects their chance of being drafted (it is positive and significant) and thus affects the expected future value terms. Yet, the probability of being drafted in the NFL is $\approx 7\%$ and $\approx 23\%$, respectively, indicating that the expected value terms are smaller than 5* athletes. But the arguments presented above for the impact of NIL on $\Delta\mathbb{E}[V(\cdot)]$ and $\Delta g(\cdot)$ for 5* recruits also hold for these 3* and 4* players, albeit likely on a smaller scale. Given this, the impact of NIL on program choice is empirically unclear.

[27] We ignore the error term again.

Table 4: Sorting Table 1

	Top 25	Rank>25
5* Recruits	α	β
4* Recruits	γ	δ

3.2 Assortative Matching

From the theoretical model above, it is unclear how NIL has impacted program choice for high school football recruits. To empirically study how the mix of recruits and football programs has changed due to the implementation of NIL, we draw from research on the measurement of assortative matching in the labor and marriage markets. This line of research is appropriate given the lack of NIL contract data. To illustrate how we approach such a question without NIL data, let us follow a similar model as above. There are two populations, recruits and college football programs, which are sorted according to quality levels. For recruits, quality is defined by star level (e.g. 4* or 5*) with a higher star level indicating higher quality. For football programs, teams are classified by quality. Programs are ranked in the top 25 or not. Below, we define assortative matching based on this 2 x 2 case.

For ease of reference, we assume that all recruits are matched. The matching of recruits and football programs is illustrated by a 2 x 2 matching table (Table 1). Note that $\alpha + \beta$ is the number of 5* recruits and $\alpha + \gamma$ is the number of recruiting openings within the top 25 programs. Moreover, α is the number of matches between the 5* football recruits and the top 25 football programs.

According to Zhang (2024) and Chiappori et al. (2021), Table 4 exhibits positive assortative matching if the number of matches amongst similar quality levels of recruit and football program (α or δ) is larger than what would be obtained under random matching. Random matching of recruits and football programs would generate $\frac{(\alpha+\beta)(\alpha+\gamma)}{\alpha+\beta+\gamma+\delta}$ number of matches between 5* recruits and top 25 programs. Positive assortative matching is present if $\alpha\delta \geq \beta\gamma$, which means that the number of 5* recruits that match the top 25 programs is larger than random sorting (similarly for 4* recruits that match programs outside the top 25). This means that there are more matches between like types than between mixed types.

Given our motivation is to understand how NIL has impacted the sorting of recruits and football programs, it is important to compare two sorting tables–one before and one after NIL–to determine whether one presents more assortative matching than the other. We rely on Zhang (2024) and Chiappori et al. (2021) again to identify appropriate indices for this comparison. Specifically, we employ the odds ratio as it is widely used in the economics literature and possesses properties that enable the index to capture the degree of assortativeness (e.g. scale-invariant, symmetry, monotonicity, and weak positive assortative matching). The odds ratio is quite simple. It takes the form of

$$I_o(\alpha, \beta, \gamma, \delta) = ln\left(\frac{\alpha\delta}{\beta\gamma}\right)$$

Finally, a table $(\alpha, \beta, \gamma, \delta)$ is said to be more assortative in its matching when the odds ratio is greater than that of an alternative table $(\alpha', \beta', \gamma', \delta')$.

$$I_o(\alpha, \beta, \gamma, \delta) \geq I_o(\alpha', \beta', \gamma', \delta') \tag{4}$$

Below, we present two tables and their respective odds ratios. We extend the simple example above to include three quality levels for both recruits and football programs. For recruits, we add 3*s. We break the top 25 into two segments for football programs: top 10 and rankings 11-25. Note that measures of assortativeness are local. "For instance, it is easy to provide examples where [assortative matching] is positive (or increasing) at one end of the distribution while negative (or decreasing) at the other end. This implies that assortativeness measures will have to be local, in the sense that they focus on the...patterns between two groups and involve considering a (series of) 2 × 2 case(s)." (Chiappori et al., 2021) As a result, we present multiple indices for each table to capture localized effects.

Table 5: Sorting Tables: Pre and Post NIL

(a) Pre NIL (2018-2020)

	Top 10	11-25	Rank>25
5* Recruits	63	13	18
4* Recruits	344	224	477
3* Recruits	263	589	4779

(b) Post NIL (2022-2024)

	Top 10	11-25	Rank>25
5* Recruits	47	23	40
4* Recruits	371	304	591
3* Recruits	263	528	4319

Table 4 presents the number of recruits by quality level matched with a given football program, also by quality. What is most evident from this table is the striking decrease in the number of 5* recruits matching to a top-ten program before NIL (2018-2020) to post-NIL (2022-2024). While this is suggestive of assortative matching, we must be cognizant of the increase in the number of 5* matched in both periods. Given the total number of recruits differs across periods and so do the marginal totals, we move to our odds ratio measure to distinctly determine if NIL had led to more or less assortative matching relative to the years before NIL.

Table 6: Localized Odds Ratios: Pre and Post NIL

(a) Pre NIL (2018-2020)

	$I_o(.)$
(5*, 4*)(Top 10, 11-25)	1.149
(5*, 4*)(11-25, Other)	0.430
(4*, 3*)(Top 10, 11-25)	1.235
(4*, 3*)(11-25, Other)	1.338
(5*, 4*)(Top 10, Rank>10)	1.421
(4*, 3*)(Top 10, Rank>10)	2.304
(5*, 4*)(Top 25, Other)	1.266
(4*, 3*)(Top 25, Other)	1.899

(b) Post NIL (2022-2024)

	$I_o(.)$
(5*, 4*)(Top 10, 11-25)	0.515
(5*, 4*)(11-25, Other)	0.111
(4*, 3*)(Top 10, 11-25)	0.896
(4*, 3*)(11-25, Other)	1.437
(5*, 4*)(Top 10, Rank>10)	0.588
(4*, 3*)(Top 10, Rank>10)	2.033
(5*, 4*)(Top 25, Other)	0.427
(4*, 3*)(Top 25, Other)	1.830

The sorting of athletes amongst football programs matters for efficient production of output (wins)–just as it does in the economy with workers and jobs. Any changes to the allocation of players to football programs may have a large and direct impact on the competitiveness of college football. Table 5 presents the odds ratio measures associated with Table 4. We first list the odds ratios for the localized measures and then provide measures that rely on the aggregation across football program quality levels (e.g. top 10 and 11-15 become top 25). For localized measures, we only consider measures of quality that are tangential to each other. That is, our first odd ratio is for 4* or 5* recruits matched to programs either in the top 10 or ranked from 11-25. We provide all possible localized measures. The results of the odds ratios across periods are striking and consistent. We determine that the "rich" are NOT getting richer. Instead, our analysis illustrates quite the opposite. We see an extensive increase in the mixing of recruits post-NIL–lower-ranked programs match with higher-quality players, especially 4* and 5* recruits. This holds for all but the local measure of 3* and 4* recruits matching with programs outside of the top 10. **We thus determine that NIL is likely beneficial to the competitive balance of college football.** In the sections below, we discuss in more detail how a recruit's behavior changes due to NIL as well as provide plausible explanations for such a behavior change that is consistent with the data we observe.

4 Empirical Strategy: How are Recruits' Behaviors Changing?

We showed in Section 3.2 that positive assortativeness has decreased in the post-NIL recruiting world. However, our prior analysis is local and can only comment on relative behavior between groups of recruits with adjacent star ratings. Here, we take a closer look at recruits' behaviors for each star rating and how NIL has causally affected their school choices. We then provide a plausible rationale for the recruit behavior form the causal estimates.

4.1 Objectives

We want to recover the average treatment effect (ATE) or the average treatment effect on the treated (ATT) of the 2021 NIL policy on various college football recruiting outcomes using observational data from high school football recruits' school choices. In particular, we care if the characteristics of the schools being chosen by recruits post-NIL are different from the characteristics of schools chosen before NIL.

To do so, we turn to a potential outcome framework with discrete treatment. Define our potential outcome of interest $Y_i(W)$, which is directly a function of i's choice of school. This can be anything from the size of recruit i school's DMA to the prior year's performance by recruit i's chosen school. Our treatment is the binary indicator $W_i \in \{0, 1\}$, where the value 1 is realized if i is in the High School class of 2022 or later. The value of 0 corresponds to high school classes before 2020. High school athletes graduating in 2022 are the first to fully benefit from the NIL policy and to have it potentially impact their college choice. Although the NCAA relaxed its policy on July 1, 2021, athletes have already signed their letters of intent in February 2021 and are legally bound to attend that school.

The key identification assumption is unconfoundedness - that is, being in a pre- or post-NIL world is as good as random after conditioning on observable athlete characteristics X_i:

Assumption 1 (Uncounfoundedness) $\{Y_i(0), Y_i(1)\} \perp W_i | X_i$

where X_i are athlete-specific characteristics. In all of our methods below, we use the same characteristics in X_i: 247Sports Composite Rating, position, height, weight, hometown state, and hometown DMA ranking.

We will examine a few dependent Y variables. First, following the analysis in Section 3.2, we estimate the effects that NIL had on the quality of the school chosen by the recruits, using the performance of the previous year and the recruiting class classification of the prior year as a proxy of quality.[28] We look at other dependent variables (Ys), including the distance from school to home, the size of the DMA where the school is located, and the stadium capacity.

We measure these effects with a few methods. The first is a simple OLS regression. If the treatment is randomly assigned conditional on observables, then the coefficient on the treatment dummy will capture the true treatment effect. We use more sophisticated methods to account for empirical concerns. One such method is matching as nonparametric preprocessing (Ho et al., 2007). The idea here is that by matching an athlete from the post-treatment period with an athlete that has very similar observable X's from the pre-treatment period, we can compute treatment effects by treating the matched athlete from the pre-period as a control for the treated athlete. A second method uses an augmented inverse propensity score estimator, which employs theory from the causal inference and potential outcomes literature to accurately estimate treatment effects using conditional means and propensity scores.

4.2 Methods

4.2.1 Ordinary Least Squares

We first measure effects using an OLS regression as a reference. Consider the following regression equation:

$$Y_i = \alpha + \beta X_i + \tau W_i + \varepsilon_i \tag{5}$$

Assumption 1 implies that $\varepsilon_i \perp W_i | X_i$. This independence is generally a strong assumption in observational studies, but is somewhat plausible in our setting. After controlling for athlete-specific characteristics, the population of recruits before and after NIL is likely similar. We dropped the year (2021) around NIL implementation, which helps with the possibility that athletes chasing NIL deals deferred enrollment in 2020 to fully take advantage of NIL in 2021. There are no other ways for athletes to selectively choose into W - for example, an athlete's parents likely did not think

[28] A recruiting class is the set of all student-athelets that have gradated high school in a given year.

about timing their children to fully take advantage of NIL almost two decades ago. Lastly, it seems plausible that the motivation behind choosing college football programs has stayed constant over time - the goal for many of these athletes is to maximize their career earnings or maximize their possibilities of entering the NFL. Although we believe these assumptions hold, if they do not, the OLS regression serves as a baseline to compare the estimates from the other methods.

4.2.2 Matching on Observables - Nonparameteric Preprocessing

The idea of matching on observables is attractive in our setting. It makes intuitive sense to compare the results of players who share very similar physical attributes, play the same position, and originate from the same state. We use nonparametric preprocessing to form optimal subclasses and then use linear regression to recover treatment effects.

The ultimate goal of nonparametric preprocessing is to adjust the data prior to parametric analysis to mitigate any relationships between W_i and X_i and to reduce bias and / or inefficiencies. This greatly reduces the source of model dependence in the parametric analysis resulting from functional form assumptions. Another advantage is that this procedure is doubly robust; If either the matching or the parametric model is correct, causal estimates will be consistent.

We preprocess our data according to the best practices of Ho et al. (2007).[29] We force a match on the position and state covariates but allow for the rest to be matched by minimizing the Mahalanobis distance between the covariates. Because we have multiple covariates to match on, exact one-to-one matches may be difficult. We form optimal subclasses using full matching (Hansen, 2004) so that the distributions of the covariates for the pre- and post-NIL groups are as similar as possible. Match balance checks are displayed in Appendix A.2.

We estimate the average marginal treatment effect (on the treated) by fitting a linear regression model with Y_i as the outcome and the treatment, covariates, and their interaction as predictors, including the full matching weights in the estimation.[30]

[29] We use the R package `Matchit` (Stuart et al., 2011).

[30] The `marginaleffects` package was used to perform g-computation in the matched sample to estimate the ATE (ATT).

4.2.3 Augmented Inverse Propensity Score (AIPW)

Lastly, we use the augmented inverse propensity weighting (AIPW) estimator of Robins et al. (1994). Intuitively, AIPW estimates the ATE by first estimating the conditional means; then, it corrects for the biases of this estimation by applying inverse propensity score weighting to the residuals. We also estimate treatment effects using standard propensity score weighting with a logit regression to compare. One of AIPW's best statistical properties is double robustness - AIPW is consistent if the conditional mean or propensity score estimate is consistent (Wager, 2022).

We estimate the conditional means and propensity scores using random forests (Athey et al., 2019; Athey and Wager, 2021), which allow us to take a nonparametric stance on how our athlete characteristics X affect both.[31] We tune all parameters of our causal forest using cross-validation.

4.3 NIL Effects

4.3.1 Five-star recruits

We first discuss the behaviors of 5* recruits. The results of 5* recruits are quite noisy because there are not that many of them. In our data period, there are only 94 "control" (2018-2020) five-star recruits and 110 "treated" (2022-2024) recruits. We still are able to find a significant effect where 5* recruits choose schools with worse-performing records in the previous season.

Table 7 displays the measured effects of NIL on the probability that 5* recruits choose a school ranked in the top 10 of the previous season or a school ranked in the top 25 of the previous season. We see a statistically significant and economically meaningful decrease in the probability of 5* recruits going to the top 10 and top 25 ranked schools. These magnitudes are quite large - on average, 5* recruits are more than 15% less likely to attend top 10 or top 25 ranked schools, and the schools they do attend have a winning percentage that is about 7% lower than the prior season. This corresponds to about 1 fewer win over a standard 13-game college football season, which could be the difference between a national championship contender or a run-of-the-mill bowl-bound team. Prior year school performance is highly indicative of future performance, so choosing a worse-performing team means a lower flow utility from prestige, $f(\cdot)$.[32]

[31] This is implemented with the `grf` package in R.

[32] See Table 14, where last year's win percentage has a larger and more significant coefficient than any school-specific fixed effect

Y	Method	Effect	Estimate	Std. Error
College ranked top 10	Prop score (logit)	ATE	-0.377	0.093
prior season		ATT	-0.350	0.123
	AIPW + Rand Forest	ATE	-0.242	0.069
Pre-NIL mean: 0.646		ATT	-0.230	0.069
	Matching	ATE	-0.421	0.102
	(nonpar preprocess)	ATT	-0.335	0.124
	OLS	ATE	-0.294	0.075
College ranked top 25	Prop score (logit)	ATE	-0.252	0.099
prior season		ATT	-0.209	0.123
	AIPW + Rand Forest	ATE	-0.166	0.062
Pre-NIL mean: 0.822		ATT	-0.154	0.062
	Matching	ATE	-0.413	0.080
	(nonpar preprocess)	ATT	-0.399	0.070
	OLS	ATE	-0.155	0.068
Win percentage	Prop score (logit)	ATE	-0.093	0.034
prior season		ATT	-0.075	0.040
	AIPW + Rand Forest	ATE	-0.078	0.025
Pre-NIL mean: 0.776		ATT	-0.064	0.025
	Matching	ATE	-0.154	0.035
	(nonpar preprocess)	ATT	-0.139	0.034
	OLS	ATE	-0.083	0.027

Table 7: Treatment effects of NIL on the probability of 5* recruits attending top-ranked schools. Total sample size is 204; treated sample size is 110

Our theoretical model's simplified choice prediction implies that lower quality schools would be chosen ($a_t = 2$) if Equation 3 was satisfied. We find that 5* recruits' NFL draft outcomes are not affected by the rank of the school they initially commit to (Table 3). This also provides some assurance that *future* NIL payments should be independent of initial college choice because these recruits remain highly relevant throughout their college careers regardless of initial school quality. Hence, the difference in $\mathbb{E}[V(\cdot)]$ terms in the second line of Equation 3 zeroes out, leaving us with the inequality:

$$\underbrace{g(z_1, NIL_1, a_1 = 2) - g(z_1, NIL_1, a_1 = 1)}_{\text{Difference in flow util as a function of NIL payments}} > \alpha = f(\cdot, a_1 = 2) - f(\cdot, a_1 = 1)$$

We are able to rationalize the results in Table 7 where 5* recruits increasingly favor lower-ranked schools post-NIL.[33] The portion of flow utility affected by NIL, $g(\cdot)$ must necessarily be larger for lower-quality schools than higher-quality schools by at least α, the difference in prestige utility between lower and higher-quality schools.

[33]See Appendix A.3 for directionally similar but weaker evidence that 5* recruits are choosing lower-quality schools

Our model implies that 5* recruits already possess immense talent and look to be willing to trade off prestige at higher-ranked or higher-quality schools to obtain NIL money. The effects of program quality have shown to be ineffective at improving 5* recruit's future outcomes, so colleges can seemingly convince 5* recruits to attend simply by paying them more.

Anecdotes seem to support our data-driven and theoretical findings. The most noticeable example occurred in 2021, when the number one ranked high school football recruit, Travis Hunter, decided to enroll at Jackson State University. This decision was unprecendented as Hunter became the first 5* high school recruit to ever sign with a Historically Black College and University (HBCU)[34] and the first 5* recruit to sign with an FCS school (collegiate second division).[35] It turns out that Hunter received NIL deals specifically for signing with an HBCU.[36]

4.3.2 Four-star recruits

Four-star recruits are athletes ranked outside the top 30 or 40 of the class but are still in the top 2-3 percentile of recruits. They are immensely talented but lack the pedigree and recognition of their 5* counterparts. Given that only ≈ 250 college players are selected to the NFL every year, 4* players are far from guaranteed a shot at becoming a professional NFL player (23%),[37] meaning that player development in college is crucial to take the next step to the NFL. Our results suggest that, on average, 4* recruits have not drastically changed their behavior post-NIL. Although some may chase NIL deals, they are balanced out by others who still value development and exposure.

Table 8 shows that post-NIL, 4* recruits are slightly more likely to attend a school ranked outside the top 10 in the previous season, but are about as equally likely to attend a top 25-ranked program. Unlike 5* recruits, 4* recruits' NFL draft probabilities have historically been affected by the rank of the school they commit to (Table 3), so it is unsurprising that they continue to prioritize joining a high quality football program. These results are consistent with the Section 3.2 findings of a local decrease in positive assortativeness between 5* and 4* recruits as a result of NIL.

We observe 4* recruits joining schools that recruited more poorly in the previous season post-NIL (Table 9). A weak recruiting class can be a signal for poor unobservable school characteristics

[34] https://www.profootballnetwork.com/national-signing-day-2021-travis-hunter-flips-from-florida-state-to-jackso

[35] https://www.axios.com/2021/12/16/hbcu-jackson-state-travis-hunter-florida-football]

[36] e.g. https://www.forbes.com/sites/michaellore/2022/09/15/travis-hunter-signs-nil-deal-with-michael-strahan-bran ?sh=1a2b07cf6a5d

[37] See Table 3 or https://lastwordonsports.com/collegefootball/2021/07/12/what-do-those-star-ratings-mean/

Y	Method	Effect	Estimate	Std. Error
College ranked top 10	Prop score (logit)	ATE	-0.018	0.022
prior season		ATT	-0.016	0.024
	AIPW + Rand Forest	ATE	-0.032	0.019
Pre-NIL mean: 0.335		ATT	-0.037	0.020
	Matching	ATE	-0.033	0.021
	(nonpar preprocess)	ATT	-0.041	0.023
	OLS	ATE	-0.026	0.019
College ranked top 25	Prop score (logit)	ATE	-0.007	0.024
prior season		ATT	-0.023	0.026
	AIPW + Rand Forest	ATE	-0.003	0.021
Pre-NIL mean: 0.559		ATT	-0.002	0.021
	Matching	ATE	0.001	0.023
	(nonpar preprocess)	ATT	-0.004	0.024
	OLS	ATE	0.002	0.021
Win percentage	Prop score (logit)	ATE	0.005	0.010
prior season		ATT	-0.000	0.011
	AIPW + Rand Forest	ATE	0.006	0.008
Pre-NIL mean: 0.654		ATT	0.008	0.009
	Matching	ATE	0.009	0.010
	(nonpar preprocess)	ATT	0.010	0.010
	OLS	ATE	0.006	0.008

Table 8: Treatment effects of NIL on the probability of 4* recruits attending top-ranked schools. Total sample size is 2311; treated sample size is 1266

Y	Method	Effect	Estimate	Std. Error
College recruiting ranking	Prop score (logit)	ATE	2.079	0.091
prior season		ATT	2.608	1.041
	AIPW + Rand Forest	ATE	3.147	0.747
Pre-NIL mean: 19.160		ATT	3.220	0.782
	Matching	ATE	3.278	0.797
	(nonpar preprocess)	ATT	3.622	0.798
	OLS	ATE	2.617	0.769

Table 9: Treatment effects of NIL on prior season's recruiting rankings. Total sample size is 2311; treated sample size is 1266

such as a bad coaching staff who can't convince recruits to enroll. However, the results from Table 8 above suggest that poor quality isn't the likely interpretation since the effects on ranking and win percentage are insignificant. A more plausible explanation is that athletes committing to a college with a worse recruiting class in the prior year will have less competition for playing time. Holding team quality constant, more playing time leads to a higher $\mathbb{E}[V(\cdot)]$; athletes get more opportunities to develop their talent and give NFL teams more film to analyze their quality and potential.

Y	Method	Effect	Estimate	Std. Error
DMA Rank	Prop score (logit)	ATE	-0.125	2.194
		ATT	-1.093	2.410
	AIPW + Rand Forest	ATE	-0.147	1.906
		ATT	-0.497	1.986
	Matching	ATE	-2.570	2.124
	(nonpar preprocess)	ATT	-3.723	2.400
	OLS	ATE	-0.416	1.922
Log venue capacity	Prop score (logit)	ATE	-0.012	0.013
		ATT	-0.021	0.015
	AIPW + Rand Forest	ATE	-0.024	0.011
		ATT	-0.024	0.012
	Matching	ATE	-0.026	0.012
	(nonpar preprocess)	ATT	-0.034	0.013
	OLS	ATE	-0.023	0.011

Table 10: Treatment effects of NIL on the DMA ranking of the chosen school by 4* recruits.

Four-star recruits are also attending schools with slightly smaller stadiums (Table 10), a metric that proxies for the quality of facilities or wealth of a school. However, Table 20 suggests that wealth may not be the explanation because these schools pay coaches a similar amount. While we aren't able to identify the direction of the effect, the values of $\mathbb{E}[V(\cdot)]$ or $g(\cdot)$ from Equation 3 are certainly changing for 4* recruits post-NIL.

Overall, it is unclear how the post-NIL utility components from Equation 2 move. Some of our finding suggest that 4* recruits prefer to maximize their NFL prospects ($\mathbb{E}[V(\cdot)]$), rather than maximize NIL pay ($g(\cdot)$). Other findings suggest that $\mathbb{E}[V(\cdot)]$ may not be as prioritized post-NIL, which then requires higher a $g(\cdot)$ to rationalize the fact that the quality of schools remain constant. Regardless, it appears that even if some 4* recruits are chasing the proverbial NIL "bag," others value development enough to choose high quality teams, balancing out any effects.

4.3.3 Three-star recruits

Three-star recruits are in the next level down, representing about the 15th-33rd percentile of high school seniors in any given class. Although they are quite talented, the odds that a 3* recruit makes the NFL are much lower than those of a 4* or 5* recruit at 5-7%.[38] These players leverage their talent - just good enough to get recognition in college, but not good enough to become professional - for NIL deals. We observe that 3* recruits' behavior is consistent with maximizing present-day NIL income rather than improving their chances of making the NFL.

Y	Method	Effect	Estimate	Std. Error
College ranked top 10	Prop score (logit)	ATE	-0.011	0.005
prior season		ATT	-0.014	0.005
	AIPW + Rand Forest	ATE	-0.011	0.004
Pre-NIL mean: 0.049		ATT	-0.014	0.005
	Matching	ATE	-0.012	0.004
	(nonpar preprocess)	ATT	-0.013	0.006
	OLS	ATE	-0.013	0.004
College ranked top 25	Prop score (logit)	ATE	-0.037	0.007
prior season		ATT	-0.040	0.008
	AIPW + Rand Forest	ATE	-0.033	0.007
Pre-NIL mean: 0.169		ATT	-0.035	0.008
	Matching	ATE	-0.039	0.007
	(nonpar preprocess)	ATT	-0.038	0.009
	OLS	ATE	-0.038	0.007
Win percentage	Prop score (logit)	ATE	-0.026	0.004
prior season		ATT	-0.026	0.004
	AIPW + Rand Forest	ATE	-0.026	0.004
Pre- NIL mean: 0.522		ATT	-0.026	0.004
	Matching	ATE	-0.025	0.004
	(nonpar preprocess)	ATT	-0.023	0.005
	OLS	ATE	-0.026	0.004

Table 11: Treatment effects of NIL on the probability of 3* recruits attending top-ranked schools. Total sample size is 10741; treated sample size is 5110

Like 5* recruits, 3* recruits join college teams that performed worse in the previous season after NIL versus before NIL (Table 11). The magnitude of the effect sizes is not as large, but it is still meaningful. For example, there are more than 1,500 three-star recruits every year. A five-percent decrease in the probability of attending a top 25 ranked teams means that at least 75 three-star recruits are not choosing top-ranked schools post-NIL. Relatively speaking, these estimates imply that there are about 20% fewer 3* recruits at top 10 and top 25 schools post-NIL. Furthermore, 3*

[38] https://lastwordonsports.com/collegefootball/2021/07/12/what-do-those-star-ratings-mean/

recruits are significantly affected by the quality of school they initially choose to attend (Table 3), so choosing a lower-ranked school has big implications for their future outcomes.

Y	Method	Effect	Estimate	Std. Error
College recruiting ranking	Prop score (logit)	ATE	10.667	0.789
prior season		ATT	11.889	0.799
	AIPW + Rand Forest	ATE	10.312	0.652
Pre-NIL mean: 68.629		ATT	11.709	0.668
	Matching	ATE	10.817	0.719
	(nonpar preprocess)	ATT	11.199	0.709
	OLS	ATE	10.931	0.690

Table 12: Treatment effects of NIL on prior season's recruiting rankings. Total sample size is 10741; treated sample size is 5110

We find more evidence that 3* recruits go to schools that are lower quality post-NIL. Recruiting classes at the schools they attend are at least ten ranks worse in the previous year (Table 12). Additionally, these schools have smaller stadiums as measured by venue capacity (Table 13) and pay their coaches less (Table 23). These magnitudes are so large that lower quality must explain some of the decrease, even if there are alternative explanations.

Y	Method	Effect	Estimate	Std. Error
Log venue capacity	Prop score (logit)	ATE	-0.142	0.010
		ATT	-0.146	0.010
	AIPW + Rand Forest	ATE	-0.137	0.009
		ATT	-0.141	0.009
	Matching	ATE	-0.144	0.010
	(nonpar preprocess)	ATT	-0.136	0.009
	OLS	ATE	-0.140	0.009

Table 13: Treatment effects of NIL on chosen school's stadium capacity. Total sample size is 10741; treated sample size is 5110

Going back to Equation 3 of our theoretical model, the difference in $\mathbb{E}[V(\cdot)]$ should be non-positive given the worse recruiting classes, the smaller stadium sizes, the lower paid coaches, and the positive impact of high-ranked schools on 3* player's NFL draft outcomes. But 3* recruits are choosing lower-ranked schools more frequently post-NIL, which necessarily means that these schools must have decently attractive NIL offers $g(\cdot)$. The situation here is somewhat similar to that of the 5* recruit; 3* recruits recognize that it's unlikely for them to make it to the NFL regardless of school choice and decide to take advantage of NIL payments in college.

Our estimates suggest that the rich are not getting richer. Three- and five-star recruits are choosing programs that are notably worse in observable characteristics and arguably also worse in unobservable characteristics. These recruits are choosing to go to schools with substantially worse prior-season performance and recruiting classes post-NIL relative to the same metrics at schools they chose before NIL. Four-star recruits are not choosing schools that are statistically significantly better. Therefore, better talent is going to worse schools on average, so NIL has decreased positive assortative matching and created more competitive teams in college football.

5 Managerial Implications and Conclusions

Our findings in this paper can provide insight to firms operating in competitive environments for talent acquisition. We highlight two settings where competing on compensation rather than non-pecuniary benefits may decrease positive assortative matching and provide less advantaged firms with better talent.

The first setting is Ph.D. student recruitment, particularly in a business or economics-related field. Doctoral candidates need faculty guidance, a factor that parallels the developmental coaching received by collegiate athletes. Elite academic institutions often provide their doctoral cohorts with access to eminent advisory faculty to facilitate their research trajectory, paralleling the high-caliber coaching staff in athletic programs. In addition, the provision of sophisticated computational resources and research facilities to these candidates is reminiscent of the advanced training facilities built for football athletes. The academic progression of doctoral students culminates in their entry into the job market, mirroring the transition of collegiate football players as they enter the NFL draft.

Currently, stipends vary minimally between schools and are predominantly influenced by disparities in the cost of living across geographical locations. In this sense, the current environment for recruiting doctoral candidates is very similar to pre-NIL college football recruiting. Our paper suggests that drastically increasing stipends could serve as an effective strategy for lower-tier academic institutions to attract high-quality doctoral candidates. Competing on non-pecuniary benefits is difficult because faculty hiring and investment into computational hardware or research facilities can be expensive and slow to materialize. On the contrary, a generous stipend presents a more expedient alternative to recruiting prospective doctoral students, particularly those for whom immediate financial stability is important.[39]

[39] Of course, there could be adverse selection by those looking to cash out quickly to go into industry

More broadly, our paper demonstrates that talent prefers immediate financial compensation and that their behavior quickly changes once cash is involved even in the presence of substantial non-pecuniary benefits. This has major implications for labor markets with budget constraints where non-pecuniary benefits are leveraged as competitive differentiators. The tech industry, characterized by its offering of various non-cash perks such as complimentary meals and liberal leave policies, stands as a case in point. Our findings suggest that young firms and startups within this space might reap greater benefits from prioritizing direct financial remuneration, either via salaries or equity options, as opposed to investing in non-pecuniary amenities. Doing so may attract better talent, provide a higher return on investment for these companies, and be a better use of constrained talent budgets.

Our paper also provides an interesting perspective on mechanisms for talent redistribution. In professional sports leagues in the United States, amateur talent is allocated into teams through a draft process in which the worst performing teams get first choice on selecting talent–thus ensuring negative assortativeness in player-team matching for the first round. The draft seems "fair" to sports fans because it redistributes talent by letting low-quality teams have a greater opportunity to select high-quality talent. In recent years, the criticism of professional sports drafts has increased, with the main critique being that "Drafts don't exist to make leagues more fair. They exist to allow owners more power over players, to grab hold of their rights, at under market value, for as long as they can."[40] We demonstrate that a free-market system can allocate high-quality talent to low-quality teams in the absence of an amateur draft. A free-market talent allocation mechanism akin to college football recruiting has already been implemented in various international sports, such as soccer. However, media and sports fans have often criticized soccer for lack of parity. Our paper demonstrates that these criticisms may not be a result of the talent allocation process but rather from other idiosyncratic league factors. We conclude by stating that with the right free-market design, league parity may be possible even in the absence of a draft.

[40]https://nymag.com/intelligencer/2019/05/a-case-for-abolishing-sports-drafts.html

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A Appendix

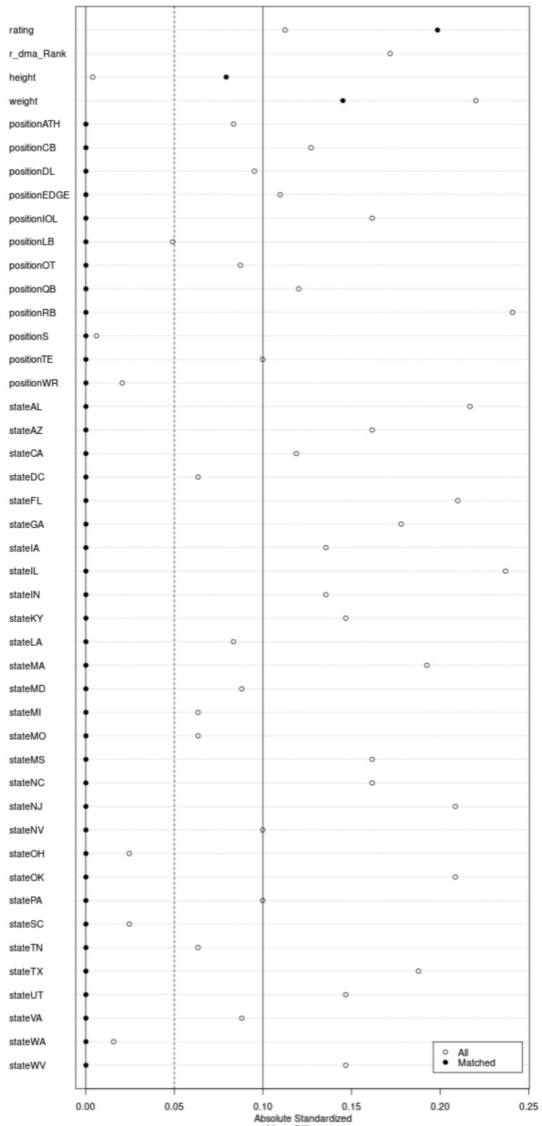
A.1 College football win probabilities

	Y: Current year win percentage
Last year win percentage	0.30^{***}
	(0.02)
log(s_recruiting_points)	0.02
	(0.02)
Largest school fixed effect:	Alabama (0.25^{***}[0.06])
Num. obs.	2237
School FE	Y
Conference FE	Y
Adj R^2	0.36

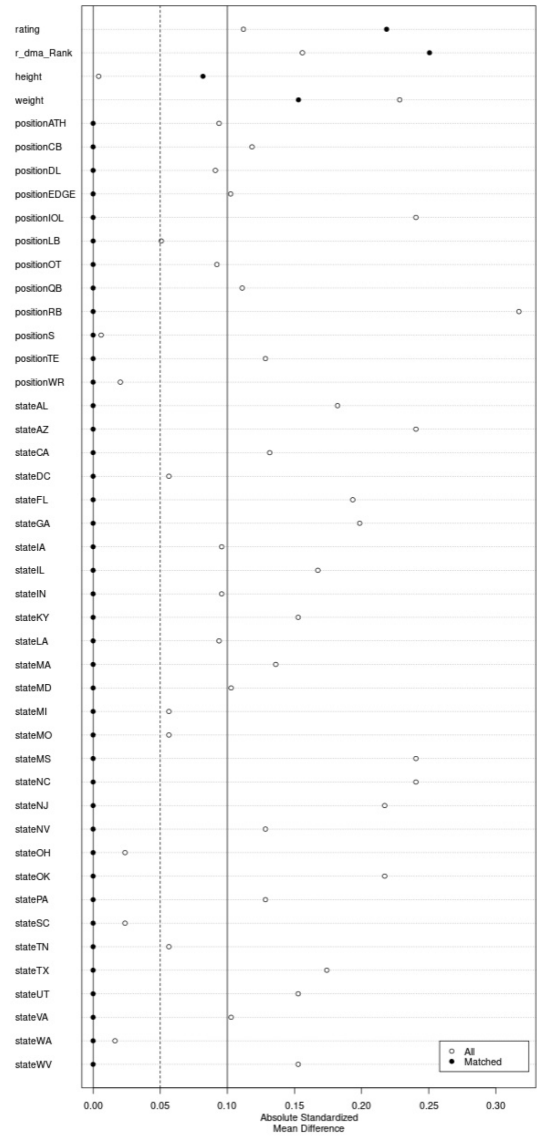
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 14: Regression of win percent on last year's win percent, recruiting class strength, and school and conference fixed effects. Years 2005-2023

A.2 Match Balance

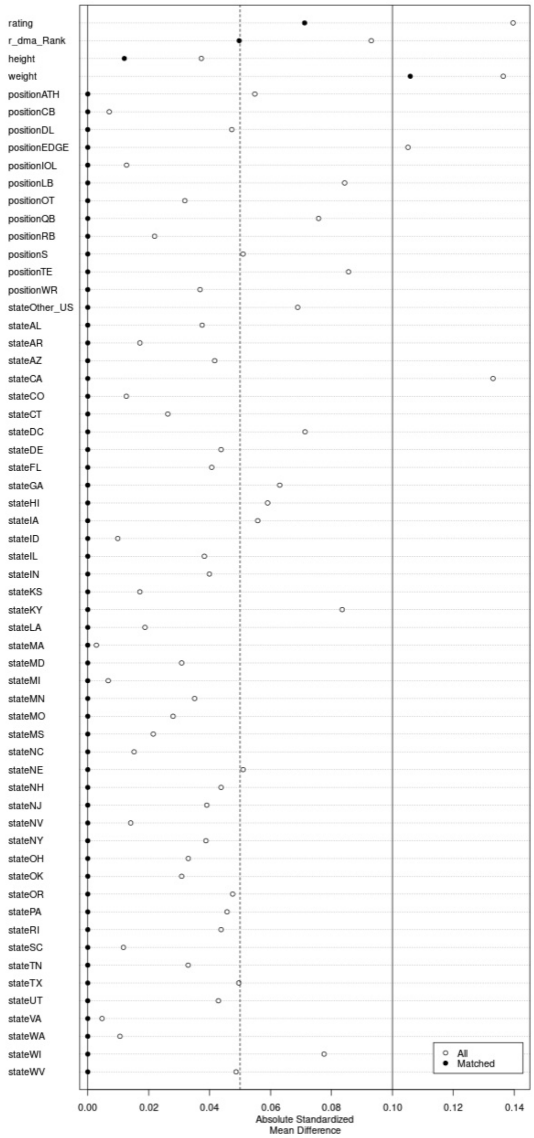


(a) Match balance for ATE

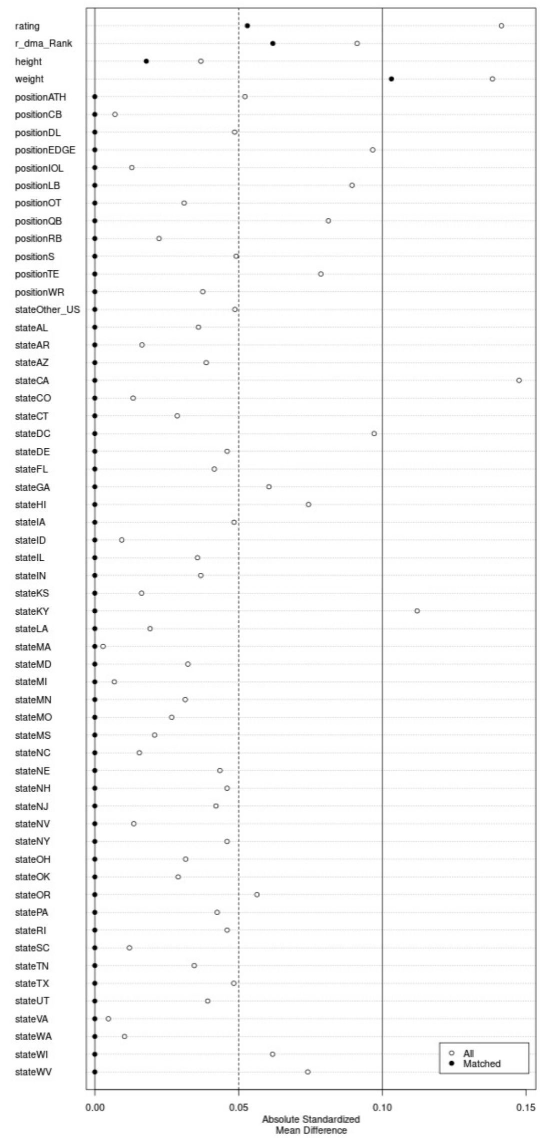


(b) Match balance for ATT

Figure 2: Match balance checks for nonparametric preprocessing, 5* recruits only; forced match on position and state

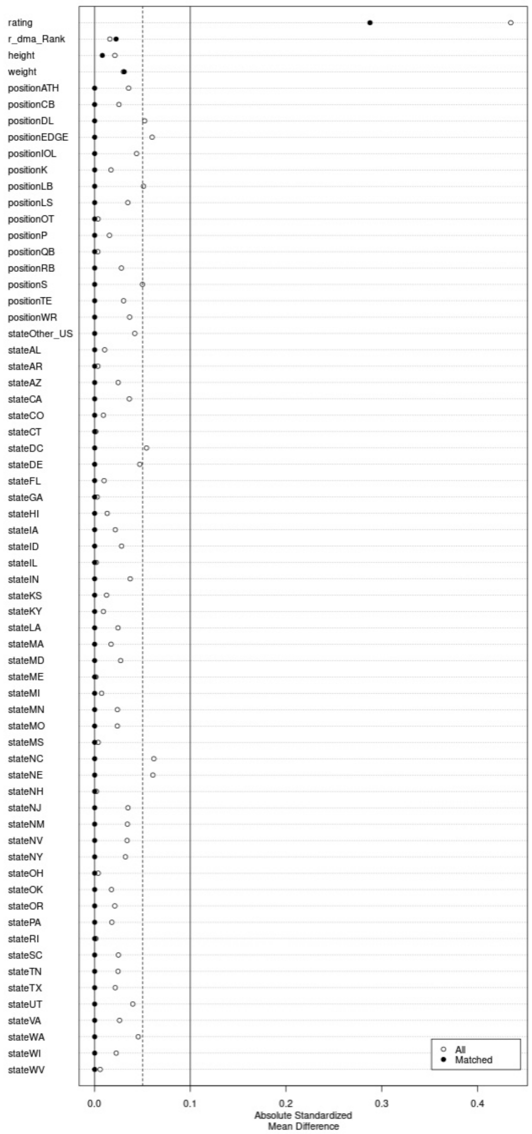


(a) Match balance for ATE

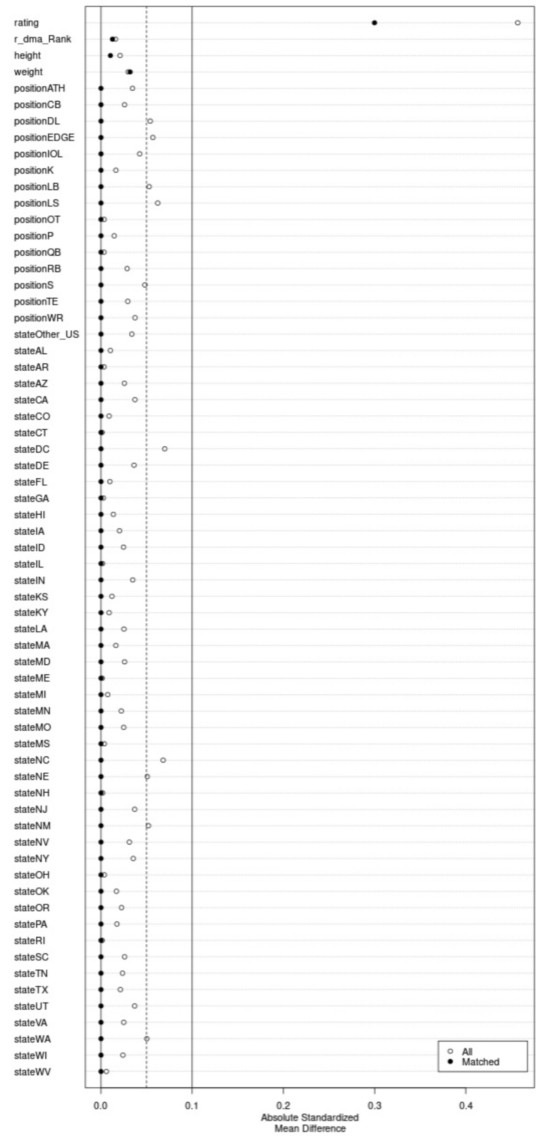


(b) Match balance for ATT

Figure 3: Match balance checks for nonparametric preprocessing, 4* recruits only; forced match on position and state



(a) Match balance for ATE



(b) Match balance for ATT

Figure 4: Match balance checks for nonparametric preprocessing, 3* recruits only; forced match on position and state

A.3 Other Tables

A.3.1 Five-star recruit results

Y	Method	Effect	Estimate	Std. Error
DMA Rank prior season	Prop score (logit)	ATE	-3.218	8.194
		ATT	-3.805	10.484
	AIPW + Rand Forest	ATE	2.023	5.569
		ATT	1.978	5.590
	Matching (nonpar preprocess)	ATE	15.256	7.635
		ATT	11.215	8.272
	OLS	ATE	3.955	6.082
Log venue capacity	Prop score (logit)	ATE	-0.094	0.047
		ATT	-0.077	0.051
	AIPW + Rand Forest	ATE	0.004	0.029
		ATT	0.007	0.030
	Matching (nonpar preprocess)	ATE	-0.060	0.031
		ATT	-0.082	0.031
	OLS	ATE	-0.005	0.028

Table 15: Treatment effects of NIL on the DMA ranking of the chosen school by 5* recruits. Total sample size is 204; treated sample size is 110

Y	Method	Effect	Estimate	Std. Error
College recruiting ranking prior season	Prop score (logit)	ATE	2.257	2.706
		ATT	1.723	3.524
	AIPW + Rand Forest	ATE	1.437	1.755
		ATT	1.597	1.786
	Matching (nonpar preprocess)	ATE	5.517	2.424
		ATT	6.534	2.350
	OLS	ATE	2.291	1.959

Table 16: Treatment effects of NIL on prior season's recruiting rankings. 5* recruits

Y	Method	Effect	Estimate	Std. Error
Log coach pay prior season	Prop score (logit)	ATE	-0.070	0.094
(within year z-score)		ATT	0.037	0.106
	AIPW + Rand Forest	ATE	0.033	0.064
		ATT	0.049	0.065
	Matching	ATE	-0.166	0.076
	(nonpar preprocess)	ATT	-0.100	0.085
	OLS	ATE	-0.048	0.063

Table 17: Treatment effects of NIL on prior season's z-score of log coach salaries. 5* recruits. Data only from public school salaries. Total sample size is 190; treated sample size is 101

Y	Method	Effect	Estimate	Std. Error
Distance from Home	Prop score (logit)	ATE	-29.629	138.776
(km)		ATT	37.296	169.179
	AIPW + Rand Forest	ATE	80.643	99.302
		ATT	68.564	97.192
	Matching	ATE	44.084	174.816
	(nonpar preprocess)	ATT	-38.681	199.272
	OLS	ATE	41.577	102.495
Stay in State = 1	Prop score (logit)	ATE	0.096	0.100
		ATT	0.023	0.123
	AIPW + Rand Forest	ATE	0.010	0.067
		ATT	0.010	0.068
	Matching	ATE	-0.049	0.108
	(nonpar preprocess)	ATT	-0.034	0.122
	OLS	ATE	0.012	0.071

Table 18: Treatment effects of NIL on distance from home. 5* recruits

A.3.2 Four-star recruit results

Y	Method	Effect	Estimate	Std. Error
Distance from Home (km)	Prop score (logit)	ATE	51.116	41.703
		ATT	48.872	44.083
	AIPW + Rand Forest	ATE	55.320	31.313
		ATT	53.139	31.317
	Matching (nonpar preprocess)	ATE	79.568	32.543
		ATT	64.032	32.722
	OLS	ATE	65.235	31.397
Stay in State = 1	Prop score (logit)	ATE	-0.032	0.023
		ATT	-0.043	0.026
	AIPW + Rand Forest	ATE	-0.008	0.020
		ATT	-0.009	0.020
	Matching (nonpar preprocess)	ATE	-0.024	0.023
		ATT	-0.014	0.024
	OLS	ATE	-0.020	0.020

Table 19: Treatment effects of NIL on distance between college and hometown for 4* recruits. Total sample size is 2311; treated sample size is 1266

Y	Method	Effect	Estimate	Std. Error
Log coach pay prior season (within year z-score)	Prop score (logit)	ATE	0.020	0.023
		ATT	-0.002	0.026
	AIPW + Rand Forest	ATE	0.020	0.019
		ATT	0.017	0.020
	Matching (nonpar preprocess)	ATE	0.020	0.021
		ATT	0.013	0.022
	OLS	ATE	0.024	0.020

Table 20: Treatment effects of NIL on prior season's z-score of log coach salaries. 4* recruits. Data only from public school salaries. Total sample size is 2130; treated sample size is 1131

A.3.3 Three-star recruit results

Y	Method	Effect	Estimate	Std. Error
DMA Rank	Prop score (logit)	ATE	-1.244	1.018
		ATT	-1.104	1.060
	AIPW + Rand Forest	ATE	-1.447	0.901
		ATT	-1.210	0.948
	Matching	ATE	-1.123	0.996
	(nonpar preprocess)	ATT	-1.689	1.068
	OLS	ATE	-1.201	0.937

Table 21: Treatment effects of NIL on the DMA ranking of the chosen school by 3* recruits. Total sample size is 10741; treated sample size is 5110

Y	Method	Effect	Estimate	Std. Error
Distance from Home	Prop score (logit)	ATE	-10.645	17.786
(km)		ATT	-10.661	18.262
	AIPW + Rand Forest	ATE	-9.221	14.354
		ATT	-4.105	14.935
	Matching	ATE	-3.362	15.896
	(nonpar preprocess)	ATT	0.320	16.096
	OLS	ATE	-13.880	14.792

Table 22: Treatment effects of NIL on distance from home. 3* recruits

Y	Method	Effect	Estimate	Std. Error
Log coach pay	Prop score (logit)	ATE	-0.255	0.018
(within year z-score)		ATT	-0.249	0.019
	AIPW + Rand Forest	ATE	-0.248	0.014
		ATT	-0.237	0.015
	Matching	ATE	-0.264	0.016
	(nonpar preprocess)	ATT	-0.245	0.017
	OLS	ATE	-0.256	0.015

Table 23: Treatment effects of NIL on prior season's z-score of log coach salaries. 3* recruits. Data only from public school salaries. Total sample size is 9164; treated sample size is 4358