# Are the Effects of Racism Really That Black and White? A Study on the Effect Racism Has on the Productivity of Black Footballers in the Premier League

**Advik Banerjee**

**April 28th, 2022**

University of California, Berkeley
Department of Economics

Undergraduate Honors Thesis
Advised by Professor Jonathan Kolstad

**Abstract**

In this paper we analyze the impact that the presence of supporters has on the performance of soccer players in the English Premier League. In order to isolate this effect, we use the 2019/2020 season as a case study. During the 2019/2020 season 29 out of the 38 rounds of fixtures for that season took place with fans present in stadiums. However, for the last 9 rounds of fixtures all matches took place 'behind closed doors' with no fans present as a result of the coronavirus pandemic. Thus, we use a difference in differences method to observe whether or not there was a change in the performance of players after fans stopped attending games. We extend the analysis to explore if the presence of fans affects the performance of non-white players in light of the increasing levels of racist abuse players in the United Kingdom have been facing in recent years. [1]

[1] Acknowledgements: I would like to thank Professor Jonathan Kolstad, Professor David Card, Professor Ryan Edwards and Professor Conrad Miller for their help in guiding and advising me throughout this process. I would also like to thank Fabrizio Colella for his support. Any mistakes in this paper are mine.

## Introduction

There has been extensive research into the impact of extrinsic motivation on labor productivity. A study in the District 4 Fire District of the Tulsa fire department showed a positive correlation between worker morale and productivity (Neely, 1999). Conversely, another study analyzing the effects of performance enhancing compensation practices and worker productivity showed that abrasive workplace behaviors such as bullying can have a negative impact on worker productivity (Samnani and Singh, 2014). Elite level soccer players have a unique working environment in that their relationship with soccer fans in stadiums during soccer matches exposes them to both positive and negative interactions. Soccer fans tend to dish out abuse to players during matches in which they lose or don't play well. On the other hand, soccer fans can also generate levels of support for players that propels players to push themselves harder to improve their performance. This paper aims to explore which of the two aforementioned effects is stronger in determining the quality of a soccer player's performance. As an extension of this analysis, we also aim to explore any differences in the levels of performance between white and non-white players. Although both white and non-white players are subject to abuse from supporters in situations where they aren't playing well, non-white players often receive another dimension of abuse on the basis of their race. In recent years there has been a steady increase in the number of reported incidents of racial abuse at English Premier League soccer games. Official figures show that the number of racist incidents across both grassroots and professional football in England rose 32% between the 2017/2018 season and the 2018/2019 season from 319 to 422.[2] We utilize player performance data in order to explore the potential effects of racist abuse on the performance of non-white soccer players, using white players as a control.

[2] Statistics obtained from Kick It Out's "Reporting Statistics" page which they keep in order to track changes in the number of racist incidents taking place in English soccer from season to season.

In this paper I explore the true impact that supporters have on the performance of soccer players, by exploiting a unique scenario that presented itself as a result of the COVID-19 pandemic. During the 2019/2020 soccer season, the first 288 matches took place under normal circumstances with fans in the stadium. However, after the onset of the coronavirus pandemic, the remaining 92 matches of the season took place without fans present. This unique discontinuity allows us to explore whether supporters have a net positive or negative impact on player performance since the absence of supporters removes the energy that players can derive from a raucous atmosphere, but also removers any negativity in the form of racism or other modes of abuse. We implore a difference in differences method to study the way in which the performance of players changed between these two time periods.

This paper contributes to existing literature in the field of race and the effects of racism on people of color. Kevin Nadal et al (2014) showed in their study that there is a statistically significant negative relationship between racial microaggressions and mental health outcomes. The study showed that individuals who received racial microaggressions were more likely to display symptoms of depression and anxiety. Furthermore, the study also showed that Black, Latino/a, Asian and multiracial individuals were more likely to be subject to racial microaggressions than White individuals. A more recent study on the impacts of workplace racism similarly showed that nurses who were subject to racial abuse displayed higher levels of emotional distress (Thomas-Hawkins et al., 2021). This field of literature validates our hypothesis that footballers who receive racial abuse would be more likely to be negatively affected with regards to their performance.

This paper also contributes to existing studies in the field of how racial abuse from soccer fans impacts the performance of non-white players. The first paper in this field was conducted by Mauro Caselli et al. (2021) which studies the difference in player performance before and after the coronavirus pandemic split by different ethnic groups. The study finds that players of African descent had the most significant increase in performance after the pandemic hit and matches were played in the absence of fans. However, this paper largely builds on the work of Fabrizio Colella (2021), who conducted a similar analysis on soccer players in Serie A- the premier division Italian soccer league. Colella also exploits the no-supporters shock resulting from the onset of the COVID-19 pandemic in order to conduct a difference in differences analysis on player performance before and after the shock. A key difference to note between Serie A and the Premier League is the prominence of non-white (specifically black) players in each league. The English Premier League is home to some of the leading non-white soccer players in the world, with all of the top 6 most successful teams comprising of several non-white players. This is not the case in Serie A. Using my method of classification of non-white players, I find that in the 2019/2020 season being studied the teams that finished in the top 6 in Serie A contained only 34 non-white players on their rosters. The corresponding figure for the top 6 Premier League teams in the same season was 88.[3] An important way in which this study attempts to build on Colella's analysis is in the way in which the sample of players being examined is constructed. Colella uses an algorithm that classifies players as white or non-white based on an analysis of skin color from images taken of each player in his database. However, one drawback from this is that this excludes players with potentially lighter skin-tones who are also subject to racial abuse- for example Asian players. Asian players in the Premier League are subject to racial abuse just as any other ethnic minority demographic. High profile examples of Asian players suffering racial abuse include Tottenham's South Korean forward Son Heung Min receiving racist messages on social media platforms after a defeat to Manchester United (Church, 2021) and Japanese

---

[3] I conducted this analysis by looking at Transfermarkt.com's player database for the 2019/20 season. Transfermarkt's is a website that contains details on soccer players in major European leagues and compiles data on each soccer club's roster.

Arsenal defender Takehiro Tomiyasu receiving discriminatory chants in a match against West Ham United (Wright, 2021).

Analysis of player performance data obtained from shows that soccer players in the English Premier League experienced a 1.9% decrease in performance level in the absence of supporters. Furthermore, this effect was accentuated for white players who experienced a 2.4% decline in performance level, whereas non-white players only experienced a 0.93% decrease in performance. These results show interesting similarities to the results in the Italian league study. In the Italian league, non-white players showed a 1.5% increase in average performance relative to white players in the absence of fans (Colella, 2021). Similarly, in the case of the English Premier League we can see that although both white and non-white players display a decrease in performance level, non-white. players fare better relative to white players.

## Background

In the English Premier League racist abuse towards non-white players has usually taken the form of monkey chants from supporters in stadiums or the use of foul language attacking players on the basis of their race. Recent high-profile incidents include Antonio Rüdiger receiving monkey chants from supporters in a Premier League game and Pierre-Emerick Aubameyang having a banana thrown at him after scoring a penalty against Tottenham Hotspur (The Independent, 2019). Professional soccer player Danny Rose even came out in an interview recently stating that he couldn’t wait to retire due to the incessant racist abuse that he receives (The Independent, 2019). Anti-racist initiatives have been implemented in an attempt to curb the rising number of racist incidents at soccer games in England. There are three main bodies that have spearheaded the attempt to eradicate racism in soccer: Kick It Out, The Football Association (The FA) and soccer clubs themselves. Kick It Out is a charity organization that collects data on racist abuse in soccer, publishes annual reports on racism in English soccer and organizes workshops for black and ethnic minority soccer players in the Premier League on how to deal with racist abuse especially on social media (Kilvington and Price, 2019). The Football Association is English soccer's primary governing body and are responsible for setting punishments for racist incidents that take place amongst soccer players themselves. One such example took place in 2011 when Liverpool player Luis Suarez was charged and banned for 10 games by the FA for racially abusing Manchester United player Patrice Evra during a match (British Broadcasting Corporation, 2011). Finally, clubs themselves also play a role in policing racism in soccer. Clubs retrospectively use CCTV camera footage in order to identify individuals guilty of racially abusing players during matches. One such instance took place in 2019 when a Manchester City supporter was convicted of racial abuse after being caught by the club, using the stadium's CCTV cameras, for making monkey gestures at a non-white soccer player (Slater and Britton, 2021).

Although there have been clear and conscious efforts to discourage racism in soccer, the efficacy of these attempts can be called into question. In the aforementioned example of the FA acting against racism they banned Luis Suarez for 8 games for using a derogatory term against Patrice Evra. However, two years later in 2013 the FA once again banned Luiz Suarez for 10 games for biting a fellow soccer player during a match. Handing out a harsher penalty for biting than for racial abuse sets a worrying precedent for an organization supposedly committed to eradicating racism in all of its forms. Furthermore, in spite of all the conversation surrounding racism nowadays soccer still lacks ethnic minority representation at the highest level. In the 30 years that the English Premier League has existed there have been only 10 black managers that have taken charge of Premier League teams.[4] Furthermore, the

[4] https://www.londonworld.com/sport/football/crystal-palace/crystal-palace-boss-patrick-vieira-says-he-is-disturbed-by-the-lack-of-black-managers-in-the-premier-league-3457358

FA itself remains a predominantly white male organization. This has prompted the FA to launch a diversity code in which it pledged that 15% of new executive appointments would be individuals of Black and Ethnic Minority (BAME) backgrounds (Sport Resolutions, 2020).

**Theory**

In order to better understand our difference in differences model we explore the theory and key assumption behind a difference in differences estimation.

Note- The following is adapted from Miguel (2020).[5]

Assume we have an estimation equation:

$$Y_{it} = a + bT_{it} + dX_i + e_i$$

Where Y measures the outcome for individual *i* in time period *t*, T is a treatment that takes on a value of 0 or 1 and X accounts for control variables. In the case of our study Y measures the performance of soccer player *i* in week *t.* Since we are using a difference in differences estimation to evaluate the impact that racism has on the performance of non-white players, variable T would be a dummy variable for whether or not a player is white or non-white, taking on a value of 1 for non-white players and 0 for white players. We set time period $t = 0$ to be the time period before the treatment is implemented and $t = 1$ to be the time period after the treatment is implemented. In our case this means that when $t = 0$ fans were present in the stadium and when $t = 1$ fans were not allowed in stadiums. In time period $t = 1$ we can observe the difference that the absence of supporters has on our treatment (non-white players) and control (white players) groups by looking at the difference in the expected value of each:

$$E(Y_{i1}|\, T_{i1} = 1) - E((Y_{i1}|\, T_{i1} = 0)$$

[5] This section is adapted from lectures given by Professor Edward Miguel at the University of California Berkeley in the Economics 172 module, which explores Case Studies in Economic Development. Specifically, this material is adapted from lectures given by Edward Miguel on the difference in differences estimation model.

The term on the left-hand side of the expression gives us the expected performance of a non-white player in time period *t* = 1. The term on the right-hand side of the expression gives us the expected performance of a white player in the time period *t* = 1. Thus, by taking the difference between these two terms we get an idea of how non-white players fare compared with white players after the implementation of the ban on fans in stadiums. Substituting in our expression for $Y_{it}$ from the first equation into the expression for the difference in expected values we get:

$$[\ a + b + d \times E(X_{i1}|\ T_{i1} = 1) + E(e_{i1}|\ T_{i1} = 1)\ ] - [\ a + (b \times 0) + d \times E(X_{i1}|\ T_{i1} = 0) + E(e_{i1}|\ T_{i1} = 0)]$$

Cancelling this out gives leaves us with:

$$b + d[E(X_{i1}|\ T_{i1} = 1) - E(X_{i1}|\ T_{i1} = 0)$$

Where b gives us the true effect of the treatment in period *t* = 1 and the rest of the expression gives us the extent of omitted variable bias in our analysis. We can repeat this same analysis for time period *t* = 0 to identify any baseline differences between our treatment and control groups.

$$E(Y_{i0}|\ T_{i0} = 1) - E((Y_{i0}|\ T_{i0} = 0)$$

Expanding this expression as shown above and then cancelling gives us:

$$d[E(X_{i0}|\ T_{i0} = 1) - E(X_{i0}|\ T_{i0} = 0)$$

We perform our analysis by taking the difference in the differences calculated between our treatment and control groups in time period *t* = 1 and *t* = 0.

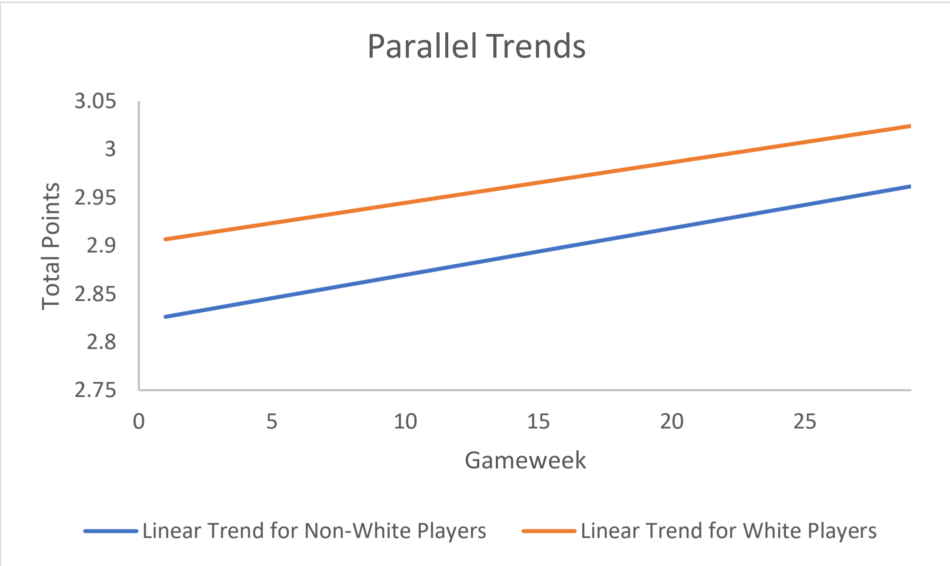
$$\text{Difference in time period t} = 1 - \text{Difference in time period t} = 0$$

$$b + d[E(X_{i1}|\ T_{i1} = 1) - E(X_{i1}|\ T_{i1} = 0) -\ d[E(X_{i0}|\ T_{i0} = 1) - E(X_{i0}|\ T_{i0} = 0)$$

This can be simplified into the following expression:

$$\text{True effect} + \{(OVB\ in\ t = 1) - (OVB\ in\ t = 0)\}$$

Where OVB denotes omitted variable bias. Therefore, if we are able to construct a model in which the extent of omitted variable bias is constant over both time periods, then our difference in differences analysis will give us an estimate of the true effect of the event being investigated on our treatment group. This is often referred to as the parallel trends assumption. By constructing a graph of the average performance of white players and non-white players during the period in which supporters were present in stadiums we can see that the trend in performances between the two subgroups appears to be roughly parallel. This makes our data a good fit for a difference in differences analysis.




## Data

I obtained my data from an online database[6] containing extensive player statistics from the English Premier League's official fantasy football game. Fantasy football is a virtual game in which soccer fans assemble a squad comprising of soccer players playing in the Premier League and receive points based on how the players in their squad perform. At the end of each week, players are assigned points evaluating their performance in games played during that week. The method of assigning points to players is purely objective and based on performance statistics such as goals scored, assist contributions, clean-sheets, penalty saves.

[6] The data was obtained from Github- an open-source online database. The data used for this study was uploaded to Github by Vaastav Anand, a master's student at the University of British Columbia. Vaastav used python to scrape the data from the official Premier League Fantasy Football webpage.

In cases when these metrics fail to adequately evaluate a player's performance bonus points are assigned based on an index that measure a player's influence within a game.[7] I compiled data on the points received by each player in a given game-week and manually classified each player as either white or non-white on the basis of my own judgement. Although this brings a level of subjectivity and potential bias into my analysis, racial abuse itself is somewhat subjective. A fan's decision to racially abuse a player is based on their external perception of what they believe to be foreign rather than necessarily what race or ethnicity a player themselves identify as. Thus, unlike previous studies in this field, I decide not to implement an algorithm to classify players as being white or non-white based on thresholds for skin color. After classifying each player, I added variables to the dataset to include a dummy variable for whether or not a player was playing in their home stadium, a variable with the final league placing of the player's opposition to account for the quality of opponent and further variables to control for team and individual fixed effects. In the end, my database comprised of 515 players, with 10,615 observations spread across the 38 game-weeks. Non-white players accounted for 37% of the players in the database and 3,919 of the observations.

Figure 1 shows a scatter plot of the average total points received by white and non-white players in each game-week. The graph has been divided to show the moment when the closed-stadiums shock was implemented and lines for average performance have been added in to show how player performance changed for white and non-white players before and after the shock.

**Figure 1**

White vs Non-White Player Performance

[7] https://www.premierleague.com/news/106533

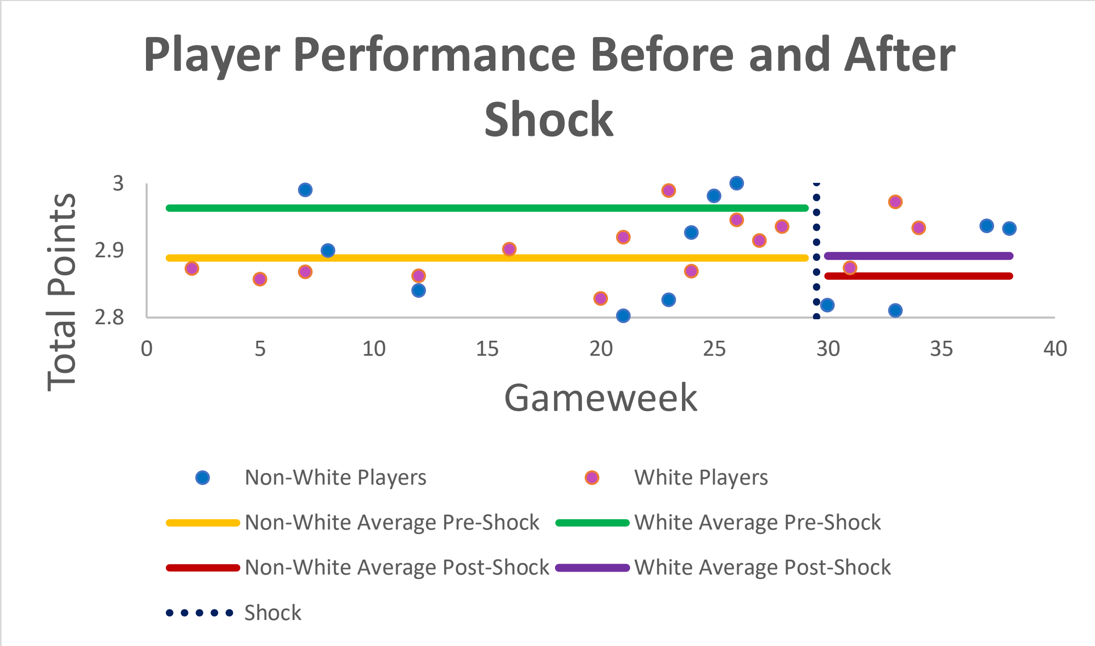
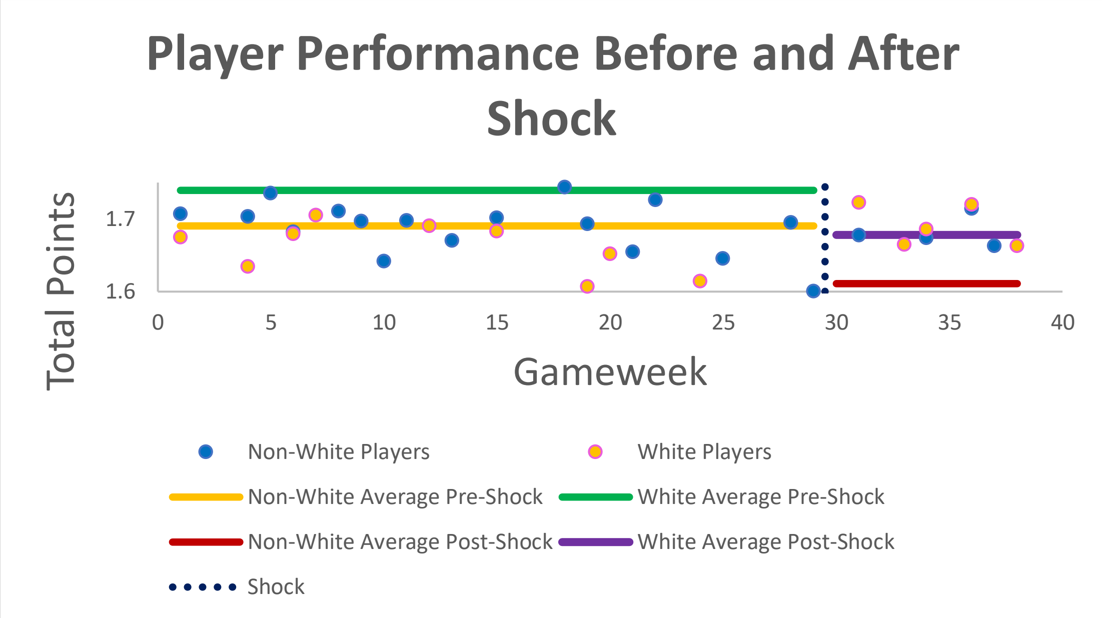



Figure 1 shows that the decrease in performance level for non-white players isn't as significant as the decrease in the performance level for white players. This appears to suggest that the presence of fans has a net positive impact for both subgroups of players. However, the decrease in performance for non-white players might theoretically be dampened by the absence of racist abuse after the no supporters shock was implemented.

In order to account for any potential impact from outliers I conducted the same analysis whilst removing all datapoints that were more than 1.5 times the interquartile range away from the first and third quartiles.

**Figure 2**

White vs Non-White Player Performance Without Outliers




Once again, we obtain similar results in that both player groups experience a decrease in performance level in the absence of supporters. However, in this case the fall in performance appears to be more pronounced for non-white players. We dive deeper into the relationship between player performance, the presence of supporters and the impact race has on these two in the analysis portion of this paper. However, based on this preliminary data visualization what appears to be certain is the fact that the net impact of supporters on player performance is positive- contrary to the conclusions drawn from the study conducted on Serie A where both player groups fared better in the absence of supporters (Colella, 2021).

## Analysis

In order to estimate the impact that supporters have on player performance we conducted a difference in differences analysis using the following equation:

$$Y_{igw} = \alpha + \beta NW + \gamma NF + \delta(NW \times NF) + in + t + T + \zeta C + \varepsilon \qquad (1)$$

In this equation $Y_{igw}$ refers to the points accrued by player *i* in game *g* played during game-week *w*. NW is a dummy variable with value 1 if a player is classified as non-white. NF is also a dummy variable indicating whether or not supporters were present during the game. $\delta$ provides the coefficient for the interaction term of our non-white and no supporters dummy variables. We have also added individual fixed effects (*in*), team fixed effects (*t*) and time fixed effects (*T*) to our regression as well as other control variables (C) that take into account for the quality of a player's opposition and whether or not a player was playing in their home stadium.

Just as in the study on the effects of racism in the Italian soccer league, in order to conduct our difference in differences analysis we make two key assumptions. Firstly, we assume that if the no-supporters shock had never taken place there would be no change in player performance before and after game-week 29 (when the shock was implemented). Thus, we can conclude that any change in performance after the shock is solely due to the absence of supporters. We attempt to prove the validity of this assumption by conducting a robustness test by analyzing changes in player performance only during periods of the season when fans were present. Secondly, we assume that there are no other factors that cause differentials in performance between white and non-white players other than the effects of racial abuse. We attempt to make this assumption valid through the inclusion of controls in our regression with the intent of accounting for all other factors that can explain differences in performance between white and non-white players.

Table 1 shows the results of carrying out a difference in differences regression with the variables from equation (1).

**Table 1**

Difference in Differences Estimation

Difference in Differences Estimation

Dependent Variable: Total Points

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Non-white | -0.07441<br>(0.06929) | -0.07319<br>(0.068608) | -0.06939<br>(0.068378) | -0.68643<br>(1.75919) | -0.68643<br>(1.7591908) | -0.60702<br>(1.762950) |
| No Supporters | -0.07133<br>(0.08374) | -0.067438<br>(0.082913) | -0.066621<br>(0.082634) | -0.11331<br>(0.083415) | -0.1133110<br>(0.0834156) | -0.61652*<br>(0.242417) |
| Non-White*No Supporters | 0.04442<br>(0.13574) | 0.049348<br>(0.134395) | 0.046328<br>(0.133943) | 0.1579501<br>(0.1353434) | 0.1579501<br>(0.1353434) | 0.157512<br>(0.135452) |
| Opposition | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Home-game dummy | | | ✓ | ✓ | ✓ | ✓ |
| Individual fixed effects | | | | ✓ | ✓ | ✓ |
| Team fixed effects | | | | | ✓ | ✓ |
| Time fixed effects | | | | | | ✓ |

Significance Level codes: 0= ‘***’ 0.001= ‘**’ 0.01= ‘*’ 0.05=‘.’ 0.1= ‘ ’

Table 1 shows that non-white players tend to perform worse than their white counterparts with and without the inclusion of control variables. We can also see that the absence of supporters tends to have a negative impact on player performance, and the effect of this is more significant as we include more and more control variables. Once all the control variables are included the regression yields our only statistically significant result- the coefficient for the absence of supporters on player performance. The interaction term in our regression shows that the performance of non-white players increased in the aftermath of the no-supporters shock. However, none of these results were statistically significant.

Comparing these results to the ones in Colella’s study we find some key similarities and differences. The Serie A study also showed that:

1) Non-white players tended to perform worse than white players.
2) Players tended to perform worse without supporters.
3) Non-white players performed better in the absence of supporters.

Much like the results we have obtained. However, the results in Colella's study were all statistically significant. Thus, at this point we extend our analysis in order to ensure that we have not missed any potentially statistically significant impacts. In order to do this, we decided to manually add players' nationalities and the continents from which they originate to control for player ethnicity.

**Table 2**

Difference in Differences with Added Controls

| Difference in Differences Estimation | | | |
|---|---|---|---|
| Dependent Variable: Total Points | | | |
| | (1) | (2) | (3) |
| Non-white | -0.607028<br>(1.762950) | -0.607028<br>(1.762950) | -0.607028<br>(1.762950) |
| No Supporters | -0.61652*<br>(0.242417) | --0.616525*<br>(0.242417) | -0.616525*<br>(0.242417) |
| Non-White*No Supporters | 0.157512<br>(0.135452) | 0.157512<br>(0.135452) | 0.157512<br>(0.135452) |
| Opposition | ✓ | ✓ | ✓ |
| Home-game dummy | ✓ | ✓ | ✓ |
| Individual fixed effects | ✓ | ✓ | ✓ |
| Team fixed effects | ✓ | ✓ | ✓ |
| Time fixed effects | ✓ | ✓ | ✓ |
| Nationality fixed effects | | ✓ | ✓ |
| Continent fixed effects | | ✓ | ✓ |

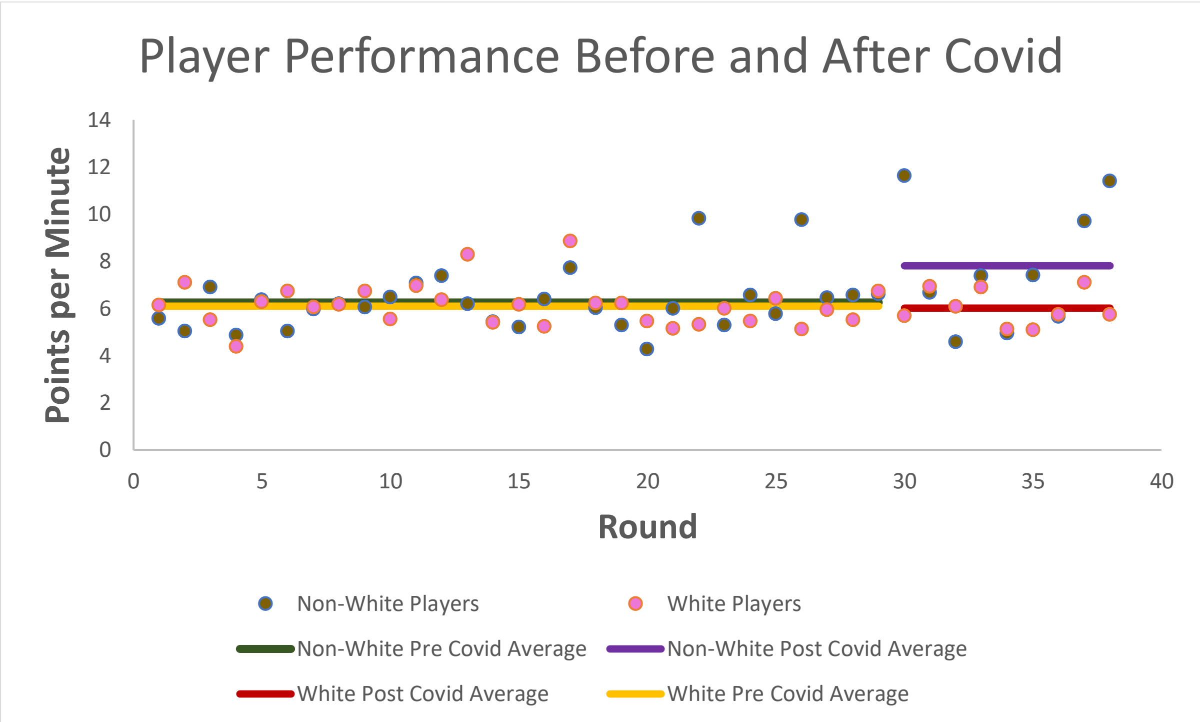
Significance Level codes: 0= '***' 0.001= '**' 0.01= '*' 0.05='.' 0.1= ' '

We can see that in spite of the addition of further controls the coefficients have remained exactly the same suggesting that the control variables used in the initial regression were relatively effective.

In order to rule out the possibility that our equation is simply unable to capture statistically significant impacts of the variables we're trying to measure we decide to take another approach. I decide to scale the points earned by each player and change it to the number of points earned by each player per 90 minutes played. This is done in order to capture the true impact of players who may get less game time and be limited to substitute appearances throughout the season. Although the bonus points system in Fantasy Football should in theory should allocate points to substitutes if they have a significant impact on a game, the points system does discriminate against players who play fewer than 60 minutes. After scaling the points, we obtain the following effect:

**Figure 3**

White vs Non-White Player Performance with Scaled Points




From figure 3 we can see that there is a clear increase in the performance of non-white players compared to white players after the empty stadiums shock takes place in game-week 29. However, from the graph we can also see that the increase in the average non-white performance is likely to be driven by outliers, especially those in game-weeks 30, 37 and 38. This hypothesis is corroborated when looking at the data. Players such as Alexandre Lacazette, Curtis Jones and Michael Obafemi all scored when making substitute appearances that lasted less than 7 minutes. Thus, when scaling their scores, these players all received scaled scores of 103, 108 and 150 respectively. Michael Obafemi even received a scaled score of 360 one game-week after claiming an assist having only been on the field for one minute. Although these extreme results do also take place before the shock was implemented, their effect is dampened in previous weeks by extreme low scores as a result of red cards or own goals. There are two ways to get around this issue. One way would be to remove outliers entirely and concentrate on data-points that are only within 1.5x the interquartile range of the 1st and 3rd quartiles. The second way to get around this issue would be to filter the data to only include players who played above a certain threshold of minutes. For the sake of being comprehensive we do both.

First, we rerun our initial difference in differences regression removing all outliers in the data.

**Table 3**

Difference in Differences with Outliers Removed

| Difference in Differences Estimation | | | | | | |
|---|---|---|---|---|---|---|
| Dependent Variable: Points per 90 minutes played | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Non-white | 0.017275<br>(0.028521) | 0.0140113<br>(0.0282300) | 0.01538<br>(0.02802) | -1.756767*<br>(0.879434) | -1.756767*<br>(0.879434) | -1.73376*<br>(0.879247) |
| No Supporters | 0.051932<br>(0.034341) | 0.0587069<br>(0.0339941) | 0.05963<br>(0.03396) | 0.006617<br>(0.032413) | 0.006617<br>(0.032413) | --0.130536<br>(0.094058) |
| Non-White*No Supporters | -0.008184<br>(0.056582) | 0.0008185<br>(0.0560081) | 0.000973<br>(0.05595) | 0.012997<br>(0.053013) | 0.012997<br>(0.053013) | 0.011504<br>(0.052913) |
| Opposition | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Home-game dummy | | | ✓ | ✓ | ✓ | ✓ |

| | | | |
|---|---|---|---|
| Individual fixed effects | ✓ | ✓ | ✓ |
| Team fixed effects | | ✓ | ✓ |
| Time fixed effects | | | ✓ |

Significance Level codes: 0= '***' 0.001= '**' 0.01= '*' 0.05='.' 0.1= ' '

With outliers removed we obtain slightly different results. Initially when none of the fixed effects control variables are added, non-white players appear to perform better than white players. Furthermore, with no controls added, non-white players perform worse after the no-supporters shock is implemented. However, after the addition of more controls all the results in the table display the same trends that we obtained in our previous models. The key difference being that in this case the only statistically significant results we get are that the performance of non-white players is markedly worse than the performance on white players. Having run our difference in differences model with the scaled points and no outliers, it still appears as though we have not missed many statistically significant impacts since even though we do get more statistically significant results, the coefficients on the variables of our analysis are largely the same.

We repeat our analysis using the scaled points per 90 minutes variable. However, this time instead of removing outliers we filter the results by minutes played by each player in the hope that this will remove the impact of extreme results that were discussed earlier. We start the analysis by filtering the results by all players who played more than 20 minutes, 25 minutes and 30 minutes.

**Figure 4**

Player Performance Before and After Shock- 20 Minute Filter

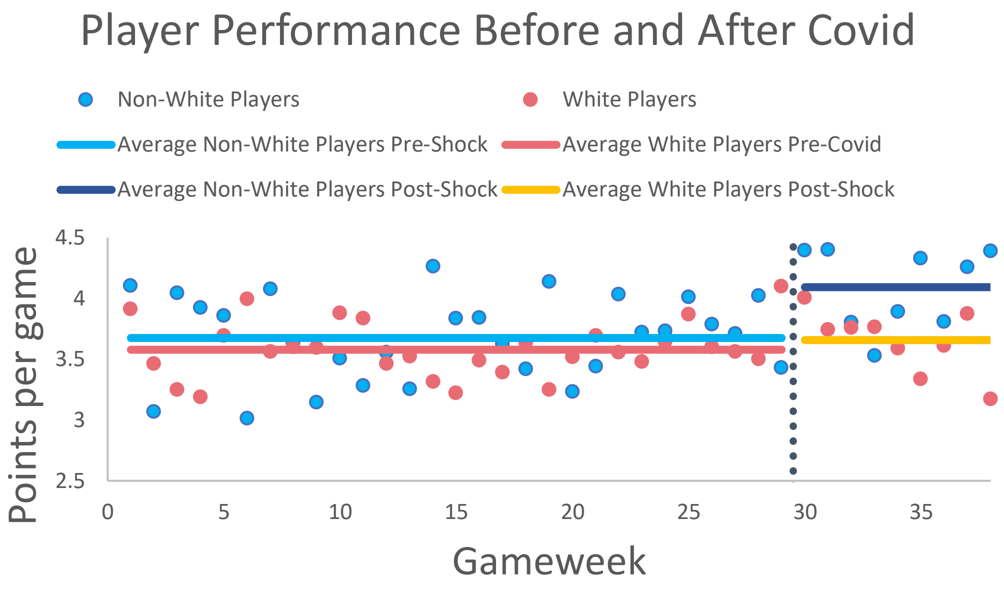



Figure 4 shows the trend that we witnessed in Figure 3 with non-white players experiencing a more significant increase in performance after the implementation of the no supporters shock than white players. Once again, although the direction of this trend appears to contradict the initial trends that we witnessed in Figure 1 where both player subgroups experienced decreases in performance in the absence of supporters. We continue our analysis by studying how increasing the threshold for minutes played by a player changes our results.

**Figure 5**

Summary Statistics for Players with 25-Minute Filter

| *White Players Pre-Shock* | | *White Players Post-Shock* | |
|---|---|---|---|
| Mean | 3.522798351 | Mean | 3.61374393 |
| Standard Error | 0.050860701 | Standard Error | 0.08960236 |
| Median | 2 | Median | 2.33766234 |
| Standard Deviation | 3.35911732 | Standard Deviation | 3.36575846 |
| Minimum | -10.8 | Minimum | -10.8 |
| Maximum | 40 | Maximum | 26.1290323 |
| Count | 4362 | Count | 1411 |
| Confidence Level (95.0%) | 0.099712817 | Confidence Level (95.0%) | 0.17576827 |

| *Non-White Players Pre-Shock* | | *Non-White Players Post-Shock* | |
|---|---|---|---|
| Mean | 3.63617524 | Mean | 4.01901571 |
| Standard Error | 0.07245673 | Standard Error | 0.14836506 |
| Median | 2 | Median | 2.20867209 |
| Standard Deviation | 3.51471151 | Standard Deviation | 4.28464317 |
| Minimum | -6.75 | Minimum | -2 |
| Maximum | 35.3571429 | Maximum | 31.0344828 |
| Count | 2353 | Count | 834 |
| Confidence Level (95.0%) | 0.1420857 | Confidence Level (95.0%) | 0.2912133 |

**Figure 6**

Summary Statistics for Players with 30-Minute Filter

| *White Players Pre-Shock* | | *White Players Post-Shock* | |
|---|---|---|---|
| Mean | 3.492190839 | Mean | 3.59264057 |
| Standard Error | 0.049774333 | Standard Error | 0.0887741 |
| Median | 2 | Median | 2.22222222 |
| Standard Deviation | 3.255180502 | Standard Deviation | 3.28464156 |
| Minimum | -7.5 | Minimum | -5.2941176 |
| Maximum | 31.93548387 | Maximum | 26.1290323 |
| Count | 4277 | Count | 1369 |
| Confidence Level (95.0%) | 0.097583522 | Confidence Level (95.0%) | 0.17414811 |

| *Non-White Players Pre-Shock* | | *Non-White Players Post-Shock* | |
|---|---|---|---|
| Mean | 3.593091868 | Mean | 3.823027 |
| Standard Error | 0.070696266 | Standard Error | 0.1391798 |
| Median | 2 | Median | 2.11764706 |
| Mode | 2 | Mode | 2 |
| Standard Deviation | 3.377920549 | Standard Deviation | 3.91439321 |
| Range | 30.75 | Range | 32.3896104 |
| Minimum | -6.75 | Minimum | -2 |
| Maximum | 24 | Maximum | 30.3896104 |
| Count | 2283 | Count | 791 |
| Confidence Level (95.0%) | 0.138635666 | Confidence Level (95.0%) | 0.27320596 |

We can see that even though we have increased the threshold for minutes played by each player increased from 20 to 25 minutes we obtain a similar trend. Non-White players experience a 10.5% increase in performance after the empty stadiums shock takes place, whereas white players only experience a 2.6% increase in performance. However, when looking at the summary statistics when the 30-minute threshold is used to filter the data we start to see a trend. Although all of the situations in which we have filtered the data by minutes played have yielded results in which non-white players perform better than white players in the absence of supporters, the impact of this starts to get dampened as we increase the threshold for the number of minutes played. When the 30-minute filter is used non-white players experience a 6.4% increase in performance in the absence of supporters compared with a 10.5% increase when the 25-minute filter is used and an 11.4% increase when the 20-minute filter is used. In order to get an overall view of the way in which changing the filter threshold impacts the results and significance of the results we run our difference in difference analysis on the data filtering the data in increments of 10 minutes.

**Table 4**

Difference in Difference Coefficients with Minutes Played Filter

| Difference in Differences Estimation | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Dependent Variable: Points per 90 minutes played | | | | | | | | | | |
| Minutes Played Filter | 0 | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 |
| Non-white | 27.419**<br>(9.0071) | -1.2003<br>(2.9857) | -0.911<br>(2.5307) | -0.7151<br>(2.3904) | -0.6348<br>(2.3379) | 2.6929<br>(3.2069) | 2.8445<br>(3.1979) | 2.8612<br>(3.1542) | 3.0455<br>(3.1036) | 3.1478<br>(3.0625) |
| No Supporters | -0.0750<br>(1.2385) | -0.613 .<br>(0.3585) | -0.673*<br>(0.3142) | -0.570 .<br>(0.3044) | -0.582 .<br>(0.3023) | -0.594 .<br>(0.3113) | -0.610 .<br>(0.3172) | -0.6658*<br>(0.3231) | -0.655 .<br>(0.3370) | -0.747*<br>(0.3474) |
| Non-White*No Supporters | 1.3351 .<br>(0.6920) | 0.3902 .<br>(0.2007) | 0.375*<br>(0.1776) | 0.1729<br>(0.1743) | 0.16252<br>(0.1734) | 0.1829<br>(0.1794) | 0.1297<br>(0.1833) | -0.005<br>(0.1898) | -0.2371<br>(0.1999) | -0.2939<br>(0.2081) |
| Opposition | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Home-game dummy | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Individual fixed effects | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Team fixed effects | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time fixed effects | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Significance Level codes: 0= '***' 0.001= '**' 0.01= '*' 0.05='.' 0.1= ' ' | | | | | | | | | | |

Table 4 displays some interesting differences compared with results from previous difference in difference analyses. We obtain more statistically significant results and obtain statistically significant coefficients for the interaction term between the non-white no supporters variables for the first time. However, as we increase the threshold for the number of minutes played the statistical significance of the coefficient for the interaction term decreases. The only coefficient that remains statistically significant throughout is the no supporters coefficient- implying that the absence of supporters is significant in explaining the performance of soccer players. As shown by Figure 1, the absence of supporters results in an overall drop off for the players in our dataset. However, the interaction term shows that non-white players experience an increase in performance levels in the absence of supporters compared to white players. However, as we increase the threshold for the number of minutes played by players the coefficient for the interaction term becomes negative. Now that we have obtained some statistically significant results after manipulating our dependent variable it would be interesting to see if the statistical significance holds if we revert back to our original dependent variable of the total points obtained by each player in each game. However, this wouldn't be a useful exercise given that filtering the data by minutes played would have a very different effect when using total points as the dependent variable. When using points per 90 minutes played filtering the data by minutes played helps us get rid of outliers that would cause the data to be skewed in the case of players who play very few minutes but have significant contributions to the game. However, when using total points as our dependent variable filtering the data by minutes played would in all likelihood remove a lot of datapoints at the lower end of our dataset leaving us with a skewed dataset. This is because players that play few minutes and have significant contributions will have the same total points as players who play the majority of a match. Thus, filtering out players who played few minutes will likely remove a majority of players with a low number of total points since most substitutes who play a relatively small number of minutes won't have a significant impact on a match.

Finally, before delving deeper into our results we perform a robustness test on our difference in differences analysis. In order for our difference in differences analysis to be valid we need to show that the reason for any change in the performance of players is due to the absence of supporters and not anything else. By conducting this robustness test we ensure that any statistically significant results in our model are due to the shock in game-week 29 and not due to any changes that may have taken place earlier in the season. Thus, we split the season into two periods both of which had supporters present in stadiums. We then compare player performance across the two periods in order to see if player performance may have changed prior to the imposition of the ban on supporters in stadiums. 29 game-weeks took place with supporters present and so in order to maintain an equal number of games in the two periods of our analysis we split up the season into one period containing game-weeks 1-14 and a second period containing game-weeks 15-28. For the sake of conducting this analysis we implement an artificial closed stadiums shock after game-week 14 in our data by setting the dummy variable for fans to 0 for all games after game-week 14. We obtain the following results:

**Figure 7**

Player Performance Before and After Artificial Shock

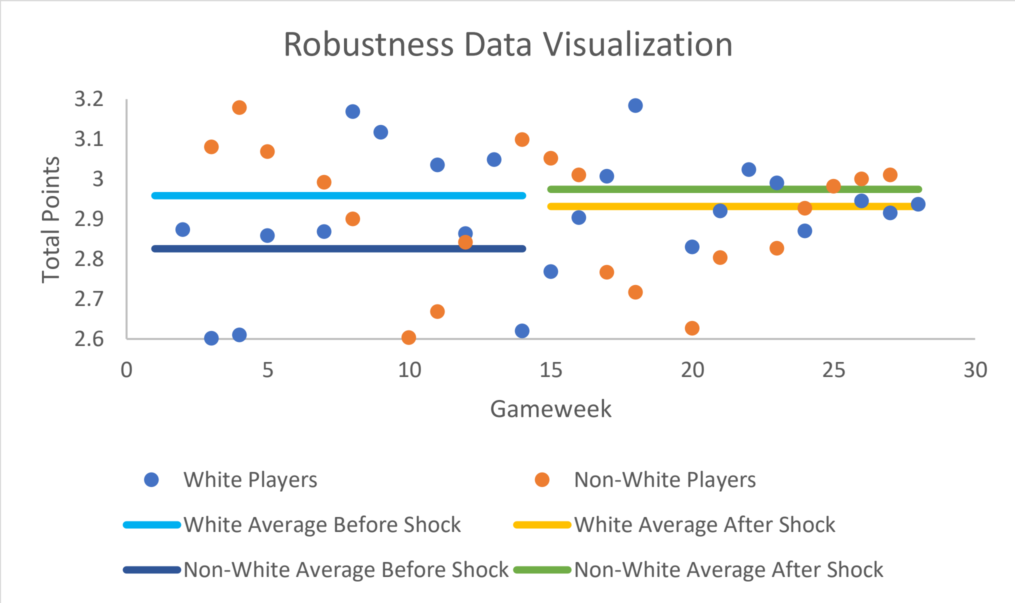



Figure 7 shows that non-white players in general appear to be underperforming compared to white players before game-week 15. After the implementation of the artificial shock the performance of non-white players increases to a level similar to that of white players however the average performance level of non-white players remains below that of white players. White players also experience a very slight improvement in average performance after the artificial shock, however their performance level remains relatively consistent throughout the time period being analyzed. Although there does appear to be an increase in performance level for non-white players, we carry out a difference in differences analysis to see whether or not this change is statistically significant.

**Table 5**

Difference in Differences Robustness Analysis

| | Difference in Differences Estimation | | | | | |
|---|---|---|---|---|---|---|
| Dependent Variable: Total Points | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Non-white | -0.13274<br>(0.09871) | -0.133975<br>(0.098030) | -0.131345<br>(0.097773) | -2.3323847<br>(1.8877811) | -2.3323847<br>(1.8877811) | -2.398275<br>(1.891767) |
| No Supporters | -0.02703<br>(0.08456) | -0.029639<br>(0.083970) | -0.029029<br>(0.083749) | -0.0112102<br>(0.0832663) | -0.0112102<br>(0.0832663) | -0.242080<br>(0.263445) |
| Non-White*No Supporters | 0.17568<br>(0.14043) | 0.181119<br>(0.139456) | 0.181342<br>(0.139089) | 0.1270784<br>(0.1392026) | 0.1270784<br>(0.1392026) | 0.124860<br>(0.139355) |
| Opposition | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Home-game dummy | | | ✓ | ✓ | ✓ | ✓ |
| Individual fixed effects | | | | ✓ | ✓ | ✓ |
| Team fixed effects | | | | | ✓ | ✓ |
| Time fixed effects | | | | | | ✓ |

Significance Level codes: 0= '***' 0.001= '**' 0.01= '*' 0.05='.' 0.1= ' '

We can see that over the period analyzed there is no statistically significant change in the performance of non-white players, the performance of all players after the implementation of the artificial shock, and the performance of non-white players compared to white players after the implementation of the shock. Thus, we can conclude that any changes that we obtained in our initial difference in differences analysis were due to the no supporters shock in game-week 29.

## Discussion

From our results we find that there is a statistically significant relationship between the presence of supporters and the performance of soccer players in the English Premier League. This relationship was only statistically significant once we implemented all the controls in our regression, however not including them would make the estimation susceptible to omitted variable bias. However, unlike Colella's paper, this study finds no statistically significant relationship between race and player performance (Colella, 2021). Our difference in difference analysis showed that there was indeed an improvement in the performance of non-white players after the no supporters shock took place. However, this improvement in performance was not statistically significant. It is important to note that when we manipulated the data and changed the dependent variable to measure points per 90 minutes as opposed to the absolute number of points obtained in a game-week, we did obtain some statistically significant results for our interaction term measuring the change in performance of non-white players in the absence of supporters. However, we only obtain statistically significant results in scenarios when we do not significantly filter the data and allow for the presence of extreme results. Statistically significant results are obtained when we applied no filter, a filter to include only players who played more than 10 minutes in a given match and a filter to include only players who played more than 20 minutes in a given match. The first category includes a data point for Dennis Srbeny who scored a goal having only played one minute of the game. This gave him a total of 6 points, however when converting to points scored per 90 minutes played, he received a score of 540. Given that the average score per 90 minutes in our sample of 10,615 observations was 6.34, including a score of 540 in our analysis would be absurd. Similarly, when only filtering for players who played more than 10 minutes, we include observations who have scores ranging from 45 to 63 points per 90 minutes. Once again it would be absurd to include these values given the average value for points per 90 minutes we have. Furthermore, when taking into account that on most game-weeks entire teams of players in Fantasy Football won't reach 45 or 63 points, including these datapoints would significantly skew our analysis.

A second potential explanation for the lack of statistically significant results in our study compared with the Italian study is the differences in racism between the United Kingdom and Italy. Although there is no tangible metric to measure the intensity of racial abuse, reading news reports on racist incidents in the United Kingdom and Italy gives us a sense on ways in which they might differ. In recent times, soccer player Mario Balotelli has been targeted with the chant “non ci sono Negri Italiani”, which translates to “there are no black Italians” (Antonsich, 2019). In another instance the then Juventus striker Moise Kean was subject to monkey chants throughout a match against Cagliari. These chants only intensified when Kean scored (The Local, 2019). It would be ignorant to say that incidents like these do not take place in the United Kingdom. There have been several instances at soccer games of fans making racist gestures or monkey noises at non-white soccer players, however it is rarely entire sections of supporters. Furthermore, what appears to be more disturbing in Italy is the lack of support for non-white players who endure racist abuse. When Moise Kean was targeted by monkey noises as he celebrated his goal against Cagliari, his own captain Leonardo Bonucci spoke in a post-match interview claiming the blame was “50-50”- implying that Kean shouldn’t have been so provocative when celebrating his goal (The Local, 2019). Further examples of a lack of support for non-white players in Italy include an anti-racist campaign launched by Serie A that depicted black players as chimpanzees, an article by Corriere dello Sport that advertised a match between Roma and Inter Milan with the headline “Black Friday” above pictures of 2 black players (Smith, 2019), and a comment made by Carlo Tavecchio in which he described foreign players as players who “previously ate bananas” (Antonsich, 2019). Tavecchio was subsequently appointed as the president of the Italian Football Federation. Moreover, in an interview soccer player Edin Dzeko- who has played in both England and Italy- described racist abuse in Italy as “heavier than elsewhere” (Mastrodonato, 2019). These examples present the argument that the atmosphere surrounding racism and racist abuse in soccer stadiums in Italy appears to be more intense than in the United Kingdom. This would explain why the Serie A study obtained statistically significant changes in the performance of non-white players when supporters were not able to attend games.

Throughout the paper we have discussed the importance of there being no external factors that may affect the performance of players beyond the empty stadiums shock in order to maintain the integrity of our difference in differences analysis. Our robustness test appears to show that this is the case given that there are no statistically significant changes in player performance throughout the first portion of the season when fans were present at all games. However, our study does have some limitations. During the interval between the last game in front of supporters and the first game in a closed stadium being played, there was a major incident in black history that could potentially have had repercussions for the performance of black players. On May 25th, 2020, George Floyd- a black individual in Minneapolis was murdered by police officer Derek Chauvin (Arango et al., 2020). Footage circulated around social media of Floyd's murder and protests began to take place against the mistreatment of black people as a result of police brutality in the United States. Awareness and education around the topic of black history and the oppression black people today face began to gather pace. We saw the impacts of this in the world of soccer as players began to 'take the knee' at the start of each soccer match in order to show their solidarity against racism (Butterworth, 2021). Furthermore, once the English Premier League resumed in closed stadiums after game-week 29, all Premier league players wore jerseys with "Black Lives Matter" printed on the back. This relates to our study since we have to take into account the potential impact that the increased discourse surrounding black lives and the increased support globally for movements such as Black Lives Matter would have had on non-white players in our dataset, especially black players. The increased global support for and education about black lives in the aftermath of George Floyd's death may have helped black players feel more empowered and given them a psychological boost in the final weeks of the season after the no supporters shock took place. This can be considered to be an external factor that might bring into question the validity of our difference in differences estimation. A second limitation to our analysis is the fact that we are attempting to estimate the effects of racial abuse on the performance of non-white players using the absence of supporters as a mechanism to do this. Although it is true that soccer players do receive racial abuse through the medium of soccer fans in stadiums shouting derogatory terms or making racial gestures. However, nowadays soccer players also receive a barrage of abuse on social media platforms whenever they don't perform well. Furthermore, in the case of white players we are attempting to estimate whether or not the impact of abuse or support has a larger effect on their performance. Our study operates under the assumption that the only abuse white players receive that would impact their performance comes from abuse received within stadiums. However, just as with non-white players, white players are also susceptible to abuse from other avenues. Recently, England captain Harry Maguire received a bomb threat in the mail which required the police to investigate and search his house (Jackson, 2022). Thus, even though the empty stadiums shock would have eradicated the potential negative impacts of supporters on player performance as a result of abuse received in stadiums, it doesn't completely eradicate the overall impact of abuse on a player's performance.

## Conclusion

In summary, this study did not display as many statistically significant relationships as the corresponding study on Serie A. However, we do still find supporters to be an important factor in determining the performance of soccer players. More specifically, we find evidence to suggest that the presence of supporters has a net positive impact on the performance of soccer players. This suggests that the impacts of fan support are stronger than the impacts of fan abuse. Although our analysis doesn't appear to show a significant relationship between the performance of non-white players and the presence of supporters as was the case in the Italian study, this could also be down to differences in player characteristics between non-white players in Serie A and the Premier League and the potential limitations of our study. As alluded to earlier the Premier League is home to some of the most prominent and successful non-white players in the world. In the 2021 Ballon D'Or top 30[8] 5 of the 30 players were non-white players playing in the Premier league. No non-white players from Serie A were named in the top 30 (Carr, 2021). Colella shows that the impacts of fan abuse are intensified for lower skilled players (Colella, 2021), so it could be precisely this effect that results in no statistically significant change in the performance of non-white players when fans weren't present in stadiums. For the purposes of this study, we were not able obtain data on social media abuse of soccer players or the number of racist incidents taking place at soccer games. Data on social media abuse of soccer players may be hard to collect given the frequency at which it takes place. However, being able to control for abuse received by players on social media would give us a more accurate image of the way in which supporters in stadiums impact player performance. United Kingdom based organization Kick It Out do collect data on the number of racist incidents reported at soccer games in the Premier League for their annual report. Unfortunately, we weren't able to obtain this data, but future studies in this field should look to incorporate data on the number of racist incidents reported in a given game-week. Including this in our analysis will give us a clearer picture of the way in which tangible instances of racism affect the performance of non-white players since it would become possible to track how a player's performance changes in weeks in which they receive racial abuse and the weeks immediately after.

[8] The Ballon D'Or is an annual award in soccer that is given to the player who is considered to have performed the best in that given year. The top 30 referred to in this paper is a ranking that is also released as a part of this award which lists the top 30 best performing soccer players in the world in a given year. The Ballon D'Or is one of the most reputed awards in soccer and that is why we have used the Ballon D'Or top 30 as a metric for comparing players in this paper.

In summary, in spite of the limitations of this study, we have been able to find that supporters have a significant positive impact on the performance of players, rightfully earning themselves the clichéd name of being the “12$^{th}$ man”. However, based on the findings in this study we cannot conclude that non-white players experience any significant changes in their performance when supporters are not present at games.

**References**

Antonsich, Marco, Racism in Italian Football Reflects the Everyday Migrant Experience, The Conversation, 2019.

Arango, Tim et al. How George Floyd Died and What Happened Next?, The New York Times, https://www.nytimes.com/article/george-floyd.html, 2020.

British Broadcasting Corporation, Liverpool Striker Luis Suarez Handed Eight-Match FA Ban, BBC Sport, https://www.bbc.com/sport/football/16186556, 2011.

Butterworth, Benjamin, What is the History of taking the knee? Origins of the anti-racism gesture- and why England Players do it, i-news UK, https://inews.co.uk/news/uk/taking-the-knee-what-history-orgin-meaning-why-england-players-explained-1103131, 2021.

Carr, Damon. Official: Ballon D'Or Top 30 Announced as PSG and Argentina Forward Lionel Messi Wins Again, LFC Transfer Room, https://www.si.com/soccer/liverpool/nonlfc/ballon-dor-top-30-players-in-order-the-came-in-this-years-award-ceremony, 2021.

Caselli, Maurom Paolo Falco and Gianpiero Mattera. When the Stadium Goes Solent: How Crowds Affect the Performance of Discriminated Groups. Available at SSRN (2021).

Colella, Fabrizio. Who Benefits from Support?: The Heterogeneous Effects of Supporters on Athletes' Performance by Skin Color. Université de Lausanne, Faculté des hautes études commerciales (HEC), Département d'économie, 2021.

Church, Ben. Tottenham Star Son Heung-Min Racially Abused Online After Premier League Defeat. CNN, https://www.cnn.com/2021/04/12/football/son-heung-min-tottenham-racist-abuse-spt-intl/index.html, 2021.

Jackson, Jamie. Manchester United's Harry Maguire Receives Bomb Threat to his Home, The Guardian, https://www.theguardian.com/football/2022/apr/21/manchester-united-harry-maguire-receives-bomb-threat-to-his-home , 2022.

Kick It Out. Reporting Statistics 2019/20. https://www.kickitout.org/Pages/FAQs/Category/reporting-statistics. 2020

Kilvington, Daniel, and John Price. Tackling social media abuse? Critically assessing English football's response to online racism. Communication & Sport 7.1 (2019): 64-79. DanielKick It Out. Reporting Statistics 2019/20. https://www.kickitout.org/Pages/FAQs/Category/reporting-statistics. 2020

Nadal, Kevin L., et al. The impact of racial microaggressions on mental health: Counselling implications for clients of color. Journal of Counselling & Development 92.1 (2014): 57-66

Neely, Greg H. The relationship between employee morale and employee productivity. National Fire Academy, 1999.

Mastrodonato, Luigi. A Brief History of Racism in Italian Football, L'Ulitimo Uomo, https://www.ultimouomo.com/razzismo-calcio-italiano-breve-storia/, 2019.

Samnani, Al-Karim; Singh, Parbudyal. Performance Enhancing Compensation Practices and Employee Productivity: The Role of Workplace Bullying. 2014.

Slater, Chris and Paul Britton, The CCTV Footage that saw City fan convicted of making racist gestures during the derby as the world watches- he's now banned from the Etihad for life, Manchester Evening News, https://www.manchestereveningnews.co.uk/news/greater-manchester-news/cctv-footage-saw-city-fan-20734042, 2021.

Smith, Rory. When the Monkey Chants are for you: A soccer star's view of racist abuse, The New York Times, nytimes.com/2019/12/22/sports/soccer/romelu-lukaku-inter-italy-racism.html, 2019.

Sport Resolutions, FA launches Football Leadership Diversity Code to increase BAME and Female Representation, https://www.sportresolutions.com/news/view/fa-launches-football-leadership-diversity-code-to-increase-bame-and-female-representation#:~:text=15%25%20of%20new%20executive%20appointments,10%25%20of%20senior%20coaching%20appointments, 2020.

The Independent. The damning list of racist incidents which marred football in 2019. The Independent, https://www.independent.co.uk/sport/football/premier-league/racism-in-football-premier-league-serie-a-antonio-rudiger-epl-a9257966.html, 2019.

The Local, Why do Italian football fans get away with Racially abusing black players?, https://www.thelocal.it/20190403/moise-kean-racial-abuse-italy-football-juventus/, 2019.

Thomas-Hawkins, Charlotte, et al. Effects of Race, Workplace Racism, and COVID Worry on the Emotional Well-Being of Hospital-Based Nurses: A Dual Pandemic. *Behavioural* Medicine (2021): 1-14.

Wright, Duncan. West Ham Vow to ban two sick fans who were filmed shouting vile racist abuse during defeat to Arsenal. The Sun, https://www.the-sun.com/sport/football/premier-league/4283363/west-ham-ban-fans-racist-arsenal/, 2021.