Racial Discrimination in the Labor Market: The Case of Black Soccer Players in Europe*

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Abstract

Although many European professional soccer clubs employ dark-skinned players who are of African descent, racial discrimination is a severe issue and Black players are often targets of abuse. Certain aspects of this labor market make it possible to quantify the impact of racial discrimination—professional players are hired to perform the same task, individual performance and salary data are available, and about 15% of the players in top leagues in England, Germany, Italy, and Spain are Black. I find that, on average, Black players do not earn statistically different salaries from non-Black players, after controlling for past performance and player characteristics. However, it appears that top-earning Black players earn a premium while those at the bottom earn a discount. This pattern is consistent with the notion that Black players encounter discriminatory practices and are held to higher standards. The presence of a higher standard implies that those who achieve success are better.

JEL Classification: J31, J44, J71

Keywords: Direct discrimination, Black labor, African descent, Labor market

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1 Introduction

The intersection of race and labor market dynamics has long been a focal point of economic inquiry. Recently, Hurst, Rubinstein, and Shimizu (2024) project over 300 occupations across four task measures and examine "task-based discrimination." They consider three types of task-specific racial barriers—racial skill gaps, pecuniary discrimination, and nonpecuniary discrimination—and conclude that the nature and extent of racial barriers can vary significantly depending on the task requirements of a given occupation.

In this paper, I explore the nuances of racial discrimination in the context of Black soccer players in Europe. All soccer players fall under the category of athletes, and they perform "Manual" tasks according to Hurst, Rubinstein, and Shimizu's (2024) task measures. By focusing on one occupation, I employ the concept of "direct discrimination," as outlined by Bohren, Hull, and Imas (2025). This framework allows for the examination of differential treatment based on race, controlling for observable skills and qualifications. Specific features of the European soccer player market allow for the measurement of racial effects: professional players are hired to perform nearly identical tasks, there is accessible data on individual performance and salaries, and approximately 15% of players in the top leagues of England, Germany, Italy, and Spain are Black.

I examine whether Black soccer players, despite possessing similar skill sets and performance metrics, face inequitable pay relative to their white peers. The disparities in compensation may reflect underlying biases in the labor market. European soccer clubs regularly play in professional leagues and competitions. Although many clubs employ dark-skinned players who are of African descent, racial discrimination is a severe issue and even top players can be targets of abuse. Paul Pogba, who was born in France to Guinean parents and was one of the highest paid players at Manchester United, was racially abused on Twitter after he missed a penalty in 2019. The Union of European Football Associations (UEFA), the governing body of European soccer, runs a "No to Racism" campaign and gives power to referees to suspend or abandon a match in case of racist behaviors. Clubs are often punished

for racist incidents in stadiums.

Using a sample of all professional players in the top leagues in England, Spain, Italy, and Germany (The Premier League, La Liga, Serie A, and Bundesliga, respectively) for around ten seasons, I first show that, on average, Black players do not earn statistically different salaries from non-Black players, after controlling for past and current performance, player characteristics, and team-season or league-season fixed effects. While one may conclude that there is no differential racial treatment in this market, I further examine the cross-section of players. A quantile regression analysis reveals that the effect of Black is different at the lower, median, and upper ends of the income distribution—there is evidence of a Black discount at the lower end and a Black premium at the upper end, while the median end continues to show no significant discount or premium.

A different approach yields consistent results. Here I focus on one country, England. Salary information in the second-best league, The Championship, is also available, allowing me to include more players in the lower end of the income distribution. In this analysis, rather than using a Black dummy variable as an independent variable, I adopt the methodology employed by Cameron, Goetzmann, and Nozari (2019), who investigate the auction sales of female and male artists' works. I regress salary on performance, player characteristics, and team-season or league-season fixed effects, and estimate an individual fixed effect for each player in The Premier League and The Championship. Then I compare the fixed effects of Black players and those of non-Black players. The two sets of fixed effects exhibit a similar distribution when using the full sample. However, the fixed effects for Black players are significantly higher than those for non-Black players when we concentrate on top players, defined as those who have spent at least half of their careers in The Premier League.

The observed pattern is perhaps attributed to a more complicated mechanism. It is possible that a higher standard is imposed on Black players. For those who make it to the very top, Black players have to surpass the hurdle and be better than non-Black players, and such difference is not captured by the performance measures that are controlled for. As

a result, the very top Black players earn a premium. Note that the higher standard imposed on Black players is still a result of discrimination against Black players.

This conjecture is in fact consistent with the observation made by Cameron, Goetzmann, and Nozari (2019). They argue that female artists face institutional barriers that limit their participation in the professional art market. Female artists' work is underrepresented at auction; however, conditioning on appearing at auction, female artists' works are sold at higher prices than male artists'. A similar "higher standard" mechanism also affects female economists (Hengel, 2022) and female physicians (Tsugawa et al., 2017), who outperform their male counterparts.

Although this mechanism is, as noted above, documented in other disciplines, the current results are different in two ways: first, the other studies only show evidence that the top group earns more or performs better, but do not examine the ordinary group because such data are often unavailable; second, the focus has been on gender bias, in which the burden of motherhood is also a factor. The burden of motherhood makes some women voluntarily choose more family-friendly careers and drop out of the labor force. Establishing evidence for the pay difference in the market of male soccer players, where family responsibilities should play a much less significant role, highlights the "higher standard" mechanism. My results also emphasize the importance of examining the cross-section of workers, as racial effects may not be statistically significant in the full sample when some individuals earn a premium while others experience a discount.

While racism is likely to exist in other sports, European soccer is one of the most visible labor markets that employ large numbers of black players and white players, and data are readily available. As Silver (2015) points out, individual statistics in other team sports such as basketball and American football do not capture the full picture. Major League Baseball offers another possible platform with comprehensive individual statistics, but the majority of the players are from the U.S. and most foreign players come from Latin American countries. In contrast, a wide range of nationalities and ethnicities are represented in major European

soccer leagues, as clubs can freely hire players from countries in the European Union and include a few non-EU players. This paper takes the first step to analyze an important market and the methodology is extendable to other markets and different ethnic groups.

The remainder of the paper is structured as follows. In Section 2, we describe the soccer player market in Europe. Section 3 lists the data sources, and Section 4 presents the results. Section 5 concludes.

2 The Soccer Player Market

The best soccer players are almost all professional players. Most of the best players are contracted to a professional club or team (e.g., Real Madrid) in Europe in our sample period. The players earn a salary plus performance-based bonus from the club they play for.[1] In each season, a professional club plays around 40–50 matches in their domestic league and cups, while top clubs play up to 15 more matches in European and international competitions. In each match, there are 11 starting players and around 7 players on the bench (3 to 5 of them can replace the starting players within the match).

Before the contract matures, another club can pay a transfer fee to the current club to end the existing contract prematurely and acquire the player's service. A lot of players are transferred in and out before their contract matures. Transfer fees are negotiated between the two clubs and are based on expected future performance, age, and position, etc. (see, e.g., Frick, 2007).

A club usually has at least 25 squad members, with some members playing almost all the matches and some playing none of them. A team manager (sometimes also called the head coach) is responsible for picking the players for each match. The manager is also contracted to the club. While the transfer fees and salaries are not paid by them, they are required to manage the club within budget, including deciding which players to buy/sell and whether

[1]There are competitions at the national-team level, such as the World Cup. Not every player in our sample represents their national team. Relative to what they earn at the club-level, they get little from playing in national-team competitions.

to extend players' contracts.

Racism has been a persistent issue in European soccer. UEFA, the governing body of European soccer, runs a "No to Racism" campaign. A "Respect" badge is displayed on players' jerseys in UEFA competitions. The Respect project co-operates with another organization, The Fare network (formerly Football Against Racism in Europe). Besides Paul Pogba, who was mentioned in the Introduction, many other players are victims of racial abuse. Thompson (2013) of ESPN FC publishes a feature article on racism in Italian soccer. In particular, Kevin-Prince Boateng (born in Germany to a German mother and a Ghanaian father) and Mario Balotelli (born in Italy as the son of Ghanaian immigrants) were targets of monkey chanting by stadium fans on multiple occasions and Boateng walked off the field in a friendly match.

Pew Research Center conducted a survey in 2018 on different countries' views on diversity. For the four countries in my sample, 45% of the respondents in Italy oppose increased diversity in their country, followed by Germany (32%), Spain (23%), and U.K. (20%).[2]

Even commentators often stereotype players based on ethnicity. In an analysis of 80 European games and 2,000 statements about 643 players, McLoughlin (2020) finds that when commentators talk about intelligence, 62.6% of the praise was aimed at players with lighter skin tone but 63.3% of the criticism was aimed at players with darker skin tone. Madu (2018) criticizes commentators' racial stereotypes in the World Cup match between Senegal and Poland in 2018.

3 Data

The data sources utilized in this analysis encompass a comprehensive range of soccer leagues and player characteristics. The primary datasets include player-season observations from four major European leagues: the Premier League in England, the Bundesliga in Germany,

[2]The survey results are reported at `https://www.pewresearch.org/global/2019/04/22/how-people-around-the-world-view-diversity-in-their-countries/`.

Serie A in Italy, and La Liga in Spain. The analysis covers a total of 17,017 player-season observations from the 2013/14 season (2010/11 for Serie A) through the 2021/22 season.

Player characteristics, including images, age, nationality, and position, are sourced from Transfermarkt. To identify Black players, I employ the VGG-Face classifier, integrated within the DeepFace Python package (Greenwald, Howell, Li, and Yimfor, 2024). This method enables me to classify players as Black or non-Black based on their images from Transfermarkt, while also recognizing other racial and ethnic categories such as Asian, Indian, Latino Hispanic, and Middle Eastern. For the purpose of this study, my focus remains solely on the binary classification of players as Black or non-Black.

Performance data are obtained from WhoScored.com, which provides player ratings based on their performance in each match. Players receive a rating out of 10, calculated in real-time using over 200 raw statistics that reflect various match events. These ratings are designed to be objective and should be color-blind, encompassing both domestic league matches and European club-level competitions, including the UEFA Champions League and UEFA Europa League from the 2013/14 season onward.

Finally, compensation data are obtained from Capology, a sports website that provides details on players' salaries for each season. Salaries in British pounds were converted into Euros using the applicable exchange rates from that time. While bonus information is only available for the 2023/24 season, this dataset offers valuable insights into the financial aspects of player contracts over the specified period. Together, these data sources provide a comprehensive framework for analyzing the intersection of race, performance, and compensation in European soccer.

Table 1 shows the summary statistics. The average player age is 25.88, and the average salary is 2.2 million Euros per year. Players' salaries vary from 280,000 Euros in the 10th percentile to 4.8 million Euros in the 90th percentile. The average Whoscored.com rating is 6.52.

Roughly half of the players are domestic (from the country where the league is based in)

and the other half are foreign. The VGG-Face classifier classifies 15% of the players as Black, while also recognizing 10% as Latino Hispanic, 18% as Middle Eastern, and small portions as Asian and Indian. Latino Hispanic and Middle Eastern are more difficult to identify than Black, given their smaller differences from other ethnicities in terms of skin color. In this paper, I compare the 15% Black players and the 85% non-Black players. I also manually go over more than 100 players to verify the validity of the classifier.

The observations are distributed across the four leagues, with Serie A in Italy having the largest share due to the availability of data in the earlier period. 8% of the players are keepers, 35% are defenders, 28% are midfielders, and 29% are forwards.

4 Results

4.1 Full Sample

I begin the main analysis by running the following regression:

$$\begin{aligned} log(salary) =& \beta_1 past_average_performance + \beta_2 past_standard_deviation_of_performance \\ &+ \beta_3 current_average_performance + \beta_4 current_standard_deviation_of_performance \\ &+ \beta_5 Black + \beta_6 domestic + \beta_7 age + \beta_8 age^2 \\ &+ \beta_9 position_fixed_effects \\ &+ \beta_{10} team_season_fixed_effects \text{ or } league_season_fixed_effects, \end{aligned} \tag{1}$$

where $log(salary)$ is the natural log salary in Euros in the current season, $past_average_performance$ and $past_standard_deviation_of_performance$ are the average WhoScored.com rating and the standard deviation of Whoscored.com ratings in the past five seasons (as available), and $current_average_performance$ and $current_standard_deviation_of_performance$ are the average WhoScored.com rating and the standard deviation of WhoScored.com ratings in the current season. *Black* and *domestic* are dummies, which equal 1 when the player

is Black and domestic, respectively, and 0 otherwise. I include Age and Age^2 to control for the non-linear relationship between salary and age (players typically peak at around 30 and retire before 40). Position fixed effects capture the salary differences across positions. Team-season or league-season fixed effects are included, as players' salaries vary across these dimensions.

The coefficient of interest is β_5, the coefficient of $Black$. What this tries to document is "direct discrimination" (Bohren, Hull, and Imas, 2025)—the differential treatment of Black men in the labor market conditional on observed skills. In contrast, Hurst, Rubinstein, and Shimizu (2024) examine "Task-based discrimination." They study over 300 occupations and show that the size and nature of racial barriers faced by Black workers vary by the task requirements of each job.

Table 2 shows the results. In Column (1), when Team-season fixed effects are controlled for, the coefficient of $Black$ is -1.1% and is statistically insignificant. $Domestic$ captures a statistically significant discount of 6.6%. Salary is increasing with age and decreasing with age^2. Past and current average ratings and standard deviation of ratings are positively related to salary. Column (2), which controls for League-season fixed effects, displays similar results. The coefficient of $Black$ is 2.1% and is statistically insignificant.

It is crucial to control for individual performance, as salary differences can arise from players' different performances. There are two advantages of using WhoScored.com data. First, their ratings are calculated based on objective raw match statistics, unlike ratings issued by other soccer newspapers and websites, which are subjectively given by reporters or voted by readers.[3] Subjective measures are likely to take into account the expectation on the players and do not measure their absolute performance (a star player is expected to do more, and will be given a poorer rating despite performing similarly to an average player). Second, WhoScored.com ratings are comparable across different positions. Other

[3]As explained on WhoScored.com, "Our player ratings are based on each event recorded in the game calculated live automatically using our own algorithms, which comprise of over 200 raw statistics. All events are valued based on a researched perception of the effect on the outcome of the match. Positive events are valued against negative events."

objective measures such as number of goals scored are incomparable when players play different positions. Although WhoScored.com does not publish its algorithm, it is widely used by the media and is involved in nominating players for Professional Footballers' Association of England and Wales Awards.

In Tables 3 and 4, I control for another measure of performance, which replaces the WhoScored.com ratings. This measure, *CoScore*, is developed by Flores-Szwagrzak and Treibich (2020). *CoScore* leverages the differing membership and success levels of all teams to concurrently assess an individual's productivity and their contribution to each team's achievements. For example, if a team wins more games when a certain player plays but tends to lose when the player is absent, then the *CoScore* of that player is high. The advantage of *CoScore* is that it uses the actual match outcome to estimate individuals' contributions. A parameter $\alpha \in [0, 1]$ allocates a fixed share α of the credit on each project proportionally to the time participation of each teammate, and the remaining share $(1 - \alpha)$ is allocated proportionally to each teammate's endogenous score weighted by their time participation. A low α corresponds to situations where individual contributions determine team success.

Tables 3 and 4 report regression equation (1) with Team-season fixed effects and League-season fixed effects, respectively. The performance measure is *Coscore* in the current season, which is positive and statistically significant in all columns. The columns vary α from 0.1 to 0.9. In all but one column, the coefficient of *Black* is statistically insignificant, and the magnitude is between -0.6% and -2.3%. It is significant at the 10% level in Table 3 Column (1), with a magnitude of -2.6%. The results are consistent with those in Table 1.

4.2 Quantile Regressions

While one may conclude from the previous tables that there is no significant salary difference between Black and non-Black players, here I examine whether the results hold for different subsets of players. In particular, there is a wide range of salaries, as shown in Table 1. Table 5 runs quantile regressions of equation (1) with team-season fixed effects, at the following

quantiles (0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95). If race does not play a role in salaries, the coefficient of *Black* should be close to zero in all these quantiles.

However, this is not the case. Table 5 shows that the coefficient goes from negative and significant in Column (1), at quantile 0.05, to positive and significant in Columns (5)–(7), at quantiles above 0.75. There is an increasing trend as one moves from the lowest to the highest quantiles. The coefficient goes from a discount of 5.3% in Column (1) to a premium of 4.8% in Column (7), at quantile 0.95. Table 6 shows similar results when league-season fixed effects are used. In Column (7), the coefficient is 7.6%, demonstrating a significant *Black* premium.

4.3 Individual Fixed Effects

I use another specification to estimate the discount/premium of Black players. Here I drop *domestic* and *Black* indicators and position fixed effects. I focus on England only: The Premier League (the top league) and The Championship (second-best league). Capology only provides salary information for the second-best league in England but not other countries.

Cameron, Goetzmann, and Nozari (2019) examine the auction sales of works by female and male artists. In my analysis, I adopt their methodology and regress salary against past performance, player characteristics, and fixed effects for team-season or league-season, while also estimating an individual fixed effect for each player in The Premier League and The Championship.

Figure 1 compares the fixed effects of Black players with those of non-Black players. The two sets of fixed effects show a similar distribution across the full sample, similar to Tables 2–4. In Figure 2, the fixed effects for Black players are notably higher than those for non-Black players when focusing on top players, defined as those who have spent at least half of their careers in The Premier League. This finding is consistent with the Quantile regressions in Tables 5 and 6.

The observed pattern may be attributed to a more complex mechanism. It is possible

that Black players face a higher standard of expectation. For those who reach the highest levels, Black players may need to outperform their non-Black counterparts, and this disparity may not be reflected in the controlled performance measures. Consequently, the top Black players tend to earn a premium. It is important to note that this elevated standard is still a result of discrimination against Black players.

This hypothesis aligns with the findings of Cameron, Goetzmann, and Nozari (2019), who suggest that female artists encounter institutional barriers that restrict their participation in the professional art market. Although female artists' works are underrepresented at auctions, those that do appear tend to sell for higher prices than those of male artists. A similar "higher standard" mechanism has also been observed among female economists (Hengel, 2022) and female physicians (Tsugawa et al., 2017).

5 Conclusion

In 2020, an African American, George Floyd, was killed by the police during an arrest in Minneapolis. It triggered a series of "Black Lives Matter" protests in the U.S. and worldwide against racial discrimination. There is plenty of empirical evidence of racial discrimination in various settings. Dougal et al. (2019) show that historically black colleges and universities (HBCUs) pay higher underwriting fees to issue tax-exempt bonds than similar non-HBCUs, while a few other papers (Bayer, Ferreira, and Ross, 2016; Blanchflower, Levine, and Zimmerman, 2003; Cavalluzzo and Cavalluzzo, 1998) find evidence that blacks are treated unfairly in the mortgage and lending markets. U.S. employers (Bertrand and Mullainathan, 2004) and investors (Kumar, Niessen-Ruenzi, and Spalt, 2015) tend to avoid employees and mutual fund managers with foreign-sounding names, respectively.

How does racism play a role in the labor market? I focus on a highly specialized market, the soccer player market in Europe. Racism in English soccer was studied by Garland and Rowe (2001), Preston and Szymanski (2000), Szymanski (2000). Szymanski (2000)

shows that teams with an above-average proportion of black players outperform those with a below-average proportion of black players, after controlling for the wage bill. Preston and Szymanski (2000) attribute this to discrimination by club's owners rather than by fans. In other sports, Price and Wolfers (2010) find that more personal fouls are awarded against NBA players by opposite-race referees than by own-race referees. However, Bryson and Chevalier (2015) find no evidence of taste-based discrimination in an online game, the Fantasy Football Premier League.

In this paper, I uncover a nuanced relationship between salary and race. I find that, on average, Black players do not receive statistically different salaries compared to non-Black players when accounting for past performance and player characteristics. However, it seems that top-earning Black players receive a premium, while those who are at the bottom face a discount. This trend aligns with the idea that Black players experience discriminatory practices and are held to higher standards. The existence of a higher standard suggests that those who succeed are, in fact, outperforming their peers.

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Table 1: Summary Statistics

	N	Mean	Median	S.D.	Min	P10	P25	P75	P90	Max
Age	17,017	25.88	26	4.40	15	20	23	29	32	42
Salary (in Euros)	17,017	2,184,742	1,208,464	3,221,425	10,000	280,000	560,000	2,590,000	4,833,857	7.10e+07
Rating	17,017	6.52	6.36	0.63	3.96	5.94	6.09	6.83	7.37	10
Domestic	17,017	0.49								
Non-Domestic	17,017	0.51								
Race:										
Black	17,017	0.15								
Asian	17,017	0.03								
Indian	17,017	0.01								
Latino Hispanic	17,017	0.10								
Middle Eastern	17,017	0.18								
White	17,017	0.53								
League:										
Premier League	17,017	0.24								
Serie A	17,017	0.32								
La Liga	17,017	0.22								
Bundesliga	17,017	0.22								
Position:										
Keeper (K)	17,017	0.08								
Forward (F)	17,017	0.29								
Midfield (M)	17,017	0.28								
Defense (D)	17,017	0.35								

Table 2: Baseline Regressions

	(1) ln(Salary)		(2) ln(Salary)	
Past Average Performance	0.5164	(0.0352)***	1.2358	(0.0477)***
Average performance (Current)	0.1987	(0.0279)***	0.4452	(0.0361)***
Past Standard Deviation	0.5424	(0.0542)***	0.5640	(0.0706)***
Standard Deviation (Current)	0.1979	(0.0435)***	0.1000	(0.0541)*
Domestic	-0.0655	(0.0114)***	-0.1778	(0.0148)***
Age	0.4224	(0.0188)***	0.2773	(0.0222)***
Age^2	-0.0070	(0.0003)***	-0.0047	(0.0004)***
Black	-0.0110	(0.0173)	0.0208	(0.0216)
Position FE	Yes		Yes	
Team-season FE	Yes		No	
League-season FE	No		Yes	
Observations	10,874		10,874	
R-squared	0.7381		0.4825	

Table 3: Baseline Regressions (with Co-Scores and Team-Season Fixed Effects)

	(1) ln(Salary)		(2) ln(Salary)		(3) ln(Salary)		(4) ln(Salary)		(5) ln(Salary)	
Past Co-Score	5.5382	(0.2458)***	4.0493	(0.1480)***	2.8732	(0.1024)***	2.2081	(0.0779)***	1.7893	(0.0628)***
Co-Score (Yearly)	31.2753	(1.0880)***	18.2163	(0.6016)***	12.3443	(0.4072)***	9.3042	(0.3069)***	7.4593	(0.2461)***
Age	0.3591	(0.0132)***	0.3382	(0.0130)***	0.3339	(0.0129)***	0.3320	(0.0129)***	0.3309	(0.0129)***
Age^2	-0.0053	(0.0002)***	-.0050	(0.0002)***	-0.0049	(0.0002)***	-0.0049	(0.0002)***	-0.0049	(0.0002)***
Domestic	-0.1508	(0.0114)***	-0.1544	(0.0112)***	-0.1548	(0.0112)***	-0.1549	(0.0112)***	-0.1549	(0.0111)***
Black	-0.0257	(0.0152)*	-0.0234	(0.0150)	-0.0232	(0.0150)	-0.0232	(0.0150)	-0.0232	(0.0150)
Position FE	Yes		Yes		Yes		Yes		Yes	
Team-season FE	Yes		Yes		Yes		Yes		Yes	
α	0.1		0.3		0.5		0.7		0.9	
Observations	13,518		13,518		13,518		13,518		13,518	
R-squared	0.7295		0.7338		0.7352		0.7358		0.7361	

Table 4: Baseline Regressions (with Co-Scores and League-Season Fixed Effects)

	(1) ln(Salary)		(2) ln(Salary)		(3) ln(Salary)		(4) ln(Salary)		(5) ln(Salary)	
Past Co-Score	12.1246	(0.3859)***	8.6182	(0.1956)***	6.0541	(0.1315)***	4.6305	(0.0990)***	3.7420	(0..0794)***
Co-Score (Yearly)	39.5185	(1.3718)***	23.2710	(0.7391)***	15.8792	(0.4968)***	12.0122	(0.3733)***	9.6515	(0.2988)***
Age	0.2268	(0.0182)***	0.2043	(0.0170)***	0.1999	(0.0167)***	0.1981	(0.0166)***	0.1970	(0.0166)***
Age^2	-0.0032	(0.0003)***	-.0029	(0.0003)***	-0.0029	(0.0003)***	-0.0028	(0.0003)***	-0.0028	(0.0003)***
Domestic	-0.3452	(0.0150)***	-0.3388	(0.0144)***	-0.3361	(0.0142)***	-0.3347	(0.0141)***	-0.3339	(0.0141)***
Black	-0.0122	(0.0205)	-0.0067	(0.0198)	-0.0060	(0.0197)	-0.0057	(0.0196)	-0.0056	(0.0195)
Position FE	Yes		Yes		Yes		Yes		Yes	
League-season FE	Yes		Yes		Yes		Yes		Yes	
α	0.1		0.3		0.5		0.7		0.9	
Observations	13,518		13,518		13,518		13,518		13,518	
R-squared	0.4275		0.4682		0.4769		0.4807		0.4829	

Table 5: Quantile Estimation (with Team-Season Fixed Effects)

	(1) 0.05		(2) 0.1		(3) 0.25	
Past Average Performance	0.5199	(0.0246)***	0.4391	(0.0280)***	0.5263	(0.0179)***
Average Performance	0.2344	(0.0218)***	0.2310	(0.0231)***	0.1727	(0.0136)***
Past Standard Deviation	0.6100	(0.0407)***	0.6938	(0.0462)***	0.4751	(0.0307)***
Standard Deviation	0.2177	(0.0326)***	0.1312	(0.0398)***	0.2019	(0.0206)***
Domestic	-0.0807	(0.0211)***	-0.0852	(0.0105)***	-0.0648	(0.0059)***
Age	0.7189	(0.0211)***	0.6181	(0.0208)***	0.4968	(0.0136)***
Age^2	-0.0119	(0.0004)***	-0.0103	(0.0004)***	-0.0083	(0.0002)***
Black	-0.0529	(0.0145)***	-0.0230	(0.0168)	0.0070	(0.0081)
Position FE	Yes		Yes		Yes	
Team-season FE	Yes		Yes		Yes	
Observations	10,839		10,839		10,839	
R-squared	0.5144		0.5094		0.4980	

	(4) 0.5		(5) 0.75		(6) 0.9		(7) 0.95	
Past Average Performance	0.5301	(0.0101)***	0.4673	(0.0123)***	0.4054	(0.0083)***	0.3959	(0.0067)***
Average Performance	0.1611	(0.0091)***	0.2242	(0.0117)***	0.2361	(0.0067)***	0.2263	(0.0065)***
Past Standard Deviation	0.4205	(0.0203)***	0.3739	(0.0220)***	0.3271	(0.0151)***	0.3689	(0.0083)***
Standard Deviation	0.1925	(0.0141)***	0.0922	(0.0164)***	0.0719	(0.0153)***	-0.0251	(0.0124)**
Domestic	-0.0447	(0.0037)***	-0.0206	(0.0040)***	-0.0093	(0.0028)***	-0.0121	(0.0022)***
Age	0.3377	(0.0082)***	0.2580	(0.0079)***	0.2055	(0.0070)***	0.2006	(0.0045)***
Age^2	-0.0056	(0.0001)***	-0.0042	(0.0001)***	-0.0033	(0.0001)***	-0.0032	(0.0001)****
Black	0.0085	(0.0063)	0.0100	(0.0059)*	0.0193	(0.0059)***	0.0473	(0.0069)***
Position FE	Yes		Yes		Yes		Yes	
Team-season FE	Yes		Yes		Yes		Yes	
Observations	10,839		10,839		10,839		10,839	
R-squared	0.5405		0.5596		0.5822		0.6072	

Table 6: Quantile Estimation (with League-Season Fixed Effects)

	(1) 0.05		(2) 0.1		(3) 0.25	
Past Average Performance	0.7677	(0.0595)***	0.8768	(0.0435)***	1.0752	(0.0358)***
Average Performance	0.3577	(0.0375)***	0.3840	(0.0420)***	0.3356	(0.0292)***
Past Standard Deviation	0.8267	(0.0882)***	0.8142	(0.0638)***	0.5973	(0.0573)***
Standard Deviation	0.2249	(0.0684)***	0.1270	(0.0686)*	0.1433	(0.0515)***
Domestic	-0.1862	(0.0191)***	-0.1835	(0.0191)***	-0.1536	(0.0153)***
Age	0.6264	(0.0472)***	0.4752	(0.0318)***	0.3097	(0.0251)***
Age^2	-0.0107	(0.0008)***	-0.0081	(0.0005)***	-0.0053	(0.0005)***
Black	-0.0357	(0.0411)	-0.0527	(0.0267)**	-0.0050	(0.0282)
Position FE		Yes		Yes		Yes
League-season FE		Yes		Yes		Yes
Observations		10,839		10,839		10,839
R-squared		0.3003		0.2901		0.2975

	(4) 0.5		(5) 0.75		(6) 0.9		(7) 0.95	
Past Average Performance	1.3628	(0.0404)***	1.4382	(0.0466)***	1.5470	(0.0376)***	1.4000	(0.0487)***
Average Performance	0.3549	(0.0360)***	0.4427	(0.0400)***	0.5618	(0.0394)***	0.5867	(0.0376)***
Past Standard Deviation	0.3802	(0.0602)***	0.2636	(0.0721)***	0.0416	(0.0667)	0.0387	(0.0795)
Standard Deviation	0.0696	(0.0546)	-0.0338	(0.0575)	-0.2050	(0.0650)***	-0.2189	(0.0632)**
Domestic	-0.1553	(0.0159)***	-0.1565	(0.0177)***	-0.1190	(0.0193)***	-0.0844	(0.0214)***
Age	0.2115	(0.0214)***	0.1928	(0.0259)***	0.1275	(0.0346)***	0.1339	(0.0293)***
Age^2	-0.0037	(0.0003)***	-0.0034	(0.0005)***	-0.0022	(0.0006)***	-0.0023	(0.0006)***
Black	0.0311	(0.0218)	0.0367	(0.0260)	0.0465	(0.0213)**	0.0756	(0.0174)***
Position FE		Yes		Yes		Yes		Yes
League-season FE		Yes		Yes		Yes		Yes
Observations		10,839		10,839		10,839		10,839
R-squared		0.3103		0.2997		0.2980		0.3048

Figure 1: Black vs Non-Black
(Top 2 English Leagues Only)

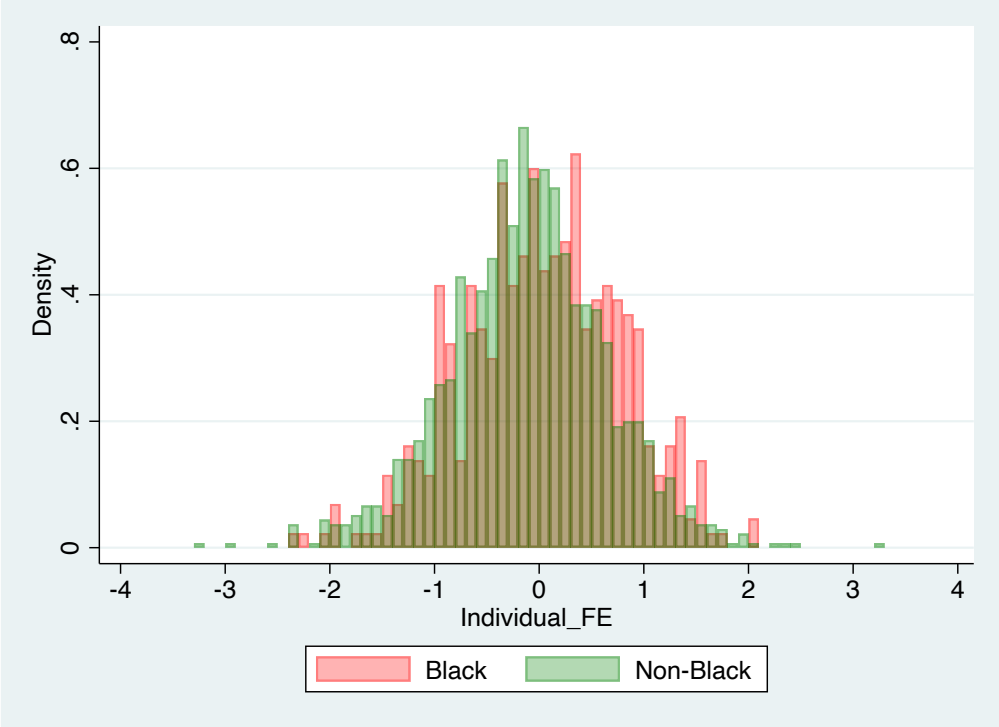


Figure 2: Top Black vs Bottom Black
(Top: Spent at least half of their career in Premier League)

