Does Personalized Pricing Increase Competition: Evidence from NIL in College Football

Ivan Li * Tim Derdenger†

November 2024

Abstract

We investigate the impact of personalized pricing through Name, Image, and Likeness (NIL) rights within college athletics on the recruitment of high school football players by college programs. We focus on whether the new policy disrupts competitive balance by increasing the concentration of talent among top-ranked institutions. Using a dataset that encompasses pre- and post-NIL recruitment patterns to examine the distribution of 3, 4, and 5* recruits at college football programs, we find a notable increase in the dispersion of talent. Contrary to the hypothesis that NIL would lead to a "rich get richer" dynamic, we observe a tendency for lower-ranked football programs to attract higher-quality recruits post-NIL, especially among 5- and lower ranked 4* athletes. Furthermore, we show that post-NIL 3* recruits are sacrificing schooling for NIL money, attending colleges that are less selective, have lower SAT class averages, and whose graduates earn a lower mid-career income. We also do not find evidence that schools that spend more money on football are attracting better talent post-NIL. Competitiveness improves post-NIL as sportsbooks set smaller point differentials even after controlling for talent, performance, and the transfer portal. 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: Personalized Pricing, Price Discrimination, College Football, NIL, Merit Aid

*Ivan Li is an Assistant Professor of Marketing at the Jindal School of Management, University of Texas at Dallas. Email: yilun.li@utdallas.edu

†Tim Derdenger is an Associate Professor of Marketing and Strategy at the Tepper School of Business, Carnegie Mellon University. Email:derdenge@andrew.cmu.edu.

1 Introduction

Price discrimination is a widely used tool for firms to maximize profits. Through personalized pricing–a specific form of price discrimination where firms tailor prices to individual consumers–some consumers pay more and others pay less compared to a uniform pricing policy. In a monopoly setting, theory predicts that price discrimination increases prices and profits (Pigou, 1920). However, when competition is included, the direction is unclear–theoretical models of oligopolistic competition provide conditions under which personalized pricing can both increase and decrease competition (e.g. Rhodes and Zhou (2024)). Empirically, studying the competitive effects of personalized pricing is challenging for two main reasons: first, it is extremely difficult to obtain individual price data across an entire industry; second, contexts where personalized pricing is suddenly implemented throughout an entire industry are virtually nonexistent. What empirical research that does exist focuses on a single firm and the maximizing of its own profits through personalized pricing (Belloni et al. (2012), Shiller (2020), Dubé and Misra (2023)).

This paper studies whether personalized pricing increases competition through the introduction of Name, Image, and Likeness (NIL) rights in July 2021, a novel policy change in college athletics that suddenly introduced personalized pricing across the entire industry. Prior to NIL, student-athletes selected a college to attend based on promises for football development and a "full ride" scholarship which included a complete price reduction in the amount equal to the total of tuition and room and board. Schools were unable to differentiate beyond this scholarship amount to provide a personalized price and further incentivize selection, leading to an effective uniform college price of zero for all student-athletes. After the introduction of NIL, coaching staffs work directly with alumni-backed "collectives" to determine each recruit's NIL package.[1] These NIL payments act as additional individual-specific price reductions based on player quality to incentivize the selection of a college athletic program.

Although we do not observe individual prices or firm profits directly, the introduction of NIL provides a unique natural experiment to study the competitive effects of personalized pricing. By observing the universe of schools (firms) and athletes (consumers) before and after this policy change, we can analyze equilibrium outcomes such as athletes' revealed preferences in college selec-

[1] https://www.on3.com/nil/news/how-are-recruiters-working-with-nil-collectives-in-states-where-its-allowed/

tion and the performance of football programs. This comprehensive data allows us to specifically attribute changes in competitive dynamics to the implementation of personalized pricing through NIL.

The launch of NIL sparked an intense debate about its potential impact on the recruitment and competitive balance of collegiate sports. Critics speculate that NIL could exacerbate existing inequalities within college sports, allowing wealthier, top-ranked programs to dominate recruitment by offering lucrative NIL deals. One such critic is Nick Saban, the former head coach and seven time national college football champion. He believes that NIL will *"create a caste system where the rich will get richer and the poor get poorer."*[2] In contrast, 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 and increasing competition.

We ask: Has NIL led to the "rich" getting richer? Or does oligopoly price discrimination lead to increased competition? Specifically, we empirically determine whether personalized pricing leads to increased competition for players by analyzing which college football program a high school recruit selects, as well as football game outcomes by analyzing point spreads from sportsbooks. Using revealed preference data, we are able to recover the impact of NIL by analyzing the assortment of top-tier college recruits before and after the implementation of NIL.

The settings in which personalized prices are deployed and the questions around competition extend beyond collegiate athletics. Price discrimination is widely used in academic admissions. Administrators in charge of enrollment management for colleges and universities play a central role in how universities compete in the marketplace for students and in rankings. Over the last several decades, the posted price of tuition has become less and less the price students actually pay. One direct benefit of a high posted price is that it "signals quality and prestige, yet it also burdens families who cannot afford to pay tuition."[3] So colleges price discriminate, "discounting" tuition by returning tuition revenue in the form of scholarship aid (Belloni et al., 2012). To attract first-year students, private colleges discount tuition by more than 56%.[4] That said, not all colleges offer merit aid because they simply do not need to (e.g., the Ivy League, Stanford and the Massachusetts

[2] `https://theathletic.com/5339689/2024/03/13/nick-saban-nil-college-sports-congress/?campaign=9248378&source=untilsaturday_newsletter&userId=437916`
[3] https://www.bestcolleges.com/news/hidden-truth-behind-merit-scholarships/
[4] https://www.bestcolleges.com/news/hidden-truth-behind-merit-scholarships/

Institute of Technology).[5]

Public institutions are also engaging in price discrimination to attract students in order to build their optimal entry class, a trend that began after the 2008 recession.[6] According to New America's 2020 report, "Crisis Point: How Enrollment Management and the Merit-Aid Arms Race Are Derailing Public Higher Education" public universities and colleges increased spending on non-need-based aid from $1.1 billion in 2001 to $3 billion in 2017. During this time, 52% of public colleges more than doubled their merit aid spending, and over 25 percent more than quadrupled it. Specifically, during that same period of time the University of Alabama increased its non-need aid spending by more than $123 million.[7]

Like NIL, the consequences of using merit-based aid to offer personalized prices to students are unclear. Does merit aid increase the sorting of students (by quality) across the university marketplace, or does it lead to an increase in the mixing of students? Furthermore, what impact does merit-based aid have on the competitive balance in the university marketplace? Some academic research has theoretically and through calibrated models, studied the likely effects of policy changes in higher education financing. These include Winston (1999), Epple et al. (2002), Epple et al. (2006), Waldfogel (2015), and Fillmore (2023).

While our research focuses on the 5-billion dollar annual college football industry, the introduction of NIL in college athletics parallels the use of merit-based aid in higher education. Both serve as financial incentives to attract top talent and to build the best (student or football recruiting) class possible. Moreover, it provides insights to the Presidents of those very same universities on how to compete in the university marketplace with merit-aid and understand its potential equilibrium effects.

To address our research questions, we first build a theoretical scholarship choice model for high school recruits. In doing so, we highlight the role that program prestige, player development, future income from being drafted in the NFL, and NIL income may have on program choice. Next, we use multiple causal inference methods to determine that the "rich" are NOT getting richer and that competition has increased. We see an extensive increase in the mixing of recruits. We

[5] https://www.bestcolleges.com/news/hidden-truth-behind-merit-scholarships/

[6] https://www.insidehighered.com/news/admissions/traditional-age/2023/12/11/rise-non-need-merit-aid-raises-equity-concerns

[7] https://www.insidehighered.com/news/admissions/traditional-age/2023/12/11/rise-non-need-merit-aid-raises-equity-concerns

use propensity score methods like inverse probability weighting (IPW) and the augmented inverse probability weighting (AIPW) estimator, which treat NIL as a natural experiment. Additionally, we leverage international recruits as a control group in a difference-in-difference strategy, since they are not eligible for NIL as student visa holders.

In general, lower-ranked programs match more with higher-quality players in a post-NIL world, so NIL and personalized prices decrease the degree to which matching is positively assortative. Our results show that post-NIL five-star (5*) recruits choose schools with worse historical performance, especially in the previous year. They take advantage of their existing talent and social media presence, choosing the most profitable NIL contract while minimally sacrificing player development, as these athletes have a 65% probability of being drafted into the National Football League (NFL).[8] Their post-NIL chosen schools still maintain large TV audiences and spend plenty on their football programs, indicating that NIL has been a tool for "temporarily embarrassed" football programs to chase after top talent in an attempt to return to their former glory.

We find that 3* recruits exhibit behavior that is also consistent with maximizing NIL money - they choose schools that are less popular and have lower education quality. Notably, 3* recruits attend colleges post-NIL that have a higher admission rate, lower SAT averages, and lower mid-career earnings. Unlike 5* recruits, 3* have a much lower probability of being drafted (8.4%), making immediate financial gain through NIL deals more lucrative than developing their skills to improve their NFL draft prospects. Lower-ranked 4* recruits behave similarly to 5* and 3* recruits, choosing football programs post-NIL with significantly worse historical performances. However, higher-ranked 4* recruits do not display this trend, suggesting that they may be beneficiaries of 5* and lower 4* recruits choosing lower-ranked football programs.

Finally, we test whether NIL price discrimination has led to an increase in competitiveness by directly analyzing spreads. Sportsbooks/gambling platforms set the "spread," which is the predicted point differential by which a favored team will win a football game. When a powerhouse college team plays one from a small school, the spread is large because everyone expects the powerhouse to beat the small school by many points. A small spread means that the game is predicted to be close, indicating more competitiveness. We obtain evidence that NIL is correlated with smaller betting spreads and more losses by the favored team after controlling for talent, performance, and

[8] From our own analysis in Section 3

the transfer portal.

Literature Review. Personalized pricing is a growing area for academic research. The seminal piece of research is that of Pigou (1920) that studies price discrimination in a monopoly setting. Thisse and Vives (1988) extends Pigou's work to study personalized pricing in a competitive setting using a Hotelling model. They determined that when consumers are uniformly distributed, "each firm tries to poach consumers on its rival's "turf" with low prices, which then forces the rival to charge less even to consumers with a strong preference for its product." This result is also found in Chen et al. (2020), where users are assumed to be unable to manage their identity, and thus "consumer information intensifies competition because firms can effectively defend their turf through targeted personalized offers." However, research from Armstrong (2006) and Ali et al. (2023) overturns the results of Thisse and Vives (1988). When consumers are distributed along the Hotelling line according to a symmetric and strictly log-concave line, personalized prices do not change, but uniform prices fall, resulting in some personalized prices being higher than the uniform price. Additionally, "less is known about whether implementing [personalized pricing] is profitable when changes in positioning and hence differentiation are also possible.(Li et al., 2024)"

Empirically, Dubé and Misra (2023) study the impact of personalized pricing through the use of machine learning on consumer welfare and found that it led to a 55% increase in the focal firm's profits. Personalized pricing also raises privacy concerns through the use of a large amount of personalized data. Shiller (2020) demonstrates that Netflix could increase profits by 13% by using consumer-level browsing data to price discriminate. Ali et al. (2023) study the impact of information disclosure on personalized pricing and determine that consumer control can improve consumer welfare relative to both perfect price discrimination and uniform pricing.

Beyond personalized pricing, our paper contributes to the empirical evidence on merit aid in higher education, particularly its impact on student choice and outcomes. Much of this literature uses observational data from state merit-aid programs (Dynarski, 2000; Cohodes and Goodman, 2014; Fitzpatrick and Jones, 2016; Scott-Clayton and Zafar, 2019), with only Angrist et al. (2022) offering experimental evidence. A subset of this literature has also studied how merit aid is used to price discriminate (Waldfogel, 2015; Epple et al., 2019). Our setting is unique in that all high school athletes can solicit competing NIL offers across all colleges, whereas state merit-aid programs are only available to residents of that particular state. Furthermore, we can analyze the equilibrium impact of merit aid on the competitiveness of the university marketplace because we observe athlete choices, athlete and school rankings, and a world where NIL doesn't exist.

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 of interest. By employing regression models, propensity score techniques (such as augmented inverse probability weighting, or AIPW), and difference-in-differences methods, we ensure that we determine the causal impact of the NIL policy change. The leading research in this field originates from the pioneers of Rubin (1974), Rosenbaum and Rubin (1983), and Imbens and Angrist (1994). 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 nonparametric position on how the model characteristics X affect both. We follow the best differences-in-differences practices as recommended by the recent literature (Roth et al., 2023).

In addition to the methodological research, we highlight several important papers in the field of the economics of sports. We contribute to the literature on how policies affect the competitiveness of sports leagues (Fort and Quirk, 1995; Fort and Lee, 2007), empirically documenting an increase in competitiveness as recruitment restrictions are relaxed. Eckard (1998) and Blair and Wang (2018) study the competitiveness of college football/athletics in through the economic theory of cartels. This theory suggests that cartels reduce competitive balance because "restrictions inhibit weak teams from improving, and protect strong teams from competition." Our paper supports Eckard (1998)'s findings in that competitiveness improves post-NIL as the NCAA "cartel" loses its ability to regulate compensation. Garthwaite et al. (2020) also studies college athletics and characterizes the economic rents in intercollegiate athletics in a pre-NIL world, simulating a post-NIL world by calculating a wage structure for college athletes using collective bargaining agreements in professional sports leagues as a benchmark. (Romer, 2006) leverages data and evidence from the NFL to assess whether firms maximize profits. Chung (2013) 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 changing 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 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 2022, the 110 public schools in Division 1 (D1) FBS college football – the highest level of competition – generated $4.7 billion in revenues, with the median D1 FBS public school generating $22 million dollars.[9] Every other college sport at these schools only generated a combined total of $4.3 billion in revenue. In addition, 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 (PBS, 2023).

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[10]. 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 college football in D1 and D2.[11]

	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. Data from the NCAA Sports Sponsorship and Participation Rates Database for 2023-2024.

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 to scout potential recruits.[12] If

[9] https://www.sportico.com/business/commerce/2023/college-sports-finances-database-intercollegiate-1234646029/

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

[11] www.ncaa.org/sports/2018/10/10/ncaa-sports-sponsorship-and-participation-rates-database.aspx

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

a school likes an athlete enough, they can make a scholarship offer. The 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.[13]

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 a 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.[14] 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). 65% of 5* high school football recruits end up being drafted by an NFL team (Table 4). 4*s are slightly less prestigious than 5*s, 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 are freshmen, 4* 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.[15] 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

[13] 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`

[14] See `https://247sports.com/article/247sports-rating-explanation-81574/` for an explanation of how 247Sports assigns star ratings

[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

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

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

school and college football players is to play professionally, reality is often very different.

2.1.1 Transfer Portal

While we focus our attention on high school seniors and their recruiting decisions, we would be remiss to not discuss the importance of the college football transfer portal for athletes who have already played one year of athletics at a given college. The NCAA transfer portal launched on October 15, 2018 in order to manage and facilitate the process for student athletes seeking to transfer between schools (but with very limited use until 2021). In 2021, the NCAA relaxed its policy allowing student-athletes to change schools using the portal once without sitting out a year after transferring.

A concern for our analysis is the potential for the transfer portal to systematically change the number of high school athletes being recruited and thus the composition of the team by class (freshman to senior). In order to mitigate this concern, we use the 247Sports transfer rankings to illustrate that transfers are used to replace athletes who leave rather than as substitutes for high school athletes (Table 3). Of all schools in D1 FBS, the average number of transfers in is about 6-8 fewer than the average number of transfers out per year. Moreover, in every year, almost 90% of the schools had fewer transfers in than out.

Year	Avg. Transfers In	Avg. Transfers Out	# Schools out > in (D1 FBS)
2021	6.2	12.8	112/125
2022	8.2	16.2	115/126
2023	10.7	17.2	110/126
2024	15.3	22.5	108/126

Table 3: Transfer portal statistics by year, D1 FBS schools only. 126 out of 134 schools represented in data sample.

One potential reason for this data pattern is the NCAA rule that limits football programs to a maximum number of 85 scholarship athletes. Consequently, coaches appear to be managing their rosters by continuing to smooth offers over each class so that they do not find themselves in a situation where they are required to bring in (e.g., 50+) new high school scholarship athletes in a given year.

2.2 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 more than 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] In D1 FBS, 58% of the players are black,[17] and disproportionately come from the American South.[18]

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, 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.[19] 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 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

[16] The Pac-12 has dissolved with notable schools like USC and UCLA leaving for the other Power 5 conferences
[17] See: https://www.ncaa.org/sports/2018/12/13/ncaa-demographics-database.aspx
[18] https://ncaaorg.s3.amazonaws.com/research/pro_beyond/2020RES_HSParticipationMapByState.pdf
[19] This playoff expanded to 12 teams in the 2024-25 season.

top 25 are not ranked. Rankings are sticky within a season; a team's rank in week $t+1$ is highly dependent on its rank in week t, but the ranks reset at the beginning of the next season. For the purposes of this paper, our analysis uses only 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.[20]

2.3 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. Traditionally, the 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.

With the rise of social media and influencer marketing, student-athletes have become increasingly valuable to brands seeking to engage with young and active audiences. Schools collaborate with their collectives, groups of boosters and donors, to facilitate NIL packages for student-athletes. According to a recruiting coordinator at a top SEC school, coaches highlight potential recruits for their collectives who then come up with a personalized NIL package: "We like this guy, can you [the collective] get in touch with him," the recruiter said.[21] "We don't even need to know what the number is. I don't care. Figure out what his number is, and if we can do it, do it."

These collectives receive millions in funding from alumni, businesses, and increasingly, student fees: "According to On3, more than two-thirds of NIL transactions come from school-specific collectives."[22][23] Through these college-associated collectives, coaches use NIL "opportunities" to recruit top athletic talent by offering financial incentives, similar to how merit-based scholarships are used to attract academically gifted students. As evidenced from the SEC recruiter's comments,

[20]Note: the national championship game for the 2023 season is played in January 2024.
[21]https://www.on3.com/nil/news/how-are-recruiters-working-with-nil-collectives-in-states-where-its-allowed/
[22]https://collegefootballnetwork.com/human-cost-of-nil-2024/
[23]https://apnews.com/article/nil-college-boosters-67da0dc7cc98f6508915b36d629c99ec

these NIL deals are highly personalized and are affected by a variety of factors such as performance, social media followers, and even a recruit's own name.[24] Program administrators believe that "At the end of the day, NIL is probably the most direct line to being competitively relevant."[25]

To put the monetary potential of NIL in perspective for the reader, Josh Petty, a 4* high school recruit in the class of 2025, committed to Georgia Tech with a disclosed annual NIL payment of $800,000.[26] 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* or 4* recruits. A 3* defensive tackle secured $500k over four years for his NIL rights.[27]. According to the NCAA, The *average* D1 FBS football player has earned $45,000 from NIL deals in the first ten months of 2024.[28]

Below, we provide a timeline that covers key events that led 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 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 in part 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.[29]

[24] E.g. a popular commercial was done by 3* recruit DeColdest Crawford for an air conditioning company.
[25] https://collegefootballnetwork.com/human-cost-of-nil-2024/
[26] https://www.on3.com/nil/news/josh-petty-georgia-tech-yellow-jackets-multi-million-dollar-nil-package-five-sta
[27] https://theathletic.com/3256808/2022/04/19/college-football-recruiting-nil/
[28] Data accurate as of 10/18/2024, see https://nilassist.ncaa.org/data-dashboard/
[29] These laws were to force the NCAA to permit NIL for athletes. It is important to note that it was not illegal to make a 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.

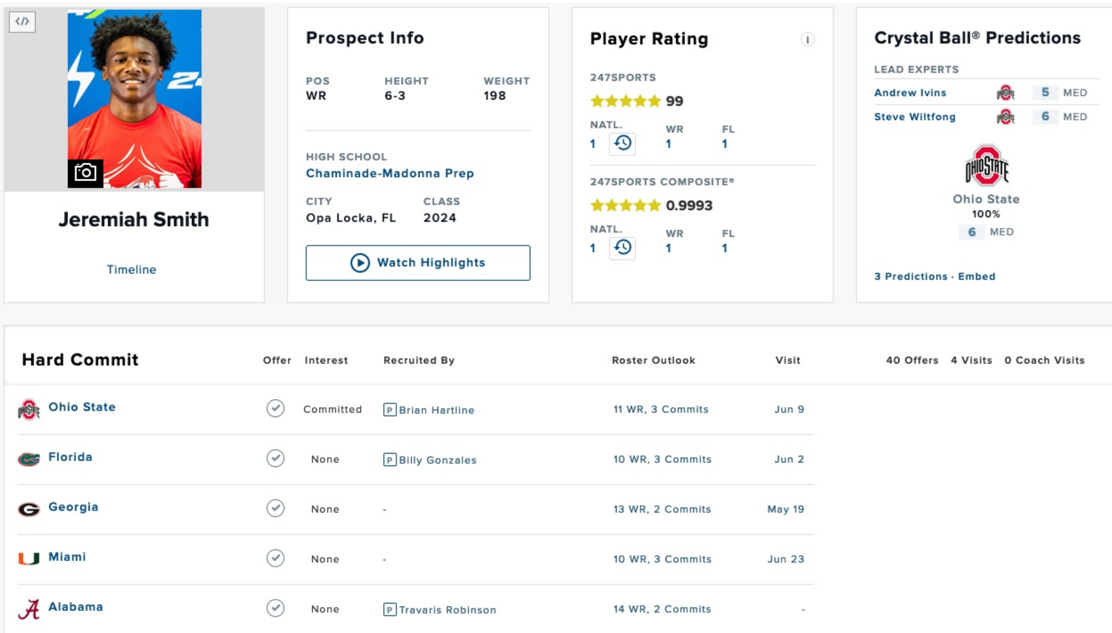

Figure 1: A screenshot of the *247Sports* website for Jeremiah Smith, the #1 ranked recruit in the class of 2024. Everything observable in this screenshot is available in our data.

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

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, school choice set, 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 the number of households.

Our data sample is divided 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 recruiting changes implemented in 2017.[30] 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 in late 2020 and every

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

collegiate conference had different rules regarding recruiting during the COVID-affected seasons.[31] We also drop international recruits, Army / Navy / Air Force commitments, and rated prospects who ultimately committed to another sport except for when we deploy our difference in difference estimator. 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.

3 Impact of NIL on Program Choice: Theory

To understand the possible impact of NIL and personalized pricing, we provide a scholarship choice model for high school recruits. With our theoretical choice model we 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 $q_i \in (5*, 4*, 3*)$ 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 $j_t \in 1, 2$ 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.[32] If recruit i decides to accept the scholarship offer from football program j in time period t, he obtains the utility given by

$$u_{i,j,t}(z_t) = f_j(z_t) + s_i(p_{j,t}) - p_{j,t} + \beta \mathbb{E}[V_{i,j}(z_{t+1}|z_t)] + \epsilon_{i,j,t}, \tag{1}$$

where $f_j(z_t)$ is the flow utility associated with choice j in period t, $p_{j,t}$ is the posted price of college j, $s_i(p_{j,t})$ is the individual $i's$ scholarship award from program j, $\beta \mathbb{E}[V_{i,j}(z_{t+1}|z_t)]$ represents recruit i's discounted expected future value of choice j in period $t+1$ conditional on being in state z_t, while β is the discount factor. In practice, $s_i(p_{j,t}) - p_{j,t} = 0$ with a full scholarship and is the case for all college football scholarship recipients. We assume that the flow utility captures the prestige of

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

[32] 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).

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, regardless of quality, value a high-quality (ranked) program at $\alpha > 0$.[33]

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

$\beta \mathbb{E}[V_{i,j}(z_{t+1}|z_t)]$ 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.[34]

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 j_1. A high school recruit will select the low-quality program (2) over the high-quality (1) when $u_{i,2,1}(z_1) > u_{i,1,1}(z_1)$ which leads to the condition of

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

Here, the recruit will choose the initial low-quality program (2) 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 gain insight into the sign of the term on the left-hand side, we analyze a player's likelihood of being drafted into the NFL based on his and the school's quality (Table 4). We construct a dataset with 10 years worth of NFL draft data (2014 - 2024), tracking the universe of high school recruits 3* and above throughout college and into the NFL. We observe their 247 Composite Score and star rating, the school they initially committed to, the last college they played football at before they

[33] See Table A.1 in the appendix for empirical support that prior season performance is indicative of performance in the subsequent season.

[34] We should highlight that our utility function for player i ignores the impact of future income from academic quality in order to focus on what we believe are first order effects of NIL and to keep the model interpretable. Below we do discuss how NIL has shifted college decisions based on academic quality, particularly for 3* recruits.

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

Y: 1{Selected in NFL Draft}	3 Star	4 Star	5 Star
Height	0.093^{***}	0.098^{***}	-0.015
	(0.027)	(0.037)	(0.077)
Weight	-0.001	0.001	0.002
	(0.002)	(0.002)	(0.004)
School Top 25 before recruit	0.301^{***}	0.229^{*}	-0.010
	(0.069)	(0.122)	(0.315)
Num. obs.	12806	2736	293
Position FE	Y	Y	Y
Conference FE	Y	Y	Y
Recruit Year FE	Y	Y	Y
Mean Y:	0.084	0.266	0.655

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

Table 4: NFL Draft logit regressions by stars; 2014 - 2024 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' NFL draft probability is not positively correlated with committing to a ranked program. However, the draft outcomes of the 3* and 4* star recruits are correlated (Table 4). Such an 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, $\mathbb{E}[V_{i,1}(z_2|z_1)]$ would be larger than $\mathbb{E}[V_{i,2}(z_2|z_1)]$. 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 with uniform prices (or without NIL).

Under NIL, all football programs are effectively able to engage in personalized pricing, and as a result the state variables that enter the decision processes for a high school recruit change. High school recruits now also incorporate the impact of personalized pricing through 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 of signing with a college football program.[35] NIL also impacts a recruit's future value through the potential of additional NIL contracts above and beyond the initial ones.

[35] Or shortly after

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

$$u_{i,j,t}(z_t, NIL_t) = h_{i,j}(z_t, NIL_t) + \beta\mathbb{E}[V_{i,j}(z_{t+1}, NIL_{t+1}|z_t, NIL_t)] + \epsilon_{i,j,t}, \tag{2}$$

Where NIL_t is an indicator variable such that $NIL_t = 1$ indicates a post-NIL world. If $NIL_t = 0$ for all t, then Equation 2 collapses back to Equation 1. The function $h_{i,j}(z_t, NIL_t) = f_j(z_t) + g_{i,j}(z_t, NIL_t)$ includes the program prestige, $f_j(z_t)$, and the impact of personalized pricing $g_{i,j}(z_t, NIL_t)$ which equals $s_i(p_{j,t}) + \nu_{i,j}(z_t, NIL_t) - p_{j,t}$ through NIL income ($\nu_{i,j}(z_t, NIL_t)$), and his net scholarship cost of $s_i(p_{j,t}) - p_{j,t} = 0$ for all scholarship recipients. 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 k under NIL requires the following condition.[36]

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

This condition differs from the earlier one without NIL in that the choice depends on the difference in expected values, $\mathbb{E}[V_i(z_t, NIL_t)]$, and the difference in NIL income, $\nu_i(z_t, NIL_t)$, 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 programs with their "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),

[36] We ignore the error term again.

and thus affects the expected future value terms. However, the probability of being drafted into the NFL is $\approx 8\%$ and $\approx 26\%$, 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 (personalized pricing) on program choice is empirically unclear.

4 Impact of NIL on Program Choice: Empirical Strategy

We now take a closer look at recruit behavior for each star rating and how NIL has causally affected their school choices. We then discuss the rationale for the recruit behavior from the causal estimates.

4.1 Empirical Model Setup

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 first 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 $NIL_i \in \{0, 1\}$, 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 from the class of 2021 had already signed their letters of intent in February 2021 and were legally bound to attend that school.

A 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) $\{Y_i(0), Y_i(1)\} \perp NIL_i | X_i$

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

We will examine a few dependent variables. First, we estimate the effect that NIL has on the football program quality of the school chosen by the recruits, with the historical performance over a variety of time periods as our Y variable. We then check if NIL is making recruits choose a lower quality education. Third, we proxy for "rich" schools with TV viewership, which can be indicative of fan support and team performance. Finally, we take "rich" in a literal sense and look if NIL is leading recruits to choose schools with more spending on their football programs (football spending, coaches salaries, and university donations).

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 also use an inverse probability weighting (IPW) estimator, where NIL is the binary treatment and weights are calculated based on the propensity scores. A third estimator we use is an augmented inverse probability weighting (AIPW) estimator, which enhances the IPW method by incorporating outcome models to improve efficiency and reduce bias. We discuss these methods next.

4.1.1 Ordinary Least Squares

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

$$Y_i = \alpha + \beta X_i + \tau NIL_i + \varepsilon_i \tag{4}$$

Assumption 1 implies that $\varepsilon_i \perp NIL_i | X_i$. 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 NIL - for example, an athlete's parents likely did not think 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.

4.1.2 The Augmented Inverse Propensity Score (AIPW) estimator

As a benchmark, we use the classic inverse probability weighting (IPW) estimator. The IPW estimator of the average treatment effect (ATE) is calculated as:

$$\widehat{\tau}_{\mathrm{IPW}} = \frac{1}{N} \sum_{i=1}^{N} \left[\frac{NIL_i \cdot Y_i}{\hat{e}(X_i)} - \frac{(1 - NIL_i) \cdot Y_i}{1 - \hat{e}(X_i)} \right]. \tag{5}$$

where $\hat{e}(X_i)$ is the estimated propensity score and NIL_i is the treatment indicator from Equation 4. The propensity score $e(X_i) = P(NIL_i = 1 \mid X_i)$ is the probability that recruit i is in the post-NIL period given their observable characteristics X_i. We estimate the propensity scores using logistic regression:

$$NIL_i = \alpha + \beta X_i + \varepsilon_i. \tag{6}$$

However, a challenge in our setting is the potential for poor overlap in propensity scores, particularly because covariates like recruit rank are highly predictive of treatment status as the number of 3* and above recruits has increased in the post-NIL period. When propensity scores $e(X_i)$ are close to 0 or 1, IPW estimators can become unstable due to extreme weights.[37]

To improve robustness, we use the augmented inverse propensity weighting (AIPW) estimator of Robins et al. (1994). The AIPW method first estimates the ATE by estimating the conditional means; then, it corrects for the biases of this estimation by applying inverse propensity score weighting to the residuals. 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).

[37] In estimation on the subset of top 3* recruits, we have to resort to a binned rank metric versus actual rank because of poor overlap

The AIPW estimator for the ATE is given by:

$$\widehat{\tau}_{\text{AIPW}} = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{\mu}_1(X_i) - \hat{\mu}_0(X_i) + NIL_i\frac{Y_i - \hat{\mu}_1(X_i)}{\hat{e}(X_i)} - (1 - NIL_i)\frac{Y_i - \hat{\mu}_0(X_i)}{1 - \hat{e}(X_i)}\right), \tag{7}$$

where $\hat{\mu}_1(X_i)$ and $\hat{\mu}_0(X_i)$ are the estimated conditional mean outcomes under treatment and control, respectively. 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.[38]

To further address issues with poor overlap, we compute an overlap-weighted average treatment effect (OW-ATE) as proposed by Li et al. (2018). The OW-ATE uses weights that emphasize observations with propensity scores near 0.5, reducing the influence of units with extreme propensity scores and mitigating instability from dividing by values close to 0 or 1. This approach improves the estimator's efficiency and robustness in the presence of limited overlap. We tune all parameters of our random forests using cross-validation.

4.2 Differences-in-Differences

While the previous methods provide estimates of the effect of NIL policies, they may be confounded by contemporaneous changes in the recruiting environment that coincide with NIL implementation. Factors such as conference realignment and the introduction of the transfer portal could independently influence athlete outcomes and recruiting patterns, making it challenging to isolate the causal effect of NIL.[39] To address these potential confounders, we employ a differences-in-differences (DiD) strategy that leverages a natural experiment arising from U.S. visa restrictions on foreign college football players.

International recruits playing on F-1 student (or other) Visas are not allowed to make money in the United States.[40][41] While loopholes exist that allow these students to earn outside the U.S., American football is much less relevant outside the U.S. than other sports like basketball or soccer.

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

[39] Note: results of the AIPW estimator are robust to dropping the class of 2024, the only class to be affected by conference realignment in our data.

[40] https://www.bakerlaw.com/insights/international-student-athletes-and-their-eligibility-for-nil-partnerships/

[41] For example, Zach Edey, a famous Canadian college basketball star at Purdue, was unable to earn NIL money: https://www.espn.com/mens-college-basketball/story/_/id/39882011/purdue-zach-edey-missing-profits-due-us-nil-law

This creates a natural control group — international recruits — that was not affected by the change in the NIL policy, allowing us to control for factors that vary over time and affect both groups in a similar way.[42]

Our DiD approach compares the changes in outcomes for domestic recruits before and after NIL implementation to the changes in outcomes for international recruits over the same periods. The key identifying assumption of DiD is the *parallel trends* assumption, which posits that, in the absence of the treatment (NIL policies), the average outcomes for domestic and international recruits would have evolved similarly over time. We have repeated cross sectional data and our treatment is not staggered, so we are able to recover ATT estimates using a standard DiD regression estimator (Roth et al., 2023):

$$Y_{it} = \alpha + \gamma \text{Domestic}_i + \beta \text{NIL}_t + \delta(\text{Domestic}_i \times \text{NIL}_t) + \theta X_{it} + \varepsilon_{it} \tag{8}$$

where Domestic_i is an indicator variable equal to 1 if recruit i is a domestic student and 0 if international. Post_t is an indicator variable equal to 1 for observations in the post-NIL period and 0 for the pre-NIL period. $\text{Domestic}_i \times \text{Post}_t$ is the interaction term capturing the differential effect of NIL on domestic recruits. All other variables are defined as above as in Section 4.1

The coefficient of interest is δ, which measures the average treatment effect of NIL policies post-NIL on domestic recruits relative to international recruits.[43]

We plot all event studies in Appendix A.4 and use them to check for the existence of pretrends, which helps test the parallel trends assumption. Our event studies use the following regression specification:

$$Y_{it} = \alpha + \gamma Domestic_i + \lambda_t + \sum_{\tau \neq 2020} \delta_\tau (1\{t = \tau\} \times Domestic_i) + \theta X_{it} + \varepsilon_{it} \tag{9}$$

which is the standard two-way fixed effects estimator adopted to our current setting of repeated cross-sectional data. Because treatment occurs for everyone at the same date (2021), we can use this event-study specification without worrying about heterogeneous treatment effects from timing

[42] Note that "international" does not necessarily imply that the athlete attended high school internationally. In fact, many top "international" recruits end up playing football in a U.S. high school because the sport is so localized to the U.S. and high school football in the U.S. is the best pathway to be recognized by college scouts.

[43] i.e. δ is a measurement of the ATT

(Roth et al., 2023).

One challenge facing the DiD is the small sample size of international recruits. There are no 5* international recruits post-NIL and only a handful of 4* international recruits each year. Because we can control for unobserved time-varying factors with the DiD, we expand upon the dataset used in Section 4.1 to obtain a larger sample. We reintroduce the 2021 class and we extend the pre-period from 2018 to 2015 as recruiting rules and challenges affected both international and domestic athletes equally. While power issues may persist, our goal with the DiD is for it to act as a robustness check for the propensity score estimators in Section 4.1 as it uses a different source of variation to identify the effects of NIL.

5 NIL Effects

5.1 Football program quality

We begin by assessing the impact of NIL on recruits' selection of football programs based on program quality. We use five quality metrics: two indicator variables for whether the program finished in the top 10 or top 25 in the season before the recruit's arrival, two count variables for the total number of top 10 and top 25 finishes in the previous three seasons, and a final measure based on the program's winning percentage over the prior three seasons. In Appendix A.3, we provide alternative measures for program quality, such as advanced statistics measurements like SP+ and ELO (Table A.5 and A.9),[44] historical draft success (Table A.4, A.8, and A.12) and historical recruiting rankings (Table A.6, A.10, and A.13). Our results are robust to all of these alternative measures.

5.1.1 Five-star recruits' football program quality

We first discuss the behaviors of 5* recruits. In our data period, there are only 94 "control" (2018-2020) 5* recruits and 110 "treated" (2022-2024) recruits. We do not compute the differences-in-differences estimates for 5* recruits because there are no 5* international recruits post-NIL. We find a significant effect where 5* recruits choose schools with worse-performing records in the

[44] SP+ is a metric created by Bill Connelly of ESPN. See: `https://www.sbnation.com/college-football/2017/10/13/16457830/college-football-advanced-stats-analytics-rankings`

Y	Method	Treatment	5* recruits		4* recruits		3* recruits	
			Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
College ranked top 10 prior season	IPW	ATE	-0.328	0.070	-0.024	0.021	-0.047	0.004
	IPW	ATT	-0.269	0.094	-0.044	0.023	-0.014	0.008
	AIPW	OW-ATE	-0.253	0.069	-0.025	0.024	0.009	0.008
	AIPW	ATT	-0.229	0.069	-0.035	0.021	0.009	0.004
	OLS	ATE	-0.293	0.078	-0.016	0.020	-0.000	0.005
	DID	ATT	–	–	0.008	0.152	0.020	0.028
College ranked top 25 prior season	IPW	ATE	-0.207	0.073	0.005	0.022	-0.120	0.012
	IPW	ATT	-0.134	0.087	-0.026	0.024	-0.008	0.012
	AIPW	OW-ATE	-0.182	0.063	0.003	0.025	0.013	0.014
	AIPW	ATT	-0.164	0.063	0.003	0.022	0.012	0.007
	OLS	ATE	-0.166	0.073	-0.045	0.034	-0.049	0.017
	DID	ATT	–	–	0.012	0.120	0.082	0.039
Total top 10 finishes prior three seasons	IPW	ATE	-0.405	0.177	-0.083	0.048	-0.154	0.009
	IPW	ATT	-0.103	0.207	-0.120	0.054	-0.070	0.019
	AIPW	OW-ATE	-0.361	0.173	-0.041	0.057	-0.011	0.018
	AIPW	ATT	-0.288	0.174	-0.058	0.050	-0.012	0.009
	OLS	ATE	-0.422	0.253	-0.042	0.050	-0.029	0.010
	DID	ATT	–	–	-0.459	0.356	-0.007	0.064
Total top 25 finishes prior three seasons	IPW	ATE	-0.332	0.152	-0.085	0.049	-0.185	0.011
	IPW	ATT	-0.325	0.196	-0.118	0.054	-0.101	0.029
	AIPW	OW-ATE	-0.240	0.147	-0.067	0.055	0.013	0.029
	AIPW	ATT	-0.220	0.148	-0.077	0.049	-0.041	0.016
	OLS	ATE	-0.203	0.174	-0.045	0.042	-0.049	0.017
	DID	ATT	–	–	-0.133	0.322	0.114	0.097
Win percentage prior three seasons	IPW	ATE	-0.050	0.019	-0.010	0.007	-0.041	0.016
	IPW	ATT	-0.028	0.023	-0.013	0.008	-0.020	0.005
	AIPW	OW-ATE	-0.045	0.022	-0.007	0.008	-0.019	0.007
	AIPW	ATT	-0.039	0.022	-0.006	0.007	-0.026	0.003
	OLS	ATE	-0.047	0.029	-0.005	0.006	-0.021	0.005
	DID	ATT	–	–	-0.078	0.036	0.020	0.018

Table 5: Treatment effects of NIL on the probability of recruits attending top-ranked schools. Standard errors clustered at the position level

previous season.

Columns 4 and 5 of Table 5 display the measured effects of NIL on the football programs that 5* recruits choose. 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. Over a three-year horizon we see similar magnitudes - the teams that 5* recruits join have on average 0.2 to 0.3 fewer top 10 and top 25 finishes. The three-year winning percentage is also negative with a magnitude of about 4%. This translates to about two fewer wins over the three college football seasons, which could be the difference between a national championship contender or just a good team. Historical school performance is highly indicative of future performance and school prestige, so choosing a worse-performing team means a lower flow utility from prestige.[45]

Our theoretical model's simplified choice prediction implies that lower quality schools would be chosen ($j_t = 2$) if Equation 3 was satisfied. We find that the NFL draft outcomes of 5* recruits are not affected by the rank of the school they initially commit to (Table 4). 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:

$$\underbrace{\nu_{i,2}(z_1, NIL_1) - \nu_{i,1}(z_1, NIL_1)}_{\text{Difference in flow utility as a function of NIL payments}} > \alpha$$

We are able to rationalize the results in Table 5 where 5* recruits increasingly favor lower-ranked schools post-NIL.[46] The portion of flow utility affected by NIL, $\nu(\cdot)$ 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.

Our model implies that personalized pricing greatly affects 5* recruits who already possess immense talent and are 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*

[45]See Table A.1, where last year's win percentage has a larger and more significant coefficient than any school-specific fixed effect

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

recruit's future outcomes (Table 4), so colleges can seemingly convince 5* recruits to attend simply by paying them more.

Anecdotes seem to support our theoretical and data-driven 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)[47] and the first 5* recruit to sign with an FCS school (collegiate second division).[48] It turns out that Hunter received NIL deals specifically for signing with an HBCU.[49]

5.1.2 4* recruits' football program quality

Columns 6 and 7 of Table 5 shows that post-NIL, 4* recruits are equally as likely to attend a top 10 or top 25-ranked program from the previous season. The three-year horizon tells a similar story; although the estimates suggest that 4* recruits attend schools with fewer top finishes, none are significant.

It is interesting to understand why 4* recruits' behaviors do not seem to be changing on average. One explanation could be that within 4* recruits, quality is spread out. The top 4* recruits talent-wise may be very close to 5* recruits, while the bottom 4* recruits may only be as skilled as 3* recruits.[50] With 5* recruits seemingly moving to lower-quality schools, top 4* recruits could potentially be replacing them at higher-quality schools. We augment our analysis by separating the 4* recruits into the top 100 4* recruits and 101st ranked 4* recruit and worse to see if football program quality of top 4* recruits are being averaged out by the lower tier 4* recruits.

Across all five football program quality measures and estimation methods (Table 6), lower ranked 4* recruits go to worse football schools while top ranked 4* recruits attend similar quality programs or slightly better. The observed heterogeneity within the 4* recruit group can be interpreted through the lens of our theoretical framework. With 5* recruits increasingly attending lower-ranked programs post-NIL, vacancies and opportunities arise at higher-ranked programs that

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

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

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

[50] 247Sports gives this exact interpretation for their rankings https://247sports.com/article/247sports-rating-explanation-81574/

Y	Method	Treatment	Top 100 4* recruits		101+ ranked 4* recruits	
			Estimate	Std. Error	Estimate	Std. Error
Top 10 Prior Season	IPW	ATE	0.069	0.081	-0.055	0.031
	IPW	ATT	0.025	0.091	-0.097	0.047
	AIPW	OW-ATE	-0.013	0.042	-0.035	0.030
	AIPW	ATT	-0.018	0.041	-0.043	0.028
	OLS	ATE	-0.022	0.053	-0.021	0.023
	DID	ATT	0.409	0.494	-0.112	0.152
Top 25 Prior Season	IPW	ATE	0.163	0.075	-0.031	0.033
	IPW	ATT	0.113	0.120	-0.029	0.048
	AIPW	OW-ATE	0.019	0.041	-0.009	0.032
	AIPW	ATT	0.019	0.041	-0.011	0.027
	OLS	ATE	0.052	0.048	-0.012	0.025
	DID	ATT	0.028	0.389	-0.005	0.120
Total Top 10 Prior 3 Seasons	IPW	ATE	0.276	0.198	-0.157	0.077
	IPW	ATT	0.211	0.246	-0.236	0.122
	AIPW	OW-ATE	0.027	0.103	-0.087	0.068
	AIPW	ATT	0.018	0.101	-0.086	0.056
	OLS	ATE	0.015	0.117	-0.075	0.060
	DID	ATT	0.931	1.232	-0.874	0.195
Total Top 25 Prior 3 Seasons	IPW	ATE	0.364	0.197	-0.202	0.072
	IPW	ATT	0.336	0.331	-0.239	0.107
	AIPW	OW-ATE	0.067	0.092	-0.149	0.070
	AIPW	ATT	0.064	0.092	-0.141	0.058
	OLS	ATE	0.097	0.124	-0.125	0.055
	DID	ATT	0.915	0.768	-0.423	0.274
Win Percentage Prior 3 Seasons	IPW	ATE	0.072	0.036	-0.030	0.011
	IPW	ATT	0.065	0.058	-0.034	0.016
	AIPW	OW-ATE	0.014	0.014	-0.020	0.008
	AIPW	ATT	0.013	0.014	-0.016	0.008
	OLS	ATE	0.022	0.019	-0.019	0.008
	DID	ATT	0.121	0.139	-0.078	0.036

Table 6: Treatment effects of NIL on the probability of recruits attending top-ranked schools for 4* recruits. Standard errors clustered by position.

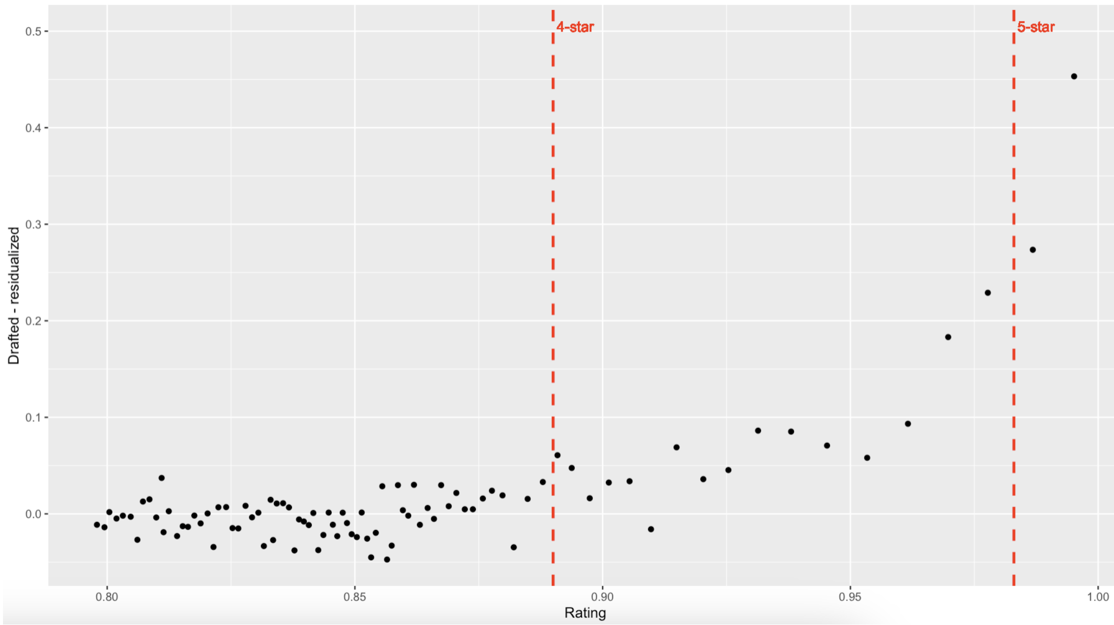

Figure 2: Residualized binscatter of NFL draft outcome on 247Sports Composite Rating, controlling for height, weight, position, year, and college attended in final year.

were previously less accessible to top 4* recruits. This shift allows the top 4 * recruits to fill the roles and positions left open by the departing 5* recruits to potentially obtain better development and increase their prospects in the NFL Draft.[51]

Figure 2 displays the residualized binscatter (Cattaneo et al., 2024) where the dependent variable is an indicator that the athlete is drafted by an NFL team and the independent variable is the 247Sports Composite Rating. We control for height, weight, position of the athlete, year, and graduating program. Beyond a rating of around 0.96, the probability that an athlete is drafted increases exponentially. This rating corresponds to just about the top 90-100 recruits in each draft class, or the top 60-70 4* recruits. Thus, the marginal value of development on the top 4* recruits is uniquely large; these recruits' draft success is not guaranteed, but the development of their talent increases their draft prospects, and thus their $\mathbb{E}[V(\cdot)]$, the most.[52]

[51] Table A.8 also supports this claim that top 4* recruits seem to be focusing on schools with good historical draft success.

[52] We cannot break the binscatter out by pre- and post- NIL recruits because the high school athletes who were recruited at the legalization of NIL (class of 2021) are now just eligible for the NFL draft (2024 NFL Draft). Some recruits may stay at college for five years or more before being drafted.

5.1.3 Three-star recruits' football program quality

Columns 8 and 9 of Table 5 show that NIL has mixed effects on the football program quality chosen by 3* recruits. There is some indication that 3* recruits are choosing schools that performed better in the previous year. Conversely, there are more significantly negative effects over the lagged three-year horizon. The effect magnitudes are small, and the DiD estimates often returns a positive but insignificant result. Small effect sizes can be attributed to the fact that 3* recruits generally do not choose football programs with many top finishes. The schools chosen by the three stars post-NIL win 2% fewer games - which is about one game over the previous three seasons.

Like 4* recruits, the top ranked 3* recruits could be different from the bottom ranked; recruiting websites like 247Sports even mention that some 3*s should be valued as much as 4* recruits.[53] To see if top 3* recruits are affected differently, we conduct the same exercise as before, splitting the 3* recruits into the top 100 and 101+ ranked 3* recruits and rerunning our estimators. The results are in Table A.11, which shows similar results across top and bottom 3* recruits. Overall, the pattern for 3* recruits seems to be that they are going to football programs that perform slightly worse post-NIL.

5.2 Academic Quality

Being talented at football affects a recruit's expected future earnings, but the quality of education that they receive at their enrolled college can also affect $\mathbb{E}[V(\cdot)]$. Here, we take a look at if NIL has affected recruits' college choices in terms of academic quality. We use metrics such as admission rate, SAT scores, and median cohort earnings (all demeaned yearly) to determine if recruits are trading off a better education because of NIL money today.

Table 7 displays the effects of NIL on the academic quality of recruits' chosen schools by star level. Overall, there does not seem to be consistent evidence that 5* or 4* recruits are trading off academic quality for NIL money. These recruits are the most likely to make the NFL, so it makes sense that their focus is on developing their football talent and not academic merit. However, 3* recruits are significantly more likely to attend schools with higher admission rates (less selective), lower SAT scores, and lower career earnings post-NIL. We would expect this group to have the

[53]See: `https://247sports.com/article/247sports-football-recruiting-rankings-what-the-ratings-mean-when-they-are-`

Y	Method	Treatment	5* recruits		4* recruits		3* recruits	
			Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Admit Rate (demeaned)	IPW	ATE	-0.023	0.040	-0.001	0.011	0.124	0.018
	IPW	ATT	-0.034	0.031	-0.005	0.011	0.000	0.008
	AIPW	OW-ATE	0.001	0.029	-0.007	0.012	0.029	0.010
	AIPW	ATT	0.003	0.029	-0.010	0.010	0.011	0.005
	OLS	ATE	0.011	0.028	-0.005	0.015	0.012	0.006
	DID	ATT	–	–	0.079	0.073	0.040	0.024
SAT Average (demeaned)	IPW	ATE	3.405	12.265	0.884	3.659	-95.296	5.889
	IPW	ATT	10.653	11.886	0.891	3.936	-3.848	3.579
	AIPW	OW-ATE	-1.139	9.671	4.436	4.251	-26.228	4.826
	AIPW	ATT	-1.990	9.899	4.334	3.691	-18.014	2.513
	OLS	ATE	-6.169	10.724	2.301	4.641	-13.611	3.248
	DID	ATT	–	–	-55.086	36.194	-19.973	17.240
Log Median Income 10 years post-graduation (demeaned)	IPW	ATE	0.000	0.021	0.001	0.007	-0.129	0.021
	IPW	ATT	-0.002	0.017	0.003	0.008	-0.003	0.006
	AIPW	OW-ATE	0.000	0.018	0.006	0.008	-0.040	0.008
	AIPW	ATT	-0.003	0.019	0.008	0.007	-0.030	0.004
	OLS	ATE	-0.003	0.010	0.003	0.008	-0.020	0.006
	DID	ATT	–	–	-0.094	0.081	-0.009	0.028

Table 7: Treatment effects of NIL on academic quality of recruits' chosen schools. Standard errors clustered by position.

greatest change with respect to academic prestige because they are the least likely group in our study to make the NFL; Another way to maximize future earnings or $\mathbb{E}[V(\cdot)]$ is getting a better education. With the advent of NIL, 3* recruits trade off future earnings from education by taking NIL money today.

To further assess the behaviors of 3* recruits, we split them into two groups: the top 100 ranked and those ranked 101 and beyond. Table 8 presents the treatment effects of NIL on academic quality measures for these subgroups. For the top 100 ranked 3* recruits, our results show no significant changes in the academic quality of their chosen schools post-NIL. In contrast, almost all of our estimators indicate that lower-ranked 3* recruits (ranked 101 and beyond) exhibit a notable shift toward schools with lower educational quality—characterized by higher admission rates, lower SAT scores, and reduced future earnings.[54]

This finding is significant as it suggests that personalized pricing is negatively impacting the education quality that 3* high school recruits are choosing. These recruits are unlikely to secure an NFL career, so education is important to their future earnings ($\mathbb{E}[V(\cdot)]$ term in Equation 2). Whether these players are worse off due to NIL depends on the size of their NIL contracts and their time preference for money. Our results indicate that these athletes choose schools where the median income a decade after graduation is approximately 3% lower (roughly $1,500 less per

[54]The only occasional exception is the IPW estimate for the ATT, which is included again only as a benchmark because of the lack of overlap at times. Estimates may be directionally dissimilar, but remain statistically and economically insignificant.

Y	Method	Treatment	Top 100 3* recruits		101+ ranked 3* recruits	
			Estimate	Std. Error	Estimate	Std. Error
Admit Rate (demeaned)	IPW	ATE	0.036	0.169	0.125	0.019
	IPW	ATT	-0.068	0.112	-0.005	0.007
	AIPW	OW-ATE	0.055	0.049	0.036	0.010
	AIPW	ATT	0.015	0.049	0.017	0.005
	OLS	ATE	-0.030	0.038	0.017	0.006
	DID	ATT	0.192	0.193	0.037	0.029
SAT Scores (demeaned)	IPW	ATE	-12.350	173.652	-96.068	6.223
	IPW	ATT	23.868	31.245	3.031	3.330
	AIPW	OW-ATE	-25.842	19.721	-28.669	5.120
	AIPW	ATT	-0.773	20.449	-19.277	2.638
	OLS	ATE	9.393	15.905	-17.843	3.494
	DID	ATT	-127.910	88.452	-17.393	17.521
Log Median Income	IPW	ATE	-0.010	0.030	-0.128	0.023
10 years post-graduation	IPW	ATT	-0.014	0.443	0.007	0.006
(demeaned)	AIPW	OW-ATE	-0.025	0.026	-0.044	0.008
	AIPW	ATT	-0.039	0.025	-0.033	0.004
	OLS	ATE	-0.073	0.033	-0.026	0.006
	DID	ATT	0.071	0.152	-0.003	0.029

Table 8: Treatment effects of NIL on academic quality related numbers for different groups of 3* recruits. Standard errors clustered by position.

year) post-NIL. Given that the difference in NIL offers likely exceeds this projected decrease in future earnings, the immediate financial benefits from NIL deals probably outweigh the potential long-term earnings loss from attending a lower-quality educational institution.[55]

5.3 TV Ratings and Media Markets

A college football player's NIL valuation is largely driven by quality and exposure. The more visibility a player has, the greater their reach, allowing them to command higher compensation for endorsements and advertising services. One significant factor influencing exposure is TV ratings—the frequency and scale at which a school's games are broadcasted can enhance a player's national profile. Consequently, we assess whether recruits in the post-NIL era tend to choose schools located in larger media markets or with more extensive TV coverage in previous years.

Table 9 presents the treatment effects of NIL on TV ratings for different groups of recruits. We examine three metrics: the log of total TV audience size over the three years preceding the recruit's enrollment adjusted by subtracting the yearly mean to control for time trends, the number of times

[55] See https://www.nytimes.com/interactive/2024/08/31/business/nil-money-ncaa.html, https://www.nytimes.com/2023/10/21/us/college-athletes-donor-collectives.html, and https://www.cbssports.com/college-football/news/inside-the-college-football-nil-market-how-much-players-at-each-position-are-actually-getti for discussions on NIL earnings and their impact on college athletes.

a school's games were broadcasted on TV over the prior three years, also demeaned annually, and the DMA size of the college the recruit committed to.

Y	Method	Treatment	5* recruits		4* recruits		3* recruits	
			Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Log 3 year total TV viewership (demeaned)	IPW	ATE	0.012	0.150	0.035	0.035	-2.651	0.765
	IPW	ATT	0.019	0.190	-0.001	0.041	-0.156	0.117
	AIPW	OW-ATE	0.001	0.174	0.060	0.042	-0.618	0.191
	AIPW	ATT	0.004	0.190	0.048	0.038	-0.829	0.083
	OLS	ATE	0.023	0.207	0.062	0.029	-0.482	0.154
	DID	ATT	–	–	-0.102	0.165	-0.204	0.416
Three year total TV broadcasts (demeaned)	IPW	ATE	-0.012	0.896	-0.020	0.308	-7.243	0.700
	IPW	ATT	0.323	0.907	-0.017	0.336	-1.016	0.295
	AIPW	OW-ATE	-0.186	0.928	0.095	0.352	-1.908	0.346
	AIPW	ATT	-0.048	0.931	0.133	0.311	-2.139	0.176
	OLS	ATE	0.469	1.043	0.006	0.170	-1.482	0.215
	DID	ATT	–	–	0.478	2.453	0.564	1.157
School DMA % of US Population	IPW	ATE	0.133	0.157	0.030	0.044	0.111	0.110
	IPW	ATT	0.180	0.154	0.035	0.043	0.004	0.032
	AIPW	OW-ATE	-0.076	0.146	0.021	0.049	-0.041	0.040
	AIPW	ATT	-0.070	0.148	0.027	0.041	-0.039	0.020
	OLS	ATE	-0.028	0.176	0.021	0.042	-0.008	0.027
	DID	ATT	–	–	-0.527	0.388	-0.086	0.197

Table 9: Treatment effects of NIL on TV ratings for different groups of recruits. Standard errors clustered by position.

For 3* recruits, the results generally suggest a negative effect of NIL on their selection of schools with greater TV exposure. The estimates for the log of the total TV viewership over three years are all negative (and some significant), with magnitudes suggesting at least a 25% or more decrease in viewership. The total TV broadcasts are negatively affected, but the DiD results do not align with the others. Interestingly, there appears to be little effect on the DMA size where the school is located, aside from a small, negative effect measured by the AIPW ATT estimator. We show in Table A.14 that these changes are mainly driven by lower-ranked 3* recruits going to lower visibility schools.

For 5* and 4* recruits, the findings are mixed, but generally indicate no significant change in school selection based on TV exposure post-NIL. So even as 5* recruits select slightly worse-performing football programs and top 4* recruits go to slightly better ones post-NIL, they still choose schools with similar amounts of viewership and TV broadcasts. However, no significant result means that popular schools are not disproportionately attracting the best talent, so the rich are not getting richer in this sense.

5.4 School Wealth

Thus far, our discussion of "rich" schools has referred to institutions abundant in athletic talent. However, financial resources vary significantly between colleges and some have considerably more wealth than others. In this section, we investigate whether NIL policies have influenced high school recruits to favor schools with greater financial assets, interpreting "rich" in a literal financial sense. We leverage expenditure data from the Knight-Newhouse database, which provides comprehensive revenue and spending information for all public universities in Division 1 FBS and FCS college football.

A key limitation of this data is that it only includes public institutions. If recruits are systematically choosing private schools over public ones in the post-NIL era, this could pose a challenge to our analysis. In general (Table 10), it seems that not much has changed with regard to public vs. private school choice. However, there seems to be an increase in the selection of international recruits to private schools, which may affect our DiD estimates.

	Pre-NIL (international)	Post-NIL (international)
5*	0.064	0.049
4*	0.117 (0.000)	0.120 (0.308)
3*	0.191 (0.195)	0.201 (0.215)

Table 10: Proportion of recruits choosing private schools, pre- and post-NIL

We proceed by examining three key dependent variables to assess the impact of NIL policies. The first variable is football coaching salary, which includes all assistants and scouts. The second variable is total football spending, which includes expenditures training, facilities, recruiting, and other football-related activities. We also assess if alumni donations to the school are affecting recruits' choices.

Again, we find no discernible impact of NIL on the wealth of 5* and 4* recruits' schools. Even by changing our definition of rich to material wealth, we fail to show that the richest football schools get "richer" post-NIL. At best, there is no effect of NIL on the positive assortativeness of high school recruits and schools. Our evidence even suggests the contrary; the DiD results for 4* recruits and the AIPW results for 3* recruits reveal a notable negative relationship between NIL implementation and the financial wealth of the schools they choose.[56] These results reject

[56] Although the DiD estimates are positive (but insignificant).

Y	Method	Treatment	5* recruits		4* recruits		3* recruits	
			Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Log Football Coach Salaries	IPW	ATE	-0.004	0.049	0.006	0.019	-0.636	0.055
(demeaned)	IPW	ATT	-0.026	0.060	-0.002	0.021	-0.060	0.024
	AIPW	OW-ATE	-0.010	0.064	0.014	0.023	-0.177	0.026
	AIPW	ATT	0.008	0.065	0.015	0.020	-0.184	0.014
	OLS	ATE	0.023	0.061	0.010	0.017	-0.122	0.020
	DID	ATT	–	–	-0.164	0.104	0.088	0.086
Log Football Spending	IPW	ATE	0.046	0.054	0.004	0.018	-0.595	0.050
(demeaned)	IPW	ATT	0.065	0.076	0.003	0.020	-0.059	0.022
	AIPW	OW-ATE	-0.002	0.060	0.005	0.022	-0.157	0.024
	AIPW	ATT	0.014	0.060	0.008	0.019	-0.159	0.013
	OLS	ATE	0.047	0.052	0.004	0.018	-0.110	0.020
	DID	ATT	–	–	-0.200	0.083	0.101	0.080
Log Alumni Donations	IPW	ATE	0.022	0.084	0.014	0.085	-1.146	0.204
(demeaned)	IPW	ATT	0.002	0.110	0.019	0.036	-0.080	0.039
	AIPW	OW-ATE	-0.004	0.099	0.037	0.040	-0.259	0.047
	AIPW	ATT	0.010	0.099	0.032	0.035	-0.258	0.024
	OLS	ATE	0.086	0.127	0.036	0.038	-0.197	0.032
	DID	ATT	–	–	-0.183	0.141	0.242	0.147

Table 11: Treatment effects of NIL on log football spending, log coach salaries, and log alumni donations for different groups of recruits. Standard errors clustered by position. Public school data only.

a hypothesis that wealthier schools are obtaining better talent, and instead weakly suggest that recruits are increasingly opting for schools with fewer financial resources in the post-NIL era.

5.5 Impact on Competition

We have shown that personalized pricing through NIL has had consequences for the initial distribution of high school talent among colleges. Five-star and lower-ranked four-star recruits are choosing lower-performing teams. Three star recruits are choosing teams that are slightly worse historically. A natural follow-up question would be - has this distributional shift created any impact on the competitiveness of college football games?

We now assess if college football has become more competitive post-NIL. We leverage data from betting markets to measure "competitiveness." The "spread" of a football game is the expected point differential between the two teams. Instead of betting on who will win a football game outright, bettors often bet if a team will "cover" the spread.[57] For example, the 2024 Texas vs Oklahoma college football game had a spread of Texas -16.5, indicating that Texas was a 16.5 point favorite to win the game. Bettors who bet on Texas to cover, won if and only if Texas won by 17 or more points.[58] Sportsbooks are market makers who have an incentive to set spreads close to

[57]Popular podcasts and TV programs often focus on the spread. For example, the popular sports podcast *The Bill Simmons Podcast* dedicates an entire episode every week during football season to "Guess the Lines (spreads)" for NFL games.

[58]Spread provided by ESPN Bet. Texas ended up winning 34-3, covering the spread `https://www.espn.com/college-football/game/_/gameId/401628390/texas-oklahoma`

50/50 because it generates the most volume and also minimizes their risk. In our data, the spread was covered by the favorite 50.6% of the time pre-NIL and 49.4% of the time post-NIL.[59]

A spread close to zero means that the favorite is expected to win by fewer points, indicating a more competitive game. Therefore, we can assess if games are more competitive if the absolute value of the predicted spread is smaller on average. We run the following regression:

$$
\begin{aligned}
|\text{Spread}_{gt}| = \beta_0 &+ \beta_1 \, \text{NIL}_t \\
&+ \beta_2 \, |\Delta\text{Rank}_{gt}| + \beta_3 \, |\Delta\text{RecruitingClass}_{gt}| + \beta_4 \, |\Delta\text{TransfersRating}_{gt}| \\
&+ \beta_5 \, \text{NIL}_t \cdot |\Delta\text{Rank}_{gt}| + \beta_6 \, \text{NIL}_t \cdot |\Delta\text{RecruitingClass}_{gt}| + \beta_7 \, \text{NIL}_t \cdot |\Delta\text{TransfersRating}_{gt}| \\
&+ \mathbf{x}'_{gt}\boldsymbol{\beta} + \gamma_g + \varepsilon_{gt},
\end{aligned}
$$

Game g occurs in season t between two teams, $\|Spread_{gt}\|$ is the absolute value of the spread, $\|\Delta Rank_{gt}\|$ is the difference in AP ranking between the two teams competing in game g, $\|\Delta RecruitingClass_{gt}\|$ is the difference in recruiting class metrics for the incoming recruiting class between the teams according to two separate metrics, $\|\Delta TransfersRting_{gt}\|$ is the difference in two separate incoming transfer class metrics between the two teams, $\mathbf{x}'_{gt}$ are other observable game and time-varying characteristics, γ_g are team fixed effects, and ε_{gt} is the error term. We display the results in the first column of Table 12.

Controlling for recruiting class ratings and the transfer portal, we observe that NIL has a significant and economically meaningful 1.2 point decrease in the spread, meaning that games are predicted to be about 1.2-points closer on average post-NIL. NIL interaction terms aside from the transfer portal coefficients are largely insignificant, with the exception that the interaction of NIL and |ΔTotal recruit rating| is significantly negative.[60] In Table 12 column 2, we find that NIL is positively correlated with more underdog teams winning, even after controlling for the spread. By teasing apart the transfer portal effect on the spread and underdog teams winning, we have provided additional evidence that NIL has, in fact, made college football more competitive.

[59] $N_{pre} = 6301$ and $N_{post} = 4348$. There is no statistically significant difference with a z-score of 1.217

[60] Almost all transfers before 2021 were ineligible for one year after a transfer, 247Sports doesn't even provide a transfer class rating pre-NIL.

	Y: |spread|	Y: 1{underdog win}
NIL	−1.273	0.558
	(0.681)	(0.311)
|ΔRank|	0.541	0.010
	(0.021)	(0.009)
|Δ247 recruiting class rating|	0.050	0.000
	(0.004)	(0.001)
|ΔTotal recruit rating|	0.149	−0.011
	(0.042)	(0.010)
Home team unranked	−0.069	0.125
	(0.351)	(0.119)
Away team unranked	3.130	0.169
	(0.345)	(0.119)
Home team recruiting class unranked by 247	1.296	−0.136
	(1.550)	(0.371)
Away team recruiting class unranked by 247	−0.797	0.284
	(1.134)	(0.549)
Home team no ranked recruits	0.010	0.131
	(1.451)	(0.294)
Away team no ranked recruits	−0.262	0.248
	(0.558)	(0.300)
NIL x |ΔNet number of transfers|	0.027	0.002
	(0.035)	(0.012)
NIL x |ΔNet 247 rating of transfers|	0.060	−0.038
	(0.055)	(0.018)
NIL x |ΔRank|	0.010	−0.018
	(0.038)	(0.018)
NIL x |Δ247 recruiting class rating|	0.002	−0.001
	(0.006)	(0.002)
NIL x |ΔTotal recruit rating|	−0.155	−0.009
	(0.064)	(0.017)
NIL x Home team unranked	−0.060	−0.101
	(0.594)	(0.195)
NIL x Away team unranked	0.456	−0.183
	(0.619)	(0.221)
NIL x Away team recruiting class unranked by 247	−0.082	−0.275
	(1.278)	(0.583)
NIL x Home team no ranked recruits	−0.189	0.094
	(0.866)	(0.239)
NIL x Away team no ranked recruits	1.481	0.158
	(0.612)	(0.266)
|spread|		−0.131
		(0.006)
NIL x |spread|		−0.002
		(0.010)
Num. obs.	9849	9630
Team FE	Y	Y
Game week FE	Y	Y
R^2 (full model)	0.601	–
Log Likelihood	–	−4273.389

Table 12: Column 1: OLS regression of betting spread on various NIL, ranking, recruiting, and transfer portal variables. Negative coefficients imply a smaller spread and a more competitive football game.
Column 2: Logit regression of an indicator variable for an underdog winning on various NIL, ranking, recruiting, and transfer portal variables. Positive coefficients imply a positive correlation with an upset victory occurring.
Standard errors clustered at the team level. Data from games 2013-2023.

5.6 Discussion

Our findings indicate that NIL policies have introduced significant changes in the college football recruiting landscape, affecting recruits differently according to their star ratings. Post-NIL, 5* recruits move to football programs who have performed poorly in the past one to three years. Even then, these programs still command TV attention and are financially well supported. Our interpretation is that 5* recruits are choosing to attend "temporarily embarrassed" programs that have a lot of support but have done poorly recently. Fans, donors, and boosters of the program want to see these once great programs do well again, so they contribute large amounts of NIL money to attract 5* recruits.

For 4* recruits, the impacts are more nuanced. Top-ranked 4* athletes are entering roles in higher-performing programs post-NIL, possibly filling the gaps left by 5* recruits. They have the highest marginal value for development, which allows them to capitalize on improved development opportunities and potentially improve their future NFL prospects at better programs. However, lower-ranked 4* recruits appear to be attracted to lower performing programs, perhaps drawn by the NIL opportunities. Outside of football program performance, the impact of NIL on other characteristics of schools chosen by 5* and 4* recruits is generally null.

One pertinent question remains: Why are 3* recruits moving to less popular and lower educational quality schools? Figure 2 provides some evidence, where we observe almost no effect of rating on the draft outcomes for 3* recruits. Thus, these recruits might explicitly seek environments in which they can prioritize immediate NIL benefits over long-term career development or educational opportunities. Local businesses in smaller markets may be more inclined to partner with these athletes, providing them with meaningful NIL deals that they might not receive at larger programs where they could be overshadowed by higher-ranked players. These 3* recruits are likely to be the "big fish" for a smaller program, so the school may throw disproportionately more resources into securing a top 3* recruit versus a 4* or 5* recruit who they have no chance of obtaining.

An alternative explanation for a 3* recruit's behavior may not be entirely due to their own preferences but rather a result of intensified competition stemming from changes in 4* recruits' behaviors. Lower-ranked 4* recruits might be targeted with NIL deals by worse performing schools, thinking that NIL can sway them. Consequently, the trend of 3* recruits attending less prestigious programs could be partially attributed to this cascading talent redistribution. Both NIL resources and playing time are scarce, so they may find themselves with fewer options among traditionally stronger schools. Ultimately, our methodology does not allow us to clearly disentangle which of these explanations is the prevailing one for these 3* athletes, but our finding that 3* attend schools with lower educational quality supports NIL-chasing and an increased emphasis on present day income.[61]

In general, the introduction of NIL has not enriched already wealthy programs but has reshaped the recruiting landscape in a way that promotes a more equitable distribution of talent. Even by using multiple definitions of "rich" - from historical school performance to football budgets - we find negative or null effects of NIL on the positive assortative matching between recruits and schools. This democratization of talent acquisition challenges the notion that "the rich get richer" and opens up possibilities for increased competitiveness across college football.

6 Managerial Implications and Conclusions

Does personalized pricing increase competition in oligopolistic markets? As discussed in our introduction, theoretical models offer ambiguous predictions about the impact of price discrimination on competition. Our empirical evidence from the introduction of Name, Image, and Likeness (NIL) rights suggests that yes, personalized pricing has increased competition among college football teams. The rich are not getting richer; instead, top-end talent is attending lower-quality football schools, games are closer in point differentials, and upsets are more likely to happen.

An outcome implied by both our theoretical model and empirical analysis is the result that lower quality programs are often offering more lucrative personalized NIL packages than higher quality programs. This behavior aligns with the strategic use of personalized pricing in oligopolistic competition, where firms (schools) tailor financial incentives to attract high-value consumers (athletes), thereby intensifying competition. To understand why, we turn to the academic literature on merit-based aid and competition in university admissions. In Epple et al. (2003), the authors seek to understand the relationship between merit-based aid and student quality as a function of university rank. They determine that merit aid increases as university rank decreases–top universi-

[61] We also find that 3* recruits seemingly choose schools with worse historical NFL draft success (Table A.4 and A.12)

ties offer less merit aid because “top schools face no competition from above.” Ability discounting exists in equilibrium among lower-quality schools because at lower-ranked universities, the gap in quality between accepted and rejected candidates tends to be larger. With universities valuing student ability, lower ranked universities are willing to provide merit aid to attract high-quality students. The same is not true for high-ranking universities, which have less incentive to provide merit aid due to the availability of similarly qualified candidates.

The result maps to our setting by suggesting that NIL offers and program quality are negatively correlated for 5* players. Epple et al. (2003) determines that the merit-based aid increases with the difference in the valuation of the prospective candidate and pool of safety candidates. Therefore, high-quality programs do not need to offer large NIL deals to attract top talent because they can rely on their prestige and the availability of high-quality substitutes (e.g., top 4* players). This creates a competitive environment where lower-ranked programs use personalized pricing strategically to attract top recruits, increasing overall competition in the market. As a result, 5* athletes may choose lower-ranked schools offering better NIL deals without significantly harming their NFL draft prospects. These findings are consistent with the theory of personalized pricing affecting competition in oligopolistic markets.

Our findings can provide further insight into the financial aid, college choice, and return to the education literature (Card, 1999; Dynarski et al., 2023). Tracking individual long-term outcomes for college athletes is challenging, especially post-NIL recruits. However, we do provide evidence that financial packages (NIL) steer students (3* recruits - very unlikely to make NFL) into choosing lower educational quality colleges as measured by admission rate and SAT averages, as well as worse long-term outcomes when measured by median mid-career earnings. This is one of the few papers to document any causal *negative* effect of merit aid or scholarships (Cohodes and Goodman, 2014), especially on post-college outcomes. These results tie back to our initial discussion on personalized pricing, suggesting that while it can increase competition, it may also lead to suboptimal long-term outcomes for certain groups, raising important policy considerations. Our paper provides further evidence to policy makers and college administrators that short-term financial instruments influence education choices from racially diverse and underprivileged communities more than longer-term benefits.

Furthermore, what has not been studied, and specifically in the education literature, is the impact of personalized pricing (merit aid) on the competitiveness of the marketplace. For example, is there a casual effect of competition, and in which direction? Specific to merit-aid, does it casually shift university rankings? This is difficult to study because the question requires a unique dataset of industry-wide personal prices, and for merit-aid, student choices, rankings, and a world where merit-aid is shut off across the university marketplace. Although this data is not possible to retrieve, the data requirements and setting are available in studying a college athlete's program choice with the introduction of NIL.

In conclusion, our research demonstrates that personalized pricing through NIL has increased competition in college football, providing valuable empirical evidence to inform economic theory and policy. The introduction of NIL in college athletics parallels the use of merit-based aid in higher education, as both serve as financial incentives to attract top talent, athletic or academic. Thus, our research is pertinent to regulators and policymakers concerned about the increasing adoption of personalized pricing, the multi-billion dollar college football industry, and the Presidents of those very same universities competing in the university marketplace with merit-aid.

References

Ali, S. N., Lewis, G., and Vasserman, S. (2023). Voluntary disclosure and personalized pricing. *The Review of Economic Studies*, 90(2):538–571.

Angrist, J., Autor, D., and Pallais, A. (2022). Marginal effects of merit aid for low-income students. *The Quarterly Journal of Economics*, 137(2):1039–1090.

Armstrong, M. (2006). *Recent Developments in the Economics of Price Discrimination*, page 97–141. Econometric Society Monographs. Cambridge University Press.

Athey, S., Tibshirani, J., and Wager, S. (2019). Generalized random forests.

Athey, S. and Wager, S. (2021). Policy learning with observational data. *Econometrica*, 89(1):133–161.

Belloni, A., Lovett, M. J., Boulding, W., and Staelin, R. (2012). Optimal admission and scholarship decisions: Choosing customized marketing offers to attract a desirable mix of customers. *Marketing Science*, 31(4):621–636.

Blair, R. D. and Wang, W. (2018). The ncaa cartel and antitrust policy. *Review of Industrial Organization*, 52:351–368.

Card, D. (1999). The causal effect of education on earnings. *Handbook of labor economics*, 3:1801–1863.

Cattaneo, M. D., Crump, R. K., Farrell, M. H., and Feng, Y. (2024). On binscatter. *American Economic Review*, 114(5):1488–1514.

Chen, Z., Choe, C., and Matsushima, N. (2020). Competitive personalized pricing. *Management Science*, 66(9):4003–4023.

Chung, D. J. (2013). The dynamic advertising effect of collegiate athletics. *Marketing Science*, 32(5):679–698.

Chung, K. Y., Derdenger, T. P., and Srinivasan, K. (2013). Economic value of celebrity endorsements: Tiger woods' impact on sales of nike golf balls. *Marketing Science*, 32(2):271–293.

Cohodes, S. R. and Goodman, J. S. (2014). Merit aid, college quality, and college completion: Massachusetts' adams scholarship as an in-kind subsidy. *American Economic Journal: Applied Economics*, 6(4):251–285.

Derdenger, T. P., Li, H., and Srinivasan, K. (2018). Firms' strategic leverage of unplanned exposure and planned advertising: An analysis in the context of celebrity endorsements. *Journal of Marketing Research*, 55(1):14–34.

Dubé, J.-P. and Misra, S. (2023). Personalized pricing and consumer welfare. *Journal of Political Economy*, 131(1):131–189.

Dynarski, S. (2000). Hope for whom? financial aid for the middle class and its impact on college attendance. *National tax journal*, 53(3):629–661.

Dynarski, S., Page, L., and Scott-Clayton, J. (2023). College costs, financial aid, and student decisions. In *Handbook of the Economics of Education*, volume 7, pages 227–285. Elsevier.

Eckard, E. W. (1998). The ncaa cartel and competitive balance in college football. *Review of Industrial Organization*, 13:347–369.

Epple, D., Romano, R., Sarpça, S., Sieg, H., and Zaber, M. (2019). Market power and price discrimination in the us market for higher education. *The RAND Journal of Economics*, 50(1):201–225.

Epple, D., Romano, R., and Sieg, H. (2002). On the demographic composition of colleges and universities in market equilibrium. *American Economic Review: Papers and Proceedings*, 92:310–314.

Epple, D., Romano, R., and Sieg, H. (2003). Peer effects, financial aid, and selection of students into colleges. *Journal of Applied Econometrics*, 18:501–525.

Epple, D., Romano, R., and Sieg, H. (2006). Admission, tuition, and financial aid policies in the market for higher education. *Econometrica*, 74:885–928.

Fillmore, I. (2023). Price discrimination and public policy in the us college market. *The Review of Economic Studies*, 90(3):1228–1264.

Fitzpatrick, M. D. and Jones, D. (2016). Post-baccalaureate migration and merit-based scholarships. *Economics of Education Review*, 54:155–172.

Fort, R. and Lee, Y. H. (2007). Structural change, competitive balance, and the rest of the major leagues. *Economic Inquiry*, 45(3):519–532.

Fort, R. and Quirk, J. (1995). Cross-subsidization, incentives, and outcomes in professional team sports leagues. *Journal of Economic literature*, 33(3):1265–1299.

Garthwaite, C., Keener, J., Notowidigdo, M. J., and Ozminkowski, N. F. (2020). Who profits from amateurism? rent-sharing in modern college sports. Technical report, National Bureau of Economic Research.

Imbens, G. and Angrist, J. (1994). Identification and estimation of local average treatment effects. *Econometrica*, 62:467–475.

Li, F., Morgan, K. L., and Zaslavsky, A. M. (2018). Balancing covariates via propensity score weighting. *Journal of the American Statistical Association*, 113(521):390–400.

Li, X., Wang, X. S., and Nault, B. R. (2024). Is personalized pricing profitable when firms can differentiate? *Management Science*, 70(7):4184–4199.

PBS (2023). Analysis: Who is winning in the high-revenue world of college sports? — pbs.org. `https://www.pbs.org/newshour/economy/analysis-who-is-winning-in-the-high-revenue-world-of-college-sports`. [Accessed 27-10-2024].

Pigou, A. (1920). *The Economics of Welfare*. Number v. 1 in The Economics of Welfare. Macmillan and Company, Limited.

Rhodes, A. and Zhou, J. (2024). Personalized pricing and competition. *American Economic Review*, 114(7):2141–70.

Robins, J. M., Rotnitzky, A., and Zhao, L. P. (1994). Estimation of regression coefficients when some regressors are not always observed. *Journal of the American statistical Association*, 89(427):846–866.

Romer, D. (2006). Do firms maximize? evidence from professional football. *Journal of Political Economy*, 114(2):340–365.

Rosenbaum, P. and Rubin, D. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70:41–55.

Roth, J., Sant'Anna, P. H., Bilinski, A., and Poe, J. (2023). What's trending in difference-in-differences? a synthesis of the recent econometrics literature. *Journal of Econometrics*, 235(2):2218–2244.

Rubin, D. (1974). Estimating causal effects of treatments in randomized and non-randomized studies. *Journal of Educational Psychology*, 66:688–701.

Scott-Clayton, J. and Zafar, B. (2019). Financial aid, debt management, and socioeconomic outcomes: Post-college effects of merit-based aid. *Journal of Public Economics*, 170:68–82.

Shiller, B. R. (2020). Approximating purchase propensitites and reservation prices from broad consumer tracking. *International Economic Review*, 61(2):847–870.

Thisse, J.-F. and Vives, X. (1988). On the strategic choice of spatial price policy. *The American Economic Review*, 78(1):122–137.

Wager, S. (2022). Stats 361: Causal inference.

Waldfogel, J. (2015). First degree price discrimination goes to school. *The Journal of Industrial Economics*, 63(4):569–597.

Winston, G. (1999). Subsidies, hierarchies, and peers: The awkward economics of higher education. *Journal of Economic Perspectives*, 13:13–36.

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 A.1: Regression of win percent on last year's win percent, recruiting class strength, and school and conference fixed effects. Years 2005-2023

A.2 Talent distribution within or across conferences

Here, we analyze if high school recruits post-NIL are resorting within conferences or going to different schools in different conferences. We restrict our attention to a 8-year interval: 4 years before and 4 years after NIL implementation. We define have-nots as teams who have not had a single finish in the top half of their conference in the 4 years pre-NIL. We then run the regression:

$$Y_{st} = \beta_0 + \beta_1 \text{have\_not}_s + \mathbf{x}'_{st}\beta + \gamma_s + \tau_t + \varepsilon_{st},\ t >= T_{NIL}$$

where we subset our data on years after NIL implementation, T_{NIL}. Y_{st} is our outcome of interest, like conference rank or wins. $\mathbf{x}_{st}$ is a vector of time-varying school characteristics, like lag wins and transfers. We also include a conference fixed effect γ_s and a year fixed effect τ_t. We use the 247Sports Composite Team points as the Y variable of choice, which measures the strength of the incoming recruiting class of school s in year t. We run a "placebo" where we set $T_{NIL} = 2017$ such that the 8-season interval does not include a true NIL year. The placebo treats the years 2017-2020 as if NIL was implemented, and the results of the regression are in Table A.2 column 1. Column 2 displays the actual results where the NIL years are 2021-2024. Column 3 introduces the transfer portal as a factor into team wins performance. The have-nots seem to be performing worse in the

	Placebo	$T_{NIL} = 2021$	
	Y: 247Sports Composite Team Points		
have_notTRUE	−11.964	−17.671	−9.974
	(9.200)	(7.028)	(4.307)
lag_wins	4.094	4.397	3.602
	(1.472)	(1.308)	(0.882)
net_transfers_rating_247			−1.126
			(0.749)
Num. obs.	512	512	503
R^2	0.398	0.401	0.399
Conference FE		Yes	
Year FE		Yes	

Table A.2: Recruiting outcomes regression on "have nots," prior season performance, and transfer ratings

seasons after NIL was implemented, although the difference −11.964 vs −17.671 is not statistically significant.

To assess across-conference talent, we regress

$$Y_{st} = \beta_0 + \mathbf{x}'_{st}\beta + \gamma_s + \delta(\gamma_s \cdot NIL_t) + \tau_t + \varepsilon_{st}$$

Where γ_s is now a *conference* fixed effect. The other variables remain as above. Coefficients δ tell us if NIL has affected each conference's outcome disparately. In Table A.3, we display the results of the regression. We drop the SEC conference, arguably the best conference, to avoid perfect colinearity with the FBS indicator variable. We find that the conference $\times$ post-NIL interaction terms are mostly negative, with some conferences like Conference USA and the Mountain West Conference being significantly negative. This suggests that recruiting classes are weaker post-NIL versus a powerhouse conference like the SEC. The coefficients on other powerhouse conferences like the Big Ten are null, suggesting that talent is choosing the bigger FBS conferences over smaller ones. Talent doesn't seem to be leaving or entering the FBS, as the coefficient on NIL $*$ FBS is null.

	Y: 247Sports Composite Team Points
FBS (True)	237.116
	(2.783)
Big Ten Conference	−31.152
	(3.323)
Big 12 Conference	−50.033
	(4.595)
Pac-12 Conference	−32.442
	(4.545)
ACC Conference	−38.064
	(5.050)
American Athletic Conference	−111.122
	(2.562)
Conference USA	−137.480
	(3.556)
FBS Independents	−148.073
	(2.076)
Mid-American Conference	−115.147
	(1.690)
Mountain West Conference	−106.555
	(1.862)
Sun Belt Conference	−146.196
	(2.320)
NIL x FBS	1.564
	(4.149)
NIL x Big Ten Conference	0.024
	(4.228)
NIL x Big 12 Conference	5.078
	(4.901)
NIL x Pac-12 Conference	−16.696
	(7.755)
NIL x ACC Conference	−2.602
	(6.752)
NIL x American Athletic Conference	−4.406
	(6.846)
NIL x Conference USA	−17.566
	(6.745)
NIL x FBS Independents	−9.668
	(8.447)
NIL x Mid-American Conference	1.962
	(7.149)
NIL x Mountain West Conference	−9.292
	(5.414)
NIL x Sun Belt Conference	−3.396
	(5.441)
Num. obs.	5412
Year FE	Y

Table A.3: Recruiting outcomes regression on conferences. The conference "SEC" is dropped from the regression and should be interpreted as the baseline. Data from years 2017-2024

A.3 Other Tables

We have other measures of football quality that are not included in the main text. First, we use the number of players drafted by a school in the prior year and the prior three years as a measurement of a program's quality. These results suggest that 4* and 5* recruits choose schools that have more NFL draft success historically, but the DiD results are negative and insignificant. The results for 3* recruits suggest that they are attending schools with worse track records of getting athletes drafted by the NFL, which is consistently negative for all estimators.

Y	Method	Treatment	5* recruits		4* recruits		3* recruits	
			Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Last year # drafted	IPW	ATE	0.436	0.419	0.261	0.130	-1.320	0.060
	IPW	ATT	0.448	0.518	0.168	0.140	-0.166	0.063
	AIPW	OW-ATE	0.733	0.441	0.412	0.151	-0.144	0.067
	AIPW	ATT	0.816	0.444	0.363	0.132	-0.082	0.035
	OLS	ATE	0.506	0.639	0.347	0.119	-0.098	0.056
	DID	ATT	–	–	-1.387	1.005	-0.114	0.261
Last 3 years # drafted	IPW	ATE	0.611	1.157	1.077	0.313	-3.124	0.190
	IPW	ATT	0.844	1.267	0.943	0.336	-0.641	0.163
	AIPW	OW-ATE	1.863	1.116	1.424	0.360	-0.586	0.161
	AIPW	ATT	2.112	1.115	1.335	0.310	-0.566	0.084
	OLS	ATE	1.238	1.518	1.364	0.324	-0.420	0.121
	DID	ATT	–	–	-2.568	2.258	-1.213	0.611

Table A.4: Treatment effects of NIL on committed school's number of NFL draftees in prior season, by 5*, 4*, and 3* recruits. Standard errors clustered by position.

We also use stickier metrics of quality that do not vary as much year-to-year, like SP+ and ELO. Results using these metrics suggest that talent is being redistributed across all star levels, although the DiD estimate is positive and insignificant.

Y	Method	Treatment	5* recruits		4* recruits		3* recruits	
			Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Last year SP+ rating	IPW	ATE	-5.877	1.296	-2.150	0.461	-5.762	1.159
	IPW	ATT	-4.916	1.336	-2.359	0.508	-1.511	0.397
	AIPW	OW-ATE	-5.045	1.360	-2.149	0.529	-0.637	0.473
	AIPW	ATT	-4.754	1.364	-2.105	0.463	-1.442	0.230
	OLS	ATE	-5.399	1.911	-1.841	0.478	-0.745	0.184
	DID	ATT	–	–	1.627	2.744	1.075	1.404
Last year Elo	IPW	ATE	-120.748	35.016	-27.244	11.738	-115.118	25.586
	IPW	ATT	-74.311	39.679	-34.118	12.675	-22.798	8.717
	AIPW	OW-ATE	-109.561	36.821	-22.996	13.503	-7.621	10.396
	AIPW	ATT	-99.506	36.822	-20.703	11.724	-33.040	5.110
	OLS	ATE	-121.389	48.334	-21.075	10.961	-22.885	5.105
	DID	ATT	–	–	5.148	53.368	29.088	35.959

Table A.5: Treatment effects on last year SP+ rating and Elo for different groups of 5*, 4*, and 3* recruits. Standard errors clustered by position.

We can use the 247Sports Composite Team Ranking to determine the strength of recruiting classes in the previous year and the average strength over the prior three years.

Y	Method	Treatment	5* recruits		4* recruits		3* recruits	
			Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Last year recruit points	IPW	ATE	-2.572	5.518	-3.681	1.800	-41.973	4.945
	IPW	ATT	3.863	6.620	-4.517	2.005	-12.014	1.779
	AIPW	OW-ATE	0.655	5.397	-3.880	2.038	-16.393	2.058
	AIPW	ATT	0.849	5.373	-5.492	1.754	-20.853	1.019
	OLS	ATE	-5.398	7.275	-2.389	1.369	-12.760	1.016
	DID	ATT	–	–	-23.398	9.448	-7.217	5.659
Last 3 years recruit points average	IPW	ATE	-3.869	4.720	-1.016	1.639	-33.071	4.705
	IPW	ATT	-0.790	4.756	-1.700	1.861	-6.049	1.793
	AIPW	OW-ATE	-0.589	4.838	-0.435	1.845	-2.306	1.928
	AIPW	ATT	0.210	4.879	-1.442	1.614	-5.509	0.970
	OLS	ATE	-3.013	5.817	0.526	1.148	-2.875	0.943
	DID	ATT	–	–	-18.676	9.672	-4.529	5.112

Table A.6: Treatment effects on last year and last 3 years recruit points for different groups of 5*, 4*, and 3* recruits. Standard errors clustered by position.

Finally, we can also observe if athletes are more willing to stay in state or close to home post-NIL:

Y	Method	Treatment	5* recruits		4* recruits		3* recruits	
			Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Distance from Home (km)	IPW	ATE	-0.022	0.167	0.074	0.061	-0.317	0.182
	IPW	ATT	0.110	0.179	0.103	0.069	-0.007	0.043
	AIPW	OW-ATE	0.167	0.180	0.028	0.069	-0.062	0.056
	AIPW	ATT	0.175	0.182	0.045	0.060	-0.065	0.027
	OLS	ATE	0.142	0.210	0.065	0.067	-0.008	0.029
	DID	ATT	–	–	-0.833	0.386	0.001	0.258
Probability Stay in State	IPW	ATE	0.062	0.074	-0.025	0.021	0.063	0.066
	IPW	ATT	-0.010	0.089	-0.040	0.024	0.015	0.014
	AIPW	OW-ATE	-0.015	0.067	-0.001	0.024	0.023	0.020
	AIPW	ATT	-0.019	0.068	-0.005	0.021	0.018	0.010
	OLS	ATE	-0.002	0.100	-0.022	0.022	0.006	0.010
	DID	ATT	–	–	0.027	0.086	-0.012	0.031

Table A.7: Effects of NIL on distance from home and probability of staying in state for 3*, 4*, and 5* recruits. Standard errors clustered by position.

A.3.1 Four-star recruit results

We now take a look at the alternative measures of football program quality, such as historical draft and recruiting metrics, as well as SP+ and ELO ratings and study top and bottom 4* recruits.

Y	Method	Treatment	Top 100 4* recruits		101+ ranked 4* recruits	
			Estimate	Std. Error	Estimate	Std. Error
Last year n drafted	IPW	ATE	1.397	0.485	0.087	0.199
	IPW	ATT	1.133	0.531	0.039	0.313
	AIPW	OW-ATE	0.834	0.273	0.204	0.183
	AIPW	ATT	0.762	0.273	0.219	0.150
	OLS	ATE	0.715	0.297	0.120	0.158
	DID	ATT	0.470	3.070	-1.996	0.688
Last 3 years n drafted	IPW	ATE	4.970	1.476	0.286	0.429
	IPW	ATT	3.315	0.984	0.440	0.632
	AIPW	OW-ATE	2.943	0.653	0.643	0.434
	AIPW	ATT	2.771	0.650	0.824	0.352
	OLS	ATE	2.818	0.802	0.479	0.335
	DID	ATT	1.276	7.719	-3.921	1.913

Table A.8: Treatment effects of NIL on draft rates for top 100 and bottom ranked 4* recruits. Standard errors clustered by position.

Y	Method	Treatment	Top 100 4* recruits		101+ ranked 4* recruits	
			Estimate	Std. Error	Estimate	Std. Error
Last year SP+ rating	IPW	ATE	1.320	1.802	-3.184	0.736
	IPW	ATT	0.715	2.729	-3.305	1.150
	AIPW	OW-ATE	-0.973	0.879	-2.876	0.672
	AIPW	ATT	-1.000	0.883	-2.768	0.547
	OLS	ATE	-0.814	1.029	-2.559	0.543
	DID	ATT	4.114	6.734	0.829	4.291
Last year Elo	IPW	ATE	101.843	61.136	-50.469	18.793
	IPW	ATT	78.140	103.625	-55.702	29.742
	AIPW	OW-ATE	3.637	23.077	-40.145	17.004
	AIPW	ATT	2.356	23.110	-32.844	13.763
	OLS	ATE	14.118	24.807	-35.324	13.577
	DID	ATT	19.030	166.109	-2.127	69.444

Table A.9: Treatment effects on last year SP+ rating and Elo for top 100 and bottom ranked 4* recruits. Standard errors clustered by position.

Y	Method	Treatment	Top 100 4* recruits		101+ ranked 4* recruits	
			Estimate	Std. Error	Estimate	Std. Error
Last year recruit points	IPW	ATE	20.694	7.157	-13.169	2.672
	IPW	ATT	16.067	11.626	-13.708	3.870
	AIPW	OW-ATE	6.454	3.257	-9.892	2.633
	AIPW	ATT	6.337	3.226	-9.275	2.097
	OLS	ATE	8.266	3.361	-9.124	1.707
	DID	ATT	-2.201	28.497	-29.201	12.021
Last 3 years recruit points	IPW	ATE	15.910	5.995	-8.402	2.335
	IPW	ATT	13.823	8.878	-9.952	3.333
	AIPW	OW-ATE	6.139	2.935	-4.231	2.411
	AIPW	ATT	5.456	2.949	-4.149	1.936
	OLS	ATE	6.158	3.880	-4.075	1.368
	DID	ATT	4.066	24.086	-25.098	13.562

Table A.10: Treatment effects on last year and last 3 years recruit points for top 100 and bottom ranked 4* recruits. Standard errors clustered by position.

A.3.2 Three-star recruit results

We now break down behaviors by 3* recruits. Table A.11 looks at measures of football program quality from the main text, broken down by top and bottom 3* recruits.

The next few tables look at the alternative measures of program quality.

We now analyze popularity of schools chosen by 3* recruits as measured by TV ratings, number of broadcasts, and DMA size where the school is located.

Y	Method	Treatment	Top 100 3* recruits		101+ ranked 3* recruits	
			Estimate	Std. Error	Estimate	Std. Error
Top 10 Prior Season	IPW	ATE	-0.049	0.045	-0.036	0.003
	IPW	ATT	-0.001	0.415	0.007	0.005
	AIPW	OW-ATE	-0.021	0.069	0.010	0.007
	AIPW	ATT	-0.045	0.084	0.015	0.004
	OLS	ATE	0.005	0.081	0.007	0.005
	DID	ATT	0.079	0.366	0.021	0.026
Top 25 Prior Season	IPW	ATE	-0.023	0.655	-0.111	0.011
	IPW	ATT	0.080	0.179	0.021	0.009
	AIPW	OW-ATE	0.040	0.091	0.022	0.014
	AIPW	ATT	0.019	0.096	0.021	0.007
	OLS	ATE	-0.104	0.068	0.016	0.007
	DID	ATT	0.411	0.269	0.080	0.042
Total Top 10 Prior 3 Seasons	IPW	ATE	-0.153	0.284	-0.118	0.007
	IPW	ATT	-0.112	0.372	0.004	0.013
	AIPW	OW-ATE	-0.059	0.156	-0.004	0.016
	AIPW	ATT	-0.094	0.139	-0.003	0.008
	OLS	ATE	-0.100	0.169	-0.007	0.011
	DID	ATT	-0.499	0.995	0.032	0.071
Total Top 25 Prior 3 Seasons	IPW	ATE	-0.185	2.147	-0.261	0.054
	IPW	ATT	0.092	1.355	0.025	0.020
	AIPW	OW-ATE	-0.094	0.201	0.012	0.028
	AIPW	ATT	-0.117	0.190	-0.041	0.015
	OLS	ATE	-0.314	0.184	-0.025	0.016
	DID	ATT	-0.312	0.755	0.161	0.116
Win Percentage Prior 3 Seasons	IPW	ATE	-0.042	0.036	-0.032	0.018
	IPW	ATT	-0.014	0.443	-0.004	0.005
	AIPW	OW-ATE	-0.025	0.026	-0.016	0.008
	AIPW	ATT	-0.039	0.025	-0.022	0.004
	OLS	ATE	-0.073	0.033	-0.019	0.005
	DID	ATT	0.071	0.152	0.022	0.021

Table A.11: Treatment effects of NIL on the probability of recruits attending top-ranked schools for 3* recruits. Standard errors clustered by position.

Y	Method	Treatment	Top 100 3* recruits		101+ ranked 3* recruits	
			Estimate	Std. Error	Estimate	Std. Error
Last year n drafted	IPW	ATE	-0.116	4.540	-1.224	0.056
	IPW	ATT	0.668	5.318	0.125	0.047
	AIPW	OW-ATE	0.662	0.456	-0.173	0.064
	AIPW	ATT	0.624	0.375	-0.097	0.033
	OLS	ATE	0.602	0.483	-0.078	0.050
	DID	ATT	-1.790	2.285	-0.045	0.244
Last 3 years n drafted	IPW	ATE	-0.182	2.768	-2.777	0.198
	IPW	ATT	1.105	5.124	0.199	0.116
	AIPW	OW-ATE	1.544	1.014	-0.625	0.153
	AIPW	ATT	1.211	0.825	-0.612	0.079
	OLS	ATE	-0.241	1.259	-0.361	0.125
	DID	ATT	-6.192	4.151	-0.937	0.624

Table A.12: Treatment effects of NIL on committed school's number of NFL draftees in prior season for top 100 and bottom ranked 3* recruits. Standard errors clustered by position.

Y	Method	Treatment	Top 100 3* recruits		101+ ranked 3* recruits	
			Estimate	Std. Error	Estimate	Std. Error
Last year recruit points	IPW	ATE	-7.968	43.091	-36.931	5.302
	IPW	ATT	8.922	20.525	-2.372	1.483
	AIPW	OW-ATE	0.362	8.674	-16.073	2.180
	AIPW	ATT	1.935	11.604	-21.334	1.065
	OLS	ATE	-22.079	7.145	-12.916	1.170
	DID	ATT	-46.624	28.611	-5.207	5.426
Last 3 years recruit points	IPW	ATE	-10.777	31.211	-28.185	5.117
	IPW	ATT	7.950	26.018	3.920	1.501
	AIPW	OW-ATE	-2.040	8.237	-1.843	2.037
	AIPW	ATT	1.171	10.424	-5.953	1.016
	OLS	ATE	-5.197	7.055	-2.483	1.043
	DID	ATT	-46.176	25.604	-2.418	4.760

Table A.13: Treatment effects on last year and last 3 years recruit points for top 100 and bottom ranked 3* recruits. Standard errors clustered by position.

Y	Method	Treatment	Top 100 3* recruits		101+ ranked 3* recruits	
			Estimate	Std. Error	Estimate	Std. Error
Log 3 year ratings	IPW	ATE	-0.040	0.989	-2.534	0.819
(demeaned)	IPW	ATT	0.195	0.392	0.186	0.123
	AIPW	OW-ATE	0.102	0.219	-0.638	0.211
	AIPW	ATT	0.158	0.227	-0.856	0.091
	OLS	ATE	-0.081	0.386	-0.557	0.171
	DID	ATT	-0.145	0.680	-0.232	0.438
TV broadcasts over 3 years	IPW	ATE	0.155	6.295	-6.670	0.749
(demeaned)	IPW	ATT	1.374	6.286	0.293	0.251
	AIPW	OW-ATE	0.612	1.458	-1.980	0.363
	AIPW	ATT	0.867	1.561	-2.312	0.183
	OLS	ATE	-0.727	1.478	-1.647	0.263
	DID	ATT	3.422	6.621	0.476	1.352
School DMA	IPW	ATE	0.149	0.712	0.136	0.121
% of US Population	IPW	ATT	0.550	0.999	0.013	0.027
	AIPW	OW-ATE	0.099	0.157	-0.034	0.041
	AIPW	ATT	0.186	0.186	-0.032	0.021
	OLS	ATE	-0.089	0.158	-0.011	0.025
	DID	ATT	0.120	0.223	-0.115	0.202

Table A.14: Treatment effects of NIL on TV ratings for different groups of 3* recruits. Standard errors clustered by position.

A.4 DiD event studies

Here, we plot all of the event studies for the DiD results. The formulation of the event studies is laid out in Equation 9. For most of the even studies there do not seem to be any significant pre-trends, although standard errors are quite large due to the small sample of international recruits (especially for 4* recruits).

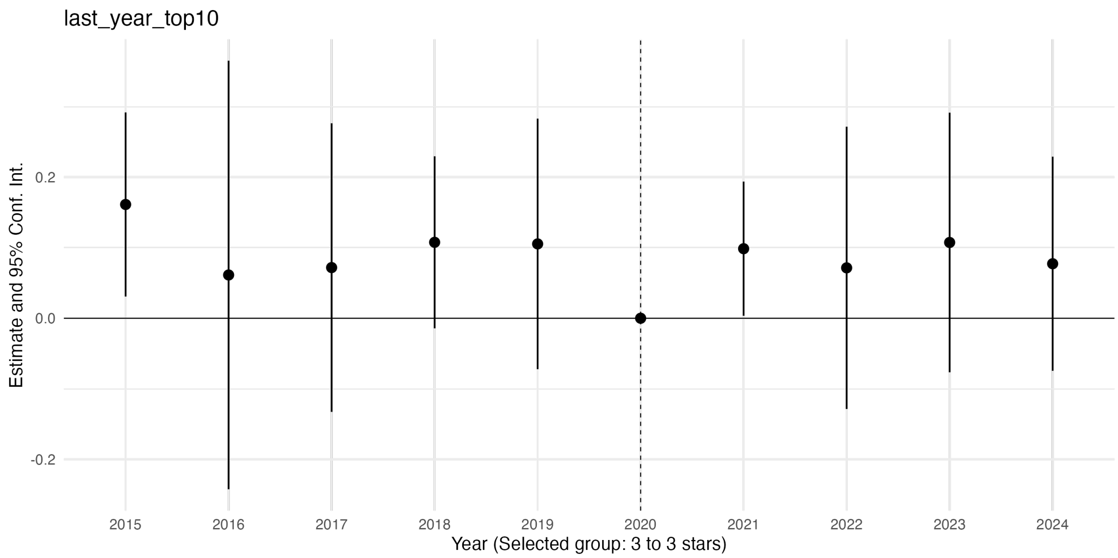

Figure A.1: Event study: NIL effects on 3* recruits' chosen schools' ranking in prior season. NIL first implemented in 2021. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

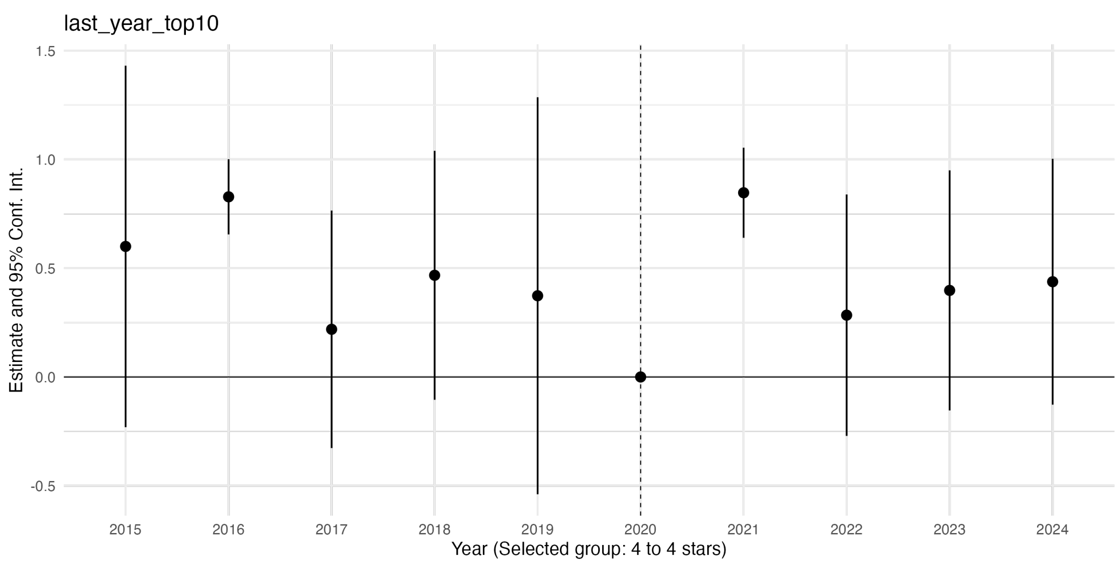

Figure A.2: Event study: NIL effects on 3* recruits' chosen schools' ranking in prior season. NIL first implemented in 2021. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

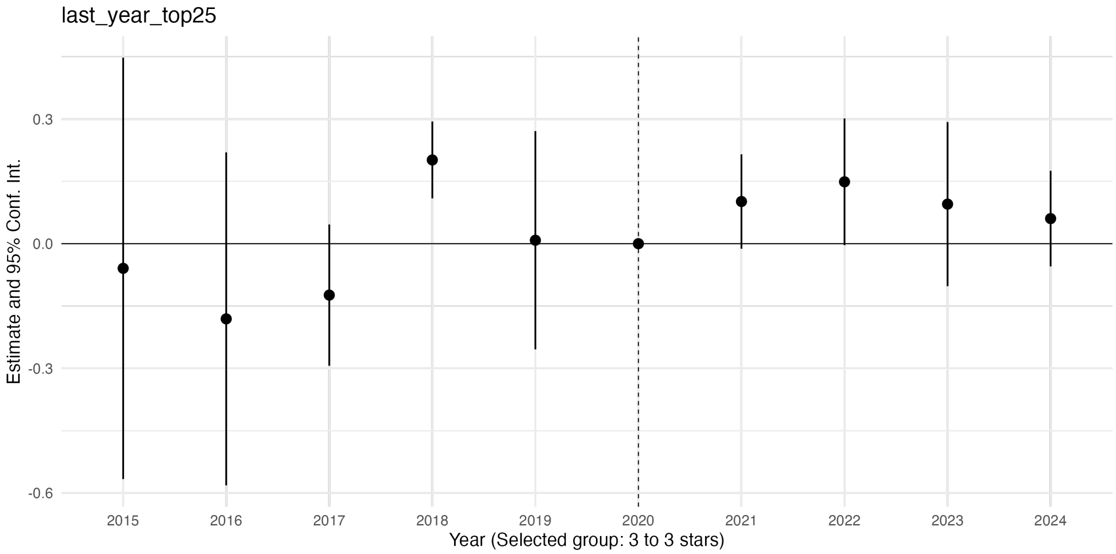

Figure A.3: Event study: NIL effects on 3* recruits' chosen schools' ranking in prior season. NIL first implemented in 2021. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

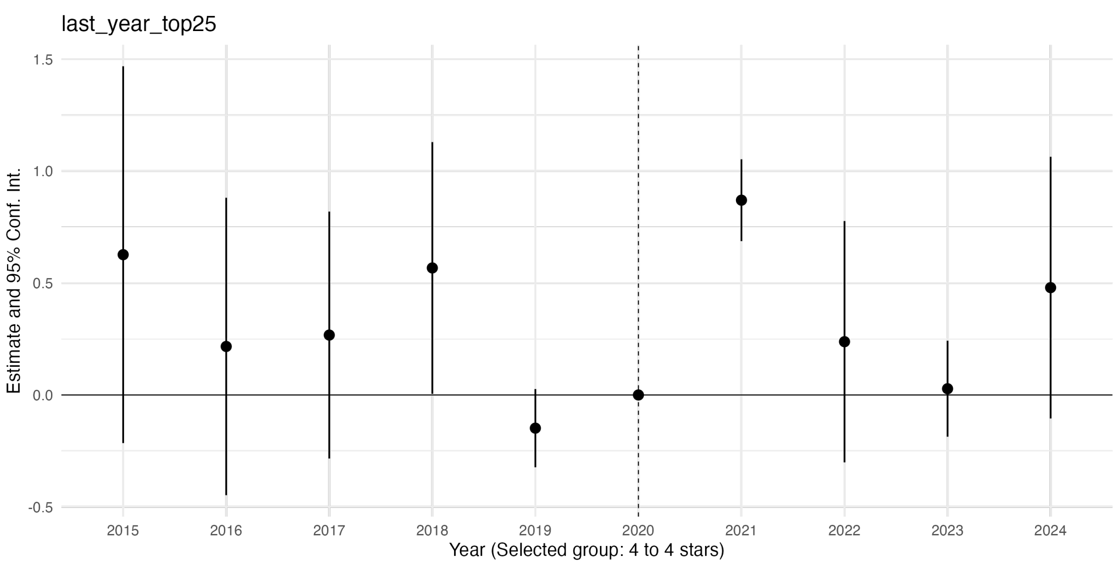

Figure A.4: Event study: NIL effects on 4* recruits' chosen schools' ranking in prior season. NIL first implemented in 2021. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

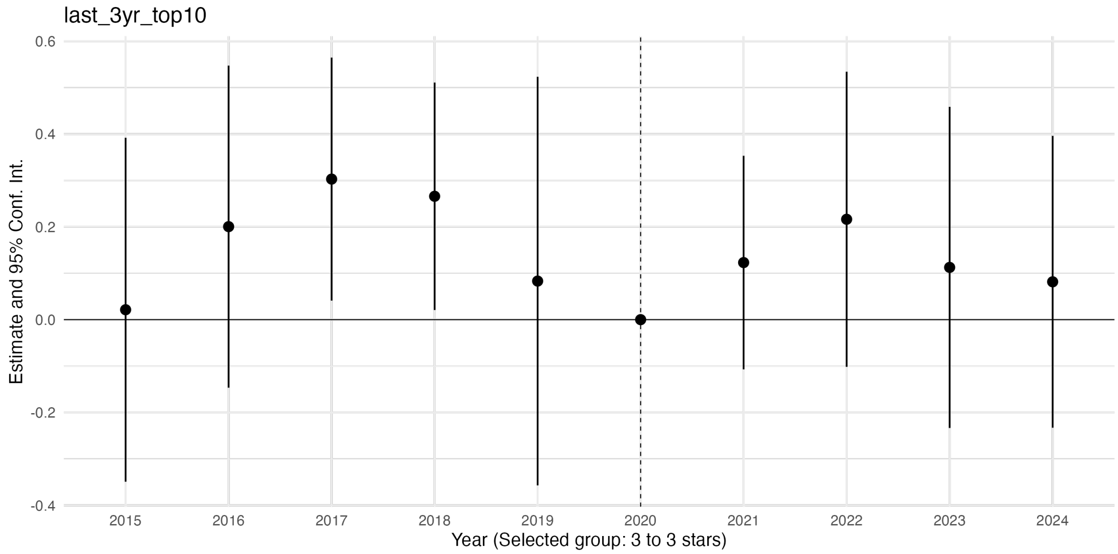

Figure A.5: Event study: NIL effects on 3* recruits' chosen schools' total top 10 finishes in prior 3 seasons. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

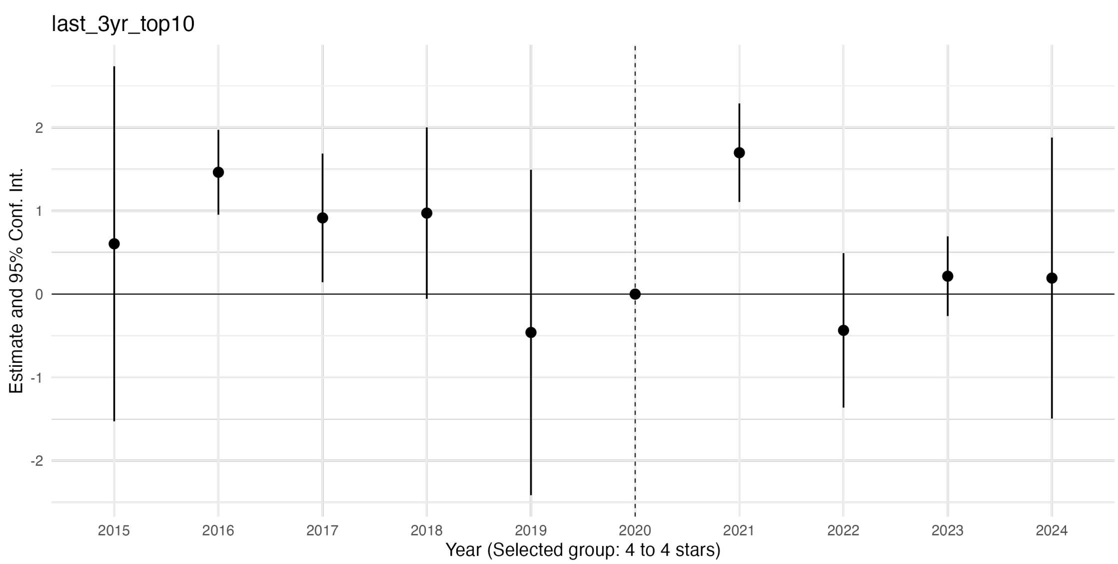

Figure A.6: Event study: NIL effects on 4* recruits' chosen schools' total top 25 finishes in prior 3 seasons. NIL first implemented in 2021. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

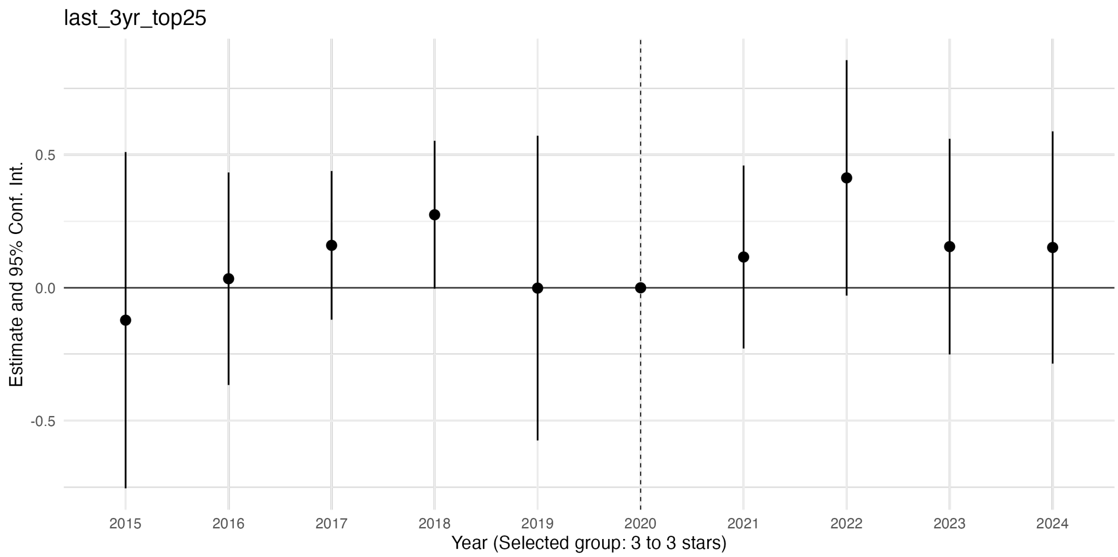

Figure A.7: Event study: NIL effects on 3* recruits' chosen schools' total top 10 finishes in prior 3 seasons. NIL first implemented in 2021. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

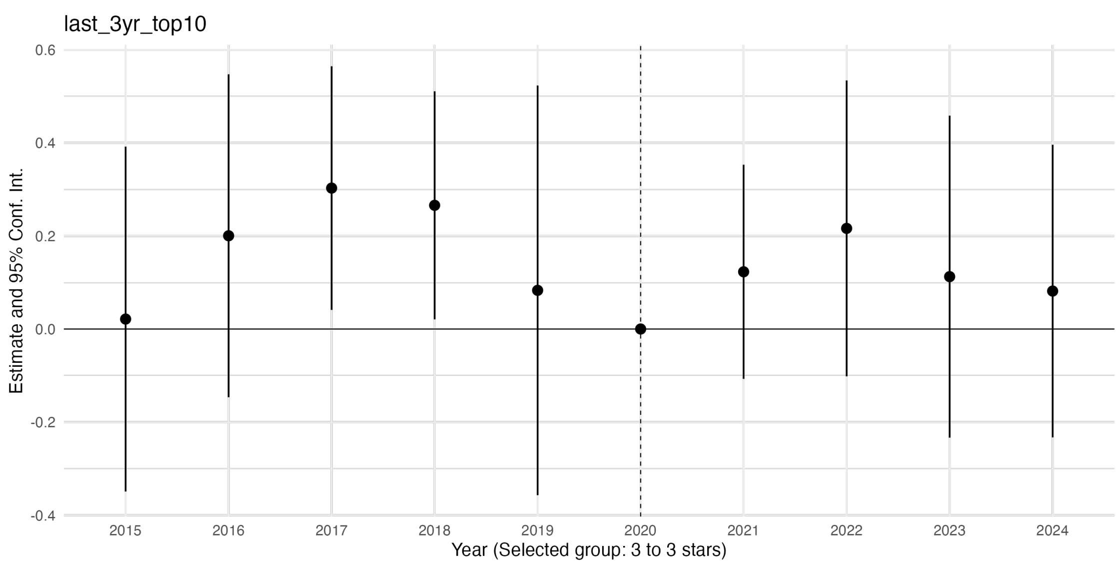

Figure A.8: Event study: NIL effects on 4* recruits' chosen schools' total top 25 finishes in prior 3 seasons. NIL first implemented in 2021. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

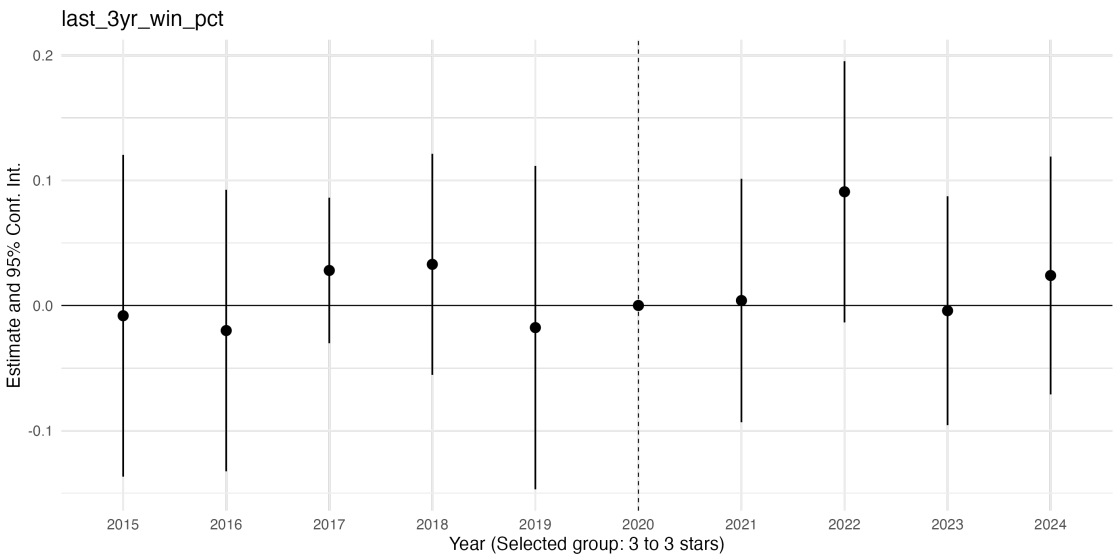

Figure A.9: Event study: NIL effects on 3* recruits' chosen schools' winning percentage in prior 3 seasons. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

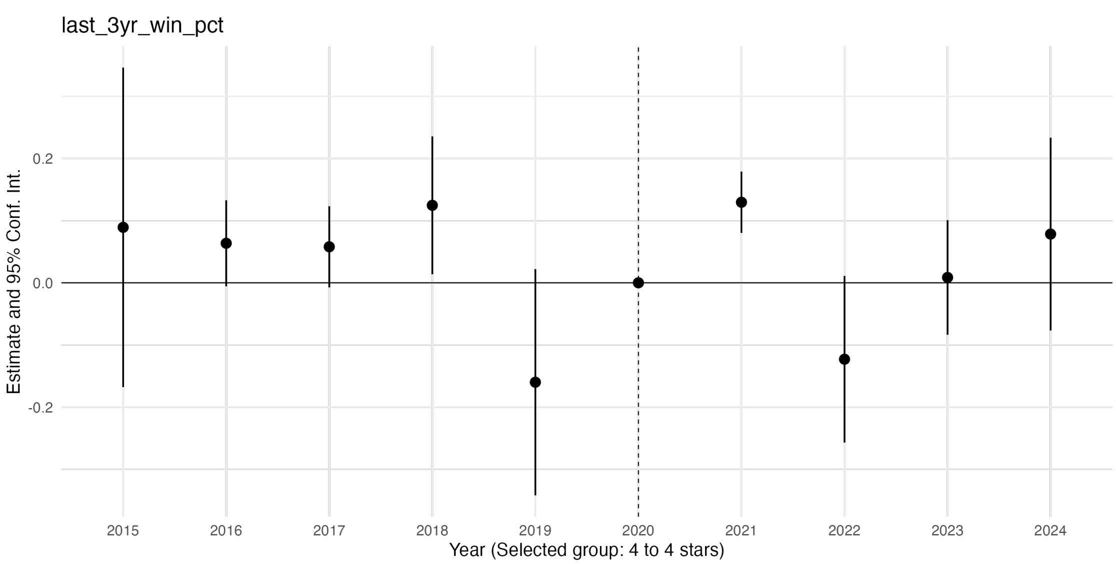

Figure A.10: Event study: NIL effects on 4* recruits' chosen schools' winning percentage in prior 3 seasons. NIL first implemented in 2021. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

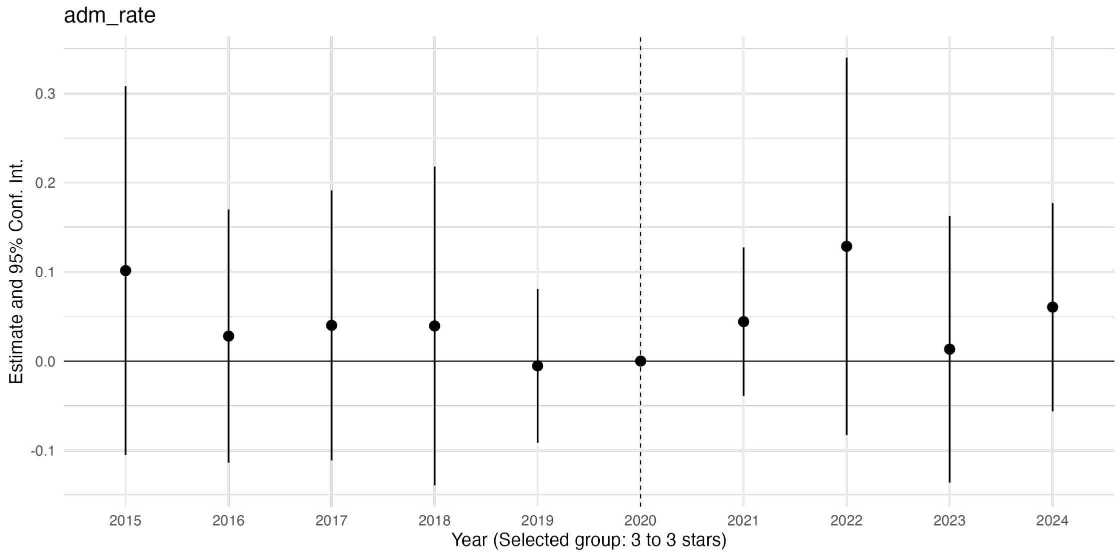

Figure A.11: Event study: NIL effects on 3* recruits' chosen schools' admission rate. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

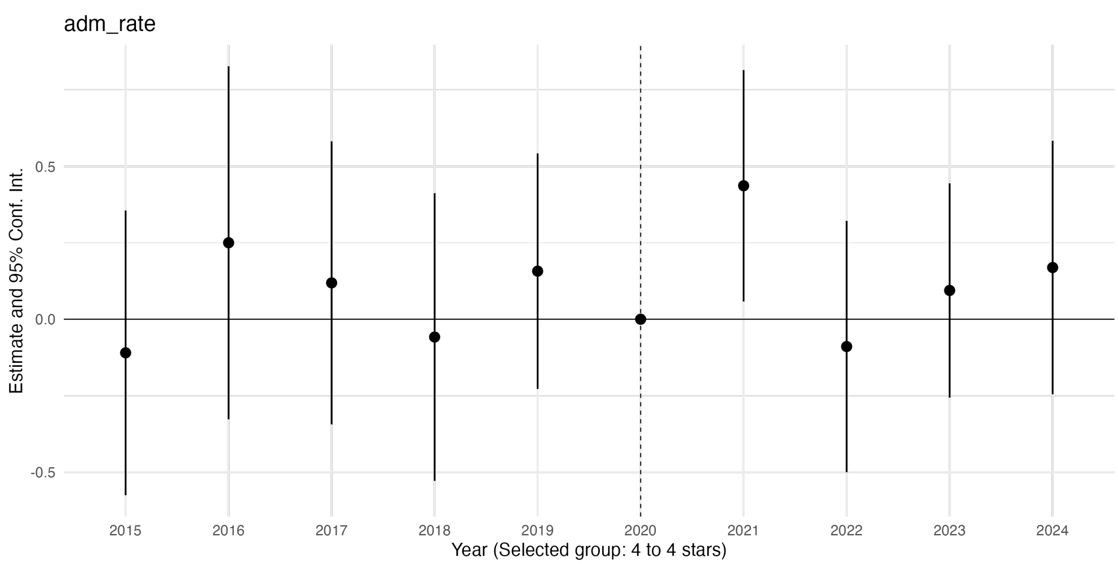

Figure A.12: Event study: NIL effects on 4* recruits' chosen schools' admission rate. NIL first implemented in 2021. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

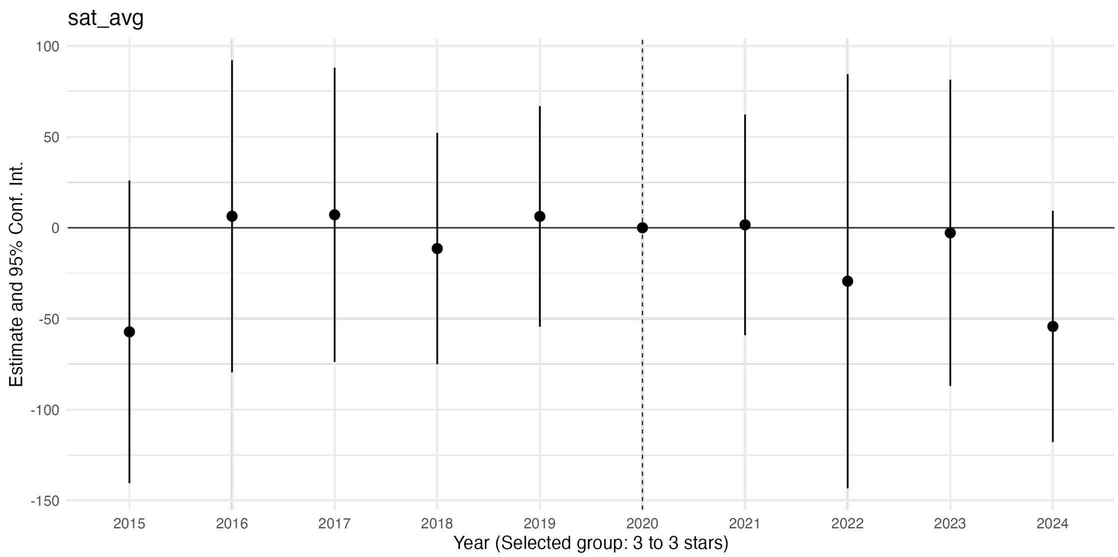

Figure A.13: Event study: NIL effects on 3* recruits' chosen schools' average SAT score. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

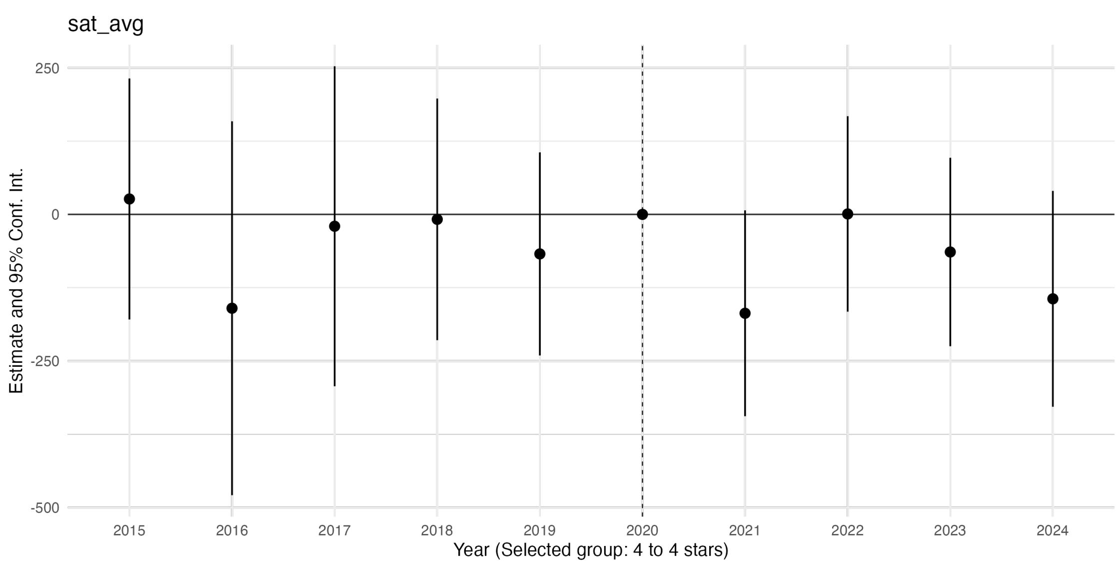

Figure A.14: Event study: NIL effects on 4* recruits' chosen schools' average SAT score. NIL first implemented in 2021. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

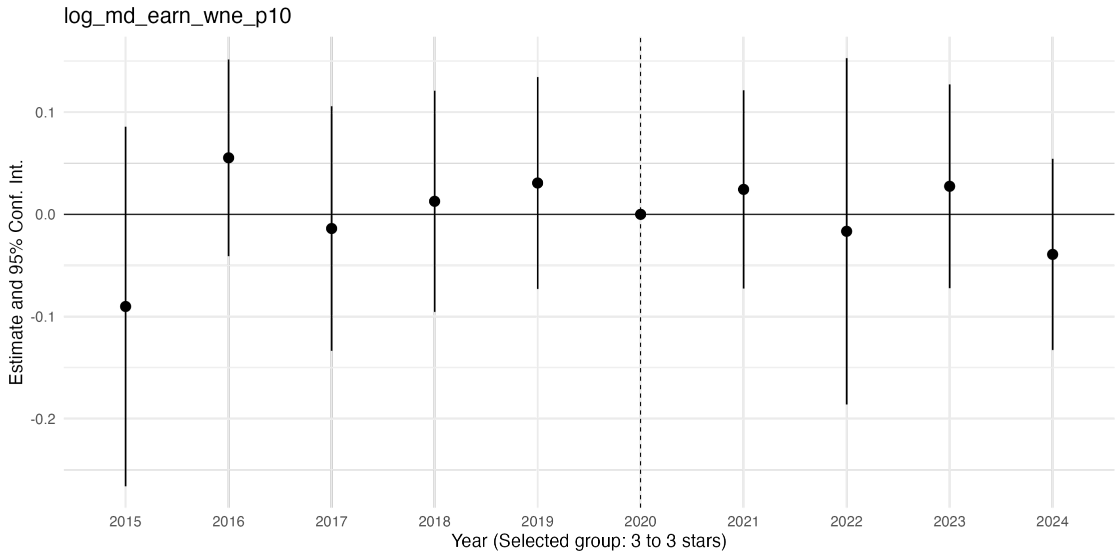

Figure A.15: Event study: NIL effects on 3* recruits' chosen schools' median income 10 years post graduation. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

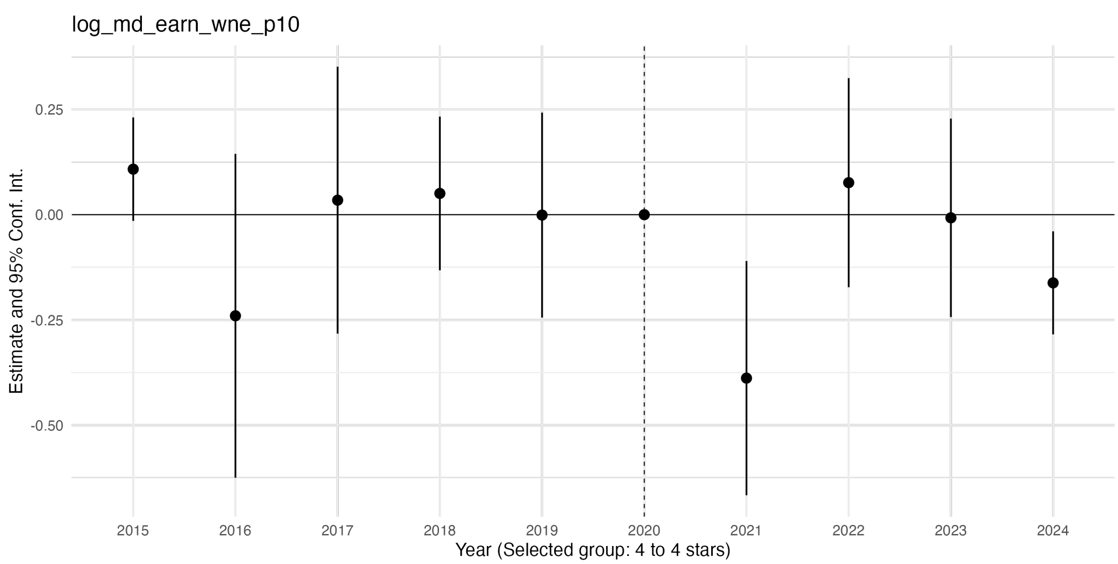

Figure A.16: Event study: NIL effects on 4* recruits' chosen schools' median income 10 years post graduation. NIL first implemented in 2021. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

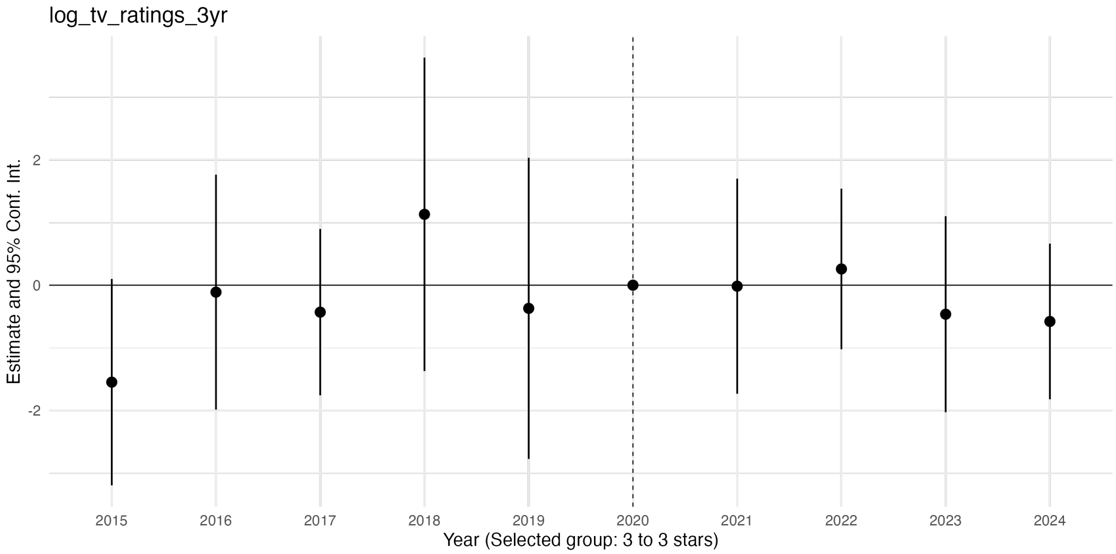

Figure A.17: Event study: NIL effects on 3* recruits' chosen schools' TV ratings in prior 3 years. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

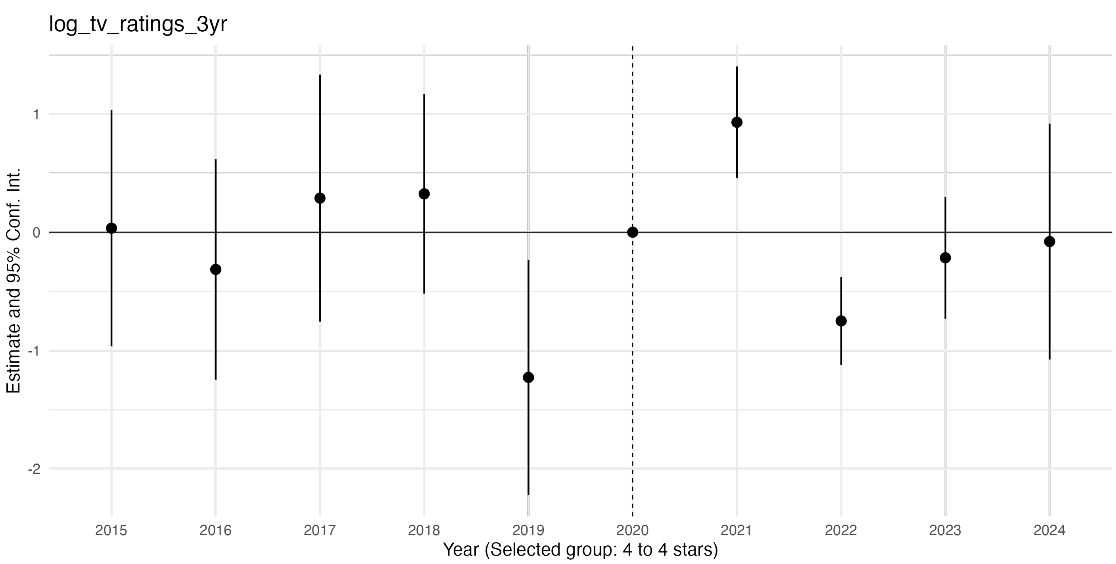

Figure A.18: Event study: NIL effects on 4* recruits' chosen schools' TV ratings in prior 3 years. NIL first implemented in 2021. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

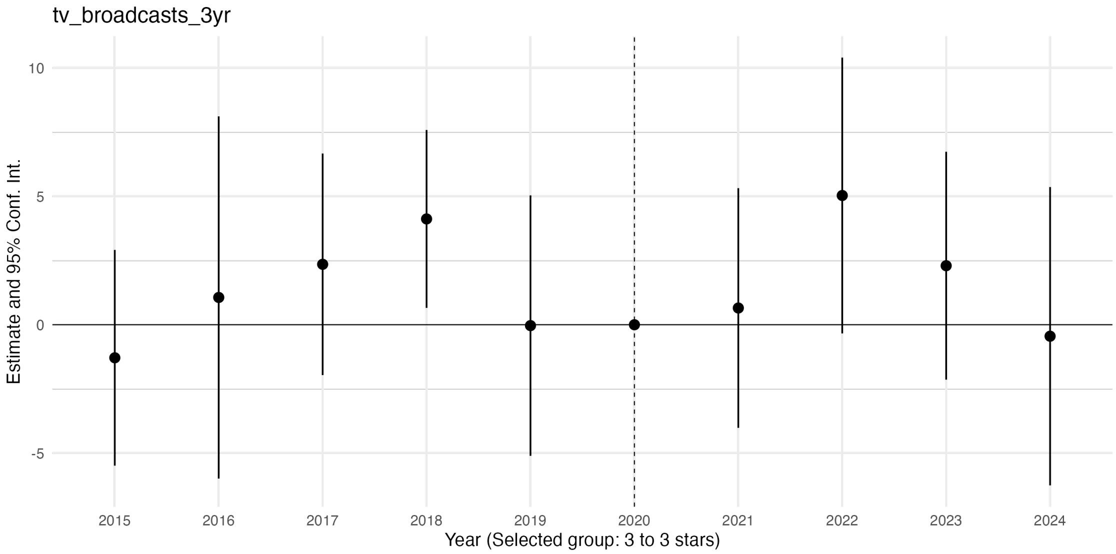

Figure A.19: Event study: NIL effects on 3* recruits' chosen schools' TV broadcasts in prior 3 years. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

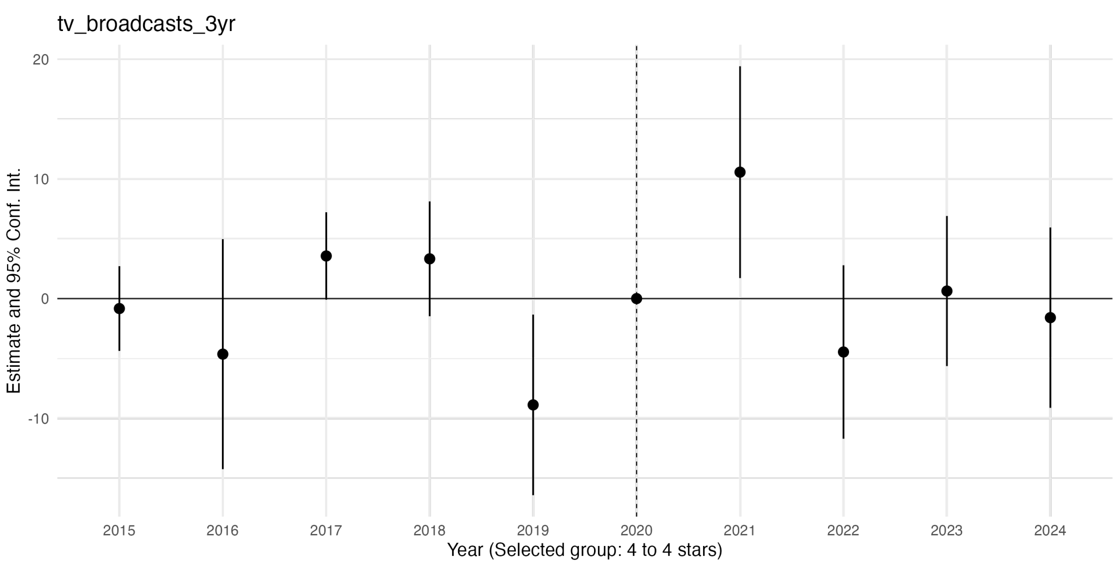

Figure A.20: Event study: NIL effects on 4* recruits' chosen schools' TV broadcasts in prior 3 years. NIL first implemented in 2021. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

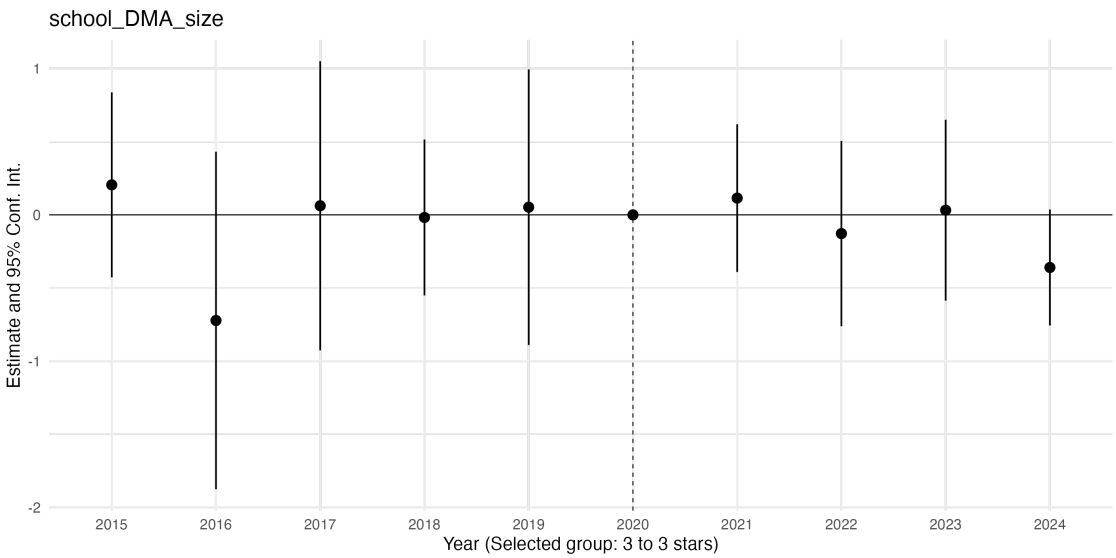

Figure A.21: Event study: NIL effects on 3* recruits' chosen schools' DMA, as a percentage of the US population. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

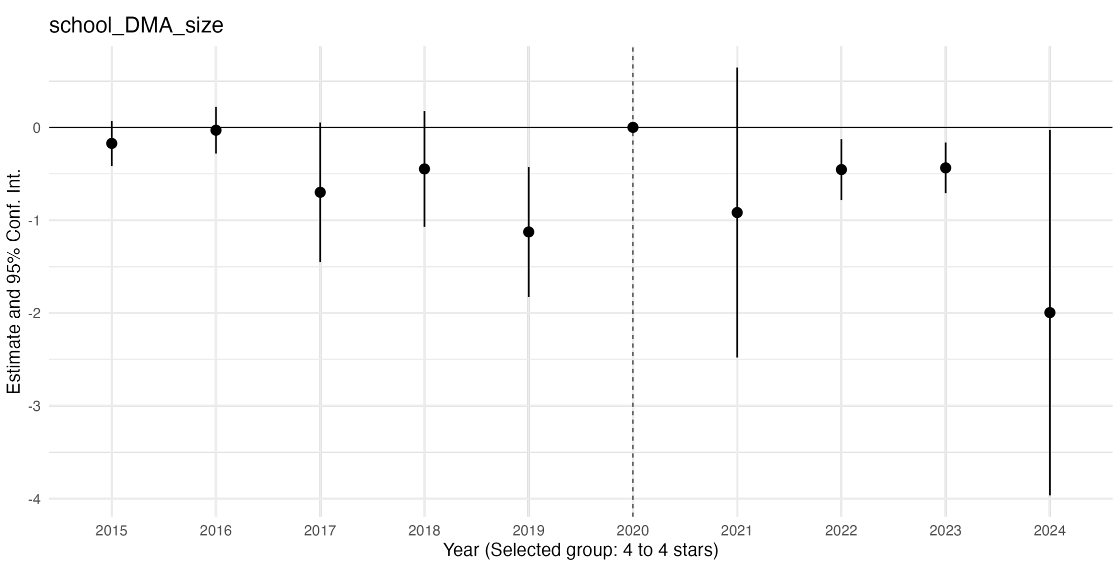

Figure A.22: Event study: NIL effects on 4* recruits' chosen schools' DMA, as a percentage of the US population. NIL first implemented in 2021. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

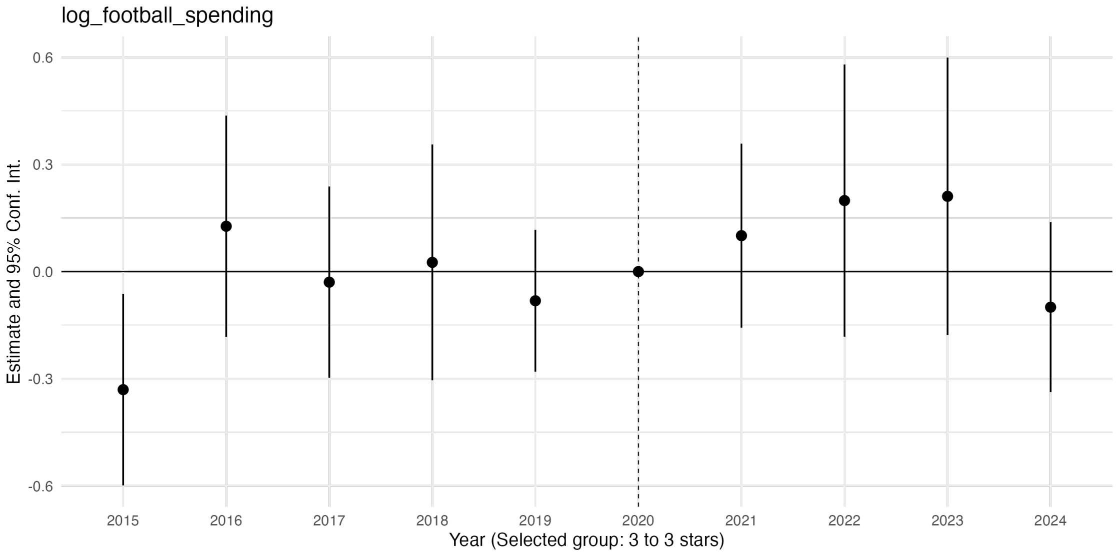

Figure A.23: Event study: NIL effects on 3* recruits' chosen schools' football spending in prior season. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

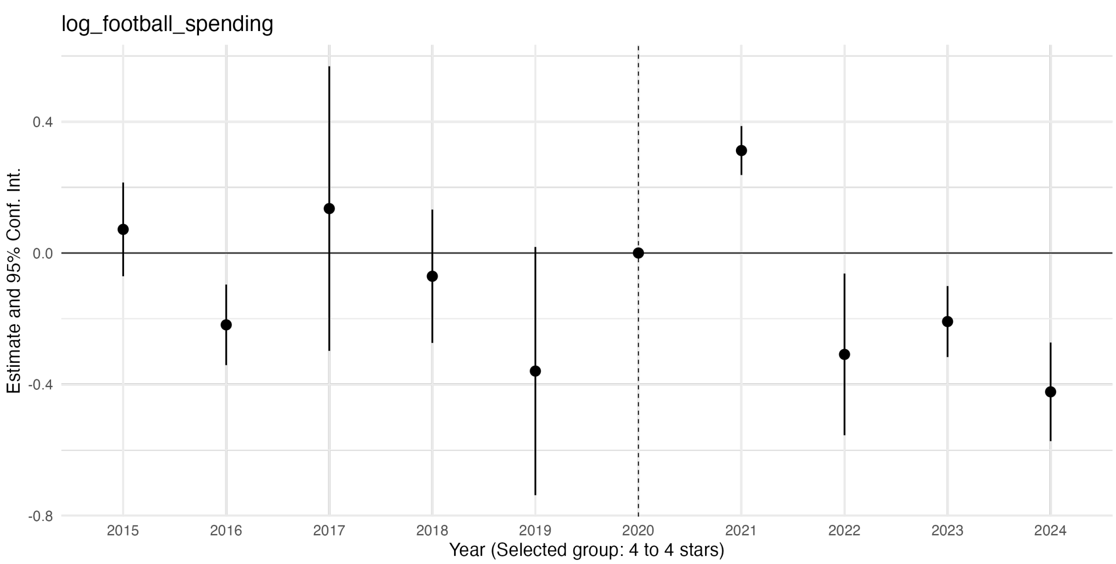

Figure A.24: Event study: NIL effects on 4* recruits' chosen schools' football spending in prior season. NIL first implemented in 2021. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

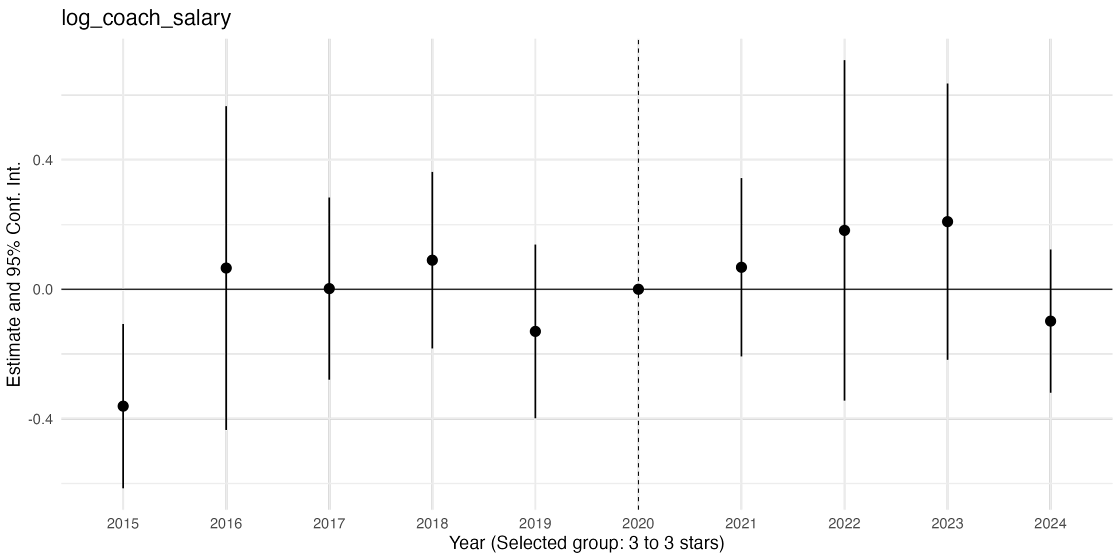

Figure A.25: Event study: NIL effects on 3* recruits' chosen schools' football coach salary in prior season. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position

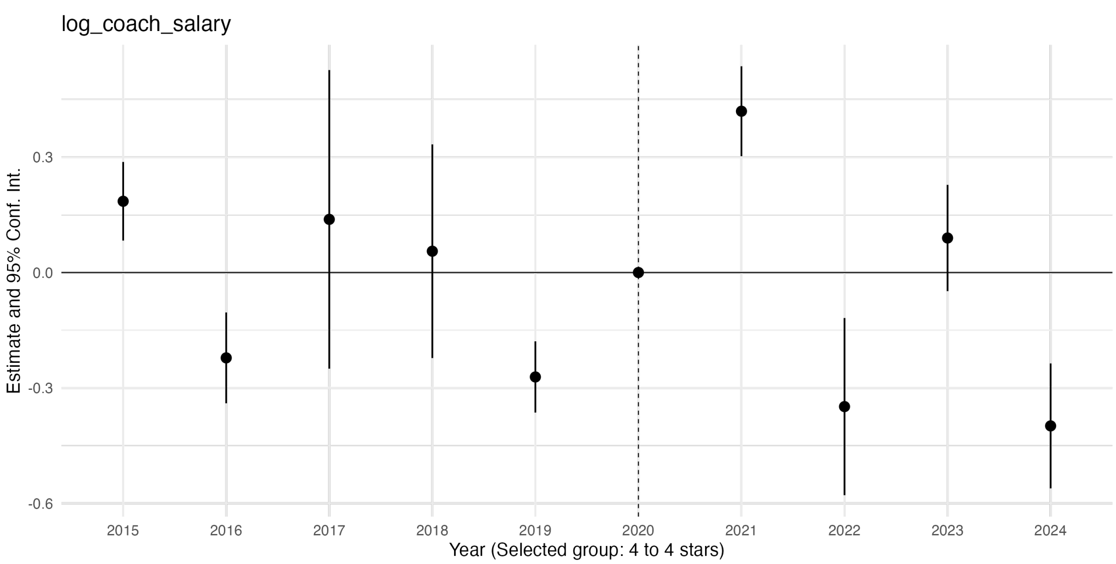

Figure A.26: Event study: NIL effects on 4* recruits' chosen schools' football coach salary in prior season. NIL first implemented in 2021. Error bars represent 95% confidence intervals around the estimated coefficient. Standard errors clustered by position