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Is Racial Salary Discrimination Disappearing in the NBA? Evidence from Data during 1985–2015

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Abstract

This study re-examines racial salary discrimination of National Basketball Association players by constructing a long unbalanced panel covering the 1985–1986 to 2015–2016 seasons. Contrary to the results of previous studies, we find that non-white players are paid equally to white players with similar characteristics in the 1980s and 1990s, but that white players started to be paid 20 percent more than non-white players in the last 10 years. Our results are robust in all specification checks such as the quantile regressions, controlling the sample selection and controlling different contract types. Non-parametrically estimated density of the counter-factual salary of non-white players confirms our results. In addition, we find that neither the employers preference nor income gap of white and black fans explain this increasing salary gap.

JEL Classification: C25

Keywords: racial discrimination, NBA, labor markets, salary discrimination

1 Introduction

The issue of whether discrimination in the labor market is disappearing has important policy implications. Because various external factors, such as globalization, taxes, and competition with other product markets, affect the degree of wage discrimination, it is important to know how wage discrimination changes over time.

In the literature of discrimination in labor markets pioneered by Becker (1971), researchers have used the data of professional sports athletes to analyze the issue of discrimination because of the availability of information on each player's productivity in a large number of dimensions (Kahn, 2000). Among studies that used information of professional sports athletes, studies that use information of players of the National Basketball Association (NBA) provide an interesting case for several reasons. First, in the previous studies that utilized the data in 1980s and 1990s, it is reported that in the 1980s, there was a white premium of the NBA's salary—the salary of a white player is higher than that of a non-white player with the same productivity (Kahn and Sherer, 1988; Koch and Vander Hill, 1988; Wallace, 1988; Brown et al., 1991).[1] However, several studies report that such a premium reduced or disappeared in the 1990s (Dey, 1997; Hamilton, 1997; Gius and Johnson, 1998; Bodvarsson and Brastow, 1998; Eschker et al., 2004; Hill, 2004; Groothuis and Hill, 2013).[2] Some studies report that in the 2000s, there was even reverse discrimination against white players (Yang

[1]For example, Kahn and Sherer (1988) found a strong white (20 percent) premium controlling productivity and other covariates using the salary data in the 1985–1986 season.

[2]Hamilton (1997) found evidence of racial pay differences only at the upper end of the 1994–1995 season of salary distribution. Hill (2004) showed that the importance of controlling the height or position. He argued that the white premium was the return of the height, not the racial gap. A study most closely related to the current study is Groothuis and Hill (2013). They used unbalanced panel data from 1990 to 2008 and controlled for the sample selection problem. They found that there was no discrimination against black players in their dataset.

and Lin, 2012; Groothuis and Hill, 2013). Thus, it is natural to examine whether this trend continues in more recent years and whether salary discrimination eventually disappeared.

Second, there is discrepancy on anecdotal and empirical evidence regarding discrimination in the NBA. Although the previous literature suggests that salary discrimination is disappearing in the 1990s and might even be moving in the opposite direction (reserve discrimination against white) in the 2000s, there is opposite anecdotal and empirical evidence of racial discrimination against black players in the NBA. For example, in April 2014, the owner of Los Angeles Clippers was banned from the NBA permanently and fined $2.5 million for his racial comments. Kanazawa and Funk (2001) found that TV viewing is affected strongly by the ratio of white players in the team by examining the viewing data in the 1996–1997 season. Price and Wolfers (2010) showed that a referee prefers a player whose race is the same as that of the referee when he or she makes a decision on fouls. Such anecdotal or empirical evidence warrants further investigation of racial salary discrimination by using longer data.

Third, the NBA experienced important changes in the 2000s. First, the NBA experienced substantial globalization in the 2000s. In 2002, 2005, and 2006, the first pick in the draft was an international player.[3] The season's MVP during the 2004–2005, 2005–2006, and 2006–2007 seasons were international players.[4] In addition, broadcasting the NBA's games to countries outside the United States became common in those years. In the literature of labor economics, there is increasing interest whether globalization would lead to a decrease or increase of discrimination in the labor market (Berik et al., 2004; Black and Brainerd, 2004; Busse and Spielmann, 2006). The salary data

[3]The first picks in the draft of 2002, 2005, and 2006 were Yao Ming (China), Andrew Bogut (Australia), and Andrea Bargnani (Germany), respectively.

[4]The MVP of the 2004–2005 season, the 2006–2006 season, and the 2006–2007 season were Steve Nash (South Africa), Steve Nash (South Africa), and Dirk Nowitzki (Germany), respectively.

of the NBA provides an interesting case for the study. Second, from the 2002–2003 season, the NBA introduced luxury tax to penalize the team whose total salary to players exceeds the upper limit determined by the NBA.[5] The standard tax theory of the public finance (Salanie, 2011) showed that even when the tax is imposed on the employers (teams), some portion of the tax burden is shifted to the employees (players) through lower wage rates (salary). Thus, it is possible that the luxury tax could affect the salary of players and thereby, affected white and black players differently.[6] Interestingly, as we show later, we find that the white premium increased in the 2000s and 2010s, although the causality is not clear.

This study revisits the issue of the white premium of the salary of NBA players by making long unbalanced panel data of the salary and other indices of performance, which covers the 1985–1986 season to the 2015–2016 season for annual salary and the 1984–1985 season to the 2014–2015 season for indices of performance. First, we find that in the 1980s, non-white players were paid equally to white players.[7] Second, consistent with the previous literature, which shows that racial salary discrimination was disappearing in the 1990s, we find that during the 1980s and 1990s, there was no white premium. However, in the 2000s, we find that the white premium becomes about 9 percent ($p < 0.05$) and in the 2010s, it reached 26 percent ($p < 0.01$). Our results show that the result of the previous literature that racial salary discrimination

[5] Although the NBA introduced a salary cap from the 1985–1986 season, this salary cap was the so-called "soft cap" in the sense that there are lots of exceptions on the salary cap and that the team could exceed the salary limit by using those caps. The luxury tax introduced from the 2002–2003 season was a hard cap. Thus, any team that exceeded the limit needs to pay the luxury tax.

[6] In addition, the NBA started the official minor league (D-league). This could affect the wage rate of the black and white players differently.

[7] This result shows a sharp contrast to the results of early literature. We find that the lack of several important variables in previous studies leads to the conclusion that there was salary discrimination against black players in the 1980s. See the discussion of Subsection 2.5.

is disappearing is quite temporary, and in fact, it increased in the late 2000s and, especially, in the 2010s.

To confirm the robustness of our results, we conduct robustness checks by running the quantile regression at several quantiles, restricting the sample to players with more than or equal to 5 years of experience, restricting the sample to US-born players, controlling the performance at t-2 and t-3 instead of at t-1, controlling the sample selection problem, and adding the team's fixed effect interacted with year dummy. In addition, we reconcile the difference of the results between our study and the previous studies. We find that when we drop some control variables from our regression equation, which are not included in the previous studies, the magnitude of the coefficient and statistical significance becomes similar to the results of the previous studies. This suggests the importance of including those control variables.

In addition, to visually identify the counter-factual salary distribution, we non-parametrically estimate the density of the actual salary of white players and non-white players, the counter-factual density of the salary of non-white players by using the method developed by DiNardo et al. (1996). We find that during 1985–1995, the salary density of non-white players is located slightly to the right of the salary density of white players—on average, non-white players earn more than white players. However, the difference of the two densities could be explained by the difference of the performance and other covariates between the white and non-white players. In 1995–2005, both salary density of white and non-white players becomes quite similar. Even after adjusting the performance and other covariates, the salary density of white and non-white players is similar. However, in 2005–2015, the salary density of white players is located slightly to the right of the salary density of non-white players—on average, white players earn more than black players. This difference persists even if we adjust the performance and other covariates between white and black players. This implies that the difference in 2005–2015 mainly comes from other factors that cannot be explained by the performance and other covariates.

Although we do not find the exact cause of the rise of salary discrimination, we examine two possible causes. First, we examine whether the race of the owner or GM of the team affects the white premium. We find that even if we control the race of owner and GM, the pattern of the white premium does not change at all. In addition, we examine the effect of income distribution of white and black fans. Again, we find that the pattern of the white premium does not change, even if we control the income distribution of residents in the team's state.

Our results have several implications. First, the disappearance of the white premium reported by previous studies (Bodvarsson and Brastow, 1998; Dey, 1997; Eschker et al., 2004; Hamilton, 1997; Gius and Johnson, 1998) is temporary.

Second, although our result is not consistent with previous studies, that racial salary discrimination is disappearing in the NBA, it is consistent with the broader literature that racial discrimination is persistent in different forms in the NBA (Kanazawa and Funk, 2001; Price and Wolfers, 2010).

The organization of the rest of our paper is as follows. In Subsection 2.1, we discuss the data and how we construct the variables. In Subsection 2.2, we present our main results. In the Subsection 2.3, we estimate the actual and counter-factual salary distribution and examine how they changed over time. In Subsection 2.4, we discuss why our results differ from the estimates of the previous literature. In Section 3, we provide a brief conclusion.

2 Analysis

2.1 Dataset

This study obtains information on salaries and player productivity from several sources. For information on the annual salaries of players, we obtain information of the annual salaries from the ESPN salary-ranking website[8], NBA's reference website[9], and fans' website[10]. We check the consistency of the salary information among three sources and find that information on those three sources is consistent. For indices of performance, birthplace, nationality, height, weight, and birth year, we collected data from the ESPN website[11] and the reference website of NBA players[12]. In addition, we check the consistency of indices from these two sources and find that the information is consistent between these two sources. The salary data are available from the 1985–1986 to the 2015–2016 seasons, except for the 1986–1987 and 1989–1990 seasons.[13] The information on performance is available from the 1984–1985 to 2014–2015 seasons. The median income of black and white residents in each state and year is calculated from the CPS data available from the IPUMS CPS.[14]

Some players are posted on the waiver list during the season after the contract is signed. When another team makes a claim on this waived player within 48 hours after he was posted on the waiver list, the contract is transferred to this new team and the new team needs to take full responsibility for the contract, including payment of the remaining salary. In most cases, however, no team lodges a claim within 48 hours to

[8] `http://espn.go.com/nba/salaries`

[9] `http://www.basketball-reference.com/players/`

[10] `https://www.eskimo.com/~pbender/`

[11] `http://espn.go.com/nba/statistics`

[12] `http://www.basketball-reference.com/players/`

[13] For the 1989–1990 and 1989–1990 seasons, the NBA, player's union, and individual teams refused to release salary information.

[14] `https://cps.ipums.org/cps/`

this posted player. In this case, the player obtains free agency. In this case, a new team can make an offer to this player with the minimum salary that is determined by the NBA. In our dataset, about 5 percent of observations experience these kinds of transfers during the season. It is natural to assume that the characteristics of those waived players are different from non-waived players. Thus, we exclude those waived players from our dataset. To check the sensitivity of our regression result due to the exclusion of those waived players, we conduct robustness checks by including those players and re-estimating the equation. Our robustness checks show that the result does not change, even if we include those players.

The number of players in our dataset is 1,856 and the number of observations is 9,822. As we discuss in the next section, we use ordinary least squares (OLS) with clustering robust standard errors, instead of the random-effect model of the panel data. For the indices of player performance, we use 16 indices listed in Table 2. In addition to those 16 indices, we include the height and weight, current team dummy, year dummy, and foreign player dummy as additional control variables. The foreign dummy is equal to 1 if a player is born outside of the United States. For our regression, we do not put the team's average salary or attendance as a control variable. Instead, we put the team dummy or team dummy and its interaction with year dummy to control time-invariant and time-variant team's effect

2.2 Empirical Analysis

The main regression equation that we utilize in this study is as follows:

$$\ln S_{ijt} = \beta_0 + \gamma White_{ijt} + \beta_1 X_{1,ij,t-1} + \beta_2 X_{jt} + \gamma_j + \gamma_t + \varepsilon_{ijt} \tag{1}$$

where i is an index of individual, t is the index of the season, and j is the index of the current team. S_{ijt} is the annual salary of the player i in the season t who belongs to the team j. γ_j is the team's fixed effect. γ_t is the time fixed effect; ε_{ijt} is the error term. $X_{i,t-1}$ is player i's productivity in season t-1. It is possible that the player's salary is determined by the performance a few years before the season t, and we conduct a robustness check by replacing $X_{i,t-1}$ with $X_{i,t-k}$ where $k = 2$ or 3.

Since we use panel data instead of cross-sectional data, ε_{ijt} can be serially correlated for the same i. We use the OLS with the assumption that the error term is clustered at the player's level. We do not use the random effect of the panel data. The random effect model is more efficient than the OLS with the clustering robust standard error if it is correctly specified. However, once misspecified, the random effect model generates the inconsistent estimate of the coefficients and standard error. Thus, we use the OLS with the clustering robust standard error for the robustness of the results.

Our main interest is β_1, which measures how much percent the annual salary increases when the race of a player is white, controlling the productivity of this player and the characteristics of the team he belongs to.

Tables 1 provides the summary statistics of the variables used in our regression. Among 9,822 observation, 24 percent of the observations is white, and 13 percent are foreign players. We classify the positions of players into three categories—center, guard, and forward. About 40 percent of the observations is guard, another 40 percent is forward, and 20 percent is center. We control for age, age squared, experience, and experience squared. Our robustness check shows that including the quadratic term of age and experience is important. The average age is 27 years and the average experience is 5.5 years. The previous study shows the importance of controlling the height or position, as discussed in the literature section. The lower part of Table 1 lists the 16 indices of performance variables used in our regressions.

Table 2 shows our main regression results. The row White displays the estimated coefficient of the white dummy in the regression equation. In the regression equation, the dependent variable is the logarithm of the annual salary at year t. The explanatory variables are the white dummy, foreign player dummy, performance indices listed in Table 1 at season t-1, age, age squared, experience, experience squared, two position dummies, height, weight, and team dummy at season t. Our robustness check shows the importance of the square of experience and age. For calculating the standard error, we assume that the error term is clustered at the player's level and apply the clustering robust standard error. The first block of Table 2 shows the results of OLS. The first, second, third, fourth, and firth columns show the estimated coefficients of the white dummy, numbers of observations, and R squared when all observations, observations in the 1980s, observation in the 1990s, observations in the 2000s, and observations in the 2010s are used for the estimation, respectively.

The first block of Table 2 shows that in the 1980s and 1990s, black players are as equally paid as white players with similar characteristics. The coefficient of the white player dummy is economically very small and statistically insignificant. In the 2000s and 2010s, however, the white premium becomes significant economically and statistically. In the 2000s, the white premium becomes about 10 percent ($p < 0.05$). In the 2010s, the white premium becomes more than 20 percent ($p < 0.01$).

In the first block, we estimate the white premium using OLS. However, in the NBA, there are super stars in terms of salary. In addition, there is a minimum salary for NBA players. In such a situation, running the quantile regression is a useful device to detect racial discrimination, since OLS can be affected substantially by the outlier and minimum cutoff line in the presence of the outlier and minimum salary. In the second block, we run the 50 percentile quantile regression. The dependent variable and explanatory variables are the same as in the OLS case. The result of the 50 percentile quantile regression result shows that even with the quantile regression, the pattern of the white premium does not change—in the 1980s and 1990s, there was no white premium, but in the 2000s, the white premium began to emerge and, in the 2010s, it became more than 20 percent.

The third block of Table 2 shows the results of 25 percentile quantile regression. It shows that the pattern of the estimated coefficient of the white dummy is the same as the OLS case.

The fourth block of Table 2 shows the results of 75 percentile quantile regression. It shows that the pattern of the white premium is slightly different from the pattern in the OLS case. When 75 percentile quantile regression is applied, the white premium becomes insignificant in the 2000s, but becomes 20 percent in the 2010s. This suggests that the rise of the white premium occurred initially at the middle to lower distribution and expanded into higher quantiles.

In Table 3, we conduct several robustness checks. In the first block, we control the type of the contract indirectly. As shown by Kahn and Shah (2005), the white premium can be quite sensitive to the type of contract, as discussed in the introduction. Players with experience of more than 3–5 years (depending on the initial contract) can become free agent players. On the other hand, the salaries of the drafted rookie players are determined by the NBA's rules. Thus, there is no room for racial discrimination for the drafted rookie players. This implies that the inclusion of rookie players could affect the white premium substantially, as demonstrated by Kahn and Shah (2005). In the first block of Table 3, we restrict the sample to players who have 5 years or more of experience. The dependent variable and explanatory variable are the same as in Table 2. The result of the first block shows that the result of OLS with all players continues to hold even in the restricted sample. This suggests that the type of contract does not affect the change of the white premium over time.

In the second block of Table 3, we restrict the sample to US-born players.[15] Since

[15]In all the above regressions except the second block of Table 4, we include the foreign player dummy

the NBA experienced a dramatic globalization in the 2000s, fully controlling for the birthplace of players seems to be important. The result of the second block of Table 3 shows that controlling for foreign players fully does not affect the pattern of the white premium at all.

In the third block of Table 3, we control the sample selection problem. As discussed by Groothuis and Hill (2013), given the performance at season t-1, having a contract at season t is not random. If the team selectively has a contract with white players when the potential salary of players is high, such behavior would generate a white premium. To control such a sample selection issue, we apply Heckman's two-step procedure.[16] The third block of Table 3 shows that controlling the sample selection problem does not affect the pattern of the white premium.

Table 4 shows additional robustness checks. In Table 2, we use the indices of the performances of the previous season to control the productivity of players. However, it is quite possible that the salary of the player at season t is affected by the performance at $t-2$ or $t-3$. The first and second blocks of Table 5 show the coefficients of the white dummy when the indices of performance at season $t-2$ or $t-3$ are used as the control variables and the dependent variable is the log of salary at season t. The first and second blocks of Table 4 show that the pattern of the white premium does not

as an explanatory variable. Thus, we control the birthplace of players to some degree. However, we do not make other variables interact fully with the foreign player dummy. Thus, we implicitly assume that the coefficient of other explanatory variables is the same between US-born and foreign players. If the effect of those control variables differ between foreign and US-born players, our estimate of the coefficient of the white dummy can be biased. To solve this problem, we restrict our sample to US-born players and apply the same regression equation, except for the foreign player dummy.

[16]One of the important issues of implementing the Heckman two-step estimation method is to find an excluded variable that enters the selection equation but is not included in the second-stage equation. We use the performance variables at t-2 as excluded variables.

change from Table 2.

In the third block of Table 4, we control another sample selection issue. As discussed in the data section, we exclude players posted during the season. This is because often they are hired by the second team at the minimum salary. The third block of Table 4 shows the results of the regression when we include those players in the sample. The results of Table 4 show that the results of Table 2 do not change even if those waived players are included.

In all the abovementioned regressions, we include the team dummy to control the team's fixed effect. For example, suppose that the team's financial condition is time-invariant and that teams located in big cities are financially more affluent and tend to pay higher salaries, regardless of the race of players. In addition, suppose that teams located in big cities tend to hire white players for some exogenous reasons. Then, the salary regression exhibits a positive correlation between race and salary, even if there is no salary discrimination within a team. To control such an effect, we need to include the team's fixed effect. However, if the team's financial condition is time-variant, it is not sufficient to include the team's fixed effect. We need to include the interaction term of the team dummy and the year dummy. In the fourth block of Table 4, we include the interaction term of the team dummy and year dummy. The fourth block of Table 4, however, shows that the pattern of the white premium is not affected at all, even if we include the interaction of the team dummy and year dummy.

2.3 Counter-factual Salary Distribution

The previous analysis consistently shows that in the in 2000s and 2010s, the racial salary gap increased in the NBA in terms of mean and several quantiles. A natural question is how the overall salary distributions of black and white groups have changed in the last 30 years, controlling the characteristics of performance and other covariates, such as height and weight. In this subsection, we estimate the counter-factual salary distribution of black players—hypothetical salary distribution of a black player treated in the same way as a white player with a similar characteristic.

To be more accurate, let x be the attributes that characterize players, except the race of players. The attributes x include the performance of players at t-1, height, weight, year dummy, and the team that he belongs to. Let s be the log of the annual salary. Let $f_{\text{white}}(s|x)$ be the conditional salary density of a white player given x. Let $f_{non-white}(s|x)$ be the conditional salary density of a non-white player given x. Let $G(x|\text{white})$ be the distribution function of x for a white player and let $G(x|\text{non-white})$ be the distribution function of x of a non-white player. The salary density of white players is

$$\int f_{\text{white}}(s|x)dG(x|\text{white}) \tag{2}$$

The salary density of non-white players is

$$\int f_{\text{non-white}}(s|x)dG(x|\text{non-white}) \tag{3}$$

The counter-factual salary density of the black players—the density of the salary of non-white players if the attributes of non-white players were rewarded in the same way as the attributes of white players—is defined as follows:

$$\int f_{\text{white}}(s|x)dG(x|\text{non-white}) \tag{4}$$

In a very important study in labor economics, DiNardo et al. (1996) show that (4) can be calculated by non-parametric density estimation by reweighing. We calculate actual unconditional salary distribution of white and non-white players and counter-factual distribution of the salary density of non-white players. Since we do not have so many observations in the 1980s and 2010s, we divide the whole periods into 1985–1994, 1995–2004, and 2005–2015. We generate the actual density and counter-factual density in those periods and check how they change over time. Figure 1 shows that there is no discrimination against non-white players. In fact, the actual salary density of the non-white players is located slightly to the right of the counter-factual salary density of white players. However, the counter-factual salary density of non-whites is located slightly to the right of the salary density of white players. This implies that the difference of the actual salary density of white and non-white players can be explained by the difference of the attributes. In 1995–2005, the actual density of the non-white and white players is similar. In addition, the counter-factual salary density of the non-white and actual salary density of the white players becomes quite similar. However, in 2005–2010, the actual salary density of the white players is located slightly to the right of the actual salary density of the non-white players. On the other hand, the counter-factual salary density of the non-white players becomes very similar to the actual density of the white players. This implies that the difference of the actual salary density of white and non-white players does not derive from the difference of the attributes but from racial salary discrimination.

2.4 Reconciling with Previous Results

One might ask the source of the difference between our results and those of previous studies. Several studies report the presence of a white premium in the 1980s. In addition, previous studies that use data in the 2000s show that the white premium does not exist (Groothuis and Hill, 2013). To check for consistency, we run a regression that generates Table 2 separately for each year and plots the coefficient of the white dummy. Figure A1 in the appendix shows the estimated coefficient of the white dummy when the equation used in Table 3 is applied separately. Figure A1 shows that in the 1985–1986 season, the coefficient of the white dummy is positive but keeps declining and becomes almost 0 for a while. In the late 2000s, it starts to increase. Thus, the pattern in the 1980s and 1990s in Figure A1 is consistent with the previous studies.[17] In addition, Figure A1 shows the main source of the difference between Groothuis and Hill (2013) and ours. In Groothuis and Hill (2013), the year covered in their analysis is from between 1990 and 2008. However, as Figure A1 shows, the estimated coefficient of the white premium starts to be higher from 2005 when it is estimated for each year. Thus, there would be no surprise that when the data are pooled from 1990 to 2008, Groothuis and Hill (2013) did not find the white premium overall. Simply, the white premium started to rise from 2005 and the data from 1990 to 2008 are not sufficient to detect such a trend.

3 Effects of Race of Owner, GM, and Income Gap on White Premium

One natural question is why the racial salary gap increased in the 2000s and 2010s. Although we find that the exact cause of this rising salary discrimination is beyond the scope of this study, we could exclude some possibilities. First, we have examined whether the race of the owner or GM of the team affects the white premium. We find that even if we control the race of the owner and GM, the pattern of the white premium does not change at all. More specifically, we estimate equation (1) with the interaction term of the white dummy and race dummy of the owner of GM. The idea of this regression is that the coefficient of the white dummy becomes bigger in the team

[17]The estimated coefficient of the white dummy in our regression that uses the data of the 1985–1986 season alone is about 9 percent and is statistically insignificant (t=1.3). When we drop several explanatory variables (age squared, experience squared, height, and weight) from our estimating equation, the estimated coefficient of the white dummy becomes 15 percent and statistically significant (t=1.98). Thus, our result is consistent with the previous studies regarding the pattern of the estimated coefficient in the 1980s and 1990s. The difference between our analysis and the previous studies seems to derive from the exclusion of important covariates, such as the height, weight, and square of experience and age.

in which the race of the owner or GM is white if the primary reason of the rise of the white premium derives from the racial preference of owners or GM. The first block of Table 5 shows the estimated coefficient of the white premium of players when the white dummy of the owner and its interaction with the white dummy of players are included. The second block of Table 5 shows the estimated coefficients of the White dummy of players when the white dummy of GM and its interaction with the white dummy of players are included. The first block and second block of Table 5 show that the pattern of the estimated coefficient of the White dummy does not change at all, even if we control the race of owner or GM.

In the third block of Table 5, we control the relative median income of white residents over that of black residents in the state in which the team is located. If the white premium is a reflection of a consumer's willingness to pay for own race, then in an area in which the relative income of white is high, the white premium will become higher. After the mid-2000s, the median income gap between white and black increased according to the CPS data. In the third block, we estimated the following equation:

$$\begin{aligned}\ln S_{ijt} = \beta_0 + \gamma_0 White_{ijt} + \gamma_1 White_{ijt} \times (Gap_{jt} - \overline{Gap}) \\ + \gamma_2 \times (Gap_{jt} - \overline{Gap}) + \beta_1 X_{1,ij,t-1} + \beta_2 X_{jt} + \gamma_j + \gamma_t + \varepsilon_{ijt}\end{aligned} \tag{5}$$

where Gap_{jt} is the ratio of median income of white residents to the median income of black residents at time t in the state in which team j is located. $\overline{Gap}$ is the sample average of Gap_{jt}. The idea of equation (5) is that white premium becomes higher in a state in which the median income of white residents is higher than that of black residents. The ratio of the median income of black and white residents is calculated from the CPS data. The third block of Table 5 shows that the pattern of the estimated coefficient of white dummy of players does not change even when we include the median income ratio of white residents and black residents and its interaction with the white dummy.

4 Conclusion

This study revisits the issue of racial salary discrimination in the NBA using panel data that include information on annual salary from the 1985–1986 season to the 2015-2016 season and performance information from the 1984–1985 season to the 2014–2015 season. In contrast to the result of previous studies, in which racial salary discrimination disappears in the 1990s and early 2000s, we find that racial salary discrimination starts to emerge in the 2000s and reaches more than 20 percent in the 2010s. The results are quite robust with many specifications. In addition, by using a non-parametric method, we show how a counter-factual salary density of non-white players—salary density of non-white players if the attributes of non-white players are rewarded as the attributes of white players—have changed over time and confirm the rise of racial salary discrimination. One natural question is why salary discrimination in the NBA emerged in the last 10 years. We examined whether the race of owner and GM or income gap of white and black fans affects white premium. We found that those factors did not affect the white premium at all. Thus, the cause of rising racial salary discrimination is unknown and remains as a topic for future research.

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Table 1: Summary Statistics of White Players and Non-white Players

	white		non-white		Difference	
VARIABLES	mean	s.d.	mean	s.d	of the mean	S.E.
Annual Salary ($1000)	3,362	3,767	3,563	4,173	201.16	95.83
Foreign Dummy	0.327	0.469	0.0639	0.245	0.26	0.01
Age	27.07	3.775	26.95	4.079	0.12	0.09
Experience	5.150	3.509	5.620	3.823	-0.47	0.09
Weight (lb)	227.1	27.86	215.1	27.36	11.97	0.65
Height (inch)	80.64	3.731	78.64	3.594	2.00	0.09
Guard Dummy	0.285	0.452	0.413	0.492	-0.13	0.01
Forward Dummy	0.352	0.478	0.433	0.496	-0.08	0.01
Center Dummy	0.363	0.481	0.154	0.361	0.21	0.01
Performance indices						
the number of the games the athlete played in the season.	57.36	22.32	60.51	21.83	-3.15	0.52
the average minutes the athlete played in one game	20.04	9.717	23.50	9.890	-3.47	0.23
the average number of the successful field goal in one gam	2.924	1.997	3.712	2.311	-0.79	0.05
the probability of the successful shoots.	0.448	0.0796	0.447	0.0744	0.00	0.00
the average number of three point shoots in one game	1.165	1.517	1.362	1.643	0.20	0.04
the probability of the successful three point shoot	0.218	0.192	0.223	0.174	0.00	0.00
the average number of the free throw shoots in one game	1.454	1.240	1.919	1.537	-0.46	0.03
the probability of the successful free throw	0.719	0.162	0.720	0.146	0.00	0.00
the average number of taking rebound in one game	3.778	2.504	4.065	2.645	-0.29	0.06
the average number of assists in one game	1.788	1.966	2.170	1.957	-0.38	0.05
the average number of turn-over in one game	1.174	0.744	1.448	0.825	-0.27	0.02
the average number of steals in one game	0.587	0.422	0.792	0.494	-0.20	0.01
the average number of blocks in one game	0.462	0.525	0.487	0.559	-0.02	0.01
the averaged scores in one game	7.727	5.345	9.811	6.216	-2.08	0.14
the average number of fouls	2.009	0.821	2.125	0.795	-0.12	0.02
the contribution to the team	9.273	6.060	10.78	6.368	-1.51	0.15
N	n=2394		n=7428			

Table 2: Estimated Coefficients of White Dummy in OLS and Quantile Regressions

Estimation Method		(1) all	(2) 1980s	(3) 1990s	(4) 2000s	(5) 2010s
OLS	White	0.0757**	0.0295	-0.0455	0.0993**	0.259***
		(0.0322)	(0.0559)	(0.0491)	(0.0475)	(0.0618)
	N	9,822	745	3,203	3,650	2,224
	R-squared	0.655	0.712	0.589	0.566	0.492
Quantile Regression(50%)						
	White	0.0443	0.0257	-0.111**	0.104**	0.222***
		(0.0307)	(0.0672)	(0.0503)	(0.0522)	(0.0562)
	N	9,822	745	3,203	3,650	2,224
	R-squared	0.652	0.699	0.579	0.560	0.470
Quantile Regression (25%)						
	White	0.108***	0.0804	-0.0460	0.148***	0.200***
		(0.0339)	(0.0827)	(0.0740)	(0.0571)	(0.0589)
	N	9,822	745	3,203	3,650	2,224
	R-squared	0.649	0.696	0.579	0.554	0.476
Quantile Regression (75%)						
	White	0.0181	0.0100	-0.0531	0.0362	0.197***
		(0.0325)	(0.0791)	(0.0486)	(0.0480)	(0.0721)
	N	9,822	745	3,203	3,650	2,224
	R-squared	0.641	0.692	0.561	0.551	0.456

Notes: The dependent variable of the regression equation is the logarithm of the annual salary at season t. The explanary variables are the white dummy, foreign player dummy, all perfomance variables at season t-1 listed in Table 2, position dummy to control positions (guard, center, forward), age, age squared, experince, experience squared, year dummy, height, weight, and team dummy at season t. The regression equation is estimated by using the unbalanced panel data covering salary information from the 1985–86 season to the 2015–16 season. The row white shows the estimated coefficient of the white dummy in different specificatons. Clustering robust standard errors in parentheses and the error term is clustered at the player's level in all specifications. Columns (1), (2), (3), (4), and (5) show the esimated coefficients of white dummy, its standard error, the number of observations, and R^2 when we use all observations, observations in the 1980s, observations in the 1990s, observations in the 2000s, and observations in the 2010s, respectively. The first, second, third, and fourth blocks display the results of OLS, the 50 percentile quantile regression, 25 percentile quantile regresion, and 75 percentile qunatile regression, respectively.

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Estimated Coefficient of White Dummy in Restricted Samples and Heckman's Two-step Model

Specifications		(1) all	(2) 1980s	(3) 1990s	(4) 2000s	(5) 2010s
OLS: Restricted sample (Expereince≥5_)						
	White	0.105**	0.0382	-0.0231	0.161**	0.329***
		(0.0419)	(0.0711)	(0.0598)	(0.0694)	(0.0890)
	N	5,171	360	1,670	1,940	1,201
	R-squared	0.647	0.716	0.562	0.480	0.409
Restricted sample (US born only)						
	White	0.0480	0.0229	-0.0607	0.111*	0.233***
		(0.0379)	(0.0584)	(0.0531)	(0.0566)	(0.0757)
	N	8,565	715	2,988	3,089	1,773
	R-squared	0.658	0.707	0.580	0.565	0.500
Heckman two-step estimation						
	White	0.0633**	0.0161	-0.0515	0.0992**	0.229***
		(0.0305)	(0.0620)	(0.0533)	(0.0487)	(0.0575)
	Mill's ratio	-0.537***	-0.444***	-0.242	-0.592***	-0.606**
		(0.115)	(0.131)	(0.165)	(0.230)	(0.290)
	N	12,308	1,423	3,872	4,307	2,706

Notes: Clustering robust standard errors in parentheses and the error term is clustered at the player's level in all specifications. The dependent variable and the explanatory variables are the same as those in Table 3. The row white displays the estimated coefficient of the white dummy in different specificatons. In the first block, the sample is restricted to players who have 5 or more years of experience at the NBA. In the second block, the sample is restricted to US-born players. In the third block, the Heckman two-step estimation is applied to control the endogeniety of having a contract in season t. Players who played in season t-1 but who did not have a contract in season t are included in the first stage. The row Mill's ratio displays the estimated coefficients of the inverse Mill's ratio. In the third block, the standard error is calculated by using the bootstrap. The regression equation is estimated by using the unbalanced panel data covering salary information from the 1985–1986 season to the 2015–2016 season. Columns (1), (2), (3), (4), and (5) show the esimated coefficients of white dummy, its standard error, the number of observations, and R^2 when all observations, observations in the 1980s, observations in the 1990s, observations in the 2000s, and observations in the 2010s are used.

Table 4: Estimated Coefficient of White Dummy with Other Controls

Specifications		(1) all	(2) 1980s	(3) 1990s	(4) 2000s	(5) 2010s
OLS: controlling the perfomance at t-2						
	White	0.0724**	-0.00750	-0.0463	0.120**	0.275***
		(0.0360)	(0.0771)	(0.0515)	(0.0468)	(0.0749)
	N	8,248	429	2,754	3,172	1,893
	R-squared	0.612	0.681	0.560	0.528	0.416
OLS: controlling the perfomance at t-3						
	White	0.0759*	0.00390	-0.0581	0.102*	0.335***
		(0.0391)	(0.0820)	(0.0561)	(0.0549)	(0.0906)
	N	7,135	360	2,397	2,750	1,628
	R-squared	0.591	0.699	0.526	0.487	0.352
OLS: including players who experienced mutliple teams in season t						
	White	0.0696**	0.0295	-0.0366	0.0804*	0.246***
		(0.0321)	(0.0559)	(0.0486)	(0.0471)	(0.0615)
	N	10,091	745	3,265	3,773	2,308
	R-squared	0.650	0.712	0.585	0.560	0.493
Adding year dummy× team dummy						
	White	0.0761**	0.0286	-0.0471	0.0936**	0.255***
		(0.0323)	(0.0556)	(0.0499)	(0.0474)	(0.0629)
	N	9,822	745	3,203	3,650	2,224
	R-squared	0.682	0.728	0.620	0.593	0.526

Notes: Clustering robust standard errors in parentheses and the error term is clustered at the player's level in all specifications. The dependent variable and control variables are the same as those in Table 3, except the performance variables at t-1. In the first and second blocks, the performance variables at t-1 are replaced by the performance variables at t-2 and t-3. The row white dipalys the estimated coefficients of the white dummy. In the fourth block, players who experienced multiple teams are added to the sample. For such players, the total salary in season t is used as the dependent variable. The team that gave the highest salary during season t is classified as the team for such players. In the fourth block, the interaction term of year dummy and team dummy is added as an additional control variable.

Table 5: Estimated Coefficients of White Dummy in Other Specifications

Specifications		(1) all	(2) 1980s	(3) 1990s	(4) 2000s	(5) 2010s
OLS: Adding owner's race dummy and its interaction with the white dummy						
	White	0.128	-0.0933	0.0447	0.297*	0.259***
		(0.0919)	(0.131)	(0.153)	(0.160)	(0.0618)
	N	9,822	745	3,203	3,650	2,224
	R-squared	0.655	0.713	0.590	0.566	0.492
OLS: Adding GM's race dummy and its interaction with the						
	white	0.142**	0.0578	0.0144	0.193**	0.325***
		(0.0605)	(0.112)	(0.112)	(0.0774)	(0.108)
	N	9,822	745	3,203	3,650	2,224
	R-squared	0.656	0.713	0.589	0.566	0.493
OLS: Adding relative income and its interaction with the						
	White	0.0848**	0.0336	-0.0302	0.0991**	0.261***
		(0.0337)	(0.0587)	(0.0537)	(0.0481)	(0.0634)
	N	9,470	736	3,080	3,505	2,149
	R-squared	0.659	0.714	0.595	0.570	0.494

Notes: Clustering robust standard errors in parentheses and the error term is clustered at the player's level in all specifications. The dependent variable is the log of the annual salary in all three blocks. The explanatory variables in the first block are the explanatory variables used in Table 3 and the owner's race dummy and its interaction with the white dummy of the player. The owner's race dummy is equal to 1 if the race of the owner is white, and 0 otherwise. In the second block, the explnatory variables are the variable used in Table 3 and the GM's race dummy and its interaction with the white dummy of the player. The GM's race dummy is equal to 1 if the race of the GM is white, and 0 otherwise. In the third block, the explanatory variables are the explanatory variables used in Table 3, the relative median income of white residents over black residents in the state where the team is located and its interaction with the white dummy of the player.

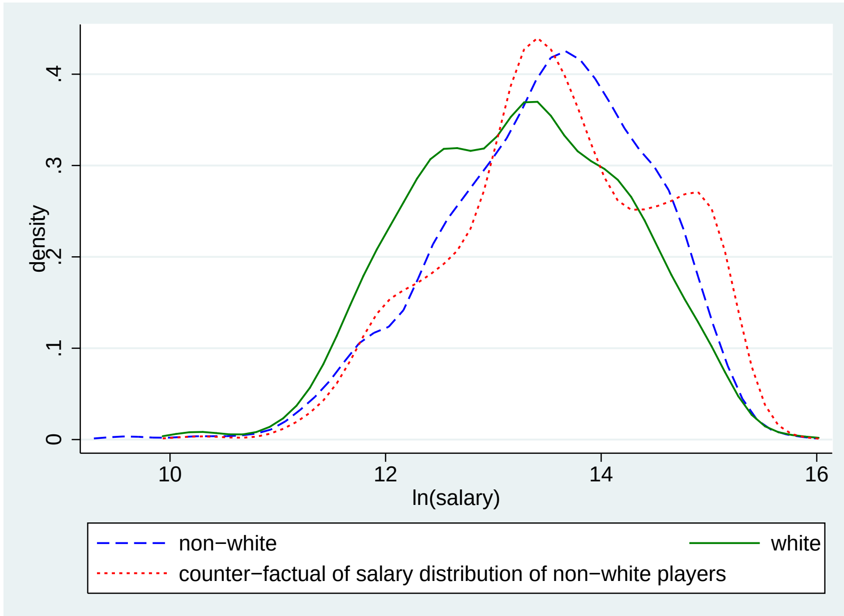

Figure 1: Estimated densities of log of annual salary of different players in 1985–1995. The solid green line is the estimated annual salary density of white players. The blue dash line is that of non-white players. The red dotted line is the counter-factual of salary density of non-white players. The counter-factual salary density is the log of the annual salary density that non-white players would have if the attributes of non-white players (other than race) were rewarded in the same way as the attributes of white players. For estimating the density, we conduct the kernel density estimation with Gaussian kernel with the optimal bandwidth. The calculated optimal bandwidth is 0.178. To calculate the counter-factual density, we use the same explanatory variables as those used in Table 3.

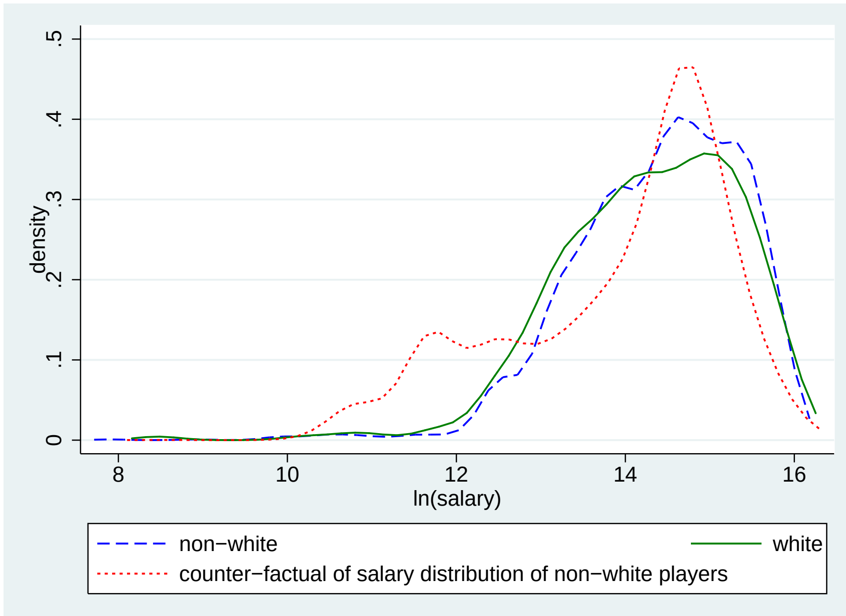

Figure 2: Estimated densities of log of annual salary of different players in 1996–2005.

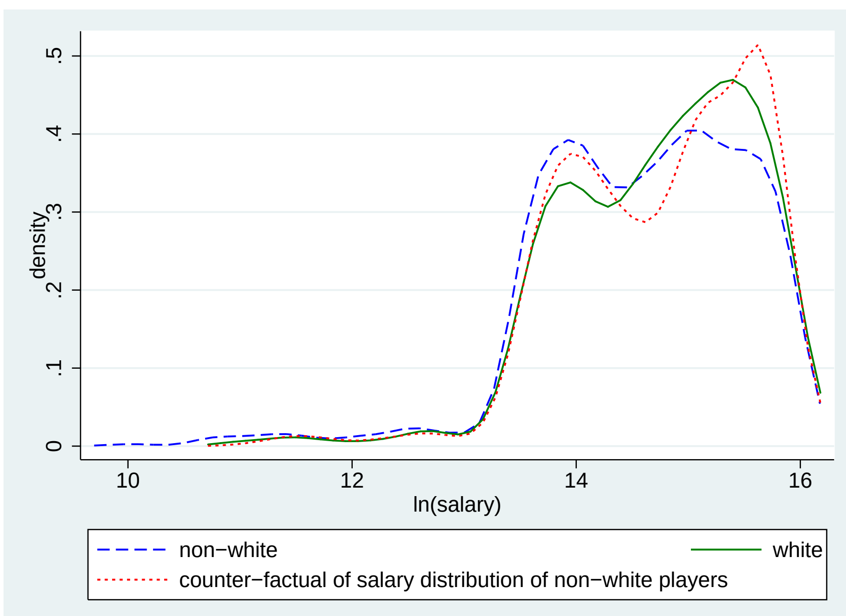

Figure 3: Estimated densities of log of annual salary of different players in 2006–2015.

Appendix(This appendix is for the purpose of refereeing. It will become available from author's website and journal's website)

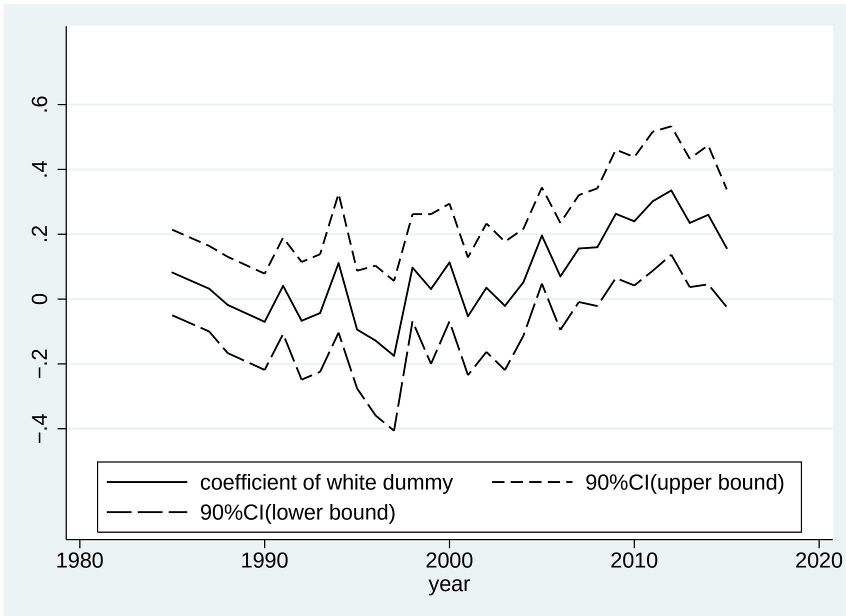

Figure A1: Coefficients of white dummy and its 90% confidence intervals. The estimated coefficient of the white dummy is plotted when the equation used in Table 3 is applied for each year separately.