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Race and NFL Playing Time

Quinn A. W. Keefer[1]

[1] California State University San Marcos

Quinn A. W. Keefer, PhD, is an assistant professor in the Department of Economics. His research focuses on the behavioral economics and labor economics of professional sports, primarily the National Football League.

Abstract

Using binary variable and decomposition techniques on two distinct datasets, we analyze the effect of race on playing time for linebackers in the National Football League (NFL). We examine both the number of games started in a season and the probability of starting each individual game within a season. The results show black linebackers start approximately one additional game, or 16% more games, in a season than non-black players. Also, the probability of starting a specific game is four to eight percentage points greater for black linebackers. Previous research suggests black linebackers are subject to wage discrimination. Therefore, if omitted variables are responsible for the effect of race on playing time, there is actually more wage discrimination than reported.

Keywords: discrimination, NFL, playing time, linebackers, wages

Introduction

Professional sports provide economists an ideal setting for studying labor markets (Kahn, 2000). One labor market phenomenon that has been extensively studied is discrimination (Gius & Johnson, 2000; Jones & Walsh, 1988; Kahn, 1991, 1992, 2009; Madden, 2004; Mogull, 1973, 1981; Palmer & King, 2006; Scully, 1973, 1974). Rosen and Sanderson's (2001) review of the literature suggests discrimination is a thing of the past; it was evident in the 1960s and 1970s, but not in recent decades. This notion is supported by Kahn's (2009) review of the discrimination literature in basketball. However, several recent studies of the National Football League (NFL) have contested this view. Berri and Simmons (2009) found possible wage discrimination in the NFL market for quarterbacks. They found that black quarterbacks' skill set more heavily relies on rushing, which is not a monetarily rewarded measure of performance. Also, Keefer (2013) found wage discrimination in the market for linebackers, with non-black players earning a premium of 10%.[1]

Discrimination can also manifest itself in forms other than wage discrimination. For example, Conlin and Emerson (2006) analyzed discrimination in the promotion and retention of NFL players. They examined the influence of race on player survival and the number of games started, within a player's first three seasons. They found white players have a 0.13 percentage point lower probability of having an active contract and start 1.56 fewer games. However, they use a sample of all NFL positions. Since productivity varies by position, it is empirically difficult to control for individual ability and productivity when examining multiple positions (Leeds & Kowalewski, 2001).

Several responses to these articles have concluded there to be little to no evidence of discrimination (Burnett & Van Scyoc, 2013, 2015; Ducking, Groothuis, & Hill, 2014). However, these studies have focused on wage discrimination for either rookies (Burnett & Van Scyoc, 2013, 2015) or in total career earnings (Ducking, Groothuis, & Hill, 2014). Analyzing wage discrimination for rookies in the NFL is especially problematic, since rookie compensation is primarily institutional and determined by the NFL draft, a confound mentioned by Burnett and van Scyoc (2013, 2015).[2]

We further examine the effects of race in the NFL linebacker market by analyzing playing time. We choose the linebacker market for four reasons. First, to more accurately control for performance and ability we limit ourselves to a single position. Second, linebackers have a wide array of performance measures, more so than other NFL positions.[3] Third, other NFL positions lack the racial diversity of linebackers. For example, Burnett and Van Scyoc's (2013) sample of rookie wide receivers only had 53 non-black players and the Ducking et al. (2014) sample consisted of only 31 white defensive observations and 34 white offensive observations. When analyzing discrimination, especially through the use of decomposition methods, having a large sample of both races is necessary. Fourth, since there is research suggesting wage discrimination exists in the linebacker market, we can test whether there are any similarities or differences between the effects of race on wages and playing time.

Empirical Method

We employ both binary variable and decomposition methods to analyze discrimination in the NFL linebacker market. We use two different dependent variables, the number of games started and the probability of starting a given game, to examine the effect of race on playing time.

Binary Variable

We begin by analyzing the number of games started in a given season.

$$G_{it} = F(R_i, I_{it}, P_{it-1}, T_{it-1})$$

where i indexes players, t indexes the year, G is the number of games started and is a function of race, $R \in \{0,1\}$ indicating a player is non-black, individual characteristics, I, individual performance, P, and team performance, T. We estimate the equation for the number of games started using several econometric techniques.

We first estimate the equation using ordinary least squares (OLS) with year and team fixed effects.

$$G_{it} = \beta_0 + \beta_1 R_i + I_{it}\beta_2 + P_{it-1}\beta_3 + T_{it-1}\beta_4 + \eta_t + \eta_T + \epsilon_{it}$$

where ϵ_{it} is the stochastic error term. Here, year fixed effects are captured by η_t and team fixed effects by η_T.

However, since G is a non-negative integer between zero and sixteen, we estimate the number of games started using count data techniques. Conlin and Emerson (2006) use ordered response estimations; however, these ignore the cardinality of the number of games started.[4] As is common in observational studies, our data exhibits overdispersion; therefore, we choose the popular negative binomial (NB) distribution as opposed to the Poisson distribution.[5]

$$\Pr(G = g|\mu, \alpha) = \frac{\Gamma(\alpha^{-1} + g)}{\Gamma(\alpha^{-1})\Gamma(g + 1)} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu}\right)^{\alpha^{-1}} \left(\frac{\mu}{\mu + \alpha^{-1}}\right)^{g}$$

where Γ is the gamma integral, α is the variance parameter of the gamma distribution, μ is the mean of the NB distribution and the NB variance is quadratic, $\mu+\alpha\mu^2$. We specify the conditional mean as the exponential function.

$$\mu_{it} = E(G_{it}|X_{it}) = \exp\,(X_{it}\beta + \epsilon_{it})$$

where X denotes all independent variables.

Our data exhibits another common characteristic of count data, excess zeros. To account for the excess zeros we use a zero-inflated negative binomial model (ZINB).[6]

$$E(G_{it}|X_{it}) = [1 - \Pr(D_{it} = 1|X_{it})] * E(G_{it}|X_{it}, D_{it} = 0)$$

where D is a binary variable for excess zeros, such that $D = 1$ for excess zeros. The model has two distinct parts, the probability of being an excess zero and the expected number of games started given the individual is not an excess zero, which are estimated simultaneously via maximum likelihood. We specify the probability of being an excess zero as the logistic function and the expected number of games started conditional on not being an excess zero as the exponential function.[7]

$$E(G_{it}|X_{it}) = \left[1 - \frac{\exp\,(X_{it}\delta + \rho_{it})}{1 + \exp\,(X_{it}\delta + \rho_{it})}\right] * \exp\,(X_{it}\beta + \epsilon_{it})$$

$$E(G_{it}|X_{it}) = \left[\frac{1}{1 + \exp\,(X_{it}\delta + \rho_{it})}\right] * \exp\,(X_{it}\beta + \epsilon_{it})$$

Therefore, race has two potential effects on the number of game started. It may impact the probability of being an excess zero and it may affect the number of games started given the individual is not an excess zero.

Our second dependent variable is whether or not a player starts a specific game within a season, $S \in \{0,1\}$. Where $S_{it} = 1$ denotes player i started the game in week t.

$$S_{it} = H(R_i, I_{it}, P_{it-1}, T_{it-1})$$

Again, the decision of whether or not a player starts is dependent on their race, individual characteristics, previous game individual performance and previous game team performance. Our first estimation of the probability of starting is a linear probability model (LPM).

$$S_{it} = Z_{it}\tau + \omega_{it}$$

where Z represents all independent variables and ω is the stochastic error term. We also estimate the relationship between race and the probability of starting using logistic regression.[8]

$$\Pr(S_{it} = 1) = \frac{\exp(Z_{it}\tau + \omega_{it})}{1 + \exp(Z_{it}\tau + \omega_{it})}$$

Decomposition

Since the returns to observable characteristics, or productivity measures, may differ between groups, we decompose the difference in the average outcomes (Blinder, 1973; Oaxaca, 1973). We use a threefold decomposition, which decomposes the difference between group outcomes into explained, unexplained, and interaction terms

(Daymont & Andrisani, 1984; Jann, 2008; Jones & Kelly, 1984). Let $Y \in \{G,S\}$ be the independent variable and X be a vector of all independent variables. Following Bauer and Sinning (2008), the general decomposition is

$$\overline{Y^N} = E_\sigma(Y_{it}^N | X_{it}^N)$$

$$\overline{Y^B} = E_\pi(Y_{it}^B | X_{it}^B)$$

$$\overline{Y^N} - \overline{Y^B} = \underbrace{\{E_\sigma(Y_{it}^N | X_{it}^N) - E_\sigma(Y_{it}^B | X_{it}^B)\}}_{A} + \underbrace{\{E_\sigma(Y_{it}^N | X_{it}^N) - E_\pi(Y_{it}^N | X_{it}^N)\}}_{B}$$

$$+ \underbrace{\{E_\pi(Y_{it}^N | X_{it}^N) - E_\sigma(Y_{it}^N | X_{it}^N)\} + \{E_\sigma(Y_{it}^B | X_{it}^B) - E_\pi(Y_{it}^B | X_{it}^B)\}}_{C}$$

where N denotes non-black players, B denotes black players and σ and π are the coefficients for the estimations on non-black and black players, respectively. Part A of the decomposition is the effect of the differences in characteristics, the explained portion. Part B is the effect of the differences in the returns to characteristics, the unexplained portion measuring discrimination. Finally, part C accounts for the fact that the characteristics and coefficients effects occur simultaneously.

For a simple linear model the decomposition simplifies to

$$\overline{Y^N} = \overline{X^N}\hat{\sigma}$$

$$\overline{Y^B} = \overline{X^B}\hat{\pi}$$

$$\overline{Y^N} - \overline{Y^B} = \underbrace{(\overline{X^N} - \overline{X^B})\hat{\sigma}}_{A} + \underbrace{\overline{X^N}(\hat{\sigma} - \hat{\pi})}_{B} + \underbrace{(\overline{X^N} - \overline{X^B})(\hat{\pi} - \hat{\sigma})}_{C}$$

where $\hat{\sigma}$ and $\hat{\pi}$ are the coefficients estimated via OLS. In the Results section we report OLS and ZINB decompositions for the number of games started in a season and logistic decompositions (Yun, 2004) for the probability of starting a game within a season.

Data and Specifications

Following our econometric method, we analyze discrimination in playing time using two different measures. As a result, we employ two distinct datasets. Both of our measures rely on data about starters, games started in a season and probability of starting a given game. However, we would ideally like to measure playing time directly, via the number or percentage of plays. Unfortunately, consistent data on the number of plays for each player is only available from Pro Football Focus beginning in 2007, which leaves only three years of data. Therefore, we rely on the assumption that starters play more; starting is an indirect measure of playing time. Also, Keefer (2015b) reports the correlation between games started and the percentage of a team's plays a player participates in is 0.88, providing support to our assumption that games started is a measure of playing time.

The Number of Games Started

To analyze the number of games started we use a panel dataset of all linebackers to play in the NFL from 2001, when the NFL began officially recording tackle data, to 2009. Since we model the number of games started as a function of previous performance, first-year players are omitted from our sample.[9] As previously mentioned, having a sufficient number of observations from each race is necessary, especially for decomposition techniques. In our panel from 2001 to 2009 we have 1,575 player-years. Of the total observations, we have 416 non-black and 1,159 black player-years. Furthermore, the data contain 117 non-black and 349 black players, a significantly larger sample of non-black players than previous studies.

The specification we use for the number of games started has three main components. First, we use a variety of variables for individual characteristics. Our variable of interest is *non-black*, a binary variable for non-black players, collected from Keefer's (2013) data. Other individual characteristics include whether or not the player is an inside linebacker, experience, and experience squared. We also control for whether or not a player was selected in the draft, selection number in the draft, and binary vari-

Table 1. Number of Games Started—Summary Statistics

VARIABLES	Mean	SD
Games Started	7.378	(6.642)
Non-Black	0.264	(0.441)
LN(Cap Value)	13.76	(0.968)
Selection #	72.37	(69.05)
Undrafted	0.235	(0.424)
First Round	0.145	(0.353)
Second Round	0.130	(0.336)
Third Round	0.152	(0.359)
ILB	0.364	(0.481)
Experience	4.175	(2.856)
Experience-squared	25.82	(34.77)
Start % (t-1)	0.500	(0.443)
Solo Tackles (t-1)	37.94	(29.72)
Sacks (t-1)	1.502	(2.420)
Interceptions (t-1)	0.441	(0.876)
Passes Defended (t-1)	1.909	(2.397)
Forced Fumbles (t-1)	0.737	(1.072)
Fumble Recoveries (t-1)	0.521	(0.779)
Pro Bowl (t-1)	0.0622	(0.242)
Points/G (t-1)	20.97	(3.598)
Yards/G (t-1)	320.9	(30.48)
Wins (t-1)	8.152	(3.085)
Playoffs (t-1)	0.387	(0.487)
Observations	1,575	

Note: t indexes years.

ables for selections in the first three rounds, as previous research has shown amateur drafts may affect labor market outcomes beyond a player's rookie season (Camerer & Weber, 1999; Keefer, 2015a; Staw & Hoang, 1995). We also include the natural logarithm of a player's salary cap value, as Keefer (2015a, 2015b) showed the number of games started depends on pay for rookies and defensive players.

The second component controls for individual productivity. We use lagged statistical performance measures. The variables include the percentage of games played that were started, solo tackles, sacks, interceptions, passes defended, forced fumbles, fumble recoveries, and whether or not the player was named to the Pro Bowl.[10]

The final component controls for team productivity and characteristics. It is important to control for team variables since they affect individual productivity. Again, we use lagged performance measures. The variables are the number of points allowed per game, the number of yards allowed per game, the number of wins, and whether or not the team made the playoffs. To control for any time invariant team characteristics we also include team fixed effects. Similarly, we control for any year-specific factors affecting all players by including year fixed effects. Table 1 presents summary statistics for the data used to analyze the number of games started.

The Probability of Starting

To analyze the probability of starting we use another panel dataset. Our data covers every game played by every linebacker in the 2009 season; therefore, observations are player-games. Since our model relies, in part, on previous season productivity, all first-year players are eliminated from our sample. We are left with 49 non-black players, a similar number to previous studies.

Our specification for the probability of starting has three main components. The first component controls for individual characteristics. Similar to the model of the number of games started, our variable of interest is *non-black*. Also, we use the same variables to control for individual characteristics as in the model of the number of games started.

The component controlling for individual performance has two parts. The first part contains variables on previous season performance. Previous season performance is controlled for with the same vector of variables as the number of games started specification. The second part includes variables on previous game performance. These variables cover the same statistical categories as previous season performance. However, we also include a vector of binary variables indicating whether or not the player started the previous game and whether or not the team won the previous game. Therefore, there are four potential outcomes: the player started and the team won, the player did not start and the team won, the player started and the team lost, or the player did not start and the team lost.

To control for the effect of team production we use two direct measures. We include the number of points allowed in the previous game and the number of yards allowed in the previous game. To capture the effect of any time-invariant team characteristics we include team fixed effects. Table 2 presents summary statistics for our sample of 2,541 player-games.

For both datasets, individual and team performance measures and characteristics were collected from the NFL, ESPN, and Pro Football Reference online databases. Weekly data was specifically collected from the NFL game logs for individual players.

Table 2. Probability of Starting—Summary Statistics

VARIABLES	Mean	SD
Starter	0.514	(0.500)
Non-Black	0.245	(0.430)
LN(Cap Value)	14.05	(0.962)
Selection #	75.17	(74.14)
Undrafted	0.226	(0.418)
First Round	0.170	(0.375)
Second Round	0.1000	(0.300)
Third Round	0.149	(0.356)
ILB	0.353	(0.478)
Experience	4.320	(3.141)
Experience-squared	28.52	(41.54)
Prior Start %	0.511	(0.438)
Prior Solo Tackles	38.24	(29.82)
Prior Sacks	1.482	(2.950)
Prior Interceptions	0.333	(0.730)
Prior Passes Defended	2.039	(2.465)
Prior Forced Fumbles	0.809	(1.198)
Prior Fumble Recoveries	0.560	(0.846)
Prior Pro Bowl	0.0661	(0.249)
Winning Starter (t-1)	0.270	(0.444)
Winning Reserve (t-1)	0.242	(0.429)
Losing Starter (t-1)	0.246	(0.431)
Solo Tackles (t-1)	2.667	(2.696)
Sacks (t-1)	0.113	(0.366)
Interceptions (t-1)	0.0228	(0.157)
Passes Defended (t-1)	0.131	(0.385)
Forced Fumbles (t-1)	0.0551	(0.245)
Points Allowed (t-1)	21.22	(10.71)
Yards Allowed (t-1)	333.3	(89.55)
Observations	2,541	

Note: t indexes years.

The determination of a whether or not a player was an inside linebacker was made by consulting team depth charts for those players who were not distinguished by the NFL. Finally, salary cap value was collected from *USA Today*.

Results

The Number of Games Started

Binary variable results for the number of games started are presented in Table 3. The effect of being a non-black player is significantly negative in all estimations. Also, from

Table 3. Number of Games Started Binary Variable Results

	Dependent Variable = Games Started				
		Ordered		ZINB	
VARIABLES	OLS	Logistic	NB		Semi-Elast.
Non-Black	-0.773***	-0.322***	-0.164**	-0.804**	-0.163**
	(0.292)	(0.119)	(0.0693)	(0.335)	(0.0649)
LN(Cap Value)	2.053***	0.816***	0.428***	2.291***	0.485***
	(0.219)	(0.0924)	(0.0498)	(0.250)	(0.0553)
ILB	0.129	0.141	0.105*	0.402	0.0732
	(0.290)	(0.114)	(0.0603)	(0.309)	(0.0601)
Experience	-0.669***	-0.281***	-0.136***	-0.793***	-0.159***
	(0.121)	(0.0558)	(0.0338)	(0.144)	(0.0303)
Experience-squared	0.0293***	0.0132***	0.00628***	0.0391***	0.00856***
	(0.00880)	(0.00397)	(0.00232)	(0.0103)	(0.00241)
Selection #	-0.00705	-0.00450**	-0.00254**	-0.00641	-0.00220**
	(0.00497)	(0.00194)	(0.00113)	(0.00570)	(0.00103)
Undrafted	-1.947**	-1.040***	-0.741***	-2.341**	-0.606***
	(0.879)	(0.331)	(0.191)	(0.992)	(0.180)
First Round	-1.398*	-0.759**	-0.503***	-1.288	-0.352*
	(0.820)	(0.315)	(0.165)	(0.911)	(0.187)
Second Round	-0.969	-0.533*	-0.298**	-0.922	-0.356**
	(0.731)	(0.274)	(0.145)	(0.765)	(0.148)
Third Round	-0.417	-0.291	-0.168	-0.379	-0.189*
	(0.559)	(0.207)	(0.111)	(0.579)	(0.113)
Start % (t-1)	4.973***	1.542***	0.929***	4.879***	0.834***
	(0.628)	(0.238)	(0.111)	(0.644)	(0.134)
Solo Tackles (t-1)	0.0339***	0.0139***	0.00326**	0.0243***	0.00466**
	(0.00907)	(0.00364)	(0.00143)	(0.00898)	(0.00211)
Sacks (t-1)	0.113*	0.0434*	0.0152	0.116	0.0245
	(0.0671)	(0.0261)	(0.0108)	(0.0793)	(0.0212)
Interceptions (t-1)	0.345**	0.110	0.0112	0.317	0.0783
	(0.165)	(0.0698)	(0.0234)	(0.204)	(0.0559)
Passes Defended (t-1)	0.00675	0.0158	-0.00522	0.0774	0.0298
	(0.0795)	(0.0312)	(0.0115)	(0.0870)	(0.0233)
Forced Fumbles (t-1)	0.00925	0.000301	0.0196	0.0827	0.0295
	(0.149)	(0.0590)	(0.0241)	(0.152)	(0.0370)
Fumble Recoveries (t-1)	0.167	0.0927	0.0408	0.183	0.0509
	(0.173)	(0.0659)	(0.0298)	(0.167)	(0.0376)
Pro Bowl (t-1)	-0.120	0.0148	-0.146*	-0.553	-0.183
	(0.513)	(0.235)	(0.0849)	(0.552)	(0.139)
Points/G (t-1)	0.0120	0.00748	-0.00648	-0.0130	-0.00664
	(0.0659)	(0.0266)	(0.0142)	(0.0706)	(0.0137)
Yards/G (t-1)	-0.0118**	-0.00533**	-0.00126	-0.00903	-0.00236**
	(0.00600)	(0.00230)	(0.00124)	(0.00630)	(0.00119)
Wins (t-1)	0.0520	0.00273	2.11e-06	0.0320	0.00306
	(0.0793)	(0.0323)	(0.0168)	(0.0841)	(0.0163)

Table 3. Number of Games Started Binary Variable Results, continued

	Dependent Variable = Games Started				
		Ordered		ZINB	
VARIABLES	**OLS**	**Logistic**	**NB**		**Semi-Elast.**
Playoffs (t-1)	-0.224	-0.0113	-0.0796	-0.336	-0.0846
	(0.400)	(0.160)	(0.0842)	(0.417)	(0.0822)
Fixed Effects	Year	Year	Year	Year	Year
	Team	Team	Team	Team	Team
Constant	-18.18***		-3.306***		
	(3.663)		(0.813)		
LN(α)			-0.0373	-1.627***	
			(0.102)	(0.0620)	
Observations	1,575	1,575	1,575	1,575	1,575
R-squared	0.500				

Note: Robust standard errors are in parentheses. ZINB standard errors are calculated via the delta method. t indexes years. Average marginal effects and average semi-elasticities reported for ZINB, calculated using discrete differences. *Significant at 10%. **Significant at 5%. ***Significant at 1%.

our results it is clear that experience and productivity are significant determinants of playing time. Experience, experience-squared, previous season starting percentage, and previous season solo tackles are highly significant in all estimations. The OLS coefficient shows that non-black players start, on average, 0.77 less games than black players. Furthermore, we conduct two robustness checks of our baseline specification. First, it is important to control for team quality, which we accomplish using previous season team statistics. If we instead include current season team performance measures the race coefficient is -0.814 and significant at the 1% level. Second, we control for draft status, as it has been shown to have an impact on labor market outcomes beyond the rookie season. However, if we eliminate draft information the race coefficient is -0.74, which is statistically significant. It is clear the effect of race on games started is robustly significant. Table 3 also includes ordered response estimation results, from an ordered logistic regression, for comparison. Similar to OLS, ordered logistic regression shows a significantly positive effect of being black on the number of games started.

Due to the specification of the conditional mean for NB regression, the coefficient of -0.16 is a semi-elasticity; non-black players start 16% fewer games than black linebackers. The interpretation of the results for ZINB estimation, perhaps the most appropriate model, is slightly more complicated since there are two effects of race. The logistic coefficient of 0.32 indicates that being non-black increases the likelihood of being an excess zero. Also, given they are not excess zeros, non-black players start 7.1% fewer games than black players. The total effect on the number of games started considers both parts of the ZINB model.

$$\frac{\partial E(G_{it}|X_{it})}{\partial R} = \frac{\partial \Sigma}{\partial R}(1 - P^D) - \frac{\partial P^D}{\partial R}\Sigma$$

$$\frac{\partial \ln E(G_{it}|X_{it})}{\partial R} = \beta_R - \frac{1}{1 - P^D}\frac{\partial P^D}{\partial R}$$

where $P^D \equiv \Pr(D = 1|X)$, $\Sigma \equiv E(G|X, D = 0)$ and β_R is the non-black coefficient in the NB portion of the ZINB model. However, since our variable of interest, *R*, is binary, the unconditional effects can be calculated better using discrete differences.

$$\frac{\Delta E(G_{it}|X_{it})}{\Delta R} = E(G_{it}|X_{it}, R = 1) - E(G_{it}|X_{it}, R = 0)$$

$$\frac{\%\Delta E(G_{it}|X_{it})}{\Delta R} = \frac{E(G_{it}|X_{it}, R = 1) - E(G_{it}|X_{it}, R = 0)}{E(G_{it}|X_{it}, R = 0)}$$

The average ZINB marginal effect of race on the number of games started is -0.82 with a delta-method standard error of 0.35. The average ZINB semi-elasticity is -0.16 with a delta method standard error of 0.063. Therefore, non-black players start approximately one less game, or 16% less games, than black players in a given season.

Since decompositions depend on which group's coefficients we use to evaluate the coefficients effect, we report both cases. Table 4 displays the decomposition results for the number of games started. For both estimation techniques discrimination is significant. The measure of discrimination ranges from 0.69 to 1.15 for threefold OLS and 0.73 to 0.76 for ZINB decompositions in favor of black players. Furthermore, we eval-

Table 4. Number of Games Started Decompositions

	OLS					ZINB	
	Threefold		Reimers	Cotton	Neumark		
	Non-Black	Black				Non-Black	Black
Difference	-1.464***	-1.464***	-1.464***	-1.464***	-1.464***	-1.452***	-1.452***
	(0.383)	(0.383)	(0.383)	(0.383)	(0.383)	(0.355)	(0.355)
Characteristics	-0.773***	-0.316	-0.545*	-0.652**	-0.805***	-0.724*	-0.689**
	(0.302)	(0.350)	(0.290)	(0.286)	(0.282)	(0.399)	(0.299)
Coefficients	-1.148***	-0.691**	-0.919***	-0.812***	0.659***	-0.763**	-0.728*
	(0.325)	(0.327)	(0.290)	(0.299)	(0.247)	(0.311)	(0.398)
Interaction	0.457	-0.457				0.0352	-0.0352
	(0.300)	(0.300)				(0.357)	(0.357)
Non-Black Obs.				416			
Black Obs.				1,159			

Note: Standard errors are in parentheses. Robust standard errors are reported for OLS decompositions. ZINB decomposition standard errors are computed from 637 bootstrap replications; 650 replications were estimated, but 13 replications failed due to convergence issues. ZINB results omit team fixed effects, due to convergence issues for stratified estimations. Decomposition titles indicate the group whose characteristics were used in evaluating the coefficients effects. *Significant at 10%. **Significant at 5%. ***Significant at 1%.

uate the robustness of our decomposition results by estimating the Reimers (1983), Cotton (1988), and Neumark (1988) twofold decompositions, as the traditional Oaxaca (1973) and Blinder (1973) decomposition returns the same estimate of discrimination as the threefold method. Reimers (1983) assumes the nondiscriminatory coefficient vector is the average of the coefficients for each group. Cotton (1988) weighs each group's coefficients based on the proportion of observations from each group in the sample. Finally, Neumark (1988) uses a pooled model's coefficients as the reference. It is clear the unexplained portion is robust to the decomposition method used.

Results for the number of games started suggest discrimination in favor of black linebackers is significant. The estimations and decompositions show that black linebackers start roughly one additional game compared to non-black players. Taken differently, there exists discrimination in favor of black linebackers of 16%; black linebackers start 16% more games than non-black players, other things equal.

The Probability of Starting

The binary variable results for the probability of starting a game are presented in Table 5. For our baseline specification, both LPM and logistic estimates for the non-black binary variable are significantly negative. The LPM model suggests that being non-black reduces the probability of starting by four percentage points. The logistic coefficient of -0.325 implies an odds ratio of 0.723. Therefore, for black linebackers the odds of being a starter, for a given game, are 1.4 times larger than the odds of starting for a non-black player. The marginal effect, at the means of all independent variables, is -0.0807; the probability of starting for black players is eight percentage points greater than for non-black players. It is also clear that previous game performance is very important. Each additional solo tackle in the previous game increases the probability of starting by 2.1 percentage points, from our LPM results. Thus, the effect of being non-black is equivalent to two fewer tackles in the previous game. The effect may seem small at first glance; however, the average number of tackles in a game is 2.7 and 4.25 conditional on starting the game.

The game-to-game decision about starting is very complex. Therefore, we analyze the robustness of our results to the inclusion of several other variables. First, the effect of a player's productivity in the previous season may depend on when the game in question takes place within the season. For example, if the game is early in the season it may be the case that previous season productivity is more influential than if the game is late in the season. To capture this potential effect we include the interaction of the week the game takes place with previous season production measures. Results from this estimation are presented in column 2 of Table 5. Second, the effect of previous game productivity may depend on whether or not the player started the game. Thus, we include whether or not the player started the previous game interacted with his productivity statistics from the previous game. These results are presented in column 3 of Table 5. Finally, we include both interactions. Column 4 of Table 5 presents logistic results including both interaction effects. The coefficient of -0.343, implying an odds ratio of 0.710, is highly significant. None of our robustness check estimates are significantly different from our baseline coefficient of -0.325.

Table 5. Probability of Starting Binary Variable Results

	Dependent Variable = Starter				
		Logistic			
VARIABLES	**LPM**	(1)	(2)	(3)	(4)
Non-Black	-0.0400**	-0.325**	-0.329**	-0.336**	-0.343**
	(0.0181)	(0.162)	(0.164)	(0.165)	(0.167)
LN(Cap Value)	0.0313**	0.355**	0.368**	0.362**	0.373**
	(0.0138)	(0.144)	(0.144)	(0.148)	(0.148)
ILB	0.0706***	0.659***	0.666***	0.675***	0.680***
	(0.0190)	(0.183)	(0.184)	(0.184)	(0.185)
Experience	0.00737	0.0180	0.0148	0.000549	-0.00206
	(0.00738)	(0.0702)	(0.0704)	(0.0720)	(0.0721)
Experience-squared	-0.000815*	-0.00596	-0.00585	-0.00501	-0.00489
	(0.000466)	(0.00477)	(0.00478)	(0.00489)	(0.00490)
Selection #	0.000680**	0.00584**	0.00579**	0.00592**	0.00589**
	(0.000299)	(0.00229)	(0.00229)	(0.00236)	(0.00236)
Undrafted	0.110**	0.858**	0.841**	0.911**	0.899**
	(0.0517)	(0.421)	(0.421)	(0.434)	(0.434)
First Round	0.109**	0.942**	0.952**	0.932**	0.946**
	(0.0485)	(0.405)	(0.406)	(0.412)	(0.413)
Second Round	0.0917**	0.988***	0.991***	1.039***	1.052***
	(0.0419)	(0.372)	(0.372)	(0.379)	(0.379)
Third Round	0.0786**	0.516*	0.511*	0.514*	0.510*
	(0.0354)	(0.285)	(0.285)	(0.288)	(0.288)
Prior Start %	0.253***	1.895***	2.726***	1.938***	2.808***
	(0.0409)	(0.347)	(0.576)	(0.355)	(0.592)
Prior Solo Tackles	-0.00171***	-0.0125**	-0.0303***	-0.0123**	-0.0295***
	(0.000616)	(0.00594)	(0.00988)	(0.00599)	(0.0100)
Prior Sacks	0.0130***	0.103**	0.0536	0.104**	0.0581
	(0.00408)	(0.0460)	(0.0840)	(0.0465)	(0.0842)
Prior Interceptions	-0.00496	0.0974	0.00327	0.0954	-0.0460
	(0.0112)	(0.136)	(0.237)	(0.137)	(0.236)
Prior Passes Defended	0.0149**	0.0945*	0.134	0.0946*	0.122
	(0.00611)	(0.0552)	(0.108)	(0.0549)	(0.108)
Prior Forced Fumbles	-0.0196**	-0.197**	0.0156	-0.199**	0.000772
	(0.00866)	(0.0916)	(0.186)	(0.0935)	(0.191)
Prior Fumble Recoveries	0.0203**	0.258**	0.300	0.253**	0.293
	(0.00914)	(0.101)	(0.221)	(0.103)	(0.222)
Prior Pro Bowl	0.00275	0.567	0.447	0.566	0.349
	(0.0363)	(0.471)	(0.921)	(0.453)	(0.863)
Winning Starter (t-1)	0.463***	2.160***	2.163***	2.626***	2.640***
	(0.0317)	(0.236)	(0.237)	(0.599)	(0.599)
Winning Reserve (t-1)	0.00533	0.0887	0.1000	0.0974	0.107
	(0.0218)	(0.218)	(0.220)	(0.246)	(0.248)
Losing Starter (t-1)	0.450***	2.008***	2.014***	2.459***	2.474***
	(0.0305)	(0.207)	(0.209)	(0.635)	(0.636)
Solo Tackles (t-1)	0.0205***	0.214***	0.211***	0.294***	0.291***
	(0.00374)	(0.0387)	(0.0388)	(0.0569)	(0.0571)

Table 5. Probability of Starting Binary Variable Results, continued

	Dependent Variable = Starter				
		Logistic			
VARIABLES	**LPM**	**(1)**	**(2)**	**(3)**	**(4)**
Sacks (t-1)	0.00858	0.0916	0.0966	0.617	0.614
	(0.0193)	(0.219)	(0.219)	(0.375)	(0.373)
Interceptions (t-1)	0.000192	-0.0906	-0.0549	-0.0289	-0.0265
	(0.0481)	(0.599)	(0.613)	(0.973)	(1.003)
Passes Defended (t-1)	0.0306	0.349	0.338	0.848	0.858
	(0.0209)	(0.287)	(0.293)	(0.550)	(0.549)
Forced Fumbles (t-1)	0.0136	0.0466	0.0556	-0.454	-0.422
	(0.0252)	(0.278)	(0.281)	(0.465)	(0.470)
Points/G (t-1)	0.00136	0.0160	0.0161	0.0172	0.0172
	(0.000988)	(0.0101)	(0.0102)	(0.0138)	(0.0139)
Yards/G (t-1)	1.62e-05	-4.81e-05	-0.000119	2.80e-05	-2.24e-05
	(0.000107)	(0.00109)	(0.00109)	(0.00144)	(0.00145)
Team Fixed Effect	Yes	Yes	Yes	Yes	Yes
Week*Prior Productivity	-	-	Yes	-	Yes
Starter (t-1)*Prod. (t-1)	-	-	-	Yes	Yes
Constant	-0.470**	-8.377***	-8.550***	-8.699***	-8.864***
	(0.197)	(2.047)	(2.051)	(2.103)	(2.107)
Observations	2,541	2,541	2,541	2,541	2,541
R-squared	0.592				

Note: Robust standard errors are in parentheses. t indexes games. *Significant at 10%. **Significant at 5%. ***Significant at 1%.

Logistic decomposition results for the probability of starting are reported in Table 6. The results show discrimination is significant and ranges from four to seven percentage points in favor of black players. Furthermore, the results are robust to the decomposition method used. These results are consistent with our binary variable estimations. For the probability of starting a given game, there is discrimination in favor of black linebackers. The probability of starting for black linebackers is four to eight percentage points greater than the probability of starting for non-black players.

Connection Between Discrimination in Pay and Discrimination in Play

One potential issue with estimates of discrimination derived from methods similar to those conducted in our analysis is the omission of unobserved characteristics or skills. If one group has significantly more unobserved skills or characteristics and these skills and characteristics are either positively or negatively valued by the market, then estimates are biased. This is especially troubling when the direction of bias is the same direction as discrimination.

If our results are driven by omitted variables, it suggests black players have more (less) of these factors that are positively (negatively) valued; since our variable of interest is *non-black* the omitted variable bias is negative. However, studies such as Berri and Simmons (2009) and Keefer (2013) suggest wage discrimination in the favor of non-black players. Therefore, if our results are driven by omitted variables there is

Table 6. Probability of Starting Logistic Decompositions

	Threefold		Reimers	Cotton	Neumark
	Non-Black	Black			
Difference	-0.182***	-0.182***	-0.182***	-0.182***	-0.182***
	(0.0186)	(0.0186)	(0.0186)	(0.0186)	(0.0186)
Characteristics	-0.144***	-0.110***	-0.139***	-0.146***	-0.152***
	(0.0141)	(0.0261)	(0.0155)	(0.0133)	(0.0120)
Coefficients	-0.0719***	-0.0378**	-0.0425**	-0.0356**	-0.0287**
	(0.0278)	(0.0177)	(0.0182)	(0.0165)	(0.0143)
Interaction	0.0341	-0.0341			
	(0.0250)	(0.0250)			
Non-Black Obs.		623			
Black Obs.		1,918			

Note: Robust standard errors are in parentheses. Team fixed effects are not included, due to convergence issues for stratified estimations. Decomposition titles indicate the group whose characteristics were used in evaluating the coefficients effects. Full model refers to model containing the interaction of the week and previous year production and the interaction of previous game starter with previous game production. *Significant at 10%. **Significant at 5%. ***Significant at 1%.

even more wage discrimination than reported, especially by Keefer (2013), who analyzes the same position. Also, it is unlikely that evidence of wage discrimination is being generated by omitted variables, as previous studies have suggested (Burnett & van Scyoc, 2013, 2015). If it were, it would be the case that non-black players have more (less) of these factors that are positively (negatively) valued by the market, meaning the omitted variable bias is positive. However, this would mean there is actually more discrimination in playing time than we report. This would imply teams pay players based on productivity, but allocate playing time non-optimally, as race is an even larger determinant of playing time. However, this is unlikely, especially if we make the simple assumption that teams attempt to maximize wins—they would attempt to optimally allocate playing time.[11]

External Validity

One way to check the external validity of our results in the linebacker market is to determine the relationship for other positions. As previously mentioned, linebackers are a relatively diverse group compared to other positions in the NFL. However, defensive linemen and tight ends are similarly diverse. Therefore, we present binary variable results for the number of games started from these positions as a check of external validity.[12] Tables 7 and 8 present defensive lineman and tight end results, respectively. Our sample of defensive linemen contains 124 non-black and 417 black players. The results are similar to our linebacker results. ZINB estimation yields an average marginal effect of -0.837, meaning a non-black defensive lineman starts 12.2% fewer games. Our sample of tight ends includes 127 non-black players and 99 black players. The

Table 7. Defensive Linemen Results

Dependent Variable = Games Started				
			ZINB	
VARIABLES	OLS	NB		Semi-Elast.
Non-Black	-0.562*	-0.165***	-0.837**	-0.122**
	(0.293)	(0.0627)	(0.329)	(0.0565)
LN(Cap Value)	2.105***	0.448***	2.523***	0.476***
	(0.193)	(0.0395)	(0.223)	(0.0400)
DT	0.815***	0.165***	0.893***	0.152***
	(0.258)	(0.0516)	(0.284)	(0.0477)
Experience	-0.336**	-0.0576**	-0.414**	-0.0663**
	(0.144)	(0.0290)	(0.162)	(0.0266)
Experience-squared	0.00798	0.00215	0.0159	0.00264
	(0.0110)	(0.00208)	(0.0119)	(0.00204)
Selection #	-0.00428	-0.00127	-0.00519	-0.0008223
	(0.00456)	(0.000971)	(0.00563)	(0.000872)
Undrafted	-0.701	-0.278	-1.263	-0.163
	(0.844)	(0.176)	(1.019)	(0.159)
First Round	0.131	-0.188	-0.695	-0.139
	(0.775)	(0.152)	(0.898)	(0.145)
Second Round	0.0490	-0.0510	-0.166	-0.0316
	(0.692)	(0.132)	(0.768)	(0.125)
Third Round	0.630	0.111	0.675	0.118
	(0.640)	(0.125)	(0.710)	(0.116)
Start % (t-1)	4.152***	0.541***	3.829***	0.601***
	(0.520)	(0.0858)	(0.529)	(0.0908)
Solo Tackles (t-1)	0.0675***	0.0148***	0.0731***	0.0126***
	(0.0150)	(0.00244)	(0.0151)	(0.00292)
Sacks (t-1)	0.0942	0.000514	0.0767	0.0174
	(0.0628)	(0.00955)	(0.0653)	(0.0134)
Forced Fumbles (t-1)	-0.0602	-0.00132	0.000546	0.00866
	(0.139)	(0.0209)	(0.148)	(0.0314)
Pro Bowl (t-1)	-0.456	-0.276***	17.31***	4.604***
	(0.469)	(0.0603)	(1.151)	(0.198)
Points/G (t-1)	-0.0198	-0.00247	-0.00901	-0.00284
	(0.0603)	(0.0112)	(0.0630)	(0.0108)
Rushing Yards/G (t-1)	-0.0160*	-0.00199	-0.0119	-0.00245
	(0.00907)	(0.00184)	(0.00998)	(0.00167)
Wins (t-1)	0.0571	0.00857	0.0560	0.0116
	(0.0771)	(0.0147)	(0.0809)	(0.0140)
Playoffs (t-1)	-0.240	-0.0292	-0.213	-0.0655
	(0.406)	(0.0766)	(0.427)	(0.0734)
Fixed Effects	Year	Year	Year	Year
	Team	Team	Team	Team
Constant	-22.89***	-4.522***		
	(3.154)	(0.644)		
LN(α)		-0.0319	-1.445***	
		(0.0866)	(0.0548)	
Observations	1,833	1,833	1,833	1,833
R-squared	0.429			

Note: Robust standard errors are in parentheses. ZINB standard errors are calculated via the delta method. t indexes years. Average marginal effects and average semi-elasticities reported for ZINB, calculated using discrete differences. *Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 8. Tight End Results

	Dependent Variable = Games Started			
			ZINB	
VARIABLES	OLS	NB		Semi-Elast.
Non-Black	-0.481	-0.147**	-0.700*	-0.130*
	(0.356)	(0.0674)	(0.395)	(0.0692)
LN(Cap Value)	2.078***	0.458***	2.715***	0.474***
	(0.303)	(0.0697)	(0.390)	(0.0648)
Experience	-0.353**	-0.0394	-0.428*	-0.0715*
	(0.178)	(0.0431)	(0.247)	(0.0402)
Experience-squared	0.00797	-0.00167	0.00796	0.000806
	(0.0126)	(0.00333)	(0.0189)	(0.00301)
Selection #	-0.00506	-0.000597	-0.00356	-0.000829
	(0.00534)	(0.00113)	(0.00639)	(0.00110)
Undrafted	-1.446	-0.306	-1.683	-0.339
	(1.002)	(0.221)	(1.241)	(0.212)
First Round	0.266	-0.113	-0.0597	-0.0453
	(1.058)	(0.200)	(1.205)	(0.223)
Second Round	0.383	0.0441	0.0899	-0.0524
	(0.850)	(0.160)	(0.925)	(0.166)
Third Round	-0.267	0.0128	-0.189	-0.0812
	(0.795)	(0.148)	(0.868)	(0.156)
Start % (t-1)	4.285***	0.749***	4.687***	0.735***
	(0.692)	(0.119)	(0.711)	(0.133)
Receiving Yards (t-1)	0.00354**	0.000346	0.00256	0.000520
	(0.00144)	(0.000212)	(0.00157)	(0.000393)
TDs (t-1)	0.203	0.0209	0.222*	0.0557*
	(0.126)	(0.0180)	(0.131)	(0.0305)
Pro Bowl (t-1)	-0.0703	-0.105	15.45***	4.516***
	(0.904)	(0.128)	(1.873)	(0.375)
Points/G (t-1)	0.0506	0.00983	0.0643	0.00940
	(0.0814)	(0.0143)	(0.0839)	(0.0156)
Total Yards/G (t-1)	-0.00660	-0.000747	-0.00728	-0.00165
	(0.00714)	(0.00128)	(0.00731)	(0.00135)
Wins (t-1)	0.0665	0.00870	0.0350	0.0231
	(0.106)	(0.0193)	(0.111)	(0.0203)
Playoffs (t-1)	-0.172	-0.0477	-0.105	-0.0688
	(0.521)	(0.0913)	(0.520)	(0.0980)
Fixed Effects	Year	Year	Year	Year
	Team	Team	Team	Team
Constant	-20.46***	-4.483***	-0.624***	-20.46***
	(4.131)	(0.915)	(0.101)	(4.131)
		-0.624***		
		(0.101)		
Observations	803	803	803	803
R-squared	0.490			

Note: Robust standard errors are in parentheses. ZINB standard errors are calculated via the delta method. t indexes years. Average marginal effects and average semi-elasticities reported for ZINB, calculated using discrete differences. *Significant at 10%. **Significant at 5%. ***Significant at 1%.

results imply a marginal effect of -0.700, meaning non-black players start 13% fewer games. Given the results for these other positions, our results seem to be externally valid; non-black players start significantly fewer games, other factors equal.

Conclusion

We analyze playing time decisions in the market for NFL linebackers and find evidence of a significant racial effect. We examine both the number of games players start in a given season and the probability of starting a specific game within a season. Employing both binary variable and decomposition estimation techniques, we find non-black linebackers start roughly one less game than black linebackers. Another way to express the result is that non-black players start 16% fewer games than black players. By analyzing game logs, we also find the probability of starting a given game for non-black linebackers is four to eight percentage points less than for black linebackers.

The effect of race on playing time we find is opposite the direction of wage discrimination found in previous research (Berri & Simmons, 2009; Keefer, 2013). Therefore, it is unlikely that wage discrimination estimates are being generated by omitted variables. If omitted variables were responsible for wage discrimination estimates, our estimates for the effect of race on playing time would be understated. Therefore, future research should focus on understanding the role of unobservable skills or characteristics in the market. Unfortunately, many of the econometric methods to correct for omitted variables are not possible in this case. For example, standard econometric corrections would include either fixed effects or instrumental variables estimation, both of which are not appropriate for estimating the effect of race on labor market outcomes. Another, potentially more fruitful, approach is to construct new statistical measures that more accurately reflect the productivity of players. This approach has been attempted for offensive skilled positions, but not for defensive players. For example, Football Outsiders reports several non-traditional statistical measures of productivity, such as defense-adjusted yards above replacement and defense-adjusted value over average. New measures, which more accurately capture the productivity of defensive players, will allow us to better understand the magnitude of the effect of race on both compensation and playing time.

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Endnotes

[1] Interestingly, the NFL allows coaches to talk to one offensive and one defensive player via a telecommunications system in their helmet. This designation is reserved for quarterbacks and linebackers.

[2] For example, Keefer (2014) shows that 94% of the variation in compensation for players selected in the first two rounds of the NFL draft is explained by only a polynomial of selection number and a round dummy variable.

[3] For example, offensive linemen do not have any official individual statistics.

[4] We present ordered response results for comparison.

[5] The likelihood ratio test of equidispersion has a *p*-value of 0.00, significantly rejecting the null hypothesis and supporting the use of the negative binomial distribution over the Poisson distribution.

[6] The Vuong statistic is 13.35 with a *p*-value of 0.00, significantly supporting the use of the ZINB model as opposed to the standard NB model.

[7] The results are not statistically different using a probit specification for the probability of being an excess zero; probit results can be obtained from the author.

[8] Using a probit specification does not significantly change the results; probit results may be obtained from the author.

[9] See Conlin and Emerson (2006) for a discussion of race and playing time for rookies in the NFL.

[10] One potential omitted variable is injuries, as they affect the number of games started. However, consistent data on injuries are only available from 2013 via Fox Sports. Furthermore, injuries would only bias our baseline estimation if it were correlated with race, if one group is injured significantly more.

[11] One potential issue is the timing of compensation and playing time. Compensation is determined prior to the beginning of a season. If a player has a significant improvement in ability during a season, he may have more playing time and receive relatively less compensation. On the other hand, a player who has a decline in ability during a season may have relatively little playing time with more compensation. However, it is only an issue if race is significantly correlated with these scenarios, if black players tend to improve more relative to their expected productivity than non-black players.

[12] Defensive lineman data is from 2001 to 2009. Tight end data is from 1999 to 2009, since we do not need to restrict the data to when the NFL began officially recording tackles.