Compensation Discrimination for Wide Receivers: Applying Quantile Regression to the National Football League

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Abstract: Keefer's recent article in the *Journal of Sports Economics (2013)* finds evidence of wage discrimination in the National Football League (NFL) market for linebackers. We examine the market for NFL wide receivers using similar techniques as Keefer, though we explore only rookies rather than all current players and wide receivers rather than linebackers. While we would expect to find stronger evidence of discrimination in the rookie market, as rookies are captured sellers, we find no pervasive pattern of pay discrimination by race in this market.

Keywords: National Football League, discrimination, compensation, rookie, quantile regression.

INTRODUCTION

The study of racial discrimination in professional sports has been an actively studied topic for decades, though much of this work has been done in sports other than the National Football League (NFL). However, the NFL itself has become highly conscious of this issue since the early 2000's. Indeed the NFL created a diversity committee in October of 2002 expressly to hunt for discriminatory practices and offer recommendations to reduce racial discrimination in the league.

Recommendations from this committee included training and development programs aimed expressly at minorities. For instance, one recommendation deals with hiring coaches: at least one minority must be considered for every high level coaching position. The opportunity to discriminate, however, cannot be fully eradicated by such rules. For instance, a coach can be interviewed but not seriously considered, even following this rule. Though this paper does not deal with coaches, as long as there exists the possibility of collusion against minorities regardless of position there may be compensation discrimination. The incentive to break this type of collusion is strong, however, as the impact of even a single extraordinarily talented player can be significant.

Becker (1973) discusses the classic types of discrimination, which usually rely on the three 'tastes' for discrimination. Those tastes consist of employer discrimination, employee discrimination, and customer discrimination. The first of these tastes, employer discrimination, represents the situation where an employer simply has a preference for hiring one type of employee and pays that group more than the non-favored group. The second form of discrimination mentioned by Becker, that of employee discrimination, is more subtle. One group of employees displays such a strong preference not to work with someone from a non-favored group that such discord essentially forces the employer to discriminate to prevent the loss of overall productivity from attempting to mix the groups. The third form of discrimination is customer discrimination, in which customers have such strong preferences that they that they change their purchasing habits significantly enough to provide an incentive for employers to discriminate against the non-favored group in order to maintain market share and profits.

Discrimination should be non-profit maximizing as a rival could hire the non-favored employees and create higher profits (in this case team wins), presumably driving the discriminating producer out of business. There have been suggestions, however, that discriminatory practices may not result in a negative outcome for the discriminators fast enough to bid it out of the market rapidly (Hellerstein, Neumark & Troske, 2002).

Professional sports, like any other for-profit business, define success by making profits. One way to make profit is to have a winning season. Having the best players is one way to attempt to have a winning record. Indeed, an argument can be made that in sports even one player can make a difference in a season record, a much stronger impact than a single employee is likely to make for a firm in other output markets. Therefore, there is a strong incentive for teams to find and recruit (drafted or undrafted) the best talent available. A team's talent scout who does not accomplish this will not retain his job. Should a team discriminate by pay, the rookie experiencing such

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discrimination will be highly unlikely to remain with that team after his initial contract expires and he becomes a free agent, so that discriminatory teams will be unable to retain the best talent. That incentive will lead to stronger incentives in sports against discriminatory actions than in the general market. It also suggests that the market for rookie players is most likely to have this type of discrimination, as a free agent player will have market forces to drive wages toward equilibrium.

Employee discrimination, when employees reduce overall productivity because they so dislike working with a fellow employee, can cause an employer to discriminate so as to prevent the reduction in overall productivity. While it is possible that players could find a fellow player so disagreeable that team cohesion would be reduced, so that the team may wish to reduce pay or eliminate that player, it is highly unlikely that this would be identifiable for a rookie player, such as those in our data set. In the case of rookies, there is little enough known about individual personalities to determine if there is likely to be strong enough clashes to cause something akin to employee discrimination, for any reason other than race. If there were strong enough group preferences, we would see teams that display such outcomes before the draft period begins, as existing preferences would have caused enough discord that teams would have been restructuring their teams in attempt to find racial harmony.

Customer discrimination, another of the classical 'tastes' for discrimination, may play a role. Customers can engender discrimination under certain circumstances, particularly where there are 'fan favourite' players who have enough fan loyalty to affect profits with stadium attendance, team memorabilia sales, or even TV market share. When players of this type come up for a new contract a team may have the incentive to overpay these players, relative to their contribution to the team's win/loss record. For instance, consider a player of average skill (or one whose skills have diminished due to age or injury). That player would likely either be released or see a compensation reduction. However, if that player is a fan favourite, the team may want to appease those fans by resigning such a player at a higher compensation than he is objectively worth. It has been shown multiple times that fans do seem to suffer from race preference (see Burnett & Van Scyoc, 2004, among many others). If this is the case, popular players may be overpaid on subsequent (non-rookie) contracts. A previous study (Keefer, 2013) use exclusively non-rookie players who may be subject to this type of discrimination. Our study uses only rookie players, making this form of discrimination unlikely to affect our results.

Academic work on salary discrimination by race among players of the NFL has been sparse, though two early studies were done by Mogul (1973, 1981). In neither of those studies did he find significant difference between black and white players' salaries. The samples involved, however, were small and were collected by surveying players, bringing in the potential for response bias. Kahn (1992), using data from the 1989 NFL Players Association, found that white players earned about 4.1% more, though this difference was not statistically significant, supporting Mogul's (1973, 1981) conclusions. Gius and Johnson (2000) used a data set of 938 NFL players from the 1995 season. Contrary to previous studies, they found that white players made 10% less than black players, even when controlling for player position. Berri and Simmons (2009) looked exclusively at the quarterback position, though that position is staffed mostly by white players. They found bias in favour of white players, perhaps because most black quarterbacks rely more on rushing than white quarterbacks, which is not rewarded as well as passing. Keefer (2013) studied 1,575 linebackers, between 2001-09, using various measures of quality and found salary discrimination against black linebackers. As his work represents all linebackers including those who have been in the league long enough to have become free (or restricted) agents and gone through multiple contract negotiation processes, he may have picked up issues involving customer discrimination as well as forms of employee and/or employer discrimination.

OUR APPROACH

Our sample of rookie players in the wide receiver position over the 2000-09 period (the only period for which data is available and consistent), represents a market with captured sellers as a drafted player is "forced" to sign with the team that drafted him. If he does not sign with his drafting team, he must sit out for a year which represents a very large opportunity cost, making this a less than fully efficient market. After being in the league for three seasons, a player becomes a restricted free agent and is able to receive bids from other clubs (the current team has the right to match any offers to a restricted free agent in order to retain the player, however). After four or more seasons and completing his initial contract, a player can become an unrestricted free agent so that he can sign with any club. In either case, the market setting a player's salary after the initial contract will be more efficient than the draft market as competition is allowed to operate, likely bidding away discrimination. Therefore, we have restricted out study to rookies with the idea that we will be more able to detect any discrimination in this market.

We concentrate on the wide receiver position. This position has players of both races, with about 13% of the players being white. Further, there are always a fairly large number of players in this position in the rookie draft and as teams generally have an ongoing need for wide receivers so the draft is fairly active for this position.

MODEL AND DATA

A. Model

We begin with the standard ordinary least squares (OLS) earnings function for player *i*'s salary for year *t*, y_{it}, with a vector of independent variables, including a racial identifier of $x_{i,t}$:

$$Y_{i,t} = \alpha + \beta x_{i,t} + \varepsilon_{i,t}$$

Equation 1: OLS Earning Function, which includes a racial identifier.

The traditional OLS earnings function approach estimates parameters at the conditional mean and is highly efficient but is quite sensitive to outlier values. The case at hand, athlete salaries, is one that is particularly prone to outliers. We follow Keefer (2013) and others, in using the quantile regression approach of Koenker and Bassett (1978), which is far more robust to the presence of outliers and non-normal distributions. Quantile regressions, whether segregated into quartiles, quintiles or other grouping, allows for the effect of the independent variables to vary across the distribution, with the assumption that the conditional θ^{th} segment of the dependent variable is a linear combination of the independent variables. There are several examples of quantile regression in the sports labor market, including Keefer (2013) and Vincent and Eastman (2009).

Interpreting the results from quantile regression to explore for discrimination can be done by examining, within each quantile, the observed net earnings differences decomposed into explained versus unexplained portions. The explained portion is due to differences in independent variables referred to as endowments, while the unexplained portion shows differences in the return to those endowments by race. It is this second portion that is the true measure of discrimination, as it suggests that different returns endowments are attributable to race.

There are two common types of decomposition of quantile regressions. The first method of decomposition is the Oaxaca Blinder decomposition using the OLS estimates at the conditional mean for each grouping of the overall dataset (white and black players). Using these separate groups, the difference in the coefficients are estimated by race within each group. As it is unknown *a priori* which race (if either) will be higher paid, the notations of H for high paid and L for low paid are used. The measure of discrimination (see Melley, 2006 and Keefer, 2013) is determined by whether the estimates of these coefficients differ by race.

$$Y_{i,t}^{H} = \alpha^{H} + \beta^{H} \times x_{i,t}^{H} + \varepsilon_{i,t}^{H}$$

$$Y_{i,t}^{L} = \alpha^{L} + \beta^{L} \times x_{i,t}^{L} + \varepsilon_{i,t}^{L}$$

$$\bar{Y}^{H} = \alpha^{H} + \beta^{H} \times \bar{x}^{H}$$

$$\bar{Y}^{L} = \alpha^{L} + \beta^{L} \times \bar{x}^{L}$$

$$\bar{Y}^{H} - \bar{Y}^{L} = (\alpha^{H} - \alpha^{L}) + (\beta^{H} - \beta^{L}) \times \bar{x}^{L} + \beta^{H} \times (\bar{x}^{H} - \bar{x}^{L})$$

Equation 2: Oaxcaca Blinder Regression Decomposition, where H and L designate the higher and lower paid group and where the coefficient differences, $(\alpha^{H} - \alpha^{L}) + (\beta^{H} - \beta^{L}) \times \bar{x}^{L}$ are the measure of discrimination.

The Oaxaca Blinder decomposition uses OLS estimates at the conditional mean, however, we extend this decomposition to the quantile regression results rather than being limited to the overall conditional mean. The overall data set is first broken down to sub-groupings by Total Salary ranking (all players with Total Salary in the lowest 10% in the lowest category regardless of race for instance). Tests for discrimination are then performed within each of these sub-groupings. Essentially, we substitute the segmented function for salary for each group, separated by a race binary variable **Black**(1 for black and 0 for white). This specification allows the estimator to be used for hypothesis testing and inference (see Melly 2006, and Keefer 2013). Bootstrapping is necessary to determine the estimated standard errors.

$$F_{Y(0)}^{-1}(\theta) - F_{Y(1)}^{-1}(\theta)$$

$$F_{Y(0)}^{-1}(\theta \mid \mathbf{Black} = 1) - F_{Y(1)}^{-1}(\theta \mid \mathbf{Black} = 1)$$

Equation 3: Quantile Treatment Effects (QTE), where $F^{-1}_{Y(\mathbf{Black})}(\theta)$ is the Θ^{th} segmented function of *Y* for **Blacks**.

B. Data

Our sample has 436 wide receivers of the 449 players in that position drafted during the 2000-2009 seasons[1]. The USA Today salary database maintained an online database of player salaries for all major sports and maintains consistency in their recording methods, at least between the years of 2000 and 2009 (they changed collection methods before that time and report no individual data after 2009). This database provides several different measures of player income, including Base Salary, Signing Bonus, Other Bonuses (incentives both personal and team based), Cap Value (the portion of a players contracted salary that contributes to the team's salary cap) and Total Salary. We follow Keefer (2013) by using the natural logarithm Total Salary for each player (substituting other measures of salary, such as Cap Value, did not significantly affect our results). Even though the rates of inflation during this period (2000-09) were quite low and fairly stable, we use inflation adjusted salary values[2] leading to the final form of our dependent variable, **Real Salary**. We also included year dummy variables for each year after 2000 so that any variations due to unusual conditions across years was picked up.

We are unable to use individual player or team statistics or other direct measures of player quality, as Keefer (2013) and others have done. In our case, using only rookie players, any of these statistics would not be directly comparable in any case as rookies come from a variety of different teams. Further, quality measures of this type may not adequately describe quality for several reasons, not the least of which is because football is a team sport: intangibles such as leadership, or attracting the opponent's blockers and thereby creating opportunities for teammates are extremely important but impossible to directly measure. Should we attempt to substitute team statistics of the teams they sign for as a measure of quality, we again run into the problem that our players are rookies, so that the only team data even remotely affected by our players would be those college teams from which they came. Again, those college teams would not be directly comparable across players. Since rookie players are chosen, and paid, based on what the team expects a player to produce rather than on past performance, using past statistics would be at most only measures of potential for skill at the professional level rather than proven ability. Other player data, such as that from the NFL combine, is not available for all our players. Of the payers that attended the combine, not all took the same tests (the most common test among this group was the sprint). As nearly a third of our players did not even attend the NFL combine, including many of the higher draft players, we would lose a significant amount of our data attempting to include such data.

Our only remaining measure of quality was draft pick order and status. We believe that major league General Managers and/or coaches (who determine the offers to incoming players), for whom judging quality is their responsibility, are likely to do a much better job than any mere compilation of barely comparable (or completely non-comparable) statistics. Certainly, they try to take into account intangibles as much as possible. Their judgments determine the draft position (or status) of each player. Our variable, **Draft** is the overall draft number regardless of round, for example, the 8th player taken would have a draft order of 8, even though he may be the first player taken in a given position taken.[3] Draft number will vary by quality as well as by need, though teams have an ongoing need for wide receivers (unlike some other positions) so they are likely to draft a high quality player even if that position is *not* a team's first priority.

Player quality is measured solely by draft pick number for those who were drafted (**Draft**) with low numbers signifying better draft picks and, presumably, higher expected quality. Those players who were not drafted were assigned a draft pick number of 0, which simply separates out those players who were not drafted and generates an intercept shift for those players. A binary variable to designate those players that ultimately received a contract without being drafted picks up those players (**Undraft**). This process generates estimated salaries that decline with increased draft pick number and greatly decreased estimated salaries for undrafted players. An example of

[1]The omitted players were those for whom we could find no pictures or mention of racial identifier.
[2]The authors also tried other variations of salary data – using Base Salary alone, with and without other bonuses, with and without inflation adjustment and find no significant differences in results.

[3]Altering the draft pick number to include round or by level (first drafted wide receiver being awarded a 1, rather than his actual draft number) do not significantly affect results. We also include annual dummy variables to account for any other variation over time than inflation rates.

this process shows predicted salary levels, using the simple OLS model (see Table **3**, below). We generated variables for three hypothetical players, all with the same racial identifier (**Black**=0, meaning a white player), but with different draft numbers and status (**Draft**=1, **Draft**=100, and **Undraft**=1), in the year 2000 (with no year dummy). We see the following results:

For a white first pick (best, meaning lowest, draft number) we would expect a ln(**Real Salary)** of 9.0886 + 0.2891 (**Black**=0) - 0.0108(**Draft**=1) - 2.5596 (**Undraft**=0) = 9.0778, for a nominal estimated total salary in 2000 of $1,443,781.93.

For a white player with draft pick of 100 (approximately the mean draft number) we would expect a **ln(Real Salary)** of 9.0886 + 0.2891 (**Black**=0) - 0.0108 (**Draft**=100) - 2.5596 (**Undraft**=0) = 8.0086 for a nominal estimated total salary in 2000 of $495,625.84.

For an undrafted player we would expect a **ln(Real Total Salary)** of 9.0886 – 0.2891 (**Black**=0) - 0.0108(**Draft=**0) - 2.5596(**Undraft**=1) = 6.5929 for a nominal estimated total salary in 2000 of $112,686.25.

These results indicate, as we would expect, that the better (lower) the draft pick, the higher the expected salary and undrafted players would see the lowest expected salary.

General summary statistics by race are found in Table **1**. We see that black players appear to be paid significantly more than white players. This prompts the thought that ‘minority’ players might indeed be seeing pay discrimination, as it is the whites in this case who are the minorities (as there are only approximately 13% of wide receivers who are white). There have been blog posts that suggest that ‘whites can’t catch’ or words to that effect, suggesting that there might be the general perception that white players in this position will be of inferior quality to blacks. We note, also, that the average draft number (of those players who were drafted) was much higher (worse) for whites than it was for blacks. Also more of the undrafted players were white than black. Again, these facts suggesting that white players are drafted later (suggesting lower quality) and a higher percentage of white players are not drafted at all in this position suggesting that even though they were eventually signed for a team, their skills were not valued highly enough to be drafted.

A further examination into salaries by race and draft status is found in Table **2**. We continue to see that black players are paid quite a bit more than white players, even separated by draft status. Overall black

Table 1: Summary Statistics by Race: Means

	All	Black	White
Total Salary	$826,826.30 ($1,290,688.06)	$892,469.70 ($1,353,625.39)	$352,459.60 ($462,912.86)
Black	.8784		
Undrafted	.3414	0.3107	0.5660
Draft(of those drafted)	116.92 (82.04)	113.55 (80.87)	153.87 (90.23)
2000	0.059633	0.0652742	0.0188679
2001	0.1146789	0.1096606	0.1509434
2002	0.1169725	0.1122715	0.1509434
2003	0.1353211	0.12532637	0.20754717
2004	0.0963303	0.0992167	0.0754717
2005	.01009174	0.1018277	0.0943396
2006	0.0917431	0.091383	0.0943396
2007	0.0894495	0.0966057	0.0377358
2008	0.0917431	0.1014439	0.0754717
2009	0.103211	0.104439	0.0943396
n	436	383	53

Standard deviations in parentheses.

Table 2: Mean Total Salary by Draft Status and Race

	Black	White
All	$892,469.70 (383)	$352,459.6 (53)
Drafted	$1,160,756 (264)	$554,733.80 (23)
UnDrafted	$297,279.40 (119)	$197,382.70 (30)

Counts in parentheses.

players are paid over two and a half times what white players are paid. Drafted black players get, on average, just over twice what drafted white players were paid. The pay ratio of undrafted players by race shows a smaller gap of only 1.5 in favor of black players. It is the difference in the ratios of draft to undrafted status by race that tip the overall pay figures.

ESTIMATION RESULTS

Examining the OLS initial results using the dummy variable approach, show that the binary racial indicator variable, **Black**, is significant and positive, suggesting that blacks are paid better than whites overall. The quantile approach does not show that blacks are paid better, when results are estimated by- sub groups. We see that in each of these income groupings (lowest 10%, lowest 25%, median group, top 25% and top 10%) it is other characteristics such as draft number or

Table 3: OLS and Quantile Estimates for Dummy Variable Regressions

Dependent Variable =Ln(Real Total Salary)						
		Quantile				
Variable	**OLS**	**Q10**	**Q25**	**Q50**	**Q75**	**Q90**
Black	0.2888491** (0.1212143)	0.1131635 (0.2855633)	0.1345493 (0.145804)	0.0277176 (0.0731198)	0.0503173 (0.0579906)	-0.0393751 (0.1302672)
Draft	-0.0112934*** (.0006519)	-0.0103819 (0.0011379)	-0.110124*** (0.0007586)	-0.0100729*** (0.0006129)	-0.0110678*** (0.0004424)	-0.109956*** (0.0006639)
Undraft	-2.649005*** (0.1170153)	-2.300579*** (0.2675123)	-2.418513*** (0.1230326)	-2.260251*** (0.1226304)	-2.435665*** (0.0966345)	-2.422118*** (0.171891)
2001	0.5632532*** (0.1995651)	-1.027565 (0.6838048)	0.2952016 (0.4190179)	0.8057821*** (0. 1626304)	1.037197*** (0.2079737)	1.085632*** (0.2830568)
2002	0.2269284 (0.1996485)	-1.54946** (0.778881)	-.0602273 (0.4190179)	0.5948165*** (0.2107555)	0.8121463*** (0.1835876)	0.8151328*** (0.2709916)
2003	1.061662*** (0.196139)	0.908565*** (0.1193892)	1.078505*** (0.1010439)	0.8625238*** (0.1234669)	0.8151084*** (0.1767375)	0.6252809* (0.3388444)
2004	0.7353344*** (0.2046076)	0.2670923 (0.5044981)	0.6409357*** (0.1309034)	0.6100573*** (0.1193308)	0.6976546*** (0.2371476)	0.9742152** (0.4871395)
2005	0.7885199*** (0.2026675)	0.6347867 (0.5420364)	0.480768*** (0.1171679)	0.7884125*** (0.1155138)	0.7615621*** (0.1842779)	0.7543718 (0.6666637)
2006	0.8632962*** (0.2083542)	0.7839079*** (0.164282)	0.8327224*** (0.0938149)	0.8047053*** (0.1016907)	0.8669749*** (0.1904839)	0.5009037* (0.2979395)
2007	0.8347231*** (0.2059055)	0.8983523*** (0.1787007)	0.8911961*** (0.0799748)	0.9762974*** (0.1305084	0.7965365*** (0.1838577)	0.72266363*** (0.2671057)
2008	1.182143*** (0.2057752)	1.072583*** (0.1036746)	1.063386*** (0.0799748)	0.9762974*** (0.1305084	1.080093*** (0.1720097)	0.7606526 (0.5797885)
2009	1.044543*** (0.2018775)	0.9703727*** (0.1423909)	1.038037*** (0.0734549)	1.00747*** (0.1287531)	0.931038*** (.01806532)	0.7581941*** (0.2766802)
Constant	8.402446*** (0.2079259)	8.9091122*** (0.3044756)	8.251208*** (0.1482655)	8.500908*** (0.1176787)	8.754061*** (0.1757691)	9.214548*** (0.25395)
R^2 (pseudo)	0.6007	0.4436 (pseudo)	0.4058 (pseudo)	0.4950 (pseudo)	0.5499 (pseudo)	0.4870 (pseudo)
N	436					

Note: Standard errors in parentheses. Quantile standard errors computed from 1,000 bootstraps. R^2 reported for OLS, Psuedo R^2 reported for quantile regressions.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

status that holds more explanatory power for salary than race (with the exception of the lowest salary group, showing no significance for draft number though there were no drafted players in that group so only the overall mean is picked up by the model).

The traditional OLS method is quite sensitive to outliers, a factor inherent in athlete salaries, which would imply that this method would not be very robust for our application. Using the quantile approach, so that outliers do not shift the overall results, creates a far more robust estimation method. The quantile approach showing no racial effect, suggests that it may be outliers driving the OLS results.

Table **4** shows results from the decomposition methods mentioned earlier as they explore further for evidence of discrimination. The Blinder-Oaxaca method splits the data set between the two racial groups, setting whites as Group 1 and blacks as Groups 2 and compares the resultant differences, so that positive differences indicate higher values for whites and negative differences show higher values for blacks. Discrimination, or differences according to group status, is seen when there is significance on the coefficient differences between the groups suggesting that players with identical characteristics are paid differently based only on their race. Differences to endowments or overall differential can be attributed to differences that are may be due to the quantifiable characteristics of the groups (for instance, since blacks have better draft numbers and we would *expect* to see players with lower draft numbers get paid better, to the extent that blacks with lower draft numbers are paid better is not due to discrimination). What we see is that, for these overall groupings, there are negative values showing higher value for blacks for total differential, endowments, and even for the coefficient estimates. However, though there is strong significance for total differential and endowments, there is no significant difference for coefficient estimates suggesting that black players who have better draft numbers are generating the overall results rather than discrimination.

The QTE decomposition performs this same sort of analysis, but with the difference that the data set is further broken down into groupings based on levels of total salary. We use the same quantile breakdowns as we did for the dummy variable approach. Our results showthat we continue to see significant differences for total differential at all levels and differences in endowments at the middle and 75% percentiles. Those differences have the black players with higher levels of total differential and endowments. It is also these two groups, 50% and 75% that show coefficient differences suggesting discrimination in favor of blacks at the 5% significance level.

CONCLUDING REMARKS

We find no body of evidence in our sample that there exists broad based racial salary discrimination in the position of wide receiver in the NFL between the years of 2000 and 2009. Traditional OLS results are suggestive that there may be such discrimination, albeit

Table 4: Decomposition Results, Oaxaca-Blinder and QTE

	Dependent Variable =Ln(Real Total Salary)					
	Oaxaca- Blinder	**QTE**				
	OLS	**Q10**	**Q25**	**Q50**	**Q75**	**Q90**
Total Differential	-0.8171429*** (0.205902)	-1.32402*** (0.078794)	-0.373873*** (0.046104)	-0.448632*** (0.10214)	-1.10164*** (0.091131)	-0.958797*** (0.081307)
Endowments	-0.5265005*** (0.1222522)	-0.62063 (0.551063)	-0.277382 (0.227455)	-0.244833** (0.092112)	-0.706426*** (0.216201)	-0.511718 (0.311516)
Coefficients	-0.3213385 (0.2127271)	-0.703387 (0.809103)	-0.096491 (0.22936)	-0.203799*** (0.046262)	-0.395212*** (0.139896)	-0.447079 (0.347517)
R^2	Group 1: 0.4782 Group 2: 0.6110					
N	Group1: 53 Group 2: 383					

Note: Standard errors in parentheses. Quantile standard errors computed from 50 bootstraps. R^2 reported for OLS Oaxaca-Blinder only.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

in favour of blacks; however, upon the disaggregation of the data into sub-groupings that evidence evaporates. Likely the naïve estimates from the OLS model are unduly influenced by outlier data. When we look at the Oaxaca-Blinder style of estimation the evidence suggests that most of the difference in salary arises from differences in characteristics of the players with black players having better draft position and more of the white players being of the undrafted (and hence lower paid) variety. There are two sub-groupings that do show some evidence of slight discrimination using the Oaxaca-Blinder decomposition by quantile. These two groups represent a small subset of players (less than one third of the players are in these two groups in total) and it contradicts the evidence found for those quantiles with our other methods of estimation. We are left to conclude that the evidence is too weak to state categorically that there were large levels of discrimination in these groups.

This result runs contrary to Keefer (2013) but supports that from Burnett and Van Scyoc (*forthcoming*) and earlier results by Mogul (1973, 1981) and Kahn (1992). This, despite the fact that we used rookie data where we would expect to find the strongest evidence of such discrimination since we are dealing with captured sellers. There are several potential explanations why Keefer found discrimination while we did not. For instance, much of our data reflects players (and their salaries) who joined the league after the initial push in the early 2000's in the NFL to uncover and remedy discrimination, while the majority of the players in Keefer's data had been hired into the league before that time as he was working with all currently active players over those years. Rookie players will be less prone to fan (customer) discrimination as they have yet to become widely known to the fan base of any particular team. Also, the possibility of collusion exists in the market for Rookies that disappears in subsequent player contracts. Therefore, we have separated out customer discrimination leaving, as much as possible, only employer discrimination by using Rookies. The fact that we find no pervasive evidence of racial discrimination suggests that teams are not acting with racial motivation when setting initial contract salaries.

Additionally, it is possible that black players actually have different skill sets, making them appear more talented based on the type of measured characteristics used by Keefer (2011), suggesting they would warrant higher salaries making it appear that there were actually discriminatory practices occurring. However, if pay is actually a reflection of overall ability (including intangibles that would not be picked up by the type of characteristics used by Keefer, but taken into account by NFL scouts and therefore reflected in draft pick numbers) and if it is the case that black players have more of these intangibles, pay may actually be appropriately allocated (cases of this would be shown with differences in endowments in the Oaxaca-Blinder and QTE decompositions like we observed).

Also, for those players in the draft, rather than for undrafted players, there is also some limit on the variability of salary offers relative to draft pick rankings. Salary and contract offers for those players are closely scrutinized and it is rare for salaries to 'overlap' draft pick ratings (for instance, the player picked second or third would not usually be paid more than the player picked first, for instance). Hence, for drafted players there is a sort of built in pay scale that does not allow much leeway for discrimination. Should that be a strong deterrent to discrimination, we would then expect to see more discrimination among the undrafted players, reflected in the lower paid groupings (lowest and next to lowest groups). Neither of these lower groups demonstrated any evidence of discrimination in either of our quintile models. Therefore, we again conclude that we see no overwhelming evidence of racial discrimination in pay in the position of wide receiver in the NFL incoming players over the years 2000-2009.

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