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*Francesco Principe*¹
*Jan C. van Ours*¹

¹ Erasmus University Rotterdam

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Tinbergen Institute Amsterdam
Gustav Mahlerplein 117
1082 MS Amsterdam
The Netherlands
Tel.: +31(0)20 598 4580

Tinbergen Institute Rotterdam
Burg. Oudlaan 50
3062 PA Rotterdam
The Netherlands
Tel.: +31(0)10 408 8900

Racial Bias in Newspaper Ratings of Professional Football Players

Francesco Principe* Jan C. van Ours[†]

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Abstract

We study whether there is a racial bias in ratings of professional football players in Italian newspapers. We find that there is such a bias. Conditional on objective performance indicators black players receive a lower rating than non-black players. This is not a difference across the board but predominantly present at the lower end of the newspaper rating distribution. The best black players are not subject to a racial bias in ratings. We also find that clubs do not have a racial bias in the wages they pay to players. We speculate that for clubs there is sufficient competition to remove racial wage discrimination. Clubs simply want value for money. Newspaper football experts do seem to have a racial bias in their rating of players. We hypothesize that this might be unconscious discrimination related to stereotyping of black players.

Keywords: racial bias; newspaper ratings; professional football
JEL-codes: J15, J71, L82, L83

*Erasmus School of Economics, Tinbergen Institute and ECASE (Erasmus Center for Applied Sports Economics), the Netherlands; principe@ese.eur.nl

[†]Erasmus School of Economics, Tinbergen Institute and ECASE (Erasmus Center for Applied Sports Economics), Rotterdam, the Netherlands; Department of Economics, University of Melbourne, Parkville, Australia and CEPR (London); vanours@ese.eur.nl.

1 Introduction

In recent years, episodes of racism have proliferated in the football stadiums of several major leagues, such as England and Italy. While national and international federations are taking serious actions against those responsible of racist acts, the issue still remains unsolved. On top of that, a recent case also involved mass media. On 5th December 2019, the front-page of Italian newspaper *Corriere dello Sport* reported the headline “Black Friday”, alongside photos of striker *Romelu Lukaku* of Inter Milan and defender *Chris Smalling* of AS Roma, to preview the Friday night’s match between their respective clubs. Even more recent, the UEFA’s Champions League match of 8th December 2020 between *Paris Saint-Germain* and *Basaksehir* was postponed due to a racial discrimination incident. After one of the UEFA-officials used a racial term addressing an assistant coach of *Basaksehir* walked off the field.

Mass media are the main source of information for football fans. The economic implications of the presence of a racial bias in mass media are not direct in the sense that individuals are harmed in their productivity or career trajectory. Nevertheless, to establish whether there is a racial bias in these ratings even if is it unconscious bias, is important in its own right.

Our paper uses data on the ratings of professional football players by Italian newspapers to establish whether there is a racial bias in these ratings. We contribute to two types of studies. First, we add to the literature on biases in subjective evaluations. Ginsburgh and van Ours (2003) for example show that even an expert jury can make biased decisions. When judging participants in a piano competition the order of appearance which was randomized turned to affect the ratings. This is attributed to the jury having to get used to the new play that was composed especially for the competition. Because of this, the first player got significant lower ratings than later performers. Coupe et al. (2018) analyze voting behavior of the jury for the prestigious football prize FIFA Ballon d’Or finding that there is a similarity bias. Jury members are more favorable to candidates from their own country, national team, continent and league team. Zitzewitz (2006)

finds a similar bias in Olympic winter sports in which judges give higher scores to athletes from their own country than other judges do. Sometimes subjective evaluations have a racial component. For example, Giuliano et al. (2011) studying quits, dismissals and promotions in a large U.S. retail firm find that outcomes are usually better for workers when their manager is of the same race.

Our second and main contribution is to the literature on racial discrimination. Generally, two theories are considered to be at the heart of economic thinking on discrimination, i.e. taste-based discrimination and statistical discrimination. Taste-based discrimination assumes that some people – employers, workers, consumers – want to avoid interaction with members of minority groups. This type of discrimination results from animus. Employers who do not like minority workers will hire fewer of them, workers who do not like minority co-workers will want to be compensated for working with them, customers who do not like minority groups will want to pay a lower price if they are served by them. Statistical discrimination is based on rational behavior with decision making based on limited information. If for example an employer has limited information about the productivity of a job applicant a hiring decision will be partly based on observed characteristics of the applicant and partly on the characteristics of the group the job applicant is related to.

Bertrand et al. (2005) argue that in addition to conscious taste-based and rational statistical discrimination there may be unconscious discrimination to which they refer as “implicit discrimination”. In taste-based discrimination, some people are supposed to have an explicit dislike for certain groups of individuals. In statistical discrimination some individuals explicitly prefer some groups of individuals to others because in expectation this provides them with more utility or higher profits. Implicit discrimination is unintentional and people who discriminate implicitly are not aware of their behavior. Carlana (2019) argues that stereotyping may lead to implicit discrimination. Stereotypes are mental constructs based on overgeneralized representations of differences between groups (Bordalo et al. (2016)).

In their overview of the main differences between statistical discrimination and taste-based discrimination Guryan and Charles (2013) emphasize that a lot of

the empirical work has been focused on establishing that there is discrimination rather than on the cause of this discrimination.¹ Often the existence of an unexplained wage gap between majority and minority workers is used as evidence of wage discrimination against the minority group. Using regression analysis, differences between for example minority and majority workers can partly be explained through differences in observed characteristics and partly through differences in returns to observed characteristics. The second type of differences is considered to be evidence of discrimination. This approach is frequently criticized as it may understate as well as overstate the extent of wage discrimination (Altonji and Blank (1999)). Some of the observed characteristics may be influenced by the existence of discrimination. When it comes to the racial wage gap, it may be that minority workers invest less in education in anticipation of wage discrimination that reduces their return to education. Then, the true effect of discrimination is understated. However, it may also be that the regression analysis suffers from omitted variables which are related to human capital variables and personal tastes. Then, the extent of discrimination may be overstated.

Some empirical studies do address the question on the origin of the discrimination. Glover et al. (2017) for example study the performance of cashiers in a French grocery store chain in relation to their managers. Managers are characterized based on an implicit association test that measures the extent to which they associate minorities – in this case North African immigrants – names with poor worker performance. From the analysis, it appears that when minority cashiers, work with managers who are biased their productivity is lower. This is not because the minority cashiers are treated poorly but because they interact less with their managers and therefore exert less effort. The lower productivity of minority cashiers generates statistical discrimination in hiring.

Sports data are suitable to analyze the existence and sometimes the nature of discrimination whereby the focus is on racial bias. In these studies often there

¹Bertrand and Duflo (2017) provide a general overview of field experiments on discrimination while Neumark (2018) presents an overview of experimental research on labor market discrimination. Lang and Kahn-Lang Spitzer (2020) discuss recent economic research on racial discrimination

is a distinction between black and non-black players based on photographs from websites or book publications. Szymanski (2000) for example uses wage data from English professional football to study racial discrimination. He finds that conditional on their wage bill clubs with a higher share of black players perform better which suggests that the black players were underpaid. For discriminating club owners, their taste for discrimination “acts like a tax on the success of the team”. Szymanski also notes that the discrimination is by the club owner and not by the fans as stadium attendance does not depend on the share of black players (see also Preston and Szymanski (2000)). Reilly and Witt (2011) analyze English Premier League data on the presence of racial bias in referee decisions during five seasons when all but one referee was white. They find no evidence of black, mixed race or Asian football players receiving more disciplinary cards or fouls committed than white players and thus no evidence on racially motivated animus against non-white players. However, Gallo et al. (2013) investigating English Premier League data find evidence of referees awarding more disciplinary warnings (yellow cards) to non-white, foreign players from low-income countries.

We contribute to the discrimination literature by investigating the relationship between race and performance evaluations of professional football players provided by mass media. We study this issue in the context of Serie A in Italy, a country where episodes of racism are often reported both on and off the sports contexts. We find evidence of racial bias. In our analysis we use a wide variety of performance indicators such that there is no issue of characteristics that are unobserved by the newspaper football experts. This rules out the possibility that the racial bias we find is related to statistical discrimination. We also find that the racial bias is not present across the board but present only at the low end of the ratings distribution. For low-ranked players race seems to be an issue. For players in the middle or at the high end of the distribution there does not seem to be a racial bias. From this, we conclude that it is not animus that drives the racial bias. If that would be the case also highly talented players would receive lower ratings conditional on their performance. Instead, we hypothesize that the racial bias at the lower end may be related to unconscious discrimination related to stereotyping.

We also investigate whether there is a racial bias in wages of the football players. We find no evidence of this. Wages are determined by the skills of the players as performance indicators are clearly correlated with wages. At no point in the skills distribution there is evidence of a racial bias. Apparently, clubs do not discriminate between black and non-black players but pay them according to their performance. We speculate that the lack of a racial bias could be because clubs are color-blind but could equally well be the outcome of competition for the best players. Clubs simply want value for money and are willing to pay market wages to all players.

The remainder of the paper is structured as follows. In section 2, we provide background information about football players ratings in Italy and we present the data we use in our analysis. Section 3 provides a descriptive analysis showing that there are unconditional differences in newspaper ratings between black players and non-black players. In section 4 we discuss our empirical strategy. Section 5 presents our main parameter estimates and a decomposition of the racial wage gap in newspaper ratings and wages of the players. Section 6 concludes.

2 Rating football players

2.1 Background

The newspaper ratings, in Italian “*pagelle*” (i.e., report cards) were introduced in the late 50’s by the sports editorial staff of the newspaper *Il Giorno*. However, they started to reach the wider audience and being part of the popular culture when *La Gazzetta dello Sport*, the most sold Italian newspaper, also started to publish them, in October 1972. Nowadays they are published by all the sports newspapers the day after every Serie A’s fixture, generally on Monday.

In the spirit of the school’s report cards, the *pagelle* are aimed at evaluating the performance of the football players, ranging in a scale from 1 (very poor performance) to 10 (excellent performance). These are assigned by professional sports journalists employed by the newspaper, however they are reported anonymously

on the newspaper. They are presented on the newspapers page by reporting the numerical rating alongside few lines of text that reflect the qualitative assessment of the performance (see Appendix Figure A1 for an example). They represent the main source of individual performance information and the only one in which all the players of the team are evaluated. In the years covered in our data, all sports journalists involved in the three newspapers analyzed are Italians and white.²

Apart from being used by the newspapers readership, the ratings are an essential part of football-related games, such as the fantasy football (*fantacalcio*, in Italian). In this game, the participants to a league have a virtual-budget to assemble an imaginary team of Serie A players and to score points based on the newspapers ratings to which bonuses are added or deducted according to each player on-field performance (e.g., plus 3 point for scoring a goal, minus one point for receiving a red card, etc.).

In Italy there are three printed sports newspapers: La Gazzetta dello Sport, Il Corriere dello Sport and TuttoSports with an average circulation of about 250,000, 170,000 and 120,000, respectively. However, most of the readers access the sports newspapers through the online websites. For example, La Gazzetta's website has a daily traffic of about 1.5 million unique users (Audiweb 2021). Albeit similar, the socio-demographic characteristics of the readership show some heterogeneity across newspapers. In particular, La Gazzetta attracts younger and more educated readers compared to the other two newspapers although the differences are small (see for details Appendix Table C1).

²The ex post rating of the performance of football players is one of the services newspapers provide to their readers. Sometimes, newspapers also provide predictions of match outcomes by football experts. There are studies on the quality of these predictions of match outcomes in particular in English football. Forrest and Simmons (2000) for example show that newspaper tipsters are superior to random predictions but their expertise is limited. Forrest et al. (2005) show that both pundits and laypeople outperform random prediction based on seasonal averages. Butler et al. (2021) find that former professional football players have superior forecasting abilities compared to laypeople. However, predicting match outcomes is different from assessing ex post performance of individual players if only because the former is based on expectations of uncertain outcomes while the latter is based on combining observations of actual performance into a rating.

2.2 Our data

We assembled a unique data set recording information about professional football players in Italian Serie A. We have data relating to 409 outfield players, covering a 9-season period, from 2009-2010 to 2017-2018. We exclude goalkeepers, following the standard approach of this kind of literature (Lucifora and Simmons (2003), Carrieri et al. (2020)), since their performance is measured differently compared to the outfield players. This provides a longitudinal dataset of 1,835 player-season observations. The panel is unbalanced. In fact, the relegation/promotion system between Serie A and Serie B and the transfer market across national and international clubs generates a turnover of players in the league. However, this turnover usually involves heterogeneous types of players, both less talented players traded with teams playing in minor leagues and more talented players traded with top European clubs. This helps to mitigate concerns about selective attrition (Carrieri et al., 2020).

We use several sources of data. First, information about individual player's characteristics (i.e., birth year, position on the pitch and international appearances) and performance are extracted from the website *whoscored.com*.

Second, we collected information about the ratings given by the three most sold Italian sports newspapers, *La Gazzetta dello Sport*, *Il Corriere dello Sport* and *Tuttosport*. These rate player's performance after every match within a scale that ranges from 0 (poor performance) to 10 (excellent performance). We use the end-of-season overall average performance provided by the newspapers.

Third, data on players yearly wages - recorded net of taxes and excluding any performance-related bonus - are taken from an annual report, published at the beginning of each football season by *La Gazzetta dello Sport*. For this reason our dataset has 1627 player-season observations for wages, as players who join the league in the following transfer windows (i.e, in January) are not recorded.

One of the recurrent issues is how to establish whether an individual is part of a minority group. We follow Grogger (2011) who studies the contribution of language differences to racial wage differences among U.S. black and white workers. For this

he uses speech samples that are classified in degree of “black-sounding” by a panel of five anonymous listeners. Race was considered to be indistinctly identified if three or less listeners correctly assessed the race of the speaker. Interestingly the racial wage gap is not present for individuals who were indistinctly identified as black, i.e. speech patterns predict racial wage gaps. Grogger (2019) performs a similar speech pattern analysis now also including Southern whites into the analysis. This analysis confirms the earlier findings with respect to racial wage differences and adds to it that Southern whites the wage gap is largely explained by residential location. The absence of a wage gap for black workers with mainstream speech is attributed to occupational sorting, i.e. into occupations that involve intensive interpersonal interactions and therefore earn a sizable wage premium.

Our variable of interest referring to the race of the player is coded through a visual inspection of players photography on the website *transfermarkt.com*. This is an established method in the economic research on discrimination in sports labor market, since the discriminators prejudge an individual based on appearances (Palacios-Huerta (2014)). In order to build this variable, we follow Grogger (2011, 2019) and Price and Wolfers (2010). We recruited four students to look at each players photography and asked them to label the player as either black or non-black.³ Then we aggregated all the scores at the player level in a unique numerical variable ranging from 0 (no one labeled the player as black) to 4 (four individuals labeled the player as black). In the regression analysis and Oaxaca-Blinder decomposition, the indicator used to identify black players takes value one if at least one of the viewers labeled the player as “black”.⁴ Our study using photographs to assess the color of an individual is also in line with several earlier studies discussed in the introduction, i.e. Szymanski (2000), Goddard and Wilson (2009) and Reilly and Witt (2011).⁵ All the variables, along with some summary statistics,

³The students were working on a thesis in discrimination in sports economics but were not aware of the purpose of the labeling.

⁴In Appendix C we show that it does not seem to be important how many of the four assessors labeled the player to be black as long as there is at least one. For this reason, we focus our analysis on the dichotomous situation in which the player is labeled black or non-black.

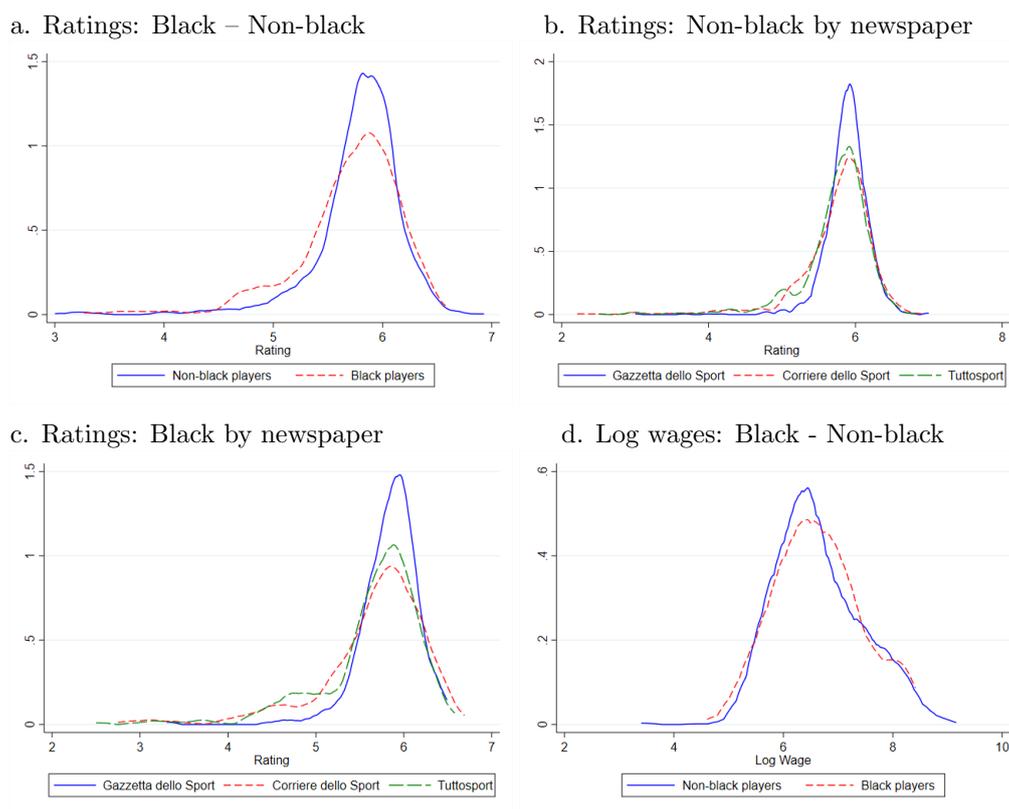
⁵Goldsmith et al. (2006) uses interviewers to grade survey-respondents according to their skin shade in three categories: dark, medium and light (with white as the reference category).

are presented in Appendix A, Table A1.

3 Descriptive Analysis

By way of descriptive analysis, Figure 1 presents kernel densities of ratings and log wages for various groups of players. Figure 1a shows the average ratings of players in which a distinction is made between non-black players and black players where black players are defined as those who received at least one of four indicators for being considered as black. There is a clear difference between the two densities whereby black players receive more low ratings than non-black players, especially between 4.5 and 5. Only a few non-black players receive such a low rating.

Figure 1: **Kernel densities black players and non-black players**



They find that light shaded earn wages similar to whites while dark and medium light earn substantially less.

Figure 1b shows the average ratings of non-black players by newspaper, Figure 1c does the same for the black players. There are obvious differences between the newspapers in the ratings. *Gazzetta dello Sport* has fewer low ratings for non-black players and in particular for black players. Tuttosport in particular has a peak of low ratings for black players. Figures 1d shows kernel densities of log wages. The density is broader for black players in particular because there are more high wages for black players although in the very high wages non-black players are over-represented. All in all, we conclude from Figure C.1 that black players receive lower ratings and higher wages whereas there is not much of a difference according to the category of black players.

Figure 2: **Cumulative distribution of newspaper ratings: black and non-black players**

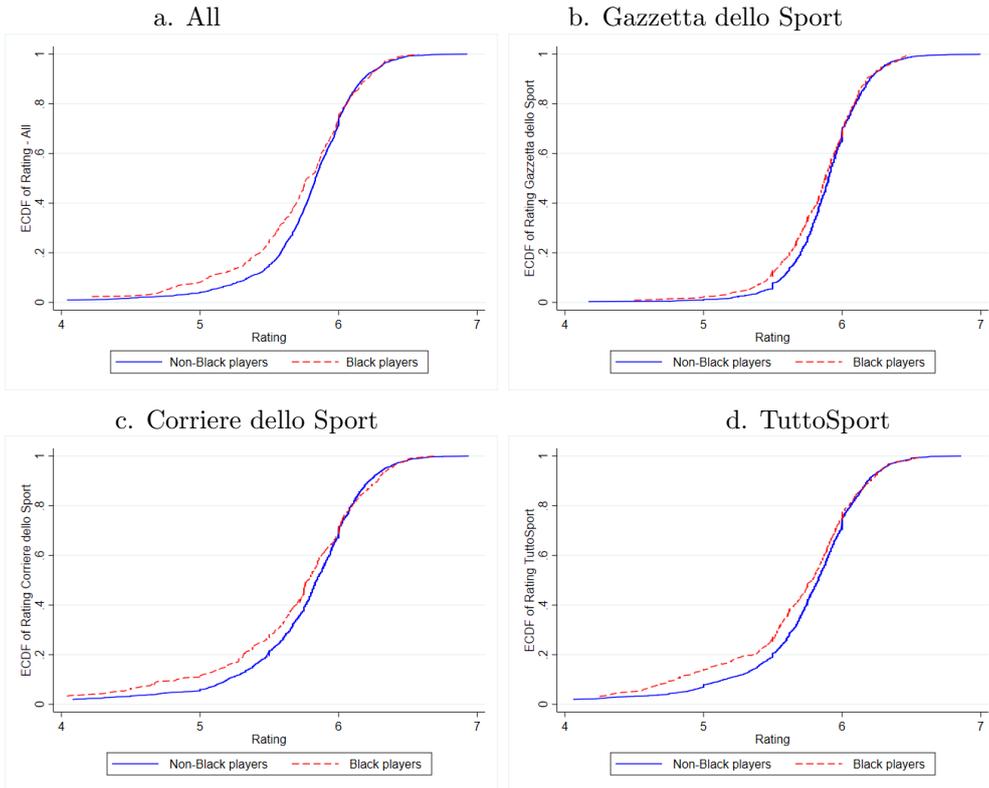


Figure 2 shows the cumulative distribution of the newspaper ratings distinguished between black and non-black players. Clearly, at the low end of the distri-

bution the distributions are different with the distribution of the non-black players shifted somewhat to the right. This difference is present for each of the newspaper although somewhat smaller for Gazzetta dello Sport. At the top end of the distribution the cumulative distributions for black and non-black players are overlapping.

Table 1 shows the means of the newspaper ratings and log wages for the two groups of players as well as the difference between the two. The first row shows that non-black players on average receive a higher newspaper rating. Whereas black players on average receive 5.67, non-black players receive 5.78, an absolute difference of 0.09, a relative difference of 1.6%. As shown, the largest difference in average rating is for Corriere and TuttoSport with 2.0%. The smallest difference is for Gazzetta with 1%. Also for wages there is a difference between black and non-black players, this is 1.1%.

Table 1: Mean newspaper ratings and mean log wages; black and non-black players

		Black	Non-black	Δ	$\Delta(\%)$
a. Ratings	All	5.687	5.780	-0.093	-1.6
b. Ratings	Gazzetta	5.828	5.884	-0.056	-1.0
	Corriere	5.630	5.741	-0.111	-2.0
	TuttoSport	5.603	5.714	-0.111	-2.0
c. Log wages		6.634	6.644	-0.010	-1.0

Note: Based on 1835 observations (wage sample 1627 observations)

Figure 2 suggests that the difference in newspaper rating between black and non-black players is bigger at the low end of the distribution than at the top end. Therefore, Table 2 shows the differences by quintile. At the lowest quintile indeed the difference between black players and non-black players is substantially larger. Whereas the mean difference for the average newspaper rating is 0.093, this is 0.288 at the lowest quintile, equivalent to 5.4%. At the lowest quintile, the difference between the ratings for non-black and black players is 0.092 for Gazzetta (1.7%), 0.70 for Corriere (7.1%) and 0.43 for TuttoSport (6.6%). The wage difference at

the bottom quintile is 7.0%. For quite a few ratings the differences become almost monotonically smaller for higher quintiles even to the extent that for the highest quintile sometimes the sign of the difference flips. This is the case for the average ratings and the ratings of Corriere and TuttoSport where at the top quintile black players receive higher ratings than non-black players. For wages black players receive less than non-black players at both ends of the distributions and get paid better in the middle of the wage distribution. That is, unconditional on the quality of the player as measured by various performance indicators.

Table 2: **Differences non-black - black; by quintile**

			q10	q30	q50	q70	q90
a. Ratings	All	Black	5.062	5.569	5.780	5.979	6.207
		Non-black	5.350	5.690	5.833	5.990	6.177
		Difference	-0.288	-0.121	-0.053	-0.011	0.030
b. Ratings	Gazzetta	Black	5.478	5.724	5.880	6.000	6.180
		Non-black	5.570	5.780	5.900	6.000	6.200
		Difference	-0.092	-0.056	-0.020	0.000	-0.020
	Corriere	Black	4.830	5.550	5.780	6.000	6.282
		Non-black	5.200	5.650	5.840	6.000	6.220
		Difference	-0.370	-0.100	-0.060	0.000	0.062
	TuttoSport	Black	4.808	5.534	5.790	5.950	6.210
		Non-black	5.150	5.647	5.830	5.990	6.190
		Difference	-0.342	-0.113	-0.040	-0.040	0.020
c. Log wages	Black		5.631	6.215	6.551	7.003	7.867
	Non-black		5.704	6.215	6.551	7.003	7.824
	Difference		-0.073	0.000	0.000	0.000	0.043

Based on 1835 observations (wage sample 1627 observations)

4 Empirical Strategy

If media are unbiased, the evaluation of a player performance reflected in the newspapers ratings should depend only on his on-field skills, regardless of the color of his skin. We empirically test this hypothesis by using a pooled cross-section approach that relates an extensive set of performance variables, alongside

our variable of interest indicating whether the player is black or not, to newspapers ratings.⁶ We estimate the following equation:

$$R_{it} = \beta B_i + \delta P_{it-1} + \gamma X_{it-1} + \eta S_t + \theta T_{jt} + \varepsilon_{it} \quad (1)$$

where R_{it} represents newspaper ratings received by player i in season t , B is a dummy variable indicating if on the basis of a photograph at least one of the four individuals labeled the player as black, P is a set of performance related variables and X is a set of player characteristics, S represents season fixed effects, T is a set of team fixed effects, δ , γ , η and θ are vectors of parameters and ε is the error terms. The parameter of main interest is β which measures the effect of being a black player as compared to a non-black player.

We start our analysis with OLS-estimates of equation (1). In order to investigate how the effect of being black changes alongside the ratings distribution we also estimate equation (1) on the pooled sample of players using the Unconditional Quantile Regression (UQR) approach, also called the Recentered Influence Function (RIF) method, proposed by Firpo et al. (2009).

The main advantage of the UQR approach over other distributional methods (i.e., the conditional quantile regression proposed by Koenker and Bassett Jr (1978)) is that it allows us to analyze the relationship between our variable of interest and the unconditional distribution of newspaper ratings. This possibility occurs because the UQR method provides a linear approximation of the unconditional quantiles of the dependent variable. The law of iterated expectations can be applied to the quantile being approximated and used to estimate the marginal effect of a covariate through a simple regression of a function of the outcome variable, the Recentered Influence Function (RIF), on the covariates.

In our setting, the RIF of newspaper ratings is estimated directly from the data

⁶Although we have panel data from 2009 to 2018, our main variable of interest, i.e. the racial status, does not change over time. Thus, it is not possible to use an individual fixed-effects approach to account for unobserved differences across individuals. The pooled cross-section nature of the data is taken into account by clustering the standard errors at the level of the player.

by first computing the sample quantile q and then estimating the density of the distribution of ratings at that quantile using kernel density methods. Then, for a given observed quantile q_τ , a RIF is generated, which can take one of two values depending on whether the observation's value of the outcome variable is less than or equal to the observed quantile:

$$RIF(W; q_\tau) = q_\tau + \frac{(\tau - 1[W \leq q_\tau])}{f_w(q_\tau)} \quad (2)$$

where q_τ is the observed sample quantile of earnings, $\tau - 1[W \leq q_\tau]$ is an indicator variable equal to one if the observation's value of ratings is less than or equal to the observed quantile and zero otherwise, while $f_w(q_\tau)$ is the estimated kernel density of ratings at the τ_{th} quantile.

The RIF defined in equation (2) is then used as a dependent variable in an OLS regression on the covariates defined in equations (1). Indeed, the unconditional quantile of ratings q_τ , may be obtained as follows:

$$q_\tau = E_x[E(\widehat{RIF}(W; q_\tau)|X)] \quad (3)$$

where $\widehat{RIF}(W; q_\tau)|X$ is the estimate of RIF as defined in equation (2), conditional on covariates X . Thanks to this linear approximation, it is now possible to apply the law of iterated expectations. Thus, q_τ can be written as

$$q_\tau = E[X](\widehat{\delta}_\tau) \quad (4)$$

where $\widehat{\delta}_\tau$ is the coefficient of the unconditional quantile regression. This linearization allows the estimation of the marginal effect of a change in distribution of covariates X on the unconditional quantile of ratings, measured by the parameter $\widehat{\delta}_\tau$.

Next, we implement the Oaxaca–Blinder decomposition (Oaxaca (1973); Blinder (1973)) in order to decompose the gap in newspaper ratings between the black and non-black players into an endowment effect (i.e., explained by differences in

productivity) and an unexplained effect due to different returns to covariates, which is typically attributed to discrimination. More formally, OB decomposes the estimated gap in newspaper evaluations between black (B) and non-black (NB) players as follows:

$$R_{NB} - R_B = (\bar{x}_{NB} - \bar{x}_B)\beta_B + \bar{x}_B(\beta_{NB} - \beta_B) \quad (5)$$

where R represents rating (and in some of the estimates R represents log wages). Then, in order to investigate the distributional gap in ratings evaluations between black and non-black players we combine the OB decomposition with the RIF as proposed by Firpo et al. (2018). The differences in estimated newspapers ratings between black and non-black players each quintile can be decomposed as follows:

$$\widehat{RIF}(R_{NB, q_{NB\tau}}) - \widehat{RIF}(R_{B, q_{B\tau}}) = (\bar{x}_{NB} - \bar{x}_B)\delta_B + \bar{x}_B(\delta_{NB} - \delta_B) \quad (6)$$

5 Estimation results

5.1 Parameter estimates

We start our empirical analysis by estimating equation (1) by OLS. Table 3 presents parameter estimates of β for various dependent variables, i.e. average ratings across the three newspapers, ratings for every newspaper separately and log wages. Taking all observable characteristics into account, the mean ratings are 0.085 points lower for black players and this is significantly different from zero. Also for the separate ratings by newspaper there are big and significant differences in the ratings. Panel c of Table 3 shows that for log wages there is no difference between black players and non-black players.

The full parameter estimates are presented in Appendix B. There it is shown that the performance-related variables have effects as might be expected. Newspaper ratings go down with age and wages go up with age although both in a non-linear way. Being an international does not affect the newspaper ratings but

Table 3: Mean ratings, mean log wages; Oaxaca Blinder-decomposition

		Parameter estimates	Oaxaca-Blinder decomposition			
			Explained		Unexplained	
a. Ratings	All	-0.085*** (0.030)	0.046 (0.045)		-0.139*** (0.041)	
b. Ratings	Gazzetta	-0.059** (0.030)	0.047 (0.039)		-0.104** (0.042)	
	Corriere	-0.095** (0.040)	0.050 (0.053)		-0.161*** (0.047)	
	TuttoSport	-0.102*** (0.038)	0.042 (0.057)		-0.153*** (0.049)	
c. Log wages		-0.005 (0.050)	-0.012 (0.079)		0.002 (0.045)	

Note: Based on 1835 observations (wage sample 1627 observations); all estimates include the complete set of explanatory variables; the full parameter estimates are presented in Appendix B; standard errors clustered at the level of the player are in parentheses; *(**): significant at 10(5)%.

has a positive and significant effect on the wage of the player. Skills which have a direct impact on the final result of the game, such as goals and assists, receive a higher weight from newspaper evaluators but do not materialize in wages. Red cards have a negative effect on newspaper ratings but a positive effect on wages. Pass success rates have a negative effect on newspaper ratings. Clearly, more risky passes can determine the outcome of a match but also have a higher probability to fail. Therefore, there are appreciated more than riskless passes over a short distance that are more likely to be successful as pas but have no influence on the match outcome. Positive effects on newspaper ratings are also caused by blocks, fouled, passes. Forwards often receive lower ratings but higher wages while mid-fielders also receive higher wages relative to defensive players. In general, from the results in Table 3 we can conclude that all sports newspapers show a degree of skin-tone bias in their ratings. However, the effect for La Gazzetta is smaller in magnitude than that for the other two newspapers. This might depend on two main factors. On one hand, the goodness-of-fit value for this newspaper’s ratings model suggests better use of the observable data by the journalists employed. On the other hand, we speculate that the socioeconomic profile of the readership plays a role here, as the younger and relatively more educated readers of La Gazzetta (see Section 2) might be less prone to receive racially biased evaluations of players’ performance.

The parameter estimates presented in Appendix B are used to do an Oaxaca-Blinder decomposition to investigate to what extent the observed characteristics between black and non-black players can explain the differences in newspaper ratings and log wages. The results are shown in Table 3. As shown, for the newspaper ratings none of the explained part of the black – non-black gap is significantly different from zero while all the unexplained differences are significant.

Table 4: **Unconditional Quintile Regression parameter estimates effects of being a black player on ratings and log wages**

		q10	q30	q50	q70	q90
a. Ratings	All	-0.059*** (0.017)	-0.074*** (0.028)	-0.025 (0.028)	0.012 (0.029)	0.020 (0.021)
b. Ratings	Gazzetta	-0.060*** (0.020)	-0.077*** (0.027)	-0.025 (0.033)	-0.007 (0.033)	-0.014 (0.018)
	Corriere	-0.057*** (0.019)	-0.048* (0.028)	-0.036 (0.029)	0.004 (0.030)	0.040* (0.021)
	TuttoSport	-0.059*** (0.018)	-0.085*** (0.028)	-0.025 (0.033)	-0.019 (0.029)	0.026 (0.020)
c. Log wage		-0.015 (0.022)	-0.013 (0.032)	0.039 (0.033)	-0.010 (0.035)	0.030 (0.028)

Note: Based on 1835 observations (wage sample 1627 observations); all regressions include the complete set of explanatory variables. Standard errors clustered at the level of the player are in parentheses; *(**,***): significant at 10(5,1)%

Table 4 shows the relevant parameter estimates for the unconditional quintile regressions. The conditional difference in average newspaper ratings between black and non-black players at the lowest quintile is significant and has a value of 0.23 whereas the unconditional difference is 0.30 (see Table 2). Taking differences in observed characteristics into account enlarges the black - non-black difference in average newspaper ratings. Also for the separate newspapers the relevant parameter estimates are significant and larger than the differences presented in Table 2. For wages the difference is insignificant and smaller than the unconditional difference presented in Table 2. For the average ratings and the ratings of Gazzetta and Tuttosport also the second quintile from the bottom shows a significant difference between black and non-black players but for higher quintiles there is no significant difference. For Corriere also the upper quintile is significant but only at a 10%

level. For log wages none of the quintile estimates is significant except for the highest where there is a negative effect that is significant at a 10% level.

All in all, the conclusion from the estimates presented in Table 4 is that the differences in newspaper ratings between black and non-black players are located at the bottom of the distribution. However, these differences display a degree of heterogeneity across newspapers. In particular, it emerges that TuttoSport and Corriere show a higher level of bias in their rating in particular at the bottom end of the distribution. On the other side, such bias seems less prominent in Gazzetta’s ratings, suggesting a better use of the productivity-related information by its journalists. By and large, for the wages it holds that there are no differences between black and non-black players.

5.2 Sensitivity analysis

To investigate the robustness of our main findings, we performed some sensitivity analysis. First, to establish that the bias in newspaper ratings indeed is related to the subjective judgment of the professional sports journalist we redid the baseline analysis with a new dependent variable, i.e. the rating based on player performance characteristics which is published on “whoscored.com” prior to every match. As in the baseline analysis we use end-of-season ratings as our dependent variable. Table 5 shows that with this dependent variable there is no significant racial bias. For reasons of comparison we also include the baseline estimate for the newspaper ratings in which there is a significant racial bias. This confirms that indeed it is the subjective judgment of the journalists that is driving our main findings.

Table 5: Effect of “Black”; Comparing newspaper ratings with a rating based on player performance characteristics

	Newspaper rating		Performance statistic	
Black	-0.085***	(0.030)	-0.018	(0.013)
N	1835		1771	

Note: The full parameter estimates are presented in Appendix B.

Furthermore, we wanted to know whether the racial bias in newspaper ratings

is at least partly driven by favoritism towards Italian players. After all, in our sample of Italian players only 3% of the observations is on a black player while among the non-Italians 37% of the observations is on a black player. It could be that the bias in newspaper ratings is related to favoritism rather than skin color. To find out whether favoritism matters we limited the sample to non-black players. As shown in the first row of Table C.3 there is evidence of favoritism towards Italian players. On average, conditional on their performance they receive a higher rating (10% significance). This is also the case for each of the newspapers although the estimated effect is not significantly different from zero for Corriere.

Table 6: Parameter estimates newspaper ratings – sensitivity analysis subsamples

Sample	Parameter	All		Gazzetta		Corriere		TuttoSport		N
Non-black	Italian	0.038*	(0.022)	0.045**	(0.022)	0.010	(0.026)	0.059*	(0.032)	1488
Non-Italian	Black	-0.074**	(0.035)	-0.047	(0.034)	-0.091**	(0.040)	-0.085*	(0.046)	866
Baseline	Black	-0.085***	(0.030)	-0.059**	(0.030)	-0.096**	(0.040)	-0.102***	(0.038)	1835

Based on 1835 observations; all regressions include the complete set of explanatory variables. Standard errors clustered at the level of the player are in parentheses; robust standard errors clustered at the level of the player in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To further investigate this issue we also did an analysis on the non-Italian sample. This reduces the sample size a lot but the effects of the dummy for a black player shown in the second row of Table C.3 are very similar to the one in the baseline estimate (shown at the bottom line of the table). The magnitude of the effect is somewhat reduced and for Gazzetta the estimate is no longer significantly different from zero but the point estimate of -0.047 is very similar to the point estimate of -0.059 in the baseline estimates. We conclude from this that there is evidence of favoritism in the newspaper ratings. However, this favoritism does not imply that after it is taken into account the racial bias disappears.

As a further sensitivity analysis we investigated to what extent it matters to make a distinction between the four categories of black players. Parameter estimates for the dummies indicating the number of observers reporting the player as “Black” are displayed in Appendix C as Table C.2. Importantly, all the estimated coefficients are negative, and they are larger in magnitude and statistically significant at 1% level when 3 observers labelled the player as “Black”. All in all, this

test confirms the conclusions of our main analysis. All newspapers show a degree of rating bias, which is more prominent in *Corriere* and *TuttoSport*'s ratings.

Finally, we estimated the Oaxaca-Blinder decomposition based on the parameter estimates related to Table 4. As shown in Appendix C Table C.3 for none of the newspaper ratings is the contribution of the explained gap significantly different from zero. The contribution of the unexplained contribution to the ratings difference is significantly only at the low end of the distribution (with the exception of the *Corriere* at the top end of the distribution). For log wages almost all of the estimates are not significantly different from zero.

6 Conclusions

Using data from the Serie A, the highest professional football league in Italy, we study the determinants of newspaper ratings of the players in this league. We focus on whether there is a racial bias, i.e. whether conditional on their performance black players receive lower ratings than non-black players. We find that there is such a bias. In an additional analysis on players' wages, we find no evidence of wage discrimination from the clubs. Our findings that the difference in results between finding evidence of discrimination in behavior but not in wages is similar to the difference in findings for the US NBA basketball league. Price and Wolfers (2010) conclude that white referees call more fouls against black players and vice versa while Hill (2004) does not find a racial bias in NBA wages.

We find that the lower ratings for black players are located at the low end of the distribution of newspaper ratings. This is present for all three newspapers, so the racial bias is not limited to one newspaper but widely present. However, our results suggest a degree of heterogeneity in the presence of such bias. Specifically, *TuttoSport* and *Corriere* show a higher degree of racial bias in their published ratings, while this bias, albeit present, seems to be much more mitigated in *La Gazzetta*'s ratings. These results suggest that the evaluation provided by sports newspapers do not only reflect on-field performance and are biased against ethnic groups. This raises concerns for several reasons in particular concerning spillover

effects from newspaper to football supporters. On the one hand, football fans might develop adverse preferences towards some players because of their race. This might be an additional trigger of violence and racism inside and out of the stadiums. On the other hand, it might generate distortions in markets with monetary prizes (i.e., betting, fantasy football).

With our data we are not able to identify the mechanisms at work. We speculate that either clubs are not racial biased in the wages they pay. Or, alternatively for clubs there is sufficient competition to remove racial wage discrimination, i.e. clubs simply want value for money and are willing to pay market wages for the players they want. Newspaper football experts do seem to have a racial bias in their rating of players. In a sensitivity analysis, we find evidence of favoritism towards Italian players but when taken into account there is still a racial bias. We hypothesize that this is unconscious discrimination related to stereotyping. Further research should be devoted to investigating these by disentangling whether newspapers implicitly respond to a “demand for discrimination” from their readers or if this is the result of biased evaluators. It is not clear that racial bias in newspaper ratings is driven by conscious discrimination driven by animus. If so, one would expect a racial bias in newspaper ratings across the board. This is not the case. Racial bias seems to be present only at the low end of the skill distribution. Therefore, it may be that the discrimination is unintentional without the discriminator being aware. This suggests that exposure to research outcomes establishing a racial bias may reduce discrimination. There is some evidence on this. When an academic study on racial bias among professional basketball referees was published nothing happened to the bias. However, when the study received media coverage and the awareness of the racial bias was raised, the bias disappeared (Pope et al. (2018)). In other words, though unintentional discrimination is as harmful to the discriminated as intentional discrimination is, there is an easy cure. Creating awareness by exposure might be able to wipe out racial bias in newspaper ratings and perhaps also in the behavior of others involved in football or sports in general. To the extent that there are spillover effects from newspaper reports to opinions in society, making clear that there is a racial bias will be helpful

in reducing discrimination across the board.

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Table A.1: Variable definitions and summary statistics

Variable	Definition	Full sample		Black		Non-black	
		Mean	St. Dev	Mean	Std. Dev.	Mean	Std. Dev
Rating Gazzetta	<i>Player rating Gazzetta dello Sport</i>	5.87	0.36	5.83	0.46	5.88	0.33
Rating Corriere	<i>Player rating Corriere dello Sport</i>	5.72	0.61	5.63	0.76	5.74	0.57
Rating TuttoSport	<i>Player rating TuttoSport</i>	5.69	0.63	5.60	0.74	5.71	0.60
Log Wage	<i>Player's wage</i>	6.64	0.80	6.63	0.79	6.64	0.80
Black	<i>Indicator for being black</i>	0.19	0.39				
Age	<i>Player's age</i>	28.40	4.14	27.17	3.94	28.68	4.14
Goals	<i>Total goals</i>	1.97	3.56	1.40	2.40	2.11	3.77
Assists	<i>Total assists</i>	1.40	2.11	1.31	2.12	1.42	2.11
Yellow cards	<i>Yellow cards received</i>	3.39	3.27	3.13	3.16	3.45	3.30
Red cards	<i>Red cards received</i>	0.19	0.44	0.18	0.42	0.20	0.45
SpG	<i>Shots per game</i>	0.80	0.83	0.79	0.80	0.80	0.84
PS	<i>Pass success percentage</i>	66.48	30.74	67.38	31.53	66.26	30.56
Aerials won	<i>Aerial duels won</i>	0.87	0.84	0.79	0.77	0.88	0.85
Tackles	<i>Tackles per game</i>	1.34	1.04	1.47	1.09	1.31	1.03
Interceptions	<i>Interceptions per game</i>	1.11	0.96	1.11	0.97	1.11	0.96
Fouls	<i>Fouls per game</i>	0.97	0.66	1.02	0.69	0.96	0.65
Offsides defensive	<i>Offside won per game</i>	0.18	0.33	0.16	0.30	0.18	0.33
Clear	<i>Clearances per game</i>	1.95	2.36	1.79	2.31	1.99	2.37
Drb defensive	<i>Dribbled past per game</i>	0.53	0.46	0.52	0.46	0.54	0.46
Blocks	<i>Outfielder block per game</i>	0.20	0.25	0.19	0.24	0.21	0.25
KeyP	<i>Key passes per game</i>	0.61	0.59	0.63	0.61	0.61	0.59
Drb	<i>Dribbles per game</i>	0.50	0.57	0.75	0.79	0.44	0.49
Fouled	<i>Fouled per game</i>	0.90	0.73	0.91	0.79	0.89	0.71
Offsides offensive	<i>Offsides per game</i>	0.15	0.30	0.10	0.19	0.16	0.31
UnsTch	<i>Bad control per game</i>	0.58	0.58	0.64	0.60	0.57	0.58
AvgP	<i>Passes per game</i>	26.13	17.29	25.94	17.09	26.17	17.35
Crosses	<i>Crosses per game</i>	0.31	0.43	0.31	0.43	0.31	0.43
Long B	<i>Long balls per game</i>	1.80	1.94	1.76	1.92	1.81	1.95
Thr B	<i>Through balls per game</i>	0.08	0.15	0.07	0.12	0.08	0.15
Off Target	<i>Shots off target</i>	0.35	0.35	0.36	0.36	0.35	0.35
On Post	<i>Shots on post</i>	0.01	0.04	0.01	0.03	0.01	0.04
On Target	<i>Shots on target</i>	0.26	0.33	0.24	0.31	0.26	0.34
Blocked	<i>Shots blocked</i>	0.19	0.22	0.20	0.22	0.19	0.23
Dispossessed	<i>Dispossessed per game</i>	0.70	0.69	0.80	0.73	0.68	0.68
In Acc Cr	<i>Inaccurate cross passes</i>	1.10	1.33	1.12	1.38	1.10	1.31
In Acc Crn	<i>Inaccurate corner passes</i>	0.16	0.41	0.14	0.33	0.16	0.42
On-field position	<i>Defender</i>	0.41	0.49	0.39	0.49	0.42	0.49
	<i>Midfielder</i>	0.40	0.49	0.46	0.50	0.38	0.49
	<i>Forward</i>	0.19	0.39	0.15	0.36	0.20	0.40

Note: Based on 1835 observations (wage sample 1627 observations);

Appendix B: Full overview parameter estimates

Variables	Ratings All	Ratings Gazzetta	Ratings Corriere	Ratings TuttoSport	Log wage	Player performance
Black	-0.085*** (0.030)	-0.059** (0.030)	-0.095** (0.040)	-0.102*** (0.038)	-0.005 (0.050)	-0.018 (0.013)
Age	-0.000 (0.027)	-0.020 (0.023)	-0.024 (0.035)	0.042 (0.043)	0.484*** (0.054)	0.050*** (0.013)
Age-squared	0.000 (0.000)	0.000 (0.000)	0.001 (0.001)	-0.001 (0.001)	-0.008*** (0.001)	-0.001*** (0.000)
Goals	0.029*** (0.004)	0.020*** (0.004)	0.037*** (0.006)	0.032*** (0.006)	0.017** (0.007)	0.020*** (0.002)
Assists	0.026*** (0.006)	0.021*** (0.004)	0.034*** (0.008)	0.023*** (0.008)	0.017* (0.009)	0.017*** (0.002)
Yellow cards	0.001 (0.003)	0.000 (0.003)	0.002 (0.004)	-0.000 (0.004)	0.002 (0.005)	-0.004** (0.002)
Red cards	-0.043*** (0.015)	-0.047*** (0.012)	-0.045** (0.020)	-0.037* (0.020)	-0.003 (0.022)	-0.040*** (0.006)
SpG	-0.015 (0.150)	0.159 (0.105)	-0.015 (0.204)	-0.189 (0.222)	0.069 (0.231)	0.081 (0.050)
PS	-0.009*** (0.001)	-0.004*** (0.001)	-0.011*** (0.001)	-0.012*** (0.002)	-0.002 (0.001)	0.001 (0.001)
Aerials won	-0.053*** (0.019)	-0.033 (0.021)	-0.065*** (0.022)	-0.062** (0.027)	-0.025 (0.029)	0.071*** (0.006)
Tackles	0.035** (0.017)	0.038** (0.016)	0.037 (0.023)	0.031 (0.023)	-0.007 (0.027)	0.118*** (0.007)
Interceptions	0.046** (0.018)	0.027* (0.015)	0.057** (0.027)	0.053** (0.025)	-0.028 (0.026)	0.099*** (0.008)
Fouls	-0.021 (0.029)	-0.011 (0.027)	-0.040 (0.038)	-0.011 (0.038)	-0.033 (0.040)	-0.025** (0.010)
Offsides defensive	-0.060 (0.042)	-0.037 (0.034)	-0.103 (0.069)	-0.041 (0.061)	0.136** (0.058)	-0.043** (0.019)
Clear	0.033*** (0.010)	0.012 (0.008)	0.048*** (0.013)	0.039*** (0.013)	0.013 (0.013)	0.032*** (0.005)
Drb defensive	-0.033 (0.037)	-0.045 (0.032)	-0.026 (0.051)	-0.027 (0.050)	-0.083* (0.048)	-0.052*** (0.011)
Blocks	0.276*** (0.057)	0.132*** (0.045)	0.313*** (0.076)	0.384*** (0.076)	-0.062 (0.083)	0.075** (0.036)
KeyP	-0.067 (0.052)	-0.003 (0.035)	-0.116 (0.073)	-0.083 (0.072)	0.055 (0.054)	0.094*** (0.014)

Variables	Ratings All	Ratings Gazzetta	Ratings Corriere	Ratings TuttoSport	Log wage	Player performance
Drb offensive	0.091*** (0.022)	0.066*** (0.019)	0.078*** (0.029)	0.128*** (0.032)	0.025 (0.039)	0.171*** (0.009)
Fouled	0.029 (0.023)	0.019 (0.020)	0.035 (0.032)	0.033 (0.029)	-0.001 (0.029)	0.039*** (0.010)
Off	0.017 (0.070)	-0.095 (0.078)	0.018 (0.090)	0.127 (0.085)	0.039 (0.073)	-0.009 (0.020)
Uns Tch	0.054 (0.034)	-0.024 (0.035)	0.124*** (0.046)	0.062 (0.051)	0.005 (0.040)	-0.052*** (0.011)
Avg P	0.013*** (0.002)	0.005*** (0.001)	0.016*** (0.003)	0.017*** (0.003)	0.012*** (0.002)	0.002*** (0.001)
Crosses	0.175*** (0.065)	0.183*** (0.049)	0.162* (0.093)	0.182** (0.089)	-0.032 (0.065)	0.125*** (0.023)
Long B	-0.012 (0.009)	0.001 (0.007)	-0.020 (0.014)	-0.018 (0.012)	0.022 (0.016)	0.016*** (0.006)
Thr B	-0.032 (0.079)	-0.122* (0.068)	0.047 (0.107)	-0.020 (0.115)	0.052 (0.144)	0.071* (0.036)
Off Target	-0.085 (0.158)	-0.247** (0.114)	-0.022 (0.214)	0.014 (0.236)	-0.007 (0.238)	-0.115** (0.053)
On Post	0.076 (0.273)	0.299* (0.169)	-0.143 (0.367)	0.071 (0.385)	0.117 (0.363)	0.350*** (0.082)
On Target	0.267* (0.147)	0.084 (0.107)	0.265 (0.204)	0.452** (0.215)	0.188 (0.228)	0.189*** (0.054)
Blocked	0.005 (0.165)	-0.096 (0.117)	-0.099 (0.237)	0.210 (0.237)	-0.033 (0.245)	-0.112** (0.053)
Dispossessed	0.046 (0.033)	0.010 (0.028)	0.034 (0.055)	0.093** (0.044)	-0.054 (0.036)	-0.033*** (0.009)
In Acc Cr	-0.043** (0.018)	-0.050*** (0.017)	-0.036 (0.025)	-0.042* (0.022)	-0.040** (0.019)	-0.032*** (0.007)
In Acc Crn	-0.052 (0.037)	-0.060** (0.027)	-0.049 (0.051)	-0.046 (0.051)	-0.062 (0.057)	-0.023* (0.012)
Forward	-0.122** (0.057)	0.020 (0.045)	-0.176** (0.074)	-0.210** (0.083)	0.340*** (0.082)	-0.006 (0.034)
Midfield	0.023 (0.032)	0.054** (0.026)	0.034 (0.043)	-0.021 (0.045)	0.153*** (0.057)	-0.019 (0.020)
N	1835	1835	1835	1835	1627	1771
R-squared	0.371	0.266	0.329	0.307	0.672	0.789

Robust standard errors clustered at the level of the player in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Parameters of the fixed effects for club and season are not reported.

Appendix C: Additional information and sensitivity analysis

C1. Additional information

Table C.1 shows detailed information about the readership of the three Italian newspapers. Gazzetta has the highest share of readers below age 35 and the lowest share of readers from age 55 onward. However, the differences are not substantial.

Table C.1: Characteristics readers Italian newspapers (percentages)

Age	14-24	25-34	35 -44	45-54	55+	Total
Gazzetta	16.1	17.6	20.0	18.7	27.6	100.0
Corriere	14.6	15.3	20.5	19.0	30.6	100.0
TuttoSport	19.9	13.1	20.0	17.5	29.5	100.0
Education	University	Upper secondary	Lower secondary	Primary	Less than primary	Total
Gazzetta	10.0	41.8	41.0	6.9	0.3	100.0
Corriere	8.5	39.8	42.9	8.2	0.6	100.0
TuttoSport	7.1	38.6	46.0	7.9	0.4	100.0
Social class	A	B	C1	C2	D	Total
Gazzetta	3.5	11.1	74.0	10.4	1.0	100.0
Corriere	3.3	12.0	69.3	13.3	2.1	100.0
TuttoSport	2.5	9.8	74.8	11.5	1.4	100.0

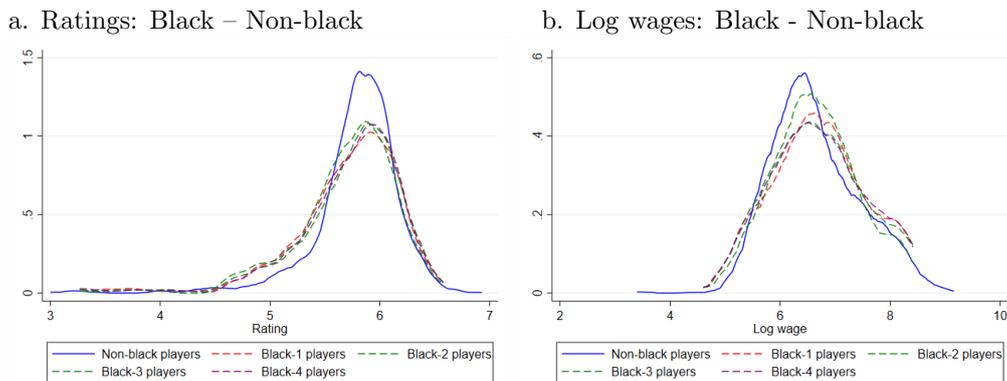
Source: Audiweb.it

Gazzetta has the highest share of readers with a university education and the lowest share of readers with primary or less than primary education. Similarly, Gazzetta has the largest share of readers from the highest social class A and the smallest share from the lowest class D. Nevertheless, as with the other characteristics, also for social class the differences are not big.

In our analysis a player is indicated as black if at least one of our four student reviewers labeled that player as black. The left-hand side graph of Figure C.1 shows that this makes sense as in terms of rating there is hardly any difference between the four categories of black players. The right-hand side graph of Figure C.1 shows that this is less so for the distribution of log wages where there is more variation between the four categories of black players. However, there does not

seem to be a systematic variation related to the number of students who labeled a player to be black.

Figure C.1: **Kernel densities non-black players and indicators of black players**



Note in Black-N, N indicates how many of the four viewers labeled a player as “black”.

C2. Details sensitivity analysis

Table C.2 shows parameter estimates of regressions in which a distinction is made between the four categories of black players. These parameter estimates can be compared with those in Table 3 in which no such distinction is made. As in Table 3, in Table C.2 all parameter estimates are negative although not always significantly different from zero. Nevertheless, there is no systematic relationship between the magnitude of the parameter estimate and the number of our student reviewers who indicated a player as being black.

Table ?? shows the Oaxaca-Blinder decomposition based on the parameter estimates related to Table 4.

Table C.2: Parameter estimates ratings distinguishing between various “Blackness” indicators

Ratings	All	Gazzetta	Corriere	TuttoSport
Black-1	-0.082 (0.051)	-0.085 (0.058)	-0.080 (0.058)	-0.081 (0.056)
Black-2	-0.147 (0.099)	-0.085 (0.089)	-0.143 (0.114)	-0.213* (0.117)
Black-3	-0.199*** (0.061)	-0.157*** (0.051)	-0.238*** (0.066)	-0.203*** (0.076)
Black-4	-0.057* (0.034)	-0.013 (0.025)	-0.074 (0.058)	-0.083 (0.053)

Note: Based on 1835 observations and including the complete set of explanatory variables.
 Note in Black-N, N indicates how many of the four viewers labeled a player as “black”.

Table C.3: Oaxaca-Blinder decomposition; Non-black - black

		q10	q30	q50	q70	q90
All	Explained	-0.009 (0.054)	-0.029 (0.023)	-0.014 (0.02)	-0.034* (0.019)	-0.012 (0.025)
	Unexplained	-0.271*** (0.086)	-0.089*** (0.033)	-0.045 (0.03)	0.022 (0.029)	0.038 (0.033)
Gazzetta	Explained	-0.002 (0.023)	-0.002 (0.018)	-0.008 (0.017)	-0.008 (0.017)	-0.001 (0.025)
	Unexplained	-0.086** (0.034)	-0.053** (0.023)	-0.02 (0.023)	0.003 (0.025)	-0.029 (0.029)
Corriere	Explained	-0.014 (0.059)	-0.032 (0.03)	-0.025 (0.024)	-0.031 (0.022)	-0.029 (0.024)
	Unexplained	-0.318** (0.142)	-0.067 (0.042)	-0.035 (0.032)	0.024 (0.034)	0.081** (0.035)
TuttoSport	Explained	-0.002 (0.085)	-0.037 (0.029)	-0.037* (0.022)	-0.032 (0.021)	-0.023 (0.026)
	Unexplained	-0.322*** (0.097)	-0.066* (0.039)	-0.005 (0.032)	0.005 (0.033)	0.029 (0.033)
Log Wage	Explained	-0.009 (0.053)	0.018 (0.068)	0.011 (0.084)	0.109 (0.121)	-0.198 (0.129)
	Unexplained	-0.127 (0.087)	-0.016 (0.069)	0.077 (0.072)	-0.055 (0.095)	0.237 (0.155)

Note: Based on 1835 observations (wage sample 1627 observations); all regressions include the complete set of explanatory variables; standard errors in parentheses; *(**,***): significant at 10(5,1)%