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Do white NBA players suffer from reverse discrimination?

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Abstract

The National Basketball Association (NBA) has been fertile ground for the study of discrimination due to demographic and cultural shifts in not only the teams but also the fan populace. The early research found evidence of black-white wage differentials and customer discrimination (Kahn and Sherer, 1988). However, this effect has gone away as customers have become more accustomed to African-Americans in the NBA. Recent research has now shown that the pendulum has swung in the other direction and find the existence of reverse discrimination (Groothuis and Hill, 2013; Yang and Lin, 2010). In this paper, I test whether there exist reverse discrimination with White athletes in the NBA. Following Altonji and Pierret (2001), I use a statistical discrimination with employer learning framework to estimate the model. Unlike previous work, I incorporate advanced basketball metrics like Player Efficiency Rating (PER) and Win Shares (WS) to measure player productivity. The results find no evidence of reverse discrimination occurring.

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1. Introduction

The study of labor market discrimination in Economics has often used sports as a platform, especially with the National Basketball Association (NBA). The NBA provides fertile ground for the study of discrimination because of the wide racial and cultural shifts over its 50 year history. Studies of racial wage discrimination have focused on three types of discrimination: employer, co-worker, and customer discrimination. Most of the research in basketball finds evidence of customer discrimination (Hamilton, 1997; Kanazawa and Funk, 2001; Stone and Warren, 1999)[1]. In general, there is little evidence of traditional racial wage discrimination in the NBA[2]. With new contract structures for rookies and rules about other categories, there should be less wage discrimination. In fact, monopsony power is only present with non-rookies with less than 3 years of experience and rookies not drafted in the first round. However, recent research has shown possible reverse wage discrimination against White American players (Groothuis and Hill, 2011; Yang and Lin, 2010).

Statistical discrimination may explain reverse discrimination because traditionally the best players in the NBA are African-American and over the past 25 years there have been few White American athletes to excel in the NBA[3]. While there have been an influx of White international players from European and South American countries, White Americans are generally not considered elite athletes. Thus, White Americans who aspire to the NBA may see lower wages, in the case where teams are able to exert monopsony power, relative to African-Americans and international players.

In this paper, I test whether potential discrimination occurs with White American NBA players, using the Altonji and Pierret (2001) statistical discrimination with employer learning (EL-SD) framework. I define White American athlete as an individual who is a Non-Hispanic White person who grew up primarily in the United States. This paper makes two significant contributions. The first contribution is testing whether statistical discrimination can explain racial wage discrimination. The second contribution is the use of advanced measures of player productivity like Player Efficiency Rating (PER) and Win Shares (WS), instead of the standard measures like points, rebounds, and assists to measure productivity. The paper does not find any evidence of wage discrimination against White NBA players.

2. Empirical Framework

Altonji and Pierret (2001) develop a model to test whether statistical discrimination occurs in the labor market. Their contribution to the literature was the first empirical test of statistical discrimination. They set up a model where labor market productivity is a function of a variable that is the basis of statistical discrimination like race. How statistical discrimination works is that an employer uses race, in addition to other observable correlates of productivity like education and work experience, to predict the productivity of a new worker. Hence, the initial wage would be low because of the new employee's race. As time passes and the employer can observe actual

[1] There have been other alternative theories to explain racial wage gaps. McCormick and Tollison (2001) give a supply side argument to explain racial wage gaps. They argue African-Americans face a different opportunity set than Whites and thus there is a greater supply of African-American NBA athletes which leads to lower wages for them. Burdekin et al (2005) argue the composition of the market area plays a role in the differential wages.
[2] Kahn (2009) provides a review of the empirical evidence of wage discrimination over the past 30 years.
[3] Kevin Love made 2nd team All-NBA is 2011-2012 season. The last White American NBA player to make 1st or 2nd team All-NBA before that was John Stockton in 1995-96.

productivity, race should play less of factor in the employee's wage. The empirical model to show statistical discrimination is given below:

$$w_i = \beta_0 + \beta_1 r_i + \beta_2 z_i + \beta_{r,x} * (r_i * x_i) + \beta_{z,x} * (z_i * x_i) + f(x_i) + \beta_\theta' \theta_i + \varepsilon_i \quad (1)$$

The log wage is a function of race (r_i), an unobservable characteristic correlated with productivity (z_i), experience (x_i), and other controls (θ_i). If statistical discrimination occurs, the coefficient on race will get smaller with the inclusion of the z variable interacted with experience. Since z is correlated with productivity, as experience increases, salary increases will be due more to the z variable rather than race.

For this study, the key to estimating this model is finding z variables. Given the wealth of information about the quality of basketball players, it is difficult to conceive of correlates to productivity that are unknown to those who follow the NBA. Kids as young as four or five have videos on Youtube showing off their basketball skills. AAU programs[4] are ubiquitous around the nation and are well-known to even casual observers. The measure I use as a z variable is the share of NBA players that came from the player's hometown. I have information on the hometowns of 3,802 NBA players[5]. For each player I find every (current and former) player whose hometown is within a 50 mile radius[6]. I divide this number by the total number of NBA players. It can be argued that athletes from the area that produces a lot of NBA talent is correlated with productivity but not readily seen by the employer, like AFQT scores[7]. It is difficult to know how talented an individual is, even if you know they are from New York or Chicago. However, growing up and playing basketball in the streets of New York or Chicago is a form of skill accumulation that can lead to NBA productivity.

3. Data and Methodology

The first model estimated tests whether discrimination against White players occurs. The traditional model of racial wage discrimination can be expressed as:

$$w_i = \beta_0 + \beta_1 r_i + f(x_i) + \beta_\theta' \theta_i + \varepsilon_i \quad (2)$$

where w_i is the individual player's salary, θ_i is a vector of player performance characteristics, team factors, and market factors, and r_i is a dummy variable representing the individual player's race. Player performance characteristics usually include points scored, rebounds, assists, steals, and blocks accumulated by the player on a per-game basis[8]. Other controls include the player's position, whether the player was born in a foreign country, where they were drafted[9], and how long they have been in the NBA. Market factors include demographic and financial data for the MSA where the team is located. Per-capita income, population, and percent of the MSA that is White represent the market factors. The data is a cross-section of 432 NBA players for the 2010-

[4] Amateur Athletic Union (AAU) is a national program to show off the skills of talented youth in a variety of sports. This is the primary avenue for young men in basketball programs to get recruited to the top college basketball programs.
[5] This data was collected by Reuben Fleischer-Baum. Methodology and description of the data can be found at this website: http://deadspin.com/infographics-where-do-pro-basketball-players-come-from-513261549
[6] I use the STATA program NEARSTAT (Jeanty, 2012).
[7] This is the Armed Forces Qualification Test (AFQT). Altonji and Pierret (2001) use this measure as a z variable.
[8] This is to control for individuals who player more and are able to accrue better statistics.
[9] This measure is the reciprocal of where the individual was drafted so the range goes from 0.017 if the player was drafted last in the 2nd round (#60) to 1, if the player was the first player drafted in the 1st round.

2011 season. Salary data comes from USA Today. Player statistics and characteristics are taken from Basketball Reference website. MSA data is taken from the Census Bureau[10].

One issue with the standard measures of player performance is that it does not quite capture productivity. Statisticians have worked over the past 30 years to improve on the standard measures to get a better understanding of an individual's value[11]. One example of this controversy over value, a player who scores 30 points per game (PPG) would normally be considered better than a player who scores 25 PPG. However, if the first player takes 35 shots to average 30PPG, while the second player takes 15 shots to average 25 PPG, this would change who is considered the better player, since the second player is more efficient. There are two primary advanced measures that express a player's value, Player Efficiency Rating (PER) and Win Shares (WS). PER was developed by John Hollinger[12] and it is a rating of a player's per-minute productivity. The formula incorporates all possible positive accomplishments and all negative accomplishments to create a single measure that is on a per-minute basis and pace adjusted[13]. One drawback of this measure is that it does not account for players whose primary role is defensive, since these individuals will accrue less offensive statistics and may accrue more negative statistics like fouls. The second measure, developed by Berri (1999), is Win Shares. Like PER, it incorporates positive and negative accomplishments. Unlike PER, WS calculates the contribution of an individual player to team statistics. WS measures the contribution of wins an individual player contributes to a team. For a team, the WS for all individual players should add up to the total number of team wins in a given year. Berri (1999) finds that for the 1997-98 season it matches very closely with only three teams that were off by more than four wins[14]. WS is the best measure of individual productivity since it accounts for the individual's place within the team. Table 1 provides summary means for the full sample and by race.

Table 1. Descriptive Statistics by Race

Variable	Mean	White	Black
Annual Salary	4,619,846.00	4,757,039.00	4,585,249.00
Per Game Statistics			
Points	8.63	7.61	8.88
Rebounds	3.69	3.90	3.63
Assists	1.82	1.68	1.86
Blocks	0.43	0.43	0.43
Steals	0.63	0.52	0.66
Advanced Statistics			
Player Efficiency Rating (PER)	13.17	13.48	13.09
Win Shares (WS)	2.92	3.00	2.90

[10] Information about Toronto is taken from Statistics Canada.
[11] In baseball, this has culminated in heated debates over who deserves the MVP and Cy Young awards.
[12] Hollinger now works as the general manager for the Memphis Grizzlies.
[13] This standardizes the measure so that an individual who plays more minutes will not have a higher value. Also, individuals are not penalized (or enhanced) by playing for a team that plays slowly (quickly).
[14] Berri (1999), Table 11.

Individual Characteristics			
White	0.20		
Foreign	0.13	0.44	0.06
Center	0.21	0.32	0.18
Forward	0.19	0.25	0.18
Experience	4.98	4.91	5.00
Draft position	0.11	0.08	0.11
Trade	0.15	0.13	0.15
Hometown Percentage	0.02	0.004	0.022
Market Factors			
Per-capita Income	37,041.24		
MSA Population	4,220,201		
% MSA that is White	0.57		

White players are more likely to be foreign, have a shorter tenure in the NBA, more likely to be drafted later, and less likely to come from an area with a lot of NBA players. White players are more likely to be Centers or Forwards.

4. Results

4.1 Traditional Model

The minimum salary for an NBA player for the 2010-2011 season was $473,604. A Tobit model is estimated with the minimum salary being the lower constraint. Table 2 provides the results of the traditional wage discrimination model with the four types of productivity measures. If discrimination is occurring, the coefficient on the White dummy will be negative. The first column displays the standard measures, the second column uses PER, and the third column uses WS.

Table 2. Tobit estimation of Wage Discrimination Models with Various Productivity Measures

	(1)	**SE**	**(2)**	**SE**	**(3)**	**SE**
White	0.2284**	0.095	0.0886	0.110	0.1105	0.103
Points	0.0691***	0.010				
Rebounds	0.0003	0.027				
Assists	0.0295	0.030				
Blocks	0.2997**	0.139				
Steals	0.2733**	0.121				
PER			0.0680***	0.008		
WS					0.1545***	0.013
Center	0.1297	0.118	-0.0749	0.103	-0.0150	0.097
Forward	0.1057	0.104	-0.0242	0.104	-0.0362	0.097
Foreign	0.1185	0.110	0.2120	0.130	0.1355	0.122

Draft position	0.3611*	0.201	0.9797***	0.225	0.7601***	0.211
Experience	0.1244***	0.009	0.1384***	0.010	0.1213***	0.010
Trade	0.6784	2.704	3.8499	3.193	6.4549**	2.988
Income	0.0604	0.268	0.3125	0.316	0.6039**	0.295
MSA Population	0.0077	0.054	0.0428	0.064	0.0184	0.060
% MSA - White	0.1593	0.406	0.2197	0.481	-0.1639	0.451
Constant	12.2531***	2.700	9.0171***	3.192	7.0621**	2.989
σ	0.6800	0.024	0.8090	0.029	0.7552	0.027
Likelihood Ratio	401.81***		257.81***		315.26***	
Pseudo R^2	0.3087		0.1981		0.2422	

*** - sig. at 1% level; ** - sig. at 5% level; * - sig. at 10% level; 22 left-censored observations (below minimum salary)

The White dummy is positive and significant in the standard model, but not significant in any of the other models using advanced statistics. The productivity measures are all significant in each model. Experience is consistently positive and significant across all models. Draft position is positive and significant in all models, but it is only mildly significant in the standard model.

4.2 Monopsony Power Model

Given the Collective Bargaining Agreement (CBA) signed most recently in 2010, the only scenarios where teams can exert monopsony power is with non-rookies with less than three years' experience and rookies not drafted in the first round. If discrimination against White players are occurring this would be exhibited with these groups. Table 3 shows the results where we interact the race dummy with three status categories: veterans (more than three years' experience), non-rookies (less than three years' experience), and rookies.

Table 3. Tobit regressions of Salary with Status Interactions

	(1)	SE	(2)	SE	(3)	SE
White	-0.1066	0.170	0.1400	0.105	0.1420	0.106
White x Veterans	0.2999	0.187				
White x Non-Rookie			-0.3646	0.275		
White x Rookie					-0.3462	0.305
WS	0.1535***	0.013	0.1547***	0.013	0.1538***	0.013
Center	-0.0066	0.097	-0.0034	0.097	-0.0166	0.097
Forward	-0.0321	0.097	-0.0397	0.097	-0.0254	0.097
Foreign	0.1388	0.121	0.1511	0.122	0.1250	0.122
Draft position	0.7625***	0.211	0.7499***	0.211	0.7595***	0.211
Experience	0.1170***	0.010	0.1197***	0.010	0.1196***	0.010
Trade	6.3298**	2.979	6.2817**	2.985	6.2077**	2.991
Per-Capita Income	0.5876**	0.294	0.5892**	0.295	0.5825**	0.295
MSA Population	0.0199	0.060	0.0166	0.060	0.0179	0.060
% MSA - White	-0.1176	0.450	-0.1596	0.450	-0.1703	0.450

Constant	7.2041**	2.980	7.2480**	2.986	7.3129**	2.991
σ	0.7526	0.027	0.7537	0.027	0.7538	0.027
Likelihood Ratio	317.81***		317.02***		316.55***	
Pseudo R^2	0.2422		0.2436		0.2432	

*** - sig. at 1% level; ** - sig. at 5% level; * - sig. at 10% level; 22 left-censored observations (below minimum salary)

The coefficients on the race dummy are negative for non-rookies and rookies, but they are not statistically significant. The results of table 3 show no evidence of discrimination occurring with White players, even in the case where teams can exert monopsony power.

4.3 Statistical Discrimination

To test for statistical discrimination, the White dummy is interacted with experience and the z variable, hometown, is interacted with experience. If teams statistically discriminate based on race, introducing the z variable interacted with the experience will cause the coefficient on the White dummy to diminish.

Table 4. Statistical Discrimination with Employer Learning model

	(1)	**SE**	**(2)**	**SE**
White	0.0249	0.167	0.0326	0.171
White*Experience	0.0170	0.027	0.0213	0.027
Hometown %			1.2057	2.405
Hometown %*Experience			0.1899	0.347
Win Shares[15]	0.1541***	0.013	0.1553***	0.013
Center	-0.0305	0.094	-0.0292	0.094
Forward	0.1350	0.121	0.1600	0.122
Foreign	0.7694	0.210	0.7551	0.210
Draft position	0.1186***	0.010	0.1139***	0.013
Experience	6.4350***	2.987	6.4731***	2.978
Trade	0.5984**	0.295	0.6058***	0.294
PC Income	0.0207**	0.060	0.0171**	0.060
MSA Population	-0.1580	0.451	-0.1518	0.449
% MSA - White	7.0927	2.987	7.0338	2.979
Constant	0.0249**	0.167	0.0326**	0.171
σ	0.7547	0.027	0.7525	0.027
Likelihood Ratio	315.65***		318.19***	
Pseudo R^2	0.2425		0.2445	

*** - sig. at 1% level; ** - sig. at 5% level; * - sig. at 10% level; 22 left-censored observations (below minimum salary)

[15] Results using PER and with the traditional measures are available from the author.

None of the terms related to statistical discrimination are significant[16]. While the coefficients on each of the terms do change, there is no evidence that teams statistically discriminate against White players.

5. Conclusion

This paper tested the alternative hypothesis that statistical discrimination could explain racial wage gaps. The focus was on recent data and the findings in recent research that there is reverse discrimination. The results show no evidence of any reverse discrimination occurring against White players. One explanation is that with detailed information about athletes at a young age and the resources devoted to scouting not just in the Unites States but overseas, there is no need for teams to statistically discriminate. This study used a cross-section of 2010-2011 season, unlike the earlier research which uses a panel of NBA seasons. While there was no evidence of statistical discrimination currently, the Altonji-Pierret framework can be used to explain historical wage discrimination in the NBA.

[16] I ran this model to test for statistical discrimination against international players and found no evidence.

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