Elite Programs and NFL Careers: Measuring Long-Run Returns *

Jordan Holbrook
jcholbrook@uh.edu

March 30, 2025

Click here for the latest version

Abstract

This chapter examines the long-run effects of attending an elite college football program on professional career outcomes in the National Football League (NFL). Using a new panel dataset of drafted players from 2000 to 2024, linked to detailed high school and college performance data, I estimate the causal impact of program quality on employer valuation, career length, productivity, and compensation. While athletes from higher-ranked programs are consistently selected earlier in the NFL draft, these early advantages do not translate into superior long-run performance or earnings. The findings suggest that the draft premium reflects institutional signaling rather than unmeasured productivity. Despite extensive data availability and evaluation resources in the NFL, employers continue to rely on program affiliation as a proxy for talent. These results have broader implications for labor markets, indicating that signaling persists not only when data is scarce, but also when information is abundant but complex.
Keywords: *Education; Signaling; Sports*
JEL Classification: *I21; J31; J45; O15*

1 Introduction

This chapter extends the analysis from Chapter 1 by shifting focus from the extensive to the intensive margin of NFL career outcomes. While Chapter 1 investigates how attending an elite college sports program influences the likelihood of being selected in the NFL draft, this chapter asks what happens after draft day. Specifically, it examines whether athletes from elite programs perform better, worse, or the same as their peers once they enter the professional labor market.

The analysis serves as a natural falsification test of the signaling model proposed in Chapter 1. If the draft premium associated with elite programs reflects unobserved productivity or superior training—consistent with a human capital framework—then we should observe persistent advantages for those athletes in the NFL. If, however, athletes from top-tier programs perform no better, or underperform compared to those from less prestigious colleges with similar observable credentials, this provides further evidence in support of the signaling explanation: that program prestige serves as a proxy for underlying ability in the presence of information frictions at the time of hiring.

This study constructs a new panel dataset of NFL players drafted between 2000 and 2024, linked to detailed information on their high school recruitment profiles, college-level

*Department of Economics, University of Houston, Houston, Texas, USA (jcholbrook@uh.edu). I am grateful to Professor Chinhui Juhn and Professor Yona Rubinstein for their guidance and mentorship. I also thank Professor Aimee Chin and Professor Blake Heller for their thoughtful feedback and support as committee members.

performance, and professional careers. The empirical approach addresses two levels of selection that may confound the estimated returns to elite programs: first, selection into college programs, and second, selection into the NFL. To account for the former, I match athletes based on their high school recruitment portfolios—sets of scholarship offers extended by college programs—to approximate selection on unobservables such as innate ability or perceived potential. To address the latter, I incorporate granular data on individual college performance to control for productivity differences among athletes entering the draft.

A key methodological innovation in this chapter is the use of unsupervised machine learning techniques to classify athletes into performance clusters based on the rich set of season-level college statistics. These clusters serve as a data-driven summary measure of college productivity and allow for fair comparisons between players from different programs and positions. This framework supports a more credible estimation of the causal impact of college program quality on a wide range of NFL career outcomes.

NFL career success is evaluated across ten distinct outcomes, grouped into four categories: employer valuation (e.g., draft round, guaranteed contract size), career duration (e.g., years active, games played), on-field performance (e.g., starts, Pro Bowl appearances), and compensation (e.g., total earnings). The breadth of these outcomes enables a comprehensive assessment of whether the benefits of attending an elite program extend beyond draft status and into long-term career returns.

The empirical motivation for this analysis stems from two observed facts. First, athletes from elite college football programs are consistently overrepresented in the NFL draft. Second, conditional on similar college performance, they tend to earn more—suggesting a premium that may be due to perceived prestige rather than realized productivity. By disentangling these effects, this chapter informs whether program affiliation signals lasting value or merely facilitates entry into the professional ranks.

Each year, over 1.2 million high school students compete in American football—the most popular sport in the United States. Yet fewer than 300 athletes are selected annually in the NFL draft. While the majority will never reach the professional level, elite college programs serve as one of the primary pipelines into the league. Understanding the long-term effects of attending such programs is of interest not only to athletes, but also to parents, coaches, school administrators, and policymakers making investment decisions in youth and collegiate sports. For many student-athletes, athletic scholarships offer a pathway to higher education, and potentially, a professional career. Knowing whether elite programs offer durable advantages helps clarify the tradeoffs involved in these high-stakes choices.

Using a panel of NFL players drafted between 2000 and 2024, I estimate the effect of elite college sports program affiliation on professional outcomes across four domains: employer valuation, career length, productivity, and compensation. Players from higher-ranked programs are consistently selected earlier in the draft, even after adjusting for recruitment characteristics and college performance. This draft premium—roughly equivalent to a 0.14 round improvement per standard deviation increase in program strength—

confirms patterns documented in prior work on institutional signaling in the NFL draft (Hendricks, DeBrock, & Koenker, 2003; Kitchens, 2015). Once in the league, however, these early advantages do not translate into better career outcomes. I find no robust relationship between program quality and long-run productivity, total earnings, or games played. In fact, players from top programs spend slightly fewer years on active NFL rosters, a pattern consistent with front-loaded usage and higher attrition among high draft picks.

These findings suggest that the draft premium associated with elite programs reflects signaling rather than unmeasured productivity. While early selection may reflect reduced uncertainty for teams evaluating athletes from prestigious programs, actual career performance and compensation are better predicted by individual-level characteristics and pre-college evaluations. The results align with existing literature documenting inefficiencies in the draft process (Massey & Thaler, 2013; Pitts & Evans, 2019a) and reinforce the conclusion from Chapter 1: college program affiliation carries informational value at the hiring stage but is not a durable factor of success in professional football.

This chapter contributes to the literature in several ways. First, it provides one of the most comprehensive investigations of NFL career returns to college program quality to date, covering a 25-year period and incorporating more granular data than prior studies. Second, it addresses concerns about bias from unobserved selection by using scholarship offer sets and performance clustering to approximate latent traits and control for prior productivity. Third, it goes beyond draft outcomes to evaluate a broader set of professional metrics, offering new insights into the extent and durability of the returns to elite college sports programs. Finally, it documents several stylized facts about how college program affiliation shapes career trajectories in professional football, providing a better understanding of the labor market for athletic talent.

The remainder of this chapter proceeds as follows. Section 2 describes the data sources and construction of the panel linking high school, college, and professional career data. Section 3 describes summary statistics and stylized facts of typical career profiles as a professional athlete. Section 4 outlines the empirical strategy, including the matching procedure and clustering approach. Section 5 presents the main findings. Section 6 concludes.

2 Data

2.1 Overview of Data Sources

This study draws on data from the National Football League (NFL) Draft covering the years 2000 to 2024. The NFL Draft is the primary way college football players enter the professional league. Each year, the 32 NFL teams take turns selecting players in a seven-round draft. About 250 players are chosen annually. Teams with weaker records from the previous season generally select earlier in the draft order, although teams may also trade picks. Being drafted gives a player the opportunity to compete for one of the 53 roster spots on a professional team.

Draft and career outcome data come from Pro-Football-Reference.com, a widely used site that tracks the history and statistics of the NFL. The site provides detailed records on each drafted player, including draft year, round, team, games played, earnings (when available), and other career measures. Pro-Football-Reference is part of the Sports Reference network, which was founded in the early 2000s to make sports data more accessible to the public.

2.1.1 High School Recruiting Data

Since 2006, ESPN—the largest sports media network in the United States—has collected and published data on top high school football players across the country. Using scouting reports, game footage, and evaluations by analysts and former coaches, ESPN assigns each player a national ranking and a recruiting grade intended to capture their readiness for college football and overall athletic potential. This data is updated annually for each graduating class and serves as a key pre-college measure of ability in this study.

Each athlete in the ESPN database has a publicly accessible profile page that includes biographical details, a detailed scouting report, and a list of scholarship offers from college football programs. The recruiting information also includes whether the athlete accepted a scholarship offer and whether they participated in an official campus visit. Additional data, such as the athlete's hometown and high school, provide useful geographic and background context.

Beginning with the top 300 players nationwide—commonly referred to as the "ESPN 300"—the rankings have since expanded to include the top 100 athletes in each position group. I collect data on all ranked players from 2006 to 2022 using a combination of web scraping and manual data collection methods. On average, the dataset includes roughly 1,600 evaluated athletes per year.

To create the analysis sample, I merge this pre-college information from ESPN with the universe of drafted athletes. This allows for the inclusion of early-life ability measures and college choice sets, both of which are central to the empirical strategy used later in the study.

2.1.2 Ranking College Football Programs

To measure the quality of college football programs, I rely on the Simple Rating System (SRS), a widely used metric published by Sports-Reference.com. The SRS is a least-squares rating method that estimates team strength based on game outcomes and average margins of victory, adjusting for the strength of opponents. The SRS has been used in prior economic studies, including Foltice and Markus (2021) and Keefer (2016, 2017).

The advantage of the SRS is that it enables comparisons across teams regardless of differences in schedule difficulty, historical longevity, or league affiliation. It is relatively stable across seasons and provides a consistent scale for comparing teams across divisions and time. These properties are similar to selectivity measures used in the economics of education, such as average SAT scores, which provide time-invariant comparisons across institutions.

College team-level data are merged from Sports-Reference.com with the high school recruiting dataset. This includes information on win-loss records, strength of schedule, and conference championships for each team that recruited athletes in the analysis sample. These data are available publicly and have been widely used across sports analytics and economics research.

To distinguish between tiers of program quality, I define a set of "blueblood" programs as those in the top quartile of the SRS distribution. These programs include historically dominant teams such as Alabama, Ohio State, Michigan, Notre Dame, USC, Oklahoma, and others.[1] These elite programs serve as a key comparison group in several descriptive analyses throughout the paper. While the descriptive figures often compare outcomes for athletes from blueblood programs versus all others, the empirical analysis uses the continuous SRS metric to account for program quality.J

2.1.3 Professional Career Outcomes

To measure professional labor market outcomes, I collect detailed career data for NFL athletes from two primary sources: Pro-Football-Reference.com and Spotrac.com. These sources provide complementary information on player performance, longevity, and earnings.

Pro-Football-Reference offers comprehensive statistics for all NFL players and games, including games played, career milestones, and individual productivity metrics. This data is used to measure indicators such as career length, total games played, years spent as a starter, and on-field productivity. Additional indicators, such as Pro Bowl selections, are included to capture peer and league recognition.

Spotrac provides publicly available salary and contract data for NFL players from 2010 to 2023. The dataset includes annual base salaries and total earnings for each player-season, along with draft round and pick information that serve as proxies for employer valuation. While originally created as a tool to support fantasy sports and general player valuation research, Spotrac has become a widely used resource for analyzing player compensation and team payrolls across major professional sports leagues.

These datasets are merged using player name and draft year to construct a panel dataset tracking each athlete's professional football career over time. The final merged dataset includes measures of NFL draft position, career duration, productivity, and earnings. Each outcome variable is defined precisely in Section **??**, but the overall framework includes the following categories: employer valuation, career legnth, career productivity, and salary outcomes.

[1] See ESPN's list of "College Football Blue Bloods" at `https://www.espn.com/college-football/story/_/id/17336754/alabama-crimson-tide-notre-dame-fighting-irish-ohio-state-buckeyes-oklahoma-sooners-usc-trojans-lead-list-college-football-blue-bloods`

2.2 Sample Construction

This study relies on two distinct samples: a broad descriptive sample used for presenting stylized facts and career patterns, and a more narrowly defined analysis sample used for causal identification.

The **Descriptive Sample** consists of two sources. First, I collect all athletes selected in the NFL Draft from 2000 to 2024 using data from Pro-Football-Reference.com. This sample is used to describe the typical NFL athlete's career in terms of non-financial outcomes such as career length, games played, and productivity. Second, I use salary and contract data from Spotrac.com, which includes all NFL athletes with an active contract between 2010 and 2023. This financial sample includes athletes drafted prior to 2010 if they were still under contract during the observation window. Together, these datasets offer a comprehensive view of NFL careers and earnings.

The **Analysis Sample** is a subset of the descriptive sample. It includes only those athletes whose professional outcomes can be reliably linked to verified high school and college characteristics. High school data come from ESPN.com and include recruit evaluations, rankings, and star ratings based on scouting reports and film reviews. College data come from CollegeFootballData.com and Sports-Reference.com and include program-level performance metrics such as team quality and conference championships. The matching procedure relies on name, draft year, and institutional affiliations to ensure accuracy.

The analysis sample is constructed to support the empirical strategy outlined in Chapter **??**. While this sample excludes some athletes due to missing or unverified high school or college data, the resulting sample remains broadly representative of the full population of drafted NFL athletes. Section 2.4 presents side-by-side summary statistics for the descriptive and analysis samples, showing that the two groups are similar across key observable dimensions. These comparisons help validate the external relevance of the analysis sample to the broader universe of NFL players.

2.3 Defining Key Variables

This section outlines the key outcome and independent variables used in the analysis. These variables are grouped into four categories: employer valuation, career length outcomes, athletic productivity, and salary outcomes.

Employer valuation is captured using two measures. The first is the draft round, which ranges from 1 to 7 and indicates the round in which the athlete was selected. The second is the overall draft pick number, ranging from 1 to approximately 250, which reflects the athlete's relative standing across all draftees in a given year.

NFL career length outcomes include three indicators. The total number of NFL games measures career longevity in terms of game participation. Total seasons as a starter captures the number of seasons in which the athlete started at least one game. Total years in the NFL is a broader measure indicating how many seasons the player appeared in at least one game.

Athletic productivity outcomes include several performance metrics. NFL career productivity is measured using cumulative statistics such as Approximate Value (AV), a widely used summary metric of player contribution. Rookie year productivity isolates performance in the athlete's first professional season. Selection to the Pro Bowl is used as an indicator of peer and league recognition and serves as a proxy for top-tier athletic performance.

One of the primary measures of athletic productivity used in this study is *Approximate Value* (AV), a metric developed by mathematician Doug Drinen in 2008 and published on Pro-Football-Reference.com (Drinen, 2008). The AV metric assigns a single numerical value to each NFL player's season, across all positions and seasons since 1950. The purpose of AV is not to resolve debates about marginal productivity between similar players, but rather to provide a consistent, position-agnostic framework for evaluating general player contributions. The scale generally ranges from 0 to 18, top Hall of Frame caliber players assigned values near the top of the range. Mid-tier players score between 6 and 12, while replacement-level or short-tenure players often fall between 0 and 4.

The methodology allocates AV points based on a combination of box score statistics and drive-level team performance data. It assigns team-level value to offensive and defensive units, then distributes these values to individual players based on position and role. Some critics have noted limitations of the AV method, including its lack of adjustment for starting field position, game context (e.g., score differential or time remaining), or environmental factors like weather.

Despite its limitations, Approximate Value (AV) remains a widely used summary statistics for evaluating NFL player performance across positions and seasons. Its appeal lies in its ability to generate a single performance metric that can be compared across players with diverse roles, making it particularly useful for large-sample, multi-position studies. AV has been used in peer-reviewed economic research on player valuation and draft outcomes (Brown & Sommers, 2020; Duquette & Cebula, 2020; Mulholland & Jensen, 2019; Schuckers, 2011; Scott, 2012), as well as in operations research and sports analytics applications. It is also widely referenced in the broader sports analytics community, including popular media such as FiveThirtyEight, which used AV in their analysis of positional risk in the NFL draft (Paine, 2015). For a comprehensive assessment of the construction, strengths, and limitations of AV, see Yurko, Ventura, and Horowitz (2019), which provides a reproducible framework for offensive player evaluation and offers important caveats for interpreting AV in empirical research.

Salary outcomes are measured using data on both base compensation and total earnings. Annual base salary refers to the player's contracted base pay in each season, while annual total earnings include bonuses and other forms of compensation. I also compute cumulative career earnings by summing total earnings across all seasons for which data are available. To account for inflation and changes in league salary structure, a contract year indicator is included as a control variable in all models involving financial outcomes.

Independent variables fall into three main categories: program quality, pre-college controls, and college performance. Program quality is measured using the Simple Rating System (SRS), a continuous index of college football team strength based on game outcomes and opponent strength. Programs in the top quartile of the SRS distribution are designated as ”elite” or “blueblood” programs. The SRS-based program quality measure is used in both continuous and categorical forms throughout the analysis. Full details on the SRS are provided in Chapter 1.

Pre-college controls capture athlete characteristics before entering college football. These include national recruiting rank, recruiting grade, and star rating—each derived from scouting evaluations published by ESPN. Additional controls include the athlete's high school position, age at the time of the draft, and physical characteristics such as height and weight. I also account for the athlete's scholarship offer set by including the total number of offers received and the average SRS of the offering programs.

Finally, college performance is inherently multidimensional, varying across positions and seasons. Let M_j denote the vector of performance metrics for player j across N_j seasons. To reduce the dimensionality of this data and avoid overfitting, I employ an unsupervised machine learning algorithm to group players into performance-based clusters. Each player is assigned to a cluster based on their observed college performance, and this cluster category is included as a categorical control variable. The methodology for the clustering procedure is described in detail in Section 4.3.

Table 1: Summary of Key Outcome Variables

Category	**Variable Description**
Employer Valuation	Draft Round (1–7)
	Overall Draft Pick Number (1–250)
Career Length Outcomes	Total NFL Games Played
	Total Seasons as Starter
	Total Years in NFL
Athletic Productivity	NFL Career Productivity (AV)
	Rookie Year Productivity (AV)
	Pro Bowl Selections
Salary Outcomes	Annual Base Salary
	Annual Total Earnings
	Contract Year (Control)

2.4 Summary Statistics

This section presents summary statistics for both the descriptive sample and the analysis sample. The descriptive sample includes all NFL athletes drafted between 2000 and 2024, while the analysis sample includes only those athletes for whom high school and college characteristics could be reliably matched.

Table 2 reports summary statistics for the descriptive sample of drafted players. The average draft round is just above the fourth round, with a mean pick number of 128. On average, players begin their NFL careers at age 22.5 and play approximately 61 games over 4.4 years. About 30% of players are selected to at least one Pro Bowl, and the average approximate value (a productivity metric) is 16.8 across all seasons played.

Table 2: Summary Statistics – Descriptive Sample (NFL Career Outcomes)

	Mean	Std. Dev.	Min	Max
Draft Round	4.20	2.00	1	7
Draft Pick	128.26	73.79	1	262
Age at Draft	22.51	0.93	20	29
Pro Bowl Selections	0.30	1.12	0	15
Games Played	61.07	49.39	0	335
Years in NFL	4.37	3.32	0	22

Table 3 presents the same statistics for the analysis sample. This sample includes 2,595 players whose pre-college data could be verified and matched. On average, these players were drafted slightly later than those in the full descriptive sample (mean pick number 125), but the overall distribution of career outcomes is similar. The average player in the analysis sample plays just over 50 games, spends about 3.9 years in the NFL, and earns roughly 13.2 million dollars in total career earnings over the contract periods observed.

Table 3: Summary Statistics – Analysis Sample (NFL Career and Pre-College Characteristics)

	Mean	Std. Dev.	Min	Max
Draft Round	4.06	2.00	1	7
Draft Pick	125.07	74.50	1	261
Age at Draft	22.36	0.94	20	27
Recruiting Rank	712.62	790.68	1	4189
Recruit Stars	3.37	0.81	1	5
SRS of College Program	5.73	5.68	-14.17	15.2
Games Played	50.97	41.19	1	239
Years in NFL	3.94	2.93	1	15

In terms of financial outcomes, **Table 4** summarizes total earnings, base salary, and contract lengths for both samples. Players in the descriptive sample earn an average of $14.2 million in total earnings, while players in the analysis sample average $13.2 million. Contract length is similar across groups, with the average player having around 3.4 years of recorded salary data.

Table 4: Summary Statistics – Financial Outcomes

	Descriptive Sample	Analysis Sample
Average Base Salary (M)	\$1.62	\$1.60
Average Total Earnings (M)	\$14.23	\$13.18
Average Contract Length (Years)	3.33	3.39
Average Age (Years)	26.31	25.76

Across all tables, the analysis sample is broadly representative of the full descriptive sample, both in terms of draft position and subsequent NFL career performance. Section **??** provides additional robustness checks and sensitivity analyses to ensure the generalizability of the findings. Small differences in earnings and career length may reflect selection into the matched sample or differences in the observation windows for contract data.

3 Descriptive Statistics

3.1 NFL Career Profiles

A professional football career in the National Football League (NFL) is often short and highly uncertain. While being drafted is a key milestone in a player's career, it is not a guarantee of long-term success or longevity in the league. This section provides a descriptive overview of the typical lifecycle of a drafted NFL athlete, focusing on career duration and retention over time.

Figure 1 presents a Kaplan-Meier-style survival plot showing the share of drafted players still active in the NFL by year since draft. The sample includes all players drafted between 2000 and 2015, which allows sufficient follow-up time to observe complete career arcs. Each line represents a draft cohort, with the y-axis measuring the proportion of players from that cohort still active in the league at each point in time.

The plot reveals a steep early drop-off in league participation, with most players exiting within the first five years of their careers. Across all cohorts, fewer than 25% of players remain active five years after being drafted. By year ten, fewer than 10% of players are still in the league, and beyond year fifteen, the share approaches zero. This pattern is consistent across draft years, although some variation is visible—draft classes from stronger draft years or those with more successful top picks (e.g., 2004, 2007) tend to have slightly flatter curves in the early years.

The median NFL career lasts approximately four years. Players with longer careers are the exception rather than the rule, and they often include quarterbacks, offensive linemen, or other positions associated with lower injury risk and greater career longevity. The short average duration of NFL careers has important implications for interpreting both career earnings and long-run labor market outcomes for professional athletes.

Overall, the survival plot underscores the transitory nature of professional football careers and motivates the empirical analysis in subsequent sections, which investigates not just entry into the NFL, but the progression, earnings, and longevity of athletes over time.

Figure 2 presents the trajectory of player compensation over the course of a professional football career in the NFL and serves as a reference point for interpreting the economic magnitude of the empirical results that follow. The figure plots both the mean and median annual earnings of NFL players by years of experience, defined as the number of years since a player's draft year. This descriptive analysis captures average career compensation profiles for players who reach the professional level and provides context for evaluating the returns to participating in elite college sports programs.

To construct the figure, individual-level salary data was aggregated by years of NFL experience. Players' experience was calculated as the difference between the final year of observation in the NFL (at the time of writing) and the draft year. The resulting data was grouped by experience level (from Year 0 to Year 15), and for each group, mean and median earnings were computed. These summary statistics were then plotted using a line chart, with separate curves representing average and median compensation at each stage of a player's career.

The figure shows features of the professional athlete earnings profile. First, compensation increases steeply with experience, particularly after Year 4, which aligns with the typical expiration of rookie contracts and eligibility for free agency. This feature of the NFL labor market marks a transition point in a player's career, after which earnings become substantially more dispersed. Second, the widening gap between mean and median salaries at higher experience levels illustrates the right-skewed nature of veteran compensation, where a small number of highly paid players drive up the average. For example, by Year 15, the mean annual earnings exceed $100 million, while the median is substantially lower, and only a small number of players remain in the sample.

This figure is useful for interpreting the effects of early career factors—such as attending an elite college football program—on long-run labor market outcomes. Understanding the shape of the typical compensation profile provides intuition for the value of entering the league and persisting over time. In the empirical sections that follow, I estimate the impact of elite college program quality on the likelihood of being drafted and subsequent NFL career outcomes using the analysis sample. Figure 1 anchors those estimates in real earnings terms, showing the high stakes associated with initial access to and survival within the NFL.

Figure 3 compares mean annual earnings for NFL players by years of professional experience, stratified by whether players survived in the league for at least ten years ("conditional") or not ("unconditional"). The unconditional group includes all players observed in the league between Years 1 and 10, regardless of whether they ultimately completed a full decade-long career. In contrast, the conditional group includes only those players who reached at least ten years of NFL experience—allowing for a descriptive view of long-run earners without the compositional effects of early exits.

The figure highlights several important features of the NFL earnings trajectory. First, players who eventually survive to Year 10 begin their careers with higher average earnings than the general population of players, even as early as Year 1. This earnings gap grows with experience. By Year 4, conditional earners make over $17 million on average, compared to about $12 million among the unconditional group. This divergence continues throughout the first decade of a player's career, reaching nearly $49 million in average annual earnings by Year 10 for those who persist.

The shape of both earnings curves reflects institutional features of NFL contracts. The inflection point around Year 4 corresponds with the end of most rookie deals and the start of free agency eligibility. Conditional earners benefit more from this transition, suggesting that sustained productivity is rewarded with significantly larger contracts. The widening gap between the two groups over time illustrates how survival in the league amplifies financial rewards, while also underscoring the selectivity of long-term NFL careers.

3.2 Program Quality and Career Outcomes

Figure 4 examines how college program quality—measured by whether a player attended an "elite sports program" (top-tier schools frequently referred to as Bluebloods)—relates to professional career longevity in the NFL. The figure plots the share of players still active in the league by years since draft, separating trajectories for players from elite programs versus those from all other colleges. Two types of curves are shown: an unconditional trajectory that includes all drafted players, and a conditional trajectory that includes only those who remained in the league for at least five years. This distinction allows for a comparison of both average outcomes and persistence among more successful cohorts.

Unconditionally, players from elite programs have slightly higher survival probabilities throughout their careers. For example, one year after being drafted, roughly 82% of Blueblood players remain in the league compared to about 79% of others. This gap widens marginally over time. By Year 10, approximately 6.6% of players from elite programs are still active, compared to 6.4% from non-elite programs. Among players who survive at least five years (conditional curves), those from elite programs again exhibit modestly higher retention, though the differences are small. The figure also highlights a notable drop-off after Year 4—corresponding to the typical expiration of rookie contracts—where player turnover accelerates across both groups. These patterns suggest that athletes from elite programs may enter the league with a slight advantage in career stability, but the long-run differences in career length are relatively modest once early attrition is accounted for.

Figure 5 presents the share of drafted NFL players each year who came from one of the top 25 "elite" or "Blueblood" college football programs. These programs, defined earlier using a persistent top-quartile ranking in the Simple Rating System (SRS), represent institutions with long-standing reputations for football performance, visibility, and strong recruitment pipelines. The figure tracks the percentage of drafted players from these programs between 2000 and 2021, offering a view into how concentrated the NFL draft pool is among top college programs.

Throughout the sample period, between 40% and 53% of drafted athletes each year came from elite programs. Although there is some fluctuation across years, the overall pattern is relatively stable, with a modest increase observed in the most recent cohorts. This figure demonstrates the central role that elite programs play in producing professional athletes. It also draws attention to the importance of accounting for college program quality when examining labor market outcomes in the NFL. Since a substantial share of draftees originate from a relatively small group of schools, distinguishing the independent effect of attending an elite program from underlying selection becomes a critical focus in the empirical analysis that follows.

3.3 Earnings Premium by Program Quality

Figures 6 and 7 explore how the earnings premium for players from elite college football programs evolves over a professional career in the NFL. These figures plot the average difference in annual earnings between players from elite (Blueblood) programs and those from all other programs, at each year of NFL experience. Shaded bands show the 95% confidence intervals obtained from bootstrapped mean differences, allowing for an assessment of statistical uncertainty at each career stage.

Figure 6 focuses on the first five years of a player's NFL career—the typical length of a rookie contract. During this period, players from elite programs consistently earn more, with the average premium ranging from approximately \$735,000 in Year 0 to over \$1.5 million in Year 4. While this early-career premium is modest, it is relatively stable and generally falls outside of zero in its confidence bounds through the early years, suggesting some advantage during the initial contract period. However, by Year 4, the confidence intervals widen considerably, signaling greater heterogeneity in earnings and less statistical precision in the estimates. This reflects the increasing variation in contract renegotiations, team fit, and role on the roster as players advance beyond their entry-level agreements.

Figure 7 examines the same earnings premium for players who remain in the league for at least five years, focusing on Years 5 through 12. In contrast to the earlier period, the earnings premiums are more volatile and the associated confidence intervals are substantially wider. By Year 10 and beyond, the range of potential values becomes very large, with intervals often spanning zero. These patterns suggest that while there may be differences in early-career compensation between players from elite and non-elite programs, such differences dissipate or become highly uncertain later in a player's career. In other words, once athletes have survived the initial years of professional play, their long-run earnings potential appears to converge regardless of college program pedigree. This finding supports other results in the paper showing that elite program affiliation strongly predicts initial placement into the league but has limited long-run predictive power over sustained success or compensation.

3.4 Observations and Stylized Facts

A number of key patterns emerge from the descriptive figures that motivate the central empirical questions of this study. First, reviewing and summarizing the selection-corrected estimates presented in Chapter 1, there is a sizable initial placement advantage for athletes from elite college football programs. A one standard deviation increase in program quality is associated with a 1.8 percentage point increase in the probability of being drafted—roughly a 32% increase relative to the baseline mean draft probability of 5.6%. This translates into a substantial edge in job placement for similarly skilled athletes: players from elite programs are approximately three to five times more likely to be drafted than their peers with comparable athletic ability and performance metrics.

Second, Figure 5 shows that this placement advantage is not only individual but also systemic. Athletes from fewer than 25 college programs account for approximately half of all drafted players in a given year, indicating that elite programs are consistently overrepresented in the NFL draft. This concentration shows to important institutional affiliation is in shaping access to professional opportunities in football, even prior to accounting for differences in performance.

Third, Figures 6 and 7 reveal that players from elite programs tend to earn more during the early stages of their careers. The earnings premium is most clearly evident during the rookie contract period (Years 0–4), after which compensation begins to level off. While mean differences in salary persist beyond Year 5, the widening confidence intervals suggest that outcomes become increasingly idiosyncratic and are shaped by a smaller, selected group of longer-tenured players. The convergence is evidence of survival bias in interpreting late-career outcomes: players who remain in the league past their initial contract are more likely to be higher performers regardless of college background.

Together, these patterns motivate the core question of the paper: does attending an elite college football program causally influence long-run labor market outcomes in the NFL? Beyond early-career placement, does the institutional pedigree of an athlete's college continue to matter for career progression? The empirical sections that follow aim to estimate the private returns to elite program participation, accounting for selection, performance, and institutional factors that are part of career success in professional sports.

4 Empirical Strategy

Building upon the empirical framework established in Chapter 1, this chapter extends the analysis from the extensive margin of employment—examining which high school athletes transition to professional careers in the NFL—to the intensive margin of employment, focusing on the career outcomes of those athletes who are drafted into the NFL. A key challenge in this analysis is addressing the dual selection process: first, selection into college football programs, and second, selection into the NFL Draft. To account for these selection mechanisms, I refine the empirical model by incorporating college athletic performance as a key determinant of NFL selection and leveraging clustering analysis to construct homogeneous performance groups. These performance groups serve as matching group fixed effects in the regression framework to control for variation in player ability and playing style, ensuring a more precise estimation of the returns to elite college programs in professional football.

4.1 Addressing Selection

Estimating the causal impact of college program quality on professional football outcomes requires addressing two key sources of selection bias. First, selection into college football programs is shaped by visibility, recruiting networks, and perceived athlete potential. Second, selection into the NFL is largely determined by observed college performance and subjective evaluations by scouts and front offices. Without accounting for both dimensions, estimates of program quality effects risk conflating institutional value with unobserved player ability or exposure.

Chapter 1 addressed selection into college using a matching estimator based on scholarship offer-set groups, enabling comparisons among athletes with similar college options. However, the smaller sample of drafted players in this chapter makes such high-resolution matching infeasible. I therefore adopt a more course specification, drawing on the framework of Dale and Krueger (2002, 2014), in which the average quality of an athlete's scholarship offers and the total number received serve as sufficient statistics for pre-college talent and exposure. These offer-set variables proxy for external valuation at the time of recruitment and act as continuous analogues to the matched group fixed effects used earlier.

To address selection into the NFL, I introduce fixed effects based on performance clusters derived from college statistics. These absorb variation in observed productivity and role-specific contributions across positions. Together, the offer-set controls and performance clusters form a unified strategy to adjust for non-random assignment of athletes to programs and mitigate selection bias in estimating the returns to elite college football programs.

4.2 Regression Framework

To evaluate how participation in elite college football programs affects professional football outcomes, I start my analysis with the empirical model from Chapter 1 (Matched Scholarship Model) as follows:

$$y_{ijg} = \beta_0 + \beta_1 SRS_j + \beta_2^{'} X_{1i} + \sum_{1}^{m} \gamma_g Group_{ig} + \epsilon_{ijg} \tag{1}$$

where y_{ijg} represents the professional career outcomes of athlete i, who played for college team j and belongs to performance cluster g. The variable SRS_j measures the quality of the college sports program using the Simple Rating System (SRS), and its coefficient β_1 captures the impact of attending an elite program on career outcomes. The vector X_{1i} includes observable player characteristics such as height, weight, and college performance statistics.

The group indicator variables Group_{ig} capture the effect of belonging to a specific matching group, where matching groups are defined using variation in the scholarship offer sets extended to student-athletes during high school recruitment. These matching groups help account for unobserved and unmeasured ability that could potentially bias the analysis. The strategy assumes that information revealed in the recruiting process can be captured and controlled for by matching players with similar or identical offer sets. The intuition is that athletes recruited by similar types of college football programs possess comparable levels of unobserved talent and external valuation, making them a natural comparison group for evaluating the causal impact of college program quality.

The error term ϵ_{ijg} accounts for unexplained variation in career outcomes.

While Equation 1 adequately addresses one dimension of selection—namely, the selection of athletes from high school into college programs—it does not account for the second and equally important dimension of selection: from college into the NFL. Because this chapter focuses on the intensive margin of employment, it is essential to address this additional layer of selection bias. In particular, NFL drafting decisions are strongly influenced by a player's observed college performance, which varies widely across position groups, teams, and individual athletes. Failing to account for this performance-based selection into professional careers could bias estimates of the effect of college program quality.

To address this concern, I augment the empirical model by incorporating detailed measures of college athletic performance. However, directly including the high-dimensional set of performance metrics into the regression model presents challenges related to heterogeneity across player positions and seasons. To overcome these limitations, I implement a data-driven clustering approach to summarize each athlete's performance profile into a latent performance type. The next subsection outlines the methodology used to construct these performance clusters and explains how they are incorporated as fixed effects in the empirical model.

4.3 Accounting for College Athletic Performance

A central challenge in estimating the causal effect of attending an elite college football program on professional career outcomes lies in accurately controlling for player ability. While high school recruiting metrics provide an early signal of talent, college performance is a more proximate and empirically rich measure of a player's ability and readiness for professional play. For instance, Craig and Winchester (2021) demonstrate that both passing and rushing performance in college are significantly correlated with selection into the NFL among quarterbacks, with rushing ability especially predictive of future professional success. Similarly, Duquette and Cebula (2020) find that on-field performance at the college level serves as a strong predictor of post-draft value and success.

Importantly, NFL scouts and front offices place considerable weight on college statistics when evaluating prospects. Pitts and Evans (2019b) provide evidence that college-level performance is significantly associated with both draft position and eventual productivity in the NFL, showing how teams can rely on observable statistics to make draft decisions. Nonetheless, these studies also highlight that NFL teams sometimes over- or under-weight specific metrics, suggesting that while college performance is informative, it is not always perfectly interpreted or utilized. The importance placed on measurable college output makes it clear that it is necessary to include college performance data in an empirical model of professional football outcomes.

The difficulty, however, lies in how to incorporate college performance into the empirical model in a tractable and theoretically sound way. I denote college athletic performance for each player i as a vector $\mathbf{Z}_i \in \mathbb{R}^{N_i \times M_i \times J_i}$, where N_i is the number of seasons played, M_i is the number of performance metrics observed, and J_i is the number of position groups applicable to the player. The performance dimensions and their relevance vary across positions—passing yards and completion percentage are informative for quarterbacks but irrelevant for offensive linemen, who are instead evaluated using metrics such as sacks allowed or team rushing yards.

Letting $\mathbf{z}_{ijt}$ denote player i's performance vector for position group j in season t, the full college performance history is:

$$\mathbf{Z}_i = \{\mathbf{z}_{ijt} \mid j = 1, \ldots, J_i;\; t = 1, \ldots, N_i\}.$$

Attempting to include this high-dimensional object directly into the regression model presents several complications. First, there is heterogeneity in the relevance of performance metrics across player positions (j). For example, passing yards are critical for quarterbacks but irrelevant for offensive linemen. Second, the temporal dimension introduces additional complexity, as players accumulate performance data over multiple seasons (t), raising the question of how best to aggregate information across time—whether to emphasize early, late, or average performance. Finally, incorporating all observed performance measures (m) would require assigning arbitrary weights to each metric, which risks introducing bias or noise into the estimation. These challenges motivate a dimensionality reduction approach that can summarize performance data without requiring a priori decisions about metric importance or aggregation rules.

To address these challenges, I apply a data-driven approach to dimensionality reduction using unsupervised learning. Specifically, I use the K-means clustering algorithm to group players based on the similarity of their overall performance profiles. Rather than manually selecting or aggregating performance variables, this method categorizes athletes into homogenous performance groups according to an objective function.

Clustering is widely recognized as a powerful dimensionality reduction tool, particularly in high-dimensional settings where feature relevance varies across units of analysis. As Cunningham (2008) explains, unsupervised learning methods like clustering are especially useful for feature extraction when direct aggregation is either infeasible or theoretically problematic. Clustering is also inherently data-driven—relying on observed variation rather than researcher-imposed weights or classifications—and does not require labeled outcomes to uncover latent structure in the data (Dutta, Yurko, & Ventura, 2020).

In sports applications, clustering has been shown to be particularly well-suited for evaluating heterogeneous performance across positions and roles. For example, Shelly et al. (2020) demonstrate the effectiveness of K-means clustering in segmenting elite college football players into training groups based on physical game demands. Similarly, Salim and Brandão (2018) and Husowitz, Mixer, and Morrow (2025) apply clustering and related machine learning techniques to NFL data to extract latent dimensions of team or player performance, highlighting its value in complex performance environments.

Finally, clustering methods have a strong tradition in economics and the social sciences more broadly. As Fonseca (2013) notes, cluster analysis—including K-means and latent class models—is an established technique for uncovering structure in unobserved heterogeneity and has been successfully applied across a wide range of empirical domains, including survey analysis, labor markets, and education.

Let $\mathbf{z}_i$ represent the standardized vector of player i's college performance metrics, incorporating all seasons and positions played. The K-means algorithm partitions players into K clusters by solving the following optimization problem:

$$\{C_1, \ldots, C_K\} = \underset{\{C_1,\ldots,C_K\}}{\operatorname{argmin}} \sum_{k=1}^{K} \sum_{\mathbf{z}_i \in C_k} \left\| \mathbf{z}_i - \boldsymbol{\mu}_k \right\|^2,$$

where each cluster centroid $\boldsymbol{\mu}_k$ is defined as the mean vector of all players assigned to cluster k:

$$\boldsymbol{\mu}_k = \frac{1}{|C_k|} \sum_{\mathbf{z}_i \in C_k} \mathbf{z}_i.$$

Choosing the Number of Clusters. A critical input to the K-means clustering algorithm is the number of clusters K. To determine an appropriate value for K, I use the elbow method, a graphical technique based on evaluating the within-cluster sum of squares (WCSS), also referred to as inertia, for different values of K. Formally, the WCSS for K clusters is defined as:

$$\text{WCSS}(K) = \sum_{k=1}^{K} \sum_{\mathbf{z}_i \in C_k} \left\| \mathbf{z}_i - \boldsymbol{\mu}_k \right\|^2.$$

I compute WCSS(K) for a range of candidate values from $K = 1$ to $K = 24$, and plot this quantity against K to identify the "elbow point"—the value of K at which the marginal gain in explained variance (i.e., reduction in WCSS) begins to level off. Figure 8 displays the results. While multiple values such as $K = 5$, $K = 7$, and $K = 11$ appear to be plausible candidates based on the curvature of the plot, I ultimately select $K = 7$ as the preferred specification. This choice balances model complexity and within-group homogeneity, and performs well in capturing meaningful variation in player performance across positions and roles.

The output of the algorithm is a function that maps a player's performance vector $\mathbf{z}_i$ to a cluster assignment $Cluster_i$:

$$Cluster(\mathbf{z}_i) = \underset{k \in \{1,\ldots,K\}}{\operatorname{argmin}} \|\mathbf{z}_i - \boldsymbol{\mu}_k\|^2 .$$

This cluster assignment is then used as a fixed effect in the regression model, allowing me to compare players with similar performance profiles while estimating the impact of elite program participation on professional career outcomes.

The output is a categorical variable $Cluster_i \in \{1, \ldots, K\}$ for each player i, which captures their latent performance type. I incorporate these cluster assignments as fixed effects in the model.

While K-means clustering is the primary specification used in the analysis due to its interpretability and computational efficiency, I also experimented with alternative unsupervised learning methods, including Gaussian Mixture Models (GMM) and Agglomerative Hierarchical Clustering. These methods produced similar groupings and regression estimates, providing reassurance that the core findings are not sensitive to the choice of clustering algorithm. Further details on these alternative specifications and robustness checks are provided in the Appendix.

Performance-Adjusted Program Quality Model. Now armed with a method to account for the second key dimension of selection—college athletic performance—I extend the baseline model from Chapter 1, Equation 1 to address the full set of potential confounding factors in this setting. The resulting empirical specification is as follows:

$$y_{ijg} = \beta_0 + \beta_1 SRS_j + \beta_2^{'} X_{1i} + \beta_3^{'} OfferSet_i + \sum_{h=1}^{K} \delta_h Cluster_{ih} + \epsilon_{ijg} \tag{2}$$

where y_{ijg} represents the professional career outcomes of player i, who played for college team j and belongs to performance cluster h. The variable SRS_j measures the quality of the college program attended, X_{1i} includes player-specific observables (e.g., height, weight, and position-specific statistics), and $Cluster_{ih}$ is a categorical indicator for the player's assigned performance cluster, derived from K-means clustering. The vector $OfferSet_i$ includes two continuous measures: (1) the average SRS of all scholarship offers received by player i, and (2) the total number of offers received. These variables act as proxies for the player's perceived potential at the time of recruitment.

Alongside the performance cluster indicators, the primary deviation from the model in Equation 1 is the replacement of the discrete matching group fixed effects with these continuous offer-set controls, $OfferSet_i$. This specification closely parallels the "self-revelation" model introduced by Dale and Krueger (2002, 2014), who show that offer-set characteristics can serve as sufficient statistics for unobserved ability and program selection. The self-revelation approach retains the core logic of the matched scholarship model by enabling comparisons among athletes with similar pre-college opportunities, but in a more scalable form. This framework has since been applied in previous studies in the economics of education literature including (Chen, Grove, & Hussey, 2013) and (Ge, Isaac, &

Miller, 2022).

Adopting this specification is especially important in the current chapter due to sample size constraints. While the analysis in Chapter 1 benefits from a large and diverse sample of high school athletes—enabling finely-grained matching across scholarship groups—the analysis here is limited to the smaller subset of athletes who are drafted into the NFL. In this reduced sample, many matched groups contain too few observations to support reliable within-group variation in SRS_j. Using continuous offer-set variables therefore improves statistical power and ensures sufficient treatment variation to identify the effects of program quality on professional outcomes.

Model Assumptions. Identification of the effect of college program quality on NFL career outcomes relies on three primary assumptions. First, I assume that after controlling for an athlete's offer-set characteristics, performance cluster, and observable traits, the choice of college program is as good as random with respect to unobserved factors that affect NFL career outcomes. This allows for the interpretation of variation in SRS_j as plausibly exogenous, once sufficient controls are included. Second, the identification strategy depends on the presence of sufficient within-group variation in program quality—i.e., among athletes with similar offer sets and college performance, there must be variation in the quality of programs attended. Evidence supporting this assumption is provided in Figure 5, which shows that 50–60% of drafted players come from non-elite programs, suggesting that treatment variation exists even among athletes who reach the professional level. Third, I assume that omitted variable bias from unobserved factors is limited in scope. For any such factor to bias the results, it would need to be uncorrelated with both pre-college valuation (captured through offer sets) and college performance (captured through cluster assignment), yet still exert an independent influence on professional career outcomes. This considerably narrows the set of plausible confounders. It is more likely that unobserved traits—such as motivation or intangibles—are correlated with the information already embedded in the offer sets and performance measures, and are therefore partially accounted for in the empirical model.

5 Empirical Results

5.1 The Effect of Elite Programs on Employer Valuation

This section examines the relationship between college football program quality and employer valuation, as reflected in the NFL draft process. Employer valuation is measured using two key outcomes: the draft pick number, which represents the order in which a player is selected, and the draft round, which categorizes selections into broader groupings. Higher draft positions (lower pick numbers) and earlier rounds indicate greater perceived value by NFL teams. The analysis follows the same model specifications as in the previous sections, incorporating controls for high school athletic ability, recruitment characteristics, and athlete attributes.

NFL Draft Round. This section estimates the association between college football program quality and employer valuation, measured using the round in which a player is selected in the NFL Draft. A lower draft round indicates earlier selection.

Table 5 Column (1) reports the unadjusted association between program quality, measured using SRS rank, and draft round. The estimate shows that players from higher-ranked programs are selected, on average, 0.238 rounds earlier.

Column (2) adds controls for high school ability, including athlete recruiting ratings. The coefficient on college program quality falls to -0.139 but remains statistically significant. High school ability is negatively associated with draft round, though only weakly significant.

Column (3) includes the average quality of a player's college offerset, capturing the competitiveness of the recruiting process. The coefficient on program quality remains stable. The offerset variable is negatively associated with draft round, suggesting that players with stronger offersets are selected earlier, although the effect is only marginally significant.

Column (4) introduces additional controls for college performance, such as statistics and accolades, and includes fixed effects for matched performance groups. The coefficient on program quality remains similar in magnitude and statistically significant. This specification accounts for player productivity and performance clustering.

Across specifications, the program quality coefficient remains consistently negative and significant, suggesting a robust association between attending a higher-ranked program and being drafted in an earlier round. The increase in model fit is modest, with the R^2 rising from 0.143 to 0.160.

NFL Draft Pick Number. This section repeats the same set of model specifications, now using draft pick number as the outcome. Draft pick number provides a more granular measure of selection order, with lower values indicating earlier picks.

As shown in Table 6, players from stronger programs are selected earlier in the draft even after adjusting for performance and recruitment factors. The coefficient on college program quality is negative and statistically significant in all specifications. The magnitude of the effect increases slightly as controls are added, ranging from -0.585 in the unadjusted model to -0.749 in the full model. This indicates that players from stronger programs are selected earlier in the draft, even after adjusting for athlete characteristics, high school ability, and college performance. The R^2 increases modestly from 0.013 to 0.020 across specifications.

Magnitude of the Effect

The coefficient estimates imply that attending a higher-ranked college program is associated with earlier draft selection. To illustrate the economic magnitude of these results, we translate changes in program quality rank into approximate changes in expected draft round and corresponding salary.

The draft round coefficient from the fully adjusted model (Column 4) is -0.14 per standard deviation increase in SRS rank. This implies that a player from a program two standard deviations stronger (e.g., moving from a mid-tier school to a top-tier school) would be selected 0.28 rounds earlier on average. A player from a program four standard deviations stronger (e.g., bottom-tier to top-tier) would be selected 0.56 rounds earlier.

The value of moving up half a round depends on the initial draft position. For example, a player projected near the top of the second round could move into the late first round. Based on 2024 NFL Draft salary data,[2] this shift could increase expected total compensation from approximately $7 million to $15 million, a gain of about $8 million. Similarly, a move from the fourth round to the early third round could raise compensation from $4.6 million to $5.8 million, about a $1.2 million difference.

Because compensation declines sharply across rounds—especially between the first and third—modest improvements in draft round driven by program quality can lead to substantial financial differences.

Relation to Prior Research

The estimated effects of program quality on draft outcomes are consistent with prior work documenting institutional signaling in the NFL Draft. Kitchens (2015) finds similar magnitudes of bias favoring players from higher-ranked programs, even after accounting for individual ability. Our findings support this result, showing that program quality remains a strong predictor of draft round and pick number even after conditioning on athlete performance and recruitment characteristics.

Pitts and Evans (2019a) suggest that teams sometimes misallocate draft capital by overweighting observable attributes not strongly tied to future productivity. This pattern is consistent with our results, which show persistent returns to program affiliation.

Finally, Keefer (2016) shows that NFL rookie compensation is shaped by discrete round-based groupings, even though the round is a grouping based on pick number. Since our outcome measures include both draft round and pick number, the economic implications of program quality that we observe—especially near round boundaries—are consistent with these compensation discontinuities.

These studies provide a framework for interpreting these findings as evidence of targeted recruiting strategies that reduce uncertainty for teams, even if they do not always align with long-run player performance.

5.2 Career Length

This section examines the relationship between college football program quality and long-run career outcomes in the NFL. Career length is a central measure of success in professional football. As shown in the summary statistics and figures in Sections 2 and 3, NFL careers are typically short, with high turnover and low survival probabilities. Players

[2] https://fansided.com/posts/nfl-draft-pick-salaries-by-round-contract-value-length-and-more-01hte697a53m

compete in an ultra-competitive, tournament-style labor market, and many are cut after a single season or never appear in a regular-season game. Given these dynamics, career length—defined by games played, seasons started, or years on a roster—is a first-order outcome in evaluating labor market returns to collegiate training environments.

We begin by examining the total number of NFL games played, presented in Table 7, using the same sequence of model specifications shown in previous sections. Column (1) reports the unadjusted relationship between college program quality (measured by SRS rank, where higher values represent stronger programs) and number of games played. The estimated effect is near zero and not statistically significant. In Column (2), the model adds controls for high school athletic ability. The coefficient on program quality becomes positive and statistically significant, suggesting that, conditional on early ability, players from stronger programs appear in approximately 2.5 more NFL games. Column (3) introduces controls for the average quality of a player's scholarship offerset. The program quality effect attenuates and becomes statistically insignificant. Column (4) includes athlete characteristics and college performance controls, with the program quality coefficient remaining positive but statistically indistinguishable from zero. Across all models, high school ability and offerset quality are consistently strong predictors of total games played, indicating that early signals of talent and recruitment context have enduring value in predicting career longevity.

To provide a broader view of career outcomes, Table 8 presents regression estimates for three outcomes: total number of NFL games played, total seasons as a primary starter, and total years on an active NFL roster. These outcomes capture different dimensions of career success: availability and durability (games), sustained employer trust (starter seasons), and long-term employment (years in the league).

Column (1) confirms the pattern described above, with no statistically significant effect of program quality on total games played after full adjustment. Column (2) shows that a one standard deviation increase in SRS rank is associated with a 0.119 increase in total seasons as a starter ($p < 0.05$), holding performance and recruitment characteristics constant. This suggests that players from stronger programs are more likely to be trusted in leadership or high-responsibility roles. In Column (3), however, the coefficient on program quality is negative and statistically significant: players from stronger programs spend, on average, 0.146 fewer years in the league ($p < 0.05$). This result diverges from the previous pattern and may reflect the incentive structures surrounding high draft picks.

One potential explanation is injury risk: players from top programs tend to be drafted earlier due to stronger college performance, which results in their placement on lower-performing NFL teams because of the draft's reverse-order ranking system. These teams may offer less protection (e.g., weaker offensive lines), increasing physical exposure. Additionally, because rookie contracts are tied to draft position, teams have a larger financial stake in high picks and may push these players into starting roles earlier. This front-loaded usage could lead to earlier burnout or higher attrition rates, consistent with the finding of shorter total years in the league.

Relation to Prior Research on Career Length

The findings in this section are consistent with prior research examining player valuation and career outcomes in the NFL. Massey and Thaler (2013) document that top draft picks are systematically overvalued, resulting in inefficient allocation of draft capital. Their analysis focuses on surplus value and trade behavior, but the observed mismatch between draft cost and realized performance aligns with our finding that early picks from top-ranked programs may not experience longer careers. Similarly, Kitchens (2015) finds that individuals from highly ranked college programs are drafted earlier, conditional on ability, but observes no significant relationship between college affiliation and career success, including total games played and career duration. These results mirror this pattern across two of three measures—total games played and years in the league—though I do detect a small positive effect on seasons started.

This study adds to this literature in two ways. First, I use a significantly larger and more recent sample of players, improving the precision of estimates and capturing more recent shifts in league practices. Second, we examine multiple dimensions of career success—games played, seasons started, and years on roster—rather than relying on a single metric. Finally, while Ducking, Groothuis, and Hill (2015) focus on potential racial disparities in career exits, they report similar baseline estimates for career length (average of 3.78 years), consistent with our descriptive statistics. These results confirm that NFL careers are short and subject to high attrition, reinforcing the importance of measuring career length as a core outcome in evaluating player development and draft strategy.

5.3 Career Productivity

This section examines the relationship between college football program quality and professional productivity in the NFL. Productivity is measured using the Approximate Value (AV) metric, a widely used statistic that quantifies a player's on-field contributions across positions and seasons. The AV metric is calculated annually and summed over a player's career to produce a measure of total career productivity. Rookie productivity is defined as the cumulative AV produced for the team that initially drafted the player. Both measures are described in greater detail in Section 2. In addition, we examine whether players were ever selected to a Pro Bowl, a binary indicator of high individual performance recognition.

AV-based outcomes capture both player usage and performance, providing a more comprehensive measure of value than contract length or games played alone. While performance is shaped by many factors—including opportunity, team fit, and injuries—these measures allow for comparisons across roles and draft positions.

Table 9 presents estimates from a sequence of regressions using total career productivity (AV) as the outcome. Column (1) shows a statistically significant positive association between college program quality and career productivity in the unadjusted model: a one standard deviation increase in SRS rank (i.e., stronger program) is associated with a 0.85-point increase in total career AV ($p < 0.05$). After adjusting for high school ability in Column (2), the coefficient declines to 0.54 and is no longer statistically significant. In Column (3), after adding controls for average offerset quality, the coefficient further attenuates to 0.24. In the fully adjusted model (Column 4), which includes athlete physical attributes, scholarship and offerset characteristics, and college performance metrics, the coefficient returns to 0.55 but remains statistically insignificant.

Across all specifications, high school ability and offerset quality are more consistent predictors of career productivity. These findings suggest that while program affiliation may influence early opportunities (e.g., draft position), long-term productivity is shaped more by individual characteristics and pre-college evaluations.

To expand the analysis beyond total AV, Table 10 reports results for three productivity-related outcomes: (1) total career AV, (2) rookie AV for the drafting team, and (3) Pro Bowl selection. The coefficient on college program quality is positive in all three cases but statistically insignificant, indicating no robust association between program strength and productivity after accounting for performance and recruitment characteristics. The coefficient for rookie AV is slightly smaller (0.50), while the marginal effect on the probability of Pro Bowl selection is close to zero (0.035, SE = 0.024).

In sum, while players from stronger college programs tend to be drafted earlier, these early advantages do not consistently translate into higher career productivity. The magnitude of the estimated effects is modest across models, and the results reinforce the pattern observed in the career length section: long-run success in the league is more strongly tied to individual-level performance indicators and pre-college evaluations than institutional affiliation alone.

Relation to Prior Research on Career Productivity

The findings in this section are consistent with prior work that questions the predictive accuracy of early evaluations in forecasting long-run player productivity. Kitchens (2015) finds no relationship between college program affiliation and career success, including a performance measure based on a player's top three seasons. Similarly, our results show that once performance and recruitment characteristics are accounted for, college program quality is not a robust predictor of Approximate Value over the course of an NFL career.

Our findings differ slightly from those of Hendricks et al. (2003), who argue that players from less prominent programs tend to outperform those from highly visible programs, suggesting a potential undervaluation at the draft stage. However, their sample focuses on players from the 1980s and 1990s and lacks rich control variables for player ability and context, which limits comparability. More recent studies, including Craig and Winchester (2021) and Berri and Simmons (2011), document systematic misalignment between pre-draft evaluations and actual performance, particularly among quarterbacks. These papers point to specific traits—such as rushing ability for quarterbacks—that are undervalued by scouts and analysts at the time of hiring.

Our results reinforce the broader conclusion across this literature: draft outcomes and institutional affiliations contain some predictive power for early-career opportunities, but long-run productivity in the NFL depends more heavily on individual performance, adaptability, and post-draft development.

5.4 Earnings Outcomes

This section examines the relationship between college program quality and labor market compensation in the NFL. Compensation is captured using two outcome measures: (1) base annual salary and (2) total annual earnings. The base salary reflects a player's negotiated pay excluding bonuses and incentives, while total earnings include all forms of monetary compensation, such as signing bonuses, performance bonuses, incentive payouts, and restructuring payments. In both cases, the dependent variable is the natural logarithm of earnings, allowing coefficients to be interpreted approximately as percentage changes.

Table 11 presents regression estimates for the log of base salary. Column (1) reports the unadjusted relationship between college program quality and log salary. The estimate indicates that a one standard deviation increase in SRS rank (i.e., stronger college program) is associated with a 5.5% increase in base salary (p ¡ 0.01). In Column (2), controlling for high school ability reduces the coefficient to 1.3% and renders it statistically insignificant. In Column (3), adding offerset quality slightly raises the estimate to 1.9% ($p < 0.01$). In the fully adjusted model (Column 4), which includes athlete attributes and college performance, the estimate remains small and statistically insignificant. Across all models, high school ability is a strong and consistent predictor of salary, while offerset quality shows a negative association.

Table 12 reports parallel estimates using total annual earnings as the dependent variable. The unadjusted association between college program quality and log total earnings is 0.164, or approximately a 16.4% increase in annual compensation per standard deviation increase in SRS rank ($p < 0.01$). As controls are added, the coefficient declines. In Column (2), the estimate is 3.1% ($p < 0.05$). In Columns (3) and (4), the effect remains positive but is no longer statistically significant. High school ability is again the strongest predictor of earnings, with each standard deviation increase associated with approximately 35% higher total compensation. Offerset quality continues to have a negative association with both salary and total earnings, possibly reflecting omitted preferences for early playing time or team fit.

Taken together, the results suggest that while players from stronger college programs earn higher compensation on average, this relationship weakens considerably after controlling for athlete characteristics and pre-college indicators. The stronger association observed in unadjusted models may reflect indirect effects through draft position and perceived market value rather than direct productivity returns.

Relation to Prior Research on Earnings Outcomes

Most prior studies examining wage and earnings outcomes in the NFL have focused on racial discrimination rather than institutional background. Classic studies by Mogull (1973), Kahn (1992), and **?** examine compensation disparities by race, with mixed findings. Several studies document a wage premium for white players, while others such as **?** and Ducking et al. (2015) find no significant differences or modest premiums for Black players in certain contexts. These studies rely largely on roster-level or career earnings data and are not designed to assess the labor market value of program affiliation.

The closest related work to this paper is by Kitchens (2015) and Hendricks et al. (2003), both of which examine institutional signaling and selection bias in the draft process. However, neither study examines post-draft compensation. Our findings extend this literature by showing that the positive association between program quality and earnings observed in unadjusted models disappears after adjusting for performance and recruitment characteristics.

These results are consistent with those from the productivity analysis in Section 5.3, and follow naturally from the well-established correlation between player compensation and productivity in the NFL. Gregory-Smith, Bryson, and Gomez (2023) uses data on player injuries to show that marginal product and salary are tightly linked in this labor market. Given the absence of a robust relationship between college program quality and career productivity, the lack of an independent earnings effect is consistent with theoretical expectations.

6 Conclusion

This chapter examines the long-run impact of elite college sports program affiliation on professional career outcomes in the National Football League (NFL). Extending the analysis from Chapter 1, which focused on selection into the NFL, this chapter investigates what happens after athletes enter the league. Using a novel panel dataset of drafted players from 2000 to 2024, matched to detailed pre-college and college performance characteristics, I assess whether the early-career advantages associated with elite programs persist throughout an athlete's professional tenure.

The results show that while players from stronger college programs are drafted earlier, this initial advantage does not consistently translate into better outcomes on the intensive margin. I find no robust relationship between program quality and long-run productivity, career duration, or total compensation. In some cases, players from top programs even exhibit shorter career spans, likely reflecting pressure from coaches and fans to play earlier and for worse teams. These findings suggest that the NFL draft premium for elite programs is not driven by unmeasured human capital but rather by institutional signaling.

This conclusion is particularly noteworthy given the nature of the NFL labor market. Professional football is a data-intensive industry. Teams have access to extensive performance metrics, biometric data, video analysis, and scouting reports across multiple stages of a player's development—from high school through college. Franchises invest heavily in analytics departments, evaluation software, and personnel to assess talent. In principle, this should reduce reliance on institutional signals like college program prestige. That signaling remains influential in such a setting indicates that the issue is not a lack of information, but rather the difficulty of synthesizing large, complex datasets into clear assessments of individual value.

This insight has broader implications for our understanding of statistical discrimination and labor market signaling. Traditional models emphasize the role of signaling in low-information environments, where employers lack sufficient data to make informed hiring decisions. The NFL case, however, illustrates that signaling may also arise in high-information environments, where the abundance of data creates its own form of noise. When decision-makers are overwhelmed by complex or multidimensional information, they may revert to simpler heuristics—such as institutional affiliation—as proxies for quality.

As firms across industries increasingly recruit from global talent pools and rely on digital evaluations, this phenomenon is likely to become more common. High-powered firms face an expanding volume of candidate data: online portfolios, skill assessments, coding tests, social media profiles, and more. Yet without the capacity to process and interpret all this information efficiently, employers may continue to rely on institutional markers such as university rank, company pedigree, or certification signals. The findings in this chapter suggest that signaling remains a durable feature of labor markets—not just when information is lacking, but also when it is abundant but difficult to interpret.

This chapter contributes to the broader literature on employer learning, talent evaluation, and market inefficiencies by showing that institutional signals play a persistent role even in contexts that appear highly meritocratic. In doing so, it shows the importance of understanding how and when signals are used in practice, and how the structure of information—rather than its mere availability—shapes labor market outcomes.

References

Berri, D. J., & Simmons, R. (2011, February). Catching a draft: on the process of selecting quarterbacks in the National Football League amateur draft. *J Prod Anal*, *35*(1), 37–49. Retrieved 2025-03-29, from https://doi.org/10.1007/s11123-009-0154-6 doi: 10.1007/s11123-009-0154-6

Brown, W. B., & Sommers, P. M. (2020, March). The Simple Analytics of Evaluating NFL Trades. *Atl Econ J*, *48*(1), 139–141. Retrieved 2025-03-29, from https://doi.org/10.1007/s11293-020-09652-8 doi: 10.1007/s11293-020-09652-8

Chen, W., Grove, W. A., & Hussey, A. (2013, March). *The Payoff to School Selectivity: An Application of Dale and Krueger's Method to MBA Programs* [SSRN Scholarly Paper]. Rochester, NY. Retrieved 2022-11-29, from https://papers.ssrn.com/abstract=2240305

Craig, J. D., & Winchester, N. (2021, December). Predicting the national football league potential of college quarterbacks. *European Journal of Operational Research*, *295*(2), 733–743. Retrieved 2023-05-17, from https://www.sciencedirect.com/science/article/pii/S0377221721002034 doi: 10.1016/j.ejor.2021.03.013

Cunningham, P. (2008). Dimension Reduction. In M. Cord & P. Cunningham (Eds.), *Machine Learning Techniques for Multimedia: Case Studies on Organization and Retrieval* (pp. 91–112). Berlin, Heidelberg: Springer. Retrieved 2025-03-30, from https://doi.org/10.1007/978-3-540-75171-7_4 doi: 10.1007/978-3-540-75171-7_4

Dale, S. B., & Krueger, A. B. (2002). Estimating the Payoff to Attending a More Selective College: An Application of Selection on Observables and Unobservables. *The Quarterly Journal of Economics*, *117*(4), 1491–1527. Retrieved 2022-12-12, from https://www.jstor.org/stable/4132484 (Publisher: Oxford University Press)

Dale, S. B., & Krueger, A. B. (2014). Estimating the Effects of College Characteristics over the Career Using Administrative Earnings Data. *The Journal of Human Resources*, *49*(2), 323–358. Retrieved 2022-12-12, from https://www.jstor.org/stable/23799087 (Publisher: [University of Wisconsin Press, Board of Regents of the University of Wisconsin System])

Drinen, D. (2008). *Approximate value.* https://www.pro-football-reference.com/about/approximate_value.htm. (Published on Pro-Football-Reference.com)

Ducking, J., Groothuis, P. A., & Hill, J. R. (2015, January). Exit Discrimination in the NFL: A Duration Analysis of Career Length. *The Review of Black Political Economy*, *42*(3), 285–299. Retrieved 2024-11-21, from https://doi.org/10.1007/s12114-014-9207-9 (Publisher: SAGE Publications Inc) doi: 10.1007/s12114-014-9207-9

Duquette, C. M., & Cebula, R. J. (2020). The Economics of the NFL Draft: Improved Estimates of Draft-Order Valuations. *International Journal of Sport Finance*, *15*(4), 155–165. Retrieved 2025-03-29, from https://muse.jhu.edu/pub/560/article/927057 (Publisher: FiT Publishing)

Dutta, R., Yurko, R., & Ventura, S. L. (2020, June). Unsupervised methods for identifying pass coverage among defensive backs with NFL player tracking data. *Journal of Quantitative Analysis in Sports*, *16*(2), 143–161. Retrieved 2025-03-30, from https://www.degruyter.com/document/doi/10.1515/jqas-2020-0017/html (Publisher: De Gruyter) doi: 10.1515/jqas-2020-0017

Foltice, B., & Markus, J. (2021, November). *Finding Value in NFL Draft Picks* [SSRN Scholarly Paper]. Rochester, NY. Retrieved 2024-09-22, from https://papers.ssrn.com/abstract=3836012 doi: 10.2139/ssrn.3836012

Fonseca, J. R. (2013, September). Clustering in the field of social sciences: that is your choice. *International Journal of Social Research Methodology*, *16*(5), 403–428. Retrieved 2025-03-30, from https://doi.org/10.1080/13645579.2012.716973 (Publisher: Routledge _eprint: https://doi.org/10.1080/13645579.2012.716973) doi: 10.1080/13645579.2012.716973

Ge, S., Isaac, E., & Miller, A. (2022, April). Elite Schools and Opting In: Effects of College Selectivity on Career and Family Outcomes. *Journal of Labor Economics*, *40*(S1), S383–S427. Retrieved 2024-09-21, from https://www.journals.uchicago.edu/doi/abs/10.1086/717931 (Publisher: The University of Chicago Press) doi: 10.1086/717931

Gregory-Smith, I., Bryson, A., & Gomez, R. (2023, September). Discrimination in a Rank Order Contest: Evidence from the NFL Draft. *J Econ Race Policy*, *6*(3), 215–231. Retrieved 2024-09-21, from https://doi.org/10.1007/s41996-023-00118-y doi: 10.1007/s41996-023-00118-y

Hendricks, W., DeBrock, L., & Koenker, R. (2003, October). Uncertainty, Hiring, and Subsequent Performance: The NFL Draft. *Journal of Labor Economics*, *21*(4), 857–886. Retrieved 2024-11-24, from https://www.journals.uchicago.edu/doi/abs/10.1086/377025 (Publisher: The University of Chicago Press) doi: 10.1086/377025

Husowitz, B., Mixer, M., & Morrow, S. (2025). NFL Data Analytics and Predictions Using Machine Learning. In B. Sriraman (Ed.), *Handbook of Visual, Experimental and Computational Mathematics : Bridges through Data* (pp. 1–21). Cham: Springer Nature Switzerland. Retrieved 2025-03-30, from https://doi.org/10.1007/978-3-030-93954-0_22-1 doi: 10.1007/978-3-030-93954-0_22-1

Kahn, L. M. (1992, January). The Effects of Race on Professional Football Players' Compensation. *ILR Review*, *45*(2), 295–310. Retrieved 2025-03-29, from https://doi.org/10.1177/001979399204500207 (Publisher: SAGE Publications Inc) doi: 10.1177/001979399204500207

Keefer, Q. A. W. (2016, October). Rank-Based Groupings and Decision Making: A Regression Discontinuity Analysis of the NFL Draft Rounds and Rookie Compensation. *Journal of Sports Economics*, *17*(7), 748–762. Retrieved 2024-09-22, from https://doi.org/10.1177/1527002514541448 (Publisher: SAGE Publications) doi: 10.1177/1527002514541448

Keefer, Q. A. W. (2017, April). The Sunk-Cost Fallacy in the National Football League:

Salary Cap Value and Playing Time. *Journal of Sports Economics*, *18*(3), 282–297. Retrieved 2024-09-22, from https://doi.org/10.1177/1527002515574515 (Publisher: SAGE Publications) doi: 10.1177/1527002515574515

Kitchens, C. T. (2015). Are Winners Promoted Too Often? Evidence from the Nfl Draft 1999–2012. *Economic Inquiry*, *53*(2), 1317–1330. Retrieved 2024-09-22, from https://onlinelibrary.wiley.com/doi/abs/10.1111/ecin.12165 (_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ecin.12165) doi: 10.1111/ecin.12165

Massey, C., & Thaler, R. H. (2013, July). The Loser's Curse: Decision Making and Market Efficiency in the National Football League Draft. *Management Science*, *59*(7), 1479–1495. Retrieved 2022-12-02, from https://pubsonline.informs.org/doi/10.1287/mnsc.1120.1657 (Publisher: INFORMS) doi: 10.1287/mnsc.1120.1657

Mogull, R. G. (1973, February). Football Salaries and Race: Some Empirical Evidence. *Industrial Relations*, *12*(1), 109–112. Retrieved 2025-03-29, from https://research.ebsco.com/linkprocessor/plink?id=d0b1f35f-ff72-3eab-92f6-d9f989d3158d (Publisher: Wiley-Blackwell) doi: 10.1111/j.1468-232X.1973.tb00539.x

Mulholland, J., & Jensen, S. T. (2019, April). Optimizing the allocation of funds of an NFL team under the salary cap. *International Journal of Forecasting*, *35*(2), 767–775. Retrieved 2025-03-29, from https://www.sciencedirect.com/science/article/pii/S0169207018301559 doi: 10.1016/j.ijforecast.2018.09.004

Paine, N. (2015, April). *Are Some Positions Riskier To Pick Than Others In The NFL Draft?* Retrieved 2025-03-29, from https://fivethirtyeight.com/features/are-some-positions-riskier-to-pick-than-others-in-the-nfl-draft/

Pitts, J. D., & Evans, B. (2019a, March). Drafting for Success: How Good Are NFL Teams at Identifying Future Productivity at Offensive-Skill Positions in the Draft? *The American Economist*, *64*(1), 102–122. Retrieved 2024-09-21, from https://doi.org/10.1177/0569434518812678 (Publisher: SAGE Publications Inc) doi: 10.1177/0569434518812678

Pitts, J. D., & Evans, B. (2019b, March). Drafting for Success: How Good Are NFL Teams at Identifying Future Productivity at Offensive-Skill Positions in the Draft? *The American Economist*, *64*(1), 102–122. Retrieved 2025-03-29, from https://doi.org/10.1177/0569434518812678 (Publisher: SAGE Publications Inc) doi: 10.1177/0569434518812678

Salim, M. D. O., & Brandão, W. C. (2018). Predicting the Success of NFL Teams using Complex Network Analysis:. In *Proceedings of the 20th International Conference on Enterprise Information Systems* (pp. 135–142). Funchal, Madeira, Portugal: SCITEPRESS - Science and Technology Publications. Retrieved 2025-03-30, from http://www.scitepress.org/DigitalLibrary/Link.aspx?doi=10.5220/0006697101350142 doi: 10.5220/0006697101350142

Schuckers, M. (2011, May). An Alternative to the NFL Draft Pick Value Chart

Based upon Player Performance. *Journal of Quantitative Analysis in Sports*, *7*(2). Retrieved 2025-03-29, from https://www.degruyter.com/document/doi/10.2202/1559-0410.1329/html (Publisher: De Gruyter) doi: 10.2202/1559-0410.1329

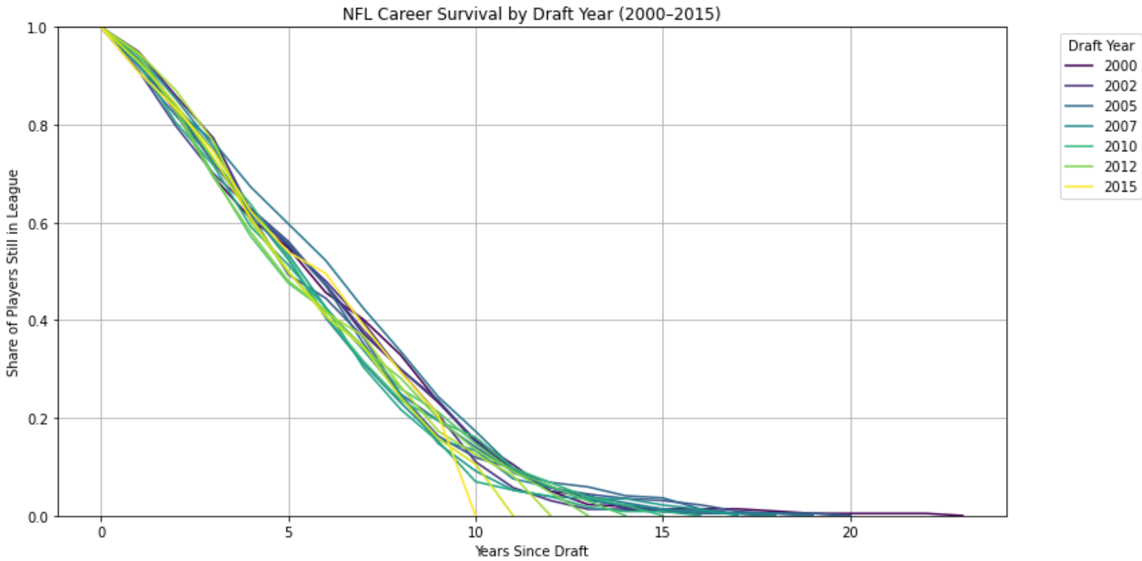
Scott, J. (2012, April). Are NFL Athletes Receiving Over-Valued Contracts? *Honors Projects in Mathematics*. Retrieved from https://digitalcommons.bryant.edu/honors_mathematics/8

Shelly, Z., Burch, R. F., Tian, W., Strawderman, L., Piroli, A., & Bichey, C. (2020, May). Using K-means Clustering to Create Training Groups for Elite American Football Student-athletes Based on Game Demands. *International Journal of Kinesiology and Sports Science*, *8*(2), 47–63. Retrieved 2025-03-30, from https://journals.aiac.org.au/index.php/IJKSS/article/view/6092 doi: 10.7575//aiac.ijkss.v.8n.2p.47

Yurko, R., Ventura, S., & Horowitz, M. (2019, September). nflWAR: a reproducible method for offensive player evaluation in football. *Journal of Quantitative Analysis in Sports*, *15*(3), 163–183. Retrieved 2025-03-29, from https://www.degruyter.com/document/doi/10.1515/jqas-2018-0010/html?ref=americansequel.com (Publisher: De Gruyter) doi: 10.1515/jqas-2018-0010

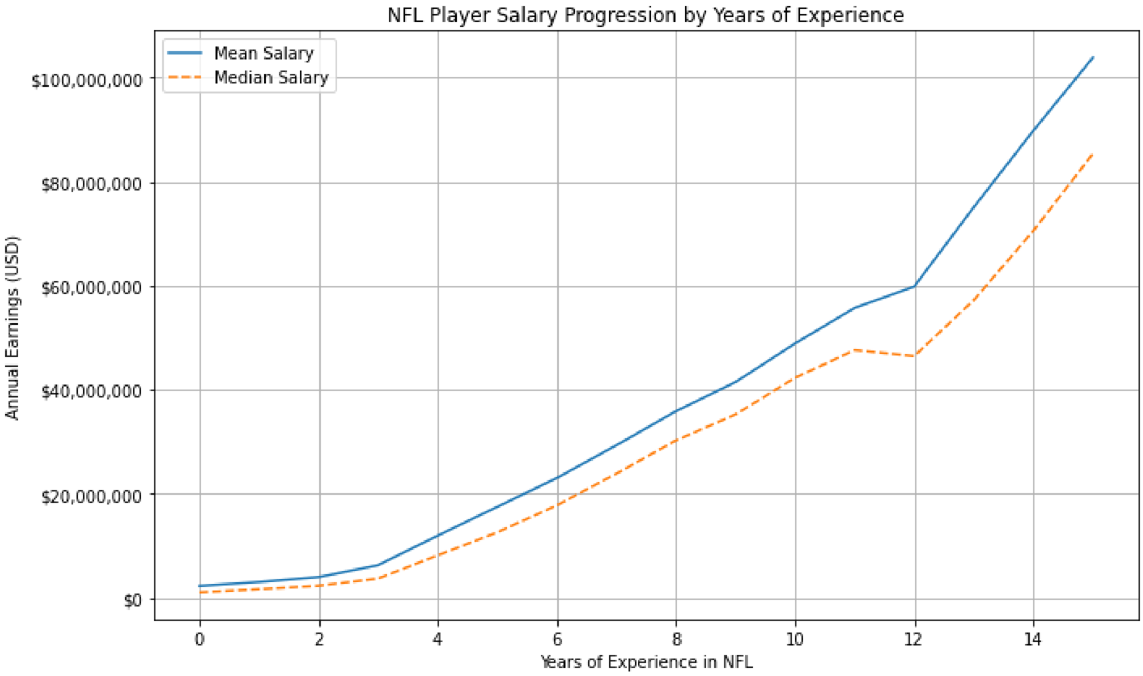
Tables and Figures

Figure 1: NFL Career Survival by Draft Year (2000–2015)



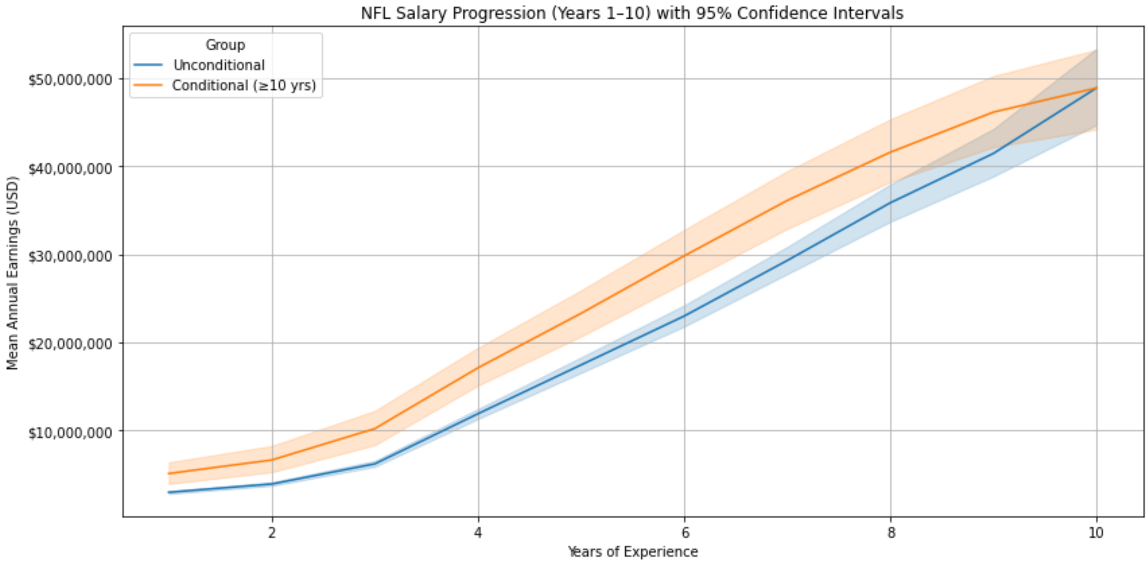
Note: This figure plots the share of drafted NFL players who remain active in the league by year since being drafted, using data from the descriptive sample of all players selected in the NFL Draft from 2000 to 2015. Each line represents a separate draft cohort. The survival probability declines sharply in the first five years following the draft, with fewer than 25% of players remaining in the league after five years. Data sourced from Pro-Football-Reference.com and constructed using career length calculations based on draft year and final year of recorded play (as of time of writing, 2025).

Figure 2: NFL Player Compensation Trajectories by Years of Experience



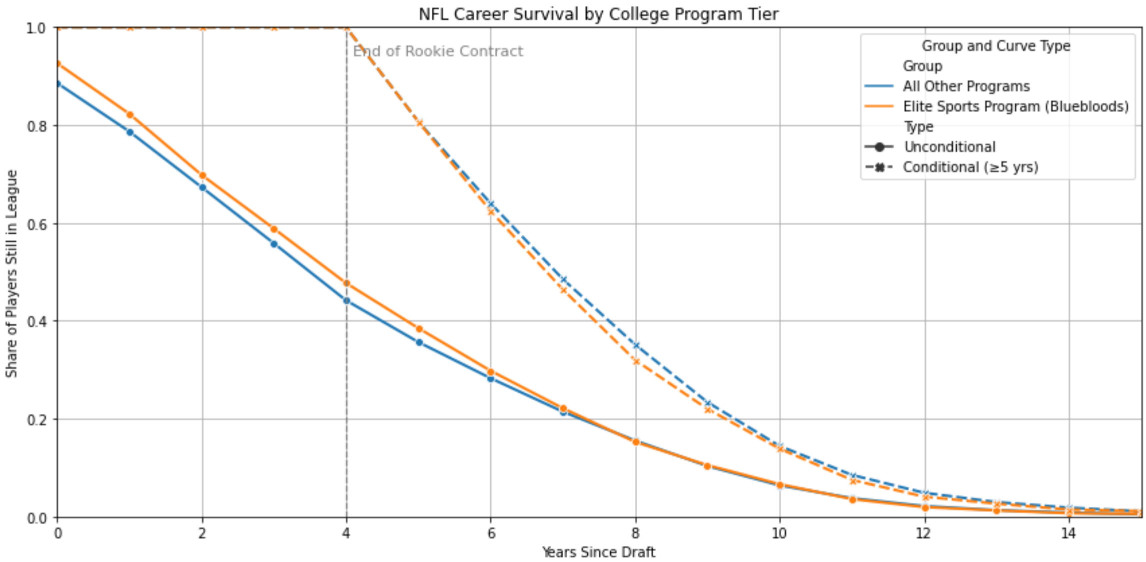
Note: This figure plots mean and median annual earnings of NFL players by years of professional experience, defined as the number of years since their draft year. Salary data is aggregated from the descriptive sample of players with valid contract information between 2010 and 2023. The sharp rise in average compensation around Year 4 reflects the typical expiration of rookie contracts and the onset of free agency eligibility. The increasing divergence between mean and median earnings at higher experience levels indicates the skewness of veteran compensation, where a small number of highly paid players raise the average. This compensation profile provides context for interpreting the estimated effects of elite college football programs on long-term labor market outcomes in the NFL.

Figure 3: Mean NFL Earnings by Years of Experience: Conditional vs. Unconditional Sample



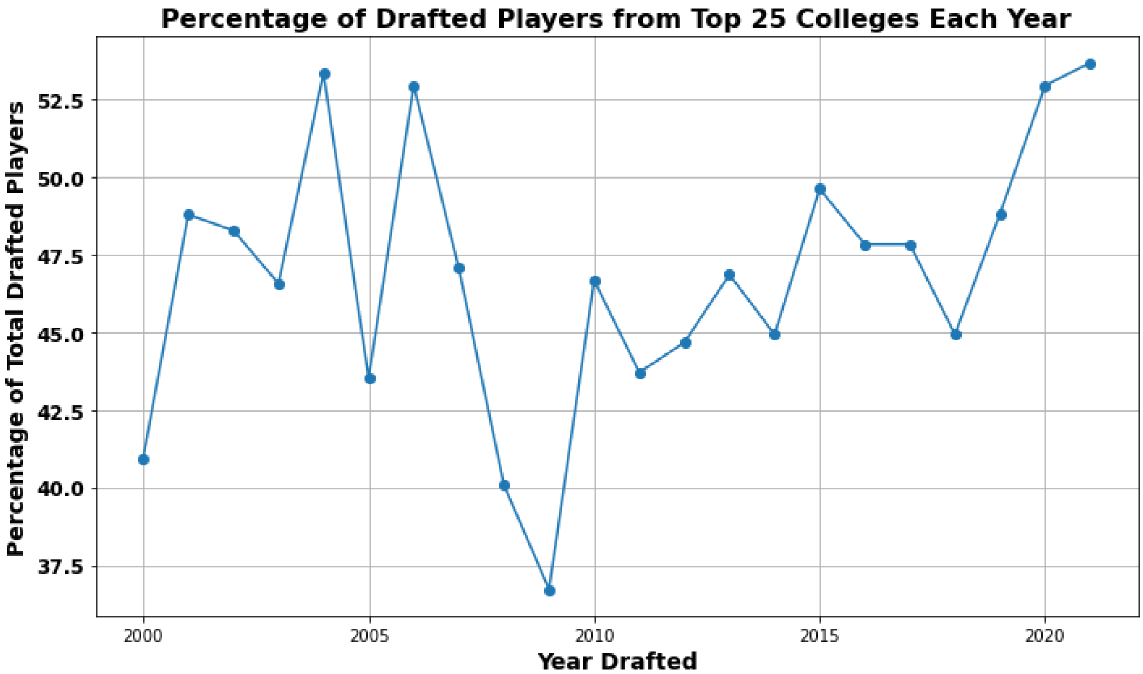
Note: This figure compares mean annual earnings of NFL players over their first ten years of experience, based on whether they ultimately remained in the league for at least ten seasons. The "Unconditional" group includes all players observed in the NFL between Years 1 and 10, regardless of career length. The "Conditional" group includes only players who completed at least ten years in the league. Conditional players consistently earn more at every stage, with the gap widening over time. This pattern reflects the premium placed on long-term performance and contract renegotiation opportunities in later career stages. Earnings are reported in nominal dollars.

Figure 4: NFL Career Survival by College Program Tier



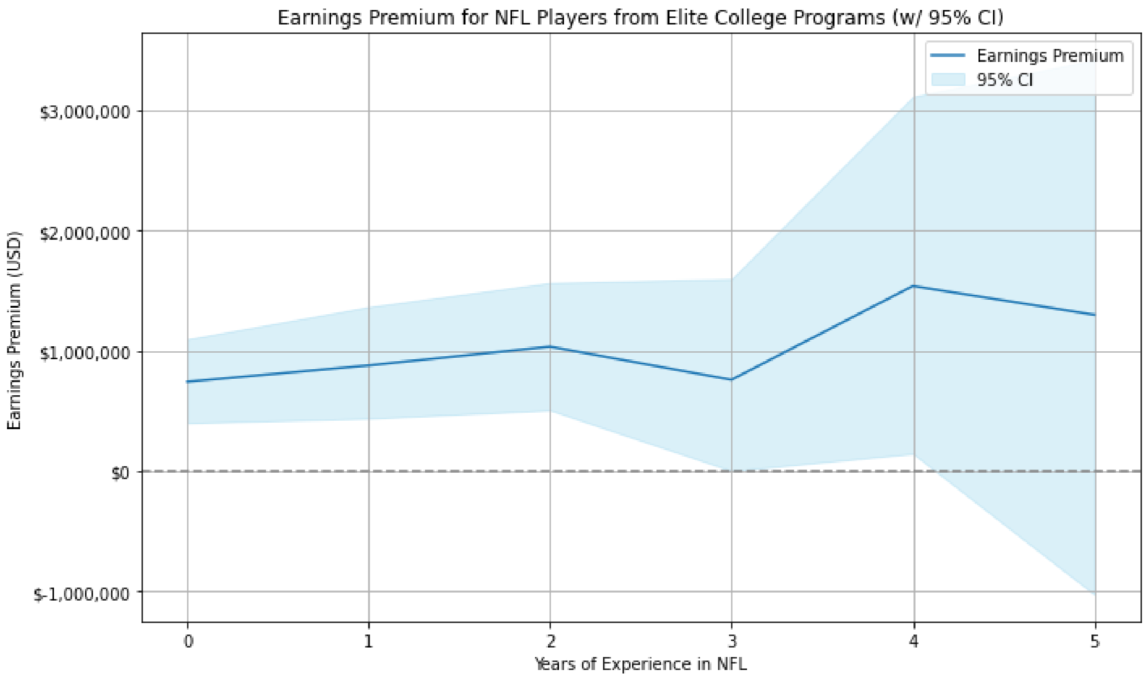
Note: This figure shows the share of NFL players still active by years since draft, separated by whether they attended an elite college football program ("Bluebloods") or another program. The sample includes all drafted players with verified career data. Solid lines represent unconditional survival probabilities, while dashed lines reflect conditional probabilities for players who remained in the league for at least five years. Players from elite programs exhibit slightly higher career retention across both samples. A vertical line at Year 4 marks the end of the typical rookie contract window, after which career exit accelerates.

Figure 5: Share of Drafted Players from Elite Programs Over Time



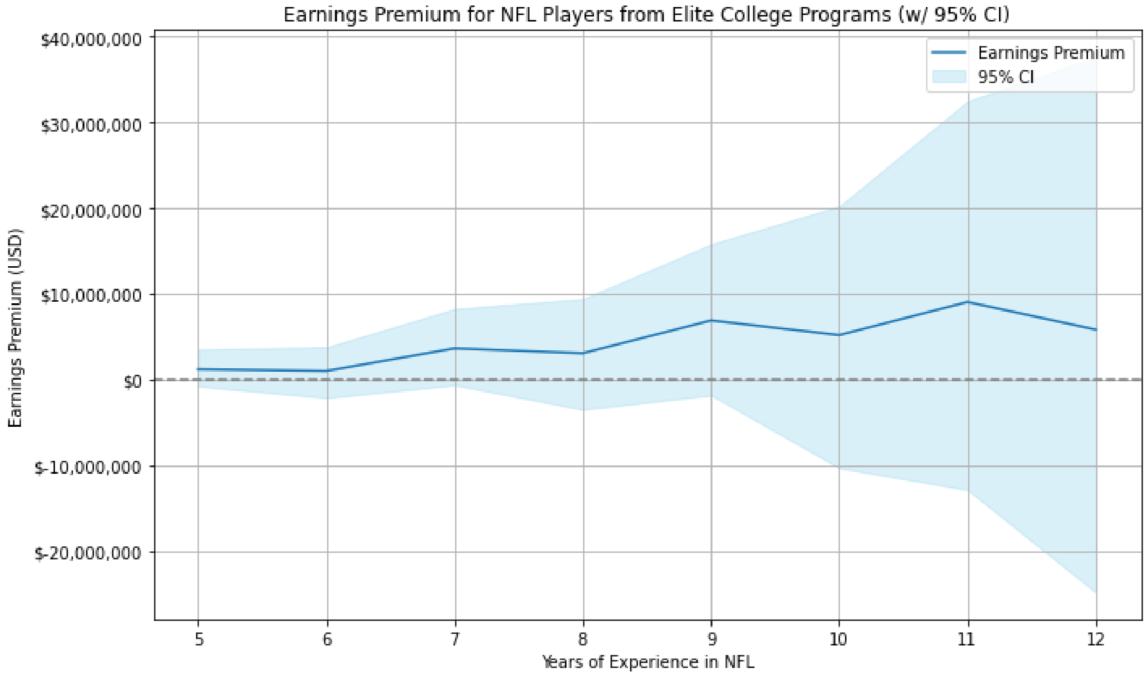
Note: This figure shows the percentage of total drafted NFL players each year who attended one of the top 25 “elite” or “Blueblood” college football programs. While there is some year-to-year variation, roughly 45–50% of drafted athletes consistently come from these programs. The figure also shows a modest upward trend in recent years, suggesting a growing concentration of NFL talent among elite colleges.

Figure 6: Earnings Premium for Players from Elite Programs (Years 0–5)



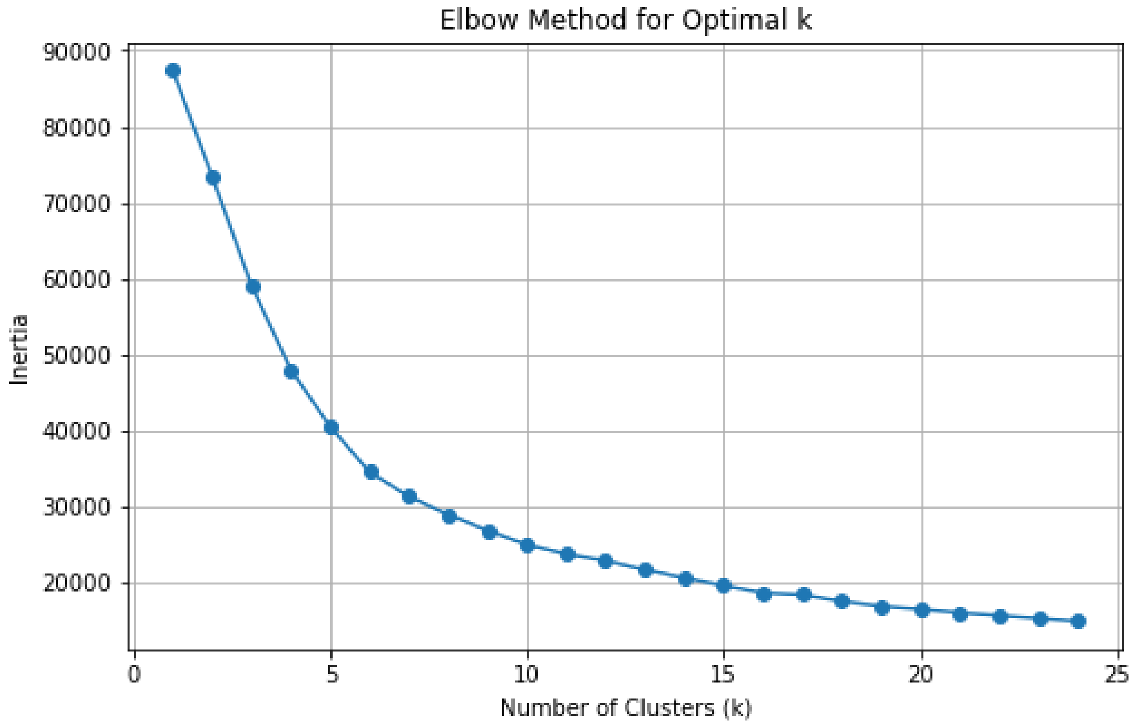
Note: This figure plots the average difference in annual earnings between NFL players from elite (Blueblood) college programs and players from all other programs during the first five years of their careers. The shaded band represents the 95% confidence interval generated from 500 bootstrap replications. Although players from elite programs tend to earn more during this early career phase, confidence intervals widen after Year 4, indicating increased earnings variability and reduced statistical precision.

Figure 7: Earnings Premium for Players from Elite Programs (Years 5–12)



Note: This figure shows the estimated earnings premium for players from elite college programs who remained in the NFL for at least five years. The plotted values represent the difference in average annual earnings at each year of experience, with 95% confidence intervals derived from bootstrap sampling. While some premiums appear at various points, the intervals are wide and span zero in many cases, implying that long-run compensation converges across players from elite and non-elite programs.

Figure 8: Elbow Method Plot for Determining Optimal Number of Clusters (K) in K-means Clustering



Note: This figure displays the within-cluster sum of squares (inertia) plotted against the number of clusters (K), using standardized college performance statistics. The "elbow" at $K = 7$ marks the point where adding additional clusters yields diminishing returns in reducing within-cluster variance. This supports the choice of 7 clusters as a parsimonious and interpretable specification for capturing latent performance types among college football players.

Table 5: Effect of College Program Quality on NFL Draft Round

NFL Draft Round (1-7)	(1) **College Quality**	(2) **HS Ability + College Quality**	(3) **HS Ability + College Quality + Offersets**	(4) **Col (3) + Athletic Perf. Match Groups**
College Program Rank	-0.238***	-0.139***	-0.123***	-0.141***
	(0.038)	(0.043)	(0.044)	(0.045)
HS Ability		-0.207*	-0.200*	-0.170
		(0.120)	(0.121)	(0.121)
Avg Quality Offer-set			-0.053	-0.061*
			(0.036)	(0.036)
Athlete Controls (Height, Weight, Age)	✓	✓	✓	✓
Scholarship Offerset Controls			✓	✓
College Athletic Performance Controls				✓
Constant	4.052	4.052	4.052	3.968
	(0.037)	(0.037)	(0.037)	(0.083)
R^2	0.143	0.150	0.152	0.160
N	2514.000	2514.000	2514.000	2514.000

Standard errors in parentheses

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

Note: This table reports estimates from OLS regressions of NFL Draft round on college program quality and controls. The dependent variable is the round (1–7) in which a player is selected in the NFL Draft. Higher-quality college programs are measured using SRS rank, where a higher value indicates a stronger program. Column (1) reports the unadjusted association. Columns (2)–(4) incrementally add controls for high school ability, college offerset quality, athlete physical attributes, and college performance. All specifications include fixed effects for matched performance clusters. Robust standard errors are in parentheses.

Table 6: Effect of College Program Quality on NFL Draft Pick Number

NFL Draft Pick	(1) **College Quality**	(2) **HS Ability + College Quality**	(3) **HS Ability + College Quality + Offersets**	(4) **Col (3) + Athletic Perf. Match Groups**
College Program Rank	-0.585***	-0.591**	-0.692***	-0.749***
	(0.220)	(0.255)	(0.259)	(0.262)
HS Ability		0.004	-0.142	-0.097
		(0.704)	(0.709)	(0.712)
Avg Quality Offer-set			0.146	0.154
			(0.211)	(0.214)
Athlete Controls (Height, Weight, Age)	✓	✓	✓	✓
Scholarship Offerset Controls			✓	✓
College Athletic Performance Controls				✓
Constant	19.066	19.067	19.067	19.737
	(0.217)	(0.217)	(0.217)	(0.489)
r2	0.013	0.014	0.017	0.020
N	2514.000	2514.000	2514.000	2514.000

Standard errors in parentheses

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

Note: This table reports estimates from OLS regressions of NFL Draft pick number on college program quality and controls. The dependent variable is the overall draft pick number (e.g., 1–259), where lower values indicate earlier selection. College program quality is measured using SRS rank, with higher values indicating stronger programs. Column (1) reports the unadjusted association. Columns (2)–(4) incrementally add controls for high school ability, college offerset quality, athlete physical attributes, and college performance. All specifications include fixed effects for matched performance clusters. Robust standard errors are in parentheses.

Table 7: Effect of College Program Quality on Total NFL Games Played

NFL Games	(1) **College Quality**	(2) **HS Ability + College Quality**	(3) **HS Ability + College Quality + Offersets**	(4) **Col (3) + Athletic Perf. Match Groups**
College Program Rank	0.006	2.527**	1.389	1.649
	(0.879)	(1.010)	(1.011)	(1.017)
HS Ability		-16.000***	-16.526***	-15.386***
		(2.751)	(2.735)	(2.730)
Avg Quality Offer-set			5.136***	4.428***
			(0.815)	(0.826)
Athlete Controls (Height, Weight, Age)	✓	✓	✓	✓
Scholarship Offerset Controls			✓	✓
College Athletic Performance Controls				✓
Constant	55.087	55.098	55.125	56.166
	(0.858)	(0.850)	(0.838)	(1.887)
r2	0.039	0.058	0.085	0.097
N	2354.000	2354.000	2354.000	2354.000

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents OLS regressions of total NFL games played on college program quality and covariates. Column (1) is the unadjusted model. Column (2) adds controls for high school ability. Column (3) adds scholarship offerset quality. Column (4) adds controls for college performance and matched performance clusters. All models include athlete physical characteristics (height, weight, age). College quality is measured using SRS rank. Higher values indicate stronger programs. Robust standard errors in parentheses.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Effect of College Program Quality on NFL Career Length Outcomes

	(1) Total NFL Games	(2) Total Seasons Primary Starter	(3) Total Years in NFL
College Program Rank	1.649	0.119**	-0.146**
	(1.017)	(0.059)	(0.069)
HS Ability	-15.386***	-0.498***	-0.932***
	(2.730)	(0.159)	(0.185)
Avg Quality Offer-set	4.428***	0.196***	0.307***
	(0.826)	(0.048)	(0.056)
Athlete Controls (Height, Weight, Age)	✓	✓	✓
Scholarship Offerset Controls	✓	✓	✓
College Athletic Performance Controls	✓	✓	✓
Constant	56.166	1.603	3.896
	(1.887)	(0.109)	(0.128)
r2	0.097	0.100	0.108
N	2354.000	2514.000	2354.000

Standard errors in parentheses

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

Note: This table reports OLS estimates of the relationship between college program quality and three measures of professional career length: total NFL games played, number of seasons as a primary starter, and total years on an active NFL roster. College program quality is measured using SRS rank (higher values = stronger programs). All models include controls for high school ability, scholarship offer-set quality, athlete attributes, and college performance. Standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Effect of College Program Quality on NFL Career Productivity

NFL Career Productivity	(1) **College Quality**	(2) **HS Ability + College Quality**	(3) **HS Ability + College Quality + Offersets**	(4) **Col (3) + Athletic Perf. Match Groups**
College Program Rank	0.851**	0.540	0.240	0.552
	(0.401)	(0.465)	(0.470)	(0.472)
HS Ability		-2.614**	-2.725**	-2.927**
		(1.267)	(1.271)	(1.266)
Avg Quality Offer-set			1.009***	0.888**
			(0.379)	(0.383)
Athlete Controls (Height, Weight, Age)	✓	✓	✓	✓
Scholarship Offerset Controls			✓	✓
College Athletic Performance Controls				✓
Constant	15.214	15.227	15.234	15.527
	(0.392)	(0.391)	(0.390)	(0.875)
r2	0.063	0.067	0.077	0.092
N	2354.000	2354.000	2354.000	2354.000

Standard errors in parentheses

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

Note: This table presents OLS estimates of the relationship between college program quality and NFL career productivity, measured using cumulative Approximate Value (AV). College program quality is measured using SRS rank (higher values = stronger programs). Columns (1)–(4) sequentially add controls for high school ability, average offerset quality, athlete characteristics (height, weight, age), and college performance. Robust standard errors in parentheses.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Effect of College Program Quality on Career and Rookie Productivity and Pro Bowl Selection

	(1) Career Productivity	(2) Rookie Productivity	(3) Selected to Pro Bowl
College Program Rank	0.552	0.503	0.035
	(0.472)	(0.423)	(0.024)
HS Ability	-2.927**	-0.995	0.038
	(1.266)	(1.122)	(0.065)
Avg Quality Offer-set	0.888**	0.073	0.027
	(0.383)	(0.335)	(0.019)
Athlete Controls (Height, Weight, Age)	✓	✓	✓
Scholarship Offerset Controls	✓	✓	✓
College Athletic Performance Controls	✓	✓	✓
Constant	15.527	12.754	0.326
	(0.875)	(0.762)	(0.045)
r2	0.092	0.087	0.048
N	2354.000	2193.000	2514.000

Standard errors in parentheses

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

Note: This table presents OLS and linear probability models estimating the relationship between college program quality (SRS rank) and three outcomes: total career AV, rookie AV (cumulative AV for the drafting team), and Pro Bowl selection (binary). All models include controls for high school ability, offerset quality, athlete characteristics, and college performance. Robust standard errors in parentheses.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Effect of College Program Quality on NFL Base Annual Salary (Log Scale)

	(1) log_base_salary	(2) log_base_salary	(3) log_base_salary	(4) log_base_salary
College Program Rank	0.055***	0.013	0.019*	0.014
	(0.008)	(0.010)	(0.010)	(0.010)
HS Ability		0.151***	0.151***	0.155***
		(0.029)	(0.029)	(0.029)
Avg Quality Offer-set			-0.051***	-0.049***
			(0.008)	(0.008)
Athlete Controls (Height, Weight, Age)	✓	✓	✓	✓
Scholarship Offerset Controls			✓	✓
College Athletic Performance Controls				✓
Constant	12.751***	12.739***	12.719***	12.760***
	(0.027)	(0.027)	(0.027)	(0.032)
r2	0.388	0.397	0.405	0.408
N	7342.000	7342.000	7342.000	7342.000

Standard errors in parentheses

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

Note: This table reports OLS estimates of the relationship between college program quality and the natural logarithm of base salary in the NFL. College program quality is measured using SRS rank (higher values = stronger programs). Models incrementally add controls for high school ability, offerset quality, athlete physical attributes, and college performance. Robust standard errors in parentheses.

Table 12: Effect of College Program Quality on NFL Total Annual Earnings (Log Scale)

	(1) log_earnings	(2) log_earnings	(3) log_earnings	(4) log_earnings
College Program Rank	0.164***	0.031**	0.022	0.021
	(0.011)	(0.013)	(0.014)	(0.014)
HS Ability		0.371***	0.359***	0.354***
		(0.038)	(0.038)	(0.038)
Avg Quality Offer-set			-0.061***	-0.058***
			(0.011)	(0.011)
Athlete Controls (Height, Weight, Age)	✓	✓	✓	✓
Scholarship Offerset Controls			✓	✓
College Athletic Performance Controls				✓
Constant	14.614***	14.583***	14.556***	14.623***
	(0.036)	(0.035)	(0.035)	(0.043)
r2	0.484	0.516	0.525	0.527
N	7315.000	7315.000	7315.000	7315.000

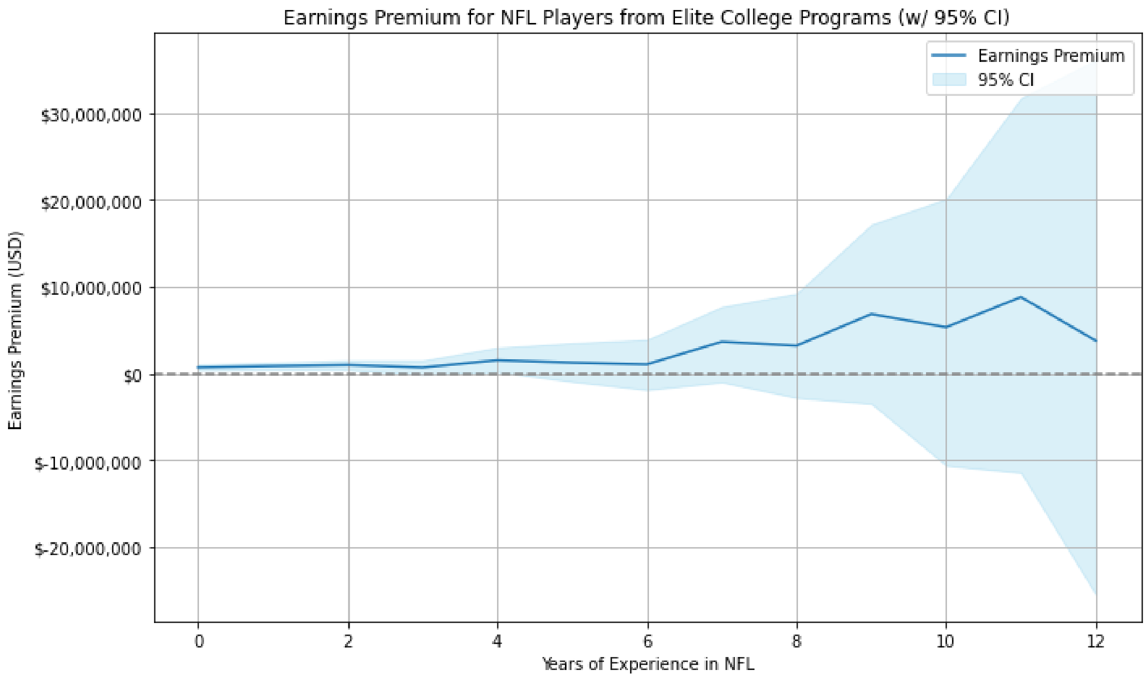
Standard errors in parentheses

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

Note: This table reports OLS estimates of the relationship between college program quality and the natural logarithm of total annual NFL earnings, which include base salary and all forms of bonus compensation. College program quality is measured using SRS rank (higher values = stronger programs). Models incrementally add controls for high school ability, offerset quality, athlete physical attributes, and college performance. Robust standard errors in parentheses.

Appendix

Figure 9



Note: This figure plots the average difference in annual earnings between NFL players from elite (Blueblood) college programs and players from all other programs during the first 12 years of their careers. The shaded band represents the 95% confidence interval generated from 500 bootstrap replications. Although players from elite programs tend to earn more during this early career phase, confidence intervals widen after Year 4.