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Natee Amornsiripanitch
Paul Gompers
George Hu
Will Levinson
Vladimir Mukharlyamov

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ABSTRACT

This paper compares the careers of Ivy League athletes to those of their non-athlete classmates. Combining team-level information on all Ivy League athletes from 1970 to 2021 with resume data for all Ivy League graduates, we examine both post-graduate education and career choices as well as career outcomes. In terms of industry choice, athletes are far more likely to go into business and Finance related jobs than their non-athlete classmates. In terms of advanced degrees, Ivy League athletes are more likely to get an MBA and to receive it from an elite program, although they are less likely to pursue an M.D., a Ph.D., or an advanced STEM degree. In terms of career outcomes, we find that Ivy League athletes outperform their non-athlete counterparts in the labor market. Athletes attain higher terminal wages and earn cumulatively more than non-athletes over the course of their careers controlling for school, graduation year, major, and first job. In addition, they attain more senior positions in the organizations they join. We also find that athletes from more socioeconomically diverse sports teams and from teams that have lower academic admissions thresholds have higher career outcomes than non-athletes. Collectively, our results suggest that non-academic human capital developed through athletic participation is valued in the labor market and may support the role that prior athletic achievement plays in admissions at elite colleges.

Natee Amornsiripanitch
Federal Reserve Bank of Philadelphia
10 N Independence Mall W
Philadelphia, PA 19106
natee.amornsiripanitch@phil.frb.org

Paul Gompers
Harvard Business School
Baker Library 263
Soldiers Field
Boston, MA 02163
and NBER
pgompers@hbs.edu

George Hu
Department of Economics
Harvard University
Cambridge, MA 02138
george_hu@g.harvard.edu

Will Levinson
Duke University
Fuqua School of Business
will.levinson@duke.edu

Vladimir Mukharlyamov
McDonough School of Business
Georgetown University
3700 O St NW
Washington, DC 20057
vladimir.mukharlyamov@georgetown.edu

1 Introduction

Recent research work (Chetty et al. 2023) and legal action against elite colleges (SFFA v. Harvard) in the United States has put the focus on equity in the admissions process. The advantage that legacy candidates and recruited athletes receive in the probability of admission highlights the role of college education in building human capital that translates into future opportunities. Chetty et al. (2023) show that recruited athletes have significantly higher probability of admission despite lower academic achievement prior to matriculation than non-recruited students applying for admission to Ivy-plus colleges. While an argument for giving athletes special consideration in admissions asserts that athletics builds types of human capital that cannot be built in the classroom, this contention has not been explored in a rigorous manner. If athletes do build human capital that is valued in the labor market, consideration of athletic accomplishments prior to college within the admissions process could be reasonable, as it admits those individuals who have the capacity to build those types of skills through participation in intercollegiate athletics.[1] We provide suggestive evidence of such skills by examining the labor market outcomes of Ivy League intercollegiate varsity athletes and non-athletes who graduated between 1970 and 2021. Our motivation of examining Ivy League graduates lies in the relatively modest differences in academic achievement prior to college between athletes and non-athletes within the Ivy League.

In a sample of more than 400,000 graduates, we find that athletes are far more likely to enter careers in Finance and other business-related fields. In terms of advanced degrees, athletes have a higher propensity to receive any MBA as well as an MBA from an elite institution than

[1] In a similar vein, Chetty et al. (2023) note "If legacy status, higher non-academic ratings, and being a recruited athlete are associated with greater chances of success after college, colleges may face a tradeoff between admitting more students from middle class families and class quality as judged by the share of students who achieve uppertail success."

non-athletes, although this difference is reduced when we control for major and the industry of their first job. Athletes are less likely to pursue an M.D. or Ph.D. When we look at career attainment, we find that athletes have significantly higher labor market outcomes than non-athletes. While early career attainment (through five years after graduation) is quite similar for athletes and non-athletes, the labor market outcomes of athletes begin to diverge five years after graduation and increase steadily over time. For cumulative seniority,[2] peak seniority, cumulative wages, and peak wages, athletes significantly outperform non-athletes. Controlling for undergraduate major, year of graduation, college, and the industry that they enter, athletes earn about 3.4% more over their entire careers than non-athletes.

While we cannot identify the specific channel of career outperformance, we explore two potential channels. First, there is some evidence that socioeconomic status plays some role. Athletes in sports that are primarily associated with elite private prep high schools (e.g., crew, squash, lacrosse, equestrian, etc.) have somewhat higher career outcomes than do athletes in sports that are primarily associated with public schools, suggesting that prior socioeconomic status may play a role in labor market success. Athletes in all sports, however, still have significantly better labor market outcomes than non-athletes. In particular, athletes from socioeconomically and racially diverse sports (football, men's and women's basketball, and men's and women's track), as well as athletes from sports with the lowest academic thresholds for admission (football, men's and women's hockey, and men's and women's basketball) have the highest unconditional labor market outcomes. For these athletes, it is reasonable to claim that labor market outperformance is

[2] Seniority is a measure of where a particular job title exists in the firm's hierarchy. We discuss its construction below. For a more complete discussion, see Amornsiripanitch et al. (2022).

less likely to come through socioeconomic channels and more likely to come through the development of skills that may be important in the labor market.

We provide suggestive evidence that at least a portion of the superior outperformance of athletes over their careers is due to development of specific types of human capital that may be valued in the labor market. We examine the prevalence of different types of skills as reported in LinkedIn for Ivy graduates. Athletes are significantly more likely to be endorsed for management related skills such as Management, Leadership, and Strategic Planning, while they are only slightly less likely to be endorsed for more analytical skills such as Research, Teaching, and Data Analysis. In addition, we find that athletes playing diverse sports or "low academic threshold" sports have the highest probability of reporting management skills on LinkedIn across all athlete groups.

Universities, as the sole purveyors of undergraduate education, are critical players in the creation of human capital, yet how they do so can vary significantly across time and space. For example, in the 1600s Harvard College's graduation requirements turned on an "[a]bility to translate passage of the Bible from the Greek, Hebrew and Aramaic into Latin, and to expound biblical texts[.]"[3] No university, to the best of our knowledge, maintains these requirements in the present day. More relevant, across most of the contemporary world, universities' undergraduate programs aim to build students' human capital primarily, if not exclusively, through the development of academic skills. A significant body of academic research has explored how this human capital translates into career outcomes and economic mobility (e.g., Black and Smith, 2004; Brand and Hallaby, 2006). In certain professions (e.g., technology, the life sciences, and education), there is a closer relation between academic skills and the required human capital for

[3] See "The Curriculum of Study at Harvard in Early Years," Harvard Crimson, 1888. https://www.thecrimson.com/article/1888/1/3/the-curriculum-of-study-at-harvard/

the profession. In other professions (e.g., consulting, management, and finance), there may be a more tenuous connection between academic skills and the human capital required to succeed. Our paper sheds additional light on these topics.

2. Motivation

Universities in the United States, however, complement academic training with institutionalized extracurricular pursuits, most notably athletics. Numerous American universities have explicitly proclaimed a direct link between their athletic programs and their more general educational goals. For example, Harvard Athletics' Mission Statement begins with the slogan "Education Through Athletics." Harvard is not unique in articulating this as the purpose of the pursuit of athletics in an intercollegiate setting.[4] At least from the perspective of the athletic departments themselves, athletics plays a critical role in the development of human capital. In fact, Harvard Athletic Department's Mission Statement goes on to say, "Athletic participation helps our students grow, learn, and enjoy themselves while they use and develop their personal, physical, and intellectual skills. Harvard values the lessons that have long been taught by athletic participation: the pursuit of excellence through personal development and teamwork, ethical and responsible behavior on the field and off, adherence to the spirit of rules as well as to their letter, leadership and strength of character, and sportsmanship – …. In teaching these lessons to its students, Harvard instills habits which will lead students to better and healthier lives. …, we

[4] Additional mission statements from other athletic departments include the following. At UC Berkeley, the Athletics Department's explicit mission is "to teach, serve, compete, and excel." The opening lines in the University of Virginia's athletic mission statement proclaims, "The Department of Athletics is an integral part of the University of Virginia's commitment to educational excellence. Its mission is to enhance and support the intellectual purpose of the University and its exemplary academic standards and traditions."

believe that the efforts by our intercollegiate athletes to be their best will lead them to succeed throughout their lives."

Despite American universities' claims that college athletics programs enhance broader educational goals, athletics' educational value within the university system has come under increasing scrutiny and skepticism over recent years, especially at elite private institutions. For example, over the course of the SFFA v. Harvard case concerning affirmative action practices, both critics and supporters of affirmative action noted that Harvard could significantly increase the racial diversity of its student body by eliminating preferential treatment for student athletes (alongside legacies and other privileged groups).[5] Similarly, the Department of Justice's "Varsity Blues" legal action against parents who allegedly paid bribes to improve their children's chances of admission to elite colleges (e.g., Yale, Stanford, USC, Wake Forest, and Georgetown) by leveraging the recruited athlete admissions channel raised further concern about potential abuse of athlete preferences in admission.[6]

In parallel, academic literature (e.g., Arcidiacono et al. 2022) has noted that recruited athletes' academic credentials significantly lag their classmates' credentials at the time of admission. Thus, empirical criticism about elite colleges' athletics programs has largely focused on athletes' racial composition, prior socioeconomic status, and less exceptional academic credentials *before and during* college. However, evaluation of college athletics programs' potential impacts on career fortunes *after* college has largely confined itself to anecdotal

[5] In her dissenting opinion in SFFA v. Harvard, Justice Sonia Sotomayor noted that nearly 70% of "ALDC" (athlete, legacy, dean's list, and faculty children) were white, and that applicants from non-underrepresented racial groups in fact benefit from the pre-SFFA v. Harvard admissions system. Likewise, in his concurring opinion, Justice Neil Gorsuch opined that Harvard could replicate the racial diversity of its current student body through the elimination of preferential treatment for athletes, legacies, donors' children, and faculty's children. *See generally Students for Fair Admissions, Inc. v. President and Fellows of Harvard College*, 143 S.Ct. 2141 (2023).
[6] https://www.justice.gov/usao-ma/investigations-college-admissions-and-testing-bribery-scheme.

evidence.[7] The relative paucity of empirical evidence on athletes' post-college outcomes in the debate on admissions policy is somewhat surprising. After all, because preparing students to have successful career outcomes and to positively impact the organizations that they join are critical components of elite universities' educational goals,[8] it may logically follow that the predictors of postgraduate success that universities seek to identify in their prospective applicants may hinge upon both academic and non-academic characteristics. To put it another way, if the role of college is to build human capital, and if both the academic and athletic activities in a college build that human capital, then admitting students who have the ability to take advantage of both paths to building that human capital may make sense.

Accordingly, to better inform discussion on college athletics programs' educational and economic value, this paper empirically documents the career trajectories of college athletes relative to their non-athlete peers. Empirically analyzing athletes' postgraduate career outcomes, we aim to examine (i) college athletics programs' efficacy in developing human capital and (ii) the resulting individual-level private value that participation in Ivy League athletics might bestow. Studying Ivy League alumni graduating from 1970-2021, we use resume data to track and study individual job histories from college graduation to the present.

Various factors motivate our focus on the Ivy League. First, admissions policies at elite private colleges have recently come under increased public scrutiny and pressure for reform.

[7] For example, an Atlantic article from 2019 titled "The Cult of Rich Kid Sports" states that "The power of fancy sports doesn't stop at the college level. It plays a shockingly large role in determining the sort of people who get hired in America's elite professional-services industry—law firms, investment banks, and consultancies."

[8] For example, Harvard College's mission statement proclaims, "The mission of Harvard College is to educate the citizens and citizen-leaders for our society," while the conclusion of Yale College's mission statement declares, "The aim of this education is the cultivation of citizens with a rich awareness of our heritage to lead and serve in every sphere of human activity." Both universities' mission statements suggest that students' postgraduate roles as societal leaders represent the ultimate standard by which they evaluate the quality of their undergraduate education.

Hence, empirical evidence that illuminates the costs and benefits of admissions preferences at these institutions has become per se important for policy discussion. Second, though Ivy League athletes' academic credentials may not, on average, match other Ivy League students' pre-admission academic achievement at the time of admission (Arcidiacono et al. 2022), academic standards for student-athletes at Ivy League schools remain very high and ensure the satisfactory completion of their undergraduate studies. The Ivy League outlines guidelines for the pre-admission academic requirements of recruited athletes. Essentially, an Academic Index (AI) is created on a scale from 0 to 240 based upon class rank, SAT, and SAT2 subject tests. The average AI of any athletic team is required to be above a relative threshold pegged to the AI of the student body as a whole.[9] While this fact may limit our results' generalizability across a broader range of colleges, this restriction ensures that our estimates of athletes' performance in the labor market may not be significantly skewed downwards due to a lack of requisite academic preparation. Finally, Ivy League schools offer an especially wide variety of sports, and we exploit this variety to examine the extent to which team-level heterogeneity in career profiles exists.

Our empirical analysis reveals a striking fact: Ivy League athletes outperform their non-athlete counterparts in the labor market. Measuring labor market achievement using both wages and seniority (a non-wage measure of achievement),[10] we show that athletes achieve higher labor market outcomes than non-athletes (i) cumulatively over the entirety of their careers and (ii)

[9] "The eight Ivy League schools use a numerical ranking system known as the Academic Index (AI) to rank students. The Ivy League originally developed the AI to ensure athletic recruits met a minimum academic standard that was relatively uniform across the eight schools. … Essentially, the AI is a score from 60 to 240 derived from an applicant's GPA or class rank and SAT scores. The AI is then used to determine a recruited athlete's eligibility for admission. The minimum score changes from year to year, and some exceptions can be made. The primary function of the AI is maintaining a high academic standard for recruited athletes at Ivy League schools. The average AI of any given team must be no more than one standard deviation below the average AI of the entire student body." Taken from https://ivyleagueprep.com/ivy-league-admission-tips-the-academic-index accessed on August 19, 2023.

[10] See Amornsiripanitch et al. (2022) for a more complete definition of seniority.

terminally at their terminal/peak job. Furthermore, along more extensive margins, athletes are more likely to hold an MBA or a C-suite position at some point in their careers, although much of this higher prevalence is due to their college major and industry choice. A clear divergence in athletes' career trajectories only begins to materialize 5 to 10 years after college graduation, yet the gap between athlete and non-athlete career achievement trajectories continues to widen at 20 and even 25 years post-college graduation. Although our data do not allow us to fully observe athletes' academic characteristics, our empirical results comparing athletes to non-athletes are robust to a full set of university, undergraduate major, graduation year, and first-job fixed effects.

Having established the phenomenon that Ivy League athletes' have superior labor market performance, we proceed to investigate and discuss potential explanatory mechanisms. We first consider the extent to which participation in certain sports serves as a labor market signal for family wealth. While data constraints preclude us from directly measuring family wealth, we use sport-level variation to infer whether family wealth explains the earnings premium for Ivy League athletes. Under the assumption that certain "niche" sports are more likely to attract student-athletes from wealthy families because they are primarily associated with elite private high schools, we empirically test whether niche sport athletes from Ivy League schools outperform their non-athlete and non-niche sport athlete counterparts in the labor market. While niche sport athletes do have superior labor market outcomes, they only marginally outperform their non-niche counterparts in career earnings and seniority-based achievement. This result offers suggestive evidence that wealth-based selection and signaling cannot explain the entirety of athletes' labor market overperformance. Second, we look at "diverse" sports, i.e., those sports that have the highest racial/ethnic and socioeconomic diversity (e.g., football, men's and women's basketball, men's and women's track) as well as sports that whose academic admission threshold is the lowest (i.e., football, men's and women's hockey, men's and women's basketball). We find that student-athletes from diverse sports and from low academic admission threshold sports also outperform their non-athlete peers. This would suggest that socioeconomic status alone cannot explain the superior labor market outcomes of Ivy League athletes.

We briefly discuss the potential role that social networks, peer effects, and management skill development could play in explaining athletes' overperformance, but we currently leave most of the empirical analysis of these potential mechanisms to future research. Examining reported skills on LinkedIn suggests that athletes are more likely to report management skills that may be valued in the labor market and are only slightly less likely to report specialist or quantitative skills. We also find that the groups of athletes that appear to have the highest labor market outperformance (diverse sport and low academic admission threshold sport athletes) have the highest propensity to report these management skills.

This paper's investigation of Ivy League athletes' labor market fortunes adds to various parts of the academic literature, and its empirical results inform policy discussion. Most directly, we build on the literature that studies linkages between youth athletic participation and adult labor market performance. Existing work (e.g., Long and Caudill 1991, Barron et al. 2000, Heckman and Loughlin, 2021) has investigated how participation in high school and college sports teams affects lifetime educational attainment and adulthood wages. These studies find a positive correlation between athletic participation and wages, but they rely on cross sectional survey data and cover a nationally representative sample of individuals whose academic characteristics will vary significantly. These papers also suffer from survey attrition over time, i.e., they only look at respondents to the survey over four or five rounds. Through its focus on Ivy League alumni, our paper adds to these existing results by establishing that a labor market premium exists for athletes even at the right tail of the earnings distribution. Furthermore, our ability to track individuals' entire career trajectories enable us to more comprehensively evaluate the dynamic evolution of athletes' exceptional labor market performance over time.

Second, we contribute to academic literature and policy discussion on university admissions practices. Existing academic work on admissions preferences (e.g., Bleemer 2022, Arcidiacono et al. 2022, Bleemer 2023) focuses on admissions policies' impacts on the demographic and academic distribution of a university's student body. More recent work (Chetty et al. 2023) has investigated the correlation between preferred admissions characteristics (e.g., strong academics, athlete status, legacy status) on postgraduate career attainment. However, this analysis relies on the imputation of future career achievement based upon attainment at age 25 to estimate the relationship between applicant characteristics and future earnings multiple years after college graduation. In contrast, this paper directly observes substantial portions of Ivy League alumni's entire career histories. Such direct observation allows us to quantify the cumulative labor market premia that Ivy League athletes achieve. In particular, we find that the outperformance by Ivy League athletes begins approximately five years after graduation then increases beyond that time. In doing so, we highlight a potential benefit that athletic admissions preferences might bring to universities' finances and reputations.

Third, this paper adds to the growing literature on the role of social networks in career development. Recent literature at the intersection of education and labor economics has emphasized the importance of social groups in facilitating career development and achievement. In the undergraduate context, Zimmerman (2019) and Michelman et al. (2022) show that membership in exclusive, "old money" social clubs predicts higher earnings and more prestigious associations in adulthood than other student characteristics, including academic performance. By distinguishing niche sports from non-niche sports in its career analysis, this paper quantifies the extent to which social groups that favor inherited privilege might explain postgraduate career success. If one believes that niche sports are prototypical exclusive social clubs, our results may reflect earlier work's conclusions that past wealth may correlate more closely with future career achievement than academic performance or merit in the elite university context. Likewise, in the workplace, Cullen and Perez-Truglia (2023) and Agarwal et al. (2016) show that workplace "schmoozing" and participation in athletic and other extracurricular activities can facilitate promotions and career advancement in the context of the gender earnings gap. Our demonstration that athletes' outperformance accumulates over time in the labor force offers additional suggestive evidence that workplace schmoozing and cross-firm socialization could play a significant role in facilitating internal promotion and job transitions for athletes.

Finally, this paper builds on existing work that aims to measure the non-academic and non-technical components of human capital. Work by Heckman and Kautz (2014) and Borghans et al. (2016) conclude that personal characteristics ("character skills") such as perseverance, curiosity, sociability, and conscientiousness may predict career success more accurately than academic intelligence. Heckman and Loughlin (2021) argue that human capital (e.g., "leadership and teamwork skills") can be developed through athletics. Sociologists and sports management scholars (Weight, Smith, and Rubin, 2022) have also argued that critical human capital is developed through participation in athletics. Athletics is one of the few extracurricular activities that is a year-round and requires a commitment of 20-30 (or more) hours per week. The extensive time commitment involved with varsity-level athletic participation in both high school and college potentially contribute to the slight underperformance of athletes academically both before and during college. On the other hand, athletic participation may be highly effective in building those types of character skills that Heckman and Kautz (2014) consider to be better predictors of career success. Although our analysis is not able to directly link participation in athletics with the development of any of these non-academic skills in particular, the finding of an athlete achievement premium that is robust to team-level variation in family wealth may further support the view that non-academic skill development proves crucial to cumulative career success. Such a linkage can inform university policies on weighting the importance of non-academic characteristics in undergraduate admissions and complementing the development of academic skills with non-academic ones throughout the undergraduate experience.

The remainder of the paper is structured as follows. Section 3 describes the data on Ivy League athletes and summarizes the merging process with resume data from Lightcast. Section 4 presents our results. Section 5 discusses differences between career outcome results and those of Chetty et al. (2023), while Section 6 concludes.

3 Data and Sample Construction

3.1 Data Sources

In this study, we draw from two data sources. First, we utilize resume information from Lightcast. Second, we have data from 44 different colleges on intercollegiate varsity athletes from 1970 through 2021. Lightcast sources its data primarily from the well-known professional network LinkedIn. This comprehensive dataset captures employment specifics such as job designations, tenure durations, corporate identities, and their NAICS classifications. Lightcast refines the descriptions of job roles through data cleaning and analysis that streamlines job titles, company names, and industries. Additionally, Lightcast pairs each job title with a matching O*NET code.

O*NET codes are created by the U.S. Department of Labor to track occupational characteristics across the U.S. economy.

Furthermore, Lightcast collects educational histories, registering the matriculation and graduation dates for particular degrees, academic institution names, the nature of academic qualifications (i.e., degrees), and academic areas of expertise (i.e., majors). Such educational data are pivotal in discerning key elements of human capital, for instance, procuring a STEM degree, securing an MBA, or graduating from a leading undergraduate institution. For profiles that provide undergraduate college names, we group them into three classifications: elite institutions (such as the Ivy League), Tier 2 colleges (which consist of top liberal arts colleges and top-tier public universities), and all other educational entities, both within the US and abroad. A comprehensive index of these colleges is available in Appendix Table 1.

Using the entire Lightcast dataset, which contains approximately 150 million profiles, we estimate the seniority of every job title based on industry and size, categorizing companies into quintiles based on employee numbers each year and assessing seniority from a diverse pool of professionals. Because wages may be influenced by the chosen industry (e.g., education or government vs. business or finance), we view seniority as a cleaner measure of career attainment. As in Amornsiripanitch et al. (2022), seniority is calculated from these data by examining all individuals who achieve a certain title in a given industry and firm size quintile as ranked by number of employees. We define seniority as the median time (in years) that it takes to first achieve that title after entering the labor force (i.e., from the year of undergraduate graduation). For example, the title “software engineer” in the IT industry and a firm in the largest quintile is associated with a seniority of 5, which indicates that the median individual in our sample who becomes a software engineer in the IT industry for a firm in the largest quintile first achieves that title five years after graduating college. Thus, software engineer is a relatively junior title. By contrast, “lead software engineer” has a seniority of 11. On the most senior end of the scale, “chief executive officer” in the same firm quintile has a seniority of 14.5, and “director” has a seniority level of 16. Intuitively, our seniority measure quantifies an individual’s position within the organization’s hierarchy.

In addition to measuring career attainment through seniority, we also look at estimated wages. We use the Bureau of Labor Statistics (BLS)-maintained Occupation Employment and Wage Statistics to estimate wages. The BLS reports median wage by Standard Occupational Classification (SOC) code from 1999-2020.[11] We adjust all dollar values for inflation, using 2020 as the base year. Administrative changes in data collection at the BLS may complicate estimation. Before 2003, the BLS used SIC rather than NAICS codes to classify industries. SOC classifications have changed over time, too, with different versions starting in 2000, 2010, and 2018. As the classifications have changed, the definitions of some codes have been adjusted, combined, or dropped. As a result, the BLS data do not cover every SOC-industry code for every year. We linearly impute any missing values. For example, if we know the SOC-industry median wage in 2011 and 2013 but are missing 2012 wages, we interpolate 2012 wages as the average of wages in 2011 and 2013. We then match the wage data to our Lightcast resume data by SOC code, 3-digit NAICS code, and year.[12] If a job is missing a NAICS code, we merge in the SOC-year national average instead.

[11] There are no BLS-maintained data prior to 1999, so we impute wages for jobs earlier than 1999 as 1999 wages. This is a relatively small part of our total sample and affects few post-founding jobs.

[12] SOC and ONET codes are basically equivalent, though they are formatted slightly differently. Each digit in the SOC code identifies a level of specificity (e.g., 11-1123 and 11-1121 are both classified under the 11-1120 grouping, which is a subset of the 11-1100 grouping). If estimated wage is missing for the exact SOC code, we move to the next most granular SOC code until we get a match (e.g., from 11-1123 to 11-1120 or from 11-1120 to 11-1100).

3.2 Sample Construction

In order to track the careers of athletes we collect data on varsity athletes at 44 U.S. colleges by scraping athletic department websites. These online resources, managed by the athletic departments, display the varsity letter awardees from each school. For teams not listed in these digital archives—typically those existing before the digital era—we consulted both digital and physical yearbooks to supplement our dataset.

The colleges for which we collect varsity athlete data include the Ivy League, elite private colleges such as Duke and Stanford, and major public universities such as the University of Florida and University of Michigan (for a complete list, see Appendix Table 1). The historical list of varsity athletes was then merged with profile data from Lightcast that included all graduates of those 44 colleges. In total we have profiles on 5.3 million graduates from these 44 institutions. We then merged the athlete data into the Lightcast profiles by name and year. Of the 5.3 million resumes, we focus only on graduates who list one of the eight Ivy League colleges as their undergraduate institution.

3.3 Summary Statistics

In this section, we examine the data for Ivy graduates within the Lightcast data. Table 1 presents basic summary statistics, and Appendix A provides definitions of all the relevant variables. We have profile information for 401,785 graduates of the Ivy League. Of these, 8% are athletes. The core analyses compare athletes to non-athletes, but in order to test various hypotheses on mechanism, we subset sports into various categories. First, we classify sports into team and individual sports. Team sports are those that require coordinated play on the part of multiple athletes during the entire match/game. A count of athletes by sports is provided in Table 2. Table

3 provides a breakdown of team sports within our data. If certain skills are learned by participation in sports with the cooperation of other athletes, then there may be differences in career choices and outcomes for team sports athletes versus individual athletes.

For example, it is possible that career performance of athletes is affected by their socioeconomic status and not by their human capital. (Chetty et al. (2023) show that athletes' socioeconomic status is substantially higher than non-athletes on average.) To test this hypothesis, we classify sports into niche and non-niche. Niche sports are those that are primarily pursued through private schools (e.g., crew, squash, fencing, etc.). If niche sport athletes do substantially better than non-niche sport athletes, then at least part of athletes' career outperformance might be due to their higher family incomes and connections.

We are similarly motivated by the advantages of socioeconomic status in our classification of diverse and non-diverse sports. We classify diverse sports as those sports in the Ivy League for whom current rosters have more than 30% underrepresented minorities (i.e., Black and Hispanic). Football, men's and women's basketball, and men's and women's track are the only sports that meet the diverse criterion. Recruited athletes in these three sports come primarily from public schools and, as such, are likely more socioeconomically diverse as well. If diverse sport athletes do as well in their careers as non-diverse sport athletes, it would likely indicate that other factors (e.g., human capital) might explain the performance premium earned by athletes during their career.

Finally, we classify football, men's and women's basketball, and men's and women's hockey as low academic standard sports. These five teams have lower academic thresholds for admissions than other varsity sports in the Ivy League. If low academic sport athletes do as well as other athletes in their careers, then it is likely the career premium for intercollegiate varsity athletes is, at least in part, due to building human capital or advantages in networked hiring.

Table 1 provides a breakdown of athletes by category; niche sports are 3% of the total sample, low academic standard sports are 2%, while diverse sports are 2%. The total career cumulative seniority, defined as summing up of the annual seniority that an individual attains over their entire career, has a mean of 127.79 years and a median of 69.00 years, suggesting a skewed distribution towards higher seniority, which is further confirmed by its standard deviation of 154.26 years. For career maximum (peak) seniority, the mean is 13.08 years, and the median is 13.00 years. We also tabulate cumulative wages (defined as the sum of wages of one's career in constant 2021 dollars). Average cumulative wages are $1.62 million, whereas average peak wages are $126,900. Males are 54% of the dataset.

On average, individuals in the Ivy League sample report a career length of 19.84 years and have held 5.18 jobs throughout their careers. Moreover, 21% of the individuals have had at least one finance job, 8% have held a position in the C-suite defined as a title that starts with "chief", 14% have an MBA (with 6% being an elite MBA), and 18% have a graduate degree in a STEM field. 12% of Ivy graduates have a J.D. while 15% have a Ph.D. Finally, 5% receive an M.D. The prevalence of advanced degrees in our sample is consistent with high academic achievement.

Table 7 summarizes the career statistics for athletes versus non-athletes. It reveals significant differences between athletes and non-athletes. On average, athletes have cumulative seniority of 147.506 years, exceeding the average for non-athletes (126.15) by 21.35 years. Similarly, athletes' career max seniority surpasses that of non-athletes by 0.89 years, averaging 13.89 years versus 13.01 years, respectively.

Table 4A presents a breakdown of undergraduate majors in our sample. We provide multiple bivariate sorts to look for patterns in student choices. First, male students are far more likely to concentrate in Economics, Computer Science, Engineering, and Finance. Women are more likely to major in English Literature, Biology, and Psychology. When we compare athletes to non-athletes, athletes are more likely to major in Business, Economics, Political Science, Finance, and Management, while they are less likely to concentrate in Computer Science, English Literature, Philosophy, and Engineering. We also provide breakdown of concentrations for various types of sports in Table 4B. Perhaps most noteworthy, diverse sport athletes and low academic sport athletes have the highest percentage of people who concentrate in Economics, Political Science, Business, Finance, and Management.

We look at advanced degree attainment in Table 5. Among advanced degrees, the only substantial difference between male and female graduates is that a higher percentage of males go on to pursue an MBA. Athletes, on the other hand, are far more likely (19.16%) to receive an MBA and an elite MBA (8.05%) than non-athletes (14.24% and 6.17%). Athletes are less likely to get an M.D. (4.89%) or Ph.D. (10.76%) than are non-athletes (5.43% and 14.81%). Across the various sport breakdowns, we see that the breakdown of advanced degrees for individual sport athletes is much closer to the breakdown achieved by non-athletes while diverse and low academic standard sport athletes have the highest percentage of MBA (19.83% and 21.17%) and Elite MBA (7.76% and 8.00%) attainment but the lowest fraction who receive a Ph.D. (8.84% and 6.81%).

Like differences in undergraduate majors, athletes have substantially different career choices, on average. Table 6 provides the industry of Ivy graduates first job. First, male graduates are more far more likely to go into Finance (12.51%), Legal (7.20%), and Technical Services (7.77%) than are women (7.77%, 6.24%, and 6.60%). Women are more likely to enter non-college

(5.75%) and college education (10.08%) as well as Healthcare (10.08%) compared to men (3.59%, 7.97%, and 6.57%). When we compare career choices of athletes versus non-athletes, athletes enter Finance (16.57%) more often than non-athletes (9.79%) while they are less likely to enter College Education (7.19%), Healthcare (6.72%), and Technical Services (6.28%) than non-athletes (9.10%, 8.46%, and 7.30%). Career choices of all types of athletes are all tilted in the same direction. We do find, however, in Table 6B that the low academic sport athletes have the highest percentage of graduates that go into Finance (20.25%) and the lowest percentage that go into College Education (3.54%).

In Figure 1 we present the average seniority over time for men and women while in Figure 2 we present a similar graph over time for estimated real wages. Both graphs show what is known from the prior literature. On average, men achieve higher seniority positions in the organizations that they join and have higher salaries. Furthermore, while the gender gaps in seniority and wages are initially small, both gaps appear to substantially widen over time. While gender differences are important and are much explored in the existing literature (for example Goldin, 2014), our primary focus will be on careers of athletes and non-athletes and whether the effect of being an athlete is different for women versus men.

Figures 3 and 4 provide a similar graph for athletes and non-athletes. In Figure 3 we graph seniority over time. Figure 3 makes it clear that early on, the careers of athletes and non-athletes, as measured by seniority, look quite similar. A gap in performance in seniority between athletes and non-athletes only opens around 5 years into one's career, but this gap widens over time. When we graph cumulative wages in Figure 4, we see the same pattern. Early career wages, though higher for athletes, are quite similar for athletes and non-athletes, but the initially small gap between athletes and non-athletes in wages begins to diverge 5 years into one's career. As with seniority, the gap in wages continues to increase over time.

Table 7 examines various career achievement metrics for our various sub-samples and tests whether these differences are statistically significant. Generally, the differences in degree achievement that we noted above are significant. We first use our measure of seniority to compare career achievement. In Panel A, male graduates have substantially higher cumulative and peak seniority than do female graduates (153.3 and 14.2 years vs. 98.3 and 11.8 years). Wages tell a similar story: men have higher cumulative and peak wages ($1.9 million and $135,000 versus $1.29 million and $118,000). Men are also twice as likely to hold a C-Suite position in their career.

The results for athletes are also quite striking in Panel B. The pattern of advanced degrees shows that athletes have a significantly higher likelihood of receiving any MBA as well as an elite MBA. Athletes are less likely to pursue and receive an M.D. or a Ph.D. When comparing seniority, athletes attain significantly higher cumulative and average seniority than non-athletes (147.5 and 13.9 years versus 126.2 and 13.0 years). Athletes also achieve substantially higher cumulative wages and peak wages ($1.82 million and $135,000) than do non-athletes ($1.60 million and $126,000). These differences are substantial. Cumulative wages and seniority for athletes are roughly 15% greater than non-athletes while peak wages are 7% higher. While these comparisons are suggestive of a superior labor market outcome for athletes, in Section 4 below, we control for observable characteristics (e.g., year of graduation, major, college, and first job) to understand whether educational and initial occupational characteristics explain these differences.

Within our sample, Table 7B shows that athletes' careers are longer, on average, at 21.1 years versus 19.7 years for non-athletes. Athletes also hold slightly more job titles, with an average of 5.3 compared to 5.2 for non-athletes. In terms of more granular information on careers, 29.8% of athletes have had at least one finance job, which is 9.6% higher than the 20.2% of non-athletes who have had at least one position in finance. Similarly, 10.4% of athletes have held a C-suite position, higher than the 7.9% for non-athletes.

Panels C through F of Table 7 provide the bivariate sorts of our various groups of athletes. In general, the differences between the groups of different types of athletes are relatively small, much smaller than the difference between athletes and non-athletes that we saw in Panel B. Each subset of athletes, when compared to non-athletes, continues to outperform on various career metrics. Perhaps surprisingly, the highest career attainment occurs in the group of athletes from low academic standard sports. This group of athletes has cumulative seniority of 171.9 years, max seniority of 14.9 years, cumulative wages of $2.1 million and maximum wages of $139,000. 12.2% of these athletes also ultimately achieve a C-Suite position. In the next section, we control for as many observable characteristics as possible to understand whether this athlete career premium is caused by selection into particular jobs or whether it exists after such controls.

4 Empirical Results

Descriptive evidence presented in Section 3, particularly Figures 3 and 4, suggests that Ivy League athletes outperform their non-athlete peers, yet this evidence is only suggestive because it does not control for other characteristics that could systematically differ between the two samples. Accordingly, this section uses the data described in Section 2 to (i) more robustly quantify Ivy League athletes' performance premium in the labor market and (ii) characterize the temporal dynamics of athletes' outperformance. Specifically, we implement fixed effect regressions that estimate the relationship between participation in Ivy League athletics and various measures of career achievement over time. We cannot perfectly control for unobservable characteristics of Ivy League athletes that may contribute to their career outcomes, and, therefore, our estimates do not admit a causal interpretation. Nonetheless, the persistence of the athlete performance premium within our regression specifications which control for various observable characteristics suggests that explanations such as academic course and initial postgraduate occupational choices do not explain the gap.

4.1 Regression Specification

To estimate the conditional correlation between athlete status and labor market outcomes, we estimate the following ordinary least squares (OLS) regression:

$$Y_i = \alpha + \beta\, \boldsymbol{I}(Athlete = 1)_i + \boldsymbol{\gamma}'\boldsymbol{Z} + \epsilon_i.$$

Y is the placeholder for labor market outcomes that we study. i is the index for individuals. The variable of interest is $I(Athlete = 1)_i$ which is an indicator variable that equals 1 if the individual is an athlete. Z is the vector of control variables which include gender, reported career length, and number of reported jobs. For robustness, we also include undergraduate major, graduation year, and undergraduate college fixed effects. The fixed effects and control variables account for systematic differences in observable characteristics between athletes and non-athletes that we present in Section 2. In some specifications, we also include industry fixed effects to ensure that initial occupational choice (e.g., entry into the financial sector) does not explain athletes' overall labor market outperformance.

Though our control variables account for various factors that may drive the athlete performance premium, the regression above does not admit a causal interpretation because many unobservable characteristics may influence labor market outcomes remain omitted.[13] For example, our data prevent us from measuring other attributes such as college GPA and family wealth in a convincing manner. Nonetheless, trial-based evidence from the SFFA v. Harvard case[14], summaries from Chetty et al. (2023), and sources discussed above demonstrate that recruited athletes have lower academic achievement at the time of admission than their non-athlete counterparts. Hence, we can conclude from this evidence that superior academic skills cannot explain athletes' labor market outperformance in expectation. We therefore largely exclude academic ability from our discussion of potential explanatory mechanisms. To directly test the academic skills channel, below we sort the athletes into those sports that have lower academic admission thresholds for (i.e., sports that have lower academic index requirements at the team and individual level) at the time of application.

4.2 Baseline Results

Table 8 estimates how athletes' post-graduate degree choice and entry into the Finance profession vary from non-athletes. We find that athletes are not more likely to receive an MBA than non-athletes once we condition for graduation year, college, and major, as well as for starting industry. This finding suggests that educational and initial occupational choices largely explain athletes' increased unconditional propensity for MBA degrees. We should note that male graduates are 0.8 percentage points (pp) more likely to pursue an MBA than female graduates. We find that male athletes pursue a J.D., M.D., or a Ph.D. less often than their non-athlete counterparts. Female athletes are not less likely than comparable non-athlete graduates to pursue a J.D. or an M.D., but are between 0.9 and 1.3 pp less likely to purse a Ph.D. Finally, male and female athletes

[13] Future refinements of our work will control for socioeconomic status and race/ethnicity at the individual, not just team level.
[14] https://www.supremecourt.gov/opinions/22pdf/20-1199_hgdj.pdf.

are far more likely (6.5 and 3.6 pp respectively) to pursue a career in Finance than are non-athletes. Career preference differences between male and female graduates is also apparent in that male graduates are 4.1 pp more likely to enter Finance than female graduates. These results, including pursuing a Finance career, are generally robust to controlling for the industry of the graduates' first job after college.

We provide estimation results in Tables 9 through 12 on our various bivariate sortings of sports to test various potential channels that might affect athletes' career outcomes. Table 9 separately considers team sport and individual sport athletes. We find that team sport athletes have similar probability of pursuing an MBA and a lower probability of obtaining a Ph.D. or advanced STEM degree, relative to similar non-athlete graduates. While all team sport athletes have a lower probability of receiving a Ph.D., female individual sport athletes do not. We find no statistically significant difference in the propensity of team or individual sport athletes to pursue Finance for females, but male team sport athletes are more likely to enter Finance than their male individual sport counterparts.

Table 10 controls for niche sport athletes (those with athletes primarily from private high schools). The results indicate that niche sport athletes have a significantly higher chance of getting an MBA or an Elite MBA than non-niche sport athletes. Female niche sport athletes attain M.D. and Ph.D. degrees at a similar rate to their otherwise similar non-athlete female counterparts. Finally, male and female niche sport athletes have a significantly higher proclivity to go into Finance (9.2 and 6.1 pp respectively).

In Table 13, we look at our various measures of labor market outcomes. Because we are interested in the overall experience in the labor market, we use measures over the entire career of an individual as well as their peak measure. We look at two measures of performance. First, we examine seniority. As discussed above, seniority is defined as the median time that it takes individuals to attain a given position in a specific industry and firm size[15] for all individuals in Lightcast who eventually attain that particular job title, in that industry, and firm size. Cumulative seniority is defined as the sum, over every year of an individual's career, of the seniority of the position that they hold in that year. Peak seniority is defined as the seniority of the position that has the highest level over the entirety of their career. We believe the use of seniority allows us to compare labor market outcomes across industries. For example, wages in the Education industry are, on average, substantially below wages in the Finance industry. Hence, seniority may be a better cross-industry measure of career outcomes and achievement.

We also analyze wages as a proxy for career success. As with seniority, cumulative wages are the sum of annual estimated wages over the entirety of a graduate's career. Peak wages are just the maximum annual estimated wage over their career. In regression results, we use log wages as the dependent variable. We believe that these dimensions of career success, i.e., seniority and wages, are particularly important for college admissions to consider, as these metrics provide insights into how a given student's college experience shape shapes their human capital and influences their ultimate labor market outcomes.

Table 13 provides the core result of comparing Ivy athlete and non-athlete labor market outcomes. In terms of seniority, athletes achieve significantly higher cumulative seniority over their careers than non-athletes. Male athletes have cumulative seniority that is 9.7 years higher than comparable non-athletes, and female athletes have cumulative seniority that is 1.8 years

[15] Seniority is defined as the median time that it takes for an individual to reach a given position in a given industry at a firm of a given size quintile, across all individuals who at some point attain such a position. Amornsiripanitch et al. (2022) provides further details on seniority's definition and construction using the Lightcast data.

higher than comparable non-athletes. Controlling for the industry of an individual's first job reduces the cumulative seniority advantage of athletes, but the difference is still substantial and statistically significant for male graduates. As the prior labor literature has shown, male graduates have significantly higher labor market outcomes than female graduates.

Cumulative wages tell a similar story. Both male and female athletes earn 4.0% higher cumulative wages over their entire careers. Controlling for first job industry reduces athlete outperformance in wages to 3.4%. We find that male graduates of the Ivy League typically have cumulative career wages that are 10.7% higher than those of female graduates. Differences in peak wages of athletes relative to non-athletes are similar, albeit somewhat smaller in magnitude. This suggests that that athletes' wage growth is steeper earlier than non-athletes'.

Finally, we also estimate the probability of achieving a C-suite title for our sample. We find that athletes, especially male athletes, have a slightly higher likelihood of reaching the C-suite. Male athletes are 0.9 pp more likely to reach the C-suite, which given a baseline probability of roughly 10%, represents a 9% increase in the probability. Once again, controlling for the industry of the first job reduces the magnitude of this effect. As with our prior measures of career outcomes, male Ivy graduates are far more likely (3.6 pp) to achieve a C-suite position than female graduates.

Table 14 examines whether team sport and individual sport athletes have different career outcomes. We find that for cumulative seniority and cumulative wages, both team sport and individual sport athletes outperform non-athletes, especially male athletes. Male team sport athletes have cumulative seniority that is 9.3 years higher and cumulative wages that are 4.0% higher than non-athletes. For individual athletes, the effect is even stronger. Male individual sport athletes have cumulative seniority that is 10.6 years higher than non-athletes and cumulative wages that are 4.7% higher.

4.3 Career Performance Over Time

Having shown that Ivy League athletes outperform their non-athlete peers over the course of their careers, we now proceed to analyze the dynamics of the outperformance. To do so, we construct additional measures of cumulative and peak-job seniority and wages to evaluate career achievement at various points in time after college graduation. Specifically, for every Ivy League athlete and non-athlete, we record cumulative and peak job seniority and wages at 5, 10, 15, 20, and 25 years after college graduation. For example, we calculate 5-year cumulative seniority as the total sum of seniority achieved by an individual via jobs up to 5 years after graduation. Accordingly, to study the temporal dynamics behind the emergence of the athlete performance premium, we use these newly constructed variables as outcome variables in the regression specification introduced in Section 3.1. To capture the marginal gains between different time increments, we also use the difference in measures of labor market outcomes from the different time periods as the outcome variable. For example, the gain in seniority premium that Ivy League athletes accrued between year 5 and year 10 of their career can be estimated by regressing the difference in cumulative job seniority between years 10 and 5 on the athlete dummy variable. We apply the same logic to peak job seniority and wages.

Figures 5 to 8 graphically summarizes the relevant results. The orange lines show cumulative outperformance of Ivy League athletes relative to their non-athlete counterparts at 5, 10, 15, 20, and 25 years after college graduation, whereas blue lines show the marginal outperformance of these athletes in years 5-10, 10-15, 15-20, and 20-25 after college graduation.

Panels A, B, C, and D consider how individual athlete status relates to cumulative seniority, cumulative wages, peak job seniority, and peak job wages at these intervals respectively.[16] For cumulative seniority (Figure 5), the orange line shows that athletes somewhat outperform similarly-situated non-athletes early on (year 0 to year 5), but the gap between the two groups continues to widen as their respective careers progress, resulting in a gap of almost 6 years in job seniority by year 25. The blue line shows the marginal gain in cumulative job seniority at each time period beyond year 5. We can see that the marginal gains do decrease over time, but they remain positive and substantial in each time period. Figure 6 plots estimated coefficients for athlete outperformance in peak seniority and marginal gains in peak seniority. Athletes achieve a maximum seniority job that is more senior, on average, than their non-athlete peers' maximum seniority jobs. Furthermore, this premium in peak job seniority continues to increase up until 15 years after college graduation, after which point it remains stable. The stability 15-25 years after graduation likely suggests that most athletes and non-athletes arrive at their most prestigious jobs within 15 years after graduation. However, the same persistent stability in an athlete premium in maximum seniority suggests that athletes' careers "top out" at a higher place in the corporate ladder than the careers of their non-athlete counterparts.

Figure 7 plots estimated coefficients for athlete outperformance in log cumulative wages. For (log) cumulative wages, athletes' wage premium, relative their non-athlete peers, emerges early on (years 0 to 5), and this premium continues to widen up to year 10. After that, the relative premium remains constant until year 25, which is the end of the sample. However, since wage levels for both athletes and non-athletes rise on expectation as more years accumulate post-

[16] The panels show the regression coefficients on individual athlete status in a regression of cumulative seniority, cumulative wages, peak job seniority, and peak job wages on athlete status and the controls mentioned in section 3.1. Starting industry fixed effects are not included.

graduation, the absolute gap in athletes' cumulative earnings advantage over non-athletes only rises over time. For example, a 10% cumulative wage premium relative to a base wage of $50K would entail $25K more over a 5-year period, whereas the same cumulative premium relative to a base wage of $200K would entail $100K more over the same period. Finally, Figure 8 plots the estimated coefficients for athlete outperformance in log peak wages and marginal additional log wage gains. The premium for athletes in their highest-paying-to-date job remains relatively stable over time at roughly 1.5%. However, as with cumulative wages, the stable premium for athletes in log wages at their highest-paying job over time suggests that the athlete premium in the highest-paying job to date is increasing in dollar terms over time.

In the seniority plots, Ivy League athletes perform slightly better than their non-athlete counterparts within the first 5 years after college graduation. However, a gap in performance favoring Ivy League athletes begins to more significantly materialize 5-15 years after college graduation. Furthermore, this athlete outperformance premium only widens 15-25 years into one's post-college career, as the marginal gain lines in blue suggest. Perhaps unsurprisingly, the later-career widening of cumulative seniority appears more dramatic than the corresponding widening of peak job seniority. This discrepancy likely reflects the fact that most individuals, even Ivy League alumni, reach their highest-prestige job within 20-25 years (if not fewer) of entering the labor market. Similarly, although the cumulative and peak logged wage premia between athletes and non-athletes remain relatively stable over time, the gradual post-graduation increase in actual wage levels for all individuals on expectation over time suggests that athletes' cumulative and peak wage premia are increasing relative to non-athletes' when measured in dollar terms. This robustness suggests that athlete outperformance is not completely driven by initial selection by

Ivy League athletes into lucrative industries and high-powered career tracks immediately upon graduation.

4.4 Potential Mechanism

The previous section empirically establishes the existence of an athlete labor market performance premium. However, potential explanatory mechanisms for this premium remain largely unexplored. Having ruled out undergraduate major, graduate year, and initial occupational choices as compositional factors that explain Ivy League athletes' career outperformance relative to non-athlete peers, in this section we explore three other mechanisms: inherited wealth/status, peer effects, and non-academic human capital.

4.4.1 Socioeconomic Status

To evaluate whether athletes' outperformance arises solely because of inherited familial wealth and status, we exploit team-level variation in familial status and wealth to ascertain whether Ivy League sports serve as a signaling mechanism for prestige that is valued in the labor market. Relatedly, family wealth and status, as proxied by participation in sports, may enhance labor market outcomes, especially in the long run, through family connections and homophily-based hiring preferences (Gompers, Mukharlyamov, and Xuan, 2016).[17] To explore these channels, we extend the regression results presented in above by examining how the athlete labor market premium might vary across different types of sport groups.

We begin our investigation by considering the difference in labor market outcomes between athletes in niche sports, athletes in other sports, and non-athletes. Niche or "Private Prep

[17] See "The Cult of Rich-Kid Sports" by Derek Thompson at https://www.theatlantic.com/ideas/archive/2019/10/harvard-university-and-scandal-sports-recruitment/599248/

School" sports include crew, equestrian, polo, fencing, golf, lacrosse, sailing, skiing, squash, water polo, and tennis. These sports are mostly played by wealthy white individuals and, therefore, can serve as proxies for family wealth and status.[18] Table 15 presents regression results where we compare job seniority and wage outcomes between athletes in niche sports, athletes in non-niche sports, and non-athletes. We find that participation in niche sports is associated with a somewhat higher cumulative job seniority and higher peak wages than non-niche sport athletes, although non-niche sport athletes continue to have higher labor market outcomes than non-athletes. The differences are also relatively small between the two groups. When we come cumulative wages over their entire career, however, there is no meaningful difference between niche sport and non-niche sport athletes. Table 15 also presents regression results for the likelihood of holding any C-suite job position for niche and non-niche sport athletes. We find that male participation in niche sports is associated with slightly higher probability of holding a C-suite job (2.0 pp) relative to non-niche sport athletes. All results are robust to the inclusion of starting industry fixed effects.

To provide further support for the notion that family wealth and status cannot explain the entire athlete labor market premium, we investigate the difference in labor market outcomes between athletes who participate in socioeconomically diverse sports and everyone else. Diversity sports include football, track, cross country, and basketball. Hirko (2007) find that 73.8% of intercollegiate varsity athletes are white. Only men's football (32%), men's and women's basketball (42%), and men's and women's track (20%) had more than 20% of athletes who were black. Similarly, Kyaw (2023) found that 44.7% of Division 1 football players were black and 52.4% of Division 1 basketball players were black. If the athlete premium can be entirely

[18] See "The Cult of Rich-Kid Sports" by Derek Thompson at https://www.theatlantic.com/ideas/archive/2019/10/harvard-university-and-scandal-sports-recruitment/599248/

explained by family wealth and status, then participation in diversity sports should not be associated with any labor market premium because, intuitively, individuals who participate in such sports are, on average, less likely to come from privileged backgrounds. Tables 11 and 16 present the regression results. We find that participation in diversity sports is associated with higher cumulative job seniority, cumulative wages, and likelihood of holding a finance job, especially for male athletes. However, participation in such sports is either non or negatively associated with higher peak job seniority, peak wages, likelihood of holding a C-suite job, and likelihood of holding an MBA or a STEM graduate degree. The results are largely robust to starting industry fixed effects, suggesting that initial occupational choice cannot explain everything about diverse sport athletes' outperformance. As such, we interpret these results as showing that the athlete premium is not entirely explained by wealth and status.

4.4.2 Non-Academic Human Capital

A potential contributor to the athlete labor market premium is the idea that participation in athletics builds non-academic human capital that is relevant to success in the labor market. For example, varsity athletes spend a significant amount of time each week training in their sport. Such repeated uptake of hard physical work requires and builds discipline, perseverance, and grit, which has been shown to be associated with long-term success (Duckworth, Peterson, and Matthews, 2007).

To show support for this channel, we study the difference in labor market outcomes between athletes in "low academic admission threshold" sports, which include football, men's and women's hockey, as well as men's and women's basketball, as compared to athletes in other sports and non-athletes. The economic intuition for this test is that, if participation in sports builds valuable human capital, then the athlete labor market premium should still accrue to those who participate in sports with lower academic admissions thresholds. Table 17 presents the regression results. We find that, relative to non-athletes participation in low academic admission threshold sports is associated with higher cumulative job seniority, cumulative wage, peak job seniority, and likelihood of holding a C-suite position. Relative to high academic admission threshold sports, low academic threshold sport athletes have cumulative seniority that is 5.2 years higher. The effect on male athletes is even higher. Relative to non-athletes, male and female low academic threshold sport athletes have 4.6% and 6.5% higher cumulative wages than comparable non-athletes. These results are largely robust to the inclusion of starting industry fixed effects.

The positive correlations support the story that participation in sports builds valuable human capital that contributes to labor market outcomes. We examine this directly by utilizing reported skills from LinkedIn to ascertain whether Ivy League athletes are more likely to have particular endorsed skills than non-athletes. LinkedIn has a feature called “endorsements" that allows users to endorse their connections for specific skills they believe the connection possesses. This feature is designed to help validate and highlight the skills and expertise of LinkedIn users. LinkedIn users can list various skills on their profiles, such as "Project Management," "Data Analysis," "Digital Marketing," etc. Connections can then endorse them for these skills by simply clicking a button on the user's profile. This endorsement serves as a vote of confidence from one's connections, affirming that the user possesses the stated skill. We use the set of “endorsed skills” in LinkedIn to explore whether Ivy athletes develop different skills from non-athletes through their participation in intercollegiate varsity athletics.

We examine two different sets of skills in the Lightcast data. First, we tabulate the presence of five “management” skills. These include Management, Leadership, Strategic Planning, Team

Leadership, and Project Management. These skills are all associated with attributes that may be important to senior positions in an organization. Similarly, we tabulate the presence of five "specialist" skills in the Lightcast data. These hard skills include Research, Operations, Teaching, Data Analysis, and Editing.

In Table 18 Panel A we tabulate the prevalence of these skills by gender. Male Ivy graduates are more likely to have management skills endorsed on LinkedIn while they are less likely, in general, to have specialist skills. In Panel B we tabulate the prevalence of each type of skill for Ivy athletes and non-athletes. Athletes are far more likely to have management skills reported. For example, 30.5% of athletes report to have management skills whereas only 26.4% of non-athletes do so. Similarly, 24.2% of athletes report leadership skills while only 20.9% of non-athletes report such skills. Specialist skills, however, are more prevalent among non-athletes. 32.5% of non-athletes report having research as a skill while only 29.5% of athletes report having it.

We explore the prevalence of management and specialist skills for team and individual sport athletes in Table 18 Panel C. Management skills are similar in both groups of athletes, but individual sport athletes have a higher propensity to possess specialist skills. Surprisingly, we find that niche sport athletes in Panel D have significantly lower management and specialist skills report than do non-niche sport athletes. Finally, Panels E and F report the comparison for diverse sports versus non-diverse sports and low academic admissions threshold versus high academic admission threshold sports. Both panels show a similar pattern. Diverse sport athletes and low academic admission threshold athletes have higher reported management skills and lower specialist skills than other athletes.

While the cross-tabulation comparisons in Table 18 are suggestive that athletes may develop certain skills by participation in their sports, we present regression results in Table 19 that control for year of graduation, college, major, and industry of first job. Panel A shows results for management skills. The results show a consistently positive and statistically significant relation between management skills and participation in intercollegiate varsity athletics in the Ivy League. All management skills are positively correlated with having been an athlete, ranging from a 0.9 pp increase in having Project Management skills as an athlete to a 4.9 pp increase in the probability of having Leadership skills. Interestingly, male graduates and male athletes do not have substantially higher likelihood of having management skills than do female graduates or female athletes.

Panel B reports the regression results for specialist skills. These results are somewhat more mixed. Athletes are less likely to have Teaching and Editing skills reported. For male athletes, they are 2.3 pp less likely to have editing skills and 0.8 pp less likely to have teaching skills. Female athletes are more likely to have operations and data analysis skills (2.3 pp and 0.9 pp), while male athletes are no more likely to have these skills than non-athletes.

Table 20 presents similar regressions for team and individual sport athletes. In general, Panel A shows that for management skills, only Leadership has a difference between the two groups of athletes. Female team athletes are 3.1 pp more likely to have Leadership as a report skill than are female individual sport athletes, though the gap is smaller for males. Across all five reported management skills, however, both individual and team sport athletes have higher reported skills. Panel B shows similar regressions for specialist skills. Individual athletes are more likely to have Research as a report skill (around 2-3 pp more likely) than team athletes. The other specialist skills have similar patterns across both groups of athletes.

We examine niche sport and non-niche sport athletes' reported skills in Table 21. Panel A demonstrates that non-niche sport athletes are significantly more likely to report having management skills as niche sport athletes. While niche sport athletes generally have higher prevalence of management skills compared to non-athletes, non-niche sport athletes consistently are more likely to report such skills. Specialist skills in Panel B show a somewhat different pattern. Female non-niche sport athletes generally have a higher propensity to report specialist skills than both non-athletes and niche sport athletes (except for Editing.) Non-niche sport male athletes, however, generally have a similar or lower chance of reporting such skills.

Tables 22 and 23 present results for diverse versus non-diverse sports and low academic admissions threshold versus high academic admission threshold sports. The patterns in the two tables are similar. In Panel A of Tables 22 and 23, we see that both diverse sport athletes and low academic admission threshold sport athletes have significantly higher probability of reporting management skills than other athletes or non-athletes. In fact, relative to non-athletes, the low academic admission threshold sport athletes have the highest increment in propensity to report management skills. Like our other athlete subgroups, specialist skills appear to be unrelated generally to status as diverse sport or low academic admission threshold sport athlete. The only specialist skill that is consistently negatively related to athlete status is Editing.

Our results for the presence of management skills in low academic admission threshold sport athletes, as well as the consistent positive relationship between all our athlete subgroups and the presence of these reported skills, is inconsistent with the idea that academic achievement alone determines the presence of these types of skills. Overall, our results with reported skills on LinkedIn support the contention that participation in athletics helps to build certain types of human capital that may be valued in the labor market.

5 Reconciliation with Chetty et al. (2023)

This paper's focus on Ivy League athletes naturally merits some comparison with recent work by Chetty et al. (2023) on the Ivy plus admissions process and its implications for alumni career success. At first glance, our results stand in contrast to those of Chetty et al. (2023). Specifically, we find that athletes generally outperform their non-athlete peers, while Chetty et al. (2023) find that high academic achievers in a sample of successful applicants at "Ivy plus" schools appear more likely to achieve right-tail career outcomes than athletes and other "preferentially treated" applicant groups. Since Chetty et al. (2023) suggest that academic ability appears to be the best readily available predictor of future career success, their paper accordingly claims that limiting athletic admissions preferences as a tool for "need-based affirmative action" would not only increase student bodies' socioeconomic diversity, but also improve alumni's right-tail labor market outcomes. In contrast, by showing that Ivy League athletes outperform their non-athlete counterparts, our paper suggests that (i) a trade-off between pure academic merit and labor market performance does exist in the context of admissions preferences for athletes and (ii) limiting athletic admissions preferences may not bolster alumni's expected labor market performance.

The difference between our results and Chetty et al.'s (2023) may be explained by the difference in the data sets used and chosen methodologies. First, our sample focuses on Ivy League schools, whereas Chetty et al.'s (2023) sample includes non-Ivy League schools such as MIT, Stanford, Duke, and the University of Chicago. While these schools are as prestigious as Ivy League schools, their practices surrounding athletic recruitment differ significantly.[19] Second,

[19] For example, athletic recruitment plays a more limited role in admissions decisions at MIT and the University of Chicago. See, for example, https://mitadmissions.org/help/faq/does-mit-recruit-athletes/ for MIT's athletic admissions policy. Conversely, Stanford and Duke are better able to attract future professional athletes who pursue less conventional careers (e.g., Christian McCaffrey, Zion Williamson) in their recruitment/admissions processes.

Chetty et al.'s (2023) use of IRS and College Board data offered more comprehensive coverage of the interested population than our Lightcast data. However, the direction of bias introduced by the selection process into the Lightcast sample is unclear.

Finally, Chetty et al. (2023) only directly observe individuals' labor market outcomes until age 25, on average, 3 years after college graduation. To extrapolate later-life labor market outcomes, Chetty et al. (2023) rely on a predictive regression that uses earlier IRS data to impute age-33 job outcomes based on age-25 job outcomes. This predictive regression implicitly assumes that any individual at a given age-25 job (conditional on gender) is equally likely to end up at a prestigious age-33 job as any other individual. In particular, they estimate the probability that a given individual will end up in the top 1% of income at age 33. However, our results suggest that this assumption may be incorrect. Specifically, our empirical results in Section 3.3 suggest that Ivy League athletes' labor market outcomes begin to noticeably diverge from non-athletes' after 5 years in the labor market. In other words, our results largely mirror Chetty et al. (2023)'s when characterizing athletes' early-career performance relative to non-athletes. However, using a longer sample, our empirical analysis reveals the later-career emergence of an athlete performance premium, which Chetty et al. (2023) assume away.

6 Conclusion

This paper examines the career trajectories of Ivy League athletes and compares them to the career paths of other Ivy League alumni. Combining a unique dataset on the Ivy League athletes who graduated between 1970 and 2021 with resume data from Lightcast, we find that Ivy League athletes earn higher cumulative wages and attain greater cumulative seniority than their non-athlete counterparts over the course of their careers. Likewise, peak career wages and seniority generally appear higher for athletes. In addition, athletes are more likely to obtain an MBA, work in Finance, and reach the C-suite during their careers, although the magnitude of these effects are somewhat reduced by controlling for major and industry of first job. Cumulative and peak measures of career achievements look similar for Ivy League athletes and non-athletes within 5 years of college graduation. However, Ivy League athletes' career trajectories begin to diverge from non-athlete Ivy graduates after this initial period, and the gap in career achievement between Ivy League athletes and non-athletes continues to widen as time passes.

Furthermore, we investigate potential explanatory mechanisms for the athlete achievement premium by leveraging team-level heterogeneity in athletics participation as an extension of our initial analysis. Under the assumption that certain Ivy League sports teams consist of athletes who, on expectation, come from similar socioeconomic backgrounds as non-athletes at their school, while other "niche" sports teams consist of athletes from wealthier family backgrounds, we show that athletes on niche sports teams perform slightly better in terms of cumulative wages and seniority relative to non-niche athletes, although both groups significantly outperform non-athletes. These results may indicate that family connections or peer effects are important in career outcomes.

We also show that athletes from diverse sports and sports with lower academic admission thresholds actually have the highest labor market outcomes on average. This would seem to indicate that socioeconomic status and academic skills alone cannot explain the superior labor market outcomes that we find for Ivy League athletes. We provide suggestive evidence of a skills-based channel. Athletes, and in particular athletes from diverse sports and low academic admission threshold sports, are far more likely to report having management skills (Management, Leadership, Strategic Planning, Team Leadership, and Project Management) than do non-athlete peers.

Our results contain important implications for university policy on athletics programming and admissions preferences; they are especially relevant for elite private colleges whose admissions practices have recently come under increased public scrutiny and debate. To begin, taken together with earlier work by Zimmerman (2019) and Michelman et al. (2022), our analysis of niche sport athletes' careers may suggest that, within the student bodies of elite private colleges, inherited wealth and social status may contribute to postgraduate career success relative to academic achievement alone. Such a wedge between current academic achievement that ignores other mechanisms of human capital building and expected future career success may cast some doubt on claims that eliminating existing admissions preferences for athletes in exchange for a stronger emphasis on academic achievement alone will improve student body outcomes at elite private institutions. Indeed, elite universities may face a trade-off between merit-based fairness and reputation maximization when weighing the role of academic achievement and current preferential treatments in admissions policy.

Our results indicating a channel for human capital development, however, suggests that prior athletic achievement may be a reasonable criterion for admissions given that those students who participate in intercollegiate varsity athletics appear to develop skills that are highly valued in the labor market. If the goal of elite academic institutions is to prepare their students to have a positive influence on the organizations that they join, then consideration of past athletic performance and the ability to compete at the intercollegiate level may be appropriate.

In addition, our results inform university policy on athletics programs beyond their intersection with admissions. The overall persistence of the athlete labor market performance premium across all sports may indicate that the development of (i) strong social networks and/or (ii) non-academic skills during college play an important role in building the requisite human capital for labor market success. Indeed, the athlete achievement premium even appears among members of sports teams where academic admissions standards for recruited students have the biggest gap relative to non-athletes, suggesting that factors in addition to academic achievement alone must contribute to athletes' labor market performance. The probable importance of strong social networks and non-academic human capital development in career success may warrant elite colleges continued funding and support of athletics and other institutionalized extracurricular activities, even if such focus may remain unique in the global context. Similarly, when combining our empirical evidence with earlier work by Heckman and Loughlan (2021), the important role of non-technical skills in positively impacting career outcomes might warrant additional consideration of broadening the role for non-academic pursuits in undergraduate curricula.

Finally, future research can address multiple open questions raised by our empirical results. First, additional work can aim to disentangle additional explanatory mechanisms that might explain the athlete career achievement premium. Specifically, additional empirical analysis on the role of social networks versus skill development in explaining athletes' labor market outperformance would both clarify the scope of this paper's results and influence the direction of policy discussion. For example, office-level studies a la Cullen and Perez-Truglia (2023) could document the extent to which "schmoozing" and peer leadership might facilitate athletes' advancement in the workplace. Second, future work could investigate the impact of broader extracurricular involvement on career achievement. While this paper's results imply that athletics might be a uniquely useful extracurricular activity in the labor market, follow-on research should aim to better understand what general characteristics of extracurricular activities might enhance the value that they bestow upon their members in the labor market. Finally, additional work could more directly consider whether interactions between athletes and non-athletes at elite universities might facilitate all individuals' career outcomes and productivity at work. By documenting potential cross-student complementarities and peer-effects in college, findings from such research could inform admissions policy as universities attempt to build future undergraduate classes that are greater than the sum of their parts.

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Figure 1: Median Seniority Over Time by Gender

This figure plots median job seniority over time by gender. Job seniority is presented in years and is calculated following the procedure described in Amornsiripanitch et al. (2022). The red line plots median seniority for females, and the blue dotted line plots median seniority for males. Median seniority over all points of the red line is calculated from all job titles held by females in the given x-axis's year after graduation. Median seniority over all points of the blue line is calculated analogously, except for males.

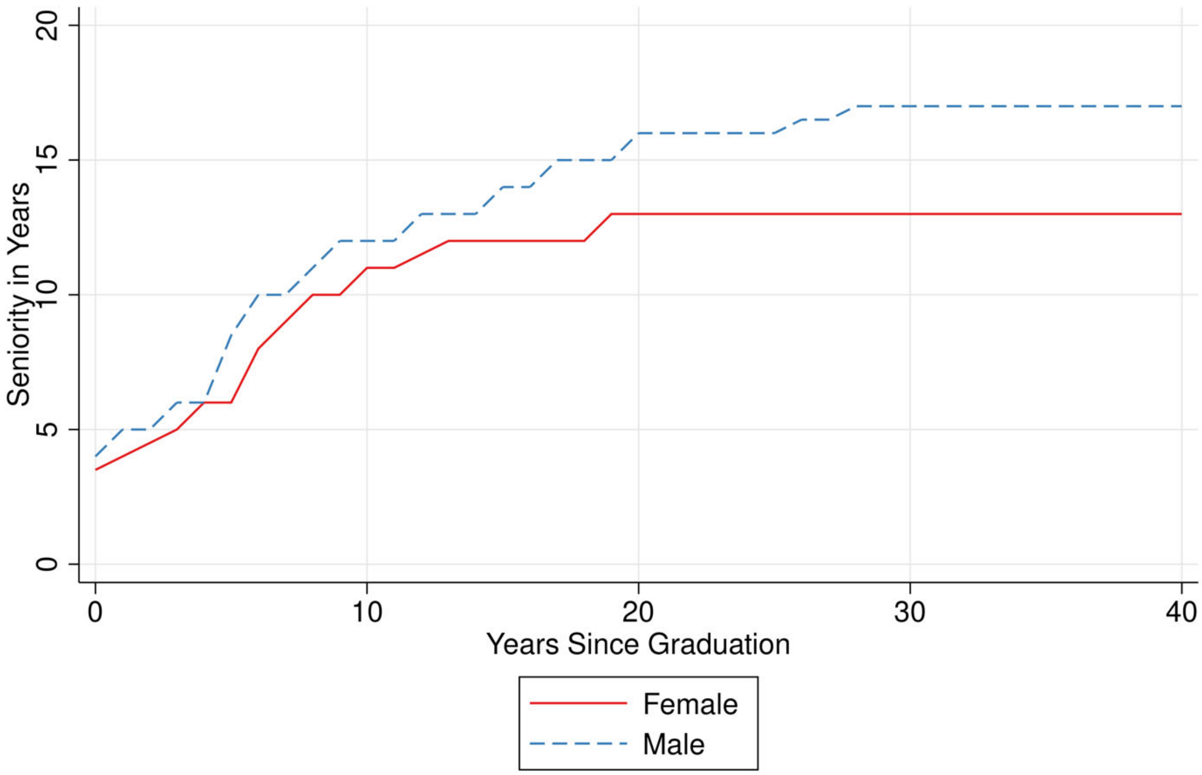

Figure 2: Median Estimated Wages Over Time by Gender

This figure plots median estimated wages over time by gender. The wage estimation procedure is described in the main text. The red line plots median estimated wages for females, and the blue dotted line plots median estimated wages for males. Median estimated wages over all points of the red line are calculated from all job titles held by females in the given x-axis's year after graduation. Median estimated wages over all points of the blue line are calculated analogously, except for males.

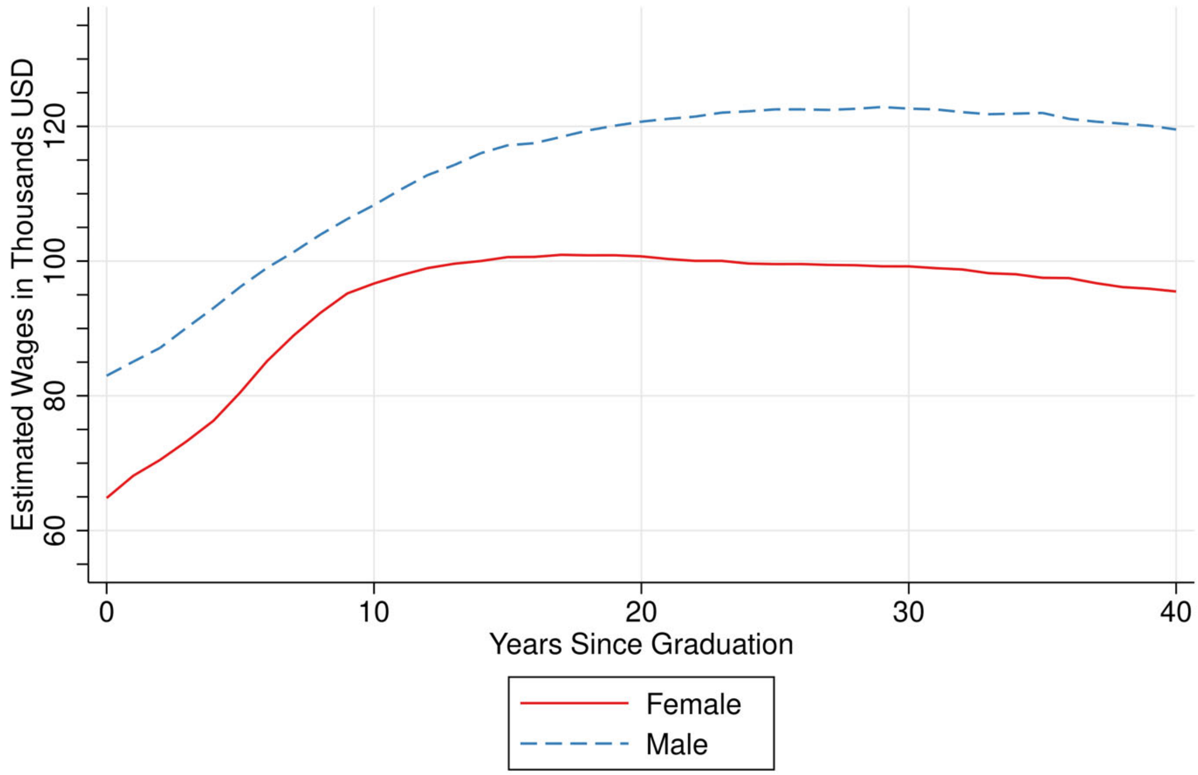

Figure 3: Median Seniority Over Time by Athlete Status

This figure plots median job seniority over time by athlete status. Job seniority is presented in years and is calculated following the procedure described in Amornsiripanitch et al. (2022). The red line plots median seniority for athletes, and the blue dotted line plots median seniority for non-athletes. Median seniority over all points of the red line is calculated from all job titles held by athletes in the given x-axis's year after graduation. Median seniority over all points of the blue line is calculated analogously, except for non-athletes.

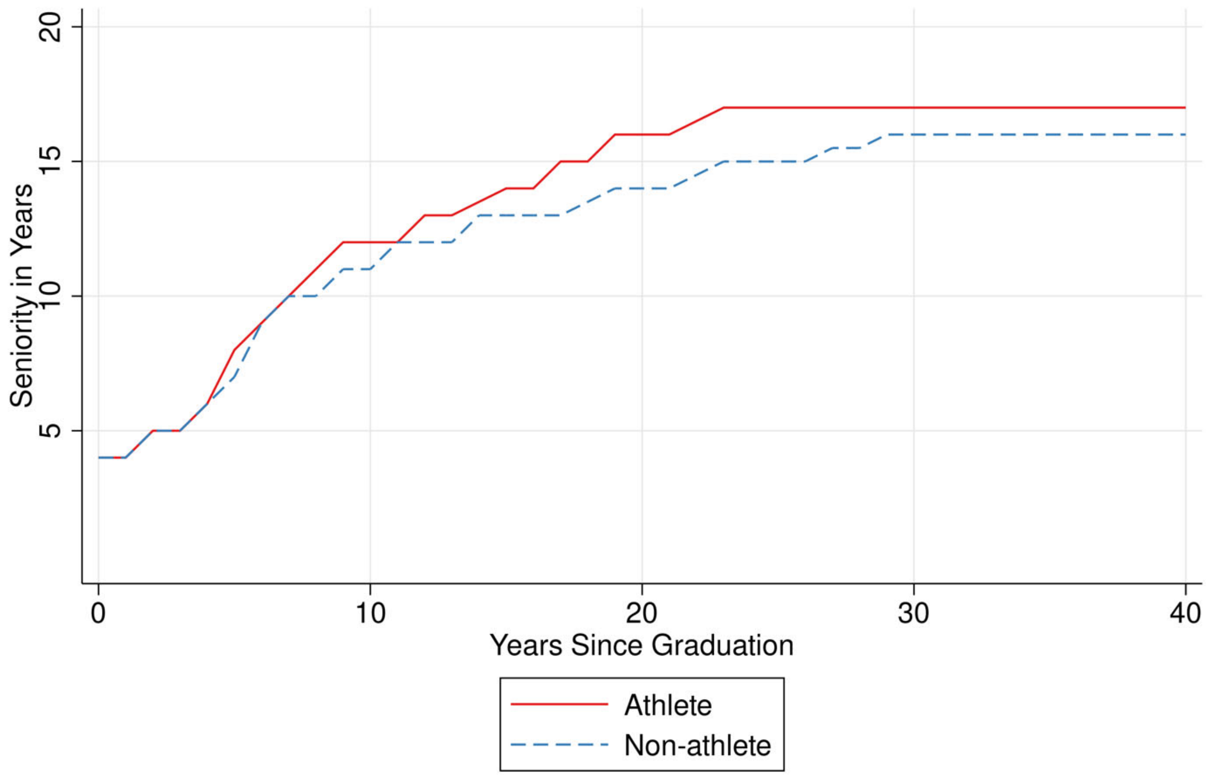

Figure 4: Median Estimated Wages Over Time by Athlete Status

This figure plots median estimated wages over time by athlete status. The wage estimation procedure is described in the main text. The red line plots median estimated wages for athletes, and the blue dotted line plots median estimated wages for non-athletes. Median estimated wages over all points of the red line are calculated from all job titles held by athletes in the given x-axis's year after graduation. Median estimated wages over all points of the blue line are calculated analogously, except for non-athletes.

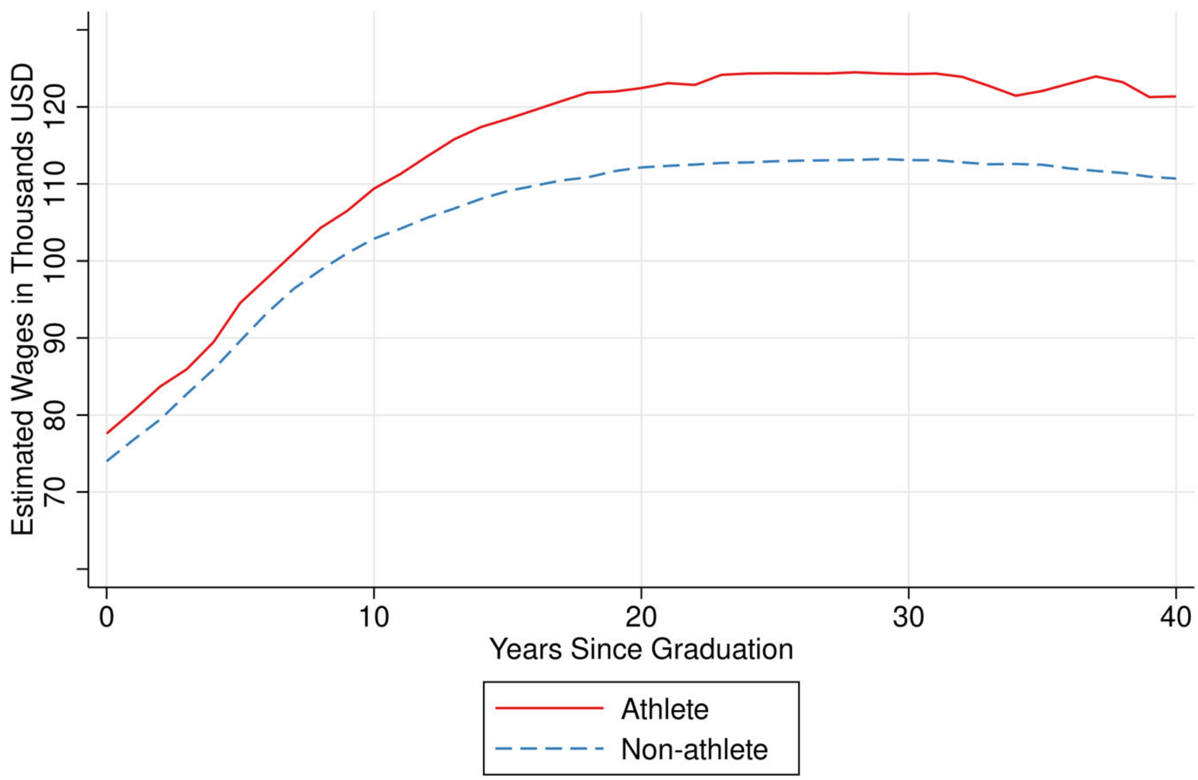

Figure 5: Athlete Premia in Cumulative Job Seniority Over Time

This figure plots regression coefficients that analyze the evolution of the athlete premium in cumulative job seniority over time. The regression coefficients in the orange line come from a regression where an individual's cumulative seniority at 5, 10, 15, 20, and 25 years after college graduation represents the outcome variable, and an individual's athlete status is the independent variable of interest. The regression coefficients in the blue line come from a similar regression as the orange line, except that marginal gains in seniority over the past 5 years (e.g., the marginal gains in cumulative seniority at 10 years after college graduation relative to 5 years after college graduation) represent the outcome variable. The right-hand side of both regressions are similar to those presented in Table 13, except that the athlete X male interaction term and starting industry fixed effects are removed here. Job seniority is measured in years and is calculated following the procedure described in Amornsiripanitch et al. (2022). The vertical lines capture 95% confidence intervals on the displayed regression coefficients.

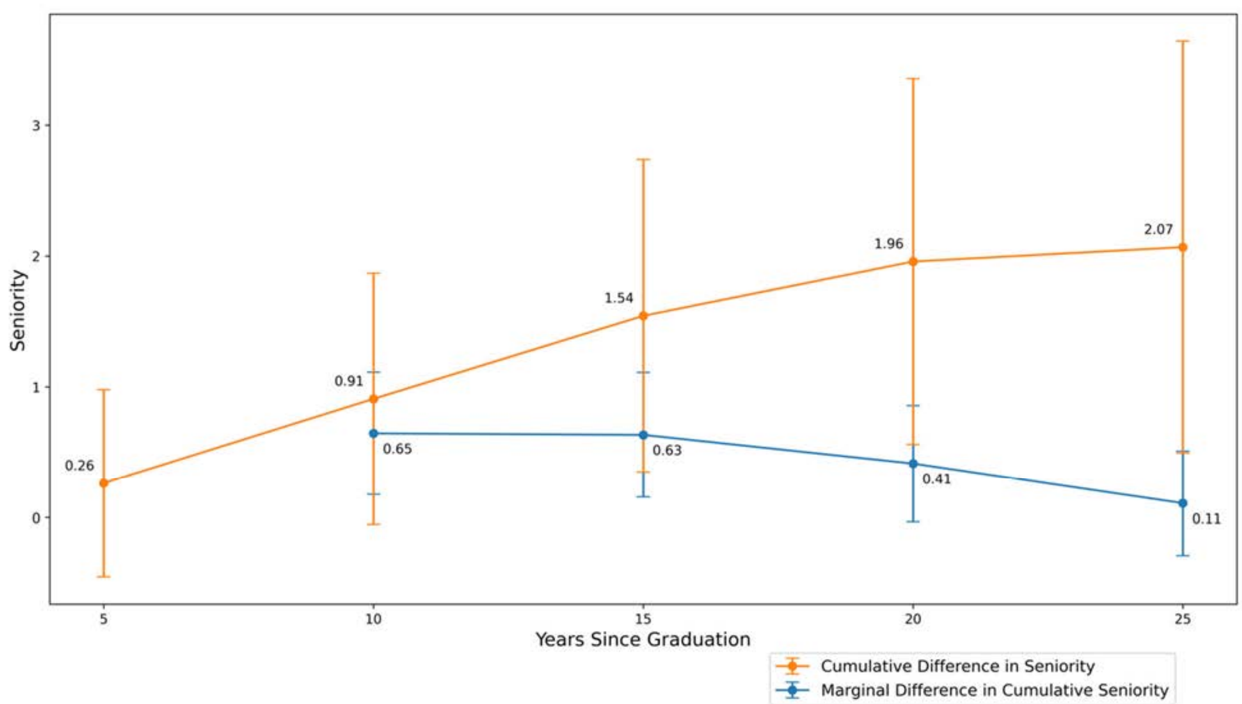

Figure 6: Athlete Premia in Peak Job Seniority Over Time

This figure plots regression coefficients that analyze the evolution of the athlete premium in peak job seniority over time. The regression coefficients in the orange line come from a regression where an individual's peak seniority at 5, 10, 15, 20, and 25 years after college graduation represents the outcome variable, and an individual's athlete status is the independent variable of interest. The regression coefficients in the blue line come from a similar regression as the orange line, except that marginal gains in seniority over the past 5 years (e.g., the marginal gains in peak seniority at 10 years after college graduation relative to 5 years after college graduation) represent the outcome variable. The right-hand side of both regressions are similar to those presented in Table 13, except that the athlete X male interaction term and starting industry fixed effects are removed here. Job seniority is measured in years and is calculated following the procedure described in Amornsiripanitch et al. (2022). The vertical lines capture 95% confidence intervals on the displayed regression coefficients.

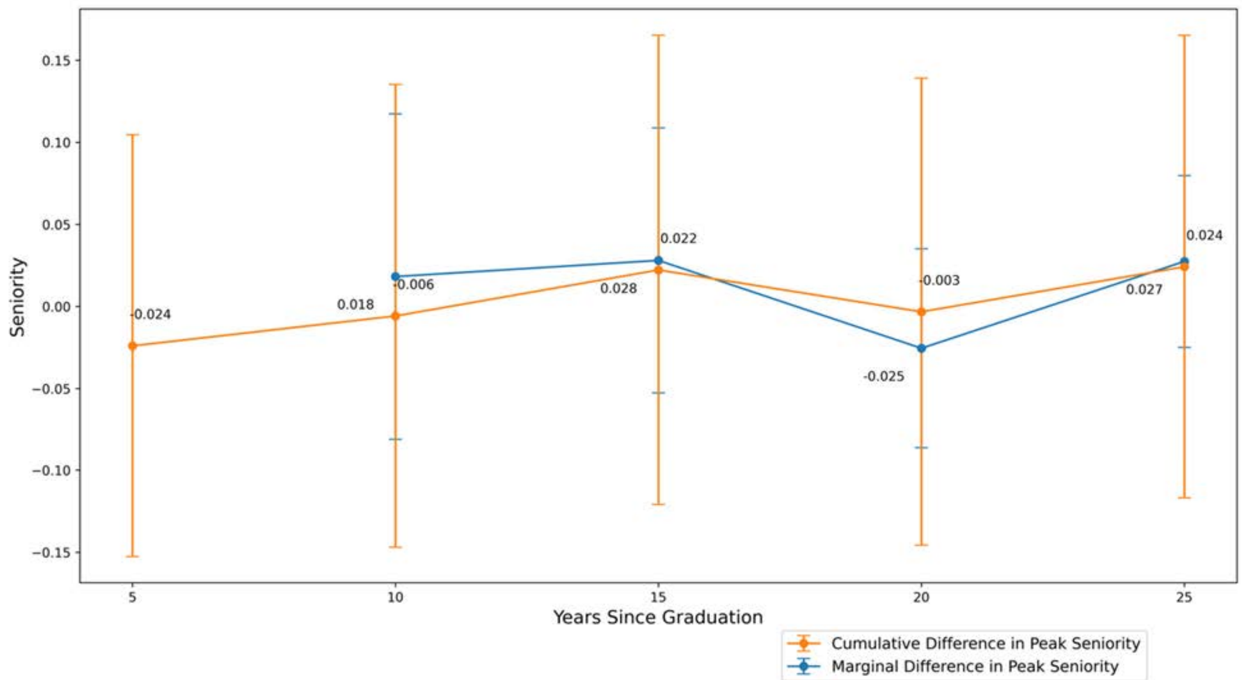

Figure 7: Athlete Premia in (Log) Cumulative Estimated Wages Over Time

This figure plots regression coefficients that analyze the evolution of the athlete premium in log cumulative wages over time. The regression coefficients in the orange line come from a regression where an individual's log cumulative wages at 5, 10, 15, 20, and 25 years after college graduation represents the outcome variable, and an individual's athlete status is the independent variable of interest. The regression coefficients in the blue line come from a similar regression as the orange line, except that marginal gains in log cumulative wages over the past 5 years (e.g., the marginal gains in log cumulative wages at 10 years after college graduation relative to 5 years after college graduation) represent the outcome variable. The right-hand side of both regressions are similar to those presented in Table 13, except that the athlete X male interaction term and starting industry fixed effects are removed here. The vertical lines capture 95% confidence intervals on the displayed regression coefficients.

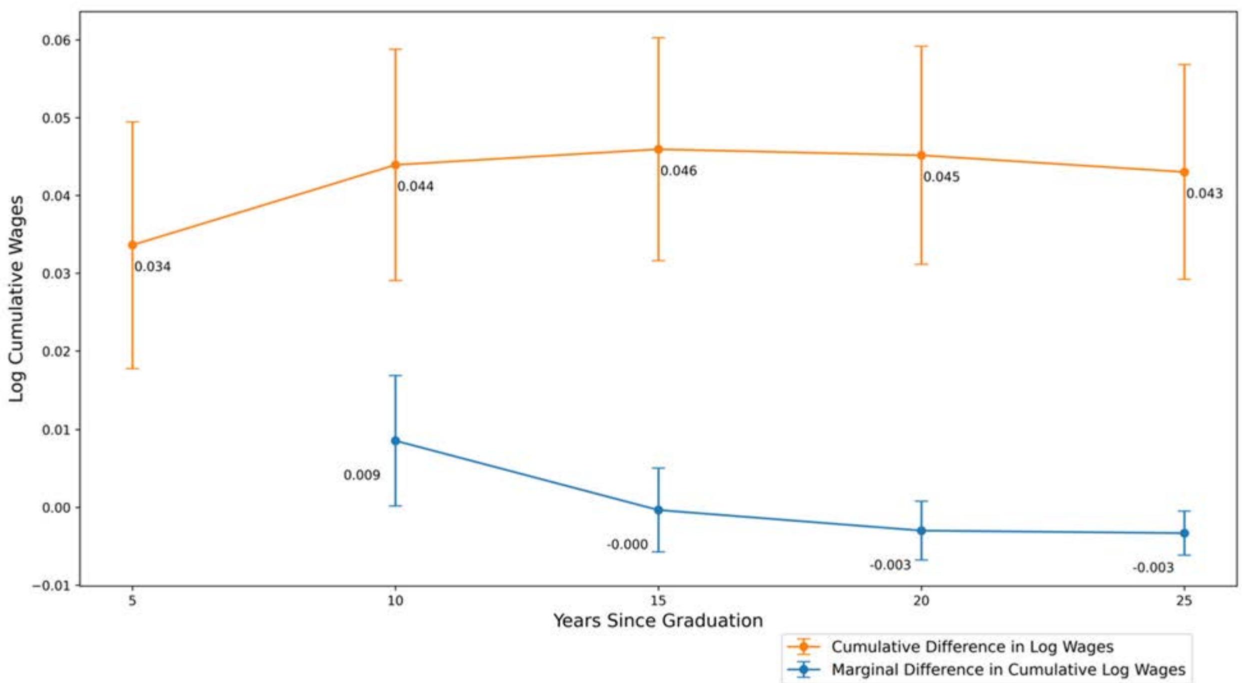

Figure 8: Athlete Premia in (Log) Peak Estimated Wages Over Time

This figure plots regression coefficients that analyze the evolution of the athlete premium in log peak/maximum wages over time. The regression coefficients in the orange line come from a regression where an individual's log peak wages at 5, 10, 15, 20, and 25 years after college graduation represents the outcome variable, and an individual's athlete status is the independent variable of interest. The regression coefficients in the blue line come from a similar regression as the orange line, except that marginal gains in log peak wages over the past 5 years (e.g., the marginal gains in log peak wages at 10 years after college graduation relative to 5 years after college graduation) represent the outcome variable. The right-hand side of both regressions are similar to those presented in Table 13, except that the athlete X male interaction term and starting industry fixed effects are removed here. The vertical lines capture 95% confidence intervals on the displayed regression coefficients.

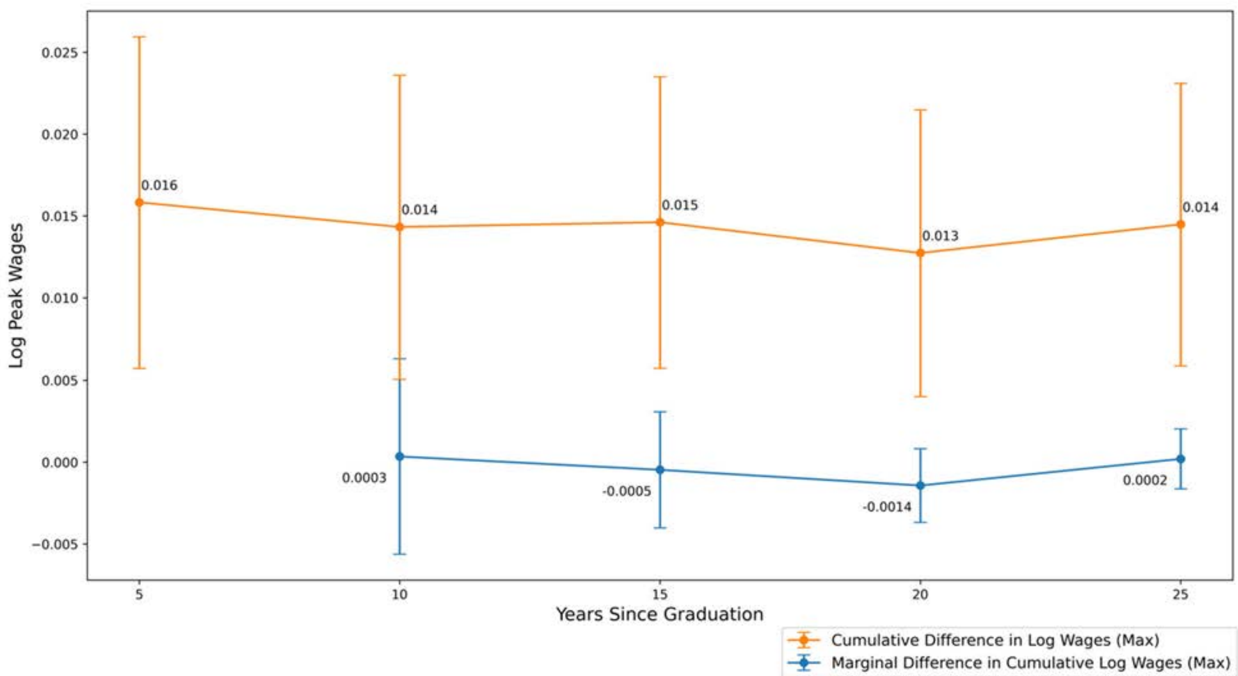

Table 1: Sample Summary Statistics

This table presents summary statistics on the sample of analysis, which consists of athletes and non-athletes who received a bachelor's degree from an Ivy League school.

	N	Mean	Median	S.D.
Athlete	401,785	0.08	0.00	0.27
Athlete (Individual Sport)	401,785	0.02	0.00	0.13
Athlete (Niche Sport)	401,785	0.03	0.00	0.16
Athlete (Diversity Sport)	401,785	0.02	0.00	0.15
Athlete (Low Academic Standard Sport)	401,785	0.02	0.00	0.13
Male	401,785	0.54	1.00	0.50
Elite MBA	401,785	0.06	0.00	0.24
Non-elite MBA	401,785	0.08	0.00	0.28
STEM Graduate Degree	401,785	0.18	0.00	0.38
J.D.	401,785	0.12	0.00	0.33
M.D.	401,785	0.05	0.00	0.23
Ph.D.	401,785	0.15	0.00	0.35
Cumulative Seniority	401,785	127.79	69.00	154.27
Peak Seniority	354,564	13.08	13.00	7.54
Cumulative Wages (Thousands USD)	401,785	1619.13	1213.55	1386.50
Peak Wages (Thousands USD)	390,652	126.85	123.14	49.52
Reported Career Length	384,515	19.84	17.00	14.58
Total Jobs	401,785	5.18	5.00	3.26
Finance Job	401,785	0.21	0.00	0.41
C-suite Job	401,785	0.08	0.00	0.27

Table 2: Sample Composition by Sport

This table presents the athlete sample breakdown by sport and gender. The percentage points are calculated within gender group.

	Male Count	Male %	Female Count	Female %
Baseball	1,407	6.64%	64	0.66%
Basketball	914	4.31%	549	5.70%
Cheerleading	17	0.08%	18	0.19%
Cricket	7	0.03%	5	0.05%
Equestrian	8	0.04%	206	2.14%
Fencing	682	3.22%	384	3.99%
Field Hockey	13	0.06%	517	5.37%
Football	4,677	22.06%	261	2.71%
Golf	430	2.03%	178	1.85%
Gymnastics	7	0.03%	215	2.23%
Heavyweight Crew	1,034	4.88%	541	5.62%
Heavyweight Rowing	425	2.00%	333	3.46%
Ice Hockey	660	3.11%	313	3.25%
Lacrosse	1,644	7.75%	678	7.04%
Lightweight Crew	522	2.46%	114	1.18%
Lightweight Rowing	260	1.23%	63	0.65%
Polo	42	0.20%	36	0.37%
Rugby	329	1.55%	249	2.58%
Sailing	344	1.62%	238	2.47%
Skiing	158	0.75%	104	1.08%
Soccer	1,236	5.83%	693	7.19%
Sprint Football	488	2.30%	27	0.28%
Squash	494	2.33%	331	3.44%
Swimming and Diving	1,387	6.54%	764	7.93%
Tennis	499	2.35%	333	3.46%
Track/XC	2,175	10.26%	1,106	11.48%
Ultimate Frisbee	168	0.79%	138	1.43%
Unclassified	21	0.10%	414	4.30%
Volleyball	154	0.73%	418	4.34%
Water Polo	264	1.25%	177	1.84%
Wrestling	736	3.47%	53	0.55%
Total	21,202	100%	9,520	100%

Table 3: Sport Type Definition

This table presents the classification for each sport into Team, Individual, Niche, Non-niche, (socioeconomically) Diverse, Non-diverse, Low Academic Standard, and Higher Academic Standard Sports. Within each pair of classification (e.g., Team vs. Individual), a sport belongs to one or the other classification.

Sports	Team Sport	Niche Sport	Diverse Sport	Low Academic Standard Sport
Archery				
Baseball	X			
Basketball	X		X	X
Cheerleading	X			
Cricket	X			
Equestrian		X		
Fencing		X		
Field Hockey	X			
Football	X		X	X
Golf		X		
Gymnastics				
Heavyweight Crew	X	X		
Heavyweight Rowing	X	X		
Ice Hockey	X			X
Lacrosse	X	X		
Lightweight Crew	X	X		
Lightweight Rowing	X	X		
Polo		X		
Rugby	X			
Sailing		X		
Skiing		X		
Soccer	X			
Softball	X			
Sprint Football	X			
Squash		X		
Swimming and Diving				
Synchronized Swimming	X			
Tennis	X	X		
Track/XC	X		X	
Ultimate Frisbee	X			
Volleyball	X			
Water Polo	X	X		
Wrestling				

Table 4A: College Major by Gender and Sport Type

This table presents sample breakdown of college major by gender and sport type. The percentages within a column can add up to be greater than 100% because an individual can have more than one college major. Refer to Table 3 for how sports are classified into each sport type.

	Male	Female	Athlete	Non-athlete	Team Sports	Individual Sports
N	215,463	186,322	30,835	370,950	23,736	6,984
Accounting	1.76%	1.12%	1.83%	1.43%	1.85%	1.75%
Aerospace Engineering	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Anthropology	1.03%	2.32%	1.40%	1.65%	1.31%	1.60%
Architecture	2.20%	2.44%	1.81%	2.35%	1.70%	2.25%
Art and Art History	0.21%	0.56%	0.51%	0.36%	0.44%	0.72%
Biochemistry	1.33%	1.07%	0.73%	1.25%	0.62%	1.06%
Biology	9.27%	11.72%	9.41%	10.49%	8.76%	11.73%
Business	1.69%	1.43%	5.04%	1.28%	5.18%	4.48%
Chemical Engineering	1.34%	0.91%	0.85%	1.17%	0.86%	0.90%
Chemistry	3.32%	2.54%	1.98%	3.04%	1.71%	2.88%
Civil Engineering	0.89%	0.53%	0.90%	0.71%	0.94%	0.74%
Classical Studies	0.38%	0.37%	0.46%	0.37%	0.43%	0.56%
Communications	1.55%	3.44%	1.89%	2.47%	1.87%	1.89%
Computer Science	7.41%	3.54%	3.13%	5.82%	2.85%	4.14%
Design	1.21%	2.43%	1.08%	1.83%	0.98%	1.43%
Earth Sciences	2.20%	3.46%	3.19%	2.75%	3.06%	3.59%
Economics	15.92%	9.96%	19.08%	12.66%	19.91%	16.52%
Education	2.74%	5.52%	3.41%	4.08%	3.45%	3.09%
Electrical Engineering	2.43%	0.76%	1.24%	1.69%	1.28%	1.19%
English Literature	6.88%	11.45%	5.77%	9.27%	5.41%	6.93%
Environmental Engineering	0.50%	0.58%	0.47%	0.54%	0.50%	0.39%
Ethnics and Language Studies	5.11%	9.06%	6.93%	6.94%	6.61%	8.26%
Film Studies	0.68%	0.89%	0.46%	0.80%	0.45%	0.50%
Finance	8.21%	3.92%	8.59%	6.03%	8.84%	8.23%
General Engineering	15.38%	8.40%	10.07%	12.32%	10.06%	10.35%
History	9.46%	9.84%	11.09%	9.52%	11.28%	10.78%
Human Development	0.18%	1.03%	0.33%	0.60%	0.34%	0.29%
Industrial and Labor Relations	1.39%	1.42%	0.69%	1.46%	0.77%	0.46%
Industrial Engineering	0.66%	0.35%	0.30%	0.53%	0.32%	0.26%
International Relations	2.68%	3.40%	3.64%	2.96%	3.52%	4.08%
Management	14.00%	12.84%	15.22%	13.32%	15.93%	12.77%
Marketing	3.19%	3.44%	3.54%	3.28%	3.48%	3.71%
Mathematics	4.64%	2.97%	2.94%	3.94%	2.75%	3.57%
Mechanical Engineering	2.85%	1.19%	2.17%	2.07%	2.19%	2.10%
Music	1.23%	1.12%	0.35%	1.25%	0.32%	0.47%
Neuroscience	0.80%	1.34%	1.03%	1.05%	0.91%	1.26%
Nursing	0.20%	2.05%	0.42%	1.11%	0.40%	0.36%

Philosophy	6.89%	6.49%	4.68%	6.87%	4.15%	6.44%
Physics	3.78%	1.66%	1.69%	2.88%	1.47%	2.51%
Political Science	9.21%	7.93%	11.08%	8.41%	11.70%	9.03%
Psychology	3.96%	8.22%	5.91%	5.94%	5.84%	5.56%
Public Policy	1.24%	1.75%	1.29%	1.49%	1.24%	1.37%
Social Studies	1.38%	1.53%	0.86%	1.50%	0.84%	0.96%
Sociology	1.44%	2.74%	2.47%	2.01%	2.67%	1.72%
Urban Studies	0.47%	0.76%	0.63%	0.60%	0.63%	0.62%

Table 4B: College Major by Sport Type

This table presents sample breakdown of college major by sport type. Each sport can be classified as either niche or non-niche, (socioeconomically) diverse or non-diverse, and low academic standard or not. The percentages within a column can add up to be greater than 100% because an individual can have more than one college major. Refer to Table 3 for how sports are classified into each sport type.

	Niche	Non-niche	Diverse	Non-diverse	Low Academic Standard	Higher Academic Standard
N	10,522	20,313	9,682	21,153	7,374	23,461
Accounting	1.72%	1.88%	2.01%	1.74%	2.36%	1.66%
Aerospace Engineering	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Anthropology	1.72%	1.23%	1.05%	1.56%	0.77%	1.59%
Architecture	2.08%	1.66%	1.28%	2.05%	0.96%	2.07%
Art and Art History	0.73%	0.39%	0.28%	0.61%	0.24%	0.59%
Biochemistry	0.88%	0.65%	0.64%	0.78%	0.50%	0.81%
Biology	10.13%	9.04%	8.07%	10.03%	6.60%	10.30%
Business	4.55%	5.29%	5.68%	4.74%	6.25%	4.65%
Chemical Engineering	0.67%	0.94%	0.86%	0.85%	0.61%	0.92%
Chemistry	2.19%	1.87%	1.87%	2.03%	1.37%	2.17%
Civil Engineering	0.69%	1.00%	1.01%	0.84%	0.94%	0.88%
Classical Studies	0.64%	0.36%	0.28%	0.54%	0.28%	0.51%
Communications	1.63%	2.03%	1.81%	1.93%	1.45%	2.03%
Computer Science	3.60%	2.88%	2.62%	3.36%	1.91%	3.51%
Design	1.26%	0.98%	0.92%	1.15%	0.62%	1.22%
Earth Sciences	3.54%	3.01%	2.70%	3.42%	2.05%	3.55%
Economics	17.81%	19.74%	21.48%	17.98%	23.47%	17.70%
Education	3.01%	3.62%	3.58%	3.33%	3.39%	3.42%
Electrical Engineering	1.32%	1.20%	1.31%	1.21%	1.03%	1.31%
English Literature	7.26%	5.00%	4.45%	6.38%	4.00%	6.33%
Environmental Engineering	0.43%	0.50%	0.57%	0.43%	0.33%	0.52%
Ethnics and Language Studies	8.58%	6.08%	5.29%	7.69%	4.76%	7.62%
Film Studies	0.48%	0.45%	0.48%	0.46%	0.46%	0.46%
Finance	8.37%	8.70%	9.16%	8.33%	9.91%	8.18%
General Engineering	9.65%	10.29%	10.30%	9.97%	8.27%	10.63%
History	13.32%	9.93%	10.37%	11.42%	11.11%	11.08%
Human Development	0.25%	0.37%	0.28%	0.35%	0.16%	0.38%
Industrial and Labor Relations	0.47%	0.81%	0.96%	0.57%	0.96%	0.61%
Industrial Engineering	0.25%	0.33%	0.36%	0.27%	0.33%	0.29%
International Relations	4.46%	3.22%	2.83%	4.01%	2.25%	4.08%
Management	12.67%	16.54%	16.74%	14.52%	19.27%	13.95%
Marketing	3.14%	3.75%	3.55%	3.54%	3.78%	3.47%
Mathematics	3.30%	2.76%	2.42%	3.18%	1.83%	3.29%
Mechanical Engineering	2.10%	2.21%	2.27%	2.13%	1.78%	2.30%
Music	0.35%	0.35%	0.38%	0.34%	0.28%	0.38%
Neuroscience	0.99%	1.05%	0.81%	1.13%	0.49%	1.20%
Nursing	0.38%	0.43%	0.32%	0.46%	0.23%	0.47%

Philosophy	5.54%	4.23%	3.79%	5.08%	2.67%	5.31%
Physics	2.29%	1.38%	1.19%	1.92%	0.90%	1.94%
Political Science	10.74%	11.26%	12.76%	10.32%	14.17%	10.11%
Psychology	4.89%	6.44%	5.96%	5.89%	6.05%	5.87%
Public Policy	1.23%	1.32%	1.25%	1.31%	0.98%	1.39%
Social Studies	1.05%	0.77%	0.89%	0.85%	0.84%	0.87%
Sociology	1.58%	2.94%	3.42%	2.04%	3.74%	2.08%
Urban Studies	0.64%	0.62%	0.59%	0.64%	0.45%	0.68%

Table 5: Graduate Degree Attainment by Gender and Sport Type

This table presents the sample breakdown of graduate degree attainment by gender and sport type. Each individual can hold more than one graduate degree. Refer to Table 3 for how sports are classified into each sport type.

	Male	Female	Athlete	Non-athlete	Team Sports	Individual Sports
N	215,463	186,322	30,835	370,950	23,736	6,984
Elite MBA	7.35%	5.11%	8.05%	6.17%	8.14%	8.08%
Other MBA	9.71%	6.68%	11.11%	8.07%	11.46%	10.29%
J.D.	12.95%	11.39%	12.07%	12.24%	12.21%	11.66%
M.D.	5.62%	5.12%	4.89%	5.43%	4.49%	6.40%
Ph.D.	14.55%	14.45%	10.76%	14.81%	9.72%	14.58%
STEM Graduate Degree	18.32%	17.17%	14.32%	18.08%	13.41%	17.54%

	Niche Sports	Non-niche Sports	Diverse Sports	Non-diverse Sports	Low Academic Standard Sports	Higher Academic Standard Sports
N	10522	20313	9682	21153	7374	23461
Elite MBA	9.69%	7.20%	7.76%	8.19%	8.00%	8.07%
Other MBA	10.44%	11.46%	12.07%	10.67%	13.17%	10.47%
J.D.	12.52%	11.84%	12.66%	11.80%	12.56%	11.92%
M.D.	5.92%	4.35%	3.89%	5.34%	3.32%	5.38%
Ph.D.	12.55%	9.83%	8.84%	11.63%	6.81%	12.00%
STEM Graduate Degree	15.69%	13.61%	12.37%	15.21%	9.51%	15.83%

Table 6A: First-job Industry by Gender and Sport Type

This table presents the sample breakdown of first-job industry by gender and sport type. Refer to Table 3 for how sports are classified into each sport type.

	Male	Female	Athlete	Non-athlete	Team Sports	Individual Sports
Accommodation/Food Services	2.31%	2.58%	2.05%	2.46%	2.00%	2.13%
Administrative/Support/Waste Mgmt.	5.58%	5.71%	5.83%	5.63%	5.83%	5.73%
Agriculture and Mining	0.67%	0.52%	0.75%	0.59%	0.75%	0.73%
Arts/Entertainment/Recreation	1.90%	2.65%	2.75%	2.20%	2.68%	3.02%
Business Services	5.73%	5.21%	5.62%	5.48%	5.63%	5.61%
Construction	2.02%	1.35%	2.19%	1.67%	2.30%	1.90%
Education (Non-college)	3.59%	5.75%	4.19%	4.63%	4.12%	4.11%
Education (College)	7.97%	10.08%	7.19%	9.10%	6.84%	8.08%
Finance and Insurance	12.51%	7.77%	16.57%	9.79%	17.27%	14.60%
Health Care/Social Assistance	6.57%	10.36%	6.72%	8.46%	6.41%	7.52%
Information	6.50%	6.93%	5.20%	6.82%	5.16%	5.32%
Legal, Accounting, and Tax Services	7.20%	6.24%	6.59%	6.77%	6.71%	6.14%
Management of Companies	0.40%	0.27%	0.53%	0.33%	0.55%	0.48%
Manufacturing	8.19%	5.47%	7.36%	6.89%	7.45%	7.23%
Other Services	5.95%	8.68%	5.73%	7.35%	5.84%	5.45%
Public Administration	5.79%	5.11%	4.82%	5.53%	4.73%	5.30%
Real Estate	1.84%	1.34%	2.10%	1.57%	2.16%	1.97%
Retail Trade	4.24%	4.78%	4.26%	4.51%	4.24%	4.31%
Technical Services	7.77%	6.60%	6.28%	7.30%	6.02%	7.16%
Transportation	0.71%	0.51%	0.73%	0.61%	0.73%	0.75%
Unclassified	0.65%	0.66%	0.57%	0.66%	0.54%	0.70%
Utilities	0.37%	0.24%	0.37%	0.30%	0.38%	0.34%
Wholesale Trade	1.56%	1.19%	1.61%	1.37%	1.68%	1.42%

Table 6B: First-job Industry by Sport Type

This table presents the sample breakdown of first-job industry by sport type. Each sport can be classified as either niche or non-niche, (socioeconomically) diverse or non-diverse, and low academic standard or not. Refer to Table 3 for how sports are classified into each sport type.

	Niche	**Non-niche**	**Diverse**	**Non-diverse**	**Low Academic Standard**	**Higher Academic Standard**
Accommodation/Food Services	2.08%	2.03%	1.82%	2.15%	1.90%	2.10%
Administrative/Support/Waste Mgmt.	6.22%	5.63%	5.47%	6.00%	5.66%	5.89%
Agriculture and Mining	0.61%	0.83%	0.74%	0.76%	0.72%	0.76%
Arts/Entertainment/Recreation	2.28%	3.00%	2.53%	2.85%	3.16%	2.63%
Business Services	5.86%	5.49%	5.01%	5.90%	5.15%	5.76%
Construction	2.13%	2.23%	2.24%	2.17%	2.57%	2.08%
Education (Non-college)	7.27%	7.15%	6.66%	7.43%	5.14%	7.83%
Education (College)	4.16%	4.20%	4.03%	4.27%	3.54%	4.39%
Finance and Insurance	17.62%	16.03%	17.65%	16.08%	20.25%	15.42%
Health Care/Social Assistance	7.01%	6.56%	5.74%	7.16%	4.87%	7.29%
Information	5.19%	5.20%	5.01%	5.29%	4.73%	5.34%
Legal, Accounting, and Tax Services	6.42%	6.68%	7.22%	6.30%	7.53%	6.29%
Management of Companies	0.63%	0.48%	0.48%	0.55%	0.50%	0.54%
Manufacturing	6.50%	7.80%	8.17%	6.99%	8.26%	7.07%
Other Services	5.55%	5.82%	5.89%	5.65%	5.25%	5.88%
Public Administration	5.08%	4.69%	4.84%	4.81%	4.35%	4.97%
Real Estate	1.82%	2.24%	2.34%	1.99%	2.74%	1.90%
Retail Trade	3.78%	4.52%	4.56%	4.13%	4.37%	4.23%
Technical Services	6.92%	5.94%	5.74%	6.52%	5.11%	6.64%
Transportation	0.55%	0.82%	0.91%	0.65%	1.09%	0.61%
Unclassified	0.59%	0.56%	0.62%	0.54%	0.61%	0.56%
Utilities	0.31%	0.40%	0.43%	0.34%	0.43%	0.35%
Wholesale Trade	1.43%	1.71%	1.90%	1.48%	2.06%	1.47%

Table 7: Differences in Observable Characteristics by Gender and Sport Type

This table presents, for each observable characteristic, the means, differences, and p-values from two-tailed t-tests of difference in means between gender and sport type groups in the sample. Each sport can be classified as either team or individual, niche or non-niche, (socioeconomically) diverse or non-diverse, and low academic standard (LAS) or higher academic standard (HAS). Refer to Table 3 for how sports are classified into each sport type. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

Panel A	**Male**	**Female**	**Difference**	**p-value**
Elite MBA	0.074	0.051	0.022	<0.001***
Non-elite MBA	0.097	0.067	0.030	<0.001***
STEM Graduate Degree	0.183	0.172	0.012	<0.001***
J.D.	0.129	0.114	0.016	<0.001***
M.D.	0.056	0.051	0.005	<0.001***
Ph.D.	0.145	0.144	0.001	0.383
Cumulative Seniority	153.294	98.303	54.991	<0.001***
Peak Seniority	14.156	11.835	2.321	<0.001***
Cumulative Wages (Thousands USD)	1903.426	1290.379	613.047	<0.001***
Peak Wages (Thousands USD)	134.699	117.774	16.925	<0.001***
Reported Career Length	22.705	16.545	6.160	<0.001***
Total Jobs	5.042	5.333	-0.291	<0.001***
Finance Job	0.243	0.170	0.073	<0.001***
C-suite Job	0.109	0.049	0.060	<0.001***

Panel B	**Athlete**	**Non-athlete**	**Difference**	**p-value**
Elite MBA	0.081	0.062	0.019	<0.001***
Non-elite MBA	0.111	0.081	0.030	<0.001***
STEM Graduate Degree	0.143	0.181	-0.038	<0.001***
J.D.	0.121	0.122	-0.002	0.400
M.D.	0.049	0.054	-0.005	<0.001***
Ph.D.	0.108	0.148	-0.041	<0.001***
Cumulative Seniority	147.506	126.154	21.352	<0.001***
Peak Seniority	13.894	13.006	0.889	<0.001***
Cumulative Wages (Thousands USD)	1822.846	1602.201	220.644	<0.001***
Peak Wages (Thousands USD)	134.743	126.191	8.552	<0.001***
Reported Career Length	21.067	19.740	1.327	<0.001***
Total Jobs	5.330	5.164	0.166	<0.001***
Finance Job	0.298	0.202	0.096	<0.001***
C-suite Job	0.104	0.079	0.025	<0.001***

Panel C	**Team**	**Individual**	**Difference**	**p-value**
Elite MBA	0.081	0.081	0.001	0.863
Non-elite MBA	0.115	0.103	0.012	0.005***
STEM Graduate Degree	0.134	0.175	-0.041	<0.001***
J.D.	0.122	0.117	0.006	0.207
M.D.	0.045	0.064	-0.019	<0.001***
Ph.D.	0.097	0.146	-0.049	<0.001***
Cumulative Seniority	150.136	145.093	5.042	0.027**
Peak Seniority	14.029	13.696	0.333	0.002***
Cumulative Wages (Thousands USD)	1849.287	1798.272	51.015	0.012**
Peak Wages (Thousands USD)	135.403	134.365	1.038	0.128
Reported Career Length	21.383	20.834	0.549	0.006***
Total Jobs	5.306	5.404	-0.098	0.030**
Finance Job	0.305	0.278	0.027	<0.001***
C-suite Job	0.107	0.098	0.009	0.020**

Panel D	**Niche**	**Non-niche**	**Difference**	**p-value**
Elite MBA	0.097	0.072	0.025	<0.001***
Non-elite MBA	0.104	0.115	-0.010	0.006***
STEM Graduate Degree	0.157	0.136	0.021	<0.001***
J.D.	0.125	0.118	0.007	0.088*
M.D.	0.059	0.044	0.016	<0.001***
Ph.D.	0.126	0.098	0.027	<0.001***
Cumulative Seniority	147.448	147.536	-0.088	0.965
Peak Seniority	13.856	13.914	-0.058	0.547
Cumulative Wages (Thousands USD)	1818.933	1824.872	-5.939	0.740
Peak Wages (Thousands USD)	136.693	133.735	2.958	<0.001***
Reported Career Length	20.885	21.161	-0.276	0.116
Total Jobs	5.401	5.293	0.107	0.006***
Finance Job	0.314	0.290	0.025	<0.001***
C-suite Job	0.109	0.101	0.008	0.031**

Panel E	**Diverse**	**Non-diverse**	**Difference**	**p-value**
Elite MBA	0.078	0.063	0.015	<0.001***
Non-elite MBA	0.121	0.082	0.039	<0.001***
STEM Graduate Degree	0.124	0.179	-0.055	<0.001***
J.D.	0.127	0.122	0.004	0.189
M.D.	0.039	0.054	-0.015	<0.001***
Ph.D.	0.088	0.146	-0.058	<0.001***
Cumulative Seniority	155.605	127.106	28.499	<0.001***
Peak Seniority	14.292	13.045	1.247	<0.001***
Cumulative Wages (Thousands USD)	1911.216	1611.922	299.294	<0.001***
Peak Wages (Thousands USD)	135.835	126.627	9.208	<0.001***
Reported Career Length	22.289	19.782	2.507	<0.001***
Total Jobs	5.228	5.176	0.052	0.113
Finance Job	0.309	0.207	0.103	<0.001***
C-suite Job	0.111	0.081	0.030	<0.001***

Panel F	**LAS**	**HAS**	**Difference**	**p-value**
Elite MBA	0.080	0.063	0.017	<0.001***
Non-elite MBA	0.132	0.082	0.050	<0.001***
STEM Graduate Degree	0.095	0.179	-0.084	<0.001***
J.D.	0.126	0.122	0.003	0.383
M.D.	0.033	0.054	-0.021	<0.001***
Ph.D.	0.068	0.146	-0.078	<0.001***
Cumulative Seniority	171.886	126.968	44.918	<0.001***
Peak Seniority	14.883	13.041	1.843	<0.001***
Cumulative Wages (Thousands USD)	2057.445	1610.940	446.505	<0.001***
Peak Wages (Thousands USD)	139.266	126.616	12.650	<0.001***
Reported Career Length	23.672	19.771	3.901	<0.001***
Total Jobs	5.092	5.178	-0.087	0.020**
Finance Job	0.349	0.206	0.142	<0.001***
C-suite Job	0.122	0.080	0.041	<0.001***

Table 8: Athletes and Non-athletes – Education Attainment and Career Choice

This table presents OLS regression results where education attainment and finance job indicator variables are regressed onto athlete status indicator variable. Athlete is an indicator variable that equals one if the individual participated in a college varsity sport and zero otherwise. Each observation is an individual. The outcome variable for columns 1 and 2 is an indicator variable that equals one if the individual holds an MBA degree. The outcome variables for the remaining columns follow the same logic for elite MBA degree (defined in the main text), J.D., M.D., Ph.D., STEM graduate degree, and any finance job. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	MBA	MBA	Elite MBA	Elite MBA	J.D.	J.D.	M.D.	M.D.	Ph.D.	Ph.D.	STEM Degree	STEM Degree	Finance Job	Finance Job
Athlete	0.004	0.001	-0.004*	-0.006***	0.002	0.005*	-0.004*	-0.001	-0.013***	-0.009***	-0.002	0.000	0.036***	0.018***
	(1.357)	(0.253)	(-1.833)	(-2.760)	(0.666)	(1.817)	(-1.924)	(-0.649)	(-4.709)	(-3.376)	(-0.655)	(0.116)	(8.785)	(5.403)
Athlete x Male	0.002	-0.000	0.000	-0.001	-0.034***	-0.028***	-0.003	-0.004*	-0.012***	-0.010***	-0.016***	-0.014***	0.029***	0.004
	(0.602)	(-0.008)	(0.135)	(-0.389)	(-8.659)	(-7.939)	(-1.512)	(-1.710)	(-3.601)	(-3.243)	(-3.990)	(-3.585)	(5.601)	(0.983)
Male	0.008***	0.005***	0.002**	-0.000	0.006***	0.005***	0.011***	0.014***	-0.003***	0.004***	-0.003***	0.001	0.041***	0.023***
	(7.358)	(4.450)	(2.333)	(-0.246)	(5.854)	(5.158)	(16.519)	(23.019)	(-2.625)	(3.916)	(-3.035)	(1.078)	(30.644)	(20.886)
Reported Career Length	-0.002***	-0.002***	-0.001***	-0.000***	0.000***	0.000	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.000**	0.001***
	(-12.206)	(-11.321)	(-5.031)	(-4.472)	(3.163)	(0.984)	(10.700)	(7.933)	(11.589)	(10.366)	(5.388)	(4.831)	(2.019)	(6.595)
Total Jobs	0.008***	0.008***	0.004***	0.004***	-0.001***	0.002***	-0.002***	-0.002***	-0.002***	-0.002***	0.000	-0.000	0.010***	0.013***
	(46.663)	(45.423)	(30.018)	(29.744)	(-4.864)	(13.065)	(-24.412)	(-22.398)	(-15.426)	(-16.661)	(1.262)	(-1.001)	(50.596)	(74.762)
Observations	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793
R-squared	0.283	0.294	0.117	0.127	0.121	0.334	0.404	0.439	0.401	0.436	0.294	0.309	0.135	0.466
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Job Industry FE		Yes		Yes		Yes		Yes		Yes		Yes		Yes

Table 9: Team Sport Athletes, Individual Sport Athletes, and Non-athletes – Education Attainment and Career Choice

This table presents OLS regression results where education attainment and finance job indicator variables are regressed onto variants of athlete status indicator variables. Each observation is an individual. Team Sport Athlete is an indicator variable that equals one if the individual participated in a team varsity sport during college and zero otherwise. Individual Sport Athlete is an indicator variable that equals one if the individual participated in an individual varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type. The outcome variable for columns 1 and 2 is an indicator variable that equals one if the individual holds an MBA degree. The outcome variables for the remaining columns follow the same logic for elite MBA degree (defined in the main text), J.D., M.D., Ph.D., STEM graduate degree, and any finance job. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	MBA	MBA	Elite MBA	Elite MBA	J.D.	J.D.	M.D.	M.D.	Ph.D.	Ph.D.	STEM Degree	STEM Degree	Finance Job	Finance Job
Team Sport Athlete	0.005	0.001	-0.006**	-0.008***	-0.000	0.003	-0.003	-0.001	-0.016***	-0.013***	-0.006	-0.004	0.036***	0.019***
	(1.215)	(0.326)	(-2.038)	(-2.796)	(-0.022)	(0.803)	(-1.429)	(-0.620)	(-4.884)	(-4.047)	(-1.427)	(-0.955)	(7.360)	(4.881)
Team Sport Athlete x Male	0.001	-0.002	0.001	-0.001	-0.033***	-0.026***	-0.006**	-0.006**	-0.012***	-0.010***	-0.015***	-0.013***	0.030***	0.001
	(0.190)	(-0.475)	(0.230)	(-0.322)	(-7.223)	(-6.270)	(-2.342)	(-2.227)	(-3.317)	(-2.691)	(-3.321)	(-2.762)	(5.004)	(0.155)
Individual Sport Athlete	0.006	0.002	0.001	-0.001	-0.000	0.005	-0.003	0.001	-0.001	0.005	0.009	0.013**	0.039***	0.016**
	(1.044)	(0.325)	(0.314)	(-0.301)	(-0.076)	(0.915)	(-0.701)	(0.387)	(-0.194)	(0.926)	(1.322)	(1.976)	(4.998)	(2.538)
Individual Sport Athlete x Male	0.006	0.007	0.000	0.000	-0.021***	-0.021***	0.004	0.001	-0.009	-0.011	-0.014*	-0.015*	0.015	0.011
	(0.800)	(0.848)	(0.039)	(0.047)	(-2.691)	(-3.077)	(0.868)	(0.317)	(-1.322)	(-1.583)	(-1.761)	(-1.885)	(1.501)	(1.312)
Male	0.008***	0.005***	0.002**	-0.000	0.006***	0.005***	0.011***	0.015***	-0.003**	0.004***	-0.003***	0.001	0.041***	0.023***
	(7.369)	(4.461)	(2.333)	(-0.248)	(5.644)	(4.950)	(16.591)	(23.094)	(-2.570)	(3.969)	(-3.034)	(1.077)	(30.729)	(20.944)
Reported Career Length	-0.002***	-0.002***	-0.001***	-0.000***	0.000***	0.000	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.000**	0.001***
	(-12.210)	(-11.323)	(-5.038)	(-4.478)	(3.159)	(0.979)	(10.703)	(7.935)	(11.586)	(10.362)	(5.388)	(4.829)	(2.023)	(6.604)
Total Jobs	0.008***	0.008***	0.004***	0.004***	-0.001***	0.002***	-0.002***	-0.002***	-0.002***	-0.002***	0.000	-0.000	0.010***	0.013***
	(46.655)	(45.415)	(30.009)	(29.735)	(-4.867)	(13.060)	(-24.423)	(-22.412)	(-15.444)	(-16.681)	(1.247)	(-1.017)	(50.591)	(74.757)
Observations	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793
R-squared	0.283	0.294	0.117	0.127	0.121	0.334	0.404	0.439	0.401	0.436	0.294	0.309	0.135	0.466
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Job Industry FE		Yes		Yes		Yes		Yes		Yes		Yes		Yes

Table 10: Niche Sport Athletes, Non-niche Sport Athletes, and Non-athletes – Education Attainment and Career Choice

This table presents OLS regression results where education attainment and finance job indicator variables are regressed onto variants of athlete status indicator variables. Each observation is an individual. Athlete (Niche Sport) is an indicator variable that equals one if the individual participated in a niche varsity sport during college and zero otherwise. Athlete (Non-niche Sport) is an indicator variable that equals one if the individual participated in a non-niche varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type. The outcome variable for columns 1 and 2 is an indicator variable that equals one if the individual holds an MBA degree. The outcome variables for the remaining columns follow the same logic for elite MBA degree (defined in the main text), J.D., M.D., Ph.D., STEM graduate degree, and any finance job. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	MBA	MBA	Elite MBA	Elite MBA	J.D.	J.D.	M.D.	M.D.	Ph.D.	Ph.D.	STEM Degree	STEM Degree	Finance Job	Finance Job
Athlete (Niche Sport)	0.020***	0.014***	0.010**	0.006	0.002	0.008*	0.002	0.005*	-0.007	-0.001	0.000	0.004	0.061***	0.028***
	(3.790)	(2.770)	(2.392)	(1.447)	(0.316)	(1.777)	(0.586)	(1.658)	(-1.605)	(-0.258)	(0.022)	(0.770)	(8.993)	(5.215)
Athlete (Niche Sport) x Male	0.009	0.007	0.009	0.008	-0.031***	-0.029***	-0.001	-0.003	-0.010*	-0.011**	-0.008	-0.007	0.031***	0.005
	(1.316)	(0.984)	(1.630)	(1.490)	(-4.765)	(-5.005)	(-0.340)	(-0.895)	(-1.934)	(-2.103)	(-1.236)	(-1.157)	(3.586)	(0.762)
Athlete (Not-niche Sport)	-0.005	-0.008*	-0.013***	-0.014***	0.002	0.003	-0.007***	-0.005**	-0.017***	-0.014***	-0.004	-0.002	0.021***	0.012***
	(-1.323)	(-1.929)	(-4.743)	(-5.152)	(0.614)	(0.942)	(-2.964)	(-2.155)	(-4.851)	(-4.173)	(-0.851)	(-0.436)	(4.153)	(2.829)
Athlete (Non-niche Sport) x Male	0.002	-0.001	-0.001	-0.004	-0.036***	-0.027***	-0.004	-0.003	-0.011***	-0.009**	-0.019***	-0.017***	0.032***	0.005
	(0.348)	(-0.225)	(-0.409)	(-1.040)	(-7.381)	(-6.238)	(-1.286)	(-1.121)	(-2.870)	(-2.242)	(-3.883)	(-3.416)	(5.027)	(1.002)
Male	0.008***	0.005***	0.002**	-0.000	0.006***	0.005***	0.011***	0.014***	-0.003***	0.004***	-0.003***	0.001	0.041***	0.023***
	(7.371)	(4.467)	(2.351)	(-0.221)	(5.855)	(5.160)	(16.526)	(23.029)	(-2.620)	(3.924)	(-3.029)	(1.086)	(30.656)	(20.895)
Reported Career Length	-0.002***	-0.002***	-0.001***	-0.000***	0.000***	0.000	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.000**	0.001***
	(-12.217)	(-11.332)	(-5.042)	(-4.483)	(3.163)	(0.982)	(10.695)	(7.926)	(11.586)	(10.361)	(5.386)	(4.828)	(2.009)	(6.587)
Total Jobs	0.008***	0.008***	0.004***	0.004***	-0.001***	0.002***	-0.002***	-0.002***	-0.002***	-0.002***	0.000	-0.000	0.010***	0.013***
	(46.633)	(45.388)	(29.978)	(29.695)	(-4.868)	(13.060)	(-24.431)	(-22.419)	(-15.437)	(-16.674)	(1.247)	(-1.020)	(50.566)	(74.742)
Observations	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793
R-squared	0.283	0.294	0.117	0.127	0.121	0.334	0.404	0.439	0.401	0.436	0.294	0.309	0.135	0.466
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Job Industry FE		Yes		Yes		Yes		Yes		Yes		Yes		Yes

Table 11: Diverse Sport Athletes, Non-diverse Sport Athletes, and Non-athletes – Education Attainment and Career Choice

This table presents OLS regression results where education attainment and finance job indicator variables are regressed onto variants of athlete status indicator variables. Each observation is an individual. Athlete (Diverse Sport) is an indicator variable that equals one if the individual participated in a (socioeconomically) diverse varsity sport during college and zero otherwise. Athlete (Non-diverse Sport) is an indicator variable that equals one if the individual participated in a non-diverse varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type. The outcome variable for columns 1 and 2 is an indicator variable that equals one if the individual holds an MBA degree. The outcome variables for the remaining columns follow the same logic for elite MBA degree (defined in the main text), J.D., M.D., Ph.D., STEM graduate degree, and any finance job. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1) MBA	(2) MBA	(3) Elite MBA	(4) Elite MBA	(5) J.D.	(6) J.D.	(7) M.D.	(8) M.D.	(9) Ph.D.	(10) Ph.D.	(11) STEM Degree	(12) STEM Degree	(13) Finance Job	(14) Finance Job
Athlete (Diverse Sport)	0.007	0.006	-0.004	-0.004	0.014*	0.012*	-0.014***	-0.013***	-0.029***	-0.027***	-0.002	-0.001	0.017*	0.009
	(0.935)	(0.804)	(-0.745)	(-0.801)	(1.850)	(1.859)	(-3.315)	(-3.045)	(-4.849)	(-4.628)	(-0.263)	(-0.145)	(1.929)	(1.250)
Athlete (Diverse Sport) x Male	-0.010	-0.015*	-0.011*	-0.014**	-0.049***	-0.039***	0.001	0.003	0.000	0.004	-0.027***	-0.023***	0.045***	0.011
	(-1.216)	(-1.782)	(-1.739)	(-2.313)	(-5.946)	(-5.200)	(0.285)	(0.701)	(0.038)	(0.576)	(-3.170)	(-2.752)	(4.335)	(1.421)
Athlete (Non-diverse Sport)	0.004	-0.000	-0.004*	-0.007***	-0.001	0.004	-0.001	0.002	-0.009***	-0.005	-0.002	0.001	0.041***	0.020***
	(1.068)	(-0.115)	(-1.687)	(-2.712)	(-0.199)	(1.110)	(-0.574)	(0.753)	(-2.955)	(-1.549)	(-0.602)	(0.217)	(8.925)	(5.452)
Athlete (Non-diverse Sport) x Male	0.009*	0.007	0.007*	0.006	-0.030***	-0.025***	-0.003	-0.004	-0.014***	-0.013***	-0.010**	-0.009*	0.026***	0.003
	(1.867)	(1.423)	(1.868)	(1.547)	(-6.525)	(-6.056)	(-1.088)	(-1.586)	(-3.585)	(-3.414)	(-2.133)	(-1.894)	(4.373)	(0.564)
Male	0.008***	0.005***	0.002**	-0.000	0.006***	0.005***	0.011***	0.014***	-0.003***	0.004***	-0.003***	0.001	0.041***	0.023***
	(7.358)	(4.451)	(2.333)	(-0.244)	(5.856)	(5.159)	(16.515)	(23.016)	(-2.628)	(3.913)	(-3.035)	(1.079)	(30.641)	(20.885)
Reported Career Length	-0.002***	-0.002***	-0.001***	-0.000***	0.000***	0.000	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.000**	0.001***
	(-12.209)	(-11.323)	(-5.037)	(-4.477)	(3.169)	(0.987)	(10.683)	(7.914)	(11.575)	(10.350)	(5.384)	(4.825)	(2.007)	(6.586)
Total Jobs	0.008***	0.008***	0.004***	0.004***	-0.001***	0.002***	-0.002***	-0.002***	-0.002***	-0.002***	0.000	-0.000	0.010***	0.013***
	(46.652)	(45.412)	(30.003)	(29.728)	(-4.866)	(13.061)	(-24.425)	(-22.411)	(-15.432)	(-16.668)	(1.251)	(-1.013)	(50.590)	(74.758)
Observations	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793
R-squared	0.283	0.294	0.117	0.127	0.121	0.334	0.404	0.439	0.401	0.436	0.294	0.309	0.135	0.466
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Job Industry FE		Yes		Yes		Yes		Yes		Yes		Yes		Yes

Table 12: Low Academic Standard Sport Athletes, Other Athletes, and Non-athletes – Education Attainment and Career Choice

This table presents OLS regression results where education attainment and finance job indicator variables are regressed onto variants of athlete status indicator variables. Each observation is an individual. Athlete (LAS) is an indicator variable that equals one if the individual participated in a low academic standard varsity sport during college and zero otherwise. Athlete (HAS) is an indicator variable that equals one if the individual participated in a higher academic standard varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type. The outcome variable for columns 1 and 2 is an indicator variable that equals one if the individual holds an MBA degree. The outcome variables for the remaining columns follow the same logic for elite MBA degree (defined in the main text), J.D., M.D., Ph.D., STEM graduate degree, and any finance job. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1) MBA	(2) MBA	(3) Elite MBA	(4) Elite MBA	(5) J.D.	(6) J.D.	(7) M.D.	(8) M.D.	(9) Ph.D.	(10) Ph.D.	(11) STEM Degree	(12) STEM Degree	(13) Finance Job	(14) Finance Job
Athlete (LAS)	-0.006	-0.008	-0.013*	-0.014**	0.014	0.016*	-0.009*	-0.005	-0.027***	-0.023***	-0.005	-0.002	0.039***	0.026***
	(-0.596)	(-0.816)	(-1.863)	(-2.032)	(1.397)	(1.714)	(-1.678)	(-0.964)	(-3.668)	(-3.227)	(-0.558)	(-0.156)	(3.174)	(2.729)
Athlete (LAS) x Male	0.001	-0.004	-0.006	-0.009	-0.059***	-0.047***	-0.006	-0.006	-0.009	-0.007	-0.033***	-0.032***	0.049***	0.006
	(0.099)	(-0.373)	(-0.719)	(-1.175)	(-5.461)	(-4.841)	(-1.049)	(-1.188)	(-1.224)	(-0.860)	(-3.285)	(-3.135)	(3.634)	(0.594)
Athlete (HAS)	0.006*	0.002	-0.003	-0.005**	0.001	0.004	-0.003	-0.001	-0.011***	-0.007**	-0.002	0.001	0.036***	0.017***
	(1.698)	(0.594)	(-1.259)	(-2.195)	(0.177)	(1.298)	(-1.474)	(-0.363)	(-3.790)	(-2.518)	(-0.494)	(0.185)	(8.241)	(4.784)
Athlete (HAS) x Male	0.006	0.004	0.005	0.004	-0.027***	-0.023***	-0.001	-0.002	-0.009**	-0.008**	-0.008*	-0.006	0.020***	0.001
	(1.321)	(0.925)	(1.597)	(1.279)	(-6.340)	(-5.994)	(-0.379)	(-0.650)	(-2.427)	(-2.234)	(-1.742)	(-1.450)	(3.523)	(0.135)
Male	0.008***	0.005***	0.002**	-0.000	0.006***	0.005***	0.011***	0.014***	-0.003***	0.004***	-0.003***	0.001	0.041***	0.023***
	(7.346)	(4.437)	(2.315)	(-0.265)	(5.851)	(5.156)	(16.506)	(23.008)	(-2.639)	(3.901)	(-3.049)	(1.065)	(30.656)	(20.897)
Reported Career Length	-0.002***	-0.002***	-0.001***	-0.000***	0.000***	0.000	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.000**	0.001***
	(-12.215)	(-11.328)	(-5.040)	(-4.478)	(3.173)	(0.995)	(10.691)	(7.927)	(11.575)	(10.353)	(5.386)	(4.831)	(2.020)	(6.602)
Total Jobs	0.008***	0.008***	0.004***	0.004***	-0.001***	0.002***	-0.002***	-0.002***	-0.002***	-0.003***	0.000	-0.000	0.010***	0.013***
	(46.634)	(45.391)	(29.976)	(29.698)	(-4.883)	(13.050)	(-24.443)	(-22.425)	(-15.458)	(-16.692)	(1.222)	(-1.040)	(50.631)	(74.784)
Observations	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793	384,515	375,793
R-squared	0.283	0.294	0.117	0.127	0.121	0.334	0.404	0.439	0.401	0.436	0.295	0.309	0.135	0.466
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Job Industry FE		Yes		Yes		Yes		Yes		Yes		Yes		Yes

Table 13: Athletes and Non-athletes – Job Seniority and Wage

This table presents OLS regression results where measures of job seniority and wages are regressed onto athlete status indicator variable. Each observation is an individual. Athlete is an indicator variable that equals one if the individual participated in a varsity college sport and zero otherwise. The outcome variable for columns 1 and 2 is the total job-year seniority summed over the individual's entire career. The outcome variable for columns 3 and 4 is the maximum job seniority that the individual achieved over his or her entire career. The outcome variable for columns 5 and 6 is the natural log of the total job-year estimated wages summed over the individual's entire career. The outcome variable for columns 7 and 8 is the natural log of the maximum estimated wage that the individual achieved over his or her entire career. The outcome variable for columns 9 and 10 is an indicator variable that equals one if the person held at least one C-suite job and zero otherwise. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Cumulative Seniority		Peak Seniority		Cumulative Wages		Peak Wages		C-suite Job	
Athlete	1.766*	0.534	-0.014	-0.056	0.040***	0.034***	0.014***	0.010**	0.003	0.002
	(1.753)	(0.539)	(-0.197)	(-0.801)	(5.951)	(4.987)	(3.300)	(2.259)	(1.164)	(0.885)
Athlete x Male	7.960***	4.927***	0.178**	0.133	0.001	-0.001	0.007	0.005	0.006*	0.005
	(5.515)	(3.518)	(2.104)	(1.573)	(0.149)	(-0.161)	(1.333)	(0.907)	(1.769)	(1.406)
Male	17.171***	15.562***	0.942***	0.881***	0.107***	0.096***	0.075***	0.066***	0.036***	0.035***
	(42.732)	(39.868)	(39.741)	(36.794)	(46.994)	(42.378)	(51.681)	(46.356)	(40.258)	(38.119)
Reported Career Length	6.606***	6.548***	0.226***	0.231***	0.073***	0.073***	0.014***	0.014***	0.003***	0.003***
	(145.442)	(148.449)	(70.425)	(70.805)	(192.096)	(192.694)	(69.933)	(71.970)	(40.913)	(41.171)
Total Jobs	9.680***	9.620***	0.614***	0.623***	0.038***	0.038***	0.027***	0.028***	0.012***	0.012***
	(133.687)	(133.978)	(162.659)	(160.855)	(105.222)	(105.715)	(116.819)	(120.808)	(69.785)	(68.690)
Observations	384,515	375,793	340,304	331,842	374,264	366,428	374,264	366,428	384,515	375,793
R-squared	0.390	0.436	0.329	0.337	0.598	0.610	0.239	0.273	0.072	0.078
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Job Industry FE		Yes		Yes		Yes		Yes		Yes

Table 14: Team Sport Athletes, Individual Sport Athletes, and Non-athletes – Job Seniority and Wage

This table presents OLS regression results where measures of job seniority and wages are regressed onto variants of athlete status indicator variables. Each observation is an individual. Team Sport Athlete is an indicator variable that equals one if the individual participated in a team varsity sport during college and zero otherwise. Individual Sport Athlete is an indicator variable that equals one if the individual participated in an individual varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type. The outcome variable for columns 1 and 2 is the total job-year seniority summed over the individual's entire career. The outcome variable for columns 3 and 4 is the maximum job seniority that the individual achieved over his or her entire career. The outcome variable for columns 5 and 6 is the natural log of the total job-year estimated wages summed over the individual's entire career. The outcome variable for columns 7 and 8 is the natural log of the maximum estimated wage that the individual achieved over his or her entire career. The outcome variable for columns 9 and 10 is an indicator variable that equals one if the person held at least one C-suite job and zero otherwise. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Cumulative Seniority		Peak Seniority		Cumulative Wages		Peak Wages		C-suite Job	
Team Sport Athlete	1.391	0.333	0.049	0.022	0.040***	0.034***	0.014***	0.011**	0.005*	0.004
	(1.178)	(0.288)	(0.591)	(0.265)	(5.085)	(4.339)	(2.785)	(2.077)	(1.736)	(1.483)
Team Sport Athlete x Male	7.944***	4.669***	0.104	0.044	-0.001	-0.005	0.004	0.001	0.004	0.002
	(4.835)	(2.923)	(1.059)	(0.447)	(-0.126)	(-0.493)	(0.745)	(0.227)	(0.960)	(0.637)
Individual Sport Athlete	3.661*	1.718	-0.016	-0.068	0.047***	0.040***	0.022***	0.015*	-0.000	-0.001
	(1.886)	(0.904)	(-0.123)	(-0.519)	(3.670)	(3.121)	(2.653)	(1.901)	(-0.017)	(-0.157)
Individual Sport Athlete x Male	6.897**	5.217*	0.173	0.142	-0.001	-0.000	0.009	0.009	0.008	0.007
	(2.339)	(1.834)	(1.058)	(0.864)	(-0.043)	(-0.030)	(0.920)	(0.919)	(1.197)	(1.096)
Male	17.189***	15.573***	0.945***	0.885***	0.107***	0.096***	0.075***	0.066***	0.036***	0.035***
	(42.800)	(39.921)	(39.911)	(36.983)	(47.068)	(42.454)	(51.771)	(46.450)	(40.343)	(38.199)
Reported Career Length	6.605***	6.548***	0.226***	0.231***	0.073***	0.073***	0.014***	0.014***	0.003***	0.003***
	(145.437)	(148.440)	(70.428)	(70.808)	(192.098)	(192.697)	(69.931)	(71.968)	(40.913)	(41.170)
Total Jobs	9.680***	9.620***	0.614***	0.623***	0.038***	0.038***	0.027***	0.028***	0.012***	0.012***
	(133.681)	(133.974)	(162.661)	(160.858)	(105.211)	(105.706)	(116.806)	(120.798)	(69.787)	(68.692)
Observations	384,515	375,793	340,304	331,842	374,264	366,428	374,264	366,428	384,515	375,793
R-squared	0.390	0.436	0.329	0.337	0.598	0.610	0.239	0.273	0.072	0.078
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Job Industry FE		Yes		Yes		Yes		Yes		Yes

Table 15: Niche Sport Athletes, Non-niche Sport Athletes, and Non-athletes – Job Seniority and Wage

This table presents OLS regression results where measures of job seniority and wages are regressed onto variants of athlete status indicator variables. Each observation is an individual. Athlete (Niche Sport) is an indicator variable that equals one if the individual participated in a niche varsity sport during college and zero otherwise. Athlete (Non-niche Sport) is an indicator variable that equals one if the individual participated in a non-niche varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type. The outcome variable for columns 1 and 2 is the total job-year seniority summed over the individual's entire career. The outcome variable for columns 3 and 4 is the maximum job seniority that the individual achieved over his or her entire career. The outcome variable for columns 5 and 6 is the natural log of the total job-year estimated wages summed over the individual's entire career. The outcome variable for columns 7 and 8 is the natural log of the maximum estimated wage that the individual achieved over his or her entire career. The outcome variable for columns 9 and 10 is an indicator variable that equals one if the person held at least one C-suite job and zero otherwise. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Cumulative Seniority		Peak Seniority		Cumulative Wages		Peak Wages		C-suite Job	
Athlete (Niche Sport)	2.572	0.614	-0.060	-0.134	0.049***	0.038***	0.031***	0.022***	0.004	0.003
	(1.626)	(0.394)	(-0.541)	(-1.213)	(4.548)	(3.511)	(4.559)	(3.272)	(1.164)	(0.805)
Athlete (Niche Sport) x Male	10.855***	8.430***	0.343**	0.302**	-0.000	-0.000	0.014*	0.013	0.016***	0.015***
	(4.533)	(3.608)	(2.512)	(2.212)	(-0.005)	(-0.014)	(1.710)	(1.575)	(2.856)	(2.635)
Athlete (Not-niche Sport)	1.264	0.485	0.015	-0.007	0.035***	0.031***	0.004	0.002	0.002	0.001
	(0.996)	(0.390)	(0.172)	(-0.082)	(4.111)	(3.682)	(0.684)	(0.347)	(0.590)	(0.511)
Athlete (Non-niche Sport) x Male	6.714***	3.284*	0.092	0.040	0.003	-0.001	0.006	0.003	0.001	0.000
	(3.807)	(1.923)	(0.875)	(0.384)	(0.315)	(-0.119)	(0.941)	(0.417)	(0.330)	(0.007)
Male	17.174***	15.565***	0.942***	0.881***	0.107***	0.096***	0.075***	0.066***	0.036***	0.035***
	(42.738)	(39.876)	(39.744)	(36.797)	(46.996)	(42.380)	(51.692)	(46.369)	(40.266)	(38.130)
Reported Career Length	6.605***	6.548***	0.226***	0.231***	0.073***	0.073***	0.014***	0.014***	0.003***	0.003***
	(145.439)	(148.446)	(70.423)	(70.804)	(192.095)	(192.693)	(69.925)	(71.962)	(40.905)	(41.163)
Total Jobs	9.679***	9.619***	0.614***	0.623***	0.038***	0.038***	0.027***	0.028***	0.012***	0.012***
	(133.686)	(133.972)	(162.655)	(160.850)	(105.215)	(105.709)	(116.802)	(120.789)	(69.772)	(68.674)
Observations	384,515	375,793	340,304	331,842	374,264	366,428	374,264	366,428	384,515	375,793
R-squared	0.390	0.436	0.329	0.337	0.598	0.610	0.239	0.273	0.072	0.078
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Job Industry FE		Yes		Yes		Yes		Yes		Yes

Table 16: Diverse Sport Athletes, Non-diverse Sport Athletes, and Non-athletes – Job Seniority and Wage

This table presents OLS regression results where measures of job seniority and wages are regressed onto variants of athlete status indicator variables. Each observation is an individual. Athlete (Diverse Sport) is an indicator variable that equals one if the individual participated in a (socioeconomically) diverse varsity sport during college and zero otherwise. Athlete (Non-diverse Sport) is an indicator variable that equals one if the individual participated in a non-diverse varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type. The outcome variable for columns 1 and 2 is the total job-year seniority summed over the individual's entire career. The outcome variable for columns 3 and 4 is the maximum job seniority that the individual achieved over his or her entire career. The outcome variable for columns 5 and 6 is the natural log of the total job-year estimated wages summed over the individual's entire career. The outcome variable for columns 7 and 8 is the natural log of the maximum estimated wage that the individual achieved over his or her entire career. The outcome variable for columns 9 and 10 is an indicator variable that equals one if the person held at least one C-suite job and zero otherwise. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Cumulative Seniority		Peak Seniority		Cumulative Wages		Peak Wages		C-suite Job	
Athlete (Diverse Sport)	1.119	0.449	0.012	0.032	0.037**	0.033**	-0.001	-0.003	0.002	0.002
	(0.506)	(0.208)	(0.076)	(0.206)	(2.561)	(2.252)	(-0.146)	(-0.325)	(0.347)	(0.440)
Athlete (Diverse Sport) x Male	5.398**	2.229	0.093	0.010	-0.008	-0.012	0.009	0.005	0.004	0.002
	(1.961)	(0.835)	(0.543)	(0.056)	(-0.481)	(-0.720)	(0.846)	(0.502)	(0.606)	(0.323)
Athlete (Non-diverse Sport)	1.937*	0.562	-0.020	-0.078	0.041***	0.034***	0.018***	0.013***	0.003	0.002
	(1.735)	(0.512)	(-0.256)	(-1.000)	(5.446)	(4.513)	(3.791)	(2.705)	(1.146)	(0.783)
Athlete (Non-diverse Sport) x Male	9.650***	6.510***	0.218**	0.175*	0.007	0.005	0.011*	0.008	0.007*	0.006
	(5.679)	(3.944)	(2.244)	(1.799)	(0.790)	(0.535)	(1.849)	(1.457)	(1.877)	(1.563)
Male	17.171***	15.562***	0.942***	0.881***	0.107***	0.096***	0.075***	0.066***	0.036***	0.035***
	(42.732)	(39.868)	(39.741)	(36.794)	(46.993)	(42.378)	(51.679)	(46.355)	(40.258)	(38.119)
Reported Career Length	6.605***	6.548***	0.226***	0.231***	0.073***	0.073***	0.014***	0.014***	0.003***	0.003***
	(145.431)	(148.443)	(70.422)	(70.806)	(192.093)	(192.693)	(69.915)	(71.952)	(40.909)	(41.169)
Total Jobs	9.679***	9.620***	0.614***	0.623***	0.038***	0.038***	0.027***	0.028***	0.012***	0.012***
	(133.685)	(133.974)	(162.655)	(160.852)	(105.212)	(105.706)	(116.805)	(120.796)	(69.781)	(68.686)
Observations	384,515	375,793	340,304	331,842	374,264	366,428	374,264	366,428	384,515	375,793
R-squared	0.390	0.436	0.329	0.337	0.598	0.610	0.239	0.273	0.072	0.078
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Job Industry FE		Yes		Yes		Yes		Yes		Yes

Table 17: Low Academic Standard Sport Athletes, Other Athletes, and Non-athletes – Job Seniority and Wage

This table presents OLS regression results where measures of job seniority and wages are regressed onto variants of athlete status indicator variables. Each observation is an individual. Athlete (LAS) is an indicator variable that equals one if the individual participated in a low academic standard varsity sport during college and zero otherwise. Athlete (HAS) is an indicator variable that equals one if the individual participated in a higher academic standard varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type. The outcome variable for columns 1 and 2 is the total job-year seniority summed over the individual's entire career. The outcome variable for columns 3 and 4 is the maximum job seniority that the individual achieved over his or her entire career. The outcome variable for columns 5 and 6 is the natural log of the total job-year estimated wages summed over the individual's entire career. The outcome variable for columns 7 and 8 is the natural log of the maximum estimated wage that the individual achieved over his or her entire career. The outcome variable for columns 9 and 10 is an indicator variable that equals one if the person held at least one C-suite job and zero otherwise. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Cumulative Seniority		Peak Seniority		Cumulative Wages		Peak Wages		C-suite Job	
Athlete (LAS)	5.650*	4.135	0.420**	0.427**	0.065***	0.061***	0.020	0.020	0.008	0.006
	(1.785)	(1.346)	(2.012)	(2.038)	(3.179)	(3.042)	(1.576)	(1.550)	(1.128)	(0.856)
Athlete (LAS) x Male	7.730**	3.814	-0.117	-0.213	-0.019	-0.027	-0.004	-0.011	0.001	0.001
	(2.092)	(1.069)	(-0.521)	(-0.947)	(-0.891)	(-1.240)	(-0.280)	(-0.789)	(0.064)	(0.073)
Athlete (HAS)	1.247	0.055	-0.071	-0.120	0.037***	0.030***	0.014***	0.008*	0.002	0.002
	(1.184)	(0.053)	(-0.963)	(-1.620)	(5.198)	(4.213)	(2.962)	(1.853)	(0.812)	(0.621)
Athlete (HAS) x Male	6.958***	4.369***	0.177*	0.140	0.003	0.001	0.010*	0.008	0.006*	0.005
	(4.374)	(2.826)	(1.917)	(1.508)	(0.334)	(0.166)	(1.727)	(1.475)	(1.770)	(1.407)
Male	17.175***	15.565***	0.942***	0.881***	0.107***	0.096***	0.075***	0.066***	0.036***	0.035***
	(42.743)	(39.877)	(39.752)	(36.806)	(46.999)	(42.384)	(51.680)	(46.356)	(40.260)	(38.121)
Reported Career Length	6.606***	6.548***	0.226***	0.231***	0.073***	0.073***	0.014***	0.014***	0.003***	0.003***
	(145.464)	(148.471)	(70.443)	(70.825)	(192.117)	(192.718)	(69.935)	(71.977)	(40.920)	(41.176)
Total Jobs	9.682***	9.621***	0.614***	0.623***	0.038***	0.038***	0.027***	0.028***	0.012***	0.012***
	(133.712)	(133.999)	(162.699)	(160.901)	(105.235)	(105.729)	(116.813)	(120.805)	(69.787)	(68.690)
Observations	384,515	375,793	340,304	331,842	374,264	366,428	374,264	366,428	384,515	375,793
R-squared	0.390	0.436	0.329	0.337	0.598	0.610	0.239	0.273	0.072	0.078
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Job Industry FE		Yes		Yes		Yes		Yes		Yes

Table 18: Differences in Reported Skills by Gender and Sport Type

This table presents, for ten selected reported skill, the means, differences, and p-values from two-tailed t-tests of difference in means between gender and sport type groups in the sample. Each sport can be classified as either team or individual, niche or non-niche, (socioeconomically) diverse or non-diverse, and low academic standard (LAS) or higher academic standard (HAS). Refer to Table 3 for how sports are classified into each sport type. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

Panel A	**Male**	**Female**	**Difference**	**p-value**
Management Skill	0.278	0.254	0.023	<0.001***
Leadership Skill	0.206	0.217	-0.011	<0.001***
Strategic Planning Skill	0.145	0.120	0.026	<0.001***
Team Leadership Skill	0.078	0.062	0.017	<0.001***
Project Management Skill	0.071	0.062	0.008	<0.001***
Research Skill	0.273	0.379	-0.105	<0.001***
Operations Skill	0.125	0.106	0.018	<0.001***
Teaching Skill	0.101	0.160	-0.059	<0.001***
Data Analysis Skill	0.120	0.144	-0.024	<0.001***
Editing Skill	0.069	0.138	-0.069	<0.001***

Panel B	**Athlete**	**Non-athlete**	**Difference**	**p-value**
Management Skill	0.305	0.264	0.041	<0.001***
Leadership Skill	0.242	0.209	0.034	<0.001***
Strategic Planning Skill	0.161	0.131	0.030	<0.001***
Team Leadership Skill	0.083	0.069	0.013	<0.001***
Project Management Skill	0.064	0.067	-0.003	0.069*
Research Skill	0.295	0.325	-0.030	<0.001***
Operations Skill	0.130	0.115	0.015	<0.001***
Teaching Skill	0.101	0.131	-0.029	<0.001***
Data Analysis Skill	0.131	0.131	-0.001	0.695
Editing Skill	0.077	0.103	-0.026	<0.001***

Panel C	**Team**	**Individual**	**Difference**	**p-value**
Management Skill	0.306	0.305	0.002	0.757
Leadership Skill	0.247	0.227	0.020	0.001***
Strategic Planning Skill	0.165	0.152	0.012	0.014**
Team Leadership Skill	0.084	0.079	0.005	0.172
Project Management Skill	0.064	0.064	0.000	0.948
Research Skill	0.278	0.343	-0.065	<0.001***
Operations Skill	0.131	0.127	0.004	0.367
Teaching Skill	0.095	0.122	-0.027	<0.001***
Data Analysis Skill	0.125	0.145	-0.020	<0.001***
Editing Skill	0.072	0.088	-0.017	<0.001***

Panel D	**Niche**	**Non-niche**	**Difference**	**p-value**
Management Skill	0.284	0.316	-0.032	<0.001***
Leadership Skill	0.214	0.257	-0.044	<0.001***
Strategic Planning Skill	0.146	0.169	-0.023	<0.001***
Team Leadership Skill	0.069	0.090	-0.022	<0.001***
Project Management Skill	0.057	0.068	-0.011	<0.001***
Research Skill	0.310	0.287	0.023	<0.001***
Operations Skill	0.119	0.136	-0.017	<0.001***
Teaching Skill	0.104	0.099	0.005	0.187
Data Analysis Skill	0.127	0.132	-0.005	0.199
Editing Skill	0.085	0.072	0.013	<0.001***

Panel E	Diverse	Non-diverse	Difference	p-value
Management Skill	0.325	0.265	0.059	<0.001***
Leadership Skill	0.263	0.210	0.053	<0.001***
Strategic Planning Skill	0.179	0.132	0.047	<0.001***
Team Leadership Skill	0.093	0.070	0.023	<0.001***
Project Management Skill	0.068	0.067	0.002	0.481
Research Skill	0.255	0.324	-0.069	<0.001***
Operations Skill	0.136	0.116	0.020	<0.001***
Teaching Skill	0.089	0.129	-0.041	<0.001***
Data Analysis Skill	0.122	0.132	-0.010	0.003***
Editing Skill	0.062	0.102	-0.040	<0.001***

Panel F	LAS	HAS	Difference	p-value
Management Skill	0.345	0.265	0.080	<0.001***
Leadership Skill	0.274	0.210	0.064	<0.001***
Strategic Planning Skill	0.199	0.132	0.067	<0.001***
Team Leadership Skill	0.098	0.070	0.028	<0.001***
Project Management Skill	0.064	0.067	-0.002	0.415
Research Skill	0.218	0.324	-0.106	<0.001***
Operations Skill	0.136	0.116	0.020	<0.001***
Teaching Skill	0.074	0.129	-0.056	<0.001***
Data Analysis Skill	0.098	0.132	-0.034	<0.001***
Editing Skill	0.048	0.102	-0.054	<0.001***

Table 19A: Athletes and Non-athletes – Reported Management Skills

This table presents OLS regression results where reported management skill indicator variables are regressed onto athlete status indicator variable. Each observation is an individual. Athlete is an indicator variable that equals one if the individual participated in a varsity college sport and zero otherwise. The outcome variable for columns 1 and 2 is an indicator variable that equals one if the individual reported having the "Management" skill on their profile and zero otherwise. The remaining outcome variables follow the same logic. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Management		Leadership		Strategic Planning		Team Leadership		Project Management	
Athlete	0.037***	0.037***	0.049***	0.049***	0.021***	0.020***	0.024***	0.024***	0.008***	0.009***
	(8.035)	(8.151)	(11.022)	(11.135)	(5.954)	(5.600)	(8.501)	(8.475)	(3.036)	(3.480)
Athlete x Male	0.012**	-0.001	-0.001	-0.007	0.009**	0.002	-0.013***	-0.012***	-0.013***	-0.011***
	(2.097)	(-0.257)	(-0.268)	(-1.247)	(1.985)	(0.481)	(-3.663)	(-3.601)	(-4.181)	(-3.587)
Male	0.024***	0.014***	0.002	0.003**	0.008***	0.004***	0.018***	0.008***	0.010***	-0.000
	(16.364)	(9.422)	(1.216)	(2.398)	(7.002)	(3.556)	(20.804)	(9.280)	(11.855)	(-0.062)
Career Length	-0.004***	-0.003***	-0.002***	-0.001***	-0.001***	-0.000***	-0.002***	-0.002***	-0.002***	-0.001***
	(-20.099)	(-16.242)	(-12.099)	(-8.503)	(-6.676)	(-3.134)	(-18.596)	(-14.936)	(-15.004)	(-12.100)
Total Jobs	0.025***	0.023***	0.021***	0.019***	0.012***	0.010***	0.009***	0.008***	0.008***	0.007***
	(106.600)	(98.095)	(96.464)	(87.207)	(64.219)	(54.447)	(60.456)	(53.341)	(55.401)	(48.131)
Observations	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515
R-squared	0.111	0.163	0.102	0.136	0.071	0.107	0.035	0.070	0.031	0.060
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE		Yes		Yes		Yes		Yes		Yes

Table 19B: Athletes and Non-athletes – Reported Specialist Skills

This table presents OLS regression results where reported specialist skill indicator variables are regressed onto athlete status indicator variable. Each observation is an individual. Athlete is an indicator variable that equals one if the individual participated in a varsity college sport and zero otherwise. The outcome variable for columns 1 and 2 is an indicator variable that equals one if the individual reported having the "Research" skill on their profile and zero otherwise. The remaining outcome variables follow the same logic. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Research		Operations		Teaching		Data Analysis		Editing	
Athlete	-0.003	0.003	0.023***	0.023***	-0.031***	-0.023***	0.010***	0.009**	-0.022***	-0.014***
	(-0.564)	(0.684)	(6.595)	(6.639)	(-8.125)	(-6.132)	(2.620)	(2.477)	(-6.140)	(-4.076)
Athlete x Male	-0.025***	-0.014***	-0.012***	-0.016***	0.003	0.011***	-0.012***	-0.007	-0.008**	-0.009**
	(-4.696)	(-2.602)	(-2.925)	(-3.906)	(0.687)	(2.765)	(-2.719)	(-1.632)	(-1.978)	(-2.322)
Male	-0.055***	-0.043***	0.029***	0.021***	-0.050***	-0.032***	0.011***	0.001	-0.061***	-0.037***
	(-37.472)	(-28.683)	(26.367)	(18.731)	(-43.336)	(-27.744)	(9.392)	(0.814)	(-58.229)	(-35.522)
Career Length	-0.004***	-0.003***	-0.003***	-0.002***	0.000	0.000	-0.001***	-0.001***	-0.001***	-0.001***
	(-18.697)	(-18.950)	(-19.658)	(-16.653)	(1.287)	(0.118)	(-7.529)	(-5.360)	(-7.857)	(-8.338)
Total Jobs	0.023***	0.023***	0.017***	0.016***	0.012***	0.011***	0.007***	0.007***	0.012***	0.011***
	(100.878)	(98.767)	(91.420)	(85.604)	(63.877)	(62.439)	(45.811)	(44.134)	(70.134)	(63.823)
Observations	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515
R-squared	0.221	0.247	0.056	0.079	0.068	0.121	0.120	0.143	0.074	0.136
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE		Yes		Yes		Yes		Yes		Yes

Table 20A: Team Sport Athletes, Individual Sport Athletes, and Non-athletes – Reported Management Skills

This table presents OLS regression results where reported management skill indicator variables are regressed onto variants of athlete status indicator variables. Each observation is an individual. Team Sport Athlete is an indicator variable that equals one if the individual participated in a team varsity sport during college and zero otherwise. Individual Sport Athlete is an indicator variable that equals one if the individual participated in an individual varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type. The outcome variable for columns 1 and 2 is an indicator variable that equals one if the individual reported having the "Management" skill on their profile and zero otherwise. The remaining outcome variables follow the same logic. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Management		Leadership		Strategic Planning		Team Leadership		Project Management	
Team Sport Athlete	0.042***	0.038***	0.060***	0.057***	0.024***	0.020***	0.027***	0.026***	0.008**	0.008***
	(7.658)	(7.093)	(11.315)	(10.918)	(5.576)	(4.838)	(7.732)	(7.508)	(2.490)	(2.663)
Team Sport Athlete x Male	0.009	-0.004	-0.007	-0.012**	0.010**	0.003	-0.014***	-0.014***	-0.013***	-0.011***
	(1.387)	(-0.588)	(-1.205)	(-1.971)	(1.969)	(0.683)	(-3.510)	(-3.437)	(-3.538)	(-2.978)
Individual Sport Athlete	0.031***	0.040***	0.019**	0.026***	0.014**	0.017**	0.016***	0.017***	0.006	0.009*
	(3.448)	(4.566)	(2.280)	(3.138)	(2.012)	(2.527)	(2.932)	(3.272)	(1.187)	(1.674)
Individual Sport Athlete x Male	0.008	-0.001	0.005	0.002	-0.000	-0.004	-0.008	-0.007	-0.012*	-0.010
	(0.723)	(-0.074)	(0.483)	(0.196)	(-0.053)	(-0.457)	(-1.175)	(-1.115)	(-1.904)	(-1.607)
Male	0.024***	0.014***	0.002	0.003**	0.008***	0.004***	0.018***	0.008***	0.010***	-0.000
	(16.407)	(9.446)	(1.197)	(2.373)	(6.985)	(3.527)	(20.755)	(9.232)	(11.827)	(-0.100)
Career Length	-0.004***	-0.003***	-0.002***	-0.001***	-0.001***	-0.000***	-0.002***	-0.002***	-0.002***	-0.001***
	(-20.101)	(-16.244)	(-12.089)	(-8.495)	(-6.675)	(-3.134)	(-18.588)	(-14.928)	(-14.999)	(-12.094)
Total Jobs	0.025***	0.023***	0.021***	0.019***	0.012***	0.010***	0.009***	0.008***	0.008***	0.007***
	(106.604)	(98.088)	(96.485)	(87.220)	(64.232)	(54.453)	(60.458)	(53.340)	(55.400)	(48.126)
Observations	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515
R-squared	0.111	0.163	0.102	0.136	0.071	0.107	0.035	0.070	0.031	0.060
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE		Yes		Yes		Yes		Yes		Yes

Table 20B: Team Sport Athletes, Individual Sport Athletes, and Non-athletes – Reported Specialist Skills

This table presents OLS regression results where reported specialist skill indicator variables are regressed onto variants of athlete status indicator variables. Each observation is an individual. Team Sport Athlete is an indicator variable that equals one if the individual participated in a team varsity sport during college and zero otherwise. Individual Sport Athlete is an indicator variable that equals one if the individual participated in an individual varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type. The outcome variable for columns 1 and 2 is an indicator variable that equals one if the individual reported having the "Research" skill on their profile and zero otherwise. The remaining outcome variables follow the same logic. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Research		Operations		Teaching		Data Analysis		Editing	
Team Sport Athlete	-0.010*	-0.003	0.026***	0.025***	-0.033***	-0.024***	0.010**	0.009**	-0.021***	-0.013***
	(-1.775)	(-0.609)	(6.287)	(5.937)	(-7.428)	(-5.642)	(2.150)	(2.066)	(-4.924)	(-3.199)
Team Sport Athlete x Male	-0.025***	-0.012**	-0.014***	-0.018***	0.003	0.013***	-0.014***	-0.009*	-0.010**	-0.011**
	(-3.987)	(-1.992)	(-2.796)	(-3.578)	(0.630)	(2.682)	(-2.716)	(-1.731)	(-2.155)	(-2.387)
Individual Sport Athlete	0.020**	0.023***	0.013**	0.018***	-0.020***	-0.013*	0.011	0.011	-0.023***	-0.016**
	(2.284)	(2.657)	(2.009)	(2.628)	(-2.698)	(-1.841)	(1.498)	(1.451)	(-3.292)	(-2.361)
Individual Sport Athlete x Male	-0.021**	-0.016	-0.009	-0.012	0.002	0.005	-0.003	0.000	-0.003	-0.004
	(-2.007)	(-1.494)	(-1.108)	(-1.435)	(0.263)	(0.576)	(-0.296)	(0.004)	(-0.376)	(-0.481)
Male	-0.055***	-0.043***	0.029***	0.021***	-0.050***	-0.032***	0.011***	0.001	-0.061***	-0.037***
	(-37.464)	(-28.670)	(26.330)	(18.682)	(-43.302)	(-27.701)	(9.358)	(0.785)	(-58.229)	(-35.529)
Career Length	-0.004***	-0.003***	-0.003***	-0.002***	0.000	0.000	-0.001***	-0.001***	-0.001***	-0.001***
	(-18.696)	(-18.949)	(-19.656)	(-16.651)	(1.282)	(0.112)	(-7.531)	(-5.362)	(-7.855)	(-8.335)
Total Jobs	0.023***	0.023***	0.017***	0.016***	0.012***	0.011***	0.007***	0.007***	0.012***	0.011***
	(100.851)	(98.744)	(91.428)	(85.605)	(63.869)	(62.435)	(45.803)	(44.125)	(70.135)	(63.823)
Observations	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515
R-squared	0.221	0.247	0.056	0.079	0.068	0.121	0.120	0.143	0.074	0.136
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE		Yes		Yes		Yes		Yes		Yes

Table 21A: Niche Sport Athletes, Non-niche Sport Athletes, and Non-athletes – Reported Management Skills

This table presents OLS regression results where reported management skill indicator variables are regressed onto variants of athlete status indicator variables. Each observation is an individual. Athlete (Niche Sport) is an indicator variable that equals one if the individual participated in a niche varsity sport during college and zero otherwise. Athlete (Non-niche Sport) is an indicator variable that equals one if the individual participated in a non-niche varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type. The outcome variable for columns 1 and 2 is an indicator variable that equals one if the individual reported having the "Management" skill on their profile and zero otherwise. The remaining outcome variables follow the same logic. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Management		Leadership		Strategic Planning		Team Leadership		Project Management	
Athlete (Niche Sport)	0.022***	0.026***	0.017**	0.021***	0.011**	0.012**	0.009**	0.011***	0.000	0.002
	(3.051)	(3.709)	(2.504)	(3.157)	(2.044)	(2.252)	(2.156)	(2.577)	(0.079)	(0.633)
Athlete (Niche Sport) x Male	0.009	0.001	0.004	0.002	0.005	0.001	-0.008	-0.007	-0.010**	-0.008
	(1.076)	(0.116)	(0.503)	(0.262)	(0.658)	(0.147)	(-1.491)	(-1.286)	(-2.096)	(-1.609)
Athlete (Non-niche Sport)	0.047***	0.044***	0.069***	0.066***	0.028***	0.025***	0.034***	0.033***	0.013***	0.013***
	(7.929)	(7.565)	(12.091)	(11.749)	(5.996)	(5.393)	(8.928)	(8.607)	(3.714)	(3.876)
Athlete (Non-niche Sport) x Male	0.010	-0.004	-0.009	-0.015**	0.009*	0.001	-0.018***	-0.017***	-0.016***	-0.014***
	(1.480)	(-0.615)	(-1.350)	(-2.252)	(1.648)	(0.263)	(-3.879)	(-3.853)	(-3.924)	(-3.476)
Male	0.024***	0.014***	0.002	0.003**	0.008***	0.004***	0.018***	0.008***	0.010***	-0.000
	(16.360)	(9.418)	(1.211)	(2.390)	(6.998)	(3.551)	(20.801)	(9.275)	(11.854)	(-0.064)
Career Length	-0.004***	-0.003***	-0.002***	-0.001***	-0.001***	-0.000***	-0.002***	-0.002***	-0.002***	-0.001***
	(-20.095)	(-16.240)	(-12.088)	(-8.493)	(-6.672)	(-3.131)	(-18.590)	(-14.931)	(-15.001)	(-12.097)
Total Jobs	0.025***	0.023***	0.021***	0.019***	0.012***	0.010***	0.009***	0.008***	0.008***	0.007***
	(106.620)	(98.106)	(96.501)	(87.233)	(64.236)	(54.457)	(60.477)	(53.356)	(55.410)	(48.136)
Observations	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515
R-squared	0.111	0.163	0.102	0.136	0.071	0.107	0.035	0.070	0.031	0.060
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE		Yes		Yes		Yes		Yes		Yes

Table 21B: Niche Sport Athletes, Non-niche Sport Athletes, and Non-athletes – Reported Specialist Skills

This table presents OLS regression results where reported specialist skill indicator variables are regressed onto variants of athlete status indicator variables. Each observation is an individual. Athlete (Niche Sport) is an indicator variable that equals one if the individual participated in a niche varsity sport during college and zero otherwise. Athlete (Non-niche Sport) is an indicator variable that equals one if the individual participated in a non-niche varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type. The outcome variable for columns 1 and 2 is an indicator variable that equals one if the individual reported having the "Research" skill on their profile and zero otherwise. The remaining outcome variables follow the same logic. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Research		Operations		Teaching		Data Analysis		Editing	
Athlete (Niche Sport)	-0.010	-0.006	0.011**	0.013**	-0.040***	-0.032***	-0.005	-0.004	-0.020***	-0.017***
	(-1.413)	(-0.804)	(2.009)	(2.356)	(-6.780)	(-5.505)	(-0.843)	(-0.604)	(-3.480)	(-2.911)
Athlete (Niche Sport) x Male	-0.005	0.004	-0.008	-0.010	0.013*	0.018***	0.002	0.005	-0.008	-0.007
	(-0.597)	(0.499)	(-1.157)	(-1.449)	(1.907)	(2.818)	(0.218)	(0.786)	(-1.206)	(-1.175)
Athlete (Non-niche Sport)	0.002	0.009	0.031***	0.030***	-0.025***	-0.017***	0.020***	0.018***	-0.024***	-0.013***
	(0.385)	(1.515)	(6.833)	(6.630)	(-5.205)	(-3.634)	(3.961)	(3.595)	(-5.204)	(-2.971)
Athlete (Non-niche Sport) x Male	-0.036***	-0.024***	-0.017***	-0.021***	-0.003	0.007	-0.021***	-0.015***	-0.008	-0.010**
	(-5.383)	(-3.605)	(-3.088)	(-4.006)	(-0.598)	(1.298)	(-3.722)	(-2.728)	(-1.543)	(-2.098)
Male	-0.055***	-0.043***	0.029***	0.021***	-0.050***	-0.032***	0.011***	0.001	-0.061***	-0.037***
	(-37.469)	(-28.678)	(26.365)	(18.729)	(-43.335)	(-27.745)	(9.392)	(0.814)	(-58.228)	(-35.522)
Career Length	-0.004***	-0.003***	-0.003***	-0.002***	0.000	0.000	-0.001***	-0.001***	-0.001***	-0.001***
	(-18.697)	(-18.950)	(-19.653)	(-16.649)	(1.289)	(0.121)	(-7.524)	(-5.356)	(-7.858)	(-8.337)
Total Jobs	0.023***	0.023***	0.017***	0.016***	0.012***	0.011***	0.007***	0.007***	0.012***	0.011***
	(100.866)	(98.756)	(91.431)	(85.610)	(63.876)	(62.440)	(45.814)	(44.133)	(70.131)	(63.823)
Observations	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515
R-squared	0.221	0.247	0.056	0.079	0.068	0.121	0.120	0.143	0.074	0.136
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE		Yes		Yes		Yes		Yes		Yes

Table 22A: Diverse Sport Athletes, Non-diverse Sport Athletes, and Non-athletes – Reported Management Skills

This table presents OLS regression results where reported management skill indicator variables are regressed onto variants of athlete status indicator variables. Each observation is an individual. Athlete (Diverse Sport) is an indicator variable that equals one if the individual participated in a (socioeconomically) diverse varsity sport during college and zero otherwise. Athlete (Non-diverse Sport) is an indicator variable that equals one if the individual participated in a non-diverse varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type. The outcome variable for columns 1 and 2 is an indicator variable that equals one if the individual reported having the "Management" skill on their profile and zero otherwise. The remaining outcome variables follow the same logic. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Management		Leadership		Strategic Planning		Team Leadership		Project Management	
Athlete (Diverse Sport)	0.073***	0.066***	0.097***	0.091***	0.053***	0.047***	0.057***	0.055***	0.021***	0.021***
	(7.160)	(6.585)	(9.695)	(9.226)	(6.289)	(5.651)	(7.829)	(7.609)	(3.365)	(3.446)
Athlete (Diverse Sport) x Male	-0.008	-0.020*	-0.026**	-0.030***	-0.011	-0.017*	-0.040***	-0.039***	-0.023***	-0.021***
	(-0.733)	(-1.798)	(-2.343)	(-2.764)	(-1.209)	(-1.830)	(-5.070)	(-4.985)	(-3.397)	(-3.103)
Athlete (Non-diverse Sport)	0.028***	0.030***	0.037***	0.039***	0.013***	0.013***	0.016***	0.016***	0.005*	0.006**
	(5.489)	(5.906)	(7.555)	(7.921)	(3.430)	(3.365)	(5.341)	(5.433)	(1.671)	(2.133)
Athlete (Non-diverse Sport) x Male	0.011*	-0.000	-0.003	-0.007	0.010**	0.004	-0.007*	-0.007*	-0.012***	-0.010***
	(1.783)	(-0.024)	(-0.496)	(-1.117)	(2.006)	(0.857)	(-1.925)	(-1.807)	(-3.282)	(-2.712)
Male	0.024***	0.014***	0.002	0.003**	0.008***	0.004***	0.018***	0.008***	0.010***	-0.000
	(16.370)	(9.426)	(1.225)	(2.405)	(7.008)	(3.561)	(20.810)	(9.288)	(11.858)	(-0.059)
Career Length	-0.004***	-0.003***	-0.002***	-0.001***	-0.001***	-0.000***	-0.002***	-0.002***	-0.002***	-0.001***
	(-20.080)	(-16.227)	(-12.066)	(-8.475)	(-6.655)	(-3.116)	(-18.571)	(-14.912)	(-14.994)	(-12.090)
Total Jobs	0.025***	0.023***	0.021***	0.019***	0.012***	0.010***	0.009***	0.008***	0.008***	0.007***
	(106.620)	(98.111)	(96.492)	(87.233)	(64.232)	(54.459)	(60.465)	(53.352)	(55.407)	(48.137)
Observations	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515
R-squared	0.111	0.163	0.102	0.136	0.071	0.107	0.035	0.070	0.031	0.060
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE		Yes		Yes		Yes		Yes		Yes

Table 22B: Diverse Sport Athletes, Non-diverse Sport Athletes, and Non-athletes – Reported Specialist Skills

This table presents OLS regression results where reported specialist skill indicator variables are regressed onto variants of athlete status indicator variables. Each observation is an individual. Athlete (Diverse Sport) is an indicator variable that equals one if the individual participated in a (socioeconomically) diverse varsity sport during college and zero otherwise. Athlete (Non-diverse Sport) is an indicator variable that equals one if the individual participated in a non-diverse varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type. The outcome variable for columns 1 and 2 is an indicator variable that equals one if the individual reported having the "Research" skill on their profile and zero otherwise. The remaining outcome variables follow the same logic. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Research		Operations		Teaching		Data Analysis		Editing	
Athlete (Diverse Sport)	-0.005	0.001	0.043***	0.040***	-0.018**	-0.009	0.030***	0.026***	-0.017**	-0.006
	(-0.484)	(0.073)	(5.305)	(5.023)	(-2.138)	(-1.146)	(3.515)	(3.114)	(-2.152)	(-0.796)
Athlete (Diverse Sport) x Male	-0.033***	-0.018*	-0.027***	-0.031***	-0.011	0.000	-0.033***	-0.025***	-0.015*	-0.018**
	(-3.019)	(-1.657)	(-3.046)	(-3.500)	(-1.188)	(0.002)	(-3.628)	(-2.733)	(-1.837)	(-2.244)
Athlete (Non-diverse Sport)	-0.002	0.004	0.019***	0.019***	-0.034***	-0.026***	0.005	0.005	-0.024***	-0.017***
	(-0.393)	(0.735)	(4.744)	(4.942)	(-8.102)	(-6.353)	(1.211)	(1.241)	(-5.850)	(-4.196)
Athlete (Non-diverse Sport) x Male	-0.020***	-0.011*	-0.010**	-0.014***	0.006	0.014***	-0.006	-0.002	-0.005	-0.006
	(-3.286)	(-1.771)	(-2.126)	(-2.835)	(1.328)	(2.910)	(-1.240)	(-0.485)	(-1.188)	(-1.453)
Male	-0.055***	-0.043***	0.029***	0.021***	-0.050***	-0.032***	0.011***	0.001	-0.061***	-0.037***
	(-37.474)	(-28.683)	(26.370)	(18.734)	(-43.334)	(-27.741)	(9.394)	(0.817)	(-58.229)	(-35.521)
Career Length	-0.004***	-0.003***	-0.003***	-0.002***	0.000	0.000	-0.001***	-0.001***	-0.001***	-0.001***
	(-18.701)	(-18.954)	(-19.643)	(-16.641)	(1.296)	(0.127)	(-7.514)	(-5.348)	(-7.854)	(-8.333)
Total Jobs	0.023***	0.023***	0.017***	0.016***	0.012***	0.011***	0.007***	0.007***	0.012***	0.011***
	(100.870)	(98.761)	(91.428)	(85.609)	(63.876)	(62.442)	(45.812)	(44.136)	(70.132)	(63.823)
Observations	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515
R-squared	0.221	0.247	0.056	0.079	0.068	0.121	0.120	0.143	0.074	0.136
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE		Yes		Yes		Yes		Yes		Yes

Table 23A: Low Academic Standard Sport Athletes, Other Athletes, and Non-athletes – Reported Management Skills

This table presents OLS regression results where reported management skill indicator variables are regressed onto variants of athlete status indicator variables. Each observation is an individual. Athlete (LAS) is an indicator variable that equals one if the individual participated in a low academic standard varsity sport during college and zero otherwise. Athlete (HAS) is an indicator variable that equals one if the individual participated in a higher academic standard varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type. The outcome variable for columns 1 and 2 is an indicator variable that equals one if the individual reported having the "Management" skill on their profile and zero otherwise. The remaining outcome variables follow the same logic. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Management		Leadership		Strategic Planning		Team Leadership		Project Management	
Athlete (LAS)	0.094***	0.074***	0.130***	0.115***	0.073***	0.060***	0.061***	0.054***	0.022***	0.019**
	(6.770)	(5.424)	(9.676)	(8.689)	(6.171)	(5.093)	(6.263)	(5.607)	(2.591)	(2.303)
Athlete (LAS) x Male	-0.010	-0.017	-0.049***	-0.048***	-0.020	-0.023*	-0.041***	-0.035***	-0.029***	-0.023***
	(-0.702)	(-1.178)	(-3.366)	(-3.368)	(-1.570)	(-1.819)	(-3.887)	(-3.431)	(-3.233)	(-2.627)
Athlete (HAS)	0.030***	0.032***	0.038***	0.040***	0.014***	0.014***	0.020***	0.020***	0.006**	0.008***
	(6.074)	(6.716)	(8.178)	(8.687)	(3.869)	(3.941)	(6.588)	(6.842)	(2.261)	(2.852)
Athlete (HAS) x Male	0.005	-0.005	-0.005	-0.008	0.006	0.001	-0.012***	-0.011***	-0.011***	-0.009***
	(0.780)	(-0.870)	(-0.856)	(-1.421)	(1.260)	(0.256)	(-3.123)	(-3.085)	(-3.109)	(-2.690)
Male	0.024***	0.014***	0.002	0.003**	0.008***	0.004***	0.018***	0.008***	0.010***	-0.000
	(16.397)	(9.443)	(1.258)	(2.433)	(7.035)	(3.582)	(20.827)	(9.302)	(11.859)	(-0.059)
Career Length	-0.004***	-0.003***	-0.002***	-0.001***	-0.001***	-0.000***	-0.002***	-0.002***	-0.002***	-0.001***
	(-20.066)	(-16.220)	(-12.041)	(-8.456)	(-6.637)	(-3.104)	(-18.559)	(-14.905)	(-14.990)	(-12.090)
Total Jobs	0.025***	0.023***	0.021***	0.019***	0.012***	0.010***	0.009***	0.008***	0.008***	0.007***
	(106.689)	(98.151)	(96.561)	(87.283)	(64.290)	(54.499)	(60.495)	(53.375)	(55.404)	(48.131)
Observations	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515
R-squared	0.111	0.163	0.102	0.136	0.071	0.107	0.035	0.070	0.031	0.060
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE		Yes		Yes		Yes		Yes		Yes

Table 23B: Low Academic Standard Sport Athletes, Other Athletes, and Non-athletes – Reported Specialist Skills

This table presents OLS regression results where reported specialist skill indicator variables are regressed onto variants of athlete status indicator variables. Each observation is an individual. Athlete (LAS) is an indicator variable that equals one if the individual participated in a low academic standard varsity sport during college and zero otherwise. Athlete (HAS) is an indicator variable that equals one if the individual participated in a higher academic standard varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type. The outcome variable for columns 1 and 2 is an indicator variable that equals one if the individual reported having the "Research" skill on their profile and zero otherwise. The remaining outcome variables follow the same logic. Refer to the appendix for control variable definitions. Heteroskedasticity-robust standard errors are used to calculate t-statistics, which are reported in parentheses. ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Research		Operations		Teaching		Data Analysis		Editing	
Athlete (LAS)	-0.025*	-0.013	0.053***	0.044***	-0.025**	-0.013	0.001	-0.002	-0.043***	-0.029***
	(-1.897)	(-0.957)	(4.803)	(4.056)	(-2.330)	(-1.231)	(0.101)	(-0.184)	(-4.496)	(-3.112)
Athlete (LAS) x Male	-0.032**	-0.019	-0.036***	-0.037***	-0.014	-0.002	-0.015	-0.005	0.005	-0.000
	(-2.297)	(-1.357)	(-3.119)	(-3.210)	(-1.225)	(-0.150)	(-1.335)	(-0.479)	(0.539)	(-0.011)
Athlete (HAS)	0.000	0.005	0.020***	0.021***	-0.032***	-0.024***	0.011***	0.011***	-0.020***	-0.013***
	(0.099)	(1.083)	(5.242)	(5.587)	(-7.845)	(-6.108)	(2.751)	(2.692)	(-5.028)	(-3.296)
Athlete (HAS) x Male	-0.016***	-0.007	-0.011**	-0.014***	0.008*	0.014***	-0.008*	-0.005	-0.007*	-0.008**
	(-2.679)	(-1.252)	(-2.312)	(-2.980)	(1.800)	(3.112)	(-1.705)	(-0.976)	(-1.715)	(-2.013)
Male	-0.055***	-0.043***	0.029***	0.021***	-0.050***	-0.032***	0.011***	0.001	-0.061***	-0.037***
	(-37.495)	(-28.697)	(26.380)	(18.739)	(-43.342)	(-27.741)	(9.380)	(0.803)	(-58.242)	(-35.533)
Career Length	-0.004***	-0.003***	-0.003***	-0.002***	0.000	0.000	-0.001***	-0.001***	-0.001***	-0.001***
	(-18.713)	(-18.961)	(-19.632)	(-16.635)	(1.292)	(0.127)	(-7.539)	(-5.372)	(-7.878)	(-8.352)
Total Jobs	0.023***	0.023***	0.017***	0.016***	0.012***	0.011***	0.007***	0.007***	0.012***	0.011***
	(100.828)	(98.728)	(91.446)	(85.615)	(63.860)	(62.438)	(45.785)	(44.107)	(70.110)	(63.802)
Observations	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515	384,515
R-squared	0.221	0.247	0.056	0.079	0.068	0.121	0.120	0.143	0.074	0.136
Graduate Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE		Yes		Yes		Yes		Yes		Yes

Appendix A – Regression Variable Definitions

Athlete – An indicator variable that equals one if the individual participated in a college varsity sport and zero otherwise.

Individual Sport Athlete – An indicator variable that equals one if the individual participated in an individual varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type.

Team Sport Athlete – An indicator variable that equals one if the individual participated in a team varsity sport during college and zero otherwise. Among athletes, team sports make up the set that is the complement of individual sports. Refer to Table 3 for how sports are classified into each sport type.

Athlete (Niche Sport) - An indicator variable that equals one if the individual participated in a niche varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type.

Athlete (Non-niche Sport) – An indicator variable that equals one if the individual participated in a non-niche varsity sport during college and zero otherwise. Among athletes, non-niche sports make up the set that is the complement of niche sports. Refer to Table 3 for how sports are classified into each sport type.

Athlete (Diverse Sport) – An indicator variable that equals one if the individual participated in a (socioeconomically) diverse varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type.

Athlete (Non-diverse Sport) - An indicator variable that equals one if the individual participated in a non-diverse varsity sport during college and zero otherwise. Among athletes, non-diverse sports make up the set that is the complement of diverse sports. Refer to Table 3 for how sports are classified into each sport type.

Athlete (Low Academic Standard Sport) or Athlete (LAS) – An indicator variable that equals one if the individual participated in a low academic standard varsity sport during college and zero otherwise. Refer to Table 3 for how sports are classified into each sport type.

Athlete (High Academic Standard Sport) or Athlete (HAS) – An indicator variable that equals one if the individual participated in a higher academic standard varsity sport during college and zero otherwise.

Among athletes, HAS sports make up the set that is the complement of LAS sports. Refer to Table 3 for how sports are classified into each sport type.

Male – An indicator variable that equals one if the person is male and zero if the person is female.

MBA – An indicator variable that equals one if the individual holds an MBA degree and zero otherwise.

Elite MBA – An indicator variable that equals one if the individual holds an MBA degree from one of the elite schools and zero otherwise. Elite schools include Harvard University, Stanford University, the University of Pennsylvania, the University of Chicago, and Northwestern University.

STEM Graduate Degree – An indicator variable that equals one if the individual holds a STEM graduate degree and zero otherwise.

J.D. – An indicator variable that equals one if the individual holds a Doctor of Jurisprudence (J.D.) degree and zero otherwise.

M.D. – An indicator variable that equals one if the individual holds a Doctor of Medicine (M.D.) degree and zero otherwise.

Ph.D. – An indicator variable that equals one if the individual holds a Doctor of Philosophy (Ph.D.) degree and zero otherwise.

Cumulative Seniority – The total job-year seniority summed over the individual's entire career.

Peak Seniority - The maximum job seniority that the individual achieved over his or her entire career.

Cumulative Wages – The total job-year estimated wages summed over the individual's entire career. In summary statistic tables, this variable is presented in thousands of USD, adjusted for inflation using 2020 as the base year. In regressions, the natural log of this variable is used as the outcome variable.

Peak Wages – The maximum estimated wage that the individual achieved over his or her entire career. In summary statistic tables, this variable is presented in thousands of USD, adjusted for inflation using 2020 as the base year. In regressions, the natural log of this variable is used as the outcome variable.

Reported Career Length – The reported career length, in years, of the individual, calculated as the number of years between the individual's first job start year and most recent job's end year. If the individual did not provide his or her current job's end year, then 2021 is used as the end year.

Total Jobs – The total number of jobs that the individual reported on his or her Lightcast profile.

Finance Job – An indicator variable that equals one if the person held at least one finance job and zero otherwise.

C-suite Job – An indicator variable that equals one if the person held at least one C-suite job and zero otherwise.

Appendix Table 1: Elite and Tier-2 universities

This table presents the elite and Tier-2 classification of colleges.

Elite universities	Tier 2 universities
Brown University	Amherst College
Columbia University	Boston University
Cornell University	Georgetown University
Dartmouth College	Johns Hopkins University
Duke University	Macalester College
Harvard University	New York University
Massachusetts Institute of Technology	Northeastern University
Northwestern University	Pomona College
Princeton University	Rice University
Stanford University	Tufts University
University of California, Berkeley	University of California - San Diego
University of Chicago	University of Michigan
University of Pennsylvania	University of North Carolina at Chapel Hill
Yale University	University of Southern California
	University of Virginia
	Vanderbilt University
	Wesleyan University
	Williams College