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Abstract

In this study, we examine how racially exclusive selection strategies would have affected the England men's national soccer team's performance using counterfactual modeling. Relying on Transfermarkt player valuations as proxies for individual productivity, we develop and validate an ordered logistic regression model to predict match outcomes in international soccer from 2016 to 2024. We simulate two counterfactual scenarios: one excluding all Black players ("Non-Black England") and another composed exclusively of Black players ("Black-Only England"), replacing affected players with the highest-valued eligible alternatives by position, matchday availability, and footedness. Our findings show that team valuations and expected win probabilities decrease under both scenarios – by 22.9% in the Non-Black England scenario and 25.8% in the Black-Only England scenario, and by 2.7 and 3.3 percentage points in expected win probability, respectively. Position-level analysis reveals concentrated value losses in key attacking and goalkeeping roles. We also find no evidence that racial diversity of a national selection affects team productivity once player ability is accounted for. This approach extends discrimination theory into applied performance modeling, illustrating the measurable cost of structural exclusion in elite soccer, while showing that diversity's primary performance benefit operates through access to a larger talent pool.

1. Introduction

How does diversity impact team performance? What is the best way to measure this impact? It appears immediately obvious that the chances of finding the best players increase when the talent pool increases. Arbitrary restrictions on admission to the pool (e.g. only the brown-eyed, only Southerners, only those born on a Tuesday) will reduce the quality of the selected team. Yet, to our knowledge, this proposition is seldom, if ever, tested in a setting where individual productivity can be observed with sufficient precision to construct credible counterfactual teams. This question is especially important in sports, where racial integration has often proceeded unevenly: racialized workers may become highly visible in performance roles while remaining underrepresented in decision-making and managerial positions (Cunningham, 2010; Cashmore & Cleland, 2011).

English professional soccer is a useful context base for examining this issue. Black players account for a large share of elite playing talent in England, yet this representation has not translated into comparable access to coaching and leadership roles. A report commissioned by the Black Footballers Partnership shows that Black players represented 43% of English Premier League players and 34% of English Football League players in 2021, but only 4.4% of managerial positions usually filled by former players were held by Black employees (Szymanski, 2022). For reference, around 5% of England's population self-identifies as Black as per the 2021 UK Census. This gap is not merely a descriptive imbalance; it raises a broader labor-market question about how exclusion operates when productivity is easy to observe – such as in the case of soccer players and managers.

This paper is motivated by the asymmetry in representation of Black players vs. Black managers in English soccer. We cannot directly estimate how English clubs would perform if Black coaches were systematically substituted into managerial positions, because coaching opportunities are themselves rationed, managerial productivity is difficult to isolate, and the relevant counterfactual candidates are often never available to the public. We can, however, examine an adjacent question: what would happen to the expected national team performance if racial restrictions were imposed at the *player*-selection stage? Player performance and value data is more observable and can be used to measure the cost of segregation.

We analyze this question in the context of the racial composition of the England men's national soccer team and find that artificial segregation of the team, based on racial characteristics (either all-Black or non-Black), would reduce expected team performance. We have an external measure of individual player ability through Transfermarkt values that accurately predicts the results of national team games. Using this measure of ability, we simulate two restrictive counterfactuals: one in which Black players are excluded from selection and one in which the team is composed only of Black players. These counterfactuals are not intended as realistic policy proposals. Rather, they are analytical stress tests designed to quantify the performance consequences of limiting access to the full talent pool. We treat race here as a socially constructed and institutionally salient category, not as a biological category; the empirical question is how socially meaningful racial boundaries, if used to constrain selection, would affect team quality and expected outcomes.

Segregation can take many forms. Segregation on the basis of race has a long history and was a notorious practice of European colonial regimes, the United States prior to civil rights legislation and regimes such as South Africa under apartheid (see, e.g., Nightingale (2022)). Segregation also has a long history in sports, both in the US (e.g., Shropshire (1996)) and elsewhere (e.g., Nauright & Wiggins (2017)). Sports remain a productive empirical setting for studying racialized labor-market processes, including positional segregation, rank-order selection, and managerial representation (Ducking & Groothuis, 2023; Gregory-Smith et al., 2023; Mills et al., 2026). Our paper contributes to this literature by shifting the focus from whether unequal treatment can be detected to what exclusion costs are when access to all available talent is restricted.

Whether or not segregation is inefficient was a matter that the original literature on discrimination considered at length – see e.g. Becker (1957); Stiglitz (1973); Cain (1986). Segregation is different from discrimination, specifically in the sense that workers in two different countries without free movement of labor are segregated but may not face discrimination. Under constant returns to scale with free trade in commodities, the factor price equalization theorem ensures that labor is allocated efficiently and gains from trade are exploited (Stiglitz, 1973, p. 288). However, selecting a national soccer team is not a constant returns technology. Rather, the winner-take-all nature of competitive sports implies that team selection is more like the superstar model in Rosen (1981), where there are increasing returns to talent.

Segregating talent limits the potential to create the single best team. Put differently, the cost of segregation is likely to be especially large when output depends on assembling the extreme upper tail of the talent distribution. If the objective is to maximize the probability of winning, any non-performance-based restriction on the selection pool can impose a measurable competitive penalty. This argument also connects our study to recent evidence on diversity and performance in sports. Huang et al. (2023), for instance, find that cultural diversity can enhance national soccer team performance, particularly when shared team tenure supports tacit knowledge and within-team communication. Their study speaks to the performance implications of heterogeneous teams once they are assembled. In our study, we ask a related but distinct question of what is lost when a team cannot be assembled from the full distribution of eligible talent.

Our approach also speaks to debates about representation in leadership. Mills et al. (2026) show that racial matching between coordinators and quarterbacks in US college football can shape recruitment and performance, suggesting that managerial representation may affect how human capital is identified and used. The English soccer case raises an analogous concern: if Black former players are underrepresented in coaching despite their wide representation among elite players, then the sport may be failing to convert playing experience and tacit knowledge into leadership capital. Our paper does not directly estimate the performance effect of Black coaches, but it provides a complementary estimate of the cost of restricting access to Black talent in the domain where such a counterfactual is observable.

We find that restricting the selection pool would reduce the expected win percentage of the national team by 2.7% to 3.3%. England men's national soccer team decreases meaningfully under segregation – whether Black players are excluded or the team consists solely of Black players. In championship formats where progress depends on winning, the cumulative impact can be very large.[1] The broader implication is that racial segregation is not only an equity problem but also an efficiency problem. In high-performance labor markets, where small differences in expected performance can determine success, exclusionary selection imposes costs on both the excluded group and the organization that narrows its own talent base.

[1] We also test for team composition effects independent of the aggregate measure of team ability and find that these have no statistically significant impact on results.

2. Literature Review

2.1. The Team Diversity Literature

There is now a large literature on the effect of diversity on team performance, both in sports and in the wider management literature. Generally speaking, the literature posits two possible effects, working in opposite directions. Diversity could exert a positive effect if it stimulates learning and the development of innovative solutions to problems, but it could also exert a negative effect if it leads to cross-cultural misunderstandings and conflict. For this study, the key question is not simply whether diverse teams perform better once assembled, but what happens when teams are denied access to the full talent pool based on race. Diversity may improve performance through communication and knowledge-sharing, but it also matters because a larger, unrestricted pool increases the likelihood of selecting the best players.

Table 1. Summary of Studies on Diversity and Performance in Professional Sports

Study	Diversity Factor	Effect	Context	Measure of Individual Ability
Nüesch (2009)	Nationality	None	Bundesliga	Payroll
Weiss & Sommers (2009)	Race	None	NBA	None
Dolles et al. (2011)	International experience	None	Men's Soccer World Cup	None
Papps et al. (2011)	Ability	Mixed	MLB	ERA and OPS
Haas & Nüesch (2012)	Nationality	Negative	Bundesliga	None
Kahane et al. (2013)	Nationality	Positive	NHL	Payroll
Maderer et al. (2014)	Nationality	Negative	Five men's European soccer leagues	Transfermarkt value
Ben-Ner et al. (2017)	Nationality	Sometimes positive	Bundesliga	Performance rating
Balsmeier et al. (2019)	Nationality	Positive	Bundesliga	Performance rating
Tovar (2020)	Nationality	Mixed	EPL and La Liga	Transfermarkt value

Study	Diversity Factor	Effect	Context	Measure of Individual Ability
Brox & Krieger (2022)	Nationality	Mixed	Bundesliga	Transfermarkt value
Di Domizio et al. (2022)	Wages	Negative	Serie A	Wages
Wegelin et al. (2022)	Ability	None	NBA	In-game stats
Lago et al. (2023)	Ethnicity	None	Five men's European soccer leagues	Transfermarkt value
Bosker & Gürtler (2024)	Nationality	None	Ten men's European soccer leagues	Transfermarkt value
Wang (2024)	Nationality	Positive	NBA	None
Gasparetto (2025)	Nationality	Sometimes positive	Six men's European soccer leagues	Transfermarkt value

Notes: This table summarizes, in chronological order, empirical studies examining the relationship between various diversity factors and team performance in various (mostly) professional sports. Reported effects range from positive to negative or mixed, and measures of individual ability vary widely, from none to detailed performance statistics and market valuations.

Table 1 summarizes a selection of papers from the sports literature on diversity. The majority of these studies have focused on nationality as the source of diversity. Others use international experience, ability, ethnicity, and wages as the diversity factor. One study – a two-page note by Weiss and Sommers (2009) – investigates racial diversity in the NBA and finds no significant effect of diversity on season win percentage. Szymanski (2000) and Deschamps and De Sousa (2021) investigate the impact of discrimination on team performance, but not diversity per se.

The results in Table 1 are mixed, with diversity variables sometimes positive, sometimes negative, frequently insignificant, and often quadratic in nature, with positive effects at low diversity levels and negative effects at high diversity levels. These inconsistent results could be explained by local contingencies which lead to different results in different times, places, and contexts. Or, it could be that the econometric challenges are too great, given issues of identification, selection bias, endogeneity, and unobserved heterogeneity. A further difficulty is that many diversity-performance studies estimate the effect of observed diversity among selected

workers, rather than the cost of excluding potential workers before team formation occurs. If the selection pool has already been shaped by discrimination, positional sorting, or unequal access to development pathways, observed team diversity may be an endogenous outcome of earlier labor-market processes.

A key issue in this research area is the relationship between player ability, team diversity, and team performance. If player ability itself is affected by team diversity, then some mechanism for separating 'intrinsic' ability from diversity-mediated ability is required. Some studies, such as Papps et al. (2011), address this by using an estimate of ability based only on past performances – even if past metrics of ability are biased by past team diversity, at least current diversity can be distinguished from the current measure of ability.

One notable feature of Table 1 is the reliance of soccer-related studies on Transfermarkt (TM) values as a measure of ability. Six of the twelve soccer studies use TM values to proxy ability, including all but three of the studies published since 2014. TM is a website that publishes crowd-sourced estimates of player values. The website includes details of more than half a million soccer players since 2004, including personal information, club records, and regularly updated valuations. When aggregated at the team level, these valuations have been shown to be highly correlated with player salaries in the rare cases where the latter are publicly available (Prockl & Frick, 2018) and exceptionally good predictors of match results (Peeters, 2018). This helps to explain why TM values have become the gold standard for measuring player ability.

2.2. Contribution of Black Players to English Soccer

Black players have consistently occupied some of the most tactically and creatively influential roles within the England men's national team over the past two decades (Campbell, 2018). Across recent major tournaments – including the 2018 FIFA World Cup, UEFA Euro 2021, and the 2022 FIFA World Cup – players like Raheem Sterling, Bukayo Saka, Jude Bellingham, and Marcus Rashford have regularly started in attacking, midfield, or wide positions and contributed to goals, assists, and overall match impact. Notably, Saka and Sterling alone were involved in 10 of England's 11 goals on the path towards to the FIFA Euro 2021 final.[2]

[2] Derived from own calculation.

In many matches, Black players make up between one-third and one-half of the starting eleven, and several have captained youth and senior national selections (BelfastTelegraph.co.uk, 2019). In valuation terms, they frequently rank among the highest-valued members of the squad, both by TM valuations and through actual transfer fees. This centrality makes it possible and analytically meaningful to simulate team performance under counterfactual scenarios involving their absence. Because these players are not fringe contributors but essential starters, their removal would likely lead to meaningful changes in expected outcomes for the England men's national soccer team. Assessing that impact through a model grounded in player valuation and international match results allows us to estimate the performance cost associated with racially exclusive selection – as an illustrative exercise in structural bias, even when exclusionary policies are hypothetical.[3]

The contribution of Black players to English soccer is even more striking given the size of the Black population in the UK. According to the 2021 UK Census – with the full ethnicity breakdown table reported in Appendix A – only 4% of the UK population self-identifies as Black, with an additional 1.3% identifying as Black mixed race. This means that Black players are concentrated among the very top of high-productivity players. Hence, a selection rule that excludes them should reduce expected team quality. Conversely, if a team were restricted only to Black players, the much smaller underlying population and thinner positional coverage should also reduce expected team quality. Both counterfactuals therefore test the same economic proposition: restricting access to the full talent pool imposes a performance cost.

For the purposes of this paper, we treat race as a socially constructed but institutionally consequential category. The relevant question is not whether race reflects biological difference, but whether racialized boundaries, when used to organize access to opportunity, alter competitive outcomes in soccer. In this sense, the case of top-level English soccer allows us to connect

[3] The contribution of black players to English soccer is all the more striking given the size of the Black population in the UK. According to the UK Census (2021) – with the full 2021 Ethnicity breakdown table reported in Appendix A – only 4% of the UK population self-identifies as Black, with an additional 1.3% identifying as Black mixed race. In that respect, it mirrors the disproportionate representation of Black athletes in the NFL or NBA, or in track and field events at the Olympics. The causes of this phenomenon are not well understood, but most scientists now reject the notion of race as a scientific category and consider it to be a social construct – e.g., Lopez (1994); Corbie-Smith et al. (2008); Bryant et al. (2022). Whatever the reasons, this is not central to our paper.

debates about race, representation, and leadership in sports to a measurable performance outcome of expected win probability.

2.3. Performance Measurement in Sport and the Validity of Transfermarkt Valuations

Economic models of sports leagues generally posit that increasing expenditure on playing talent improves expected team performance (Rottenberg, 1956; Fort & Quirk, 1995; Késenne, 2000; Szymanski, 2003). Research on professional soccer has produced robust support for this conclusion (Szymanski & Smith, 1997; Torgler & Schmidt, 2007; Carmichael et al., 2011; Frick, 2013; Coates et al., 2016; Di Domizio et al., 2022).

This insight aligns with standard production theory: teams that spend more on talent tend to outperform those that do not, especially in markets where player contracts are not tightly regulated. However, individual player wage data is not available[4] and, in any case, national teams do not pay players to represent their country – players are instead motivated by pride and publicity effect (Elling et al., 2014). [5]

We view TM values as a player productivity indicator at a given point in time, and part of their usefulness lies in the fact that they are regularly updated to account for changes in player performance. This approach is similar to that of Peeters (2018), who demonstrates that crowdsourced evaluations of soccer players provide better predictions of match results than alternative measures such as the country-wide FIFA ranking and Elo ratings.[6] In this paper, we extend the application of TM values to the measurement of team diversity and performance.

2.4. Forecasting and Counterfactual Modeling in Sports

Forecasting sporting outcomes is a well-established component of both academic research and industry practice. In soccer, prediction models based on historical results, betting market odds, or

[4] The MLS Players Association publishes individual wage data, but in general individual-level data is not available for other leagues, although aggregate team wage spending can often be found in published financial statements.

[5] Bonuses for success may be paid, but, once again, data is not available.

[6] Empirical research has shown that TM values also correlate strongly with transfer fees and club wage bills (Herm et al., 2014). Coates and Parshakov (2022) argue that TM values are in fact biased estimators of the reported transfer fee paid. This is not relevant to the current paper, since our approach to validation in unconnected to the payment of transfer fees.

team ratings such as Elo have long been used to estimate match outcome probabilities (Dixon & Coles, 1997; Goddard & Asimakopoulos, 2004; Hvattum & Arntzen, 2010; Reade & Royle, 2025). Still, modeling based on structural team characteristics and player-level valuations has only recently gained traction. The growing availability of granular data, including TM valuations, allows researchers to simulate team strength directly from input-level data rather than past results, improving out-of-sample predictive accuracy and applicability to counterfactual scenarios.

Despite progress in forecasting, counterfactual modeling remains a frontier in sports economics. Most studies in the field focus on prior results instead of incorporating alternate team compositions or selection policies, especially those that engage explicitly with race, nationality, or structural segregation. In other fields of economics – like industrial organization – counterfactual estimation is a well-recognized tool for policy evaluation and impact assessment (Adao et al., 2017; Head & Mayer, 2023). Our contribution is to bring this counterfactual logic to the study of racial segregation in elite soccer. Rather than asking whether observed diversity correlates with performance, we ask how expected performance changes when the talent pool itself is racially constrained. This approach is consistent with the rise in use of sport settings for studying labor-market questions under unusually rich data conditions (Palacios-Huerta, 2025).

3. Data and Variables

The objective of this study is to identify the expected performance of the England men's national team under the counterfactual assumption that it was segregated – either all-Black or all-non-Black. In so doing, we are able to identify benefits from diversity in player selection.

To measure the impact of diversity on performance, one needs to know the counterfactual outcome – in other words, what performance would have been in the absence of diversity. The standard solution to this problem is the randomized control trial, where the control group identifies the counterfactual. However, here we use an alternative approach to the identification of the counterfactual.

We calculate the expected performance of national teams from player TM values and compare these with the predicted outcome using bookmaker odds. Bookmaker odds represent the average of opinions in the marketplace, and evidence suggests that these estimates are efficient (Smith et

al., 2009; Vlastakis et al., 2009; Franck et al., 2010). We find that the TM-based estimates of win probabilities are very close to the probabilities based on the bookmaker odds. We are then able to generate estimates of the England men's national team performance, assuming that the non-Black (Black) players are replaced by the highest value Black (non-Black) player in their team position.

For the purposes of this study, we compile data on international soccer matches and player valuations from 2016 to 2024. Match outcomes, participating teams, and scores are drawn from FBref.com, which includes official competitive fixtures such as the FIFA World Cup and UEFA European Championship games.[7] We use individual player TM valuations to calculate aggregate team valuations in both actual and counterfactual scenarios.

For the case of England, in order to construct counterfactual models, each player's appearance on the England men's national soccer team is linked to a TM valuation and coded for race. For empirical classification, players are coded as Black or non-Black using a publicly available archival source, the "England's Black Players – Most Appearances" archive, hosted by englandfootballonline.com.[8] The potential selection pool for the counterfactual England men's national soccer team squads is aggregated from the top 40 – where positional eligibility allows – players in each position with the same footedness across the 9 top European leagues for the respective seasons. In total, we identified 2,571 unique player valuations of English nationals, including players with dual citizenship who were eligible to represent England.

For a given player in a counterfactual scenario, the procedure is as follows.[9] First, when constructing a "Non-Black England" counterfactual, a target player is identified within the England squad for a specific match, e.g., right-winger Bukayo Saka in the Euro 2024 final. Second, an appropriate non-Black counterpart is selected by identifying the highest-valued non-Black English player who plays the same position and was not already included in the matchday

[7] For full list of tournaments used and the breakdown and the mix of competitive international tournaments from which the data is sourced, please refer to Appendix B.

[8] For a small subset of English players who have never played for the national team but are suitable counterfactual replacements, race coding was provided to us by Delroy Corinaldi of Black Footballers Partnership (https://www.bfporg.com/about-us/who-we-are/).

[9] The procedure described is for the construction of the "Non-Black England" counterfactual scenario.

squad at the time. This selection is subject to two additional constraints: the replacement player must not have been injured – as verified using TM injury records – and must share the same preferred foot as the original player; players who are equally skilled and listed as ambipedal ("Both" footedness on TM) are also acceptable substitutes. Finally, the impact of this replacement is quantified by calculating the resulting change in total squad market value. For example, replacing Bukayo Saka, valued at €150 million, with Jarrod Bowen, the highest-value non-Black available alternative for the Euro 2024 final, valued at €45 million, implies a €105 million reduction in the squad's market value in that game.[10]

In our regression analysis provided in Section 4.2, the dependent variable is the match outcome, recorded as a categorical variable (win, draw, or loss). The primary independent variable is the logarithm of aggregate team valuation, derived from player-level TM values in the starting eleven. We make a conscious choice not to account for the player-level TM values of substitutes, despite the documented effectiveness and goal-scoring ability of so-called "super-subs" in international soccer (Jankowski, 2015). While substitutions can, in principle, alter the effective strength of a team during a match, incorporating substitute valuations in a counterfactual framework poses a fundamental identification problem. At kickoff, only the starting eleven are guaranteed to appear, whereas substitutes – although known ex ante – may or may not enter the match, and if they do, the timing, duration, and positional context of their involvement are uncertain. Moreover, although many substitutions are "neutral" in the sense that they replace players in the same position (Wittkugel et al., 2022), a nontrivial share of them involve positional reshuffling or tactical adjustments that cannot be inferred ex ante. Crucially, under counterfactual roster constructions, we do not observe how substitution patterns would respond to changes in team composition. Accounting for substitutes would therefore require strong and untestable assumptions about the invariance of substitution timing, player usage, and tactical roles across actual and counterfactual lineups. To avoid introducing such assumptions, as well as to preserve comparability between observed and counterfactual scenarios, we restrict the valuation measure

[10] An additional list of the top right-wingers with TM value and footedness is provided in Appendix C. Phil Foden, though a possible non-Black replacement, is already with the team for the Euro 2024 final. Ethan Nwaneri, the second-best alternative, is Black. Jarrod Bowen is the third-best alternative and is non-Black – hence, Jarrod Bowen is the highest valued possible replacement player for Bukayo Saka.

to the starting eleven in the main part of the analysis. Still, our results are robust to the substitutions – and such analysis is reported in Appendix D.

An additional covariate is the binary variable for neutral-field games. We define bookmaker probabilities (win, draw, and loss) in the standard way – see, e.g., Feddersen et al. (2017); Deutscher et al. (2018); Winkelmann et al. (2024). For each of the 3,380 international high stakes matches (except for 40 for which the odds are not publicly available), we locate the bookmaker odds using the oddsportal.com website.

Table 2. Summary Statistics: Full Match Sample (n = 3,380 matches)

Variable	Mean	Median	St. Dev.	Min.	Max.
Goals Scored (Home)	1.486	1	1.516	0	14
Goals Scored (Away)	1.133	1	1.308	0	14
Team Valuation (in mln. €)	96.960	29.188	491.888	0.011	3,836.026
Log-Adjusted Team Valuation	16.835	17.189	2.171	9.210	24.370
Win Probability (Home)	0.442	0.428	0.254	0.007	0.968
Draw Probability	0.237	0.258	0.081	0.024	0.509
Win Probability (Away)	0.321	0.264	0.238	0.007	0.969

Notes: This table reports descriptive statistics for the full match sample, covering 3,380 competitive international soccer matches. Team valuations are expressed in millions of euros, with log-adjusted values calculated as the natural logarithm of team valuations. Win and draw probabilities are derived from betting market odds and expressed on a 0–1 scale.

Table 3. Summary Statistics: Player Valuation Statistics by Year (n = 548,420; n(unique) = 130,086 distinct players)

Year	N (Player-Year Obs.)	Mean (tho. €)	Median (tho. €)	St. Dev. (tho. €)	Min. (tho. €)	Max. (tho. €)
2016	52,702	757.528	200	2,847.860	10	120,000
2017	53,708	896.918	200	4,178.115	10	180,000
2018	58,391	978.953	200	4,507.408	10	200,000
2019	54,285	934.517	200	4,018.796	10	180,000
2020	61,578	910.199	200	3,939.877	10	160,000
2021	67,214	857.070	175	3,731.220	10	160,000

2022	69,279	902.779	175	4,045.189	10	180,000
2023	72,694	940.166	175	4,308.573	10	180,000
2024	58,029	1,045.428	175	4,746.429	10	200,000

Notes: This table reports annual summary statistics for player market valuations from 2016 to 2024, based on TM data. Values are expressed in thousands of euros, with minimum truncated at €10,000. For graphical distributions of valuations by year, please see Appendix E.

Table 2 presents summary statistics for key match-level variables including goals scored, valuations, and win probabilities. Table 3 reports player valuation statistics by year to assess trends in market values for all 130,086 player-year values. We use this sample of 130,086 player-year values from 116 domestic tier-1, tier-2, and select tier-3 leagues available on TM to construct the population of national team-eligible players from the best levels of competition. Some players – generally playing in the lower leagues – have not been given a TM value, in which case we attribute a value of €10,000 – the lowest value attributed to any player. When multiple valuations of a given player in a given year exist due to transfers between clubs during the season, we average across these valuations. If there is more than one valuation for a player who has not changed clubs, we use the most recent valuation.

4. Predictive Model Estimation

To assess how team quality predicts match outcomes, we fit an ordered logistic regression model using TM valuation data. Our objective is to model the probability of match outcomes (win, draw, or loss for the home team) as a function of the relative strength of the two teams. We define team strength based on cumulative squad valuation and assume that higher-valued teams have a greater likelihood of winning. Our estimation uses log-transformed ratios of team value and a standard cumulative link model structure.

4.1. Ordered Logistic Regression

We estimate the probability of a match resulting in a home team loss ($Y_i = 0$), draw ($Y_i = 1$), or win ($Y_i = 2$) using an ordered logistic regression framework. The primary independent variable is the log ratio of home team to away team value, and its calculation is shown in equation (1) below. A positive value of X_i would indicate that the home team has a higher valuation than the away team and should be considered the match favorite, and vice versa. A value of zero

represents a matchup between teams with equal aggregate TM valuations of their starting squads.[11]

$$X_i = \log\left(\frac{\text{TM Value}_{\text{home},i}}{\text{TM Value}_{\text{away},i}}\right) \tag{1}$$

The ordered logistic regression assumes the existence of a latent continuous variable that determines the categorical outcome via estimated threshold parameters. We then specify the set of equations (2.1) through (2.3), where we specify β to be the slope coefficient associated with X_i, and κ_1 and κ_2 are specified as the estimated threshold (cut point) parameters that divide the latent outcome into three ordered categories.

$$\begin{aligned}
\pi(Y_i = 0 \mid X_i) &= \frac{1}{1 + \exp(X_i\beta - \kappa_1)} \\
\pi(Y_i = 1 \mid X_i) &= \frac{1}{1 + \exp(X_i\beta - \kappa_2)} - \pi(Y_i = 0 \mid X_i) \\
\pi(Y_i = 2 \mid X_i) &= 1 - \pi(Y_i = 0 \mid X_i) - \pi(Y_i = 1 \mid X_i)
\end{aligned} \tag{2.1 - 2.3}$$

These probabilities are mutually exclusive and collectively exhaustive. As X_i increases (i.e., as the away team becomes stronger relative to the home team), the model increases the probability of a home loss and decreases the probability of a home win, consistent with the expected direction of team strength. This specification offers several desirable properties for modeling match outcomes. First, it respects the ordinal nature of results – treating a win, draw, and loss as ordered but not assuming equal spacing between them. Second, the log-transformed ratio of team valuations, X_i, exerts a monotonic effect on the outcome categories, governed by a single coefficient β, which increases the likelihood of better outcomes as the team improves in aggregate TM valuation of its players. Moreover, the specified thresholds, κ_1 and κ_2, partition the unobserved latent match dominance scale into regions that map to each observed outcome. These thresholds are assumed to be constant across observations, reflecting the proportional odds assumption inherent to ordered logistic regression. In Table 4, we also include a neutral-venue indicator to ensure that valuation-based predictions are not conflated with venue effects (Clarke & Norman, 1995). Home advantage is defined by the predicted home win probability when team

[11] If two teams have the same TM value, the implied home win probability is 44%, draw probability is 30%, away win probability is 26%.

valuations are equal, while the neutral indicator simply removes this effect in matches played at neutral sites.

4.2. Regression Results

Table 4 presents the results from two ordered logistic regression models predicting match outcomes for the home team, based on the relative strength of team rosters as proxied by TM valuations. The purpose of this analysis is not to maximize predictive accuracy, but to establish that aggregate TM valuations contain sufficient information about team strength to support counterfactual simulation. The ordered logit specification provides a parsimonious mapping from relative team valuation to win, draw, and loss probabilities, which can then be applied to actual and racially restricted England lineups. In both models, the coefficient on the log ratio of home to away team value is positive and highly statistically significant, indicating that increases in relative roster valuation shift the latent match dominance index toward more favorable outcomes for the home team. Substantively, this implies a monotonic increase in the probability of a home win, and corresponding decreases in the probabilities of a draw or home loss, as the valuation advantage of the home team grows. The ordered logistic specification allows home advantage to arise endogenously through the intercept structure rather than through a separate coefficient.

Table 4. Ordered Logistic Regression Results

Variable / Statistic	**Model 1**	**Model 2**
log(TM Value Ratio)	0.562***	0.565***
	(0.019)	(0.019)
Neutral Venue (= 1)		-0.386***
		(0.077)
Cut Point (0‖1)	-0.940***	-1.063***
	(0.043)	(0.050)
Cut Point (1‖2)	0.342***	0.228***
	(0.040)	(0.046)
Observations (n)	3,340	3,340
AIC	5986.8	5963.5
McFadden R^2	0.166	0.170

Notes: Ordered logistic regression predicts the outcome for the home team (0 = Loss, 1 = Draw, 2 = Win). The main independent variable is the natural log of the ratio between TM team values for the home and away teams. Model 2 includes a binary indicator for neutral-site matches. Cut points (0‖1 and 1‖2) are estimated thresholds between outcome categories. Standard errors are in parentheses. McFadden R^2 reported as a measure of model fit, AIC values are reported for model selection criteria. Significance codes: *** p < 0.01, ** p < 0.05, * p < 0.1.

The neutral-venue indicator introduced in Model 2 captures deviations from this baseline by shifting the latent match dominance index downward when matches are not played at a true home venue. Its negative and statistically significant coefficient indicates an attenuation of the baseline home advantage under neutral conditions, rather than the creation of a disadvantage per se. This interpretation is consistent with the probability structure implied by equations (1.1) – (1.3). The estimated cut points, κ_1 and κ_2, define the thresholds on the latent match dominance scale that separate losses from draws and draws from wins, respectively, and together with the valuation coefficient determine how changes in relative team strength translate into shifts across outcome probabilities. Both models have reasonable fit for a parsimonious ordinal model – McFadden R^2 values of 0.166 and 0.170, respectively. The estimated threshold parameters (cut points) between outcome categories are statistically significant in both models and remain relatively stable across specifications. Overall, our results confirm that relative roster valuation is a powerful predictor of international match outcomes.

4.3. Model Validity

To assess the predictive performance of our model relative to bookmaker expectations, we compare predicted match outcomes against actual results across all international games in the sample. In Table 5, we present the number of games where each method – bookmaker probabilities or the log-ratio model – correctly predicted the match result, disaggregated by whether the outcome was a home win, draw, or away win. Bookmakers perform best when predicting home wins, with an accuracy rate of approximately 85%, followed by away wins at roughly 72%. Draws remain notoriously difficult to predict, with both methods performing poorly; neither method correctly classifies any draws in this sample, which is consistent with prior inference by Winkelmann et al. (2024).

Table 5. Prediction Accuracy and Model-Bookmaker Agreement by Match Outcome (n = 3,340)

Outcome	Total Games	Bookmaker Correct	Bookmaker Accuracy (% Correct)	Model Correct	Model Accuracy (% Correct)	Correlation
Home Win	1,508	1,278	0.847	1,278	0.847	0.869
Draw	772	15	0.019	0	0.000	0.633
Away Win	1,060	767	0.724	744	0.702	0.852

Notes: This table reports the number of games where the outcome (home win, draw, or away win) was correctly predicted by either the bookmaker (based on the highest implied probability) or the ordered logistic model (based on the log of the TM team value ratio). While both methods perform well for home and away wins, neither method predicts draws reliably. The final column reports the Pearson correlation between bookmaker and model predicted probabilities for each outcome. Note that the games predicted correctly by each method may differ.

Interestingly, the model's performance closely matches that of bookmakers for home and away wins, despite relying only on team valuation data and not incorporating other match-specific covariates. The final column shows the Pearson correlation between bookmaker and model probabilities for each outcome category. The correlations are very high for wins and losses ($\geq$ 0.85), suggesting that the model captures similar directional strength as the odds market – even if not exact categorical matches. In order to transition to counterfactual modeling in Section 5 of this paper, we first repeat the same procedure for just the games featuring England men's national soccer team. We report the associated results in Table 6.

Table 6. Prediction Accuracy and Model-Bookmaker Agreement by Match Outcome – Only for England (n = 80)

Outcome	Total Games	Bookmaker Correct	Bookmaker Accuracy (% Correct)	Model Correct	Model Accuracy (% Correct)	Correlation
Home Win	33	21	0.750	20	0.714	0.969
Draw	19	0	0.000	0	0.000	0.896
Away Win	28	28	0.848	27	0.818	0.965

Notes: This table reports the number of games where the outcome (home win, draw, or away win) was correctly predicted by either the bookmaker (based on the highest implied probability) or the ordered logistic model (based on the log of the TM team value ratio) just for England. As in Table 5, the final column reports the Pearson correlation

between bookmaker and model predicted probabilities for each outcome. Games predicted by each method do not differ, and the bookmaker odds model is slightly more accurate.

The results show that both the bookmaker model and our TM-based ordered logistic regression model perform similarly when it comes to predicting match outcomes for England, suggesting that the log-ratio model captures much of the same team strength signal embedded in bookmaker odds. This strong model-bookmaker agreement gives us confidence in using the estimated ordered logistic specification to simulate counterfactual performance scenarios. To further assess probabilistic calibration and economic relevance, we evaluate model performance using Brier score calculations and robustness checks underlying Tables 6 and 7 – these are reported in Appendix F. In the next section of our paper, we leverage the validated framework to estimate expected match outcomes under alternative national team compositions: first under the "Non-Black England" scenario that excludes all Black players, and then under the "Black-Only England" scenario that features only Black players in the squad.

5. Counterfactual Modeling

We begin counterfactual modeling by identifying counterfactual roster compositions and their effects on the strength of the England men's national soccer team by position. We decompose the previously calculated total TM value across functional areas of play – attack, midfield, defense, and goalkeeping – under three different team constructions: actual squads, the "Non-Black England" counterfactual scenario, and the "Black-Only England" counterfactual scenario.[12] The counterfactual scenarios are intentionally restrictive. They are not intended to represent plausible selection policies, but rather to quantify the performance cost of limiting access to the full eligible talent pool. We first estimate how these restrictions affect aggregate team value and then translate those valuation changes into predicted match-outcome probabilities using the ordered logit model estimated above.

[12] The "Black-Only (Except Goalkeeper) England" counterfactual scenario is reported in Appendix G. The inclusion of this scenario may be justified by a clearly captured trend of underrepresentation of Black goalkeepers in English professional soccer (Melnick, 1988; Mills et al., 2018). As shown in Appendix G, there is no significant deviation from the other two counterfactual scenarios in terms of negative impact on aggregate team valuation and win probability.

In Table 7, we present the mean positional values by position for the three scenarios. As Table 7 demonstrates, for almost all the individual positions, valuations are higher in the "actual" case than in either of the counterfactual scenarios.

Table 7. Mean Player Valuations by Position Across Actual, "Non-Black England," and "Black-Only England" Scenarios (in Million €)

Group	Position	Actual Mean	"Non-Black England" Mean	"Black-Only England" Mean	"Non-Black England" to "Black-Only England" Ratio
Attack	CF	92.000	89.723	36.398	2.465
	LW	72.535	42.753	67.163	0.637
	RW	104.350	48.388	85.369	0.567
Midfield	AM	89.494	47.600	80.443	0.592
	CM	55.978	55.085	29.300	1.880
	DM	41.458	20.208	38.250	0.528
Defense	CB	34.121	31.051	28.362	1.095
	LB	33.750	33.792	25.740	1.313
	RB	32.434	26.995	32.302	0.836
	GK	23.844	23.844	1.441	16.547

Notes: This table compares mean player valuations (in millions of euros) for England's national team across the actual roster, a counterfactual "Non-Black England," and a counterfactual "Black-Only England." The distribution of higher values between "Non-Black England" and "Black-Only England" shows that neither counterfactual group consistently has an advantage or disadvantage in positional market value. This notion is also supported by the ratios in the "Non-Black" to "Black-Only" Ratio column. The following position codes are used: CF = center-forward, LW = left-winger, RW = right-winger, AM = attacking midfielder, CM = central midfielder, DM = defensive midfielder, CB = center-back, LB = left-back, RB = right-back, GK = goalkeeper.

The data reveal clear patterns of positional imbalance across scenarios. For instance, the actual England squad shows especially high valuations in attacking roles, particularly at right winger (€104.4 mln.) and center-forward (€92.0 mln.). In the "Non-Black England" scenario, the valuation at right wing drops by more than half, while the "Black-Only England" scenario sees a dramatic reduction in goalkeeper value (€1.4 mln.), pointing to the long-observed absence of Black players in elite goalkeeping roles as noted in prior literature and stressed earlier in this

paper. This breakdown offers a more nuanced understanding of how racialized roster constraints affect team strength. Rather than merely measuring total valuation losses, it highlights disproportionately impacted positions. These patterns underscore key implications: from a diagnostic standpoint, they reveal where performance losses are most concentrated; from a policy standpoint, they suggest where underrepresentation might stem from structural gaps in talent development; and from a strategic perspective, they explain why the overall team may remain competitive in some positions but not others.

Next, in Table 8, we present the overall values of the England men's national soccer team, as well as the two counterfactual scenarios, across 80 competitive matches (excluding friendly matches, for instance) from 2016 to 2024. Notably, for both counterfactual scenarios, the mean and maximum aggregate TM values for the counterfactual squads are lower than the mean and the maximum values for the "actual" England.

Table 8. Summary Statistics: Cumulative Team Valuations for England Under Actual and Two Counterfactual Scenarios (n = 80 matches – for England only)

Scenario	Mean (mln. €)	Median (mln. €)	St. Dev. (mln. €)	Min. (mln. €)	Max. (mln. €)	% Change in Mean
"Actual" England	604.590	615.010	135.549	219.000	985.000	—
"Non-Black England"	465.885	474.750	103.761	190.500	660.000	-22.942%
"Black-Only England"	448.791	444.850	113.011	125.750	780.800	-25.769%

Notes: This table reports cumulative market valuations (in millions of euros) for England's national team under the actual roster and three counterfactual scenarios. The "Non-Black England" scenario replaces Black players with the next-highest-valued non-Black English players, while the "Black-Only England" scenario includes only Black players. Percentage changes reflect the difference in mean valuation relative to the actual roster.

The predictive modeling framework developed in Section 4 allows us to estimate win, draw, and loss probabilities based on TM team valuation ratios. With this, we can estimate the change in England's expected performance under racially constrained team compositions. The results presented in Table 9 provide an assessment of how England's expected match outcomes vary under racially structured counterfactual team compositions. Using the ordered logistic regression model introduced earlier, we compute average predicted win probabilities across six scenarios. Based on the actual player selections, England's predicted probability of winning is 73.5%. The

first two rows in Table 9 show that predicted win probability falls significantly under either counterfactual scenario – "Non-Black England" or "Black-Only England." The decline is slightly larger under the "Black-Only England" counterfactual scenario. The difference between the two counterfactual scenarios is statistically significant, but the difference in win percentage is marginal. That there is a difference in win percentage is to be expected, given that Black players are drawn from only 5.3% of the English population, as opposed to 94.7%, based on the 2021 UK Census. As mentioned before, there are some positions, such as goalkeeper, where Black representation is especially low; Appendix H examines the impact of this effect in more detail.

Table 9. Changes in England's Expected Win Probability Under Counterfactual Scenarios

Scenario Pairs	**Mean Win Probability (1)**	**Mean Win Probability (2)**	**Mean Difference**	**95% Conf. Interval**	**p-value**
Actual (1) vs. Non-Black England (2)	0.735	0.708	0.027	(0.022, 0.032)	0.0000
Actual (1) vs. Black-Only (2) England	0.735	0.702	0.033	(0.029, 0.037)	0.0000
Non-Black (1) vs. Black-Only (2) England	0.708	0.702	0.006	(0.000, 0.011)	0.0337

Notes: This table compares England's mean predicted win probabilities across actual and counterfactual team compositions. The second and third columns show the average predicted win probability for each scenario. The fourth column reports the mean difference between scenarios. Confidence intervals and p-values are based on paired t-tests.

Even under the counterfactuals, England still maintains a substantial TM valuation advantage over its opponents. The average valuation ratio declines from 3.65 in the actual case to 2.84 in the Non-Black England scenario and to 2.76 in the Black-Only scenario. While this reduction does erode England's relative dominance, it remains well above parity. Hence, the drop in expected win probability – though meaningful – is tempered by the continued imbalance in team aggregate TM value.

Table 10. Progression Probabilities of Actual England and the Counterfactual "Non-Black England" in UEFA Euro 2024 Playoffs

UEFA Euro 2024 Stage	England's Opponent	Actual Progression Probability	Counterfactual Progression Probability	Change in Progression Probability
Round of 16	Slovakia	0.644	0.605	-6.056%
Quarterfinals	Switzerland	0.395	0.347	-12.152%
Semifinals	Netherlands	0.177	0.141	-20.339%
Finals	Spain	0.070	0.050	-28.571%

Notes: Progression probabilities are calculated as the product of England winning a game based on the log-transformed TM value ratios of the two teams involved and the probability that England advanced through the previous round.

We briefly present the analysis on the progression probabilities of "Non-Black England" in UEFA Euro 2024. Through the playoffs, as depicted in Table 10, the probability of progressing to a later round decreases progressively, which implies that there are consequences to segregational national team policies in games that matter most in the international context.

While the "Non-Black England" scenario still predicts a high chance of winning early matches, its relative underperformance accumulates and becomes more visible in later stages of the UEFA Euro 2024. By simulating tournament pathways using actual and counterfactual valuations, we not only quantify the loss of expected win probability but can also show its practical implications for team success in a knockout tournament scenario.

6. Testing for Interaction Effects

A potential flaw in our research design is that our measure of ability might confound individual skill with team interaction effects. While TM valuations provide a consistent, exogenous proxy for individual player ability, they cannot, by construction, capture interaction effects among players once assembled into a national team. Any synergies or frictions arising from racial diversity would therefore be invisible in a model based solely on aggregated individual valuations.

In contrast, bookmaker odds reflect an equilibrium view of expected match performance in the betting market, incorporating both measurable player ability and unobserved factors – such as tactical cohesion, interpersonal compatibility, and potential cultural or communication frictions – that could arise from team diversity. We can test to see if our individual-based estimates are failing to capture such interaction effects. If interaction effects exist, and the market is at least weakly efficient, these effects should be embedded in bookmaker-implied win probabilities.

We denote Δp_i as the difference between bookmaker-implied win probability for England and the TM-model predicted win probability in match i. We estimate:

$$\Delta p_i = \beta_0 + \beta_1 \text{DivIndex}_i + \beta_2 \text{Home}_i + \beta_3 \text{OppVal}_i + \sum_{y=2018}^{2024} \gamma_y \{\text{Year} = y\} + \varepsilon_i \qquad (3)$$

The diversity measure, DivIndex_i, is based on Blau's index (Blau, 1977), defined as:

$$B = 1 - \sum_{j=1}^{k} p_j^2,$$

where p_j is the proportion of group members in category j and k is the number of categories for the attribute of interest. In the two-category racial context considered here (Black vs. non-Black), let s_i denote the share of Black starters in match i. Then:

$$B = 1 - [s_i^2 + (1 - s_i)^2] = 2s_i(1 - s_i),$$

which ranges from 0 (completely homogeneous) to 0.5 (equal representation). For interpretive convenience, we use a scaled Blau's index:

$$\text{DivIndex}_i = 4s_i(1 - s_i),$$

which rescales the measure to range from 0 to 1.

In equation (3), Home_i = 1 if England played at home, 0 otherwise, OppVal_i is a standardized TM valuation of the opponent's starting eleven. Additionally, year fixed effects control for temporal variation in team strength and market conditions.

Table 11. Testing for Interaction Effects: Bookmaker-TM Probability Difference as a Function of Team Diversity

Variable / Statistic	Model Coefficient
Diversity Index	0.164
	(0.134)
Home (=1)	0.093***
	(0.017)
Opponent Valuation (std.)	-0.009
	(0.009)
Year = 2018	-0.045
	(0.046)
Year = 2019	0.033
	(0.045)
Year = 2020	0.007
	(0.050)
Year = 2021	0.123***
	(0.043)
Year = 2022	0.029
	(0.046)
Year = 2023	0.101**
	(0.047)
Year = 2024	-0.007
	(0.044)
Constant	-0.432***
	(0.137)
Observations (n)	80
Adjusted R^2	0.475

Notes: This table reports the results of an OLS regression where the dependent variable is the difference between bookmaker-implied win probability for England and TM-model predicted win probability (Δp_i). Diversity Index is a scaled Blau's index, defined as $4s_i(1 - s_i)$, where s_i is the share of Black starters in match i; this rescales the standard Blau's index. Opponent valuation is standardized by sample mean and standard deviation. Year effects are relative to the 2016–2017 base period. Standard errors are in parentheses. Significance codes: *** p < 0.01, ** p < 0.05, * p < 0.1.

We report the results of the diversity index analysis in Table 11. The point coefficient on *Diversity Index* is positive but not statistically significant, suggesting no systematic adjustment in

bookmaker probabilities for different levels of racial diversity once ability is accounted for. The only strongly significant covariate is the home indicator, with England's bookmaker probability exceeding the TM-based estimate by roughly 9.3 percentage points in home matches. The absence of a significant relationship between the diversity index and the bookmaker-TM probability gap suggests that racial diversity does not materially influence market-based assessments of England's win probability once player ability is accounted for. This supports our earlier findings from Section 5 that diversity's primary performance benefit operates through enlarging the pool of available high-ability players, while any interaction effects are at most second-order considerations.

7. Conclusion

In this paper, we set out to estimate the performance consequences of racially exclusive selection policies in national soccer teams. Using TM player valuations as proxies for individual productivity and overall team quality, we built a forecasting model for international match outcomes and simulated two counterfactual scenarios for the England men's national team: one excluding Black players entirely, and the other composed solely of Black players. Both counterfactuals produced lower cumulative team valuations – driven largely by positional constraints – and, in turn, lower expected win probabilities. Although the estimated effects are modest in magnitude, they are meaningful in high-stakes knockout tournament context (e.g., UEFA Euro 2020), where small changes in win probability can compound across knockout rounds and affect the likelihood of reaching higher playoff stages.

The central contribution of this paper is not to estimate racial prejudice directly, nor to claim that racially restrictive national team selection rules are realistic contemporary policies. Instead, using the case of England national team, we quantify the opportunity cost of restricting access to the full eligible talent pool on the basis of race. In high-performance labor markets, where organizations compete to assemble the upper tail of the productivity distribution, even small restrictions on the selection set can reduce expected output. The England case demonstrates this mechanism clearly: when selection is constrained by race rather than player quality, expected team quality declines under both racially restricted counterfactuals.

Recognizing that valuations cannot capture player interaction effects by design, we complemented the counterfactual analysis with a market-based robustness check. For 80 competitive England matches between 2016 and 2024, we compared our model's win probability forecasts to bookmaker-implied probabilities, which reflect both observable ability and unobservable factors such as tactical cohesion, interpersonal compatibility, or cultural frictions. Regressing the bookmaker-TM probability gap on a match-level scaled diversity index and controlling for venue, opponent strength, and year fixed effects yielded no statistically significant association. This suggests that betting markets do not systematically adjust expectations for racial diversity once ability is accounted for, reinforcing the view that the primary performance benefit of an unrestricted selection policy operates through access to a broader pool of high-productivity players, rather than through measurable interaction effects associated with racial composition itself.

This finding also speaks to broader debates about racial representation in soccer labor markets. Black players constitute a substantial share of elite English playing talent, yet this representation has not translated into comparable access to coaching and managerial roles. Our analysis does not directly estimate the performance consequences of excluding Black coaches, because coaching productivity is harder to observe and credible counterfactual appointments are rarely available. However, the player-side counterfactual provides a useful analogue. This raises the possibility that exclusion in less observable leadership markets may also carry organizational costs that are harder to quantify but no less important.

While England represents a distinctive case, similar counterfactual exercises could be applied to other national teams where the politics of identity and belonging are contested. In France, far-right political figures such as Jean-Marie Le Pen have criticized the racial composition of the national team, even in the wake of major international successes (Morrissey, 2009; Storey, 2020). In Italy, racialized constructions of "Italianness" have shaped debates over national team legitimacy, particularly with respect to Black and immigrant-background players (Kyeremeh, 2020). These contexts illustrate how national identity and racial representation remain deeply intertwined with sport, and how counterfactual modeling can help quantify the potential costs of culturally or racially exclusive selection strategies.

Future work could refine valuation proxies, integrate tactical compatibility metrics, and extend the analysis to women's and youth national teams. Future research should also examine the transition from playing careers into coaching and executive roles, where racialized exclusion may be especially consequential but empirically harder to measure. More broadly, we encourage researchers to view counterfactual modeling not merely as a statistical exercise, but as a tool for revealing the often-hidden competitive costs of exclusion in high-performance sport.

References

Adao, R., Costinot, A., & Donaldson, D. (2017). Nonparametric counterfactual predictions in neoclassical models of international trade. *American Economic Review*, *107*(3), 633–689. https://doi.org/10.1257/aer.20150956

Balsmeier, B., Frick, B., & Hickfang, M. (2019). The impact of skilled immigrants on their local teammates' performance. *Applied Economics Letters*, *26*(2), 97–103. https://doi.org/10.1080/13504851.2018.1441495

Becker, G. S. (1957). *The economics of discrimination*. University of Chicago Press.

BelfastTelegraph.co.uk. (2019). *Raheem sterling becomes England's seventh black captain*. https://www.belfasttelegraph.co.uk/sport/football/raheem-sterling-becomes-englands-seventh-black-captain/38189471.html.

Ben-Ner, A., Licht, J. G., & Park, J. (2017). Bifurcated effects of place-of-origin diversity on individual and team performance: Evidence from ten seasons of German soccer. *Industrial Relations: A Journal of Economy and Society*, *56*(4), 555–604. https://doi.org/10.1111/irel.12188

Blau, P. M. (1977). *Inequality and heterogeneity: A primitive theory of social structure*. Free Press.

Bosker, J., & Gürtler, M. (2024). The impact of cultural differences on the success of elite labor migration – evidence from professional soccer. *Annals of Operations Research*, *341*(2), 781–824. https://doi.org/10.1007/s10479-024-06200-4

Brox, E., & Krieger, T. (2022). Birthplace diversity and team performance. *Labour Economics*, *79*, 102288. https://doi.org/10.1016/j.labeco.2022.102288

Bryant, B. E., Jordan, A., & Clark, U. S. (2022). Race as a social construct in psychiatry research and practice. *JAMA Psychiatry*, *79*(2), 93–94.

https://doi.org/10.1001/jamapsychiatry.2021.2877

Cain, G. G. (1986). The economic analysis of labor market discrimination: A survey. In O. Ashenfelter & R. Layard (Eds.), *Handbook of labor economics* (Vol. 1, pp. 693–785). Elsevier. https://doi.org/10.1016/S1573-4463(86)01016-7

Campbell, P. I. (2018). *Football and race relations have progressed a lot since Cyrille Regis's day – but not enough*. https://theconversation.com/football-and-race-relations-have-progressed-a-lot-since-cyrille-regiss-day-but-not-enough-90274

Carmichael, F., McHale, I., & Thomas, D. (2011). Maintaining market position: Team performance, revenue and wage expenditure in the English premier league. *Bulletin of Economic Research*, *63*(4), 464–497. https://doi.org/10.1111/j.1467-8586.2009.00340.x

Cashmore, E., & Cleland, J. (2011). Why aren't there more black football managers? *Ethnic and Racial Studies*, *34*(9), 1594-1607. https://doi.org/10.1080/01419870.2011.595556

Clarke, S. R., & Norman, J. M. (1995). Home ground advantage of individual clubs in English soccer. *Journal of the Royal Statistical Society: Series D (The Statistician)*, *44*(4), 509 521. https://doi.org/10.2307/2348899

Coates, D., Frick, B., & Jewell, R. T. (2016). Superstar salaries and soccer success: The impact of designated players in major league soccer. *Journal of Sports Economics*, *17*(7), 716–735. https://doi.org/10.1177/1527002514547297

Coates, D., & Parshakov, P. (2022). The wisdom of crowds and transfer market values. *European Journal of Operational Research*, *301*(2), 523–534. https://doi.org/10.1016/j.ejor.2021.10.046

Corbie-Smith, G., Henderson, G., Blumenthal, C., Dorrance, J., & Estroff, S. (2008). Conceptualizing race in research. *Journal of the National Medical Association*, *100*(10), 1235–1243. https://doi.org/10.1016/S0027-9684(15)31470-X

Cunningham, G. B. (2010). Understanding the under-representation of African American coaches: A multilevel perspective. *Sport Management Review*, *13*(4), 395–406. https://doi.org/10.1016/j.smr.2009.07.006

Deschamps, P., & De Sousa, J. (2021). Labor mobility and racial discrimination. *European Economic Review, 135*, 103738. https://doi.org/10.1016/j.euroecorev.2021.103738

Deutscher, C., Frick, B., & Ötting, M. (2018). Betting market inefficiencies are short-lived in German professional football. *Applied Economics*, *50*(30).

https://doi.org/10.1080/00036846.2017.1418082
Di Domizio, M., Bellavite Pellegrini, C., & Caruso, R. (2022). Payroll dispersion and performance in soccer: A seasonal perspective analysis for Italian Serie A (2007–2021). *Contemporary Economic Policy*, *40*(3), 513–525. https://doi.org/10.1111/coep.12566
Dixon, M. J., & Coles, S. G. (1997). Modelling association football scores and inefficiencies in the football betting market. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, *46*(2), 265–280. https://doi.org/10.1111/1467-9876.00065
Dolles, H., Söderman, S., Ruigrok, W., Greve, P., & Engeler, M. (2011). International experiential diversity and performance at project organizations: The case of national football teams. *Sport, Business and Management*, *1*(3), 267–283. https://doi.org/10.1108/20426781111162675
Ducking, J., & Groothuis, P. A. (2023). Positional Segregation and Career Length in Major League Baseball in the 1990s. *Journal of Economics, Race, and Policy*, *6*(3), 149–159. https://doi.org/10.1007/s41996-023-00123-1
Elling, A., Van Hilvoorde, I., & Van Den Dool, R. (2014). Creating or awakening national pride through sporting success: A longitudinal study on macro effects in the Netherlands. *International Review for the Sociology of Sport*, *49*(2), 129–151. https://doi.org/10.1177/1012690212455961
England's black players - most appearances. (n.d.). http://www.englandfootballonline.com/TeamBlack/PlyrsBlckMtchUsage/PlyrsBlackMostCapped.html.
Feddersen, A., Humphreys, B. R., & Soebbing, B. P. (2017). Sentiment bias and asset prices: Evidence from sports betting markets and social media. *Economic Inquiry*, *55*(2), 1119–1129. https://doi.org/10.1111/ecin.12404
Football statistics and history | FBref.com. (n.d.). https://fbref.com/en/.
Fort, R., & Quirk, J. (1995). Cross-subsidization, incentives, and outcomes in professional team sports leagues. *Journal of Economic Literature*, *33*(3), 1265–1299.
Franck, E., Verbeek, E., & Nüesch, S. (2010). Prediction accuracy of different market structures—bookmakers versus a betting exchange. *International Journal of Forecasting*, *26*(3), 448–459. https://doi.org/10.1016/j.ijforecast.2010.01.004
Frick, B. (2013). Team wage bills and sporting performance: Evidence from (major and minor)

European football leagues. In D. J. Berri (Ed.), *The Econometrics of Sport* (pp. 63–80). Edward Elgar Publishing. https://doi.org/10.4337/9781781002865.00012

Gasparetto, T. (2025). Multicultural teams: Does national diversity associate with performance in professional soccer? *PLoS One*, *20*(5), e0325025. https://doi.org/10.1371/journal.pone.0325025

Goddard, J., & Asimakopoulos, I. (2004). Forecasting football results and the efficiency of fixed odds betting. *Journal of Forecasting*, *23*(1), 51–66. https://doi.org/10.1002/for.877

Gregory-Smith, I., Bryson, A., & Gomez, R. (2023). Discrimination in a rank order contest: Evidence from the NFL draft. *Journal of Economics, Race, and Policy*, *6*(3), 215–231. https://doi.org/10.1007/s41996-023-00118-y

Haas, H., & Nüesch, S. (2012). Are multinational teams more successful? *The International Journal of Human Resource Management*, *23*(15), 3105–3113. https://doi.org/10.1080/09585192.2011.610948

Head, K., & Mayer, T. (2023). Poor substitutes? Counterfactual methods in IO and trade compared. *Review of Economics and Statistics*, 1–51. https://doi.org/10.1162/rest_a_01369

Herm, S., Callsen-Bracker, H. M., & Kreis, H. (2014). When the crowd evaluates soccer players' market values: Accuracy and evaluation attributes of an online community. *Sport Management Review*, *17*(4), 484–492. https://doi.org/10.1016/j.smr.2013.12.006

Huang, Y., Washington, M., Soebbing, B. P., & Mason, D. S. (2023). Wearing the same jersey? The impact of players' cultural diversity and shared team tenure on national soccer team performance. *Journal of Economics, Race, and Policy*, *6*(3), 160–172. https://doi.org/10.1007/s41996-023-00120-4

Hvattum, L. M., & Arntzen, H. (2010). Using ELO ratings for match result prediction in association football. *International Journal of Forecasting*, *26*(3), 460–470. https://doi.org/10.1016/j.ijforecast.2009.10.002

Jankowski, T. (2015). *Successful German soccer tactics: The best match plans for a winning team*. Meyer & Meyer Sport.

Kahane, L., Longley, N., & Simmons, R. (2013). The effects of coworker heterogeneity on firm level output: Assessing the impacts of cultural and language diversity in the National Hockey League. *Review of Economics and Statistics*, *95*(1), 302–314.

https://doi.org/10.1162/rest_a_00221

Késenne, S. (2000). Revenue sharing and competitive balance in professional team sports. *Journal of Sports Economics*, *1*(1), 56–65. https://doi.org/10.1177/152700250000100105

Kyeremeh, S. A.-G. (2020). Whitening Italian sport: The construction of "Italianness" in national sporting fields. *International Review for the Sociology of Sport*, *55*(8), 1136–1151. https://doi.org/10.1177/1012690219878117

Lago, I., Lago-Peñas, C., & Lago-Peñas, S. (2023). Work group diversity in professional football: An individual-level approach to the effects of diversity in organizations. *Social Science Quarterly*, *104*(4), 927–941. https://doi.org/10.1111/ssqu.13262

Lopez, I. F. H. (1994). The social construction of race: Some observations on illusion, fabrication, and choice. *Harvard Civil Rights–Civil Liberties Law Review*, *29*, 1–62.

Maderer, D., Holtbrügge, D., & Schuster, T. (2014). Professional football squads as multicultural teams: Cultural diversity, intercultural experience, and team performance. *International Journal of Cross Cultural Management*, *14*(2), 215–238. https://doi.org/10.1177/1470595813510710

Melnick, M. J. (1988). Racial segregation by playing position in the English football league: Some preliminary observations. *Journal of Sport and Social Issues*, *12*(2), 122–130. https://doi.org/10.1177/019372358801200204

Men's football | Black Footballers Partnership. (2022). https://www.bfporg.com/mens-football/.

Mills, B. M., Bopp, T., & Turick, R. (2026). Leadership Representation and Team Performance: Evidence from Collegiate Football. *Journal of Economics, Race, and Policy*, *9*(1), 12–29. https://doi.org/10.1007/s41996-025-00179-1

Mills, J. P., Ing, C., Markham, T., & Guppy, F. (2018). It is not black and white: A comparison of skin tone by playing position in the Premier League and English football. *International Journal of Sports Science & Coaching*, *13*(3), 398–404. https://doi.org/10.1177/1747954117749747

Morrissey, S. (2009). "Un homme avant tout": Zinedine Zidane and the sociology of a head-butt. *Soccer & Society*, *10*(2), 210–225. https://doi.org/10.1080/14660970802601696

Nauright, J., & Wiggins, D. K. (Eds.). (2017). *Routledge handbook of sport, race and ethnicity.* Routledge. https://doi.org/10.4324/9781315745886

Nightingale, C. H. (2022). *Segregation: A global history of divided cities.* University of Chicago

Press.
Nüesch, S. (2009). Are demographic diversity effects spurious? *Economic Analysis & Policy*, *39*(3), 379–388. https://doi.org/10.1016/s0313-5926(09)50034-3
Palacios-Huerta, I. (2025). The Beautiful Dataset. *Journal of Economic Literature*, *63*(4), 1363–1423. https://doi.org/10.1257/jel.20241616
Papps, K. L., Bryson, A., & Gomez, R. (2011). Heterogeneous worker ability and team-based production: Evidence from Major League Baseball, 1920–2009. *Labour Economics*, *18*(3), 310–319. https://doi.org/10.1016/j.labeco.2010.11.005
Peeters, T. (2018). Testing the wisdom of crowds in the field: Transfermarkt valuations and international soccer results. *International Journal of Forecasting*, *34*(1), 17–29. https://doi.org/10.1016/j.ijforecast.2017.08.002
Prockl, F., & Frick, B. (2018). Information precision in online communities: Player valuations on www.transfermarkt.de. *International Journal of Sport Finance*, *13*(4), 319–335. https://doi.org/10.1177/155862351801300402
Reade, J. J., & Royle, D. (2025). Management mathematics in sport – Moneyball and soccer. *IMA Journal of Management Mathematics*, *36*(2), 181–196. https://doi.org/10.1093/imaman/dpaf015
Rosen, S. (1981). The economics of superstars. *The American Economic Review*, *71*(5), 845-858.
Rottenberg, S. (1956). The baseball players' labor market. *Journal of Political Economy*, *64*(3), 242–258. https://doi.org/10.1086/257790
Shropshire, K. L. (1996). *In black and white: Race and sports in America.* NYU Press.
Smith, M. A., Paton, D., & Williams, L. V. (2009). Do bookmakers possess superior skills to bettors in predicting outcomes? *Journal of Economic Behavior & Organization*, *71*(2), 539–549. https://doi.org/10.1016/j.jebo.2009.03.016
SRO, L. (n.d.). *Odds comparison, sports betting odds | odds portal*. https://www.oddsportal.com/
Stiglitz, J. E. (1973). Approaches to the economics of discrimination. *American Economic Review*, *63*(2), 287–295.
Storey, D. (2020). National allegiance and sporting citizenship: Identity choices of "African" footballers. *Sport in Society*, *23*(1), 129–141. https://doi.org/10.1080/17430437.2018.1555228
Szymanski, S. (2000). A market test for discrimination in the English professional soccer

leagues. *Journal of Political Economy*, 108 (3), 590–603. https://doi.org/10.1086/262130

Szymanski, S. (2003). The economic design of sporting contests. *Journal of Economic Literature*, *41*(4), 1137–1187. https://doi.org/10.1257/jel.41.4.1137

Szymanski, S., & Smith, R. (1997). The English football industry: Profit, performance and industrial structure. *International Review of Applied Economics*, *11*(1), 135–153. https://doi.org/10.1080/02692179700000008

Torgler, B., & Schmidt, S. L. (2007). What shapes player performance in soccer? Empirical findings from a panel analysis. *Applied Economics*, *39*(18), 2355–2369. https://doi.org/10.1080/00036840600660739

Tovar, J. (2020). Performance, diversity and national identity evidence from association football. *Economic Inquiry*, *58*(2), 897–916. https://doi.org/10.1111/ecin.12861

Transfermarkt.com. (n.d.). https://www.transfermarkt.com/

UK Census (2021). (n.d.). https://www.ons.gov.uk/census

Vlastakis, N., Dotsis, G., & Markellos, R. N. (2009). How efficient is the European football betting market? Evidence from arbitrage and trading strategies. *Journal of Forecasting*, *28*(5), 426–444. https://doi.org/10.1002/for.1085

Wang, G. Y. (2024). The role of diversity in determining team efficiency: An empirical sports team analysis. *Journal of Data, Information and Management*, *6*(1), 85–98. https://doi.org/10.1007/s42488-024-00115-2

Wegelin, P., Orlowski, J., & Dietl, H. M. (2022). The importance of high performing team members in complex team work: Results from quasi-experiments in professional team sports. *Economic Inquiry*, *60*(3), 1296–1310. https://doi.org/10.1111/ecin.13076

Weiss, J. B., & Sommers, P. M. (2009). Does team racial composition affect team performance in the NBA? *Atlantic Economic Journal*, *37*(1), 119–120. https://doi.org/10.1007/s11293-008-9156-4

Winkelmann, D., Ötting, M., Deutscher, C., & Makarewicz, T. (2024). Are betting markets inefficient? Evidence from simulations and real data. *Journal of Sports Economics*, *25*(1), 54–97. https://doi.org/10.1177/15270025231204997

Wittkugel, J., Memmert, D., & Wunderlich, F. (2022). Substitutions in football–what coaches think and what coaches do. *Journal of Sports Sciences*, *40*(15), 1668–1677. https://doi.org/10.1080/02640414.2022.2099177

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