COMPENSATION DISCRIMINATION IN THE NATIONAL FOOTBALL LEAGUE

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ABSTRACT

Keefer's recent article in the Journal of Sports Economics (2013), "Compensation discrimination for defensive players: applying quantile regression to the National Football League market for linebackers," finds wage discrimination in the National Football League (NFL) for linebackers. We examine the market for NFL tight ends using the same techniques as Keefer, though we explore only rookies rather than all current players and tight ends 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 for tight ends.

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 discrimination in both hiring and compensation by race since the early 2000's. The NFL created a diversity committee in October of 2002 expressly to hunt for discriminatory practices and offer recommendations to reduce racial discrimination of all types in the league.

Recommendations from the diversity committee included training and development programs aimed expressly at minorities. For instance, one recommendation, the so-called 'Rooney Rule' named after the chair of the committee Dan Rooney, ensures that at least one minority coach must be considered for every high level coaching position that opens in the league. The opportunity to discriminate against either coaches or players, however, cannot be fully eradicated by such rules. Though this paper does not deal with coaches, there exists the possibility of compensation discrimination by race as long as there is the possibility of collusion again black players or coaches. Without collusion, teams not discriminating would be able to hire talented black players at lower cost and increase their winning record, effectively bidding out most of the discrimination among teams (assuming teams put winning as a top priority). The incentive to break collusion of this type is strong, however, because even a single extraordinarily talented player can make a huge impact on a team.

When it comes to discrimination, Becker (1973) discusses the three classic types or 'tastes' of discrimination. They are employer discrimination, employee discrimination, and customer discrimination. 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 type of discrimination mentioned by Becker, that of employee discrimination, is more subtle. In that case, one group of employees displays such a strong preference not to work with someone from a non-favored group that the resultant 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, likely driving team revenue and profit), 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 retain the best talent available, regardless of race. This reduces the likelihood of employer discrimination in a for-profit scenario where profit hinges on having talented players. A team's talent scout or general manager who does not accomplish this will not retain his job. Should a team discriminate by pay, the rookie experiencing such 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 sufficiently so that a team may wish to reduce pay or eliminate that player, it is highly unlikely that this would be identifiable for a rookie player at least based on an individual's personality. A team with significant racist tendencies may attempt to ostracize all players of the other race to the extent that a team would recruit with such tendencies in mind; however, if a team were to be so racist, one would expect to see such a team already exhibit race bias in previous player choices. Such teams would already be nearly all white or all black, in other words. The fact that we do not currently see teams with such bias in membership suggests that this type of racism is not terribly prevalent.

Customer discrimination, another of the classical 'tastes' for discrimination, may play a more significant role in sports. 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). Logically 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, even potentially paying 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) uses 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, as fans have yet to establish strong favourites among pre-professional players.

Academic work has been done on salary discrimination by race among players of the NFL. Mogul (1973, 1981) did not show difference between black and white players' salaries. The samples involved, however, were small and were collected by survey, bringing in the potential for response bias. Another fairly dated study by Kahn (1992), using data from the 1989 NFL Players Association, found that white players earned about 4.1% more than non-whites, 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 Simms (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 usually 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 'captive' market since the 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. The result is a market that is less than fully efficient. This problem does not dissipate until competition is brought to bear on a player's salary. In this case, after a player has been in the league for three seasons and completed his initial contract, 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, so the market becomes fully competitive for those players. 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 to at least some extent, likely bidding away discrimination. Therefore, we have restricted our study to rookies with the idea that we will be more likely to detect generalized racial discrimination in this market. Individual players may be paid at a rate not commensurate with their measurable talents even in the case of free agents for non-race related reasons such as being a fan favorite, though this is not likely to be the case with rookies. One drawback to this approach is that we are unable to use quality measurements obtained from play within the NFL as rookies have yet to play at that level.

We concentrate on the tight end position. This position has players of both races, with about 44.5% of the players being black. 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 tight ends, the draft is fairly active for this position.

MODEL AND DATA

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, in $x_{i,t}$:

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

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 expanding the analysis to the use of quantile regressions (see 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), Burnett and Van Scyoc (*forthcoming*) and Vincent and Eastman (2009).

Quintile regressions subdivide the data into five sub-groups based on the dependent variable. In our case, we follow Keefer (2013), and others, and use sub-groups of the lowest 10%, up to 25%, median, upper 25%, and top 10% (listed as 10%, 25%, 50%, 75%, and 90%). Once the data has been broken up in that way, OLS regressions are run (including a racial identifier) for each sub group. That way, the coefficients are determined not relative to the overall mean of the dataset but for the mean of each sub group. Discrimination is found if there are significant differences by race in each group. As the top and bottom groups will likely have the biggest outliers, we are able to reduce the outlier effect on the remaining results.

A second method of exploring data for discrimination, involves breaking the data into two groups by a common characteristic (such as race), then estimating each group separately. A statistical comparison of those two groups is performed for overall differences, then differences due to endowment or characteristic differences (such as player quality variables), and then by coefficient on the contribution of those characteristics to the total differential. If there are any significant differences in the coefficient estimates between the racial groups, that indicates quality is paid differently dependent upon race and discrimination is identified. This is known as the Oaxaca-Blinder decomposition. In general, using H as the designator for the higher paid group and L for the lower paid group, and the various vectors of income (Y_{it}) and descriptive variables ($x_{i,t}$, less the racial descriptive), our model becomes:

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

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

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, due to the impact of outlier data inherent in athlete salaries. 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.

$$F^{-1}_{Y(0)}(\theta) - F^{-1}_{Y(1)}(\theta)$$
$$F^{-1}_{Y(0)}(\theta|\mathbf{Black} = 1) - F^{-1}_{Y(1)}(\theta|\mathbf{Black} = 1)$$

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

Data

Our sample consists of an original data set of 281 players that joined the NFL in the position of tight end during the 2000-2009 seasons (there are a small number of omitted players for whom we could find no pictures or mention of racial identifier). USA Today maintained an online database of player salaries for all major sports and maintained consistency in their recording methods only between the years of 2000 and 2009 (they changed collection methods before that time and report no individual data after 2009). The database provides several different measures of player income, including Base Salary, Cap Value (the portion of a players contracted salary that contributes to the team's salary cap) and Total Salary (Base Salary including all Bonuses). We take the natural logarithm of Total Salary, adjust for inflation, and obtain **Ln Real Salary** for each player in our dataset (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 these inflation adjusted salary values as our dependent variable (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).

We measure player quality using draft pick order and status. We believe that major league general managers and scouts, for whom judging quality is an integral part of their job, are likely to have a better idea of quality than any mere compilation of barely comparable (or completely non-comparable) statistics. Certainly, teams try to take into account intangibles as much as possible, even though such characteristics do not show in any measurable variable. College playing statistics are non-comparable due to variances across the wide array of college teams. Not all players even attend the NFL combine before the draft, and even those that do attend do not all compete with the same tests, making those scores also non-comparable.

Our first variable, **Draft,** is the overall draft number regardless of round, for example, the 8^{th} player taken would have a draft order of 8, even though he may be the first tight end player taken. Draft number will vary by quality as well as by need, though teams have an ongoing need for tight ends (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 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 then designates 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 this process shows predicted salary levels, using the simple OLS model (see 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) assuming the year is 2005 (approximately half way through the timespan of our data). We see the following results:

> For a white first pick (best, meaning lowest, draft number) we would expect an **Ln Real Salary** = 9.084221 + 0.1373058 (**Black**=0) - 0. 0101995 (**Draft**=1) - 1.895866 (**Undraft**=0) = 9.0740215 , for a nominal estimated total salary of $1,658,723.
> For a white player with a draft pick of 100 we would expect **Ln Real Salary =** 9.084221 + 0.1373058 (**Black**=0) - 0. 0101995 (**Draft**=100) - 1.895866 (**Undraft**=0) = 8.064271 , for a nominal estimated total salary of $620,827.06.
> For a white player that was not drafted, but merely signed at some point after the draft we would expect an **Ln Real Salary =** 9.084221 + 0.1373058 (**Black**=0) - 0. 0101995 (**Draft**=0) - 1.895866 (**Undraft**=1) = 7.188355 , for a nominal estimated total salary of $258,562.27.

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, on average, quite a bit more than white players. Further, we note that the average draft number (of those players who were drafted) was higher (worse) for whites than it was for blacks, which may explain the pay differential. However, draft pick number and status are based upon team preferences and if those preferences are discriminatory, draft numbers may simply reflect the racist views of the league. If that is the case a single *non*-discriminating team would appear to be able to pick up a player whose talent is under estimated (or under-appreciated due to the race of the player) for less salary than he would otherwise be worth. Should that be the case, the non-discriminating team would get more talent for less overall pay than other teams. That should prove significant incentive to break any collusion for race based pay discrimination. Additionally, we see slightly more black players were undrafted than white players, suggesting that teams were not completely passing over white players in favor of black players.

Table 1 Summary Statistics (Means) by Race			
	All	Black	White
Total Salary	$620,873.90	$674,964.40	$577,532.20
Black	0.4448		
Undrafted	0.5338078	0.5440	0.525641
Draft (of those drafted)	130.458	125.0351	134.6351
N	281	125	156

A further examination into salaries by race and draft status is found in Table 2. We continue to see that black players are paid more than white players and that pay differential becomes much larger among drafted players than among undrafted players. Among the undrafted players pay is far more equal, though there is, again, a slight positive differential in favor of black players.

Table 2 Mean Total Salary by Draft Status and Race		
	Black	White
All	$674,964.4 (125)	$577,532.2 (156)
Drafted	$934,909.7 (57)	$749,559.9 (74)
UnDrafted	$457,069.0 (68)	$422,287.6 (82)

Counts in parentheses.

ESTIMATION RESULTS

Examining the OLS initial results using a dummy variable as a racial indicator, we find the binary racial indicator variable, **Black**, is significant at the 20% level and positive, suggesting that blacks are paid better than whites overall. The quantile approach, as pioneered by Melly (2006) does not show that blacks are paid better until reaching the top 10% of players when results are estimated by sub-groups, and that difference is only significant at the 20% level as well, suggesting that outlier salaries may be driving the overall OLS results. In all of these income groupings (lowest 10%, lowest 25%, median group, top 25% and top 10%) it is clear that the other characteristics of player quality (draft number and draft status) holds more explanatory power for salary than race.

One characteristic of the traditional OLS method is that it is quite sensitive to outliers, a factor inherent in athlete salaries. Therefore, the very nature of this type of dataset would suggest strongly that traditional OLS methodology would be less than optimal. Using the quantile approach, so that outliers do not shift the overall results, creates a far more robust estimation method. In this type of estimation, outliers only skew the bottom and top sub-groupings. Indeed, in our results we see that race only shows significance (and then only at the 20% significance level) in the top group which is potentially prone to the outlier effect.

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	0.1373058* (0.0916631)	0.2638502 (-0.009608)	-0.0148139 (0.0657167)	0.0503832 (0.0743598)	0.1216598 (0.1260055)	0.2296609* (0.1420985)
Draft	-0.0101995*** (0.0009509)	-0.009608*** (0.0029646)	-0.0096281*** (0.0010964)	-0.0090869*** (0.0008266)	-0.0093056*** (0.0009613)	-0.0115692*** (0.000923)
Undraft	-1.895866*** (0.153916)	-1.968088*** (0.4769316)	-2.020471*** (0.1486877)	-1.85943*** (0.1426745)	-1.713681*** (0.1828468)	-1.662762*** (0.2718102)
Constant	9.084221*** (0.1479093)	8.9091122*** (0.3044756)	8.874375*** (0.1477246)	9.015474*** (0.1265668)	9.294398*** (0.1497514)	9.214548*** (0.25395)
R^2 (pseudo)	0.3619	0.0898 (pseudo)	0.1873 (pseudo)	0.2789 (pseudo)	0.3014 (pseudo)	0.2947 (pseudo)
Observations	281					

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 20%.
**Significant at 5%.
***Significant at 1%.

Table 4 shows results from the Blinder-Oaxaca decomposition method, which breaks down the data set into high and low paid groups and then compares regression results from the two groups (either from the overall dataset or the quantile sub-groups). It is in the comparison of the two groups that discrimination can be seen if differences arise from different estimates of the coefficients rather than from different endowments (or characteristics). In the two groups, one would expect that the higher paid group would have better measured characteristics (in this case, we would expect higher paid athletes to have been drafted, rather than undrafted, and have lower draft pick numbers. As long as differences across the two groups can be accounted for with such measurable characteristic differences, there would be no evidence of discrimination. It is if the two groups *also* have different estimated coefficients that we would be seeing discrimination. For example, that would be the case if one group were paid an average of $50,000 for each incremental better draft pick, while for the other group the players were paid an average of $20,000 for each incremental better draft pick. This method, then, 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. The differences are only significant at the 20% level for overall differences and coefficients. Since these results are not broken down by quintile they may reflect outliers that overshadow the results. Indeed, when looking at the QTE results of this decomposition method, it becomes clear that in no case are there significant differences between coefficients across the higher and lower groups within the quintile sub-groups.

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	-0.1723601* (0.1125624)	0.203304** (0.101427)	0 (0.054332)	-0.010831 (0.127886)	-0.240324* (0.129338)	0.050901 (0.127282)
Endowments	-0.0353832 (0.0667955)	0 (0.188346)	-0.013554 (0.043622)	0.030629 (0.0943)	0.11159 (0.118754)	0.072988 (0.119991)
Coefficients	-0.1373646* (0.089948)	0.203304 (0.180736)	0.013554 (0.037085)	-0.04146 (0.084984)	0.128734 (0.118528)	-0.022087 (0.125282)
R^2	Group 1: 0.3138 (White) Group 2: 0.4282 (Black)					
N	Group 1: 156 (White) Group 2: 125 (Black)					

Note. Standard errors in parentheses. Quantile standard errors computed from 50 bootstraps. R^2 reported for OLS Oaxaca-Blinder only.
*Significant at 20%.
**Significant at 5%.
***Significant at 1%.

CONCLUDING REMARKS

We find no body of evidence in our sample that there exists broad based racial salary discrimination in the position of tight end in the NFL between the years of 2000 and 2009. Traditional OLS results suggest that there may be such discrimination, albeit in favour of blacks; however, upon 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 is only one two sub-grouping that shows any slight evidence of discrimination and that is the top sub group of the OLS/Melly(2006) QTE. That evidence is only at the 20% significance level, and could well be due to a few outliers (specifically, outliers that would be a the top of the drat pick or ‘stars’ that could well be overpaid due to the hype of the draft). In the Oaxaca-Blinder decomposition method again we see significance at the 20% level for the overall group for different coefficients but that disappears in all of the Oaxaa-Blinder quintile analysis. In general, what slight evidence we see in favour of discrimination shows first that blacks are *better* paid than whites and second is likely to be true only because of a few outliers from the very top of the drafted players.

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 (2013) 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.

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 (2013), 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 general managers 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). Hence, for drafted players there is a sort of built in pay scale that does not allow much leeway for discrimination. If drafted players are simply paid much more than undrafted players, there could be some discrimination if, say, black players are more likely to be drafted and white players are more likely to be signed as undrafted players. In our dataset, however, more of the undrafted players are black rather than white (though this is by a slim margin). Therefore, we again conclude that we see no overwhelming evidence of racial discrimination in pay in the position of tight end in the NFL incoming players over the years 2000-2009.

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