I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16289

Injury Risk, Concussions, Race, and Pay in the NFL

Quinn A.W. Keefer
Thomas J. Kniesner

JULY 2023

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16289

Injury Risk, Concussions, Race, and Pay in the NFL

Quinn A.W. Keefer
California State University San Marcos

Thomas J. Kniesner
Claremont Graduate University, IZA and Syracuse University

JULY 2023

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Injury Risk, Concussions, Race, and Pay in the NFL*

We make two main contributions to the literature on work-related injury risk and economic outcomes in the context of American professional football. One is to examine an increasingly important specific injury, concussions, and compare its subsequent economic effects to those of other types of football injuries. Our other contribution is to study the role of race in understanding injury risk and severity and their resulting economic consequences, which has been overlooked in previous sports injury research. Using a specific position, tight ends, which allows conditioning on fine-grained relevant measures of player demographics, playing time, and performance, we find that whether a player continues to play NFL football from year to year is affected by type of injury and the player's race. We calculate that the average ex post loss in annual compensation from a concussion is about 7%. Moreover, the effect of games missed due to concussion on continued employment is triple that of other injuries. Being white positively affects length of playing career independent of the measured productivity of the players involved. The racial gap in career length is approximately equal to the effect of an additional game missed from concussion. With respect to heterogeneity in the effects of injuries, both concussions and other injury types affect ex post economic outcomes equally for white and nonwhite players. Both injuries and race affect compensation solely through their effects on career length.

JEL Classification: D81, J31, J81, Z21, Z22, C23

Keywords: work-related injuries, concussions, race, pay, NFL, tight ends, panel data

Corresponding author:
Thomas J. Kniesner
Claremont Graduate University
Harper East 216
Claremont, CA 91711
USA

E-mail: tom.kniesner@cgu.edu

* The authors declare no conflicts of interests. Computer code and data used are available from the authors upon request

1. INTRODUCTION

Professional football players in the U.S, have a unionized monopsony labor market. Players are highly paid but have very short careers. For example, in 2019 the NFL minimum salary for a player with no NFL experience was $495,000. Furthermore, the average quarterback salary was $5,897,696 and the average tight end salary was $1,660,526 (Spotrac). However, the average career in the NFL lasts only 3.3 years (ESPN/National Football League Players Association). A simple back-of-the-envelope calculation shows that a tight end earning the position's average salary would make approximately $5 million for his entire career. Compensation in the NFL is also uncertain in that player contracts are not guaranteed. A player may sign a five-year contract with a team but may be released before the end of the five-year period and not paid the remaining compensation.[1] The pay system is even more complicated because not all NFL labor contracts are like this. For example, coaching contracts are guaranteed. If a coach is released after three years of a five-year contract the coach must be paid for the remaining two years. Thus, the ability of a player to remain in the NFL labor market has major consequences for their career earnings. It is the financial risk aspect of the NFL labor market that we examine.

In particular, we study the effect of an injury on the probability that a player remains in the NFL labor market. As expected, previous research has concluded that injuries are an important factor in the NFL. For example, Allen (2015) determined that injuries in college affect a player's draft position, and for veterans the number of times listed on injured reserve increased players' time waiting to be signed in free agency. Secrist et al. (2016) examined the labor market

[1] As a result, player contracts must specify the amount of compensation that is guaranteed. For all contracts, a player's signing bonus is guaranteed, and contracts may specify other money as guaranteed as well.

consequences of anterior cruciate ligament (ACL) injuries and found that ACL injuries shorten careers and, in turn, lower earnings. Navarro et al. (2017) found that concussions impact tenure with a team, career length, salary, and subsequent performance. However, all of the studies analyze samples comprised of players at multiple positions, which is problematic for two basic reasons.[2] First, different positions in the NFL have very different roles and responsibilities. Any attempt to control for playing time or player productivity across positions is impossible; there are no reliable cross-position measures of performance.[3] The inability to consider playing time and performance is an issue because they are strong determinants of whether a player has an active contract the following season. It is also probable that the effects of injuries are heterogeneous based on position. For example, an ACL injury to a wide receiver may have a very different impact than a similar injury to an offensive lineman, or a concussion for a cornerback versus a defensive lineman. NFL labor market research needs to be position specific.

Previous research examining injuries has been done for individual positions. For example, Gregory-Smith (2020) examined how within-game injuries to quarterbacks affect the probability of winning a given game. Similarly, Keefer and Kniesner (2022) examined how a team's starting quarterback missing a game due to injury affects scoring and how the injury's effect varies by starting quarterback quality. Keefer and Kniesner (2022) also analyzed, using running backs, how endogenous risk-taking affects productivity and, as a result, compensation.[4]

---

[2] Navarro et al. (2017) conduct position-specific analyses when examining the effects of concussions on future performance, but they ignore positions when examining career survival.
[3] There have been attempts to create cross-position measures of performance, such as Football Outsiders' defense-adjusted value over average (DVOA) or Pro Football Reference's approximate value, among others.
[4] Some other papers analyzing injuries in the NFL are Borghesi (2008) who constructs a measure of injury-adjusted pay, for analyzing the distribution of salaries and team success and Salaga, Mills, and Tainsky (2020) using being placed on injured reserve as a robustness check in their examination of how employer-assigned workload affects productivity over a career.

However, to the best of our knowledge, there have not been position-specific studies done for the effects of injuries on NFL players' employment.

Another issue with the previous research on injuries is the absence of race.[5] The literature on racial differences in professional sports labor markets is rich because professional sports provide an ideal setting to test for labor market discrimination (Kahn 2000).[6] Although the effect of race has been studied on many aspects of professional football labor markets, there has been a focus on racial pay differences. The compensation literature has come to conflicting conclusions, with some studies documenting compensation discrimination (Berri and Simmons 2009; Ducking, Groothuis, and Hill 2017; Keefer 2013) and others finding none (Burnett and Van Scyoc 2013, 2015; Ducking, Groothuis, and Hill 2014).[7] With respect to retention in professional sports, Keefer (2016) found that black NFL linebackers were significantly more likely to start a given game within a season. However, Volz (2017) found that black starting quarterbacks are approximately two times more likely to be benched within a season. Finally, Ducking, Groothuis, and Hill (2015) found no evidence of exit discrimination using data on player career lengths in the NFL. To the best of our knowledge, there have been only two analyses of race

[5] The lone exception we are aware of is Allen (2015) who included race in his analyses; however, the samples pool all positions.

[6] In professional sports, labor market outcomes are high stakes and involve expert decision makers and highly skilled workers. Even more beneficial to researchers is the fact that firm and worker information is officially recorded and includes rich information on both firm and worker performance, which is rare for labor market data (Kahn 2000).

[7] Berri and Simmons (2009) found that black quarterbacks rush the ball significantly more, but rushing is not a skill compensated for in the market for quarterbacks. Keefer (2013), using quantile regression decompositions, found salary discrimination against black linebackers across the whole distribution. Ducking, Groothuis, and Hill (2017) also found discrimination in pay against black linebackers; however, they found no evidence of discrimination for defensive linemen or defensive backs. Examining only rookies, Burnett and Van Scycoc (2013) and Burnett and Van Scycoc (2015) find no discrimination in compensation for wide receivers, and linebackers and offensive linemen respectively. Ducking, Groothuis, and Hill (2014) found no discrimination when analyzing players' career earnings.

directly examining retention or employment as an outcome for players in the NFL.[8] Conlin and Emerson (2006) found white players have a lower probability of having an active contract in their first three seasons after being drafted. In contrast, Jepsen et al. (2021) found no evidence of racial differences in continued employment.

We make two main contributions to the literature. First, we focus an important specific injury risk, concussions, and compare its labor market effects to those of non-concussion injuries. Second, we test whether the effects of injuries on labor market outcomes vary by race. We use a specific position, which allows us to condition on fine grained relevant measures of player demographics, playing time, and performance. Specifically, we choose to analyze the market for tight ends, due to the distribution of race, a key variable in our analysis, in the position.

For the NFL as a whole the percentage of white players has remained relatively constant over time. Figure 1 displays the percentage of NFL players who identify as black or African American and white from 2010 to 2020 (The Institute for Diversity and Ethics in Sport). However, when examining positions within the NFL, racial composition varies greatly. Gertz (2017), using Pro Football Logic's database of players, tabulated the number of players at each position by race for the 2016 season. The percentage of white players ranged from 0% for cornerbacks to about 79% for quarterbacks.[9] In the Appendix we present the complete breakdown by position. There are only three positions with relatively equal percentages of white and nonwhite players, fullbacks, offensive linemen, and tight ends. Because fullbacks are

[8] Other studies have analyzed survival for coaches. Kahn (2006) and Volz (2009) found no evidence of retention discrimination for black coaches in the NBA and minority managers in MLB respectively. Similarly, Keefer (2022) found retention in the WNBA is independent of a coach's sex.

[9] The percentage of white kickers was about 95%, the percentage of white punters was 97%, and the percentage of long snappers who were white was also about 97%.

relatively rare, only 33 players in 2016, and there are no official performance measures for offensive linemen, we focus on tight ends.

In what follows, we use panel data to estimate three economic concepts of labor economic interest: (1) the effect of injuries of differing severity (concussions versus other injuries) on the subsequent likelihood of being in the NFL, (2) the ex post effect of concussions versus other injuries on compensation conditional on being in the NFL, and (3) the resulting ex post total effect of injuries on compensation. Section 2 details our empirical method, which uses logistic panel data regression to examine factors affecting whether a player continues to play NFL football from year to year in light of injuries and personal characteristics, including race and length of career to date. Also developed in Section 2 is a regression model for player expected pay that considers selection bias for latent heterogeneity in the likelihood of continued employment. Section 3 then describes the panel data we use in our estimation, which cover NFL tight ends during the 2010-2019 seasons. Section 3 presents our empirical findings, which includes regression estimates of injury effects on per game performance and number of games played, including effects of concussions versus other forms of injuries on career length. Results presented also examine the robustness effects of concussion injuries and race on career length, particularly early in a player's career. Section 3 ends with results on whether race seems to affect length of playing career in light of productivity of the players involved. Section 4 concludes our research with a discussion of the similarity of our results to those in the wider context of labor markets in the United States overall.

2. EMPIRICAL METHOD

We begin by examining the effects of injuries on the probability of being an active player in the following season. To do so, we employ logistic regression for the following equation

$$\ln\left(\frac{p_{i,t+1}}{1-p_{i,t+1}}\right) = \mathbf{x}'_{i,t}\boldsymbol{\beta}. \tag{1}$$

Here, p is the conditional probability of player i being an active player the following season, $p_{i,t+1} = \Pr(E_{i,t+1} = 1|\mathbf{x}_{it})$, where E is a binary variable for being employed. The vector $\mathbf{x}$ contains data on injuries, race, and other factors affecting employment. We present results for the number of games missed due to all injuries as well as separating concussion and non-concussion injuries, which allows us to compare the effects of concussions to other injuries. In the online Appendix, we also examine the effects of injuries using survival analysis, for comparison, which yield very similar results.

In terms of specification, other than injuries and race, the vector $\mathbf{x}$ contains player and team related information. Most importantly, it contains productivity measures in year t. The performance measures we consider are whether the player was elected to the Pro Bowl, games started, offensive plays, targets (the number of times the player is thrown to), receptions, receiving yards, and touchdowns. However, because our interest is the effect of injuries, we must include performance measures that are not themselves affected by injuries. For example, the inclusion of season total measures of performance (say, receiving yards) would not allow us to estimate the total effect of injuries. This is due to the fact that missing a game because of injury necessarily impacts season totals. Therefore, we measure performance in year t using per-game performance measures, which means that we must determine whether injuries affect per-game performance. If there is no effect of injuries on per-game performance measures, we can estimate the total effect of injuries from equation (1).

There is also substantial collinearity between the performance measures to contend with. For example, the simple correlation between games started per game played and offensive plays per game is 0.839. We present evidence using both measures (in separate estimations) but focus on results with games started per game played, because data on offensive plays were not recorded for the full sample. Other measures of performance are even more highly correlated. Table 1 displays the correlation matrix for the other performance measures. Due to collinearity, we chose receiving yards per game and touchdowns per game. We chose receiving yards as they are the most fine-grained measure, compared to either targets or receptions per game.[10]

The other variables contained in **x** are games missed due to reasons other than injury, whether or not the team drafted a tight end in the first three rounds for the next season, experience in the NFL, body mass index (BMI), round selected in the draft (or undrafted), if the player is on a new team, if the player signed as a free agent, team points scored, team rushing attempts, and team rushing yards.[11] We also include year fixed effects in all estimations.

2.1 Heterogeneity

We consider three possible sources of heterogeneity in the explanatory equation for someone being an active player at the tight-end position. First, we consider a possible interaction between race and injuries. In other words, we test if injuries affect white and nonwhite players differently by estimating logistic regressions for white and nonwhite players separately. Second, we test for heterogeneity in our results by experience, similar to Jepsen et al. (2021). The average career length of an NFL player is just over three years (Keim 2016). The CBA also dictates that

---

[10] Results are robust to the use of the other performance measures. The results are available from the authors.
[11] Each offseason the NFL conducts its amateur draft. Teams select players in a reverse-order format, where the worst team from the previous season selects first. The draft consists of seven rounds. With each team having the rights to one selection per round. However, teams may trade selections in the draft, and along with compensatory picks, which are added to compensate teams based on losing players in free agency, teams may select more or less than seven players in a given draft. All draft rules are set forth in the NFL's collective bargaining agreement (NFL 2020). The NFL draft itself has been the subject of economic research. For example, Massey and Thaler (2013) found the trade market for selections in the draft is wildly inefficient, with an overemphasis on early first-round picks. The correlation between NFL experience and age is about 0.93. Results are robust to the use of age, rather than experience. These results are available from the authors.

players with three or more seasons qualify for free agency when their contract expires.[12] Therefore, we estimate the regressions separately for players who have three or more previous years of experience, whom we call veterans, and for those with less than three years prior experience. Finally, we examine possible heterogeneity based on productivity. Again, we stratify the sample, this time based on yards receiving per game and receptions per game. We split the sample into approximately equal groups using 10 yards per game and one reception per game as the cutoffs; about 48% of player-years had 10 or more yards per game and about 49% of player years had one or more receptions per game.

2.2 Effect of Injuries on Expected Compensation

Given our results to come for the effects of injuries on the probability of remaining in the NFL labor market, we then attempt to quantify the expected loss in compensation from injuries. We model compensation according to

$$\ln\left(w_{i,t+1}\right) = \begin{cases} \mathbf{z}_{it}'\boldsymbol{\alpha} + \mu_{i,t+1}, & E_{i,t+1} = 1 \\ 0, & E_{i.t+1} = 0 \end{cases} \tag{2}$$

and

$$E_{i,t+1} = \begin{cases} 1, & \mathbf{x}_{i,t}'\boldsymbol{\beta} + \epsilon_{i,t+1} > 0 \\ 0, & \mathbf{x}_{i,t}'\boldsymbol{\beta} + \epsilon_{i,t+1} \leq 0 \end{cases} \tag{3}$$

where w is compensation and **z** is a vector of covariates affecting compensation. It is important to note that neither are the vectors **x** and **z** equal, nor is **x** a subset of **z**; there are variables affecting employment that do not affect compensation, which is an exclusion restriction. For example, our main variable satisfying the exclusion restriction is whether or not the team drafted a tight end in the first three rounds for the next season. The model can be estimated via

[12] Players with three years of experience qualify for restricted free agency. Players with four or more seasons of prior experience qualify for unrestricted free agency.

maximum likelihood, and we estimate two quantities of interest (i) the effect of injuries on the probability of being in the league, $\frac{\partial \Pr(E_{t+1} = 1|\mathbf{x}_t)}{\partial inj_t}$, and (ii) the effect of injuries on compensation conditional on being in the league, $\frac{\partial \mathrm{E}\left(\ln(w_{t+1})|E_{t+1} = 1, \mathbf{z}_t\right)}{\partial inj_t}$. Using the estimates, we can also determine the effect on expected compensation $\frac{\partial \mathrm{E}(w_{t+1}|\mathbf{x}_t, \mathbf{z}_t)}{\partial inj_t}$, by constructing $\mathrm{E}(w_{t+1}|\mathbf{x}_t, \mathbf{z}_t) = \Pr(E_{t+1} = 1|\mathbf{x}_t)\,\mathrm{E}(w_{t+1}|E_{t+1} = 1, \mathbf{z}_t)$.

To estimate the parameters of the model, we must make assumptions about the marginal distributions of μ and ϵ, and their joint distribution. It is common to assume the errors have a bivariate normal distribution according to $[\mu \quad \epsilon] \sim \mathrm{N}\left(\mathbf{0}, \begin{bmatrix} \sigma_\mu^2 & \rho\sigma_\mu\sigma_\epsilon \\ & \sigma_\epsilon^2 \end{bmatrix}\right)$, which leads to Heckman's selection bias correction model (Heckman 1974). However, the model's parameters can be estimated allowing for a variety of distributional assumptions using copula functions (Candio et al. 2021; Genius and Strazzera 2008; Gomes et al. 2019; Lee 1982, 1983). The copula method allows one to specify the marginal distributions of μ and ϵ and separately model their joint distribution (Genius and Strazzera 2008; Klein et al. 2019).[13] In the discussion below we present results from the standard Heckman correction model due to its ease of interpretation and straightforward computation for the three quantities of interest. In the online Appendix, we examine the robustness of the results to different distributional assumptions applying the copula method, which yields similar results to our preferred model.

The measure of compensation we study is a player's salary cap value, which is the standard measure used in the literature. The NFL CBA sets a yearly limit on players' salaries for

---

[13] A copula function is one that maps marginal distributions to a multivariate distribution for continuous random variables. In our case, $G(E, w) = C\left(F_E(E), F_w(w)\right)$, where F_E and F_w are the distribution functions for E and w respectively, C is a copula function, and G is a joint distribution function. See Genius and Strazzera (2008), Gomes et al. (2019), and Marra and Radice (2017) for more detailed discussions.

each team. The salary cap value includes a player's base salary, pro-rated signing bonus, and likely to be earned incentives, which are performance bonuses that would have been earned based on previous season measures.[14] The vector **z** contains the same variables as the independent variables included in the employment equation with a few exceptions. First, it does not include whether the team selected a tight end in the draft, which is our main exclusion restriction. Second, it includes a quadratic specification for experience, which is standard for wage estimations. Finally, the variables for being on a new team and being a free agent are for the year in which the compensation was received. However, the results are very similar when using the same variables in the two equations, with the exception of whether the team drafted a tight end.

3. DATA

The data cover the 2010 to 2019 NFL seasons. We chose 2010-2019 because it corresponds to a single collective bargaining agreement (CBA); 2009 was the final season of the previous CBA and the 2020 season was the beginning of the current CBA. Furthermore, COVID-19 dramatically impacted the 2020 season. We obtained information on all tight ends in the NFL during 2010-2019. With a few exceptions, the data come from Pro Football Reference.[15] The first exception is that Football Outsiders provided information on offensive plays. Spotrac, a database of professional athlete salaries, provided compensation and free agency information. Finally, injury data are from Man Games Lost, which tracks all injury reports and game participation for all regular season games in the NFL, MLB, NBA, and NHL; the NFL data begin in 2009.

[14] The full definition of salary cap value is specified in the CBA. For example, signing bonuses can be pro-rated for a maximum of five years (NFL 2020).
[15] In the absence of player pictures on Pro Football Reference, internet searches for player photos were used to determine race.

The final sample we use contains 1,192 player-years with complete information, which is 3.7 players per team per year. Table 2 presents descriptive statistics for our sample. Data for injuries range from zero to 15 games missed due to injury and are, as expected, positively skewed. In the sample, about 56% of player-years had zero missed games from injury whereas about 14% missed exactly one game. Furthermore, about 14% of player-years consist of at least five missed games from injury. With respect to concussions, about 7% of player-years involved missing a game due to concussion and 2.6% missed at least two games. This is similar to the league-wide incidence of concussions. From 2018 to 2020 the average number of concussions league wide was 130, which is approximately 6.5% of player-years (Molski 2023). Considering the highly skewed nature of concussion data, one may be concerned about the influence on the results of the players with relatively large numbers of games missed from concussion. As a result, the online Appendix presents measures of influence for our analysis and confirms the robustness of our results.

For the full sample, about 76% of player-years result in continued employment in the NFL. Also, about 56% of the player-years in the sample are white players, which is similar to the percentage of tight ends that were nonblack from 2001 to 2009 reported by Keefer (2016). In terms of simple differences in proportions and means, there is a statistically significant racial difference in the probability a player is in the labor market the following year, but no significant racial difference in compensation for active players. With respect to injuries, white players miss more games due to injuries, specifically non-concussion injuries. Finally, there are no statistically significant racial differences in age, experience, or any of the performance measures (total and per game).

4. RESULTS

We begin by examining the effect of injuries on per-game performance measures. The results from OLS regressions of each of our performance measures are presented in Table 3. There are neither statistically nor economically meaningful impacts on any of the per-game performance measures; this is also true for race. Furthermore, the conclusion remains when separating concussion and non-concussion injuries. As a result, the concern that injuries affect performance measures, which would prevent us from estimating the total effect on the probability of continuing in the league, is alleviated. In other words, per-game measures allow us to control for productivity without interfering with the estimation of the causal effects.

Our logistic regression results appear in Table 4. We find that injuries have statistically significant effects. The effects are also robust to the use of a quadratic specification for experience and the inclusion of offensive plays rather than games started as a percentage of games played.[16] Specifically, the odds of being employed in the NFL are 1.12 times higher for a player having missed one fewer game due to injury. When separating concussions and other injuries, we find the odds of being employed are 1.36 to 1.40 times higher for a player with one fewer concussion. The reduction of one non-concussion leads to higher employment odds of 1.09 to 1.10. Furthermore, the difference in the effects of concussions versus other injuries is statistically significant. We can also express the results in terms of changes in the probability of being employed using average marginal effects.[17] The average marginal effect of games missed

[16] The results are also robust to the specification chosen for performance. In the online Appendix we present results from 1,023 possible combinations of individual and team performance variables. The results show the effect of injuries is very robust. Furthermore, the results are robust when considering observations with relatively high influence on the coefficients. Full influence analysis is reported in the online Appendix.

[17] Our average marginal effects calculations use a discrete change in the binary race variable. For injuries,

$$AME_{inj} = \frac{1}{n}\sum_{i=1}^{n} \Lambda'(\mathbf{x}'_{i,t}\boldsymbol{\beta})\beta_{inj}$$

due to injuries is -1.7 to -1.6 percentage points. For concussions, the average marginal effect is about -4.9 to -4.5 percentage points; for non-concussion injuries it is -1.5 to -1.3 percentage points.

However, because the marginal effects are not constant in a logistic model, we present average effects for meaningful changes in injuries. Missing four games due to injury compared to one (which is an approximately one-standard deviation increase injuries) decreases the probability by 4.8 percentage points; the effect is 5.0 percentage points going from two missed games to five missed games. Also, missing a single game due to concussion compared to missing no games decreases the probability by 4.7 percentage points; the effect is 5.1 percentage points going from one game missed from concussion to two. Finally, moving from a single game missed from non-concussion injury to four, about a one-standard deviation increase, reduces the probability by 4.1 percentage points; the effect is 4.2 percentage points going from two to five missed games from non-concussion injuries. Because these effects are extremely close to the estimates for equivalent changes using the average marginal effects, we proceed reporting the average marginal effects.[18]

Our results also show a meaningful impact of race, which too is robust across specifications. The odds of having an active contract are 1.39 times higher for white players. Interestingly, the race gap in employment continuation is about equivalent to the effect of having

---

and for race,

$$AME_{white} = \frac{1}{n}\sum_{i=1}^{n}\left[\Lambda\left(\beta_{white} + \tilde{\mathbf{x}}'_{i,t}\tilde{\boldsymbol{\beta}}\right) - \Lambda\left(\tilde{\mathbf{x}}'_{i,t}\tilde{\boldsymbol{\beta}}\right)\right],$$

where Λ is the logistic CDF, $\tilde{\mathbf{x}}$ is the vector of all covariates not including race, and $\tilde{\beta}_j = \beta_j \;\forall\, j \in \tilde{\mathbf{x}}$.

[18] For example, the average marginal effect of injuries is -1.7 to -1.6 percentage points. Thus, an increase of three games missed due to injury is estimated to reduce the probability by 4.8 to 5.1 percentage points, which is nearly identical to the estimated average effects.

a concussion. The average marginal effect of being white is an increase in the probability of continuing in the league of 4.8 to 4.9 percentage points.

4.1 Heterogeneity

We begin by examining whether injuries affect white and nonwhite players differently. Logistic regression coefficients are presented in Table 5. The odds ratios for nonwhite and white players are very similar, 0.91 and 0.88 for nonwhite versus white players. In other words, the odds of remaining in the NFL are 1.10 and 1.13 times higher from missing one less game due to injury, for nonwhite versus white players. Furthermore, the average marginal effect is -0.016, or -1.6 percentage points for both nonwhite and white players. Differentiating between concussion and non-concussion injuries, the odds ratios for games missed due to concussions are 0.75 for nonwhite players and 0.71 for white players. For non-concussion injuries the odds ratios are 0.92 and 0.91 for nonwhite versus white players. Comparing marginal effects, for nonwhite players the average marginal effects are -4.5 percentage points and -1.4 percentage points for concussions and other injuries respectively. White players average marginal effects are -4.4 percentage points and -1.3 percentage points for concussions versus other injuries. Thus, we find no estimated difference between white and nonwhite players in the effect of injuries on the probability a player remains in the labor market the following season.

Our results for the effect of injuries by experience level are also presented in Table 5. In our sample about 46% of player-years are veterans, ranging from a season low of about 43% in 2011 to about 49% in 2017. We find interesting heterogeneity based on experience in the NFL, with injuries being more impactful for veteran players. Specifically, each game missed due to injury reduces the probability of being employed by 0.94 percentage points for early career players. For early in their career players, non-concussion injuries reduce the probability by 0.99

percentage points, and concussions do not have a statistically significant effect. Furthermore, there is no significant difference in the effects of concussions and non-concussion injuries. In contrast, for veteran players each game missed due to injury reduces the probability by 2.1 percentage points. The average marginal effects are -1.6 percentage points and -5.2 percentage points for non-concussion injuries and concussions respectively; there is a significant difference between the effects of concussions and non-concussion injuries among veteran players.

There is also interesting heterogeneity in the effect of race based on experience level. Our results indicate that race is important early in a tight end's career, but not when he is a veteran. Specifically, for early career players, the average marginal effect of being white is a 6.2 to 6.3 percentage-point increase in the probability of being in the NFL the following year. However, for veterans, the average marginal effect is 3.5 to 3.6 percentage points and not statistically significant.

Finally, our results for heterogeneity based on performance are contained in Table 6. Again, we find interesting heterogeneity with injuries impacting high performing players but not lower performing ones.[19] The average marginal effect of games missed due to injury is estimated to be -0.60 and -0.75 percentage points for the low yards per game group and the low receptions per game group respectively; neither are statistically different from zero. For the high-performance groups, the average marginal effect of games missed due to injuries is -1.9 and -2.0 percentage points using yards per game and receptions per game respectively and are highly statistically significant. When analyzing concussions and non-concussion injuries, neither have a meaningful, economically nor statistically, impact for the lower-performance groups. For the higher-performance groups, both are statistically and economically significant. The average

[19] Results available from the authors are similar using touchdowns per game. Secrist et al. (2016) found that ACL injuries are not important for the highest earning players.

marginal effect of concussions is -3.5 and -3.2 percentage points for yards per game and receptions per game respectively. Also, the average marginal effect of non-concussion injuries is -1.7 and -1.8 percentage points for yards per game and receptions per game respectively.

Similar to experience level, there is also interesting heterogeneity in the effect of race based on performance. For players with fewer than 10 receiving yards per game, the average marginal effect of being white is 10.7 to 10.9 percentage points. However, for those with more than 10 receiving yards per game, the average marginal effect is 0.93 to 1.3 percentage points and is not statistically different than zero. The same pattern holds when using receptions per game to measure performance. For players with less than one reception per game, the average marginal effect of being white is 10.2 to 10.4 percentage points. For those with more than one reception per game, the average marginal effect is 0.57 to 0.84 percentage points and is not statistically significant. Thus, race appears to be a major determinant of continued employment in the NFL, but only for less productive players.

4.2 Career Injuries

It may be the case that injuries in past seasons also affect the probability of remaining in the NFL. Ex ante, we believe, if there is an effect of injuries in prior years, the effect would be less than injuries in the current season. We examine the effect of prior injuries in two ways. First, we include the one-season lag of injuries in our models. The results for the remaining 798 player years are reported in Table 7. Previous-season games missed due to injury are significant; however, as expected, the magnitude of the effect is less than for current-season injuries. The average marginal effect of current-season injuries is -2.6 percentage points whereas it is -0.84 for injuries in the previous season, both of which are statistically significant. For concussions, the average marginal effect is -4.7 percentage points for games missed in the current season, but it is

-1.9 percentage points for the previous season, which is not statistically significant. For non-concussion injuries, the estimated average marginal effect is -1.5 and -0.87 for games missed in the current and previous season respectively, which are both statistically significant.

Second, we limit the sample to players who began their careers within the time period we analyze; we cannot retroactively collect injury data, as it is not available for older seasons. We then calculate the total career injuries for sample period players and estimate the effect. We now have with 584 player years, where the average number of career games missed due to injury is 4.86 (standard deviation = 6.58), the average for concussions is 0.30 (standard deviation = 1.11), and the average for non-concussion injuries is 4.56 (standard deviation = 6.30). The results are presented in Table 7. We find no effect of the total number of career injuries on contract continuation, whether we use all injuries or differentiate between concussions and non-concussion injuries. However, contemporaneous injuries remain statistically and economically significant. We therefore conclude that previous injuries other than concussions also matter, but only in the recent past.

4.3 Effect of Injuries on Expected Compensation

Finally, we present the results from our analysis of expected compensation. There are 44 player years for which we have productivity information but no compensation information; they are omitted from the analysis, leaving 1,148 player years. Table 8 summarizes results from our Heckman (1974) estimation of the model in equations (2) and (3). Concerning the probability of remaining employed in the NFL, the average marginal effect of games missed because of injuries is -1.7 percentage points. When separating concussions and non-concussion injuries, the average marginal effects are -4.7 and -1.5 percentage points for games missed due to concussions and non-concussion injuries respectively. Thus, the results are very similar to our previous analyses.

Next, we find, conditional on being employed, injuries have no significant, economically or statistically, effect on compensation. The effect of injuries on compensation is entirely driven by injuries' effect on employment. As a result, the effect of injuries on expected compensation is

$$\frac{\partial \mathrm{E}(w_{t+1}|\mathbf{x}_t,\mathbf{z}_t)}{\partial inj_t} = \frac{\partial \Pr(E_{t+1}=1|\mathbf{x}_t)}{\partial inj_t}\mathrm{E}(w_{t+1}|E_{t+1}=1,\mathbf{z}_t). \tag{4}$$

In percentage terms, the effect on expected compensation is

$$\left.\frac{\partial \Pr(E_{t+1}=1|\mathbf{x}_t)}{\partial inj_t}\right/\Pr(E_{t+1}=1|\mathbf{x}_t). \tag{5}$$[20]

Using our baseline results, columns (1) and (4) of Table 4, we find an average reduction in expected compensation of 2.5% per game missed due to injury. The average effect of concussions is a 7.4% decrease in expected compensation, and for non-concussion injuries the average effect is a reduction of 2.2%. Simple back-of-the-envelope calculations using the average tight end compensation in 2019 of $1,660,526 (Spotrac), suggest each game missed due to injury reduces expected compensation by $26,000. Concussions reduce expected compensation, for an average player, by $75,000 and non-concussion injuries result in a loss of expected compensation of $22,000.

Like injuries, the impact of race on compensation is entirely due to its effect on employment. Expected compensation is about 7.9% less for nonwhite players. For an average earning player, being white increases expected compensation by approximately $81,000. Finally, Table 9 presents the results examining heterogeneity in the effect of injuries by race. The results are very

[20] $\left.\frac{\partial \mathrm{E}(w_{t+1}|\mathbf{x}_t,\mathbf{z}_t)}{\partial inj_t}\right/\mathrm{E}(w_{t+1}|\mathbf{x}_t,\mathbf{z}_t) = \frac{\frac{\partial \Pr(E_{t+1}=1|\mathbf{x}_t)}{\partial inj_t}\mathrm{E}(w_{t+1}|E_{t+1}=1,\mathbf{z}_t)}{\Pr(E_{t+1}=1|\mathbf{x}_t)\mathrm{E}(w_{t+1}|E_{t+1}=1,\mathbf{z}_t)} = \frac{\frac{\partial \Pr(E_{t+1}=1|\mathbf{x}_t)}{\partial inj_t}}{\Pr(E_{t+1}=1|\mathbf{x}_t)}.$

similar between the two groups and are consistent with our previous conclusion that injuries have equal effects between races.

4. DISCUSSION

Injuries are an important determinant of total compensation via career length for NFL tight ends who average a total of $5,000,000 over their 3.3-year careers. Of increased research importance is the effect of concussions versus other types of injuries determining career length. Because tight end is the only so-called skill position (one with measurable output) that also has a mix of white and nonwhite players, we are able to study race gaps in pay that are unrelated to personal characteristics and measures of football performance. We use panel data to estimate three economic concepts of labor economic interest: (1) the effect of injuries of differing severity (concussions versus other injuries) on the subsequent likelihood of being in the NFL, (2) the ex post effect of concussions versus other injuries on compensation conditional on being in the NFL, and (3) the resulting ex post total effect of injuries on compensation.

Our principal results include that the negative effect of a concussion is triple the negative effect of the typical other type of injury on career length and subsequent earnings. We also find a statistically robust economically important subtle effect of race on career earnings of tight ends. The odds of having an active contract in the NFL is about 40 percent higher on average for white tight ends. The earning power gap between the races is equivalent to nonwhite players having one additional concussion. However, the effect of race on career length is heterogeneous by current experience level. There is no race gap, ceteris paribus, among veteran players, only those at the beginning of their careers (-6 percentage points). Finally, we found that heterogenous impacts of injuries are much more prevalent among high performing players, as one might expect arithmetically, and that race differential in employment continuation are prevalent for only the least productive players.

As a point of reference how do the two focal results here concerning the size of concussion injuries on players' career earnings and the racial gap in career earning power compare to the U.S. labor market more generally? Concerning the male race gap in wages a typical Oaxaca-type (personal characteristics held constant) measure has typically been that U.S. white men of ages similar to the NFL players we study earn about 25% more than otherwise similar black male workers (Cahuc, Carcillo, and Zylberberg 2014, Table 8.6). This is greater than the 7.9% total earnings advantage white tight ends receive due to their longer NFL careers. Concerning the injury comparisons with the private labor market Viscusi and Gentry (2015) are an exceptionally complete examination of the wage premia workers receive for exposure to non-fatal work-related injuries. They find that the value of a statistical injury (VSI) is an amount that is at least two times annual pay. By comparison we find that for NFL tight ends a concussion lowers expected career length by one year, which is a gross expected cost of a concussion equal to one year's pay, which in dollars is over 40 times that of the typical labor market participant's value of a statistical injury, which includes compensation for more than just lost earnings.

In closing, our results are important for two on-going labor economic issues, workplace safety and possible discrimination against younger workers of color. Specifically, our estimates of concussion effects on career length further emphasize the importance of preventing concussions and the highly parametrized employment continuation equations' make one pause to wonder about the source of the comparatively favorable outcomes for young white tight ends.

REFERENCES

Allen, W.D. (2015). The demand for younger and older workers: Patterns from NFL labor markets. *Journal of Sports Economics*, 16, 127-158.

Approximate Value. Pro Football Reference. Available from https://www.pro-football-reference.com/about/approximate_value.htm#:~:text=Created%20by%20PFR%20founder%20Doug,%2Dall%20end%2Dall%20metric.

Berri, D.J., & Simmons, R. (2009). Race and the evaluation of signal callers in the National Football League. *Journal of Sports Economics*, 10, 23-43.

Borghesi, R. (2008). Allocation of scarce resources: Insight from the NFL salary cap. *Journal of Economics and Business*, 60, 536-550.

Breslow, N.E. (1974). Covariance analysis of censored survival data. *Biometrics*, 30, 89-99.

Burnett, N.J., & Van Scyoc, L.J. (2013). Compensation discrimination for wide receivers: Applying quantile regression to the National Football League. *Journal of Reviews on Global Economics,* 2, 433-441.

Burnett, N.J., & Van Scyoc, L.J. (2015). Compensation discrimination for defensive players: Applying quantile regression to the National Football League market for linebackers and offensive linemen. *Journal of Sports Economics*, 16, 375-389.

Cahuc, P., Carcillo, S., & Zylberberg, Z. (2014) *Labor Economics*. Cambridge, MA.: MIT Press.

Candio, P., et al. (2021) Copula models for addressing sample selection in the evaluation of public health programmes: An application to the Leeds Let's Get Active Study. *Applied Health Economics and Health Policy*, 19, 305-312.

Conlin, M., & Emerson, P.M. (2006) Discrimination in hiring versus retention and promotion: An empirical analysis of within-firm treatment of players in the NFL. *The Journal of Law, Economics, and Organization*, 22, 115-136.

Ducking J., Groothuis, P.A., & Hill, J.R. (2014). Compensation discrimination in the NFL: An analysis of career earnings. *Applied Economics Letters*, 21, 679-682.

Ducking J., Groothuis, P.A., & Hill, J.R. (2015). Exit discrimination in the NFL: A duration analysis of career length. *The Review of Black Political Economy*, 42, 285-299.

Ducking J., Groothuis, P.A., & Hill, J.R. (2017). Compensation discrimination: An analysis of linebackers, defensive linemen, and defensive backs in the National Football League. *The Review of Black Political Economy*, 44, 251-260.

Efron, B. (1977). The efficiency of Cox's likelihood function for censored data. *Journal of the American Statistical Association*, 72, 557-565.

Football Outsiders. (2022). NFL snap counts. Available from https://www.footballoutsiders.com/stats/nfl/snap-counts.

Football Outsiders. (2022). What is DOVA? Available from https://www.footballoutsiders.com/info/methods.

Genius, M., & Strazzera, E. (2008). Applying the copula approach to sample selection modelling. *Applied Economics*, 40, 1443-1455.

Gertz, M. (April 19, 2017). NFL census 2016. Pro Football Logic. Retrieved from http://www.profootballlogic.com/articles/nfl-census-2016/.

Gomes, M., Radice, R., Brenes, J.C., & Marra, G. (2019). Copula selection models for non-Gaussian outcomes that are missing not at random. *Statistics in Medicine*, 38, 480-496.

Grambsch, P.M., & Therneau, T.M. (1994). Proportional hazards tests and diagnostics based on weighted residuals. *Biometrika*, 81, 515-526.

Heckman, J. (1974). Shadow prices, market wages, and labor supply. *Econometrica*, 42, 679-694.

Jepsen, C., Jepsen, L., Draisey, T., & Mahoney, J. (2021). Race and National Football League player salaries after controlling for fantasy statistics and arrests. *Journal of Sports Economics*, 22, 359-386.

Kahn, L.M. (2000). The sports business as a labor market laboratory. *Journal of Economic Perspectives*, 14, 75-94.

Kahn, L.M. (2006). Race, performance, pay, and retention among National Basketball Association head coaches. *Journal of Sports Economics*, 7, 119-149.

Keefer, Q.A.W. (2013). Compensation discrimination for defensive players: Applying quantile regression to the National Football League market for linebackers. *Journal of Sports Economics*, 14, 23-44.

Keefer, Q.A.W. (2016). Race and NFL playing time. *International Journal of Sport Finance*, 11, 144-162.

Keefer, Q.A.W. (2022). Sex differences in high-level managerial jobs: Evidence from professional basketball. *Journal of Sports Economics*, 23, 301-328.

Keefer, Q.A.W., & Kniesner, T.J. (2022). Performance and pay in professional football. *Foundations and Trends in Microeconomics*, 12, 269-343.

Keim, J. (July 29, 2016). With average NFL career 3.3 years, players motivated to complete MBA program. ESPN. Available from https://www.espn.com/blog/nflnation/post/_/id/207780/current-and-former-nfl-players-in-the-drivers-seat-after-completing-mba-program.

Klein, N., et al. (2019). Mixed binary-continuous copula regression models with application to adverse birth outcomes. *Statistics in Medicine*, 38, 413-436.

Lee, L.F. (1982). Some approaches to the correction of selectivity bias. *The Review of Economic Studies*, 49, 355-372.

Lee, L.F. (1983). Generalized econometric models with selectivity. *Econometrica*, 51, 507-512.

Man Games Lost. (2022). NFL. Available from https://www.mangameslost.com/category/nfl/.

Marra, G., & Radice, R. (2017). Bivariate copula additive models for location, scale, and shape. *Computational Statistics and Data Analysis*, 112, 99-113.

Marra, G., & Radice, R. (2022). GJRM: Generalised joint regression modelling, version 0.2-6.

Massey, C., & Thaler, R.H. (2013). The loser's curse: Decision making and market efficiency in the National Football League. *Management Science,* 59, 1479-1495.

Molski, M. (February 3, 2023). NFL concussion numbers make significant rise in 2022. NBC Sports. Retrieved from https://www.nbcsports.com/boston/patriots/nfl-says-concussions-made-significant-rise-2022#:~:text=NFL%20concussion%20numbers%20make%20significant%20rise%20in%202022&text=There%20were%20149%20concussions%20suffered,2020%2C%20the%20average%20was%20130.

Navarro, S.M., et al. (2017). Short-term outcomes following concussion in the NFL: A study of player longevity, performance, and financial loss*. Orthopaedic Journal of Sports Medicine,* 5, DOI:10.1177/2325967117740847.

NFL. (2020). Collective Bargaining Agreement. Retrieved from https://nflpaweb.blob.core.windows.net/media/Default/NFLPA/CBA2020/NFL-NFLPA_CBA_March_5_2020.pdf.

Pregibon, D. (1981). Logistic regression diagnostics*. Annals of Statistics*, 9, 705-724.

Pro Football Reference. (2022). List of all pro football players. Available from https://www.pro-football-reference.com/players/.

Salaga, S., Mills, B.M., Tainsky, S. (2020). Employer-assigned workload and human capital deterioration: Evidence from the National Football League. *Journal of Sports Economics*, 21, 628-659.

Secrist, E.S., Bhat, S.B., & Dodson, C.C. (2016). The financial and professional impact of anterior cruciate ligament injuries in National Football League athletes. *Orthopaedic Journal of Sports Medicine,* 4, DOI: 10.1177/2325967116663921.

Spotrac. (2022). NFL contracts. Available from https://www.spotrac.com/nfl/contracts/.

Gregory-Smith, I. (2021). Wages and labor productivity: Evidence from injuries in the National Football League. *Economic Inquiry*, 59, 829-847.

The Institute for Diversity and Ethics in Sport. The National Football League Racial and Gender Report Card. Retrieved from https://www.tidesport.org/nfl.

Viscusi, W.K. & Gentry, E.P. (2015). The value of a statistical life for transportation regulations: A test of the benefits transfer methodology. *Journal of Risk and Uncertainty*, 51, 53-77.

Volz, B.D. (2009). Minority status and managerial survival in Major League Baseball. *Journal of Sports Economics*, 10, 522-542.

Volz, B.D. (2017). Race and quarterback survival in the National Football League. *Journal of Sports Economics*, 18, 850-866.

Table 1. Correlation Matrix for Performance Measures

	Yards/Game	TD/Game	Receptions/Game	Targets/Game
Yards/Game	1.000			
TD/Game	0.769	1.000		
Receptions/Game	0.967	0.739	1.000	
Targets/Game	0.962	0.738	0.986	1.000

Table 2. Descriptive Statistics

VARIABLES	Full Sample	White	Nonwhite	Difference
White	0.559			
Contract Next Year	0.762	0.787	0.730	0.0567**
				[0.0249]
Free Agent	0.118	0.102	0.139	-0.0367*
				[0.0188]
New Team	0.437	0.413	0.468	-0.0548*
				[0.0289]
Pro Bowl	0.0529	0.0646	0.0380	0.0266**
				[0.0131]
Cap Value[a]	1,741,020	1,745,384	1,735,324	10,060
	(2,143,453)	(2,176,005)	(2,102,641)	[134,940]
LN(Cap Value)[a]	13.76	13.79	13.73	0.0627
	(1.122)	(1.077)	(1.178)	[0.0718]
Injuries	1.779	1.944	1.568	0.376**
	(3.170)	(3.345)	(2.923)	[0.182]
Concussions	0.157	0.167	0.144	0.0222
	(0.905)	(0.977)	(0.806)	[0.0516]
Non-concussion Injuries	1.622	1.778	1.424	0.354**
	(3.064)	(3.235)	(2.823)	[0.176]
Other DNP	1.167	1.086	1.270	-0.184
	(2.853)	(2.762)	(2.964)	[0.168]
Age	26.27	26.25	26.30	-0.0534
	(3.087)	(2.834)	(3.383)	[0.184]
Experience	4.110	3.956	4.304	-0.348*
	(3.078)	(2.842)	(3.347)	[0.183]
BMI	30.53	30.31	30.82	-0.508***
	(1.306)	(1.085)	(1.495)	[0.0776]
Round[b]	3.754	3.843	3.642	0.201
	(1.834)	(1.757)	(0.1922)	[0.130]
Games	11.79	11.88	11.68	0.199
	(4.915)	(4.788)	(5.073)	[0.289]
Games Started	6.092	6.110	6.070	0.0393
	(5.260)	(5.213)	(5.324)	[0.308]
Yards	219.3	221.2	216.9	4.261
	(264.1)	(277.7)	(246.0)	[15.19]
TD	1.690	1.727	1.643	0.0841
	(2.360)	(2.476)	(2.206)	[0.136]
Receptions	19.70	19.88	19.47	0.417
	(22.52)	(23.33)	(21.48)	[1.302]
Games Started/Game	0.460	0.467	0.450	0.017
	(0.353)	(0.353)	(0.353)	[0.0206]

Yards/Game	16.39	16.52	16.23	0.289
	(18.06)	(18.82)	(17.07)	[1.042]
TD/Game	0.125	0.127	0.121	0.00566
	(0.170)	(0.175)	(0.162)	[0.00980]
Receptions/Game	1.474	1.487	1.458	0.0285
	(1.153)	(1.574)	(1.468)	[0.0884]
Offensive Snaps[c]	361.8	366.3	355.9	10.33
	(286.9)	(291.3)	(281.2)	[18.75]
Offensive Snaps/Game[c]	27.89	28.31	27.34	0.97
	(17.82)	(18.25)	(17.23)	[1.161]
Observations	1,192	666	526	

Note: Proportions presented for binary variables. Means with standard deviations in parentheses reported for continuous variables. Standard errors for differences in means in square brackets, for continuous variables. Standard errors for differences in proportions in square brackets, for binary variables.
*** p<0.01, ** p<0.05, * p<0.1
[a] There are 1,019 player years, 577 white players and 442 nonwhite players, for these variables.
[b] There were 816 drafted players, 453 white players and 363 nonwhite players.
[c] There are 946 player years, 538 white players and 408 nonwhite players, for these variables.

Table 3. OLS Results for Performance Measures

VARIABLES	Games Started/Game	Yards/Game	TD/Game	Games Started/Game	Yards/Game	TD/Game
Injuries	-0.000196	-0.0247	-0.000201			
	(0.00321)	(0.179)	(0.00198)			
Concussions				0.0111	0.314	0.00444
				(0.0112)	(0.575)	(0.00771)
Non-concussion Injuries				-0.00109	-0.0517	-0.000571
				(0.00324)	(0.182)	(0.00204)
Other DNP	-0.0208***	-0.473***	-0.00647***	-0.0208***	-0.473***	-0.00647***
	(0.00307)	(0.131)	(0.00129)	(0.00307)	(0.131)	(0.00129)
White	0.0259	0.127	0.00233	0.0259	0.128	0.00236
	(0.0233)	(1.573)	(0.0133)	(0.0233)	(1.574)	(0.0133)
Experience	0.0195***	0.607	0.00282	0.0193***	0.603	0.00277
	(0.00431)	(0.378)	(0.00358)	(0.00433)	(0.380)	(0.00360)
BMI	0.00574	-1.314***	-0.00931**	0.00569	-1.315***	-0.00933**
	(0.00772)	(0.479)	(0.00380)	(0.00767)	(0.478)	(0.00379)
2nd Round	-0.0860	-5.885	-0.0210	-0.0866	-5.903	-0.0213
	(0.0564)	(4.280)	(0.0382)	(0.0566)	(4.288)	(0.0383)
3rd Round	-0.145***	-9.582**	-0.0630**	-0.146***	-9.625**	-0.0636**
	(0.0524)	(3.979)	(0.0303)	(0.0524)	(3.973)	(0.0303)
4th Round	-0.157***	-14.01***	-0.0887***	-0.159***	-14.08***	-0.0898***
	(0.0505)	(3.283)	(0.0311)	(0.0503)	(3.297)	(0.0314)
5th Round	-0.184***	-18.47***	-0.137***	-0.185***	-18.50***	-0.137***
	(0.0502)	(2.990)	(0.0244)	(0.0498)	(2.983)	(0.0243)
6th Round	-0.248***	-16.05***	-0.111***	-0.248***	-16.06***	-0.111***
	(0.0562)	(4.032)	(0.0286)	(0.0563)	(4.038)	(0.0287)
7th Round	-0.320***	-23.56***	-0.179***	-0.319***	-23.54***	-0.178***
	(0.0497)	(2.638)	(0.0242)	(0.0496)	(2.643)	(0.0243)
Undrafted	-0.345***	-21.78***	-0.141***	-0.346***	-21.80***	-0.142***
	(0.0437)	(3.122)	(0.0308)	(0.0437)	(3.131)	(0.0310)
New Team	-0.155***	-6.845***	-0.0482***	-0.155***	-6.843***	-0.0482***

	(0.0208)	(0.916)	(0.00909)	(0.0208)	(0.915)	(0.00908)
Free Agent	0.0234	-3.168*	-0.0110	0.0225	-3.195*	-0.0114
	(0.0380)	(1.869)	(0.0184)	(0.0379)	(1.873)	(0.0183)
Team Points Scored	-0.000202	0.0220**	0.000445***	-0.000194	0.0223**	0.000449***
	(0.000148)	(0.0109)	(0.000124)	(0.000147)	(0.0109)	(0.000123)
Team Rushing Attempts	1.73e-05	-0.00887	-3.47e-06	1.52e-05	-0.00894	-4.35e-06
	(0.000328)	(0.0205)	(0.000179)	(0.000329)	(0.0205)	(0.000179)
Team Rushing Yards	2.13e-05	0.000727	-1.21e-05	2.00e-05	0.000688	-1.26e-05
	(5.24e-05)	(0.00307)	(3.10e-05)	(5.23e-05)	(0.00307)	(3.09e-05)
Constant	0.525**	65.96***	0.384***	0.527**	66.02***	0.385***
	(0.262)	(16.22)	(0.137)	(0.261)	(16.23)	(0.137)
Concussions – Non-concussion Injuries				0.0122	0.365	0.00501
				(0.0114)	(0.583)	(0.00801)
Observations	1,192	1,192	1,192	1,192	1,192	1,192
R-squared	0.362	0.334	0.241	0.363	0.335	0.242

Note: Dependent variables listed as column titles. Standard errors clustered at the player level in parentheses. Concussions – Non-concussion Injuries is the difference in coefficients. All estimations include year fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Logistic Regression Coefficients

Dependent Variable = Pr(Contract Next Season)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Injuries	-0.107***	-0.106***	-0.117***			
	(0.0258)	(0.0258)	(0.0278)			
Concussions				-0.309***	-0.307***	-0.337***
				(0.0648)	(0.0644)	(0.0723)
Non-concussion Injuries				-0.0908***	-0.0908***	-0.101***
				(0.0261)	(0.0260)	(0.0282)
Other DNP	-0.0836***	-0.0848***	-0.0846***	-0.0821***	-0.0830***	-0.0833***
	(0.0249)	(0.0249)	(0.0296)	(0.0250)	(0.0249)	(0.0297)
White	0.330**	0.332**	0.324*	0.333**	0.334**	0.331*
	(0.162)	(0.162)	(0.189)	(0.163)	(0.163)	(0.189)
Team Drafted TE (Round 1-3)	-0.423**	-0.425**	-0.479**	-0.383*	-0.385*	-0.440**
	(0.201)	(0.201)	(0.215)	(0.204)	(0.203)	(0.219)
Experience	-0.241***	-0.286***	-0.274***	-0.242***	-0.277***	-0.274***
	(0.0382)	(0.0910)	(0.0504)	(0.0380)	(0.0911)	(0.0495)
Experience^2		0.00353			0.00276	
		(0.00667)			(0.00670)	
BMI	-0.0396	-0.0398	0.0249	-0.0361	-0.0363	0.0320
	(0.0553)	(0.0556)	(0.0722)	(0.0552)	(0.0554)	(0.0722)
2^{nd} Round	-0.751	-0.712	-0.755	-0.747	-0.717	-0.755
	(0.467)	(0.457)	(0.594)	(0.467)	(0.460)	(0.598)
3^{rd} Round	-0.507	-0.469	-0.608	-0.470	-0.442	-0.575
	(0.443)	(0.433)	(0.551)	(0.445)	(0.436)	(0.555)
4^{th} Round	-0.589	-0.547	-0.731	-0.516	-0.485	-0.629
	(0.470)	(0.461)	(0.603)	(0.479)	(0.472)	(0.621)
5^{th} Round	-0.437	-0.395	-0.298	-0.407	-0.375	-0.248
	(0.496)	(0.491)	(0.617)	(0.496)	(0.493)	(0.622)
6^{th} Round	-1.150**	-1.114**	-1.202*	-1.143**	-1.117**	-1.186*
	(0.491)	(0.479)	(0.628)	(0.494)	(0.484)	(0.632)
7^{th} Round	-1.033*	-0.997*	-1.006	-1.035*	-1.007*	-1.000

	(0.553)	(0.546)	(0.696)	(0.553)	(0.548)	(0.698)
Undrafted	-1.506***	-1.478***	-1.562***	-1.487***	-1.467***	-1.541**
	(0.472)	(0.460)	(0.603)	(0.473)	(0.463)	(0.604)
New Team	-0.441**	-0.468**	-0.345	-0.451**	-0.473**	-0.364*
	(0.181)	(0.192)	(0.214)	(0.184)	(0.195)	(0.217)
Free Agent	0.392	0.430	0.363	0.428	0.457	0.403
	(0.271)	(0.277)	(0.307)	(0.275)	(0.282)	(0.311)
Pro Bowl	0.400	0.359	0.336	0.345	0.313	0.255
	(0.637)	(0.637)	(0.768)	(0.639)	(0.638)	(0.764)
Games Started/Game	0.744**	0.765**		0.788**	0.804**	
	(0.334)	(0.333)		(0.334)	(0.333)	
Yards/Game	0.0260**	0.0256**	0.0126	0.0256**	0.0253**	0.0133
	(0.0118)	(0.0117)	(0.0148)	(0.0118)	(0.0117)	(0.0148)
TD/Game	1.234	1.235	1.158	1.403	1.404	1.369
	(1.071)	(1.063)	(1.153)	(1.095)	(1.088)	(1.216)
Offensive Snaps/Game			0.0327***			0.0323***
			(0.0102)			(0.0102)
Team Points Scored	0.00316**	0.00316**	0.00373**	0.00308**	0.00308**	0.00353**
	(0.00130)	(0.00130)	(0.00148)	(0.00128)	(0.00128)	(0.00148)
Team Rushing Attempts	0.00238	0.00246	0.00164	0.00228	0.00233	0.00155
	(0.00305)	(0.00306)	(0.00360)	(0.00305)	(0.00306)	(0.00360)
Team Rushing Yards	-5.48e-05	-6.62e-05	-8.32e-05	-2.50e-06	-1.09e-05	-2.07e-05
	(0.000508)	(0.000511)	(0.000566)	(0.000509)	(0.000512)	(0.000567)
Constant	2.182	2.246	0.151	2.012	2.064	-0.0958
	(2.062)	(2.076)	(2.544)	(2.055)	(2.066)	(2.537)
Concussions –				-0.218***	-0.216***	-0.236***
Non-concussion Injuries				(0.0674)	(0.0672)	(0.0751)
Observations	1,192	1,192	946	1,192	1,192	946

Note: Standard errors clustered at the player level in parentheses. Concussions – Non-concussion Injuries is the difference in *coefficients*. Offensive snaps data are only available beginning in 2012. All estimations include year fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Logistic Regression Coefficients- Heterogeneity by Race and Experience

	Dependent Variable = Pr(Contract Next Season)							
	Race				Experience			
	Nonwhite		White		Nonveteran[a]		Veteran	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Injuries	-0.0986**		-0.118***		-0.0605*		-0.154***	
	(0.0418)		(0.0328)		(0.0367)		(0.0379)	
Concussions		-0.288***		-0.337***		0.360		-0.386***
		(0.106)		(0.0813)		(0.369)		(0.0766)
Non-concussion Injuries		-0.0864**		-0.0983***		-0.0635*		-0.122***
		(0.0434)		(0.0330)		(0.0366)		(0.0381)
Other DNP	-0.0863**	-0.0881**	-0.0875**	-0.0837**	-0.0704**	-0.0704**	-0.131**	-0.123*
	(0.0369)	(0.0370)	(0.0364)	(0.0368)	(0.0290)	(0.0290)	(0.0657)	(0.0656)
White					0.396*	0.401*	0.250	0.266
					(0.212)	(0.214)	(0.239)	(0.242)
Team Drafted TE (Round 1-3)	-0.306	-0.305	-0.522*	-0.447	-0.433	-0.459	-0.375	-0.287
	(0.330)	(0.334)	(0.275)	(0.280)	(0.285)	(0.283)	(0.302)	(0.314)
Experience	-0.198***	-0.193***	-0.315***	-0.322***	-0.364**	-0.372**	-0.238***	-0.247***
	(0.0521)	(0.0516)	(0.0511)	(0.0522)	(0.157)	(0.157)	(0.0494)	(0.0506)
BMI	-0.104	-0.103	0.0765	0.0789	-0.0203	-0.0208	-0.0934	-0.0931
	(0.0687)	(0.0691)	(0.103)	(0.103)	(0.0647)	(0.0649)	(0.0902)	(0.0895)
2nd Round	-0.546	-0.603	-1.007	-0.905	1.321**	1.314**	-0.845	-0.843
	(0.583)	(0.595)	(0.713)	(0.698)	(0.661)	(0.667)	(0.523)	(0.531)
3rd Round	-0.453	-0.477	-0.619	-0.454	1.315***	1.283***	-0.342	-0.308
	(0.610)	(0.615)	(0.669)	(0.650)	(0.449)	(0.438)	(0.531)	(0.539)
4th Round	-0.540	-0.517	-0.622	-0.473	1.599***	1.583***	-0.802	-0.704
	(0.630)	(0.640)	(0.673)	(0.678)	(0.435)	(0.433)	(0.530)	(0.549)
5th Round	-0.353	-0.396	-0.632	-0.478	1.375***	1.391***	-0.419	-0.368
	(0.634)	(0.637)	(0.737)	(0.732)	(0.495)	(0.497)	(0.559)	(0.554)
6th Round	-1.054*	-1.111*	-1.269	-1.148	0.260	0.266	-0.780	-0.747
	(0.609)	(0.613)	(0.801)	(0.820)	(0.354)	(0.355)	(0.595)	(0.595)
7th Round	-1.242	-1.279	-0.988	-0.904	0.204	0.213	-0.180	-0.218

	(0.856)	(0.858)	(0.764)	(0.760)	(0.369)	(0.370)	(0.747)	(0.761)
Undrafted	-1.138**	-1.154**	-2.072***	-1.966***			-1.054*	-1.052*
	(0.566)	(0.567)	(0.722)	(0.718)			(0.574)	(0.584)
New Team	-0.186	-0.186	-0.710***	-0.722***	-0.567**	-0.583**	-0.456	-0.489
	(0.275)	(0.278)	(0.274)	(0.280)	(0.285)	(0.283)	(0.312)	(0.322)
Free Agent	0.285	0.258	0.588	0.686	-0.391	-0.356	0.593*	0.668*
	(0.389)	(0.389)	(0.440)	(0.465)	(1.211)	(1.216)	(0.350)	(0.362)
Pro Bowl	0.201	0.196	0.797	0.631			-0.137	-0.146
	(0.867)	(0.867)	(0.949)	(0.962)			(0.700)	(0.718)
Games Started/Game	0.936**	0.931**	0.530	0.615	0.652	0.660	0.710	0.812*
	(0.435)	(0.438)	(0.490)	(0.489)	(0.492)	(0.491)	(0.479)	(0.479)
Yards/Game	0.0424***	0.0420***	0.0103	0.00991	0.0164	0.0156	0.0333**	0.0304*
	(0.0164)	(0.0159)	(0.0165)	(0.0169)	(0.0179)	(0.0179)	(0.0166)	(0.0166)
TD/Game	0.0417	0.0110	2.418	2.855*	0.390	0.406	1.856	2.293
	(1.184)	(1.194)	(1.589)	(1.627)	(1.342)	(1.322)	(1.538)	(1.590)
Team Points Scored	0.00296	0.00288	0.00396**	0.00381**	0.00453**	0.00453**	0.00184	0.00164
	(0.00198)	(0.00198)	(0.00182)	(0.00181)	(0.00177)	(0.00178)	(0.00197)	(0.00197)
Team Rushing Attempts	0.00319	0.00314	0.000230	0.000297	0.00264	0.00277	0.00365	0.00344
	(0.00466)	(0.00464)	(0.00450)	(0.00453)	(0.00393)	(0.00398)	(0.00504)	(0.00514)
Team Rushing Yards	-0.000677	-0.000666	0.000642	0.000722	-8.18e-05	-7.58e-05	-1.60e-05	9.85e-05
	(0.000719)	(0.000713)	(0.000746)	(0.000759)	(0.000650)	(0.000655)	(0.000798)	(0.000820)
Constant	4.343	4.369	-0.783	-1.129	-0.457	-0.489	3.735	3.668
	(2.693)	(2.706)	(3.460)	(3.434)	(2.478)	(2.504)	(3.335)	(3.332)
Concussions – Non-concussion Injuries		-0.202*		-0.239***		0.423		-0.265***
		(0.107)		(0.0868)		(0.372)		(0.0808)
Observations	526	526	666	666	604	604	551	551

Note: Standard errors clustered at the player level in parentheses. Concussions – Non-concussion Injuries is the difference in *coefficients*. All estimations include year fixed effects.

[a] For nonveteran players, all first-round picks were active players the following season. Also, for nonveteran players, all Pro Bowl players were active players the following season. As a result, first-round picks and Pro Bowl players are not included in estimations, 37 player years. Estimating the model including these players, while omitting the variables, yields very similar results. Also, estimating the model using penalized maximum likelihood, which preserves the sample size and allows for the variables to be included, yields very similar results. All results are available from the authors.

*** p<0.01, ** p<0.05, * p<0.1

Table 6. Logistic Regression Coefficients- Heterogeneity by Performance

	Dependent Variable = Pr(Contract Next Season)							
	Yards/G				Receptions/G			
	Yards/G < 10		Yards/G ≥ 10		Receptions/G < 1		Receptions/G ≥ 1	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Injuries	-0.0346		-0.219***		-0.0402		-0.220***	
	(0.0327)		(0.0358)		(0.0318)		(0.0371)	
Concussions		-0.104		-0.422***		-0.170		-0.366***
		(0.118)		(0.0826)		(0.147)		(0.0761)
Non-concussion Injuries		-0.0317		-0.199***		-0.0360		-0.201***
		(0.0333)		(0.0378)		(0.0325)		(0.0400)
Other DNP	-0.0665**	-0.0666**	-0.194***	-0.188***	-0.0643**	-0.0644**	-0.173***	-0.171***
	(0.0287)	(0.0287)	(0.0638)	(0.0631)	(0.0287)	(0.0287)	(0.0596)	(0.0595)
White	0.568***	0.559***	0.109	0.160	0.547***	0.533***	0.0631	0.0951
	(0.196)	(0.197)	(0.303)	(0.304)	(0.195)	(0.196)	(0.296)	(0.297)
Team Drafted TE (Round 1-3)	-0.426	-0.418	-0.395	-0.340	-0.446	-0.431	-0.375	-0.341
	(0.271)	(0.272)	(0.313)	(0.317)	(0.276)	(0.279)	(0.320)	(0.319)
Experience	-0.257***	-0.256***	-0.238***	-0.239***	-0.241***	-0.240***	-0.250***	-0.251***
	(0.0473)	(0.0472)	(0.0503)	(0.0513)	(0.0479)	(0.0477)	(0.0555)	(0.0561)
BMI	-0.0535	-0.0531	0.110	0.113	-0.0327	-0.0322	-0.00907	-0.00166
	(0.0673)	(0.0672)	(0.117)	(0.117)	(0.0659)	(0.0658)	(0.107)	(0.107)
2nd Round	-0.978	-0.967	-0.837	-0.775	-0.747	-0.726	-0.788	-0.768
	(0.909)	(0.908)	(0.606)	(0.584)	(0.975)	(0.976)	(0.605)	(0.589)
3rd Round	-0.762	-0.738	-0.441	-0.310	-0.332	-0.305	-0.769	-0.656
	(0.908)	(0.909)	(0.576)	(0.562)	(0.967)	(0.968)	(0.553)	(0.552)
4th Round	-0.400	-0.364	-0.964*	-0.885	0.00513	0.0598	-1.082**	-1.023*
	(0.937)	(0.941)	(0.554)	(0.549)	(1.002)	(1.005)	(0.537)	(0.535)
5th Round	-0.505	-0.486	-0.735	-0.651	0.0567	0.0849	-1.087	-1.062
	(0.940)	(0.941)	(0.720)	(0.729)	(1.006)	(1.008)	(0.684)	(0.683)
6th Round	-1.509	-1.494	-0.956	-0.918	-1.137	-1.115	-1.039	-1.007
	(0.936)	(0.936)	(0.742)	(0.752)	(0.992)	(0.993)	(0.788)	(0.793)

7th Round	-1.356	-1.339	-0.462	-0.489	-0.769	-0.745	-1.193	-1.189
	(0.943)	(0.942)	(1.072)	(1.040)	(1.007)	(1.007)	(0.990)	(0.965)
Undrafted	-1.799**	-1.773*	-1.319**	-1.294**	-1.310	-1.270	-1.737***	-1.731***
	(0.905)	(0.906)	(0.585)	(0.570)	(0.970)	(0.972)	(0.592)	(0.585)
New Team	-0.235	-0.234	-0.796**	-0.837**	-0.162	-0.158	-0.920***	-0.948***
	(0.220)	(0.221)	(0.335)	(0.343)	(0.223)	(0.223)	(0.342)	(0.350)
Free Agent	0.503	0.500	0.367	0.474	0.581*	0.568	0.287	0.353
	(0.352)	(0.352)	(0.399)	(0.426)	(0.351)	(0.350)	(0.430)	(0.450)
Pro Bowl	-0.0226	-0.0244	0.541	0.505	-0.317	-0.312	0.380	0.365
	(1.510)	(1.507)	(0.862)	(0.860)	(1.628)	(1.623)	(0.804)	(0.802)
Games Started/Game	0.223	0.232	1.242**	1.287**	0.401	0.426	1.171**	1.148**
	(0.425)	(0.423)	(0.544)	(0.545)	(0.447)	(0.446)	(0.559)	(0.557)
Yards/Game	0.0700*	0.0702*	-9.42e-05	-0.00193	0.0795**	0.0790**	0.00539	0.00389
	(0.0376)	(0.0376)	(0.0150)	(0.0152)	(0.0345)	(0.0346)	(0.0145)	(0.0147)
TD/Game	-0.234	-0.237	1.124	1.260	-1.248	-1.238	1.553	1.643
	(1.918)	(1.922)	(1.094)	(1.167)	(1.827)	(1.831)	(1.099)	(1.176)
Team Points Scored	0.00400***	0.00400***	0.00191	0.00161	0.00421***	0.00419***	0.00171	0.00159
	(0.00153)	(0.00153)	(0.00257)	(0.00262)	(0.00156)	(0.00156)	(0.00244)	(0.00254)
Team Rushing Attempts	0.00145	0.00149	0.00247	0.00247	7.07e-05	0.000279	0.00743	0.00696
	(0.00370)	(0.00368)	(0.00586)	(0.00591)	(0.00369)	(0.00368)	(0.00615)	(0.00617)
Team Rushing Yards	0.000326	0.000318	-0.000822	-0.000728	0.000371	0.000345	-0.000965	-0.000843
	(0.000613)	(0.000612)	(0.000928)	(0.000934)	(0.000606)	(0.000606)	(0.000932)	(0.000939)
Constant	1.949	1.916	0.574	0.328	1.129	1.056	2.497	2.246
	(2.527)	(2.518)	(4.167)	(4.137)	(2.519)	(2.506)	(3.960)	(3.924)
Concussions –		-0.0719		-0.223**		-0.134		-0.165**
Non-concussion Injuries		(0.118)		(0.0878)		(0.1490		(0.0835)
Observations	622	622	570	570	613	613	579	579

Note: Standard errors clustered at the player level in parentheses. Concussions – Non-concussion Injuries is the difference in *coefficients*. All estimations include year fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

Table 7. Logistic Regression Coefficients- Prior Injuries

Dependent Variable = Pr(Contract Next Season)				
VARIABLES	(1)	(2)[a]	(3)	(4)[a]
Injuries	-0.130***	-0.111***		
	(0.0314)	(0.0343)		
Injuries (t-1)	-0.0620**			
	(0.0314)			
Injuries (Career)		-0.0149		
		(0.0236)		
Concussions			-0.354***	-0.382***
			(0.0674)	(0.0980)
Concussions (t-1)			-0.144	
			(0.140)	
Concussions (Career)				-0.117
				(0.0952)
Non-concussion Injuries			-0.111***	-0.0854**
			(0.0313)	(0.0333)
Non-concussion Injuries (t-1)			-0.0651**	
			(0.0322)	
Non-concussion Injuries (Career)				-0.0123
				(0.0254)
Other DNP	-0.0719	-0.102*	-0.0690	-0.0976*
	(0.0455)	(0.0550)	(0.0462)	(0.0558)
White	0.471**	0.435*	0.484**	0.450*
	(0.217)	(0.241)	(0.220)	(0.244)
Team Drafted TE (Round 1-3)	-0.584**	-0.543*	-0.543**	-0.509*
	(0.258)	(0.299)	(0.260)	(0.307)
Experience	-0.262***	-0.296***	-0.265***	-0.294***
	(0.0511)	(0.0877)	(0.0513)	(0.0891)
BMI	0.00386	-0.0201	0.0119	-0.00228
	(0.0836)	(0.0838)	(0.0836)	(0.0839)
2nd Round	-0.915	-1.280	-0.923	-1.174
	(0.563)	(0.914)	(0.562)	(0.885)
3rd Round	-0.573	-1.337	-0.509	-1.013
	(0.536)	(0.910)	(0.537)	(0.892)
4th Round	-0.807	-1.235	-0.703	-0.851
	(0.563)	(0.926)	(0.572)	(0.936)
5th Round	-0.530	-0.831	-0.495	-0.670
	(0.612)	(0.980)	(0.612)	(0.955)
6th Round	-1.215**	-2.462***	-1.204**	-2.189**
	(0.606)	(0.945)	(0.604)	(0.942)
7th Round	-0.899	-1.409	-0.909	-1.202
	(0.699)	(1.031)	(0.703)	(1.013)
Undrafted	-1.584***	-2.313***	-1.584***	-2.106**
	(0.585)	(0.897)	(0.585)	(0.872)

New Team	-0.554**	-0.752***	-0.569**	-0.808***
	(0.263)	(0.276)	(0.267)	(0.286)
Free Agent	0.499	0.606	0.548	0.665
	(0.326)	(0.417)	(0.337)	(0.432)
Pro Bowl	0.116		0.0702	
	(0.713)		(0.745)	
Games Started/Game	0.897**	1.069**	0.965**	1.166***
	(0.402)	(0.446)	(0.401)	(0.439)
Yards/Game	0.0324**	0.0208	0.0316**	0.0226
	(0.0135)	(0.0177)	(0.0133)	(0.0189)
TD/Game	1.308	1.024	1.565	1.120
	(1.200)	(1.567)	(1.252)	(1.698)
Team Points Scored	0.00288*	0.00281	0.00281*	0.00285
	(0.00163)	(0.00197)	(0.00163)	(0.00197)
Team Rushing Attempts	0.00357	-0.00232	0.00345	-0.00200
	(0.00438)	(0.00498)	(0.00442)	(0.00496)
Team Rushing Yards	-5.69e-05	0.000850	1.75e-05	0.000848
	(0.000688)	(0.000769)	(0.000694)	(0.000764)
Constant	0.636	2.345	0.288	1.280
	(3.056)	(3.179)	(3.058)	(3.185)
Observations	798	549	798	549

Note: Standard errors clustered at the player level in parentheses. All estimations include year fixed effects.
[a] For estimations with career injuries, all Pro Bowl players were active players the following season. As a result, Pro Bowl players are not included in estimation, 35 player years. Estimating the model including these players, while omitting the variable, yields very similar results. Also, estimating the model using penalized maximum likelihood, which preserves the sample size and allows for the variables to be included, yields very similar results. All results are available from the authors.
*** p<0.01, ** p<0.05, * p<0.1

Table 8. Selection Bias Correction Average Marginal Effects

	$\Pr(E=1\|\mathbf{x})$		$\mathrm{E}(\ln(w)\,\|E=1,\mathbf{z})$	
All Injuries	-0.0171***		-0.00211	
	(0.00371)		(0.00866)	
Concussions		-0.0469***		0.0152
		(0.0100)		(0.0351)
Non-Concussions		-0.0146***		-0.00285
		(0.00384)		(0.00894)
White	0.0342	0.0348	0.0107	0.0103
	(0.0237)	(0.0236)	(0.0480)	(0.0479)

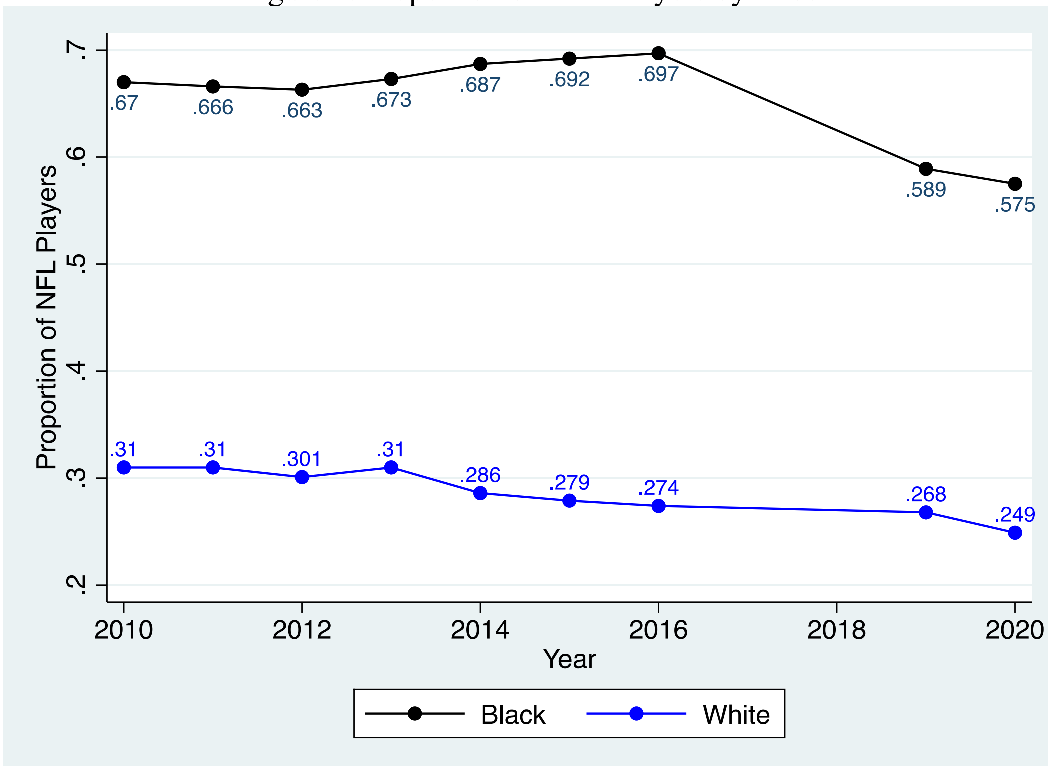
Note: Delta-method standard errors in parentheses. The sample contains 1,148 player years, 864 of which continued to be employed. All estimations include the full specification described in Section 2.1.
*** p<0.01, ** p<0.05, * p<0.1

Table 9. Selection Bias Correction Average Marginal Effects by Race

		$\Pr(E = 1 \mid \mathbf{x})$		$\mathrm{E}(\ln(w) \mid E = 1, \mathbf{z})$	
		Nonwhite	White	Nonwhite	White
Panel A	All Injuries	-0.0193***	-0.0186***	-0.0227	0.00482
		(0.00712)	(0.00420)	(0.0154)	(0.00943)
Panel B	Concussions	-0.0432**	-0.0515***	-0.0769	0.0524
		(0.0174)	(0.0102)	(0.0780)	(0.0327)
	Non-Concussions	-0.0179*	-0.0154***	-0.0217	0.00288
		(0.0100)	(0.00434)	(0.0220)	(0.00978)

Note: Delta-method standard errors in parentheses. The sample of nonwhite players contains 510 player years, 368 of which continued to be employed. The sample of white players contains 638 player years, 496 of which continued to be employed. All estimations include the full specification described in Section 2.1.
*** p<0.01, ** p<0.05, * p<0.1

Figure 1. Proportion of NFL Players by Race



Source: The Institute for Diversity and Ethics in Sport.
Note: Data were not available for the 2017 and 2018 seasons.

APPENDIX

Table A1. Race by Position in 2016

		Black		White		Other	
Position	Total	#	Proportion	#	Proportion	#	Proportion
CB	244	238	0.975	0	0.000	6	0.025
DE	201	162	0.806	31	0.154	8	0.040
DT	140	115	0.821	9	0.064	16	0.114
FB	33	11	0.333	17	0.515	5	0.152
K	37	0	0.000	35	0.946	2	0.054
LB	294	222	0.755	54	0.184	18	0.061
LS	37	0	0.000	36	0.973	1	0.027
OL	352	152	0.432	180	0.511	20	0.057
P	36	1	0.028	35	0.972	0	0.000
QB	98	18	0.184	77	0.786	3	0.031
RB	165	155	0.939	4	0.024	6	0.036
S	180	153	0.850	14	0.078	13	0.072
TE	140	58	0.414	68	0.486	14	0.100
WR	244	215	0.881	24	0.098	5	0.020

Note: Proportion refers to the proportion of players of the specific race for a given position.
Source: Gertz (2017).

Robustness to Specification of Performance

Here, we present results from estimations of equation (1) using all 1,023 combinations of the following individual and team performance variables Pro Bowl, offensive snaps per game, games started per game, receptions per game, yards per game, touchdowns per game, targets per game, points scored, team rushing attempts, and team rushing yards. Figures A1 and A2 show the results for estimations of employment on all injuries, while Figures A3-A6 display results for estimations of employment on concussions and non-concussion injuries. The results show the estimates are robust to the specification of performance.

Figure A1. Performance Specifications- All Injuries Estimations

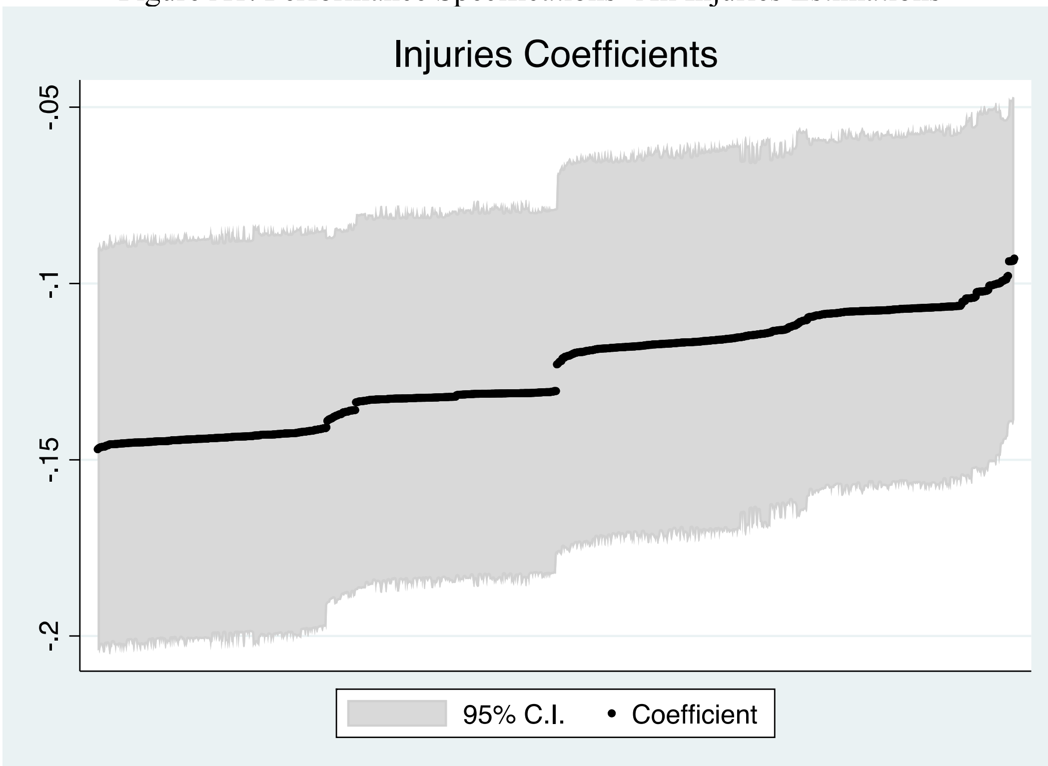


Figure A2. Performance Specifications- All Injuries Estimations

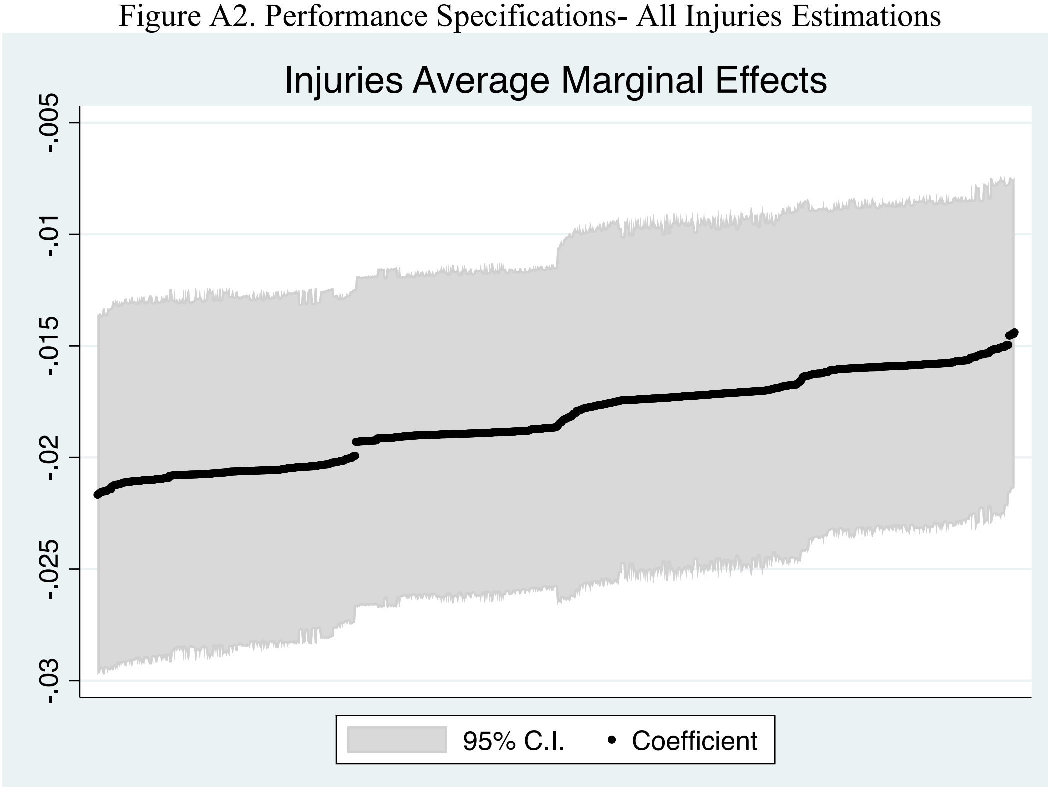


Figure A3. Performance Specifications- Concussions and Non-Concussions Estimations

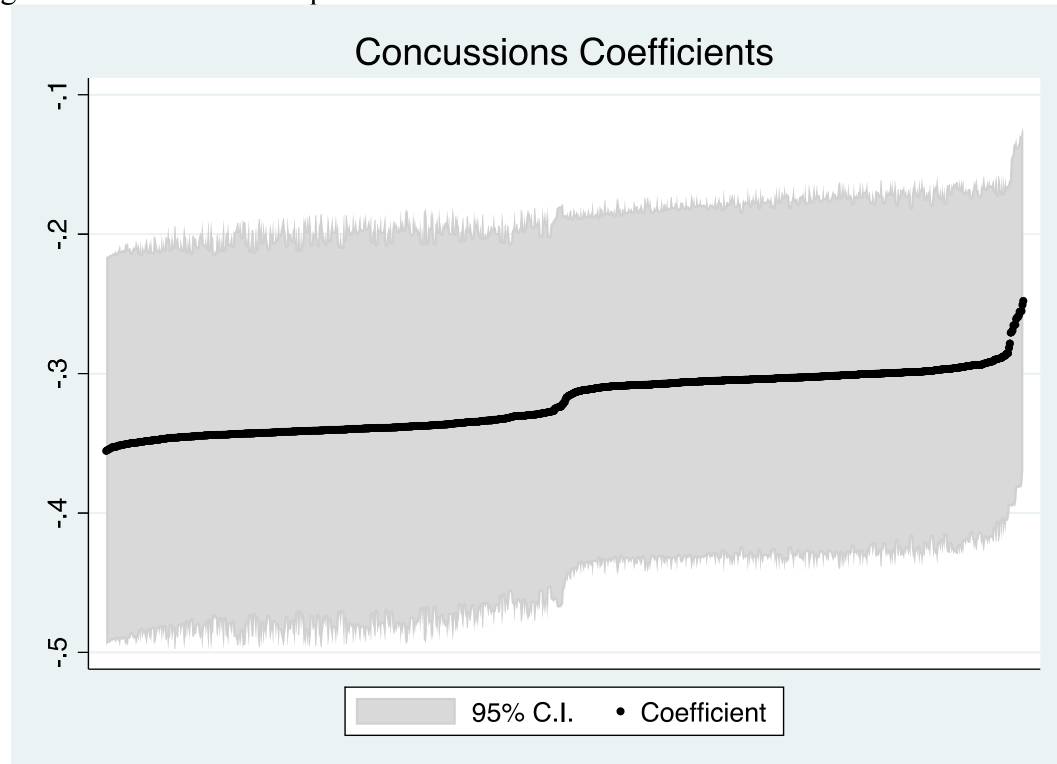


Figure A4. Performance Specifications- Concussions and Non-Concussions Estimations

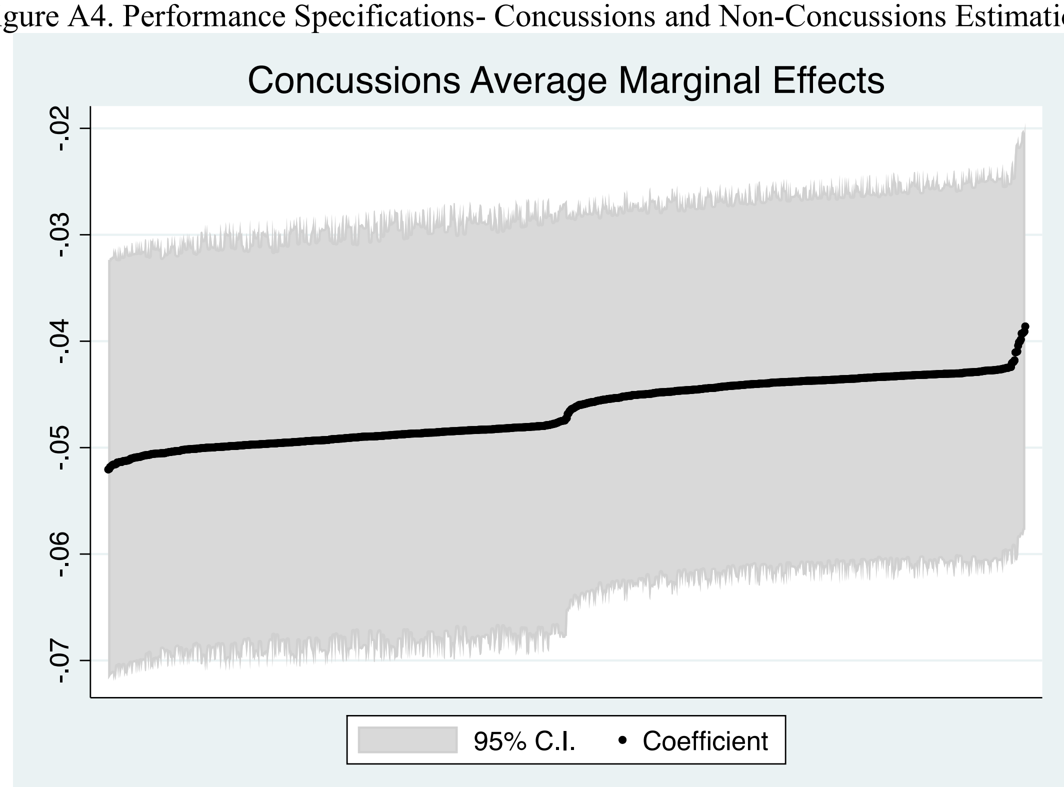


Figure A5. Performance Specifications- Concussions and Non-Concussions Estimations

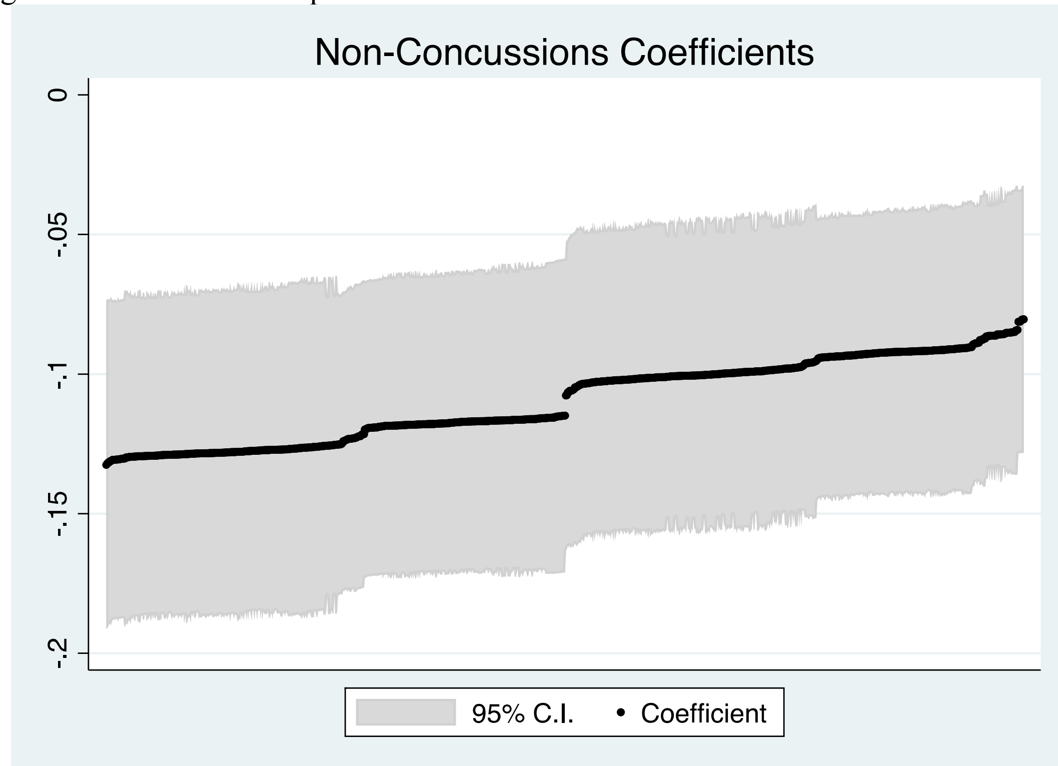
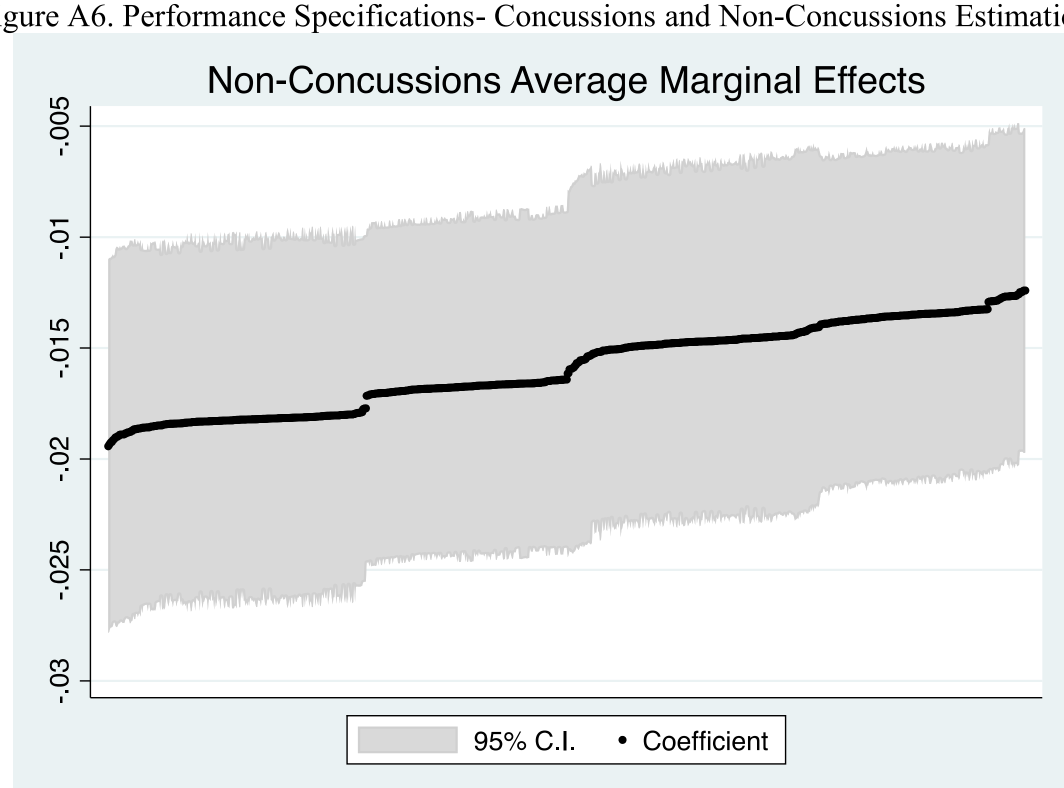


Figure A6. Performance Specifications- Concussions and Non-Concussions Estimations



Influence Analysis

As mentioned in the Data section, concussion data are positively skewed with a large mass at zero. As a result, we may be concerned about the influence of the few observations with large numbers of games missed due to concussion. As a result, we calculate Pregibon's (1981) delta beta measure, which is a measure of the change in the coefficient vector from deleting a given observation.[21] We calculate the delta beta measure for the vector of coefficients in the model as well as for the single concussion coefficient, our main interest. Figure A7 shows the influence of each observation on the coefficient vector corresponding to our baseline estimation, Column 4 of Table 4. Figure A8 displays the influence on the concussion coefficient. Data points in Figures A7 and A8 correspond to the number of games missed from concussion for each observation. Next, we estimate our model eliminating those observations with relatively large influence. Column 1 of Table A2 reports results omitting observations with an absolute influence on the coefficient vector of greater than 0.20. Column 2 of Table A2 displays coefficients from omitting observations with an absolute influence on the concussion coefficient of greater than 0.01. The average marginal effect of games missed from concussion in Column 1 is -0.052, or each game missed due to concussion reduces the probability of continuing to be employed by 5.2 percentage points. In Column 2, each game missed due to concussion reduces the probability of employment by 3.1 percentage points. Thus, we conclude our results are robust.

[21] As an alternative, we transform the concussion data, to reduce the positive skew, by using the natural logarithm and the square-root transformations. For the natural logarithm, we calculate the natural logarithm of games missed from concussion plus one. The average marginal effect on employment of missing two versus one game from concussion is a reduction of 5.2 percentage points. When taking the square root of games missed from concussion, the average marginal effect on employment of missing two versus one game from concussion is a reduction of 3.8 percentage points.

Figure A7. Influence On Model Coefficients

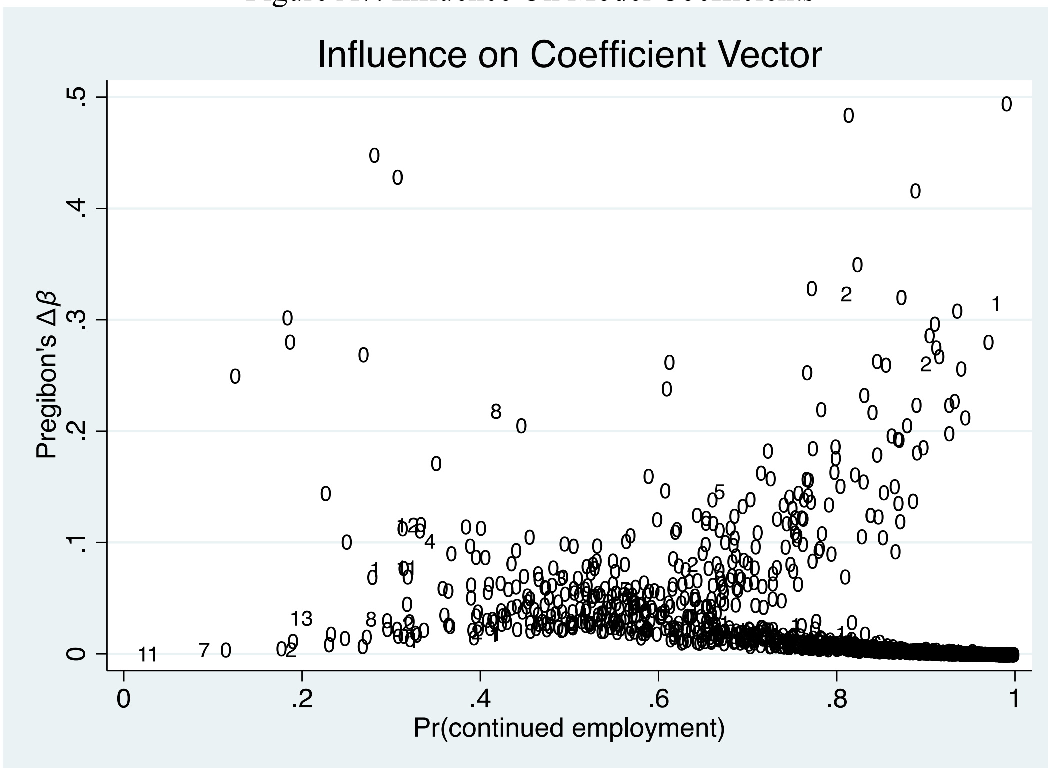


Figure A8. Influence on Concussion Coefficient

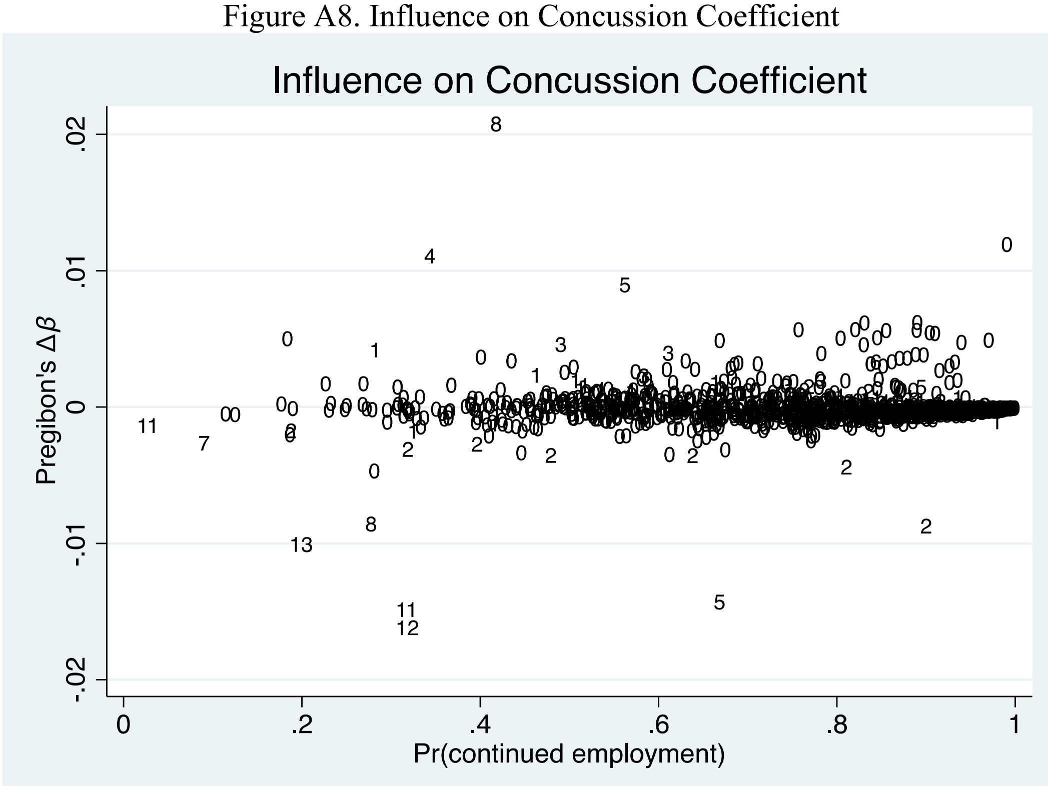


Table A2. Influence Logistic Regression Coefficients

Dependent Variable = Pr(Contract Next Season)		
VARIABLES	(1)	(2)
Concussions	-0.400***	-0.212**
	(0.0712)	(0.0970)
Non-concussion Injuries	-0.0898***	-0.0882***
	(0.0277)	(0.0264)
Other DNP	-0.0968***	-0.0821***
	(0.0280)	(0.0254)
White	0.416**	0.330**
	(0.180)	(0.165)
Team Drafted TE (Round 1-3)	-0.449*	-0.413**
	(0.236)	(0.208)
Experience	-0.340***	-0.245***
	(0.0355)	(0.0377)
BMI	-0.0194	-0.0311
	(0.0631)	(0.0555)
2nd Round	-0.979*	-0.685
	(0.558)	(0.481)
3rd Round	-0.828	-0.445
	(0.539)	(0.453)
4th Round	-0.694	-0.426
	(0.573)	(0.487)
5th Round	-0.627	-0.345
	(0.563)	(0.505)
6th Round	-1.927***	-1.148**
	(0.548)	(0.497)
7th Round	-1.449**	-0.983*
	(0.657)	(0.558)
Undrafted	-2.131***	-1.464***
	(0.532)	(0.477)
New Team	-0.468**	-0.450**
	(0.204)	(0.186)
Free Agent	0.611**	0.404
	(0.302)	(0.279)
Pro Bowl		0.255
		(0.645)
Games Started/Game	1.201***	0.779**
	(0.361)	(0.335)
Yards/Game	0.0475***	0.0268**
	(0.0129)	(0.0124)
TD/Game	1.442	1.671
	(1.239)	(1.154)
Team Points Scored	0.00463***	0.00333***
	(0.00136)	(0.00129)

Team Rushing Attempts	0.00160	0.00255
	(0.00321)	(0.00307)
Team Rushing Yards	0.000240	1.25e-05
	(0.000543)	(0.000516)
Constant	1.592	1.579
	(2.315)	(2.042)
Observations	1,095	1,185

Note: Standard errors clustered at the player level in parentheses. All estimations include year fixed effects.
[a] All Pro Bowl players were active players the following season. As a result, Pro Bowl players are not included in estimation, 35 player years. Estimating the model including these players, while omitting the variable, yields very similar conclusions. Also, estimating the model using penalized maximum likelihood, which preserves the sample size and allows for the variables to be included, yields very similar results. All results are available from the authors.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Survival Analysis

We apply the specification in (1) to a Cox proportional hazards model

$$h(t) = h_0(t)\exp\left(\beta_0 + \beta_1 inj_{i,t} + \beta_2 white_i + \mathbf{x}'_{i,t}\boldsymbol{\lambda}\right), \tag{A1}$$

where $h(t)$ is the hazard function, which depends on time, and $h_0(t)$ is the baseline hazard. We compare our results between the two methods to assess the robustness of our conclusions to approach. Table A3 presents the Cox proportional hazards models' results in the form of hazard ratios, including the same robustness checks of including a quadratic specification for experience and using offense snaps per game. For all specifications, injuries have a significant effect on survival. The hazard ratio for injuries is 1.07. When separating concussion and non-concussion injuries, the hazard ratio ranges from 1.22 to 1.24, while the effect of other injuries is 1.06. The difference between concussions and non-concussion injuries is significant as well. Also, the hazard ratio associated with race is less than one, ranging from 0.79 to 0.81. Similar to our logistic regression results, the effect of being nonwhite is equivalent to having missed an additional game due to concussion. Figure A9 presents the Kaplan-Meier survival functions by race. There appears to be a difference in the survival functions, with white players having a higher chance of survival, that exists from year three through year ten. Thus, similar to our logistic regression results, injuries and race have meaningful impacts on remaining part of the labor market.

However, the model relies on there being proportional hazards. Thus, we test the validity of the critical proportional hazards assumption for our estimations in Table A3. To do so, we examine the scaled Schoenfeld residuals, which have no relationship with analysis time, if the proportional hazards assumption holds (Grambsch and Therneau 1994). As a result, we present graphs, Figure A10, of the scaled Schoenfeld residuals against analysis time for injuries and race that correspond to the model in Column 1 of Table A3. Furthermore, we present results from the Grambsch and Therneau (1994) test, which has a null hypothesis of no relationship between the scaled Schoenfeld residuals and analysis time. We fail to reject the null hypothesis, supporting the proportional hazards assumption, which is shown in Table A4.[22]

[22] Including interactions between all variables and analysis time, allowing for time varying coefficients, yields similar results.

Table A3. Cox Proportional Hazards Model Hazard Ratios

	Dependent Variable = Pr(Not in League)					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Injuries	1.073***	1.073***	1.073***			
	(0.0166)	(0.0167)	(0.0171)			
Concussions				1.239***	1.239***	1.218***
				(0.0331)	(0.0330)	(0.0324)
Non-concussion Injuries				1.062***	1.061***	1.060***
				(0.0166)	(0.0167)	(0.0176)
Other DNP	1.050***	1.051***	1.052**	1.046**	1.046***	1.047**
	(0.0181)	(0.0180)	(0.0211)	(0.0182)	(0.0181)	(0.0213)
White	0.811*	0.810*	0.799*	0.804*	0.804*	0.785*
	(0.0935)	(0.0936)	(0.101)	(0.0926)	(0.0929)	(0.0987)
Team Drafted TE (Round 1-3)	1.271*	1.271*	1.364**	1.237	1.238	1.327**
	(0.175)	(0.175)	(0.196)	(0.168)	(0.168)	(0.191)
Experience	0.915	0.947	0.925	0.887	0.945	0.891
	(0.0677)	(0.197)	(0.0697)	(0.0673)	(0.199)	(0.0690)
Experience^2		0.997			0.994	
		(0.0177)			(0.0176)	
BMI	1.005	1.005	0.993	1.001	1.001	0.987
	(0.0417)	(0.0419)	(0.0453)	(0.0410)	(0.0414)	(0.0447)
2nd Round	1.919*	1.925*	1.535	1.978**	1.987**	1.575
	(0.642)	(0.647)	(0.556)	(0.667)	(0.672)	(0.577)
3rd Round	1.431	1.437	1.384	1.427	1.436	1.392
	(0.438)	(0.446)	(0.440)	(0.440)	(0.451)	(0.439)
4th Round	1.523	1.526	1.616	1.458	1.463	1.518
	(0.495)	(0.499)	(0.570)	(0.486)	(0.491)	(0.548)
5th Round	1.299	1.302	1.006	1.322	1.327	0.987
	(0.435)	(0.438)	(0.352)	(0.443)	(0.448)	(0.346)
6th Round	2.104**	2.104**	1.812*	2.178**	2.178**	1.867*
	(0.649)	(0.649)	(0.610)	(0.675)	(0.677)	(0.627)
7th Round	1.666	1.675	1.262	1.734	1.751	1.307

	(0.604)	(0.620)	(0.515)	(0.636)	(0.657)	(0.540)
Undrafted	2.540***	2.549***	2.562***	2.603***	2.620***	2.603***
	(0.749)	(0.760)	(0.814)	(0.773)	(0.787)	(0.829)
New Team	1.283*	1.284*	1.150	1.278	1.279*	1.136
	(0.190)	(0.190)	(0.184)	(0.190)	(0.190)	(0.185)
Free Agent	0.802	0.800	0.788	0.795	0.792	0.780
	(0.144)	(0.144)	(0.143)	(0.146)	(0.146)	(0.144)
Pro Bowl	0.675	0.680	0.631	0.694	0.705	0.658
	(0.359)	(0.357)	(0.385)	(0.372)	(0.371)	(0.401)
Games Started/Game	0.590**	0.590**		0.565**	0.563**	
	(0.132)	(0.132)		(0.126)	(0.126)	
Yards/Game	0.982**	0.982**	0.994	0.982**	0.982**	0.994
	(0.00879)	(0.00879)	(0.00940)	(0.00881)	(0.00882)	(0.00963)
TD/Game	0.441	0.442	0.506	0.374	0.375	0.374
	(0.373)	(0.373)	(0.410)	(0.310)	(0.311)	(0.306)
Offensive Snaps/Game			0.974***			0.975***
			(0.00650)			(0.00638)
Team Points Scored	0.998**	0.998**	0.997***	0.998**	0.998**	0.997***
	(0.000969)	(0.000966)	(0.00105)	(0.000940)	(0.000936)	(0.00102)
Team Rushing Attempts	0.999	0.999	0.999	0.999	0.999	0.999
	(0.00238)	(0.00243)	(0.00268)	(0.00236)	(0.00242)	(0.00265)
Team Rushing Yards	1.000	1.000	1.000	1.000	1.000	1.000
	(0.000379)	(0.000384)	(0.000394)	(0.000379)	(0.000385)	(0.000396)
Concussions – Non-concussion Injuries				0.0154***	0.154***	0.139***
				(0.0297)	(0.0296)	(0.0305)
Observations	1,111	1,111	890	1,111	1,111	890

Note: Standard errors clustered at the player level in parentheses. Concussions – Non-concussion Injuries is the difference in *coefficients*. Offensive snaps data are only available beginning in 2012. Breslow (1974) method used for ties. Results are robust to the use of the Efron (1977) method for ties. All estimations include year fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

Table A4. Grambsch and Therneau (1994) Scaled Schoenfeld Residuals Test

	(1)		(2)	
VARIABLES	ρ	p-value	ρ	p-value
Injuries	0.0177	0.817		
Concussions			-0.0585	0.540
Non-concussion Injuries			0.0175	0.826
White	0.0259	0.724	0.0244	0.737
Global		0.746		0.853

Note: Model (1) corresponds to column (1) in Table 5, and model (2) corresponds to column (4) in Table 5.

Figure A9. Survival Functions by Race

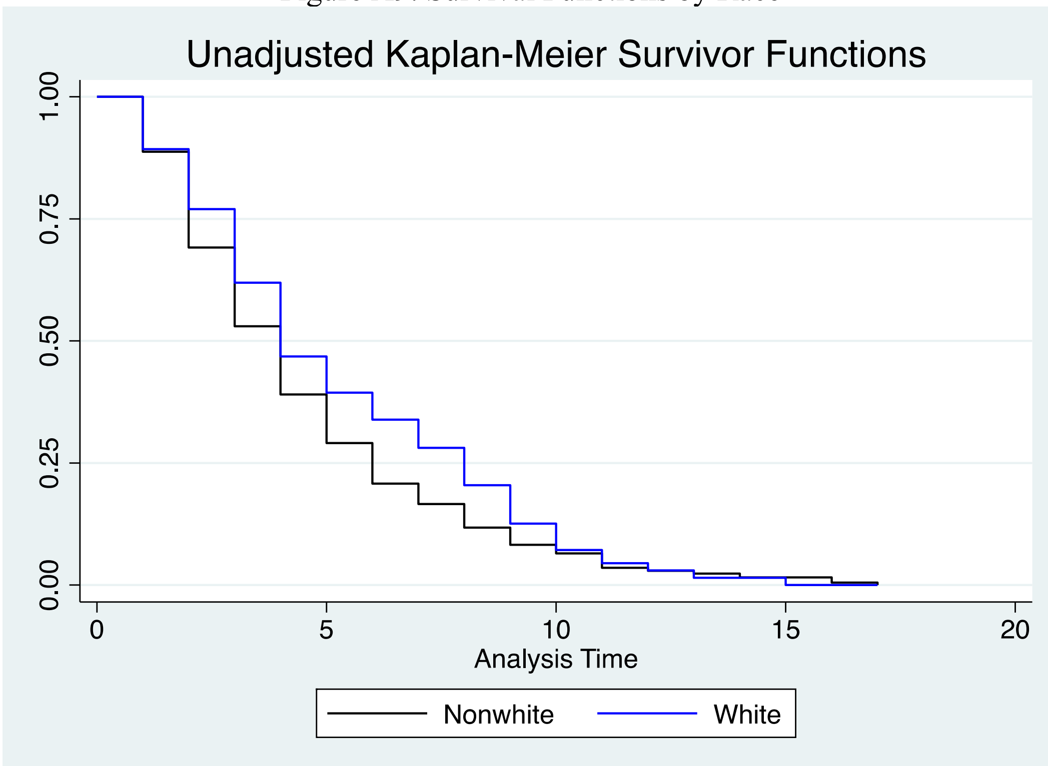
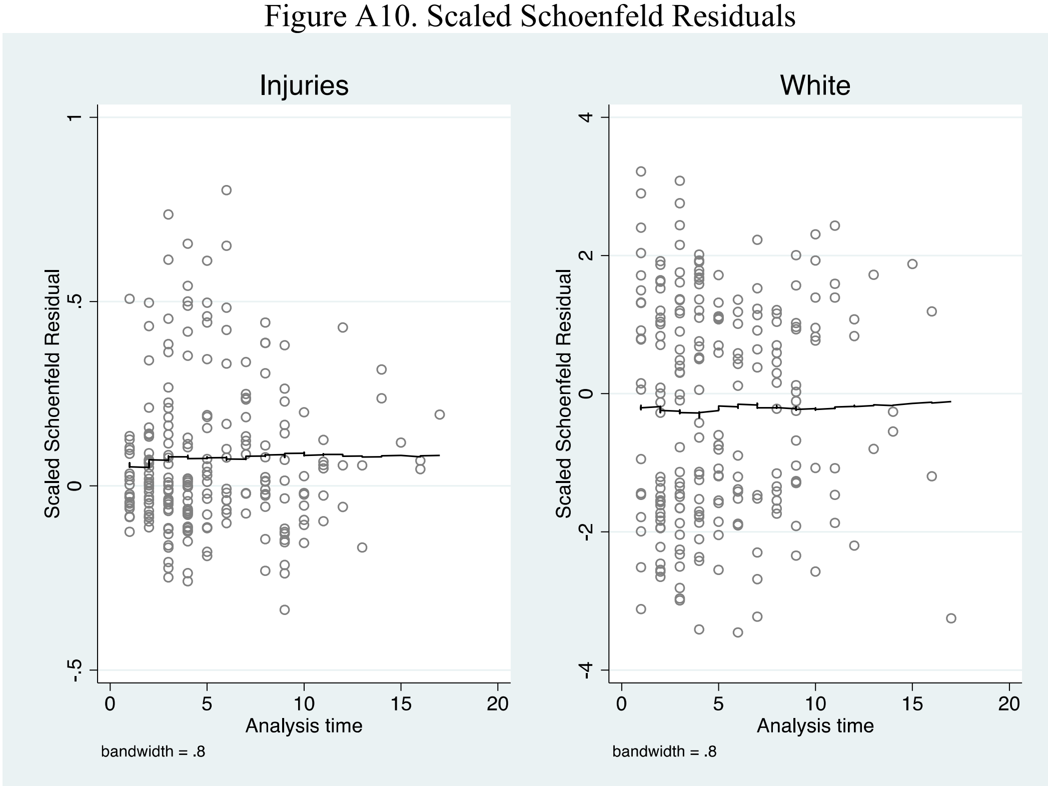


Figure A10. Scaled Schoenfeld Residuals



Copula Regression

We use a similar approach to Candio et al. (2021) and estimate several models comparing them using AIC and BIC to select the best set of distributional assumptions. Specifically, we use the R package GJRM (Marra and Radice 2022) to implement the analysis. We consider two specifications for the employment model logit and probit, three distributions for the compensation equation normal, logistic, and Gumbel, and twelve copula functions. The copula functions we consider are normal (N), Frank (F), Farlie-Gumbel-Morgenstern (FGM), Plackett (PL), Student-t (T), Ali-Mikhail-Haq (AMH), Clayton (C0), survival Clayton (C90), Joe (J0), survival Joe (J180), Galambos (G0), and survival Galambos (G180). As a result, we are comparing 72 models based on AIC and BIC. Figures A11 and A12 compare the AIC and BIC respectively for the specification of the model using all injuries. It is clear in both cases that the logit model for employment and the logistic distribution for compensation, which amounts to assuming both error terms are logistically distributed, generates the lowest AIC and BIC. For the twelve copula functions estimated with these marginal distributions, the Frank copula produces the best fit, according to both AIC and BIC; however, the normal, Plackett, and Student-t copula functions are similar. The AIC and BIC results are the same when applying our specification separating concussion and non-concussion injuries; the results are shown in Figures A13 and A14.

Table A5 presents results for the model with both error terms assumed to be logistically distributed using the Frank copula. The results for the probability of remaining employed are very similar to our initial logistic regression results. Furthermore, injuries are not meaningful in the estimation of compensation. Thus, the copula method results in the same conclusion as the standard Heckman (1974) analysis; there is a significant impact of injuries on compensation, but the effect is entirely driven by the effect of injuries on the likelihood of remaining employed in the NFL.

Table A5. Copula Estimation Results

	$\Pr(E_{t+1} = 1)$	w_{t+1}	$\Pr(E_{t+1} = 1)$	w_{t+1}
VARIABLES	(1)	(3)	(2)	(4)
Injuries	-0.109***	0.010		
	(0.023)	(0.007)		
Concussions			-0.313***	0.042
			(0.078)	(0.032)
Non-concussion Injuries			-0.092***	0.008
			(0.024)	(0.007)
Other DNP	-0.086***	0.020**	-0.085***	0.020**
	(0.026)	(0.008)	(0.026)	(0.008)
White	0.187	-0.008	0.195	-0.009
	(0.155)	(0.041)	(0.156)	(0.041)
Team Drafted TE (Round 1-3)	-0.451***		-0.424**	
	(0.172)		(0.173)	
Experience	-0.251***	0.373***	-0.252***	0.372***
	(0.033)	(0.022)	(0.033)	(0.022)
BMI	-0.021	-0.016	-0.016	-0.017
	(0.055)	(0.016)	(0.055)	(0.016)
1st Round	1.170***	0.218***	1.145***	0.220***
	(0.370)	(0.082)	(0.371)	(0.082)
2nd Round	0.916***	0.220***	0.899***	0.221***
	(0.310)	(0.073)	(0.309)	(0.072)
3rd Round	1.270***	-0.078	1.266***	-0.080
	(0.278)	(0.069)	(0.277)	(0.069)
4th Round	1.059***	-0.005	1.125***	-0.010
	(0.271)	(0.069)	(0.276)	(0.069)
5th Round	1.171***	-0.133*	1.180***	-0.135*
	(0.292)	(0.072)	(0.293)	(0.072)
6th Round	0.518*	-0.176**	0.507*	-0.179**
	(0.271)	(0.080)	(0.270)	(0.080)
7th Round	0.394	-0.103	0.373	-0.101
	(0.307)	(0.091)	(0.308)	(0.091)
New Team	-0.508***		-0.518***	
	(0.168)		(0.168)	
Free Agent	0.298		0.315	
	(0.228)		(0.228)	
Pro Bowl	0.085	-0.096	0.035	-0.093
	(0.636)	(0.098)	(0.638)	(0.098)
Games Started/Game	0.624**	0.310***	0.690**	0.306***

	(0.295)	(0.083)	(0.298)	(0.083)
Yards/Game	0.036***	0.015***	0.035***	0.015***
	(0.010)	(0.002)	(0.010)	(0.002)
TD/Game	1.564*	0.138	1.724*	0.134
	(0.914)	(0.182)	(0.922)	(0.182)
Team Points Scored	0.003**	0.000	0.003**	0.000
	(0.001)	(0.000)	(0.001)	(0.000)
Team Rushing Attempts	0.002	-0.001*	0.002	-0.001*
	(0.003)	(0.001)	(0.003)	(0.001)
Team Rushing Yards	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Experience^2		-0.017***		-0.017***
		(0.002)		(0.002)
New Team (t+1)		-0.509***		-0.509***
		(0.056)		(0.056)
Free Agent (t+1)		0.019		0.019
		(0.063)		(0.064)
Constant	0.118	13.823***	-0.175	13.843***
	(1.870)	(0.528)	(1.865)	(0.528)
Kendall's τ	-0.607		-0.610	
Observations	1,148	864	1,148	864

Note: Estimations use the logistic distribution for both error terms and the Frank copula function. Standard errors calculated using the GJRM package in R (Marra and Radice (2022)) in parentheses. Kendall's τ is a measure of the dependence between the employment and compensation equations (see Gomes et al. (2019) for further discussion about the connection of Kendall's τ to various copula functions). All estimations include year fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

Figure A11. Copula Model Comparison- All Injuries

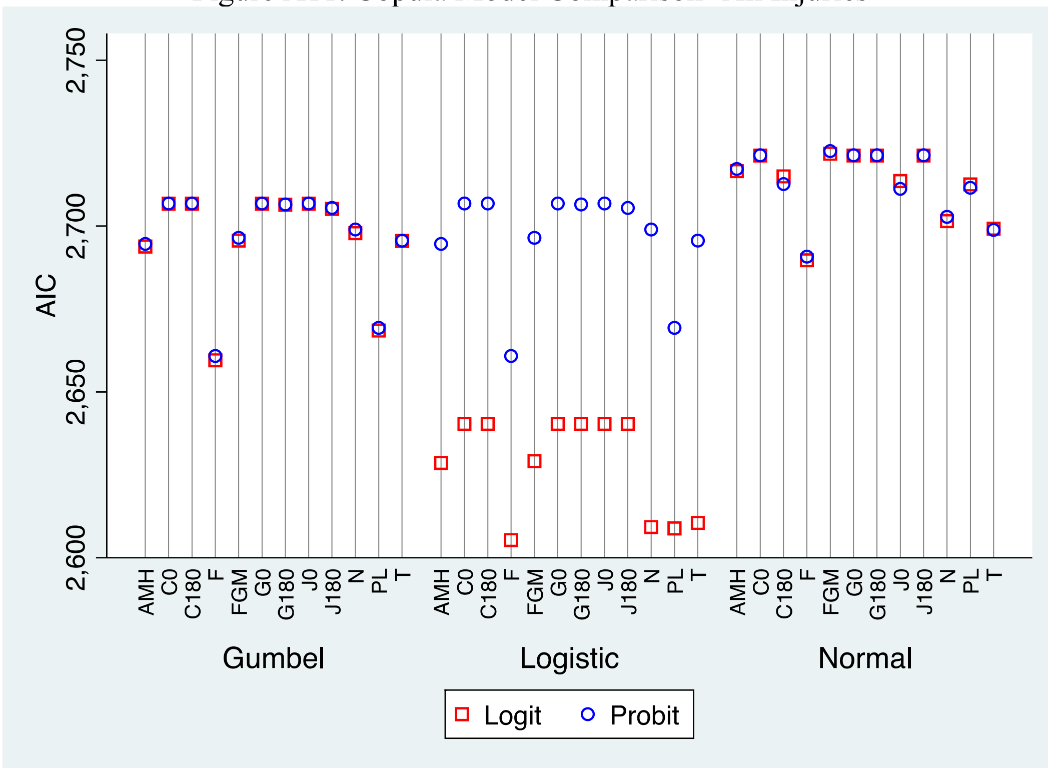


Figure A12. Copula Model Comparison- All Injuries

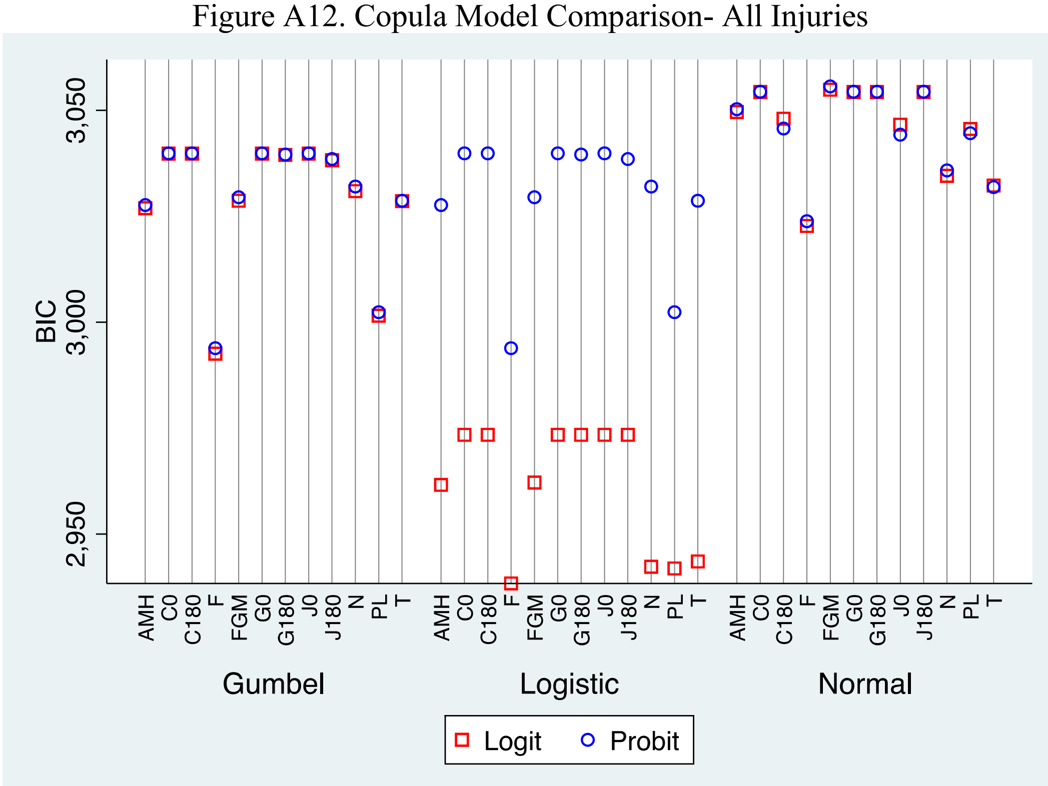


Figure A13. Copula Model Comparison- Concussions and Non-Concussion Injuries

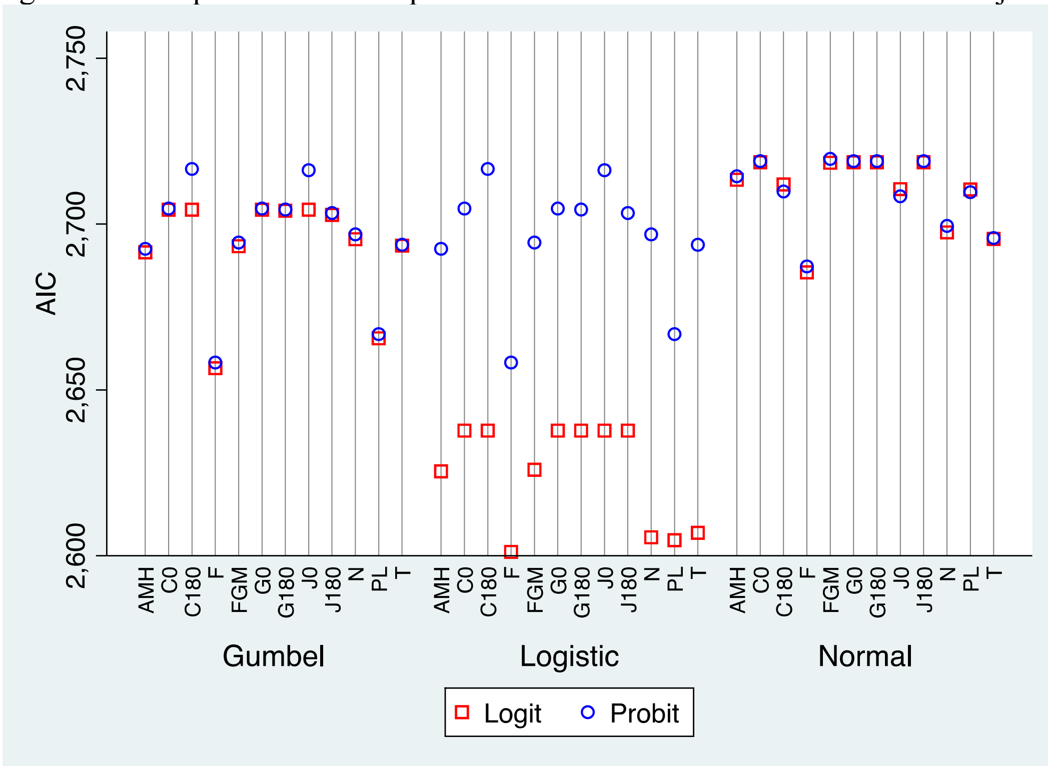


Figure A14. Copula Model Comparison- Concussions and Non-Concussion Injuries