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Race and National Football League Player Salaries After Controlling for Fantasy Statistics and Arrests

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Abstract

This paper provides a novel contribution to studies of race and labor-market outcomes by using fantasy football statistics as a measure of performance across offensive skill positions and arrest data as a proxy for negative off-the-field behavior. We investigate whether the determinants of salaries and employment vary between 2005-06 and 2015-16, as the 2011 collective bargaining agreement (CBA) introduced extensive regulation of rookie contracts. As expected, fantasy football statistics are strong predictors of salaries and employment in both time periods, whereas race and arrests are not. Fantasy statistics and experience have diminishing marginal returns for both outcomes.

Keywords

productivity, discrimination, salary, National Football League, compensation, Collective Bargaining Agreement, quantile regression

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Introduction

The National Football League (NFL) is the largest professional sports league in the U.S. in terms of revenue, earning in excess of $12 billion annually (Isidore, 2015). It employs almost 1,700 players during the regular season, and the players' salary cap is based on almost 50% of the total revenues (Davis, 2014). A major obstacle in past research on salaries and race in the NFL, such as the pioneering work by Kahn (1992), has been the inability to compare player performance across positions. In recent years, the growing popularity of fantasy football has provided one way to compare performance across many positions. The comparison is limited to offensive skill positions (quarterback, running back, tight end, and wide receiver), as fantasy points are awarded on an individual basis for yards gained and points scored. Defenses are scored as a team, rather than individually, and offensive linemen do not receive fantasy scores, so both groups of players are excluded from this research.

This paper is the first to incorporate fantasy football statistics as a means to compare the productivity of players who play different positions. We use these productivity statistics to see if race or getting arrested affect each player's salary and employment.[1] Both outcomes are measured for 2006 and 2016 in order to investigate potential effects of the 2011 collective bargaining agreement where, among other things, the salaries of rookies became largely determined by draft position rather than by negotiations between players and teams.

We find that race and arrest history have no discernible relationship with compensation or employment. Instead, performance and draft position are the primary determinants of both player salary cap values and of the likelihood of employment. Fantasy statistics alone explain nearly half of all variation in salary cap values. Given the explanatory power of this variable, excluding it (or a similar measure of performance) from an analysis of race would yield weak results. Salaries increase with experience and fantasy points, although at a decreasing rate. There is no systematic relationship between experience and employment.

Literature Review

Studies of labor-market outcomes in professional sports often address issues of racial discrimination in the form of employer, employee, or customer. Employer discrimination occurs when an employer prefers to hire or not hire employees based on characteristics unrelated to productivity (such as race or gender). In a free market economy, employer discrimination is not profit-maximizing and therefore tends to lessen over time (Becker, 1971). Some might argue that owners of NFL franchises are not profit-maximizers, given their wealth and the prestige of owning an NFL team. In a similar vein, Palmer and King (2006) point out that if Major League Baseball owners possess racial prejudices, they may have enough wealth to exercise racially-biased front office decisions for an extended period of time. Thus, employer discrimination is a possibility in the NFL.

Employee discrimination occurs when employees do not want to work with co-workers because of co-worker characteristics that are unrelated to productivity (such as race or gender) (Becker, 1971). Employee discrimination would be difficult to measure in the NFL.

Customer discrimination, unlike other forms of prejudice, is not as easily forced from the market (Becker, 1971). If customers prefer white workers, employers will react by either hiring fewer nonwhite workers or paying nonwhite workers a lower wage. In the case of the NFL, customers could reward the employers who listen to their preferences with greater purchases of tickets, player jerseys, and other purchases that increase a team's revenue.

Because employee performance is more easily observed for professional athletes than for most other employees, many papers have studied the determinants of professional athletes' salaries. For football, the earliest work on this topic is by Mogull (1973).[2] He finds similar compensation between black and white football players using data compiled from questionnaires of 96 players from the 1970 season, but he does not control for individual player characteristics aside from experience.

The seminal paper on NFL salaries is by Kahn (1992). He includes data on 1,363 players for the 1989 season. On average, white players earn a maximum of 4% more than black players, but this result is not statistically significantly different from zero when controlling for different variables such as position. He finds that white players receive higher salaries in areas with a high percentage of white residents, whereas nonwhite players receive higher salaries in areas with higher percentages of nonwhite residents. This finding is consistent with customer discrimination.

Gius and Johnson (2000) sample 938 players from the 1995 NFL season. Although they determine that black players earn, on average, 10% more than white players, they, like Kahn (1992) only have indirect measures of productivity such as position and experience. Using data from 2000 to 2008, Ducking et al. (2014) find no relationship between race and lifetime earnings for six positional groups (defensive backs, defensive linemen, linebackers, running backs, tight ends, and wide receivers).

In order to control for productivity, some studies focus on individual positions. Berri and Simmons (2009), in their analysis of quarterbacks between 1995 to 2006, find lower salaries for black quarterbacks, particularly at the higher end of the salary distribution. Keefer (2013) finds that black linebackers in the NFL earn 10% less than their white counterparts, although this result is driven by lower salaries for nonwhites in the lower part of the salary distribution. Similarly, Ducking et al. (2017) find lower salaries for black linebackers compared to white linebackers at different levels of the salary distribution, but they find no racial differences for defensive lineman or defensive backs. When focusing on rookies (players just starting in the NFL), Burnett and Van Scyoc (2013, 2015a, 2015b) find no discernible differences by race in the wage distribution of wide receivers, offensive linemen, linebackers, or tight ends.

Research on the NFL considers employment-related measures as well as salary-related measures. Using data from 1990 for multiple positions, Conlin and Emerson (2005) find that nonwhite players typically have a higher probability of having an active contract and starting more games. More recently, Keefer (2016) finds that black linebackers are more likely to start games. In contrast, Volz (2017) finds that black quarterbacks are more likely to be benched. For six positions, Ducking et al. (2015) find no differences by race in NFL career length using hazard models.

In summary, there is no consistent pattern in the relationship between race and employment or salary outcomes in the NFL. Some studies find that whites do better, others find that blacks do better, and some find similar results by race.

We contribute to the NFL earnings and employment literature in three ways. The first contribution is to use fantasy points as a comprehensive measure of productivity across players from different positions. By including this measure in regressions where we also control for player race, we contribute to the literature on discrimination in earnings and employment. Our second contribution is to study employment as an outcome rather than just focusing on player compensation. Although we cannot distinguish between the two main reasons for a player not being employed, namely not being offered employment versus turning down offered employment, our reduced-form measure of being under contract is still a useful outcome measure that is rarely analyzed. Finally, we look at the relationship between the off-the-field behavior of arrests and salaries/employment, complementing the work by Weir and Wu (2014), who show that an arrest in college correlates with a fall in draft position of 16 to 22 positions.

Although the vast literature on collective bargaining is potentially relevant for our study of the NFL, we do not contribute to that literature. Instead, our focus is solely on the relationship between race and labor-market outcomes, controlling for on-the-field determinants along with arrest records. For more information on collective bargaining and unions, see MacLeod (2011) as well as the citations therein.

National Football League Salary Cap and Collective Bargaining

In the National Football League, player salaries make up the largest portion of a team's annual costs (Associated Press, 2016). All teams in the NFL are subject to a "salary cap"—a maximum amount they can pay for labor. The salary cap contributes to a competitive balance among the 32 NFL teams by providing all teams with equal opportunities to acquire top talent (Larsen et al., 2006). Each year, the salary cap is calculated using a formula established in the collective bargaining agreement (CBA) between NFL ownership and the NFL Players Association (NFLPA).

A specific portion of each player's contract counts against the team's total salary cap. A player's cap value at the start of a year includes all guaranteed elements in the contract, any incentives deemed “likely to be earned,” as well as a fraction of the player’s signing bonus (NFLPA, 2011). Although signing bonuses are paid up-front, for cap purposes they are amortized on a straight-line basis over the life of the contract or five seasons, whichever comes first (NFLPA, 2011). In the case that incentives actually paid in a year exceed those that were likely to be earned, the excess will be credited against the team’s salary cap in the subsequent year. Within the constraints of the collective bargaining agreement, the determination of a player’s salary may depend on a number of factors. For example, the structure of rookie contracts changed significantly under the 2011 CBA and is quite different than veteran contracts.

Prior to 2011, rookies drafted into the NFL had the potential to sign extremely lucrative contracts before beginning their professional careers. During negotiations for the 2011 CBA, both owners and veteran players wanted to limit the size of rookie contracts (Brandt et al., 2013). Owners were motivated by major draft busts like Ryan Leaf and JaMarcus Russell, and veteran players were unhappy about being out-earned by rookies (Brandt et al., 2013). As a result, the pool of money allocated to rookie contracts shrank, and rookies were forced into heavily structured, 4-year contracts with 5th-year team options for first round picks (Quinn, 2012). Players do not have the option to restructure rookie contracts until after the 3rd year of the contract. Consequently, many young players receive compensation well below their value, and the value of rookie contracts has dropped significantly since the implementation of the 2011 CBA (Brandt et al., 2013).

Veteran players may not receive the intended benefits from the rookie contract restructuring. Teams can draft and sign rookie players for relatively lower salaries than veteran players without the necessity to restructure contracts to reward performance above expectations (Brandt et al., 2013). Thus, the returns to experience may differ in the two time periods.

Data and Descriptive Statistics

We use data from two time periods equally spaced before and after the 2011 collective bargaining agreement. Specifically, we link 2005 productivity data with 2006 contract and salary cap data, and we link 2015 performance data with 2016 contract and salary cap data. Because we have data for two periods rather than every year, our results are only suggestive of changes associated with collective bargaining. To rule out other explanations such as general trends in the league, a complete panel data set with all years would be needed.[3]

We have two models, each with a different dependent variable. Both are based on contract and salary data available from sportrac.com, a partner of USA Today Sports Media Group. Teams are subject to a finite salary cap that varies year to year (it was $155 million in 2016), so cap value is an accurate representation of the relative value that a team places on each player. For this reason, the amount of a player’s salary counted against the league's salary cap is the dependent variable in the first model, as this variable is the standard measure of player salaries in the sports economics literature (Berri and Simmons, 2009). Players who are not employed have a missing value for salary cap value and are excluded from the salary regressions. Salary cap values are measured in 2016 dollars using the Consumer Price Index. In the second model, the dependent variable is a dummy variable equal to one for players who have a salary cap value—e.g. who are employed—in either 2006 or 2016. The analysis captures whether productivity and other player characteristics affect the duration of players' tenure in the league.

Productivity data come from www.pro-football-reference.com, a website with extensive information on individual players. Each year, the website publishes a player-level database containing fantasy football values, as well as the individual components of the fantasy statistic related to passing, rushing, and receiving. Our productivity variable is the total number of fantasy points for the 2005/2015 season, where a higher number represents a more productive player (such as 389 for Cam Newton in 2015) than a lower number (such as 1 for Doug Flutie in 2005).[4] Because the fantasy statistics are only meaningful for the players involved in passing, rushing, and receiving, fantasy statistics are only calculated for quarterbacks, running backs, wide receivers, and tight ends. Thus, the data in this paper only include players in those positions. By awarding points for yards and touchdowns and penalizing players for turnovers, fantasy football allows cross-positional comparisons of performance.

We supplement the productivity data with additional player data available from the website. First, player race, categorized as a dummy variable equal to one for nonwhites, was calculated based on an analysis of player photographs available on the website.[5] There are insufficient numbers of nonwhites of races/ethnicities other than blacks to estimate separate coefficients for these racial/ethnic groups.

Second, we collected data on each player's draft status. We created a dummy variable for being a first-round draft pick, a dummy variable for being a second-round draft pick, a dummy variable for being a third-round draft pick, and a dummy variable for not being drafted. The omitted category is the set of players who were drafted in the fourth round or later.

Third, we include four variables to measure experience. The first two variables are the number of seasons played and its square. The years of experience measures do not include seasons that a player missed due to injury or other reasons. A player who played in each season starting in 2001, for example, has a value of 5 for experience and 25 for experience squared in the 2005-2006 data set. The third experience variable is the number of games played in either the 2005 or 2015 season. The fourth experience variable is the number of Pro Bowl invitations through the 2005 or 2015 season.[6]

We also control for the player's position with a set of dummy variables. The omitted category is wide receiver, the most common position in the data. Even though the fantasy statistic is designed to equate productivity across positions, teams need to hire players at each position. A team cannot substitute a wide receiver for a quarterback.

We have one measure of off- the-field characteristics. The USA Today Sports Media Group collects data on arrests of NFL players starting in 2000. Using these data, we create a dummy variable with a value of one if the player has been arrested at least once from when he entered the league (or 2000, for players who entered prior to 2000) through July of 2006 or 2016.[7] July is chosen as the end date because players report to training camp in August. Under the League's personal conduct policy, players miss significant playing time for criminal offenses. Consider, for example, the case of Adrian Peterson, the star running back for the Minnesota Vikings. Due to legal issues near the beginning of the 2014 season, Peterson played in only one game during that season. In this case, off-the-field actions eliminated the contributions he might have provided his team.

Team performance data indicate how effectively teams allocate finite cap space to optimize performance. Kahn (1992) included variables in his model to control for variations in demographics among the cities where NFL teams are located. Because the appropriate team variables are not standard in the literature, we instead use team fixed effects (based on the 2005 or 2015 team) to account for any team-specific effects on labor-market outcomes. Given the relatively small number of players per team, our preferred model excludes these team fixed effects.

Table 1 contains the descriptive statistics for the variables. The first two columns are for the 2005-2006 data and the second two columns are for the 2015-2016 data. In each year, the first column is for the entire sample of players in 2005 or 2015 (e.g. the regression sample for the employment regressions), whereas the second column is for the subset of players with salary cap information (e.g. the regression sample for the salary cap regressions).

Average player salaries (as measured by the salary cap value) are \$2.2 million in 2006 and \$3.1 million in 2016, both measured in 2016 dollars. Thus, average value increased by 28% in real terms. Approximately three-fourths of the players in 2005 and 2015 were employed the following season.

Approximately 70% of players are nonwhite. For all players, the average number of fantasy points was around 50 in 2005-06 and 57 in 2015-16. For players in the salary cap sample, the average fantasy points were 61 in 2005 and 71 in 2015. The most common position is wide receiver (the omitted category in the regressions), followed by running back. Around 15% of players were drafted in the first round, and approximately 30% were not drafted. The average number of Pro Bowl invitations was less than one (0.4 to 0.5). Players had an average of 4.0 to 4.5 years of experience, and they played in an average of 11 to 12 of the 16 regular-season games. Finally, approximately 8% of players had an arrest.

Table 2 illustrates differences across position and time in the fantasy points distribution, although all differences are not statistically significantly different due to the large standard deviations. Quarterbacks have the largest average fantasy points, at 95.3 in 2005-06 and 135.1 in 2015-16. Tight ends have the lowest average

Table 1. Descriptive Statistics by Year and Sample.

	2005-2006 Data		2015-2016 Data	
Variable	All Players	In 2006 Data	All Players	In 2016 Data
Cap value (2016 dollars)	2,205,845	2,205,845	3,078,038	3,078,038
	(2,602,452)	(2,602,452)	(4,516,954)	(4,516,954)
Employed, 2006/2016	0.757	1	0.727	1
Nonwhite	0.698	0.702	0.722	0.717
Fantasy points	49.3	61.4	57.6	71.1
	(64.7)	(68.5)	(70.7)	(76.2)
Quarterback	0.141	0.157	0.128	0.145
Running back	0.244	0.242	0.296	0.288
Tight end	0.217	0.202	0.208	0.206
Wide receiver	0.326	0.312	0.368	0.361
Experience	4.46	4.56	4.07	3.90
	(3.25)	(3.20)	(3.25)	(3.11)
Games played	11.1	12.2	10.7	11.6
	(5.33)	(4.87)	(5.28)	(5.05)
First round draft	0.168	0.197	0.135	0.155
Second round draft	0.126	0.139	0.107	0.126
Third round draft	0.098	0.114	0.119	0.124
Undrafted	0.278	0.222	0.330	0.288
Pro bowls	0.387	0.455	0.509	0.550
	(1.15)	(1.24)	(1.48)	(1.44)
Arrested	0.080	0.087	0.080	0.068
Observations	589	446	587	427

Note: Means are reported, and standard deviations for non-binary variables are in parentheses. Because the cap value variable is missing for players who do not have a contract, the mean cap value is the same for the "all players" column and the column for being in the 2006 or 2016 data.

fantasy points: 29.8 in 2015-16 and 42.0 in 2015-16. The table also illustrates differences across the fantasy points distribution by position as well as differences in the mean.

Methods and Predicted Effects

Following previous work such as Kahn (1992), we use ordinary least squares and conditional quantile regression to estimate the effects of the individual and team variables on the compensation and on the likelihood of being employed for NFL offensive skill-position players as shown in equation [1] and equation [2] below.

$$\ln(CapValue) = Fantasy*\beta + PlayerStats*\gamma + Arrest*\lambda + Team*\theta + \epsilon \qquad (1)$$

Table 2. Fantasy Points Distribution by Year and Position, Salary Cap Sample.

2005-2006 Data	QB	RB	TE	WR	Overall
Mean	95.3	75.9	29.8	65.6	61.4
Standard Deviation	84.0	82.6	37.3	57.9	68.5
10th Percentile	3	0	0	0	0
25th Percentile	15	8.5	2	16	7
50th Percentile	82.5	50.5	16.5	56	37.5
75th Percentile	172	111.5	41	103	92
90th Percentile	222.5	188	85.5	150	167
Observations	70	108	90	139	446
2015-2016 data	**QB**	**RB**	**TE**	**WR**	**Overall**
Mean	135.1	66.1	42.0	66.1	71.1
Standard Deviation	124.6	59.8	43.2	62.1	76.2
10th Percentile	0	2	0	2	1
25th Percentile	13	14	12.5	14	13
50th Percentile	104	49	24	45.5	44
75th Percentile	273	105	63.5	105	107
90th Percentile	303	155	102	159	173
Observations	62	123	88	154	427

In this model, the dependent variable is the natural log of the cap value. Cap value does not represent all of the cash a player may receive in a given year, but it provides an excellent way to compare salaries because it captures the value of a player relative to the total team salary cap. As mentioned previously, signing bonuses are amortized on a straight-line basis over the term of a player's contract, even though the player may receive the entire bonus up front (NFLPA, 2011).

The salaries of NFL players are highly dispersed, ranging from little-used reserve players with salary cap values around $100,000 to superstar players earning over $10,000,000 per year. To address this range, we also estimate quantile regression models as is done in several previous papers starting with Berri and Simmons (2009). By focusing on particular percentiles in the salary distribution, such as the median rather than the mean (as is done in an OLS regression), quantile regression models reduce the influence of outliers at both ends of the salary cap distribution.

Equation [2] is the model where being employed, as measured by being under contract, is the dependent variable. For the 2005-2006 data, we estimate a probit model where the dependent variable is equal to one for players who are under contract in 2006. The probit is estimated for all players who played at least one game (according to www.pro-football-reference.com) in 2005.[8] In the appendix, we show that the results are not sensitive to the choice of probit, logit, or linear probability model. We estimate standard errors that are robust to heterogeneity.

$$\Pr(Employed) = Fantasy{*}\beta + PlayerStats{*}\gamma + Arrest{*}\lambda + Team{*}\theta + \epsilon \qquad (2)$$

Both models contain quadratic terms for fantasy football points and experience. If fantasy points and experience measure productivity, standard labor economics theory predicts positive coefficients for the linear terms. If diminishing returns to productivity exist, then the coefficients for the quadratic terms would be negative. Because the adoption of the NFL's new collective bargaining agreement in 2011 resulted in many young players receiving compensation well below their values (Brandt et al., 2013), experience may have a different effect on outcomes between the two periods.

The models include several player characteristics: dummy variables for position (relative to the omitted position of wide receiver), dummy variables for being drafted in the first round, the second round, the third round, or not being drafted (relative to the omitted group of being drafted in the fourth round or later), the number of games played in 2005 or 2015, and the number of times a player was invited to the Pro Bowl. We also control for one off-the-field characteristic through a dummy variable equal to one for being arrested.

Exceptional team performance should correlate to higher salaries, but the team-level salary cap limits the influence of team characteristics. Consequently, our preferred specification excludes team characteristics. We include team fixed effects in some specifications for ease of comparison with previous studies such as Kahn (1992).

Results

2006 Salary Regressions

Table 3 contains the results from the ordinary least squares (OLS) and quantile regressions for the 2005-2006 data, where the dependent variable is the log salary cap value. The first column is the OLS regression, and the remaining columns are for the 10th, 25th, 50th (or median), 75th and 90th percentiles.

In the OLS model, nonwhite players have essentially the same salaries as white players. The point estimate is -0.018, suggesting nonwhite players are paid a very small amount less than equally productive white players, but the standard error is so large that any commonly constructed confidence interval includes non-negative values as well. In other words, the salary of nonwhite players could be smaller, larger or no different than that of equally productive white players.

At the mean (OLS), fantasy points are positively associated with salary cap value and negatively associated with salary cap value when squared, suggesting decreasing returns to fantasy points. Fantasy points and fantasy points squared explain nearly half of the variation in log salary.[9] The table also presents the effects of a 12-point increase in fantasy points, calculated at the mean value of approximately

Table 3. OLS and Quantile Regression Results for Log 2006 Salary Cap Value.

	OLS	P10	P25	P50	P75	P90
Nonwhite	−0.018	0.356***	−0.007	−0.033	−0.078	0.017
	(0.077)	(0.067)	(0.081)	(0.196)	(0.167)	(0.125)
Fantasy points	0.010***	0.010***	0.008***	0.015***	0.010***	0.012***
	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Fantasy points^2/100	−0.001***	−0.001	−0.002**	−0.001	−0.003***	−0.001*
	(0.0005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Quarterback	0.154	0.194	0.178	−0.009	0.078	0.619***
	(0.122)	(0.297)	(0.190)	(0.300)	(0.102)	(0.198)
Running back	−0.241***	−0.300**	−0.341***	−0.208**	−0.260	−0.236***
	(0.081)	(0.150)	(0.096)	(0.106)	(0.229)	(0.082)
Tight end	0.034	−0.049	0.017	−0.023	0.185*	0.037
	(0.080)	(0.110)	(0.071)	(0.107)	(0.100)	(0.177)
Experience	0.216***	0.234***	0.231***	0.235***	0.210***	0.284***
	(0.033)	(0.041)	(0.038)	(0.049)	(0.074)	(0.051)
Experience squared	−0.014***	−0.018***	−0.013***	−0.015***	−0.016***	−0.014***
	(0.002)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)
Games played	−0.009	0.014**	−0.016	−0.004	−0.012	−0.032***
	(0.009)	(0.006)	(0.014)	(0.012)	(0.017)	(0.012)
First round draft pick	0.578***	0.611***	0.278	0.642***	0.527***	0.454***
	(0.111)	(0.172)	(0.258)	(0.189)	(0.176)	(0.144)
Second round draft pick	0.384***	0.224*	0.282	0.400***	0.290**	0.319**
	(0.092)	(0.117)	(0.196)	(0.137)	(0.117)	(0.160)
Third round draft pick	0.265***	0.357***	0.166	0.064	0.329**	0.027
	(0.089)	(0.125)	(0.136)	(0.068)	(0.144)	(0.145)
Undrafted	0.026	0.025	−0.105	0.091	−0.132**	0.045
	(0.086)	(0.103)	(0.107)	(0.128)	(0.064)	(0.193)
Pro bowls	0.123***	0.104**	0.140***	0.217***	0.107***	0.082
	(0.029)	(0.051)	(0.042)	(0.022)	(0.038)	(0.062)
Arrested	−0.061	0.009	−0.148	−0.132	−0.322**	0.013
	(0.132)	(0.199)	(0.281)	(0.121)	(0.157)	(0.158)
Overall Effect of 12-Fantasy-Point Increase at Percentile						
Overall	0.100	0.115	0.085	0.173	0.040	0.098
Observations	446	446	446	446	446	446
Pseudo R-squared	0.61	0.28	0.35	0.44	0.46	0.44

Notes: Each column is from a separate regression. Robust standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively, for a two-sided test. The overall fantasy points effect measures the sum of the fantasy points and fantasy points squared coefficients.

50 points (Table 1). A 12-point increase is equal to three touchdowns passing or two touchdowns receiving or rushing. Because the standard deviation of fantasy points is approximately 70 (Table 1), an increase of 12 fantasy points is approximately one-sixth of a standard deviation. At this level, a 12-point increase in fantasy points corresponds to a salary increase of 0.100, or 10.5%.[10] The overall increase in salary

associated with an increase in fantasy points becomes smaller as the number of fantasy points increases, illustrating diminishing returns.[11] In other words, the salary gains from two to three more touchdowns are more pronounced for a player like Billy Bajema (5 points) than a player like Drew Brees (220 points).

Several player characteristics are significant determinants of player salaries in the OLS regression. Conditional on fantasy points, running backs have lower salaries of 0.241 (21.4%) compared to wide receivers (the omitted category). The linear term for experience is positive, but the quadratic term is negative, consistent with economic theory of diminishing returns to experience. An increase in experience from 4 years to 5 years is associated with a salary increase of 9%. The overall effect of experience is negative once a player has 9 years of experience. Compared to players drafted in the fourth round or later, first-round draft picks have salaries 0.578 (or 78.3%) higher. The salary premium for second and third round picks is smaller, at 0.384 (46.8%) and 0.265 (30.3%), respectively.[12] There is no discernable salary cap difference between undrafted players and players drafted in the fourth round or later. A Pro Bowl invitation correlates with a 0.123 (or 13.1%) increase in salary. One interpretation of the positive and significant effects for early-round draft picks and Pro Bowls invitations is that teams believe that these players possess particularly valuable skills, such as leadership or teamwork, that are not completely captured by their fantasy points.

Arrest history has no detectable relationship with salaries in the OLS model. The coefficient of approximately −0.061 is dwarfed by its standard error. This result, coupled with the even smaller (in magnitude) coefficient for nonwhite, suggests that salaries depend much more on on-the-field characteristics than off-the-field characteristics.

Appendix Table 1 shows that the OLS results are similar between the model in Column 1 without any team-level controls to models with either team fixed effects (Column 2) or team characteristics (Column 3). We interpret this similarity as suggestive evidence that team-level differences are unlikely to be a major influence of salary cap value.

The remaining columns of Table 3 contain the results from quantile regression models for the preferred specification that excludes team fixed effects. Again, the bottom panel contains the overall effect of a 12-point increase in fantasy points by percentile.[13] There is no discernible effect of race aside from a positive correlation for nonwhites of 0.356 (42.7%) at the bottom of the salary distribution. The coefficients for experience and experience squared are broadly similar across the distribution. The magnitude of the coefficient for fantasy points is highest at the median, whereas the magnitude for fantasy points squared is highest at the 75th percentile. Consequently, the overall effects for fantasy points are highest for the median, approximately 19%, and lowest for the 75th percentile. Quarterbacks receive a salary premium of 0.619 (or 85.7%) at the top of the distribution. Rewards for first- and second-round draft picks and Pro Bowl invitations are highest at the median. Although arrests are negatively associated with salary at the 75th percentile, the

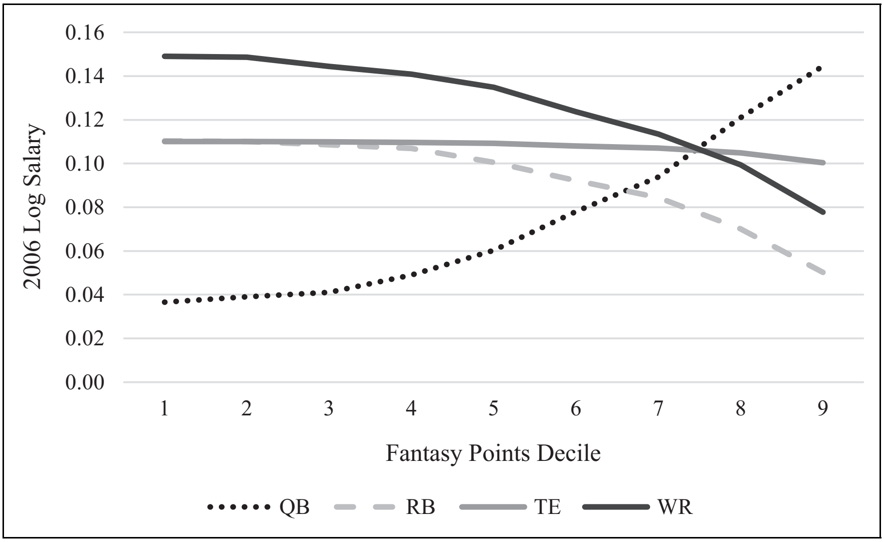

Figure 1. Effect of 12-point increase in fantasy points on 2006 log salary, by position.
Notes: Results are based on overall effect of all relevant fantasy point coefficients in the regression in Column 1 of Appendix Table 2.

insignificance at other points limits any inferences than can be drawn from this isolated result.

The model presented in equation [1] assumes that, because fantasy points attempt to equate productivity across positions, the salary returns to fantasy points are constant across position. Appendix Table 2 evaluates the plausibility of that assumption by presenting results from OLS models with interactions between position and fantasy points. Figure 1 illustrates the results by decile of fantasy points, separately for each position.

At lower levels of fantasy points, the salary gains from a 12-point increase in fantasy points are highest for wide receivers and lowest for quarterbacks. However, at the top two deciles of the fantasy points distribution, quarterbacks such as Michael Vick (227 points) have the largest increases in salary, whereas running backs such as Tiki Barber (307 points) have the lowest. For the remaining differences, we cannot reject the hypothesis that the salary gains are equal across positions.

2016 Salary Regressions

Next, we turn to the results for the 2015-2016 data. Table 4 contains the OLS and quantile regressions for 2016 log salary cap value, and the format is analogous to Table 3.[14] In the OLS regression (Column 1), the coefficient for nonwhite is −0.091, a nontrivial wage penalty, but it is not statistically significantly different from zero.

Again, most of the player characteristics are significant determinants of mean log salary (Column 1). Running backs earn nearly −0.40 less in log salary (or 33%) than wide receivers (the omitted group). Experience is positive, and experience squared is negative. Due to the increased magnitude of the experience squared coefficient, the overall returns to experience become negative after 8 years. Being drafted in the first two rounds correlate positively, whereas there are no salary distinctions for being drafted in the third round or later or being undrafted. The increase in salary of each Pro Bowl invitation is similar in both years. Although the magnitude of the arrest variable more than doubled in 2016 compared to 2006, the coefficient is still imprecisely estimated and is statistically insignificant. Appendix Table 1 illustrates the similarity in results regardless of how, if at all, the specification controls for team-level attributes (for both 2006 and 2016).

The quantile regression results for 2016, in the remaining columns of Table 4, show a lot of variation by salary quantile. Nonwhites are indistinguishable from whites throughout the distribution, although the coefficients of roughly −0.15 for the 10th and 75th percentiles are nontrivial. The coefficients for fantasy points are larger toward the top of the distribution than at the bottom. The returns to experience are positive, although at a decreasing rate, throughout the distribution, and the both the linear and quadratic terms are largest in magnitude near the top of the salary distribution. The wage penalties for running backs are large throughout the distribution, with most pronounced effects at the top. Draft position has notable effects except at the very top of the distribution. The rewards for Pro Bowl invitations are roughly consistent across the quantiles. As in 2006, arrests have the most pronounced effects at the 75th, and to a lesser extent, the 50th percentile.

Figure 2 shows how the salary gains for a 12-point increase in fantasy points varies across deciles of the fantasy points distribution. As in Figure 1, the results are from an OLS model with interactions between position and the fantasy points variables. For the lower deciles of fantasy points, the log salary increase associated with a 12-point increase in fantasy points is largest for tight ends and wide receivers, with gains in excess of 0.200 (nearly 25%). These gains are roughly double the gains for quarterbacks. However, the gains are smaller at the upper end of the distribution, regardless of position. The gains in the top two deciles are under 0.100 (in terms of coefficients or percentages). Across positions, the returns to fantasy points are noticeably higher at the lower end of the fantasy points distribution compared with the upper end. For example, the returns to two to three touchdowns for a wide receiver or tight end near the bottom of the distribution, such as Cody Latimer (12 points), are more than double the returns for a player closer to the top of the distribution, like Brandon Marshall (230 points).

We explore the sensitivity of the 2016 results to the length of time in the league. As mentioned previously, one of the changes in the 2011 CBA was the introduction of more structured, 4-year contracts for draft picks. Because our data do not contain contract information, we cannot identify players in their first contract from those on subsequent contracts. As a proxy for contract, we instead run a regression limited to players with at least 4 years of experience in 2005 or 2015. Appendix Table 3

Table 4. OLS and Quantile Regression Results for 2016 Log Salary Cap Value.

	OLS	P10	P25	P50	P75	P90
Nonwhite	−0.091	−0.150	−0.083	−0.039	−0.145	−0.014
	(0.087)	(0.159)	(0.082)	(0.102)	(0.100)	(0.137)
Fantasy points	0.010***	0.006**	0.004**	0.009***	0.011***	0.014***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Fantasy points^2/100	−0.001***	−0.001	0.0004	−0.0009	−0.002***	−0.003***
	(0.0005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Quarterback	0.224	0.508**	0.131	0.031	0.211	0.198
	(0.160)	(0.238)	(0.134)	(0.148)	(0.276)	(0.317)
Running back	−0.394***	−0.235	−0.184*	−0.299***	−0.459***	−0.549***
	(0.083)	(0.189)	(0.094)	(0.099)	(0.106)	(0.166)
Tight end	0.100	0.122	0.076	0.063	−0.012	0.036
	(0.094)	(0.098)	(0.104)	(0.117)	(0.095)	(0.197)
Experience	0.305***	0.117*	0.243***	0.333***	0.355***	0.349***
	(0.033)	(0.067)	(0.073)	(0.057)	(0.047)	(0.063)
Experience squared	−0.019***	−0.005	−0.014**	−0.020***	−0.023***	−0.023***
	(0.003)	(0.007)	(0.006)	(0.005)	(0.004)	(0.005)
Games played	−0.014	0.037**	−0.004	−0.015	−0.025**	−0.036**
	(0.010)	(0.018)	(0.010)	(0.011)	(0.010)	(0.015)
First round draft pick	0.560***	0.679***	0.544**	0.769***	0.610***	0.182
	(0.128)	(0.223)	(0.226)	(0.196)	(0.160)	(0.171)
Second round draft pick	0.304**	0.361	0.281*	0.441***	0.288*	0.227
	(0.119)	(0.260)	(0.158)	(0.122)	(0.149)	(0.157)
3rd round draft pick	0.085	0.072	0.158	0.127	−0.035	−0.144
	(0.114)	(0.260)	(0.171)	(0.121)	(0.149)	(0.198)
Undrafted	−0.010	0.096	−0.091	0.017	−0.102	−0.033
	(0.084)	(0.190)	(0.085)	(0.094)	(0.096)	(0.146)
Pro bowls	0.142***	0.144	0.154***	0.123***	0.139**	0.127*
	(0.029)	(0.103)	(0.044)	(0.036)	(0.054)	(0.077)
Arrested	−0.162	−0.201	−0.095	−0.257**	−0.291*	0.005
	(0.123)	(0.322)	(0.178)	(0.121)	(0.157)	(0.335)
Overall Effect of 12-Fantasy-Point Increase at Percentile						
Overall	0.092	0.070	0.048	0.095	0.083	0.060
Observations	427	427	427	427	427	427
Pseudo R-squared	0.67	0.28	0.35	0.47	0.52	0.53

Notes: Each column is from a separate regression. Robust standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively, for a two-sided test. The overall fantasy points effect measures the sum of the fantasy points and fantasy points squared coefficients.

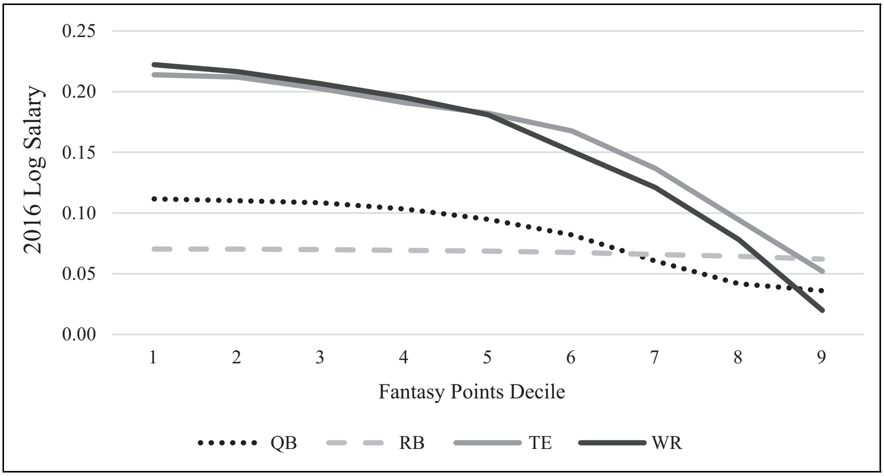

Figure 2. Effect of 12-point increase in fantasy points on 2016 log salary, by position. Notes: Results are based on overall effect of all relevant fantasy point coefficients in the regression in column 2 of Appendix Table 2.

contains the OLS results for the full sample (Columns 1 and 3) with those for players with at least 4 years of experience (Columns 2 and 4).

The overall returns to an increase of 12 fantasy points are slightly larger in the veteran sample compared to the full sample. As expected, the coefficients for experience decrease in magnitude, especially in 2015-16, when inexperienced players are excluded. The wage penalty for running backs is larger in the sample of veteran players, particularly in 2015-16. The premium for first-round draft picks becomes statistically indistinguishable from zero in the veteran sample for 2005-06. Overall, the results are broadly similar between the sample of all players and the sample of veteran players.

Pooled Salary Regressions

In Table 5, we estimate OLS regressions for the pooled 2005-06 and 2015-16 data. In the first two columns, we assume the coefficients are the same in each year, in order to see if precision is improved with the larger sample. In the pooled regression, the quarterback coefficient of 0.202 is statistically significant at the 5% level (two-sided test), compared to insignificant coefficients in Tables 3 and 4. Otherwise, the significance levels are similar between the pooled model in Table 5 and separate models in Tables 3 and 4.

In Columns 3 and 4, we include interactions between a dummy variable equal to one for observations in 2015-16 and each control variable. The purpose of this regression is to test more formally how, if at all, the coefficients change between 2005-06 and 2015-

Table 5. Pooled OLS Regression Results for Log Salary Cap Value.

	No Interaction Terms		Interaction Terms	
	Coeff	Std Err	Coeff	Std Err
Nonwhite	−0.046	0.057	−0.018	0.077
Fantasy points	0.010	0.001***	0.010	0.001***
Fantasy points^2/100	−0.001	0.000***	−0.001	0.001***
Quarterback	0.202	0.096**	0.154	0.122
Running back	−0.301	0.058***	−0.241	0.081***
Tight end	0.083	0.061	0.034	0.080
Experience	0.263	0.023***	0.216	0.033***
Experience squared	−0.017	0.002***	−0.014	0.002***
Games played	−0.011	0.007	−0.009	0.009
First round draft pick	0.591	0.084***	0.578	0.111***
Second round draft pick	0.360	0.074***	0.384	0.092***
Third round draft pick	0.190	0.072***	0.265	0.089***
Undrafted	0.0002	0.059	0.026	0.086
Pro bowls	0.131	0.020***	0.123	0.029***
Arrested	−0.109	0.093	−0.061	0.132
(Year = 2015) × Nonwhite			−0.073	0.117
(Year = 2015) × Fantasy points			−0.0004	0.0020
(Year = 2015) × Fantasy points^2/100			0.00001	0.0007
(Year = 2015) × Quarterback			0.070	0.201
(Year = 2015) × Running back			−0.153	0.116
(Year = 2015) × Tight end			0.066	0.124
(Year = 2015) × Experience			0.089	0.046*
(Year = 2015) × Experience squared			−0.005	0.004
(Year = 2015) × Games played			−0.005	0.013
(Year = 2015) × First round draft pick			−0.018	0.169
(Year = 2015) × Second round draft pick			−0.080	0.151
(Year = 2015) × Third round draft pick			−0.180	0.145
(Year = 2015) × Undrafted			−0.036	0.120
(Year = 2015) × Pro bowls			0.019	0.040
(Year = 2015) × Arrested			−0.101	0.180
Year = 2015	0.165	0.044***	0.117	0.224
Observations	873			873
R-squared	0.64			0.64

Notes: The table contains results from two regressions, one without interaction terms between each variable and a dummy variable equal to 1 for 2015 (Columns 1 and 2) and one with interaction terms (Columns 3 and 4). Robust standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively, for a two-sided test. For each model, the number of observations is 873 and the r-squared is 0.64.

16. The only significant difference is for experience, where we find marginally significant differences between years. Specifically, the linear return to experience is more positive in 2015-16, and the quadratic return is more negative. For a player with 1 year of experience, an additional year is associated with a salary increase of 19% in 2005-06

and 28% in 2015-2016. For a player with 8 years of experience, an additional year of experience is associated with a salary loss of 2.6% in 2005-06 and 1.7% in 2015-16. Otherwise, we see no discernable difference across years in the pooled model.

Arrests have no discernable relationship with log salary in the pooled model, despite the large increase in sample size. To see if the effect of arrests depends on player characteristics, we estimated pooled models with interaction terms between arrests and player characteristics. None of the interaction terms is statistically significant at the 5% level (two-sided test), further suggesting that arrests are not systematically related to salaries.

Employment Regressions

In addition to salaries, employment is another labor-market outcome of interest, particularly given the high turnover in the NFL due to the physical nature of the sport. Our second outcome measure is a dummy variable equal to one for players with a contract in 2006 or 2016. Table 6 contains the marginal effects and their corresponding standard errors from a probit model for our preferred specification. As shown in Appendix Table 4, the results are qualitatively similar for logit and linear probability models. The data are from 2005-2006 in the first column, and they are from 2015-2016 in the second column. The independent variables for productivity and player characteristics are measured in 2005 or 2015, and the sample is restricted to players who played in at least one game in 2005 or 2015.

As in the log salary regressions, race has no discernable correlation with employment. Fantasy points have a positive but diminishing association with the likelihood of employment in both columns. The effect of a 12-point increase in fantasy points from 60 points, roughly the mean, is approximately three percentage points (or 3–4%, given mean employment of around 70%). Thus, fantasy points have a much stronger impact on the intensive margin of salary (9–10%) than on the extensive margin of having employment or not (3–4%).

Only a few of the player characteristics have statistically significant effects on the likelihood of being employed in both years, in contrast to the results for log cap value where many player characteristics are statistically significant. Quarterbacks are 10.8 percentage points more likely to be employed than wide receivers (the reference position) in the 2005-2006 data, and the differential is nearly double at 18.5 percentage points in 2015-2016 data.[15] Each game played is associated with a 1.6 percentage-point increase in the likelihood of being employed.

In the final column of Table 6, we estimate a pooled model. Because we can reject the hypothesis of joint significance for interactions between calendar year and the control variables (as is done in Columns 3 and 4 of Table 5), the pooled model does not include any interaction terms. Instead, we conclude that there are no significant differences in the determinants of employment between 2005-06 and 2015-16. In the pooled model, experience is associated with a marginally significant, decreased probability of employment. The effect is larger in magnitude in 2015-16. Being

Table 6. Probit Marginal Effects for Likelihood of Having Employment.

	2005-6	2015-6	Pooled
Nonwhite	−0.011	0.036	0.015
	(0.040)	(0.050)	(0.032)
Fantasy points	0.005***	0.004***	0.005***
	(0.001)	(0.001)	(0.001)
Fantasy points^2/100	−0.001***	−0.001***	−0.001***
	(0.0003)	(0.0003)	(0.0002)
Quarterback	0.108***	0.185***	0.144***
	(0.041)	(0.043)	(0.030)
Running back	−0.023	−0.013	−0.018
	(0.044)	(0.045)	(0.031)
Tight end	−0.003	0.076*	0.032
	(0.044)	(0.043)	(0.032)
Experience	−0.0003	−0.030*	−0.020*
	(0.016)	(0.018)	(0.012)
Experience squared	−0.001	−0.001	−0.0004
	(0.001)	(0.002)	(0.001)
Games played	0.016***	0.016***	0.016***
	(0.004)	(0.004)	(0.003)
First round draft pick	0.010	−0.006	0.006
	(0.062)	(0.074)	(0.046)
Second round draft pick	0.026	0.067	0.053
	(0.050)	(0.061)	(0.038)
Third round draft pick	0.084*	−0.016	0.042
	(0.047)	(0.066)	(0.042)
Undrafted	−0.080*	−0.035	−0.055*
	(0.043)	(0.044)	(0.031)
Pro bowls	−0.015	0.016	−0.003
	(0.021)	(0.019)	(0.013)
Arrested	−0.027	−0.069	−0.059
	(0.073)	(0.078)	(0.053)
Observations	589	587	1,176
Pseudo R-squared	0.24	0.21	0.21

Notes: Each column is from a separate probit model. Robust standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively, for a two-sided test.

undrafted is also correlated with a decreased probability of employment. This time, the effect is larger in magnitude in 2005-06.

Conclusion

We provide a new approach to studying the relationship between race and labor-market outcomes for NFL players. We include two determinants that have not been used previously. First, we use fantasy points as a measure of productivity, allowing us to compare players in different positions. Second, we measure off-the-field behavior by including a dummy variable equal to one for players who have been arrested.

We find no conclusive evidence that, conditional on productivity, salaries or contracts are correlated with race or arrests. Like the early work on this topic (Kahn, 1992; Mogull, 1973) that studied players in multiple positions but did not include measures of productivity, we cannot reject the hypothesis that, holding productivity constant, white and nonwhite players receive similar salaries and are equally likely to be employed. In most cases, the coefficient for nonwhite is near zero (but imprecisely estimated). Similarly, there is no relationship between arrests and labor-market outcomes.

We find that fantasy points have a positive but diminishing association with NFL salaries and contracts 5 years before and 5 years after the adoption of the 2011 collective bargaining agreement. At approximately the mean of player productivity, 60 fantasy points, a 12-point increase in fantasy points corresponds with an increase in salary of 10–11% and an increase in the likelihood of having a contract of 3–4%. In other words, a boost in productivity of two to three touchdowns has sizable rewards for average players and even bigger rewards for below-average players. Fantasy points alone explain almost half of the variation in salaries.

We find little if any evidence of systematic changes between 2005-06 and 2015-16 in the determinants of salary and employment. Despite the introduction of heavily structured contracts for rookies in the 2011 collective bargaining agreement, we do not see any marked changes in how teams reward productivity or other player traits. Future work should use panel data spanning before and after the CBA to produce more thorough investigation of its impacts on players.

Appendix Table 1. OLS Regressions for Different Controls for Team Characteristics.

	2006 Log Salary			2016 Log Salary		
	1	2	3	4	5	6
Nonwhite	−0.018	−0.027	−0.019	−0.091	−0.091	−0.087
	(0.077)	(0.093)	(0.077)	(0.087)	(0.094)	(0.087)
Fantasy points	0.010***	0.0108***	0.011***	0.010***	0.009***	0.010***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Fantasy points^2/100	−0.001***	−0.0017***	−0.002***	−0.001***	−0.001***	−0.001***
	(0.0005)	(0.001)	(0.0005)	(0.0005)	(0.001)	(0.0005)
Quarterback	0.154	0.151	0.152	0.224	0.226	0.232
	(0.122)	(0.122)	(0.121)	(0.160)	(0.148)	(0.161)
Running back	−0.241***	−0.231***	−0.241***	−0.394***	−0.392***	−0.392***
	(0.081)	(0.084)	(0.081)	(0.083)	(0.083)	(0.083)
Tight end	0.034	0.029	0.035	0.100	0.043	0.096
	(0.080)	(0.093)	(0.081)	(0.094)	(0.101)	(0.094)

(continued)

Appendix Table 1. (continued)

	2006 Log Salary			2016 Log Salary		
	1	2	3	4	5	6
Experience	0.216***	0.226***	0.216***	0.305***	0.320***	0.306***
	(0.033)	(0.032)	(0.033)	(0.033)	(0.038)	(0.034)
Experience squared	−0.014***	−0.015***	−0.014***	−0.019***	−0.019***	−0.019***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Games played	−0.009	−0.008	−0.009	−0.014	−0.005	−0.012
	(0.009)	(0.008)	(0.009)	(0.010)	(0.009)	(0.010)
First round draft pick	0.578***	0.612***	0.583***	0.560***	0.509***	0.566***
	(0.111)	(0.099)	(0.112)	(0.128)	(0.120)	(0.130)
Second round draft pick	0.384***	0.410***	0.384***	0.304**	0.280**	0.307***
	(0.092)	(0.103)	(0.092)	(0.119)	(0.115)	(0.119)
Third round draft pick	0.265***	0.277**	0.278***	0.085	0.012	0.087
	(0.089)	(0.111)	(0.092)	(0.114)	(0.117)	(0.116)
Undrafted	0.026	0.059	0.036	−0.010	−0.024	−0.009
	(0.086)	(0.090)	(0.086)	(0.084)	(0.088)	(0.084)
Pro bowls	0.123***	0.132***	0.125***	0.142***	0.126***	0.136***
	(0.029)	(0.033)	(0.029)	(0.029)	(0.036)	(0.030)
Arrested	−0.061	−0.048	−0.067	−0.162	−0.124	−0.171
	(0.132)	(0.116)	(0.131)	(0.123)	(0.138)	(0.125)
Effect of 12-fantasy point increase						
0 points	0.121	0.127	0.124	0.116	0.110	0.116
60 points	0.101	0.103	0.102	0.096	0.091	0.095
100 points	0.087	0.086	0.087	0.082	0.078	0.081
200 points	0.052	0.045	0.050	0.047	0.047	0.046
Team Fixed Effects	No	Yes	No	No	Yes	No
Team-level Variables	No	No	Yes	No	No	Yes
Observations	446	446	446	427	427	427
R-squared	0.61	0.63	0.61	0.67	0.70	0.67

Notes: Each column is from a separate OLS regression. Robust standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively, for a two-sided test. The overall fantasy points effect measures the sum of all the relevant coefficients for a change in 12 points.

Appendix Table 2. OLS Model with Interactions between Fantasy Points and Position.

	2005-06	2015-16
Fantasy points	0.013***	0.019***
	(0.003)	(0.003)
Fantasy points^2/100	−0.002	−0.006***
	(0.001)	(0.002)

(continued)

Appendix Table 2. (continued)

	2005-06	2015-16
QB × Fantasy points	−0.010**	−0.010**
	(0.004)	(0.004)
QB × Fantasy points^2/100	0.004**	0.005***
	(0.002)	(0.002)
RB × Fantasy points	−0.003	−0.013***
	(0.003)	(0.004)
RB × Fantasy points^2/100	0.001	0.006**
	(0.002)	(0.002)
TE × Fantasy points	−0.003	−0.001
	(0.005)	(0.005)
TE × Fantasy points^2/100	0.002	−0.002
	(0.004)	(0.003)
Quarterback	0.405*	0.461**
	(0.212)	(0.180)
Running back	−0.080	0.027
	(0.115)	(0.119)
Tight end	0.134	0.251*
	(0.128)	(0.141)
Observations	446	427
R-squared	0.62	0.69

Notes: Each column is from a separate OLS regression. Although not reported in the table, each regression also includes the set of control variables listed in Column 2 of Tables 3 and 5. Standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively, for a two-sided test. The overall fantasy points effect measures the sum of all the relevant coefficients for a change in 12 points for a player of that position. For example, a running back's overall value would include the coefficients for fantasy points, fantasy points squared, as well as the interaction between running back and fantasy points and the interaction between running back and fantasy points squared.

Appendix Table 3. OLS Salary Cap Regressions for All Players Versus Veteran Players.

	2005-06		2015-16	
	All	Veteran	All	Veteran
Nonwhite	−0.018	−0.081	−0.091	0.00002
	(0.077)	(0.106)	(0.087)	(0.136)
Fantasy points	0.010***	0.013***	0.010***	0.012***
	(0.001)	(0.002)	(0.002)	(0.002)
Fantasy points^2/100	−0.001***	−0.002***	−0.001***	−0.002***
	(0.0005)	(0.0005)	(0.0005)	(0.0006)

(continued)

Appendix Table 3. (continued)

	2005-06		2015-16	
	All	Veteran	All	Veteran
Quarterback	0.154	−0.007	0.224	0.148
	(0.122)	(0.161)	(0.160)	(0.234)
Running back	−0.241***	−0.333***	−0.394***	−0.772***
	(0.081)	(0.125)	(0.083)	(0.142)
Tight end	0.034	0.134	0.100	0.060
	(0.080)	(0.106)	(0.094)	(0.149)
Experience	0.216***	0.170**	0.305***	0.018
	(0.033)	(0.069)	(0.033)	(0.101)
Experience squared	−0.014***	−0.012***	−0.019***	−0.004
	(0.002)	(0.004)	(0.003)	(0.006)
Games played	−0.009	−0.012	−0.014	−0.010
	(0.009)	(0.015)	(0.010)	(0.016)
First round draft pick	0.578***	0.165	0.560***	0.419***
	(0.111)	(0.145)	(0.128)	(0.152)
Second round draft pick	0.384***	0.340***	0.304**	0.509***
	(0.092)	(0.124)	(0.119)	(0.159)
Third round draft pick	0.265***	0.359***	0.085	0.155
	(0.089)	(0.134)	(0.114)	(0.192)
Undrafted	0.026	−0.015	−0.010	−0.090
	(0.086)	(0.125)	(0.084)	(0.161)
Pro bowls	0.123***	0.141***	0.142***	0.117***
	(0.029)	(0.031)	(0.029)	(0.031)
Arrested	−0.061	−0.098	−0.162	0.020
	(0.132)	(0.135)	(0.123)	(0.168)
Overall Effect of 12-Fantasy-Point Increase at Mean				
Quarterback	0.0885	0.0960	0.0697	0.0915
Running back	0.0952	0.1082	0.0934	0.1031
Tight end	0.1112	0.1369	0.1017	0.1302
Wide receiver	0.0988	0.1115	0.0934	0.1062
Observations	446	243	427	185
R-squared	0.61	0.62	0.67	0.68

Notes: Each column is from a separate OLS regression. Robust standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively, for a two-sided test. The overall fantasy points effect measures the sum of all the relevant coefficients for a change in 12 points (two touchdowns rushed/ received or three touchdowns thrown), calculated at the mean for that position.

Appendix Table 4. Logit and OLS Models for Having a Contract.

	2005-06 Data		2015-06 Data		Pooled Data	
	Logit	OLS	Logit	OLS	Logit	OLS
Nonwhite	−0.008	0.003	0.041	0.034	0.013	0.019
	(0.035)	(0.046)	(0.047)	(0.047)	(0.030)	(0.033)
Fantasy points	0.005***	0.003***	0.004***	0.004***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0004)
Fantasy points^2/100	−0.012***	−0.011***	−0.008**	−0.011***	−0.010***	−0.011***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)
Quarterback	0.089**	0.139**	0.171***	0.244***	0.126***	0.173***
	(0.037)	(0.059)	(0.038)	(0.076)	(0.028)	(0.045)
Running back	−0.018	−0.009	−0.010	−0.010	−0.014	−0.016
	(0.039)	(0.042)	(0.041)	(0.042)	(0.029)	(0.029)
Tight end	0.001	−0.007	0.070*	0.078	0.029	0.028
	(0.038)	(0.047)	(0.038)	(0.051)	(0.028)	(0.035)
Experience	−0.002	0.003	−0.030*	−0.035**	−0.020*	−0.022*
	(0.014)	(0.018)	(0.017)	(0.017)	(0.011)	(0.012)
Experience squared	−0.001	−0.001	−0.001	−0.0003	−0.0002	−0.0001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Games played	0.013***	0.022***	0.015***	0.019***	0.015***	0.020***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.002)	(0.003)
First round draft pick	0.000	0.003	−0.001	−0.031	0.003	−0.015
	(0.059)	(0.045)	(0.069)	(0.053)	(0.044)	(0.034)
Second round draft pick	0.015	0.018	0.069	0.039	0.047	0.037
	(0.045)	(0.048)	(0.052)	(0.052)	(0.034)	(0.035)
Third round draft pick	0.069*	0.079	−0.007	−0.030	0.034	0.023
	(0.041)	(0.049)	(0.060)	(0.056)	(0.036)	(0.038)
Undrafted	−0.070*	−0.105**	−0.032	−0.048	−0.049*	−0.070**
	(0.039)	(0.047)	(0.041)	(0.045)	(0.029)	(0.032)
Pro bowls	−0.016	−0.0001	0.014	0.021	−0.006	0.006
	(0.021)	(0.013)	(0.018)	(0.017)	(0.013)	(0.012)
Arrested	−0.015	−0.007	−0.059	−0.059	−0.051	−0.038
	(0.066)	(0.053)	(0.075)	(0.072)	(0.050)	(0.044)
Observations	589	589	587	587	1,176	1,176
(Psuedo) R-squared	0.24	0.22	0.21	0.21	0.21	0.21

Notes: Each column contains the marginal effects (for logit models)/coefficients (for the OLS model) and their standard errors from a separate regression. Robust standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively, for a two-sided test.

Authors' Note

This paper builds on the work done by Draisey (2016) and Mahoney (2009) for their respective undergraduate honors thesis projects.

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Notes

1. As we discuss in the data section, we use the terms "salary" and "salary cap value" interchangeably.
2. Kahn (1991, 2000) reviews the literature on labor economics and sports, not just football.
3. Our primary salary data source, spotrac.com (discussed further below), only provides current salary data.
4. The standard definition for fantasy points is as follows. Players receive 1 fantasy point for each 25 yards of passing thrown, 4 points for each touchdown pass thrown, −2 points for each interception thrown, 1 point for each 10 passing reception yardage, 1 point for each 10 rushing yardage, 6 points for each touchdown rushed/received, 2 points for each two-point conversion rushed/received/passed, and −2 points for each fumble lost.
5. To minimize the possibility of miscoding race, at least two people looked at each photo. If the two people disagreed, the authors looked at the photo and agreed upon the player's race.
6. As players who play in the Super Bowl do not play in the Pro Bowl, this variable measures being invited to the Pro Bowl whether or not the player actually participates in the Pro Bowl game.
7. Because so few players are arrested multiple times, we are unable to identify an effect of other measures of arrests such as the number of arrests.
8. Similarly, we estimate a probit model where the dependent variable equals one for players with a contract in 2016, where the sample is limited to players who played at least one game in 2015.
9. In results available from the authors upon request, the R-squared statistic from a model that contains only fantasy points and its square has an adjusted R-squared statistic of 0.47 in 2006 and 0.44 in 2016.
10. To convert the coefficient (β) into percentages, the calculation is percent $= 100 \times (e^{\beta} - 1)$.
11. The combined linear and quadratic effect of fantasy points is positive except for the top player, Shaun Alexander, who had 364 fantasy points in 2005.
12. In results available from the authors upon request, if we also include a dummy variable for being drafted in the fourth round, that coefficient is small in magnitude and statistically insignificant.

13. Even though the regressions are estimated on the conditional quantiles of the salary distribution, the table reports the effects for different points of the fantasy point distribution. We do so because these points on the fantasy points distribution are reported in Table 2, and they are easier to follow. Fantasy points and salary cap have a correlation of approximately 0.7.
14. Even though the salaries of rookies are highly structured after the 2011 CBA, we include all experience levels in the regressions for ease of comparison with the results for 2006 salaries. The results are similar, but much less precisely estimated, when we limit the sample to players with at least 4 years of experience (the 1st year when players can sign new contracts). These results, in Appendix Table 3, are discussed in more detail later.
15. This result is consistent with Arthur (2016), who reports longer career lengths for quarterbacks relative to other positions such as wide receiver.

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